LIQUIDITY, CONSUMPTION, AND THE CROSS-SECTIONAL RETURNS

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Abstract

My thesis attempts to examine the determinants of the cross-sectional stock returns. It mainly consists of three topics on the relation between consumption, stock liquidity, financial constraints, and expected returns.

The first is "Transaction costs, liquidity risk, and the CCAPM". I examine how the consumption-based capital asset pricing model (CCAPM) performs with transaction costs and liquidity risk adjustments. Using the effective trading costs of Hasbrouck (2009) and the high-low spread estimates of Corwin and Schultz (2012) as proxies for transaction costs, I find that a liquidity risk-adjusted CCAPM explains a larger fraction of the cross-sectional return variations than that of the traditional CCAPM. I show that my liquidity risk-adjusted model gives more plausible risk aversion estimates than the CCAPM.

The second is "The Liquidity risk adjusted Epstein-Zin model". In this chapter, I propose a liquidity risk adjustment to the Epstein and Zin (1989, 1991) model and assess the adjusted model's performance against the traditional consumption pricing models. I show that liquidity is a significant risk factor and it adds considerable

explanatory power to the model. The liquidity-adjusted model produces both a higher cross-sectional R^2 and a smaller Hansen and Jagannathan (1997) distance than the traditional CCAPM and the original Epstein-Zin model. Overall, I show that liquidity is both a priced factor and a key contributor to the adjusted Epstein-Zin model's goodness-of-fit.

The third is "Financial constraints, stock liquidity, and stock returns". I examine the different impacts of stock liquidity on the stock returns across financially constrained and unconstrained firms due to different levels of information asymmetry. My results show that financial constraints are highly correlated with liquidity and liquidity risk. More importantly, stock liquidity is a significant determinant of the cross-sectional stock returns for financially constrained firms, but it is insignificant for unconstrained firms. In addition, stock liquidity is a main driver of the different relations between financial constraints and stock returns. The liquidity premium accounts for the positive constraint premium, but it cannot be subsumed by the constraint premium.

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Contents

List of notations

AQ: accruals quality

AT: asset size

BA: quoted bid-ask spread

BL: book leverage

B/M: book-to-market ratio

BR: long-term bond rating

$B(W)$: ending bequest function

C: consumption

CF: cash flow

cGibbs: Hasbrouck's (2009) effective transaction costs measure

CH: cash holdings

CR: commercial paper rating

CSspread: the bid-ask spread estimates from daily high and low prices by Corwin and Schultz (2012)

D: dividend

DUR: durable consumption

DV: dollar volume

EP: earnings precision

H: housing services

LM: standardized turnover-adjusted number of zero daily trading volumes

MOM: momentum

MV: market capitalization

P: ex-dividend stock price

PF: profitability

PR: payout ratio

Q: Tobin's Q

R: stock return

R_f: risk-free rate

RV: absolute return to dollar volume ratio

TA: tangible asset

TC: per-share cost of selling stock

TO: turnover

W: wealth X: habit

TO: labor income

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Chapter 1

Introduction

1.1 Research questions

Stock liquidity is currently the subject of much research interest. In general, liquidity is related to transaction costs, thin or infrequent trading, and the impact of trading on price. There are several empirical measures to measure stock liquidity. I review these commonly used empirical measures in chapter 2. Many early studies concentrate on the importance of liquidity. Recent studies examine the role of liquidity risk in asset pricing. Liquidity risk is related to the difficulties of liquidating a security at a fair price. In Pastor and Stambaugh (2003), Liu (2006), and Sadka (2006), liquidity risk is defined as the covariance between stock return and market liquidity. Acharya and Pedersen (2005) study three forms of liquidity risks: commonality in liquidity of Chordia, Roll, and Subrahmanyam (2000), stock return sensitivity to the market liquidity of Pastor and Stambaugh (2003), and stock liquidity sensitivity to market returns.

While previous studies focus on the empirical measures of liquidity, recent studies also investigate the implications of liquidity in asset pricing. Early studies such as Amihud and Mendelson (1986), Brennan and Subrahmanyam (1996), and Amihud (2002) point out that investors require higher expected returns to hold less liquidity assets. Recent studies show that augmenting the traditional CAPM (Sharpe (1964) and Lintner (1965)) or the Fama-French three-factor model (Fama and French (1993)) with liquidity factors improves the performance of the CAPM and the Fama–French three-factor model (Pastor and Stambaugh (2003), Liu (2006), and Sadka (2006)). Note that these papers do not account for consumption growth and financial constraints. Financial constraints are generally related to the firms' inability to access to low-cost external finance to fund investment because of financial frictions (Lamont, Polk, and Saa-Requejo (2001)). Many studies develop several empirical proxies to measure financial constraints. I review the various financial constraints measures in chapter 2. Moreover, recent studies focus on the asset pricing implications of financial constraints (e.g., Lamont, Polk, and Saa-Requejo (2001), Whited and Wu (2006), and Livdan, Sapriza, and Zhang (2009)).

In this thesis, I attempt to understand the effects of consumption, stock liquidity, financial constraints and I ask the following research questions:

(i) How does the traditional CCAPM (Rubinstein (1976), Lucas (1978), and Breeden (1979)) perform after adjusting for transaction costs and liquidity risk? Can a liquidity-adjusted CCAPM account for a higher fraction of expected cross-sectional returns and produce a more reasonable estimate of risk aversion than that of the traditional CCAPM?

(ii) How does the Epstein and Zin (1989, 1991) model perform with liquidity risk adjustment? Does a liquidity factor make a significant contribution to a model's goodness-of-fit? Is the performance of a liquidity-augmented Epstein and Zin model better than the traditional CCAPM and Epstein and Zin model?

(iii) Is stock liquidity related to financial constraints? What is the variation of liquidity for the financially constrained firms and unconstrained firms? What is the variation of liquidity premium for the constrained firms and unconstrained firms? Do the constrained firms have higher liquidity risk than the unconstrained firms?

1.2 Research motivation and contributions

This thesis is motivated by recent studies in asset pricing that highlight the important role of liquidity in investors' consumption and investment decisions. For example, Parker and Julliard (2005) argue that concerns of liquidity are perhaps imperative components neglected by consumption risk alone. Liu (2010) and Chien and Lustig (2010) suggest that liquidity risk may originate from consumption and solvency constraints. Næs, Skjeltorp, and Ødegaard (2011) find that aggregate stock liquidity has significant ability to predict consumption growth. Lynch and Tan (2011) show that transaction costs can produce a first-order effect when they incorporate return predictability, wealth shocks, and state-dependent costs into the traditional consuming and investing problems.

Following this lead, I extend the traditional CCAPM by taking into account the liquidity effect. I decompose security risk into consumption risk (the covariance between returns and consumption growth) and liquidity risk (the covariance between transaction costs and consumption growth). I find that transaction costs, consumption risk, and liquidity risk jointly affect expected stock returns. Moreover, I show that the three channels of liquidity risk of Acharya and Pedersen (2005) can be captured by the covariance between transaction costs and consumption growth. The liquidity-adjusted CCAPM adds, contingent on specifications, up to 77% additional explanatory power to the cross-sectional variation of expected returns, compared to the traditional CCAPM. I also find that the estimated risk aversion from the liquidity-adjusted model is about 10. This is much smaller than the corresponding risk aversion estimated under the CCAPM. Therefore, my results help to understand the equity premium puzzle. Further, I find that the patterns of estimated liquidity betas conditional on the economic states provide a liquidity-risk based explanation for the countercyclical value premium.

While existing studies make adjustment to the CAPM or the Fama-French three-factor model with liquidity risk and show that models with liquidity adjustment reveal significantly increased explanatory power (e.g., Pastor and Stambaugh (2003), Acharya and Pedersen (2005), Liu (2006), and Sadka (2006), and Bekaert, Harvey, and Lundblad (2007)), there are few studies incorporating liquidity risk into consumption based pricing models. I extend the Epstein and Zin (1989, 1991) model by incorporating the liquidity effect. I show that, in my liquidity-augmented model, the expected stock return is related to the consumption risk, market risk, and liquidity risk. Kan, Robotti, and Shanken (2013) argue that examining whether a factor makes an incremental contribution to a multi-factor model's performance is different from testing whether the factor is priced. I show that the liquidity factor contributes significantly to the model's goodness-of-fit. In addition, in terms of both the cross-sectional R^2 and HJ distance (Hansen and Jagannathan (1997)), the results show that my model performs better than the traditional CCAPM and the Epstein-Zin model based on the equality tests of cross-sectional R^2 (Kan, Robotti, and Shanken (2013)) and HJ distance (Kan and Robotti (2009)).

While I have investigated the effects of stock liquidity on investors' consumption and investment decisions, I then explore whether financial constraints and stock liquidity are correlated to each other. A growing literature shows that the expected returns are positively related to stock illiquidity and liquidity risk.[1] Earlier studies show that illiquidity may arise from information asymmetry (e.g., Kyle (1985)) or unfavorable economic states (e.g., Chordia, Sarkar, and Subrahmanyam (2005)). More recently, Li and Zhang (2010) and Lam and Wei (2011) suggest that investment frictions from firms' side and transaction frictions from investors' side tend to be related

[1] Representative papers include Amihud and Mendelson (1986), Datar, Naik, and Radcliffe (1998), Amihud (2002), Pastor and Stambaugh (2003), Acharya and Pedersen (2005), Liu (2006), and Sadka (2006).

to each other.

Following these streams of literature, I examine the relation between financial constraints, stock liquidity, and expected returns under the framework of investment-based and consumption-based asset pricing.[2] In my empirical analysis, I show that the effects of stock liquidity on the cross-sectional returns are significant for financially constrained firms but insignificant for unconstrained firms. Further, I find that the mixed relation between financial constraints and stock returns are associated with stock liquidity and different constraint classifications. The illiquidity premium accounts for the financial constraint premium, but cannot be subsumed by the constraint premium. These findings help to shed light on the mixed relation between financial constraints and stock returns in existing studies.

1.3 Thesis structure

The remainder of the thesis proceeds as follows. In Chapter 2, I review the classic asset pricing models, which include the traditional CAPM, the traditional CCAPM, other advanced consumption-based asset pricing models, and the investment-based asset pricing model. In Chapter 3, I discuss the basic research methodologies. In Chapter 4, I discuss the performance of the consumption-based capital asset pricing model (CCAPM) with transaction costs and liquidity risk adjustments. I attempt to compare the cross-sectional R^2 and the implied risk aversion coefficient of my

[2]See Rubinstein (1976), Lucas (1978), and Breeden (1979) for the consumption-based asset pricing model, and Cochrane (1991), Cochrane (1996), and Zhang (2005) for the investment-based asset pricing model.

liquidity-adjusted model to those the of traditional CCAPM. In Chapter 5, I analyze the role of liquidity risk in a model's performance. I attempt to investigate whether liquidity risk is priced and whether the liquidity risk factor makes an incremental contribution to the model's goodness-of-fit. In Chapter 6, I link financial constraints and stock liquidity using the framework of the investment-based asset pricing model and the consumption-based asset pricing model. I then examine the interaction between financial constraints, stock liquidity, and expected returns. In Chapter 7, I conclude the thesis.

Chapter 2

Literature Review

2.1 Traditional CAPM

The traditional CAPM of Sharpe (1964) and Lintner (1965) provides foundations for financial research, e.g., the capital budgets, performance evaluation of managers, and creation of financial indices. It links asset returns with market risk, the covariance of individual asset returns and market returns. The traditional CAPM can be developed by maximizing expected utility of wealth. Specifically, investors maximize $U(W_T) = U(RW_0)$, where W_T is the end-of-period wealth, W_0 is the beginning-of-period wealth, and R is a random gross return on an asset. When W_0 is fixed, W_T is determined by R. Then the utility function, $U(W_T)$, can be simply expressed as $U(R)$. I expand $U(R)$ in a Taylor series around the mean of R ($E[R]$).

$$
\begin{aligned}
U(R) = & U\left(E[R]\right) + \left(R - E[R]\right) U'\left(E[R]\right) + \frac{1}{2}\left(R - E[R]\right)^2 U''\left(E[R]\right) \\
& + ... + \frac{1}{n!}\left(R - E[R]\right)^n U^{(n)}\left(E[R]\right)
\end{aligned} \tag{2.1}
$$

where $U'()$, $U''()$, and $U^{(n)}()$ are the first, second, and n^{th} derivatives of the utility function.

When the return is normally distributed, I can have $E\left[\left(R - E[R]\right)^n\right] = 0$ for any $n \in 2n+1$ and $E\left[\left(R - E[R]\right)^n\right] = \frac{n!}{(n/2)!}\left(\frac{1}{2}Var[R]\right)^{\frac{n}{2}}$ for any $n \in 2n$. Hence, I can simplify the expected utility as:

$$
\begin{aligned}
E\left[U(R)\right] = & U\left(E[R]\right) + \frac{1}{2}Var[R]U''\left(E[R]\right) + 0 + \frac{1}{8}\left(Var[R]\right)^2 U''''\left(E[R]\right) \\
& + ... + \frac{1}{(n/2)!}\left(\frac{1}{2}Var[R]\right)^{\frac{n}{2}} U^{(n)}\left(E[R]\right)
\end{aligned} \tag{2.2}
$$

.

Eq. (2.2) indicates that the expectation of utility is determined only by the mean and variance of the return.

Given the expected returns and the matrix of covariances of returns for n individual assets, Merton (1972) provides an analytical solution to the set of portfolio weights that minimizes the variance of the portfolio for each feasible portfolio expected return. The expected returns ($\bar{R_p}$) and variance (σ_p^2) of the portfolio has the form:

$$\bar{R}_p = \omega' \bar{R} \tag{2.3}$$

and

$$\sigma_p^2 = \omega' V \omega, \tag{2.4}$$

where $\bar{R} = (\bar{R}_1, \bar{R}_2, ..., \bar{R}_n)'$ is a $n \times 1$ vector of the expected returns of the n assets, $\omega = (\omega_1, \omega_2, ..., \omega_n)'$ is a $n \times 1$ vector of the portfolio weights, and V assumed to be of full rank is the $n \times n$ covariance matrix of the returns on the n assets. The portfolio weights sum to one, i.e., $\omega' e = 1$, where e is a $n \times 1$ vector of one.

According to Merton (1972), the optimal weight of n risky asset and a risk-free asset that maximize the expected utility has the form:

$$\omega^* = \lambda V^{-1}(\bar{R} - R_f e), \tag{2.5}$$

where $\lambda = \frac{\bar{R}_p - R_f}{\varsigma - 2\alpha R_f + \delta R_f^2}$, $\alpha = \bar{R}' V^{-1} e = e' V^{-1} \bar{R}$, $\varsigma = \bar{R}' V^{-1} \bar{R}$, $\delta = e' V^{-1} e$, and R_f is the risk-free rate. The amount that investors invest in the risk-free asset is $1 - e'\omega^*$.

For the portfolio that has a zero position in the risk-free asset, I can have $e'\omega^* = 1$. Using Eq. (2.5), I can have $\lambda = (\alpha - \delta R_f)^{-1}$. According to Merton (1972), Sharpe (1964), and Lintner (1965), I can write the weight of efficient frontier portfolio (ω^m) as:

$$\omega^m = (\alpha - \delta R_f)^{-1} V^{-1} (\bar{R} - R_f e). \tag{2.6}$$

Define σ_M as the $n \times 1$ vector of covariance of the efficient frontier portfolio with each of the n risky assets. Using Eq. (2.6), I can have

$$\sigma_M = V\omega^m = (\alpha - \delta R_f)^{-1} (\bar{R} - R_f e). \tag{2.7}$$

Further, I can write the variance of the efficient frontier portfolio ($\sigma_m = \omega^{m\prime} V \omega^m$) as:

$$\sigma_m = (\alpha - \delta R_f)^{-1} (\bar{R}_m - R_f), \tag{2.8}$$

where $\bar{R_m} = \omega^{m\prime} \bar{R}$ is the expected return on the efficient frontier portfolio.

Using Eqs. (2.7) and (2.8), I can have

$$\bar{R} - R_f e = \beta (\bar{R}_m - R_f), \tag{2.9}$$

where $\beta = \frac{\sigma_M}{\sigma_m}$ is the $n \times 1$ vector. Eq. (2.9) is the traditional CAPM of Sharpe (1964) and Lintner (1965).

2.2 Traditional CCAPM

Breeden (1979), Lucas (1978), and Rubinstein (1976) develop a closed-form relation between asset returns and consumption, i.e., the traditional consumption-based capital asset pricing model (CCAPM). Following these studies, I assume that there exits a representative consumer, i.e., all individuals are identical with respect to utility and initial wealth, as in Lucas (1978). I develop a model based on the representative consumer's multiperiod consumption and investment decision model of Samuelson (1969) and Merton (1969). The decision interval is a discrete time period and each period is of unit length. The representative consumer maximizes her lifetime utility functions with respect to consumption and a terminal bequest function, and chooses to invest in n risky assets and a risk-free asset.

Let the representative consumer's time t portfolio weight of the risky asset i be $\omega_{i,t}$ $(i = 1, 2, ..., n)$, the weight of the risk-free asset is then $1 - \sum_{i=1}^{n} \omega_{i,t}$. Since the representative consumer is exposed to the market where she gains the net returns, her wealth at $t + 1$ is

$$W_{t+1} = (W_t - C_t)\Big[R_{f,\,t+1} + \sum_{i=1}^{n} \omega_{i,t}(R_{i,\,t+1} - R_{f,\,t+1})\Big], \tag{2.10}$$

where C_t is consumption at t, W_t is wealth at t, $R_{i,\,t+1}$ is the return of risky asset i from t to $t + 1$, and $R_{f,\,t+1}$ is the risk-free rate from t to $t + 1$.

I assume that the representative consumer has a time-additive, monotonically increasing, and strictly concave von Neumann-Morgenstern utility function for lifetime consumption. In addition, the utility function is time separable, which means that utility at time t depends merely on the consuming quantity at t rather than the consuming quantity before or after t. I define $I(W_t)$ as the life-time utility function on wealth, which satisfies the following equation:

$$I(W_t, t) = \max_{C_s, \omega_{i,s}, \forall s,i} E_t \left[\sum_{s=t}^{T-1} U(C_t, t) + B(W_T, T) \right], \tag{2.11}$$

where $U(C_s)$ is the utility from consumption at time s, C_s, $B(W_T)$ is the ending bequest function that is monotonically increasing and strictly concave, and $E_t[\ ]$ is the expectation conditional on information at time t.

Eq. (2.11) indicates that the representative consumer makes decisions with variables C_s and $\omega_{i,s}$ ($i = 1, 2, ..., n$) so as to maximize the expected lifetime utility. The optimization problem of Eq. (2.11) is subject to the constraint condition of Eq. (2.10). Using stochastic dynamic programming, I can write the first-order conditions (FOC) of the optimal choice problem as:

$$E_t \left[\frac{U_C(C^*_{t+1}, t+1)}{U_C(C^*_t, t)} R_{f,\,t+1} \right] = 1 \tag{2.12}$$

and

$$E_t \left[\frac{U_C(C^*_{t+1}, t+1)}{U_C(C^*_t, t)} R_{i,\,t+1} \right] = 1. \tag{2.13}$$

where $U_C(C^*_t)$ is the partial derivative with respect to the representative consumer's optimal consumption. From Eq. (2.12) and Eq. (2.13), I have,

$$E_t \left[\frac{U_C(C^*_{t+1})}{U_C(C^*_t)} (R_{i,\,t+1} - R_{f,\,t+1}) \right] = 0. \tag{2.14}$$

Suppose that the representative consumer's consumption utility is the constant relative risk aversion (CRRA) function. That is, $U(C) = \frac{C^{1-\gamma}}{1-\gamma}$, where γ is the coefficient of constant relative risk aversion. When I aggregate individual consumptions, the first-order condition yields the following model:

$$E_t \left[(1 - \gamma \Delta C_{t+1})(R_{i,\,t+1} - R_{f,\,t+1}) \right] = 0, \tag{2.15}$$

According to Cochrane (2005), the beta representation of Eq. (2.15) has the form:

$$\begin{aligned} E\left[R_{i,t+1} - R_{f,\,t+1}\right] &= \frac{\gamma}{1 - \gamma E[\Delta C_{t+1}]} cov(R_{i,\,t+1}, \Delta C_{t+1}) \\ &= \frac{\gamma Var(\Delta C_{t+1})}{1 - \gamma E(\Delta C_{t+1})} \beta_{i,c}, \end{aligned} \tag{2.16}$$

where ΔC_{t+1} is the aggregate consumption growth from t to $t{+}1$ and $\beta_{i,c} = \frac{cov(R_{i,\,t+1}, \Delta C_{t+1})}{Var(\Delta C_{t+1})}$. Eq. (2.16) is the traditional CCAPM.

The traditional CCAPM provides a central insight into financial economics. It shows that assets with higher exposure to consumption risk command a higher risk premium. However, empirical tests on the performance of the CCAPM are disappointing (Hansen and Singleton (1982), Hansen and Singleton (1983), Breeden, Gibbons, and Litzenberger (1989), Campbell (1996) and Cochrane (1996)). Despite these problems, recent consumption-based research sheds new light on the application of the CCAPM. I elaborate some typical advanced models in the following sub-sections.

2.3 Recursive utility function

Epstein and Zin (1989), Epstein and Zin (1991), and Wei (1989) study a recursive form of utility function, which allows the disentanglement of risk aversion and the intertemporal elasticity of substitution. Specifically, this function is a recursive aggregation over current consumption and a certainty equivalent of future utility, which has the following form:

$$U_t = \left[(1-\beta)C_t^{1-\rho} + \beta V_t(U_{t+1})^{1-\rho}\right]^{\frac{1}{1-\rho}} \tag{2.17}$$

$$V_t(U_{t+1}) = \left(E[U_{t+1})^{1-\theta}]\right)^{\frac{1}{1-\theta}}, \tag{2.18}$$

where C_t is the consumption at date t, U_{t+1} is the continuation value of the future consumption plan, β denotes the subjective discount factor, θ is the coefficient of relative risk aversion (RRA), $\frac{1}{\rho}$ is the elasticity of intertemporal substitution (EIS) in consumption. When $\theta = \rho$, the recursive utility function will be the traditional constant relative risk aversion (CRRA) utility function. I illustrate the implications of the coefficient of relative risk aversion (RRA), θ, and the elasticity of intertemporal substitution (EIS) in consumption, $\frac{1}{\rho}$, below.

Let D_{it} be the dividend of security i, P_{it} be the price, and S_{it} be the holding shares. The beginning period wealth of a representative consumer at time t is:

$$W_t = (D_t + P_t)S_t \tag{2.19}$$

According to the definition of recursive utility function, the optimal dynamic programming is:

$$I(W_t, D_t) = \max\left\{(1-\delta)C_t^{1-\rho} + \delta E_t^{\frac{1-\rho}{1-\theta}}\left[I^{1-\theta}(W_{t+1}, D_{t+1})\right]\right\}^{\frac{1}{1-\rho}} \tag{2.20}$$

According to the homogeneity of utility (Epstein and Zin (1989), Epstein and Zin (1991), and Wei (1989)), I can write $I(W_t, D_t)$ as:

$$I(W, D) = A(D)W. \tag{2.21}$$

The holding proportion of equity i is $\omega_i = \frac{P_i S_i}{\sum P_i S_i}$. The raw return is defined as $R_{it} = \frac{D_{i,t+1}+P_{i,t+1}}{P_{it}}$. Thus, the optimal dynamic programming can be rewritten in the following form:

$$A(D_t)W_t = \max\left\{(1-\delta)C_t^{1-\rho} + \delta(W_t - C_t)^{1-\rho}E_t^{\frac{1-\rho}{1-\theta}}\left[A(D_{t+1})(\sum \omega_i R_{it})\right]^{1-\theta}\right\}^{\frac{1}{1-\rho}} \tag{2.22}$$

Accordingly, the portfolio choice is

$$\mu_t = \max E_t^{\frac{1}{1-\theta}} \left(\left[A(D_{t+1})(\sum \omega_i R_{it}) \right]^{1-\theta} \right). \tag{2.23}$$

Eq. (2.22) can be further rewritten in the form:

$$A(D_t)W_t = \max \left\{ (1-\delta)C_t^{1-\rho} + \delta(W_t - C_t)^{1-\rho}\mu_t^{1-\rho} \right\}^{\frac{1}{1-\rho}}. \tag{2.24}$$

Suppose R_{it} is independently and identically distributed over time. The optimal utility function will only depend on initial wealth, typically, $I = AW$ with A being the constant item. The portfolio choice can be rewritten as:

$$\mu_t^* = \max E_t^{\frac{1}{1-\theta}} \left[(\sum \omega_i R_{it})^{1-\theta} \right], \tag{2.25}$$

Eq. (2.25) takes the equivalent form as the constant relative risk aversion (CRRA) utility function. Therefore, the relative risk aversion of the recursive utility function is θ.

The intertemporal marginal rate of substitution (IMRS) of the recursive preference is

$$M_{t,\,t+1} = \frac{\partial U_t / \partial C_{t+1}}{\partial U_t / \partial C_t}. \tag{2.26}$$

Let $F\left(C_t,\, V_t(U_{t+1})\right) = U_t$; F_1 and F_2 be the partial differentiation to C_t and $V_t(U_{t+1})$, respectively. Then, F_1 and F_2 can be written as:

$$
\begin{aligned}
F_1\left(C_t,\, V_t(U_{t+1})\right) &= \frac{\partial U_t}{\partial C_t} \\
&= (1-\delta)C_t^{-\rho}\left((1-\delta)C_t^{1-\rho} + \delta V_t(U_{t+1})^{1-\rho}\right)^{\frac{1}{1-\rho}-1} \qquad (2.27)\\
&= (1-\delta)C_t^{-\rho}U_t^{\rho};
\end{aligned}
$$

$$
F_2\left(C_t,\, V_t(U_{t+1})\right) = \delta V_t(U_{t+1})^{-\rho}U_t^{\rho}. \qquad (2.28)
$$

Partially differentiating the recursive utility function of Eq. (2.17), I can have:

$$
\begin{aligned}
\frac{\partial U_t}{\partial C_{t+1}} &= F_2\left(C_t,\, V_t(U_{t+1})\right) \times \frac{\partial V_t(U_{t+1})}{\partial U_{t+1}} \times \frac{\partial U_{t+1}}{\partial C_{t+1}} \\
&= F_2\left(C_t,\, V_t(U_{t+1})\right) \times \left(E[U_{t+1})^{1-\theta}]\right)^{\frac{1}{1-\theta}-1} \times U_{t+1}^{-\theta} \times F_1\left(C_{t+1},\, V_{t+1}(U_{t+2})\right)
\end{aligned}
\qquad (2.29)
$$

Substituting Eq. (2.27) and Eq. (2.28) into Eq. (2.29), the intertemporal marginal rate of substitution (IMRS) of the recursive preference can be written as:

$$
\begin{aligned}
M_{t,\,t+1} &= \beta(\frac{C_{t+1}}{C_t})^{-\rho}\left(V_t(U_{t+1})^{-\rho} \times \left(E[U_{t+1})^{1-\theta}]^{\frac{1}{1-\theta}-1}\right) \times U_{t+1}^{-\theta} \times U_{t+1}^{\rho}\right) \\
&= \beta^{\frac{1-\theta}{1-\rho}}(\frac{C_{t+1}}{C_t})^{-\rho}\left(\frac{U_{t+1}}{V_t(U_{t+1})}\right)^{\rho-\theta}
\end{aligned}
\qquad (2.30)
$$

According to Eq. (2.30), I can have the following elasticity of intertemporal substitution:

$$\begin{aligned}\sigma_{EIS} &= \frac{d\ln C_t/C_{t+1}}{d\ln M_{t,\,t+1}} \\ &= \frac{1}{\rho}.\end{aligned} \tag{2.31}$$

Based on the intertemporal marginal rate of substitution (IMRS) of the recursive preference in Eq. (2.30), $\left(\frac{U_{t+1}}{V_t(U_{t+1})}\right)^{\rho-\theta}$ is the additional risk factor compared to the traditional CAPM. However, it is challenging to estimate $\left(\frac{U_{t+1}}{V_t(U_{t+1})}\right)^{\rho-\theta}$, since $\left(\frac{U_{t+1}}{V_t(U_{t+1})}\right)^{\rho-\theta}$ is a function of unobservable continuation value of future consumption and V_t is also an expectation of a nonlinear function. In Epstein and Zin (1991), they address this by defining a return to the aggregate wealth, $R_{W,\,t} = \frac{W_{t+1}}{W_t - C_t}$. Thus, I can have

$$\begin{aligned}M_{t,\,t+1} &= \beta^{\frac{1-\theta}{1-\rho}}(\frac{C_{t+1}}{C_t})^{-\rho}\left(\frac{U_{t+1}}{V_t(U_{t+1})}\right)^{\rho-\theta} \\ &= \beta^{\frac{1-\theta}{1-\rho}}(\frac{C_{t+1}}{C_t})^{-\rho}\left(\frac{R_{W,\,t}^{-1}}{\theta(\frac{C_{t+1}}{C_t})^{-\rho}}\right)^{\frac{\rho-\theta}{\rho-1}} \\ &= \beta^{\frac{1-\theta}{1-\rho}}(\frac{C_{t+1}}{C_t})^{-\rho\frac{\theta-1}{\rho-1}}R_{W,\,t}^{\frac{\rho-\theta}{1-\rho}}\end{aligned} \tag{2.32}$$

where $R_{W,\,t+1}$ is the return to wealth from date t to date $t+1$. The asset pricing implication of Epstein-Zin model is a two factor model that mixes the traditional CAPM (Sharpe (1964) and Lintner (1965)) with the traditional CCAPM (Rubinstein (1976), Lucas (1978), and Breeden (1979)).

2.4 Campbell and Cochrane's external habit model

Campbell and Cochrane (1999) argue that consumers tend to form habits of higher or lower consumption. Consumers may feel uncomfortable when consumption declines to certain level after economic booms. However, consumers may feel satisfied when they can have the same level of consumption after economic recessions. In the Campbell and Cochrane (1999) model, the representative consumer maximizes her lifetime utility with respect to the difference between consumption and habit level. The individual's habit level is determined by everyone else's current and preceding consumption rather than her own current and preceding consumption.[1] The power utility function of the representative individual has the form:

$$U = E\sum_{t=0}^{\infty}\beta^t\frac{(C_t - X_t)^{1-\theta} - 1}{1-\theta}, \tag{2.33}$$

where X_t is the level of habit and β is the subjective time discount factor.

The stochastic discount factor (SDF) in Campbell and Cochrane (1999) is

$$M_{t+1} = \beta(\frac{C_{t+1}}{C_t}\frac{S_{t+1}}{S_t})^{-\theta}, \tag{2.34}$$

where $S_t = \frac{C_t - X_t}{C_t}$ denotes the surplus consumption ratio. The aggregate consumption is assumed to follow an independent and identically distributed lognormal process:

[1] If the individual's habit level relies on her own current and preceding consumption, this habit model is referred to as the internal habit model. (see Constantinides (1990) for example.)

$$ln(\Delta C_{t+1}) = g + \nu_t, \nu_t \sim i.i.dN(0, \sigma^2), \tag{2.35}$$

where ΔC_t denotes the aggregate consumption growth. Since the habit level moves slowly to consumption, the log surplus consumption ratio is assumed to follow the autoregressive process:

$$ln(S_{t+1}) = (1 - \phi)ln\bar{(S)} + \phi ln(S_t) + \lambda(ln(S_t))\nu_{t+1}, \tag{2.36}$$

where $\lambda(ln(S_t))$ is defined as the sensitivity function, measuring the percentage change in the surplus consumption ratio arising out of the innovation to output growth.

The coefficient of relative risk aversion (RRA) in Campbell and Cochrane (1999) is

$$-\frac{C_t U_{CC}}{U_C} = \frac{\beta}{S_t}. \tag{2.37}$$

The Hansen-Jagannathan (Hansen and Jagannathan (1991)) bound of the external habit model in Campbell and Cochrane (1999) has the form:

$$|\frac{E[r_i - r_f]}{\sigma_{r_i}}| \leq -\frac{C_t U_{CC}}{U_C} = \frac{\beta\sigma_c}{S_t}, \tag{2.38}$$

where σ_c denotes the standard deviation of c_t.

Therefore, high coefficient of relative risk aversion (RRA) can generate high equity risk premium. The coefficient of relative risk aversion (RRA) is high when S_t and

C_t are low, i.e., when economies are in downturns. The relation as shown in Eq. (2.38) predicts that the equity risk premium increases during economic troughs in line with the data observed in the postwar U.S. stock market. In addition, even though consumption volatility is constant, i.e., constant σ_c, the equation can still produce a time-varying equity risk premium as the surplus consumption ratio, S_t varies over time.

Before I proceed to the next subsection, it is worth noting that the recursive preference and habit level are two developments in terms of utility function in the traditional CCAPM. In particular, Epstein and Zin (1989) develop another time inseparable and recursive utility function characterized by clearly separating the coefficient of the risk aversion and the elasticity of substitution; Constantinides (1990) and Campbell and Cochrane (1999) relax the time separable utility function and establish utility functions characterized as habit persistence. However, it seems that there exists evidence against consumption-based models in general rather than against particular utility functions, particular specifications of temporal nonseparabilities such as habit persistence or durability, and particular choices of consumption data and data-handling procedures (Campbell and Cochrane (2000)).

2.5 Long run risk

Bansal and Yaron (2004) show that a small persistent growth rate component and fluctuating volatility in the time-series process of consumption and dividend can justify the large risk premium and high sharp ratios in the U.S. data. They assume that a representative consumer has recursive preferences as in Epstein and Zin (1989), Epstein and Zin (1991) and Wei (1989). Recalling Eq. (2.32), I can write the logarithm of the intertemporal marginal rate of substitution (IMRS) as:

$$m = \frac{1-\theta}{1-\rho} log(\beta) - \rho \frac{\theta - 1}{\rho - 1} ln(\Delta C_{t+1}) + \frac{\rho - \theta}{1-\rho} ln(R_W). \tag{2.39}$$

ΔC_{t+1} denotes the growth rate of aggregate consumption. In the model of Bansal and Yaron (2004), the dynamic of the aggregate consumption and dividend growth rates $ln(\Delta C_{t+1})$ and $ln(\Delta D_{t+1})$ has the form:

$$x_{t+1} = \varrho x_t + \varphi_e \sigma_t e_{t+1} \tag{2.40}$$

$$ln(\Delta C_{t+1}) = \mu_c + x_t + \sigma_t \eta_{t+1} \tag{2.41}$$

$$ln(\Delta D_{t+1}) = \mu_d + \phi x_t + \varphi_d \sigma_t u_{t+1} \tag{2.42}$$

$$\sigma_{t+1}^2 = \sigma^2 + \upsilon(\sigma_t^2 - \sigma^2) + \sigma_w w_{t+1} \tag{2.43}$$

$$e_{t+1}, \eta_{t+1}, u_{t+1}, w_{t+1} \sim N.i.i.d(0.1) \tag{2.44}$$

The persistent component x_t, the conditional expectation of consumption growth, is associated with long run risk. Comovement of any asset with innovation in the intertemporal marginal rate of substitution (IMRS) m determines the risk of the asset. Bansal and Yaron (2004) prove analytically that the dynamic of the aggregate consumption and dividend growth rates contributes two respective risks, namely, the fluctuations in the expectation of consumption growth and the fluctuations in consumption volatility, to the equity premium.

2.6 Other advances in the traditional CCAPM

The empirical research of the CCAPM provides disappointing evidence against the well interpreted models, e.g., Hansen and Singleton (1983), Grossman, Melino and Shiller (1987), Campbell (1996), and Cochrane (1996). These studies show that the explanatory power of the CCAPM to the cross-sectional return variations is no better or even worse than that of the traditional CAPM (Lettau and Ludvigson (2001)). Lettau and Ludvigson (2001) extend the traditional CCAPM, using a scaled variable. Specifically, they show that when the CCAPM is scaled by the consumption-to-wealth ratio, cay_t, the scaled consumption-based model (Lettau and Ludvigson (2001)) performs just as well as the Fama-French three factors in explaining the 25 Fama-French portfolios. The scaled conditional variable, cay_t, is a cointegrating residual for log consumption, log asset wealth, and log labor income. The stochastic discount factor (SDF) in Lettau and Ludvigson (2001) has the following form:

$$M_{t+1} = ln(A_t) + b_t z_t \tag{2.45}$$

$$ln(A_t) = a_0 + a_1 z_t \tag{2.46}$$

$$b_t = b_0 + b_1 z_t \tag{2.47}$$

$$z_t = cay_t = ln(C_t) - \alpha_a ln(A_t) + \alpha_y ln(Y_t), \tag{2.48}$$

where A_t denotes nonhuman or asset wealth, Y_t denotes labor income, α_a and α_y are cointegrating parameters. Lettau and Ludvigson (2001) show that a conditional three-factor consumption-based model with CAY_t, consumption growth, and their interaction explains a large proportion of the expected return variations across the Fama-French 25 value-weighted size and book-to-market portfolios.

Parker and Julliard (2005) focus on long run risk to explore the explanatory power of consumption CAPM in capturing different expected returns across assets. They find that despite the fact that contemporaneous consumption risk explains few differences in expected returns of 25 Fama-French portfolios, the model with the ultimate consumption risk at an interval of 11 quarters explains a large fraction of these differences. The stochastic discount factor (SDF) of the ultimate consumption risk model (Parker and Julliard (2005)) has the form:

$$M_{t+1}^{S} = R_{t+1,t+1+S}^{f} \left(\frac{u'(C_{t+1+S})}{u'(C_t)} \right), \tag{2.49}$$

where S denotes the time interval. The reason why the long-run consumption risk matters is that consumers adjust consumption slowly to news, in particularly, due to slow adjustment of labor supply and housing stock that are related to consumption. Bansal and Yaron (2004), Parker and Julliard (2005) and Jagannathan and Wang (2007) show that measuring consumption risk on the basis of longer horizons is able to explain cross-sectional variation in expected returns.

Yogo (2006) and Piazzesi, Schneider, and Tuzel (2007) specify an intraperiod constant elasticity of substitution (CES) form of utility function to take other categories of consumption into account. Specifically, Yogo (2006) considers durable consumption and Piazzesi, Schneider, and Tuzel (2007) consider housing services. The period utility function is the power utility function consistent with the traditional CCAPM. Specifically, the period utility functions of a representative individual are

$$U(C,X) = \frac{v(C,DUR)^{1-\theta}}{1-\theta}, \tag{2.50}$$

and

$$U(C,X) = \frac{v(C,H)^{1-\theta}}{1-\theta}, \tag{2.51}$$

where θ is the coefficient of relative risk aversion (RRA); C denotes nondurables and services in Yogo (2006) and nonhousing consumption in Piazzesi, Schneider, and Tuzel (2007); DUR denotes durable consumption in Yogo (2006) DUR denotes durable consumption as in Yogo (2006); H denotes housing services as in Piazzesi, Schneider, and Tuzel (2007).

The intraperiod utility function has the constant elasticity of substitution (CES) form:

$$v(C,X) = \left((1-\delta)C^{\rho} + \delta X^{\rho}\right)^{\frac{1}{\rho}}, \tag{2.52}$$

where $\delta \in (0,1)$ and $\frac{1}{1-\rho}$ is the substitution between C and X. The marginal utility of C is given by

$$
\begin{aligned}
U_C &= (1-\delta)C^{\rho-1}\left((1-\delta)C^{\rho}+\delta X^{\rho}\right)^{\frac{1-\theta-\rho}{\rho}} \\
&= (1-\delta)C^{-\theta}\left(1+\delta\big((\frac{X}{C})^{\rho}-1\big)\right)^{\frac{1-\theta-\rho}{\rho}} .
\end{aligned}
\tag{2.53}
$$

The stochastic discount factor (SDF) is given by

$$
M_{t,t+1} = \theta(\frac{C_{t+1}}{C_t})^{-\rho}\left(\frac{\big((\frac{X_{t+1}}{C_{t+1}})^{\rho}-1\big)}{\big((\frac{X_t}{C_t})^{\rho}-1\big)}\right)^{\frac{1-\theta-\rho}{\rho}} , \tag{2.54}
$$

where $\left(\frac{\big((\frac{X_{t+1}}{C_{t+1}})^{\rho}-1\big)}{\big((\frac{X_t}{C_t})^{\rho}-1\big)}\right)^{\frac{1-\theta-\rho}{\rho}}$ is the additional risk factor compared with the traditional CCAPM. Lustig and Nieuwerburgh (2005), Yogo (2006) and Piazzesi, Schneider, and Tuzel (2007) emphasize the important role of durable consumption or housing consumption in asset pricing.

2.7 Investment-based asset pricing

While the consumption-based asset pricing models link expected returns to the intertemporal rate of substitution of consumers, Cochrane (1991), Cochrane (1996), and Zhang (2005) show that expected returns can also be related to the intertemporal rate of transformation of firms from the Q-theory of investment. The firm i maximizes the expected value of future dividends, which has the following form:

$$V_{it} = E_{it}\left[\sum_{s=0}^{\infty} M_{t,t+s} D_{t+s}\right], \tag{2.55}$$

where V_{it} is the value of firm i at time t, E_{it} [ ] is the expectation function that is conditional on information at time t, $M_{t,t+s}$ is the stochastic discount factor from time t to $t+s$, and D_{t+s} is the dividend of the firm at time $t+s$.

The dividend of firm i (D_{it}) is given by $D_{it} = \Pi(K_{it}, X_{it}) - \Phi(I_{it}, K_{it})$, where $\Pi(K_{it}, X_{it})$ is the profit function ($\Pi_K > 0$), K_{it} is the capital stock at time t, X_{it} is a vector of exogenous shocks, $\Phi(I_{it}, K_{it})$ is the adjustment cost function, ($\Phi_I > 0$ $\Phi_K < 0$, and $\Phi_{II} > 0$), and I_{it} is the investment during time t. The capital stock accumulation is given by $K_{i,t+1} = Iit + (1-\delta_i)K_{it}$, where δ is capital depreciation rate.

The firm i maximizes cum-dividend value subject to $D_{it} = \Pi(K_{it}, X_{it}) - \Phi(I_{it}, K_{it})$ and $K_{i,t+1} = Iit + (1-\delta_i)K_{it}$. According to Cochrane (1991), Cochrane (1996), and Zhang (2005), the investment first-order condition is $E_{it}\left[M_{t,t+1}R_{i,t+1}\right] = 1$. The investment return from t to $t+1$, $R^I_{i,t+1}$, is given by

$$R^I_{i,t+1} = \frac{\Pi_K(K_{i,t+1}, X_{i,t+1}) - \Phi_K(I_{i,t+1}, K_{i,t+1}) + (1-\delta_i)\Phi_I(I_{i,t+1}, K_{i,t+1})}{\Phi_I(I_{it}, K_{it})}. \tag{2.56}$$

Eq. (2.56) shows that the investment return is the ratio of the marginal benefit of investment at time $t+1$ to the marginal cost of investment at time t. Specifically,

$\Phi_I(I_{it}, K_{it})$ is the marginal cost of investment. $\Pi_K(K_{i,t+1}, X_{i,t+1})$ is the marginal operating profit. $\Phi_K(I_{i,t+1}, K_{i,t+1})$ is how an unit capital affects the adjustment cost. $(1-\delta_i)\Phi_I(I_{i,t+1}, K_{i,t+1})$ is the expected value of marginal profits, after netting out depreciation.

According to Cochrane (1991), Cochrane (1996), and Zhang (2005), the ex-dividend firm value, P_t, has the following form:

$$P_{it} = V_{it} - \Pi(K_{it}, X_{it}) + \Phi(I_{it}, K_{it}). \tag{2.57}$$

Further, the stock return of i is

$$R_{i,t+1} = \frac{P_{i,t+1} + D_{i,t+1}}{P_{it}} = R^I_{i,t+1}. \tag{2.58}$$

Eq. (2.58) shows that stock return is equal to investment return and lower investment rate is associated with higher returns.

2.7.1 The production-based model with financial constraints

Cochrane (1991) first develops the production-based asset pricing model to predict a contemporaneous relation between asset returns and investment returns. Gomes, Yaron, and Zhang (2006) extend this model by including financial constraints. According to Gomes, Yaron, and Zhang (2006) and Whited and Wu (2006), the investment return from t to $t+1$, $R^I_{i,t+1}$, is given by

$$R^I_{i,t+1} = \frac{(1+\mu_{i,t+1})[\Pi_K(K_{i,t+1}, X_{i,t+1}) - \Phi_K(I_{i,t+1}, K_{i,t+1}) + (1-\theta_i)\Phi_I(I_{i,t+1}, K_{i,t+1})]}{(1+\mu_{i,t})\Phi_I(I_{i,t}, K_{i,t})}, \tag{2.59}$$

where $\mu_{i,t}$ is the Lagrange multiplier that can be interpreted as the shadow cost of external capital. $K_{i,t}$ is the capital stock at time t, $X_{i,t}$ is a vector of exogenous shocks, $I_{i,t}$ is the investment during time t, and θ is the capital depreciation rate. $\Phi_I(I_{i,t}, K_{i,t})$ captures the marginal cost of investment at time t, where $\Phi_I > 0$, $\Phi_K < 0$, and $\Phi_{II} > 0$), $\Pi_K(K_{i,t+1}, X_{i,t+1})$ measures the marginal operating profits from the capital at time $t+1$, and $(1-\theta_i)\Phi_I(I_{i,t+1}, K_{i,t+1})$ measures the expected present value of marginal profits net of depreciation at time $t+1$. $\frac{1+\mu_{i,t+1}}{1+\mu_{i,t}}$ represents the relative shadow cost of external capital, which reflects the role of the financial frictions. When $\mu_{i,t+1} = \mu_{i,t}$, financing frictions have no impact on the investment return R^I. Eq. (2.59) indicates that the investment return is the product of the relative shadow cost of external finance and the ratio of the marginal benefit of investment at time $t+1$ to the margin cost of investment at time t. In addition, it implies that financial constraints can only affect investment return if they are time-varying, where $\mu_{i,t+1} \neq \mu_{i,t}$. According to Gomes, Yaron, and Zhang (2006), it is the cyclical variation in the shadow price of external funds that affects returns. Higher financial constraints and lower investment rate are associated with higher returns.

2.7.2 The asymmetric information asset pricing model

Fazzari, Hubbard, and Petersen (1988) and Morellec and Schürhoff (2011) find that financially constrained firms have higher information asymmetry than unconstrained firms. This motives us to explore the relation between information asymmetry, liquidity, and stock prices. Diamond and Verrecchia (1991) use disclosure of private information to public as the proxy of changing information asymmetry and examine the effects of reducing information asymmetry on liquidity and price of a stock. They model the relation between information and liquidity as follows:

$$\frac{\partial\lambda}{\partial\varepsilon} = \frac{(\delta^2/\delta+\varepsilon)\lambda(\lambda+r)}{2(\lambda+r)\delta\varepsilon + r(4\lambda^2\eta[\delta+\varepsilon]+\delta\varepsilon)} > 0, \tag{2.60}$$

where λ is the Kyle's (1985) λ as a measurement of the price impact of trading a security. It is a ratio of the amount of the insider's private information to the amount of noise trading, capturing the adverse selection costs of insiders due to information-based trading. Higher λ implies that a security is less liquid. δ and ε measure the degree of information asymmetry between the informed trader and the market. When δ or ε increase, information asymmetry increases and leads to a high price impact. δ and ε satisfy $\tilde{x} = \tilde{\delta}+\tilde{\varepsilon}$, where $\tilde{\varepsilon}$ has a normal distribution with zero mean and variance ε. $\tilde{x}$ is the disclosure of the informed trader's private information to public. r is the aggregate market maker's asymptotic risk aversion. Equation (2.60) indicates that the price impact depends on the disclosure of private information δ. The increased disclosure of private information through a decrease in δ or ε reduces the price impact

λ and makes the market more liquid.

Diamond and Verrecchia (1991) further model the relation between the price of the security and liquidity as follows:

$$\frac{\partial P_1}{\partial \lambda} = -\frac{1}{2}Q_0(\lambda + r)^{-3}(\lambda + 5r)^{-2}(7\lambda^3 r^2 + 23\lambda^2 r^3 + 35\lambda r4 + 35r5) < 0, \tag{2.61}$$

where P_1 is the transaction price of the market marker at date 1. Q_0 is the total number of shares outstanding of the firm ($Q_0 > 0$).[2] Equation (2.61) suggests that the improved liquidity causes institutional investors to take larger positions to buy shares if a firm discloses more private information to reduce information asymmetry. The increased demand pushes the current price up, which reduces the required expected return of the firm and thereby reduces the cost of capital, under the condition of holding aggregate market maker risk aversion r fixed. It also implies that the firm can get better off when it sells shares to the public from the improved future liquidity due to the increased current prices.

Given the relations between financial constraints and stock returns, information asymmetry, stock liquidity, and stock prices in equations (2.59), (2.60), and (2.61), I expect that stock liquidity is highly related to financial constraints. Specifically, firms that are more constrained tend to have higher information asymmetry. As a result, they have large price impact and low current price, and thus high expected

[2] The Diamond and Verrecchia (1991) model is a three-period model with date 0, 1, and 2.

returns. On the contrary, firms that are unconstrained tend to have low information asymmetry. Therefore, they have small price impact and low expected returns.

2.8 Stock liquidity and stock returns

Liu (2006) highlights four dimensions of liquidity: trading costs, trading quantity, trading speed, and the impact of trading on price. I review the studies of liquidity measures based on the four dimensions.

(i) The transaction costs dimension. Amihud and Mendelson (1986) show that the quoted bid-ask spread is a significant determinant of stock returns. Stocks with higher quoted bid-ask spread are less liquid. Specifically, using the NYSE stocks from 1961 to 1980, Amihud and Mendelson (1986) sort stocks into seven liquidity groups based on the quoted bid-ask spread and then within each liquidity group they sort stocks into seven market beta groups based on the beta of traditional CAPM. They find that there is a significant relation between the quoted bid-ask spread and average returns after controlling for market risk.

An expanding literature also finds that lower liquidity is related to higher expected returns while using a number of different proxies of liquidity. Lesmond, Ogden, and Trzcinka (1999) use the proportion of daily zero returns to measure liquidity. Their model is based on the framework of Glosten and Milgrom (1985) and Kyle (1985). Using the NYSE/AMEX sample stocks from 1963-1990, they find that the proportion of daily zero returns is related to both the quoted bid-ask spread and Roll's (1984) measure of the effective spread (Lesmond, Ogden, and Trzcinka (1999)). Bekaert, Harvey, and Lundblad (2007) adopt the proportion of zero returns as a liquidity measure.

Hasbrouck (2009) develops the effective trading costs measure based on the Roll (1984) model. Roll's measure involves the calculation of the negative serial correlation in returns. Since the correlation of returns is often positive, the effective trading costs measure minimizes this problem. Using the NYSE/AMEX/NASDAQ sample stocks from 1926-2006, Hasbrouck (2009) find that stocks with higher transaction costs have higher average returns, which is robust after controlling for size.

Corwin and Schultz (2012) introduce another bid-ask spread estimate based on daily high and low prices. They show that the bid-ask spread estimates of Corwin and Schultz (2012) perform better than other known transaction costs estimates such as the Roll (1984) measure and the Lesmond, Ogden, and Trzcinka (1999) measure according to the cross-sectional correlation with TAQ effective spreads. In their asset pricing tests, they find that the abnormal illiquid-minus-liquid portfolio returns sorted by their bid-ask spread estimate are significantly positive.

(ii) The trading quantity dimension. Datar, Naik, and Radcliffe (1998) introduce the turnover measure, which is defined as the ratio of the number of shares traded to the number of shares outstanding. Stocks with higher turnover are more liquid. Datar, Naik, and Radcliffe (1998) use the turnover measure to test the model prediction of Amihud and Mendelson (1986), i.e., higher expected returns are related to lower turnover. Using the NYSE sample stocks from 1962 to 1991, Datar, Naik, and Radcliffe (1998) show that turnover is an important determinant of the cross-sectional returns after controlling for known factors such as size, book-to-market ratio, and firm risk. Stocks with higher turnover are related to lower expected returns.

Brennan, Chordia, and Subrahmanyam (1998) propose the dollar volume measure, which is defined as the number of shares traded times the closing price. Stocks that have higher dollar volume are more liquid than those that have lower dollar volume. Using the NYSE/AMEX/NASDAQ sample stocks from 1966 to 1995, Brennan, Chordia, and Subrahmanyam (1998) show that stocks with higher dollar volume are significantly related to lower expected returns.

(iii) The price impact dimension. Amihud (2002) proposes the price impact measure, which is defined as the daily absolute-return-to-dollar-volume ratio. Stocks with higher price impact are less liquid. The construction of this measure is based on the model of Kyle (1985). Using the NYSE sample stocks from 1964 to 1997, Amihud (2002) shows that stocks with higher price impact have higher expected returns. Goyenko, Holden, and Trzcinka (2009) show that this liquidity proxy relates closely to price impact measures estimated from high frequency TAQ and Rule 605 data. Stocks with higher RV are less liquid.

(iv) The trading speed dimension. Liu (2006) proposes the trading discontinuity measure, LM, defined at the end of each month as the standardized turnover-adjusted number of zero daily trading volumes over the prior 12 months. Specifically, Liu's measure has the following form:

$$LM = \left[\textit{Number of zero daily volumes in prior 12 months} + \frac{1/(12\textit{-month turnover})}{\textit{Deflator}} \right] \times \frac{21 * 12}{NoTD}, \tag{2.62}$$

where 12-*month turnover* is the sum of daily turnover (in percentage) over the prior 12 months, $NoTD$ is the total number of exchange trading days in the market over the prior 12 months, and *Deflator* is chosen such that $0 < \frac{1/(12\textit{-month turnover})}{\textit{Deflator}} < 1$ for all sample stocks. The factor $21 * 12/NoTD$ standardizes the number of one-month trading days in the market to 21, which makes the LM values comparable over time.

The LM proxy measures the probability of no trading. Large LM (i.e., high infrequent trading) indicates slow trading speed (or low liquidity). Liu (2006) show that both the traditional CCAPM of Sharpe (1964) and Lintner (1965) and the Fama-French (1993) three-factor model have difficulties in accounting for the liquidity premium based on the trading discontinuity measure.

Beginning with Pastor and Stambaugh (2003), a growing literature highlights the importance of liquidity risk in asset pricing. Pastor and Stambaugh (2003) measure liquidity as the price reversal caused by the temporary price impact of trading volume. The aggregate liquidity is calculated as the innovations of market liquidity (i.e., the average liquidity across individual stocks). They define liquidity risk as the covariance of stock returns and the innovations of market liquidity.

Acharya and Pedersen (2005) develop a liquidity-adjusted CAPM based on the framework of the traditional CAPM of Sharpe (1964) and Lintner (1965). They show that the expected return is determined by the expected liquidity costs, market risk as in the CAPM, and liquidity risk. They also identify three sources of liquidity risk, namely, the covariance of stock returns and market liquidity costs, the covariance of stock liquidity costs and market liquidity costs, and the covariance of stock liquidity costs and market returns. Among these different channels of liquidity risk, they find that the covariance of stock liquidity costs and market returns is a more important determinant of the cross-sectional expected returns than other sources of liquidity risk.

Liu (2006) introduces the mimicking liquidity factor based on his trading discontinuity measure. The construction of the mimicking liquidity factor is similar to that of the size and book-to-market factors as in the Fama-French (1993) three-factor model. Then liquidity risk is defined as the covariance between stock returns and the mimicking liquidity factor. He also shows that a liquidity-augmented CAPM that has the market factor and the liquidity factor can subsume the liquidity premium based on the trading discontinuity measure. However, the traditional CAPM and the Fama-French three-factor model have difficulties in explaining the liquidity premium.

Sadka (2006) develops the aggregate liquidity innovation that measures liquidity using the components of the price impact model of Glosten and Harris (1988). He uses the constructed liquidity factor to explain momentum and post-earnings-announcement drift anomalies. He shows that a two-factor model with market risk and liquidity risk explains a larger fraction of cross-sectional expected returns than does the traditional CAPM.

2.9 Financial constraints and stock returns

While a large literature develops different proxies to measure the degree of financial constraints, there is a lack of consensus on the best choices of empirical proxies for financial constraints. Therefore, I summarize a number of financial constraints measures that are commonly used in the literature.

(i) Gertler and Gilchrist (1994) and Gilchrist and Himmelberg (1995) use asset size, which is defined as the book values of total assets (Compustat annual item AT), to measure financial constraints. These studies argue that firms that have smaller asset size appear to be younger and less known to investors than those that have larger asset size. Therefore, the effects of financial market imperfections on smaller firms will be larger than those on larger firms.

(ii) Whited (1992), among others, argues that firms that have bond ratings are less constrained than firms that have no bond ratings. The bond rating is commonly defined as a dummy variable, which is equal to one for those firms that never have their Standard & Poor's ($S\&P$) bond rated in the sample period and have positive public debt. The dummy variable is equal to zero for those that have been rated during the sample period and have positive public debt.

(iii) Calomiris, Himmelberg, and Wachtel (1995), among others, adopt the presence of commercial paper ratings to measure financial constraints. The commercial paper rating is commonly defined as a dummy variable, which is equal to one for those firms that never have their Standard & Poor's ($S\&P$) commercial paper rated in the sample period and have positive public debt. The dummy variable is equal to zero for those that have been rated during the sample period and have positive public debt.

(iv) Fazzari, Hubbard, and Petersen (1988), among other, use the payout ratio as a proxy for financial constraints. The payout ratio is defined as the ratio of total distributions including dividends for preferred stocks (Compustat annual item DVP), dividends from common stocks (item DVC), and share repurchases (item PRSTKC) divided by operating income before depreciation (item OIBDP). Firms with lower payout ratios are more financially constrained.

It is worth noting that asset size, bond rating, commercial paper rating, and payout ratio measures use one firm characteristic to proxy financial constraints. These four financial constraints classifications are widely used in the literature, e.g., Almeida, Campello, and Weisbach (2004), Almeida and Campello (2007), and Hahn and Lee (2009). The following financial constraints measures consist of a number of firm characteristics.

(v) Lamont, Polk, and Saa-Requejo (2001) use the ordered logit regression coefficients from Kaplan and Zingales (1997) to construct the KZ index. Specifically, the

KZ index is a combination of five firm characteristics, which is calculated based on the following equation:

$$\begin{aligned} KZ = &-1.001909 * CashFlow/K + 0.2826389 * Tobin'sQ \\ &+ 3.139193 * Debt/TotalCapital - 39.3678 * Dividends/K \\ &- 1.314759 * Cash/K, \end{aligned} \tag{2.63}$$

where $CashFlow/K$ is the ratio of cash flow (Compustat annual item $IB + DP$) to net property, plant, and equipment (item $PPENT$). $Tobin's\ Q$ is the ratio of market value of assets to book value of assets. The market value is calculated as the book value of asset (item AT) plus CRSP December market equity less the sum of the book value of common equity (item CEQ) and balance sheet deferred taxes (item $TXDB$). $Debt/TotalCapital$ is the ratio of debt (item $DLTT + DLC$) to total capital (item $DLTT + DLC + SEQ$). $Dividends/K$ is the ratio of dividends (item $DVC + DVP$) to net property, plant, and equipment (item $PPENT$). $Cash/K$ is the ratio of cash and short-term investments (item CHE) to net property, plant, and equipment (item $PPENT$). Firms with higher KZ index are more financially constrained. Lamont, Polk, and Saa-Requejo (2001) find that financial constraints are negatively correlated with average stock returns based on the KZ index.

(iv) Whited and Wu (2006) develop the WW index based on the generalized method of moments (GMM) estimates of the investment Euler equation. Specifically, the WW index can be calculated according to the following equation:

$$
\begin{aligned}
WW = & -0.091 * CF - 0.062 * DIVPOS + 0.021 * TLTD \\
& - 0.044 * LNTA + 0.102 * ISG - 0.035 * SG,
\end{aligned} \tag{2.64}
$$

where CF is the ratio of cash flow (Compustat annual item $IB + DP$) to total assets (item AT), $DIVPOS$ is an indicator that takes the value of one if the firm pays cash dividends (item $DVP + DVC$), $TLTD$ is the ratio of long-term debt (item $DLTT + DLC$) to total assets, $LNTA$ is natural log of total assets, ISG is the firm's three-digit industry sales growth, and SG is firm sales (item $SALE$) growth. Firms with higher WW index are more financially constrained. In contrast to the findings of Lamont, Polk, and Saa-Requejo (2001), Whited and Wu (2006) find that financial constraints are positively correlated with average stock returns based on the WW index. Using the KZ index as the financial constraints measure, Lamont, Polk, and Saa-Requejo (2001) find that financially constrained firms have lower stock returns than financially unconstrained firms. They argue that the negative premium is associated with low levels of dividends and low earnings. Moreover, the negative premium is consistent with previous studies. These studies show that zero-dividend firms earn negative returns and firms with lower cash flow and earnings earn lower returns. Using the WW index, Whited and Wu (2006) find that financially constrained firms have higher stock returns than financially unconstrained firms. They argue that firms tend to use collateral to borrow capital because of the agency costs. Therefore, the value of collateral is associated with the firms' financing ability. When the value of collateral decreases, financially constrained firms will reduce investment more than unconstrained firms. Therefore, financially constrained firms tend to be more risky than unconstrained firms. The positive relation between financial constraints and stock returns is also consistent with the model implications of Gomes, Yaron, and Zhang (2006) and Whited and Wu (2006).

(vii) Hadlock and Pierce (2010) cast doubt on the validity of the KZ index to measure the degree of firms' financial constraints. They find firms' size and age are important determinants of financial constraints and introduce the SA index. Specifically, the SA index has the following form:

$$SA = (-0.737 * Size) + (0.043 * Size^2) - (0.040 * Age), \tag{2.65}$$

where $Size$ is the log of inflation-adjusted book assets, and Age is the number of years the firm is listed with a non-missing stock price on Compustat. To calculate this index, $Size$ is winsorized at the log of \$4.5 billion, and Age is winsorized at 37 years. Firms with higher SA index are more financially constrained.

There is a growing literature that investigates the variation of firms' characteristics across the financially unconstrained firms and financially constrained firms. For example, Hahn and Lee (2009) show that the effects of debt capacity on the cross-sectional average returns are only significant for the financially constrained firms. Li and Zhang (2010) and Lam and Wei (2011) show that the investment anomalies are closely related to financial constraints. In general, the investment effect (i.e., low investment rate is related to high average returns) is more pronounced in the financially constrained groups than in the financially unconstrained groups. Li (2011) examines the interaction between financial constraints, research and development expense, and the cross-sectional returns. The results show that the impact of research and development expense on the cross-sectional returns is only significant for the financially constrained firms. Moreover, the positive relation between financial constraints and cross-sectional returns is mainly significant for research and development intensive firms.

2.10 Conclusion

In this chapter, I review the traditional CAPM, consumption-based asset pricing models, and investment-based asset pricing models. These models provide the theoretical supports to the following chapters. Specifically, the consumption-based asset pricing models are the theoretical framework of the liquidity-adjusted models I develop in chapters 4 and 5. I also review various liquidity measures and the relation between these liquidity measures and stock returns. Further, I review the empirical proxies of financial constraints. I use these liquidity measures and financial constraints measures extensively in the following empirical studies.

Chapter 3

Methodology

Following the literature in asset pricing (e.g., Fama and French (2008)), I use two main methodologies in my study. One is the portfolio sorts (e.g., Fama-French (1992, 1993)) and the other is the cross-sectional regression (e.g., Fama and MacBeth (1973)). This chapter reviews the primary asset pricing methodologies. I discuss the detailed applications of different research methodologies in the other chapters based on the specific research questions.

3.1 Portfolio sorts

There is a large body of literature that uses the methodology of portfolio sorts. In this thesis, I mainly use it to test asset pricing models and to explore the relation between firm characteristics, stock liquidity, and stock returns. Fama and French (2008) argue that the portfolio sorts method can simply show the variation of average returns related to certain variables. It provides a double check from cross-section regression as the inferences from cross-section regression might be dominated by a few extreme performance stocks. The basic research design is to sort stocks into portfolios based on variables such as market value, book-to-market ratio, liquidity measures or other firm characteristics (e.g., financial constraints). The holding period after portfolio formation can be 1 month, 3 months, 6 months, or 12 months.

I can form portfolios based on the equally-weighted method and value-weighted method. For the equally-weighted method, I assume that I invest equal amount in all stocks. For the value-weighted method, I assume that the amount of money invested in stock i is related to the ratio of the market value of stock i to the total market value of the portfolio.

The basic portfolio return calculation method is the rebalance method (e.g., Fama-French (1992, 1993)). Take a 12-month holding period value-weighted portfolio with a beginning month of July at year t, for example. The portfolio weights in each month of the holding period are assumed to be the weights at the end of June of year t. Sorting stocks based on the market capitalization and book-to-market ratios, Fama-French (1992, 1993) show that firms with smaller market capitalization have higher stock returns than those with larger market capitalization and firms with higher book-to-market ratios have higher stock returns than those with lower book-to-market ratios. However, Liu and Strong (2008) show that the rebalance method can lead to spurious statistical inference especially for small and loser stocks and propose a decomposed buy-and-hold method to calculate portfolio returns. For example, they show that the size effect is significant when the rebalance method is used. By contrast, it is insignificant when the buy-and-hold method is used. When I use quarterly data in chapter 4, I hold the formed portfolios for one quarter. According to Liu and Strong (2008), this portfolio formation strategy can obtain the same portfolio returns when I use either the rebalance method or the buy-and-hold method. Specifically, the buy-and-hold formula to calculate returns for an equally-weighted portfolio is given by

$$R_{P1}^{ew} = \frac{1}{N}\sum_{i=1}^{N} R_{i1} \tag{3.1}$$

$$R_{P\tau}^{ew} = \sum_{i=1}^{N} \frac{\prod_{t=1}^{\tau-1}(1+R_{it})}{\sum_{j=1}^{N}\prod_{t=1}^{\tau-1}(1+R_{jt})} R_{i\tau} \tag{3.2}$$

where R_{i1} is the return of stock i in the first month of portfolio formation (month 1); R_{P1}^{ew} is the equally-weighted portfolio return in month 1; R_{it} is the return of stock i in month t; $R_{P\tau}^{ew}$ is the equally-weighted portfolio return in month t; $\tau = 2, 3, ..., m$. It is worth noting that the portfolio returns calculated by the buy-and-hold method in the first holding period are the same as those calculated by the rebalancing method. However, the returns in the following holding period are the weighted average. The weight is related to the previous holding-period returns.

The buy-and-hold formula to calculate returns for a value-weighted portfolio is given by

$$R_{P\tau}^{vw} = \sum_{i=1}^{N} \frac{MV_{i,\tau-1}}{\sum_{j=1}^{N} MV_{j,\tau-1}} R_{i\tau}, \tag{3.3}$$

where MV is the market value.

3.2 Abnormal returns

After portfolio formation, a large body of literature further investigates the abnormal returns. That is, portfolio returns are regressed against traded risk factors. The common asset pricing models in this setting are the traditional capital asset pricing model (CAPM) of Sharpe (1964) and Lintner (1965) and the three-factor model (FF3) of Fama and French (1993). The abnormal returns are the regression intercepts based on these two models. Specifically, they are estimated from the following regressions:

$$R_{i,t} - R_{f,t} = \alpha_{i,t} + \beta_{i,mkt} f_{mkt,t} + \varepsilon_{i,t}; \tag{3.4}$$

$$R_{i,t} - R_{f,t} = \alpha_{i,t} + \beta_{i,mkt} f_{mkt,t} + \beta_{i,smb} f_{smb,t} + \beta_{i,hml} f_{hml,t} + \varepsilon_{i,t}, \tag{3.5}$$

where $R_{i,t} - R_{f,t}$ is the raw return of portfolio i in excess of the risk-free rate, $f_{mkt,t}$ is the excess return of the value-weighted NYSE/AMEX/NASDAQ index (market factor), $f_{smb,t}$ is the size factor, and $f_{hml,t}$ is the book-to-market factor. Fama and French (1993) show that the size factor, $f_{smb,t}$, is related to firms' market value. The traded factor, $f_{smb,t}$, is constructed as the return difference between buying portfolios with large market capitalizations and selling portfolios with small market capitalizations. Similarly, Fama and French (1993) show that the book-to-market factor, $f_{hml,t}$, is related to firms' book-to-market ratios. The traded factor, $f_{hml,t}$, is the return difference between buying portfolios with low book-to-market ratios and selling portfolios with high book-to-market ratios.

3.3 Cross-sectional regressions

Fama and French (2008) argue that the cross-section regression approach provides more accurate estimates for many explanatory variables than the portfolio sorts approach. Further, Bazdrech, Belo, and Lin (2013) argue that some issues arising from the portfolio sorts, e.g., the specification of breakpoints and the selection of the number of portfolios, may influence the analysis. Thus, in most asset pricing studies, both the portfolio sorts method and cross-section regression method are used. In this section, I review the Fama-MacBeth (1973) cross-sectional regression method. One basic model of the Fama-MacBeth (1973) cross-sectional regression is

$$R_{i,t+1} - R_{f,t+1} = \gamma_0 + \gamma_1 ln(MV)_{i,t} + \gamma_2 ln(B/M)_{i,t} + \gamma_3 MOM_{i,t} + \varepsilon_{i,t+1}, \tag{3.6}$$

where $R_{i,t+1}$ is the monthly percent raw returns between July of year t and June of year $t+1$, $R_{f,t+1}$ is the risk-free rate, $ln(MV)_{i,t}$ is the natural logarithm of market capitalization calculated with information available at the end of June of year t,

$ln(B/M)$ is the natural logarithm of the ratio of the book value of equity for the fiscal year ending in year $t-1$ divided by market equity at the end of December of year $t-1$, and MOM is the cumulative compounded stock returns of the previous 6 months at the end of May of year t (e.g., Jegadeesh and Titman (1993)).

Litzenberger and Ramaswamy (1979) develop a generalized least squares (GLS) method based on the Fama-MacBeth (1973) cross-sectional regression. Specifically, for each parameter in the above equation, γ_k (k = 0, 1, 2, 3.), its estimate has the form:

$$\hat{\gamma}_k = \sum_{t=1}^{T} w_{kt}\hat{\gamma}_{kt}, \tag{3.7}$$

where $\hat{\gamma}_{kt}$ is the cross-sectional OLS estimate of γ_k in month t, w_{kt} is the weight for $\hat{\gamma}_{kt}$, and T is the total number of cross-section regressions over the sample period. The variance of $\hat{\gamma}_k$ is computed as

$$Var(\hat{\gamma}_k) = \frac{1}{T(T-1)}\sum_{t=1}^{T}(Tw_{kt}\hat{\gamma}_{kt} - \hat{\gamma}_k)^2. \tag{3.8}$$

Litzenberger and Ramaswamy (1979) show that an efficient weighting, w_{kt}, can be calculated as $w_{kt} = \frac{1/Var(\hat{\gamma}_{kt})}{\sum_{t=1}^{T}[1/Var(\hat{\gamma}_{kt})]}$, where $Var(\hat{\gamma}_{kt})$ is the variance estimate of $\hat{\gamma}_{kt}$.

3.4 Conclusion

In this chapter, I review two methodologies, namely, the portfolio sorts and the cross-sectional regressions. These two basic methods are extensively used in the following chapters. In the following empirical studies, I generally first sort stocks into portfolios based on one variable (e.g., one stock liquidity measure). Then I use the cross-sectional regressions to examine whether the regression coefficient on one variable (e.g., liquidity risk) is statistically significant or not.

Chapter 4

Transaction Costs, Liquidity Risk, and the CCAPM

4.1 Introduction

Recent studies in asset pricing suggest that liquidity plays an important role in investors' consumption and investment decisions.[1] Following these leads, I extend the traditional CCAPM (Rubinstein (1976), Lucas (1978), and Breeden (1979)) by incorporating the liquidity effect in the spirit of Acharya and Pedersen (2005). I show that expected stock return is determined by both consumption risk and liquidity risk with the latter being defined as the covariance between transaction costs and

[1] For instance, Parker and Julliard (2005) suggest that concerns of liquidity are perhaps imperative components neglected by consumption risk alone. Liu (2010) and Chien and Lustig (2010) argue that liquidity risk may originate from consumption and solvency constraints. Næs, Skjeltorp, and Ødegaard (2011) find that stock market liquidity can predict consumption growth. Lynch and Tan (2011) show that transaction costs can generate a first-order effect when they add return predictability, wealth shocks, and state-dependent costs to the traditional consuming and investing problems. Further, Lagos (2010) develops a model with search frictions and shows the importance of the liquidity premium in explaining the equity premium puzzle.

consumption growth.[2] The liquidity-adjusted CCAPM, contingent on specifications, adds up to 77% additional explanatory power to the cross-sectional variation of expected returns, and lowers the estimated risk aversion close to the reasonable level of 10, compared to the traditional CCAPM.

Specifically, using the effective trading costs of Hasbrouck (2009) and the high-low-price-based bid-ask spread estimates of Corwin and Schultz (2012) as proxies for transaction costs, I show that my liquidity-adjusted CCAPM provides a better fit for the cross-sectional expected returns across various liquidity-based portfolios, while the traditional CCAPM fails to capture the liquidity effect.[3] My model also accounts for a larger fraction of the variation in expected returns across size and book-to-market portfolios. This is in contrast to previous studies, which show that the traditional CCAPM is less successful in explaining the variation in expected portfolio returns classified by size and book-to-market ratios (e.g., Lettau and Ludvigson (2001), Bansal and Yaron (2004), Parker and Julliard (2005) and Yogo (2006)).

Lewellen, Nagel, and Shanken (2010) demonstrate that it is necessary for asset pricing tests to include other sets of portfolios (e.g., industry portfolios) to break down the strong factor structure of size and book-to-market portfolios. I show that the

[2] Acharya and Pedersen (2005) define three sources of liquidity risks, namely, the covariance of a security's illiquidity with the market illiquidity, the covariance of a security's return with the market illiquidity, and the covariance of a security's illiquidity with the market return. Pastor and Stambaugh (2003), Liu (2006), and Sadka (2006) examine liquidity risk measured by the comovements between returns and certain aggregate liquidity factors.

[3] Acharya and Pedersen (2005) show that the CAPM (Sharpe (1964) and Lintner (1965)) fails to capture liquidity costs and liquidity risks. Liu (2006) and Liu (2010) find that both the CAPM and the Fama-French (1993) three-factor model have difficulty in capturing the liquidity effect. A few recent studies examine the explanatory power of the traditional CCAPM to the variation of expected return across portfolios sorted by different liquidity proxies. For instance, Kang and Li (2011) use the long-run consumption risk framework of Hansen, Heaton, and Li (2008) to explain liquidity premium.

liquidity-adjusted CCAPM is robust to the inclusion of industry portfolios.[4] Recent studies also highlight the importance of the ultimate or long-run consumption risk (Parker and Julliard (2005)),[5] durable consumption (Yogo (2006)), and the fourth-quarter consumption (Jagannathan and Wang (2007)) in explaining the variations of expected returns. Parker and Julliard (2005) show that the long-run consumption risk model at the interval of 11 quarters explains a large fraction of 25 Fama-French portfolios' return variations. Yogo (2006) finds that the model with nondurable consumption, durable consumption, and market factor can account for a large proportion of return variations. Jagannathan and Wang (2007) show that using the fourth-quarter consumption helps to improve the performance of the traditional CCAPM. I show that applying the long-run,[6] total (durable and nondurable), and fourth-to-fourth quarter consumption growth measures to my liquidity-adjusted model explains a larger fraction of the variation in cross-sectional expected returns than the CCAPM.

Malloy, Moskowitz, and Vissing-Jørgensen (2009) argue that risk aversion estimates can be an alternative measure of the plausibility of a model. The equity premium puzzle (e.g., Mehra and Prescott (1985) and Hansen and Jagannathan (1991)) suggests that the traditional CCAPM would require a much higher coefficient of risk

[4]Recent studies such as Savov (2011) and Kan, Robotti, and Shanken (2013) also incorporate industry portfolios. They use the 25 Fama-French (1993) size and book-to-market portfolios plus industry portfolios as test portfolios.

[5]Parker and Julliard (2005) argue: "Rather than measure the risk of a portfolio by the contemporaneous covariance of its return and consumption growth – as done in the previous literature on the CCAPM and the cross-sectional pattern of expected returns – I measure the risk of a portfolio by its ultimate risk to consumption, defined as the covariance of its return and consumption growth over the quarter of the return and many following quarters" (page 186).

[6]A growing literature, e.g., Da (2009), Malloy, Moskowitz, and Vissing-Jørgensen (2009), and Favilukis and Lin (2013), investigates asset pricing models that feature the long-run risk as in Bansal and Yaron (2004), Parker and Julliard (2005), and Hansen, Heaton, and Li (2008).

aversion to match the Sharpe ratio observed in the U.S., given the low volatility of consumption. My model, instead, requires lower risk aversion to match the average returns. For instance, employing the transactions costs measure of Corwin and Schultz (2012) and measuring consumption risk over the long run as in Parker and Julliard (2005),[7] I show that the estimated risk aversion from the liquidity-adjusted model is about 10 (the maximum level considered plausible by Mehra and Prescott (1985)), which is much smaller than the corresponding risk aversion estimated under the CCAPM.[8]

I also use a generalized method of moments (GMM), following Hansen and Singleton (1983), to estimate risk aversion. The GMM estimates the risk aversion coefficient by making the sample moments as close as possible to the population moments. Recent studies, e.g., Malloy, Moskowitz, and Vissing-Jørgensen (2009) and Savov (2011) also use the GMM method to estimate the risk aversion coefficient. Consistent with the above finding, my model yields more plausible risk aversion estimates. In addition, I show that under the same GMM settings results based on some calibrated transaction costs, as in Liu and Strong (2008), produce similar evidence. Liu and Strong (2008) use some calibrated transaction costs to calculate the transaction costs adjusted returns.

Lettau and Ludvigson (2001) and Petkova and Zhang (2005) show that value stocks have higher risk exposure than growth stocks in bad times. I find that the

[7] Malloy, Moskowitz, and Vissing-Jørgensen (2009) show that measuring stockholder consumption risk over the long run delivers more plausible risk aversion estimates.

[8] For example, Savov (2011) shows that the risk aversion from GMM estimate for the excess market return is above 60 using the long-run consumption risk of Parker and Julliard (2005).

patterns of estimated liquidity betas conditional on the economic states provide a liquidity-risk based explanation for the countercyclical value premium. Specifically, I show that value stocks have higher liquidity risk in bad times than in good times, while growth stocks have lower liquidity risk in good times than in bad times.

Overall, I make a liquidity adjustment to the consumption-based capital asset pricing model (CCAPM) and show that the liquidity-adjusted CCAPM is a generalized model of Acharya and Pedersen (2005). My results suggest that investors do care about the sensitivity of transaction costs to the aggregate consumption growth, and hence demand high return for securities with high exposure to liquidity risk. By tying transaction costs with consumption growth, I provide new evidence to the recent literature that highlights the importance of liquidity risk in asset pricing (e.g., Chordia, Roll, and Subrahmanyam (2000), Pastor and Stambaugh (2003), Acharya and Pedersen (2005), Liu (2006), Sadka (2006), and Bekaert, Harvey, and Lundblad (2007)).[9] While these studies appear to make liquidity adjustment to the CAPM or the Fama-French three-factor model and show that models with this adjustment improve the models' fit, the focus of my paper is on the liquidity adjustment to the consumption-based pricing models, an area that has attracted little attention in the literature. The liquidity-adjusted CCAPM produces a more reasonable estimate of risk aversion than that of the traditional CCAPM, which helps to understand the equity premium puzzle.

[9] See Amihud, Mendelson, and Pedersen (2005) for a review of the relation between liquidity and asset prices.

The economic meaning on incorporating the sensitivity of transaction costs to consumption growth to the CCAPM is straight-forward. When the economy is haunted by uncertainties, impacting consumption and squeezing liquidity, individual investors may unwillingly switch from their securities to cash to smooth out consumption; institutional investors may reluctantly exchange their holdings for cash to fulfill their obligations.[10] Under these circumstances, securities whose transaction costs are less sensitive to consumption fluctuations can provide a hedge function against the states of low consumption. On the contrary, securities whose transaction costs are highly sensitive to consumption fluctuations impair investors' abilities to cushion the deterioration in consumption. As a result, investors would be more reluctant to hold high liquidity-risk securities unless they offer high expected returns.

The remainder of the chapter proceeds as follows. Section 4.2 reviews the related literature. Section 4.3 derives the liquidity-adjusted CCAPM. Section 4.4 describes the data. Section 4.5 presents the cross-sectional regression results. Section 4.6 investigates the implied risk aversion. Section 4.7 carries out the robustness tests. Section 4.8 conducts alternative tests with 12-month portfolio holding period. Section 4.9 concludes the chapter.

[10] Jagannathan and Wang (2007) claim that investors are more prone to reappraise their targeted consumption and investment plans during periods of slumping stock prices.

4.2 Related literature

While transaction costs are not taken into account by the traditional CCAPM, they are the subject currently generating much research interests. Amihud and Mendelson (1986) introduce liquidity costs into the present value of stocks and show that liquidity costs are positively related to expected returns. Jacoby, Fowler, and Gottesman (2000) develop a static liquidity-adjusted CAPM using net returns after bid-ask spread adjustment and show that market risk and liquidity are related. Lo, MacKinlay, and Wang (2004), using an equilibrium model with heterogeneous agents, show that even small transaction costs can significantly affect asset prices. Acharya and Pedersen (2005) study how investors maximize expected utility with time-varying liquidity costs. They show that liquidity risk has a first-order effect on stock returns. Most recent studies show that transaction costs can generate liquidity premium which is in the same order as the costs with time-varying investment opportunity sets (Jang, Koo, Liu, and Loewenstein (2007)) and with predictable returns, wealth shocks, and state-dependent transaction costs (Lynch and Tan (2011)).[11]

My model is a generalized version of Acharya and Pedersen (2005) and suggests a novel source of liquidity risk which is the covariance between transaction costs and consumption growth. I show that the three channels of liquidity risk of Acharya and Pedersen (2005) can be captured by the covariance between transaction costs and consumption growth.

[11] Early studies such as Constantinides (1986) show that transaction costs only have a second-order effect in the model with the constant transaction costs.

One study relates to mine is Márquez, Nieto, and Rubio (2014) where the authors build a liquidity-adjusted stochastic discount factor. The differences between their model and mine are, however, that they assume a market illiquidity shock to consumption while I focus on transaction costs following Acharya and Pedersen (2005). Further, they measure liquidity risk as the covariance between returns and liquidity factor, while I measure liquidity risk as the covariance between transaction costs and aggregate consumption growth. Most importantly, except for the model's explanatory power, I also analyze the structural features in my model, namely, the estimation of risk aversion.

4.3 The model

In this section, I incorporate transaction costs, the key ingredient of this article, into the traditional CCAPM to develop my liquidity-adjusted CCAPM.

4.3.1 Transaction costs and budget constraints

The economy in this section is the same as that in section 2.2 of chapter 2. In my study, I follow Acharya and Pedersen (2005) by assuming a time-vary transaction cost, which implies that the representative consumer faces uncertainty with the future costs of trading. I later show that shocks of transaction costs are countercyclical, consistent with Acharya and Pedersen (2005) and Lynch and Tan (2011). Specifically, the return of risky asset i after netting out transaction costs is (assuming trading on the liquid risk-free asset incurs no transaction costs),

$$
\begin{aligned}
R^n_{i,t+1} &= \frac{D_{i,t+1} + P_{i,t+1} - TC_{i,t+1}}{P_{i,t}} \\
&= R_{i,t+1} - tc_{i,t+1},
\end{aligned}
\tag{4.1}
$$

where $P_{i,t+1}$ is the ex-dividend stock i's price, $D_{i,t+1}$ is the dividend, $TC_{i,t+1}$ is the per-share cost of selling stock i,[12] $R_{i,t+1}$ is the return before transactions costs, $R^n_{i,t+1}$ is the net return, and $tc_{i,t+1}$ is the relative time-varying transaction costs. In the spirit of Acharya and Pedersen (2005), investors can buy stock i at $P_{i,t+1}$ but have to sell it at $P_{i,t+1} - TC_{i,t+1}$. This assumption allows us to study the effect of liquidity risk.

Given the above assumption, I now turn to the effect of transaction costs on the budget constraints. Let the representative consumer's time t portfolio weight of the risky asset i be $\omega_{i,t}$ $(i = 1, 2, ..., n)$, the weight of the risk-free asset is then $1 - \sum_{i=1}^n \omega_{i,t}$. Since the representative consumer is exposed to the market where she gains the net returns, her wealth at $t+1$ is

$$
W_{t+1} = (W_t - C_t)\Big[R_{f,\,t+1} + \sum_{i=1}^{n} \omega_{i,t}(R_{i,\,t+1} - tc_{i,\,t+1} - R_{f,\,t+1})\Big], \tag{4.2}
$$

where C_t is consumption at t, W_t is wealth at t, and $R_{f,\,t+1}$ is the risk-free rate from t to $t+1$.

[12] Following Acharya and Pedersen (2005), $D_{i,t+1}$ and $TC_{i,t+1}$ are first-order autoregressive processes.

To provide a further intuition, I assume a simple two-period wealth dynamic without labor income. Let W_0 and C_0 be the representative consumers wealth and consumption at time 0 (the beginning of the period). She is also assumed to consume all of her wealth, C_1 at time 1 (the end of the period). Then the two-period dynamic wealth has the form:

$$C_1 = (W_0 - C_0)\Big[R_{f,1} + \sum_{i=1}^{n} \omega_i (R_{i,1} - tc_{i,1} - R_{f,1})\Big]. \tag{4.3}$$

According to Eq. (4.3), the consumption at time 1 is more negatively affected when the transaction costs ($tc_{i,1}$) are higher, consistent with Næs, Skjeltorp, and Ødegaard (2011). That is, the same stock payoff at time 1 will have a higher value today in terms of the consumption at time 1 when the liquidity is lower.

4.3.2 Liquidity-adjusted CCAPM

I assume that the representative consumer has a time-additive, monotonically increasing, and strictly concave von Neumann-Morgenstern utility function for lifetime consumption, which is time separable, i.e., utility at time t depends merely on the consuming quantity at t rather than the consuming quantity before or after t. I define $I(W_t)$ as the life-time utility function on wealth, which satisfies the following equation:

$$I(W_t) = \max_{C_s, \omega_{i,s}, \forall s,i} E_t \left[\sum_{s=t}^{T-1} U(C_s) + B(W_T) \right], \tag{4.4}$$

where $U(C_s)$ is the utility from consumption at time s, C_s, $B(W_T)$ is the ending bequest function that is monotonically increasing and strictly concave, and $E_t[\cdot]$ is the expectation conditional on information at time t.

Eq. (4.4) indicates that the representative consumer makes decisions with variables C_s and $\omega_{i,s}$ $(i = 1, 2, ..., n)$ so as to maximize the expected lifetime utility. The optimization problem of Eq. (4.4) is subject to the constraint condition of Eq. (4.2). Using stochastic dynamic programming, I can write the first-order conditions (FOC) of the optimal choice problem as:[13]

$$E_t\left[\frac{U_C(C^*_{t+1})}{U_C(C^*_t)}R_{f,\,t+1}\right] = 1 \tag{4.5}$$

and

$$E_t\left[\frac{U_C(C^*_{t+1})}{U_C(C^*_t)}(R_{i,\,t+1} - tc_{i,\,t+1})\right] = 1, \tag{4.6}$$

where $U_C(C^*_t)$ is the partial derivative with respect to the representative consumer's optimal consumption. From Eq. (4.5) and Eq. (4.6), I have,

$$E_t\left[\frac{U_C(C^*_{t+1})}{U_C(C^*_t)}(R_{i,\,t+1} - tc_{i,\,t+1} - R_{f,\,t+1})\right] = 0. \tag{4.7}$$

Suppose that the representative consumer's consumption utility is a constant relative risk aversion (CRRA) function, i.e., $U(C) = \frac{C^{1-\gamma}}{1-\gamma}$, where γ is the coefficient of

[13]See Appendix A for details.

constant relative risk aversion. Based on the representative consumer's consumptions, the first-order condition yields the following equation:

$$E_t\left[(1-\gamma\Delta C_{t+1})(R_{i,\,t+1}-tc_{i,\,t+1}-R_{f,\,t+1})\right]=0, \tag{4.8}$$

where ΔC_{t+1} is the consumption growth from t to $t+1$.

According to Cochrane (2005),[14] the beta representation of Eq. (4.8) has the form:

$$\begin{aligned} E\left[R_{i,t+1}-R_{f,\,t+1}\right] &= E\left[tc_{i,\,t+1}\right] \\ &\quad + \frac{\gamma}{1-\gamma E[\Delta C_{t+1}]}\left[cov(R_{i,\,t+1},\Delta C_{t+1})-cov(tc_{i,\,t+1},\Delta C_{t+1})\right] \quad (4.9) \\ &= E\left[tc_{i,\,t+1}\right]+\frac{\gamma Var(\Delta C_{t+1})}{1-\gamma E(\Delta C_{t+1})}(\beta_{i,c}+\beta_{i,tc}), \end{aligned}$$

where $\beta_{i,c}=\frac{cov(R_{i,\,t+1},\Delta C_{t+1})}{Var(\Delta C_{t+1})}$ and $\beta_{i,tc}=\frac{-cov(tc_{i,\,t+1},\Delta C_{t+1})}{Var(\Delta C_{t+1})}$.

Eq. (4.9) above is my liquidity-adjusted CCAPM.[15] It shows that expected excess return of an asset/portfolio is related to its expected transaction costs ($E[tc_{i,\,t+1}]$), consumption risk ($\beta_{i,c}$), and liquidity risk ($\beta_{i,tc}$). I elaborate the model below.

(i) It shows that the expected return of a stock is positively related to its expected transaction costs, $E[tc_{i,\,t+1}]$, which is consistent with prior evidence that transaction costs are related to stock returns.[16]

[14] See Cochrane (2005), chapter 1.

[15] Acharya and Pedersen (2005) show that the traditional CAPM will convert into a CAPM in net returns (returns in excess of transaction costs), i.e., their liquidity-adjusted CAPM. Breeden (1979) shows that the CAPM, as a special case, can be derived from the consumption CAPM. I show in Appendix B that I can use the liquidity-adjusted CCAPM to derive the liquidity-adjusted CAPM in Acharya and Pedersen (2005).

[16] For example, Amihud and Mendelson (1986), using the quoted bid-ask spread as a liquidity measure,

(ii) The sensitivity of stock returns to consumption growth is captured by $\beta_{i,c}$. It indicates that stocks with higher exposure to consumption risk command higher risk premium.[17]

(iii) The negative covariance between a stock's transaction costs and consumption growth is represented by $\beta_{i,tc}$, which I define as the *liquidity risk* in this chapter. Namely, if transaction costs increase when consumption growth decreases, the asset is then said to be exposed to high liquidity risk (i.e., large $\beta_{i,tc}$).

My liquidity-adjusted model shows that high liquidity risk is compensated for high expected return. The basic mechanism is fairly intuitive. During economic contractions, investors may have to give up some of their stocks in exchange of cash either to finance consumption or to honor obligations. Hence, they are more likely to be content with low expected returns on stocks whose transaction costs are impervious to plummeting consumption; while they would require high expected returns on stocks whose transaction costs are highly sensitive to plummeting consumption.

4.4 Data

To empirically test my model, I use two alternative proxies to measure transaction costs. The first is the effective trading costs (*cGibbs*) of Hasbrouck (2009),[18] and the

find that returns are positively related to stock illiquidity.

[17] For instance, Rubinstein (1976), Lucas (1978), Breeden (1979), and Breeden, Gibbons, and Litzenberger (1989).

[18] I thank Professor Joel Hasbrouck for providing his effective trading costs data on his website: http://people.stern.nyu.edu/jhasbrou/Research/GibbsCurrent/gibbsCurrentIndex.html.

second is the bid-ask spread estimates (*CSspread*) of Corwin and Schultz (2012).[19] I test my model based on portfolios classified by firm characteristics (e.g., market capitalization, book-to-market ratio, and liquidity) and industries.

Liu (2006) highlights four dimensions of liquidity: trading quantity, trading speed, trading costs, and the impact of trading on price. Apart from the two transaction costs measures mentioned above (*cGibbs* and *CSspread*), I also use the following liquidity proxies with each capturing a different dimension (While DV, RV, and LM are related to trading quantity, the impact of trading on price, and trading speed, I do not use them as transaction costs measures.):

(i) The dollar volume measure of Brennan, Chordia, and Subrahmanyam (1998), DV, which is defined as the average daily dollar volume over the prior 12 months.

(ii) The price impact measure of Amihud (2002), RV, which is defined as the daily absolute-return-to-dollar-volume ratio averaged over the prior 12 months.

(iii) The trading discontinuity measure of Liu (2006), LM, which is defined as the standardized turnover-adjusted number of zero daily trading volumes over the prior 12 months. The LM proxy measures the probability of no trading. Large LM (i.e., high infrequent trading) indicates slow trading speed (or low liquidity).[20]

[19] I thank Professor Shane Corwin for sharing with us his high-low spread data.

[20] Similar to Amihud (2002), the calculation of RV requires that there are at least 80% non-missing daily trading volumes available in the prior 12 months. Also note that the calculation of RV excludes zero trading volumes over the prior 12 months. Constructions of DV and LM require no missing daily trading volumes in the prior 12 months.

My sample period is from 1950 to 2009, which covers both NYSE and AMEX ordinary common stocks.[21] Consistent with Brennan, Chordia, and Subrahmanyam (1998), Pastor and Stambaugh (2003), and Acharya and Pedersen (2005), I exclude NASDAQ stocks since its trading volume data only become available from 1983 and are inflated compared with NYSE/AMEX stocks. I collect market capitalization (MV) and monthly stock returns from CRSP. Following Davis, Fama, and French (2000), I calculate the book equity using data from COMPUSTAT. I use the one-month treasury bill rate as the risk-free rate.

Panel A of Table 4.1 provides descriptive statistics for the main variables. RV, LM, *cGibbs*, and $CSspread$ are negatively correlated with MV and positively correlated with book-to-market (B/M). On the other hand, DV is positively correlated with MV and negatively correlated with B/M. It suggests that small stocks have a large price impact, are less frequently traded, incur high transaction costs, and have low trading quantities; and value stocks have high price impacts, discontinuous trades, high transaction costs, and low trading quantities. The correlation between *cGibbs* and $CSspread$ is high (0.705). The positive (negative) correlation of the two transaction costs measures with RV and LM (DV) indicates that trading on high-RV, high-LM, and low-DV stocks is costly.

I measure the aggregate consumption growth as the percentage change from preceding period (one quarter) of per capita real (chain-weighted) personal consump-

[21]COMPUSTAT data become available since 1950. I identify ordinary common stocks as those with CRSP share code 10 and 11.

tion expenditures on nondurable goods and services from the National Income and Product Accounts (NIPA Table 7.1). I use the "end of period" timing convention to match the aggregate consumption growth to stock returns and transaction costs.[22] Since consumption data are quarterly, I first compound monthly returns and transaction costs to quarterly values and then employ price deflator series from NIPA to convert quarterly returns and transaction costs to real terms. The compound quarterly transaction costs for quarter q of month m, $m+1$, and $m+2$ are $(1+tc_m) \times (1+tc_{m+1}) \times (1+tc_{m+2}) - 1$. I also use alternative measures for aggregate consumption growth such as the consumption growth of nondurable goods over 11 quarters as in Parker and Julliard (2005),[23] the total consumption growth of Yogo (2006), and the fourth-to-fourth quarter (Q4-Q4) consumption growth of Jagannathan and Wang (2007) to test the robustness of my results.

My liquidity-adjusted model shows that the expected return of a stock is determined by both consumption risk and liquidity risk. I use two linear functions of the aggregate consumption growth to estimate the consumption beta and liquidity beta:

$$R_{i,t} - R_{f,t} = \alpha_c + \beta_c \Delta C_t + \epsilon_{1,t}; \tag{4.10}$$

$$-u_{i,t} = \alpha_{tc} + \beta_{tc} \Delta C_t + \epsilon_{2,t}, \tag{4.11}$$

[22] Under the "end of period" timing convention, I assume that the consumption data measures consumption at the end of the quarter. An alternative convention is the "beginning of period" as in Campbell (2003).

[23] The consumption growth over a horizon of S quarters is calculated as $\Delta C_t^S = \frac{C_{t+S}}{C_{t-1}} - 1$.

where $R_{i,t} - R_{f,t}$ is the return per quarter of stock i in excess of the risk-free rate, ΔC is the consumption growth of nondurable goods and services, and $u_{i,t}$ is the residual of the following regression:

$$tc_{i,t} = \alpha_0 + \alpha_1 tc_{i,t-1} + u_{i,t}, \tag{4.12}$$

where $tc_{i,t}$ is the transaction costs of asset i in quarter t. Using innovation in transaction costs, $u_{i,t}$, is due to the persistency of liquidity, e.g., Pastor and Stambaugh (2003). The negative residual on the left-hand side of Eq. (4.11) is based on the liquidity-adjusted CCAPM (Eq. (4.9)) and the definition of liquidity risk in the chapter ($\beta_{i,tc} = \frac{-cov(tc_{i,\,t+1}, \Delta C_{t+1})}{Var(\Delta C_{t+1})}$). In this way, I expect that high liquidity risk is related to high stock returns. That is, the estimated coefficient on liquidity risk should be positive in the following empirical tests. This is consistent with prior studies, e.g., Pastor and Stambaugh (2003), Liu (2006), and Sadka (2006).

Panel B of Table 4.1 reports the descriptive statistics for various consumption growth measures and the estimated consumption beta and liquidity beta. The average quarterly growth in nondurable goods and services is 0.511% in real term, which is consistent with Yogo (2006) that reports a growth rate of 0.513% (per quarter) over the sample period 1951-2001. On average, the consumption beta is 3.908,[24] and the liquidity beta is 0.107 with *cGibbs* and 0.396 with *CSspread*. The positive liquidity beta and consumption growth indicate positive liquidity risk premium.

[24] This result is similar to Yogo (2006) that reports the consumption betas ranging from 1.196 to 6.512 with the 25 Fama-French (1993) value-weighted portfolios as test portfolios.

In order to provide a visual impression of the time-series property of transaction costs, I in Figure 4.1 plot the aggregate innovations of transaction costs which are the average of the individual transaction costs measures. The liquidity innovation (u_t) is the residual of the following regression:

$$tc_t = \alpha_0 + \alpha_1 tc_{t-1} + u_t, \tag{4.13}$$

where tc_t denotes the average of the transaction costs measures over the sample stocks in quarter t. Figure 4.1 shows that the aggregate shocks of transaction costs are higher in recessions than in expansions, consistent with Acharya and Pedersen (2005) and Lynch and Tan (2011).

4.5 Regression results

4.5.1 Cross-sectional R-squares

I perform my tests on 20 equally-weighted portfolios sorted by MV, B/M, and each of the five liquidity measures. Using NYSE breakpoints, I form portfolios at the end of each (calendar) quarter and hold them for one quarter. In addition, I also use the 4×5 $MV\&B/M$-sorted portfolios formed by independent double sort (4 MV portfolios by 5 B/M portfolios). I conduct comparative tests between my model and the CCAPM using the following cross-section regressions:

$$R_{i,t} - R_{f,t} = \gamma_0 + \gamma_1 \beta_{i,c} + e_{i,t}; \tag{4.14}$$

$$R_{i,t} - R_{f,t} = \gamma_0 + \gamma_1 tc_{i,t} + \gamma_2 \beta_{i,c} + \gamma_3 \beta_{i,tc} + e_{i,t}, \tag{4.15}$$

where $R_{i,t} - R_{f,t}$ is the quarter t return of portfolio i in excess of the risk-free rate, $\beta_{i,c}$ is the consumption beta, $tc_{i,t}$ is the transaction costs of portfolio i, and $\beta_{i,tc}$ is the liquidity beta. Consumption beta is estimated through a time-series regression of excess return on consumption growth as in Eq. (4.10). Liquidity beta is estimated through a time-series regression of the liquidity innovation on consumption growth as in Eq. (4.11).[25] Following Jagannathan and Wang (1996) and Lettau and Ludvigson (2001), I employ the Fama-MacBeth (1973) procedure to calculate the cross-sectional R-square, which has the following form:

$$R^2 = \frac{[Var_c(\bar{R}_i^e) - Var_c(\bar{\epsilon}_i)]}{Var_c(\bar{R}_i^e)}, \tag{4.16}$$

where $\bar{R}_i^e$ is the time-series average of returns in excess of the risk-free rate for portfolio i, $\bar{\epsilon}_i$ is the time-series average of residuals for portfolio i, and Var_c is the cross-sectional variance. The cross-sectional R-square measures the proportion of the cross-sectional return variations which are explained by the traditional CCAPM or the liquidity-adjusted model. This cross-sectional R-square measure is also used in Petkova (2006).

[25] I estimate the consumption beta and liquidity beta using the entire sample, e.g., Lettau and Ludvigson (2001) and Acharya and Pedersen (2005), unless noted otherwise.

Figure 4.2 plots the R-squares for the CCAPM and my model. It shows that, across the board, the fraction of cross-sectional return variations explained by the liquidity-adjusted model is larger than that explained by the CCAPM. For instance, for the 20 B/M-sorted portfolios, 89.72% (with *cGibbs*) and 88.60% (with $CSspread$) average return variations are explained by my model, while 31.97% (with *cGibbs*) and 33.77% (with $CSspread$) are explained by the CCAPM.

4.5.2 The estimates of model coefficients

To test the liquidity-adjusted CCAPM, I estimate the historical consumption beta and liquidity beta for each of the test portfolios using prior 3-year observations. I take into account both the liquidity risk and transaction costs in the following regression:

$$R_{i,t} - R_{f,t} = \gamma_0 + \gamma_1 tc_{i,t} + \gamma_2 \beta_{i,t-1,c} + \gamma_3 \beta_{i,t-1,tc} + e_{i,t}, \tag{4.17}$$

where $R_{i,t} - R_{f,t}$ is the return of portfolio i in excess of the risk free rate, $tc_{i,t}$ is the transaction costs of portfolio i, $\beta_{i,t-1,c}$ is the historical consumption beta, and $\beta_{i,t-1,tc}$ is the historical liquidity beta.

I use the generalized least squares (GLS) to estimate the above regression. Table 4.2 reports the estimated coefficients on transaction costs, consumption risk, and liquidity risk. It shows that the coefficients on liquidity risk are significantly positive for all the test portfolios at the 1% level, consistent with the expectations. It indicates that investors care about the covariance between transactions and the aggregate consumption growth. Therefore, investors demand high returns for holding high liquidity risk stocks. Moreover, the coefficients on transaction costs are generally insignificant at the conventional level. It indicates that liquidity risk matters over liquidity level, which is consistent with Acharya and Pedersen (2005) and Liu (2010).

4.5.3 Fitted versus realized returns

Figure 4.3 plots the realized average excess returns and the fitted excess returns. The realized average returns are the time-series average returns in excess of the risk-free rate. The fitted expected returns for the CCAPM are calculated as the fitted value from Eq. (4.14). The fitted expected returns for my liquidity-adjusted model are calculated as the fitted value from Eq. (4.15). Specifically, in the first step, consumption beta is estimated through a time-series regression of excess return on consumption growth as in Eq. (4.10). Liquidity beta is estimated through a time-series regression of the liquidity innovation on consumption growth as in Eq. (4.11). In the second step, the coefficients on consumption and liquidity betas are estimated. The fitted expected returns are computed using the estimated betas in the first step and their estimated coefficients in the second step. This approach is also used in Lettau and Ludvigson (2001), Parker and Julliard (2005), Petkova (2006), Yogo (2006), and Jagannathan and Wang (2007).

The points represent the 20 MV-sorted, B/M-sorted, $MV\&B/M$-sorted, DV-sorted, RV-sorted, LM-sorted, *cGibbs*-sorted, and $CSspread$-sorted portfolios, respectively. If the fitted expected returns are the same as the realized returns for each set of test portfolios, these points should lie on the 45 degree line. The vertical distance of these points to the 45 degree line represents the pricing errors. Figure 4.3 shows that, overall, the pricing errors associated with the liquidity-adjusted model are smaller than those associated with the CCAPM. I report the magnitudes of pricing errors for each portfolio for the traditional CCAPM and the liquidity-adjusted CCAPM in Tables 4.3 and 4.4. The pricing errors are the differences between the fitted returns and realized returns. The results of Tables 4.3 and 4.4 are in line with Figure 4.3.

4.5.4 Consumption beta and liquidity beta

I estimate the consumption beta and liquidity beta, using *cGibbs* and $CSspread$ as transaction costs measures, for the 20 MV-sorted, B/M-sorted, $MV\&B/M$-sorted, DV-sorted, RV-sorted, LM-sorted, *cGibbs*-sorted, and $CSspread$-sorted portfolios, respectively.

Tables 4.5 and 4.6 report the results. I find that consumption betas are related to firm size, small (large) stocks having high (low) consumption betas. However, consumption betas for the 20 B/M portfolios exhibit a counter intuitive pattern, consistent with Yogo (2006). The consumption beta for the lowest LM-sorted portfolio is larger than that for the highest LM-sorted portfolio. These paradoxical patterns of consumption betas across B/M-sorted and LM-sorted portfolios suggest that the

CCAPM has difficulties in explaining the value and liquidity premiums. In contrast, I find that the liquidity beta exhibits a consistent tendency across each of the test portfolios.

4.5.5 Liquidity risk and expected returns

In this sub-section I examine whether stocks with high liquidity betas are related to high expected returns, as indicated by my liquidity-adjusted CCAPM. To test this, I run the following cross-section regression:

$$R_{i,t} - R_{f,t} = \gamma_0 + \gamma_1 \beta_{i,c} + \gamma_2 \beta_{i,tc} + e_{i,t}, \tag{4.18}$$

where $R_{i,t} - R_{f,t}$ is the quarterly return of portfolio i in excess of the risk-free rate, $\beta_{i,c}$ is the consumption beta, and $\beta_{i,tc}$ is the liquidity beta.

Table 4.7 shows that the coefficients for the liquidity beta are significantly positive, except for the MV-sorted and $CSspread$-sorted portfolios, indicating that high liquidity risk generally commands high expected returns. In contrast, consumption beta shows no or even negative return relation, consistent with early studies that the CCAPM does a poor job in explaining cross-section stock returns.

As an alternative, I run the following regression:

$$R_{i,t} - R_{f,t} = \gamma_0 + \gamma_1 \beta_{i,t-1,c} + \gamma_2 \beta_{i,t-1,tc} + e_{i,t}, \tag{4.19}$$

where $R_{i,t} - R_{f,t}$ is the one-month ahead return of portfolio i in excess of the risk-free rate, $\beta_{i,t-1,c}$ is the historical consumption beta, and $\beta_{i,t-1,tc}$ is the historical liquidity beta.[26] I estimate the historical consumption beta and liquidity beta for each set of the 20 test portfolios using prior 10-year observations. Table 4.8 again shows that the coefficients for the liquidity beta are significantly positive for all the test portfolios, except for the $MV\&B/M$-sorted, DV-sorted, and LM-sorted portfolios in Panel A; while none of the coefficients for the consumption beta are statistically significant.

4.5.6 Liquidity betas in bad and good states

Watanabe and Watanabe (2008) and Akbas, Boehmer, Genc, and Petkova (2010) highlight the importance of time-varying liquidity risk in asset pricing. Lettau and Ludvigson (2001) and Akbas, Boehmer, Genc, and Petkova (2010) argue that the returns of value and growth stocks are related to time-varying risks. Following these studies, I, in this sub-section, examine the time-varying liquidity betas for value and growth stocks.

Figure 4.4 plots the average rolling liquidity betas for growth and value stocks in bad and good states. The rolling liquidity betas for each stock are estimated from the 10-year rolling regressions based on Eqs. (4.11) and (4.12). The estimated liquidity betas are then allocated into the 20 B/M portfolios. The plotted rolling liquidity betas are the cross-sectional time-series averages for the lowest (growth) and highest (value) B/M portfolios. I use NBER recession periods to identify bad states and other periods as good states. Figure 4.4 shows that the liquidity betas are higher

[26] I find that the relation between the historical liquidity betas and the quarterly cross-sectional returns is positive, while the statistical significance is weaker, based on the Fama-MacBeth (1973) regressions.

in bad than in good states for value stocks, while it is opposite for growth stocks, consistent with Akbas, Boehmer, Genc, and Petkova (2010).[27] The value-minus-growth betas also show a countercyclical pattern, i.e., liquidity betas decrease from bad to good states. These suggest that the return of value stocks co-moves more with market liquidity as in Eq. (4.13) in times when investors may have to give up some of their stocks in exchange of cash to either finance their consumptions or to honor their obligations. They would, therefore, require high expected returns to hold value stocks.

4.6 Implied risk aversion

Malloy, Moskowitz, and Vissing-Jørgensen (2009) argue that estimated risk aversion provides an alternative measure on the plausibility of a model. Many studies focus on the R-squares and pricing errors of different asset pricing models. Lewellen, Nagel, and Shanken (2010) also argue that the R-squares and pricing errors could lead to the inaccurate statistical inference of the models' performance especially when the testing portfolios are highly correlated with each other and contain a strong factor structure as the 25 Fama-French portfolios do. Therefore, Malloy, Moskowitz, and Vissing-Jørgensen (2009) argue that estimated risk aversion can provide the theoretical restrictions of the asset pricing models. In this section, I estimate the degree of risk aversion of investors for the CCAPM and my liquidity-adjusted model so that

[27] Akbas, Boehmer, Genc, and Petkova (2010) use a different model to estimate liquidity risk.

I can assess the plausibility of the economic magnitudes of risk aversion as a test of the liquidity-adjusted model's performance.

4.6.1 A simple illustration

Cochrane (2005) argues that, based on the slope of the mean-standard deviation frontier, risk aversion of investors for the CCAPM is approximately 50 when the historical U.S. stock returns and consumption growth data are used.[28] In this sub-section, I show mathematically that my liquidity-adjusted model yields a more plausible value of risk aversion.

I can rewrite Eq. (4.9), my liquidity-adjusted model, as follows:

$$\frac{\gamma Var(\Delta C_{t+1})}{1-\gamma E(\Delta C_{t+1})} = \frac{E\left[R_{i,\,t+1} - R_{f,\,t+1} - tc_{i,\,t+1}\right]}{\beta_{i,\,c} + \beta_{i,\,tc}}. \tag{4.20}$$

According to Breeden, Gibbons, and Litzenberger (1989), the CCAPM can be written as:

$$\frac{\gamma Var(\Delta C_{t+1})}{1-\gamma E(\Delta C_{t+1})} = \frac{E\left[R_{i,\,t+1} - R_{f,\,t+1}\right]}{\beta_{i,\,c}}. \tag{4.21}$$

According to Eq. (4.10), consumption betas for Eq. (4.20) and Eq. (4.21) will be equal in the empirical estimates for stock i. Comparing the right side of Eq. (4.20) and Eq. (4.21), I find that the liquidity-adjusted model has a smaller numerator and a larger denominator, since transaction costs and liquidity betas measured in this

[28] See Cochrane (2005), page 21.

study are generally positive. Thus, to fit the data, the coefficient of risk aversion, γ, implied by the liquidity-adjusted CCAPM does not have to be as high as the one indicated by the traditional CCAPM. This is similar to Liu (2004)'s argument that incorporating transaction costs makes the investor less risk averse overall.

4.6.2 Risk aversion estimates

In this sub-section I estimate the degree of risk aversion for the CCAPM and the liquidity-adjusted model. I aim to test whether my model, compared to the CCAPM, generates a consistently lower risk aversion that matches the average stock returns. Malloy, Moskowitz, and Vissing-Jørgensen (2009) show that measuring stockholder consumption risk over many future quarters generates more plausible risk aversion estimates.[29] Following Campbell (2003) and Malloy, Moskowitz, and Vissing-Jørgensen (2009), I estimate the risk aversion coefficient for the CCAPM and my model by using the following two equations:

$$E[R_{i,t} - R_{f,t}] + \frac{\sigma_i^2}{2} = \gamma\sigma_{i,\Delta C^S}; \tag{4.22}$$

$$E[R_{itc,t} - R_{f,t}] + \frac{\sigma_{itc}^2}{2} = \gamma\sigma_{itc,\Delta C^S}, \tag{4.23}$$

where $R_{itc,t} = R_{i,t} - tc_{i,t}$, $\sigma_{i,\Delta C^S} = Cov(R_{i,t}, \Delta C_t^S)$, $\sigma_{itc,\Delta C^S} = Cov(R_{itc,t}, \Delta C_t^S)$, and

[29] For instance, in Malloy, Moskowitz, and Vissing-Jørgensen (2009), the estimated risk aversion for stockholders is about 12 when consumption risk is measured over 8 quarters.

ΔC^S is the consumption growth over S quarters.[30]

Table 4.9 reports the mean risk aversion estimates based on nondurable goods and services consumption growth over a horizon of S ($S = 0, 1, 2, ..., 11$) quarters.[31] For each set of the 20 test portfolios, I calculate the risk aversion coefficient using $\gamma = \frac{E[R_{i,t} - R_{f,t}] + \frac{\sigma_i^2}{2}}{\sigma_{i,\Delta C^S}}$ for the CCAPM and $\gamma = \frac{E[R_{itc,t} - R_{f,t}] + \frac{\sigma_{itc}^2}{2}}{\sigma_{itc,\Delta C^S}}$ for my model. Table 4.9 shows that the risk aversion coefficients estimated under the CCAPM range between 50.06 and 301.86. These large estimates are consistent with the documented equity premium puzzle. In contrast, for each set of the 20 test portfolios, the risk-aversion coefficients estimated under the liquidity-adjusted CCAPM are smaller than that of the CCAPM. For a number of occasions, estimates of risk aversion generated under my model are less than 10, the maximum level considered to be plausible by Mehra and Prescott (1985).[32] Table 4.9 thus provides consistent evidence to my mathematical prediction that the liquidity-adjusted CCAPM implies a lower level of risk aversion than that of the CCAPM. Neglecting liquidity in the CCAPM appears to be responsible to the equity premium puzzle.

[30] For detailed derivation of Eqs. (4.22) and (4.23), see Appendix C.

[31] When $S = 0$, the consumption growth is calculated by $\Delta C_t^S = \frac{C_t}{C_{t-1}} - 1$.

[32] Lustig and Nieuwerburgh (2005) show that, under their specific empirical tests, the estimated coefficient of relative risk aversion is between 2 and 5 for different collateral CAPM models. On the contrary, the estimated coefficient of relative risk aversion is roughly 15 for the traditional CCAPM and 11 for the consumption-based model of Piazzesi, Schneider, and Tuzel (2007). Further, Malloy, Moskowitz, and Vissing-Jørgensen (2009) report that the long-run consumption risk of the wealthiest stockholders can explain the equity premium puzzle with a risk aversion around 10. Savov (2011) finds that a garbage-based CCAPM requires a relative risk aversion of 17 to match the equity premium.

4.7 Robustness tests

In this section I first test the robustness of my results by examining the R-squares of the cross-section regressions performed on the industry portfolios and many other measures. I then use the generalized method of moments (GMM) to check the robustness of risk aversion estimates.

4.7.1 Robustness on R-squares

First, Lewellen, Nagel, and Shanken (2010) argue that the tight factor structure of size and book-to-market portfolios tends to be less powerful in rejecting misspecified asset pricing models and results in high R-squares in cross-sectional tests. They advocate that asset pricing tests should incorporate other set of portfolios to disintegrate the structure of size and book-to-market portfolios. Following their study, I expand each set of the 20 test portfolios examined earlier with 10 industry portfolios and the results are reported in Panel A of Table 4.10. It shows that a greater proportion of cross-sectional variation in expected returns can be explained by the liquidity-adjusted CCAPM than the CCAPM. For example, for the set of 20 MV-sorted portfolios plus the 10 industry portfolios, the liquidity-adjusted model explains 52.45% (with *cGibbs*) and 50.98% (with $CSspread$) cross-sectional return variations, while the CCAPM explains 38.63% (with *cGibbs*) and 37.83% (with $CSspread$) variations.

Second, Parker and Julliard (2005) measure the systematic risk as the sensitivity of returns to future and contemporaneous consumption. Following Parker and Julliard, I measure consumption risk by using the consumption growth of nondurable goods over 11 quarters ($S = 11$) to test the CCAPM and the liquidity-adjusted model. Panel B shows that the liquidity-adjusted model does a better job than the CCAPM in explaining the cross-sectional return variations. For instance, the CCAPM explains 38.18% (with *cGibbs*) and 43.06% (with $CSspread$) cross-sectional return variations, whereas the liquidity-adjusted model explains larger proportions of the return variations (53.45% with *cGibbs* and 60.98% with $CSspread$).

Third, Yogo (2006) highlights the role of durable consumption in explaining the cross-sectional and time-varying expected returns. Following his method, I substitute the total consumption growth (durable and nondurable) for the consumption growth of nondurable goods and services. Panel C reports the results and shows that the liquidity-adjusted model performs better than the CCAPM. Take the 20 RV-sorted portfolios for example, with *cGibbs* as the transaction costs measure, the liquidity-adjusted model adds 17% additional explanatory power to the return variations, compared to the CCAPM.

Finally, Jagannathan and Wang (2007) show that the fourth-to-fourth quarter consumption growth has high explanatory power in cross-sectional return variations, since investors are more prone to reappraise consumption and investment decisions during the fourth quarter. Following Breeden, Gibbons, and Litzenberger (1989) and Jagannathan and Wang (2007), I construct a mimicking fourth-to-fourth quarter consumption growth factor using the maximum-correlation portfolio (MCP) approach.

I run regression of the demeaned fourth-to-fourth quarter consumption growth on annual excess returns of the 10 value-weighted industry portfolios to obtain the MCP weights.[33] I then replace the consumption growth of nondurable goods and services with the MCP. Panel D reports the results and shows that the liquidity-adjusted model explains a larger fraction of return variations than the CCAPM. For instance, for the 20 B/M-sorted portfolios, the explanatory power increases to 78.44% (with *cGibbs*) and 75.18% (with $CSspread$) for the liquidity-adjusted model, while they are 52.37% (with *cGibbs*) and 57.29% (with $CSspread$) for the CCAPM.

4.7.2 Robustness on implied risk aversion

Recent studies (e.g., Malloy, Moskowitz, and Vissing-Jørgensen (2009) and Savov (2011)) use the generalized method of moments (GMM) as in Hansen and Singleton (1983) to estimate the degree of investors' risk aversion. Malloy, Moskowitz, and Vissing-Jørgensen (2009) show that using the long-run stockholder consumption growth can generate the plausible risk aversion estimates. Savov (2011) finds that using the garbage data can produce the plausible risk aversion estimates. In this sub-section, I follow Yogo (2006) and apply a two-step GMM method. The GMM estimator $\hat{\theta}$ (estimated risk aversion) minimizes the following quadratic form of: $Q(\theta) = g'(\theta)Wg(\theta)$, where W is the positive definite matrix. Hansen and Singleton (1983) show that the optimal weighting is $W = S^{-1}$ and $S = \sum_{-\infty}^{\infty} E[u_t u_t']$, where

[33] I thank Professor Kenneth French for providing the 10 value-weighted industry portfolios data on his website: http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/.

u_t is the error term. Following Yogo (2006), in the first step, the optimal weighting matrix is based on the identity matrix, i.e., $W = I$. Thus, an initial estimate of risk aversion can be obtained. Then $S^{-1} = \hat{S^{-1}}^{(1)}$ can also be obtained. Re-minimizing $Q(\theta)$ with $\hat{S^{-1}}^{(1)}$, I can have new $\hat{\theta}^{(2)}$. This procedure continues until convergence. Moreover, the two-step GMM method can obtain asymptotic efficient statistics which are robust to the choices of test portfolios (Parker and Julliard (2005)). I also use the Newey and West (1987) adjustment to take into account heteroscedasticity and auto-correlation. To estimate risk aversion, I use the empirical moment functions Eq. (4.24) for the CCAPM and Eq. (4.25) for the liquidity-adjusted model:

$$E[M_t^S(R_{m,t} - R_{f,t})z_t] = 0, \tag{4.24}$$

$$E[M_t^S(R_{m,t} - R_{f,t} - tc_{m,t})z_t] = 0, \tag{4.25}$$

where $M_t^S = \beta(\frac{C_{t+S}}{C_{t-1}})^{-\gamma}$,[34] β is the subjective discount factor, γ is the coefficient of risk aversion, $R_{m,t} - R_{f,t}$ is the market return in excess of the risk-free rate, $tc_{m,t}$ is the aggregate transaction costs, and z_t is a 2×1 vector of instrumental variables, which are the three-time-period-lagged risk-free rate and excess return of the market portfolio. Following Hansen, Heaton, and Li (2008) and Savov (2011), I fix $\beta = 0.95$ to focus exclusively on risk aversion.[35] Results are reported in Table 4.11. It shows that

[34]This specification is based on the traditional CCAPM with long-run consumption risk as in Parker and Julliard (2005).

[35]According to Eqs. (4.24) and (4.25), all inputs are observable except β and γ. Thus, the risk aversion, γ, would be the only parameter to be estimated when β is fixed.

the risk version estimates for my model are lower compared to those for the CCAPM, mirroring the findings shown in Table 4.9. For example, with consumption growth over 7 quarters and *cGibbs* as a measure of transaction costs, risk aversion estimate declines from 44.36 for the CCAPM to 14.02 for the liquidity-adjusted model. With consumption growth over 2 quarters and *CSspread* as a measure of transaction costs, risk aversion estimate declines from 67.71 for the CCAPM to 2.91 for the liquidity-adjusted model.

I also carry out the GMM estimates based on some calibrated transaction costs. Similar to Liu and Strong (2008),[36] I assume the transaction costs to be 0.5%, 1%, or 1.5% each quarter. Again, I find that the risk aversion estimates are lower for the liquidity-adjusted model than for the CCAPM.

4.8 Alternative tests with 12-month holding period

In the following tests, I re-examine the above results by holding portfolios for 12 months. My test assets are a set of 20 equally-weighted portfolios classified by $MV - B/M$ and by each of the liquidity measures. I form portfolios at the end of June each year except for the cGibbs portfolios, which are formed at the end of December each year, and hold them for subsequent 12 months (four quarters). I decompose the buy-and-hold portfolio return over the 12-month holding period into quarterly

[36] Liu and Strong (2008) assume some levels of transaction costs to calculate transaction-cost-adjusted returns.

returns based on Liu and Strong (2008). In addition, my test also uses the 5×4 $MV\&B/M$ portfolios formed by independent double sort (5 MV portfolios by 4 B/M portfolios).

4.8.1 Estimates of consumption beta and liquidity beta with 12-month portfolio holding period

Table 4.14 using *cGibbs* as transaction costs and Table 4.15 using $CSspread$ as transaction costs report the consumption beta and the liquidity beta estimated by the multiple regressions for the 20 MV-sorted portfolios, 20 B/M-sorted portfolios, 5×4 $MV\&B/M$-sorted portfolios, 20 DV-sorted portfolios, 20 RV-sorted portfolios, 20 LM-sorted portfolios, 20 *cGibbs*-sorted portfolios, and 20 $CSspread$-sorted portfolios.

- *Consumption betas* For Tables 4.14 and 4.15, reading across the rows of Panels A and C, consumption betas are roughly associated with size premium, i.e., small stocks have high consumption betas while big stocks have low consumption betas. Reading across the rows of Panels B and C, the patterns of consumption betas exhibit the U-shaped relation between portfolio returns classified by book-to-market ratios and consumption risk. This could be attributed to the potential reasons for the failure of the CCAPM to explain the value premium (e.g. Yogo (2006)). Reading across the rows of Panel F, consumption beta for $LM1$ portfolio (5.214 with *cGibbs* costs and 5.196 with $CSspread$ costs) is larger than that for $LM20$ (4.388 with *cGibbs* costs and 4.412 with $CSspread$ costs), which is opposite to the liquidity premium. The paradoxical pattern of consumption betas across LM-sorted portfolios, meaning that illiquid stocks have low consumption betas and liquid stocks have high consumption betas, is one of the potential reasons why the CCAPM fails to explain the liquidity premium. Reading across the rows of Panel D, E, G and H, consumption betas display U-shaped patterns. Hence, these results indicate that the CCAPM has limited power in explaining the cross-sectional variation of portfolio returns sorted by DV, RV, *cGibbs*, and $CSspread$.

- *Liquidity betas* In Tables 4.14 and 4.15, liquidity betas are generally positive. This is consistent with the expectation since negative innovations in transaction costs are low when asset returns are low. Broadly speaking, liquidity risk accounts for the return characteristics across each set of portfolios. More importantly, liquidity betas are related with the liquidity premium implied by LM-sorted test portfolios: $LM1$ portfolio has smaller liquidity beta (0.089 with *cGibbs* costs and 0.304 with $CSspread$ costs) than $LM20$ (0.233 with *cGibbs* costs and 1.317 with $CSspread$ costs).

4.8.2 Pricing power with 12-month portfolio holding period

Figure 4.5 (Panel A with *cGibbs* costs and Panel B with $CSspread$ costs) plots the R-squares for the CCAPM and my liquidity-adjusted model. It shows that, across the broad, the fraction of cross-sectional return variations explained by my liquidity-adjusted model is much larger than that explained by the CCAPM. For instance, for the 20 BM-sorted portfolios, 65.60% (with *cGibbs* costs) and 63.72% (with $CSspread$

costs) average return variations are explained by my liquidity-adjusted model, while just 12.29% (with *cGibbs* costs) and 14.54% (with $CSspread$ costs) are explained by the CCAPM. The most significant gain in light of the R-squares lies in the 20 DV-sorted portfolios where my model explains 85.84% (with *cGibbs* costs) and 61.85% (with $CSspread$ costs) cross-sectional variations of average returns. By contrast, the CCAPM only accounts for 9.27% (with *cGibbs* costs) and 10.20% (with $CSspread$ costs) cross-sectional return variations.

4.8.3 Fitted versus realized returns with 12-month portfolio holding period

Figure 4.6 plots the realized average excess returns and the fitted returns. As can be seen, the pricing errors associated with my model are much smaller than those associated with the CCAPM. In particular, Figures 4.6 suggests that the CCAPM has difficulty in depicting the relation between realized average returns and predicted average returns for the 20 B/M-sorted and DV-sorted portfolios. On the other hand, Figure 4.6 shows that my liquidity-adjusted model fits average returns of these portfolios quite well. For each set of test portfolios, Figure 4.6 shows that for the CCAPM the smallest and biggest size categories, the highest and lowest book-to-market ratio categories and the most illiquidity and liquidity categories are the manifest mispricing portfolios. These portfolios generally lie farthest from the 45 degree line. By contrast, Figures 4.6 indicates that my liquidity-adjusted model shortens the vertical distance for the small and big portfolios, low and high book-to-market ratio portfolios as well as low and high liquidity portfolios. I report the magnitudes of pricing errors for each portfolio for the traditional CCAPM and the liquidity-adjusted CCAPM in Tables 4.12 and 4.13. The pricing errors are the differences between the fitted returns and realized returns. The results of Tables 4.12 and 4.13 are consistent with Figure 4.6. Overall, the liquidity risk adjusted model is more successful at pricing expected returns than the traditional CCAPM.

4.8.4 Liquidity risk and expected returns with 12-month portfolio holding period

In this sub-section, I examine whether stocks with high liquidity betas outperform stocks with low liquidity betas. My model implies that investors care about liquidity risk and require a compensation for bearing liquidity risk. I first carry out the examination using pooled cross-sectional time-series regressions of portfolio returns on the estimated consumption beta and liquidity beta. I then implement the generalized least squares (GLS) to run the regressions on the following equation:

$$R_{i,t} - R_{f,t} = \gamma_0 + \gamma_1 \beta_{i,,t-1,c} + \gamma_2 \beta_{i,t-1,tc} + e_{i,t}, \tag{4.26}$$

where $R_{i,t} - R_{f,t}$ is the returns of portfolio i in excess of the risk free rate, $\beta_{i,t-1,c}$ is the consumption beta and $\beta_{i,t-1,tc}$ is the liquidity beta. I estimate the rolling consumption beta and liquidity beta, $\beta_{i,t-1,c}$ and $\beta_{i,t-1,tc}$, for each portfolio using prior 3-year observations. Transaction costs are calculated using the *cGibbs* estimates of

Hasbrouck (2009) in Panel A of Table 4.16 and the *CSspread* estimates of Corwin and Schultz (2012) in Panel B of Table 4.16, respectively.

Panel A of Table 4.16 shows that with the *cGibbs* costs, high liquidity beta is related to high expected returns for the 20 MV-sorted portfolios, 20 B/M-sorted portfolios, 5×4 $MV\&B/M$-sorted portfolios, 20 DV-sorted portfolios, 20 RV-sorted portfolios, 20 LM-sorted portfolios, 20 *cGibbs*-sorted portfolios, and 20 *CSspread*-sorted portfolios at the 5% level. In addition, Panel B of Table 4.16 shows that with the *CSspread* costs, high liquidity beta is related to high returns for the 20 MV-sorted portfolios, 20 B/M-sorted portfolios, 20 *cGibbs*-sorted portfolios, and 20 *CSspread*-sorted portfolios at the 5% level. The coefficient on the liquidity beta is all positive which is in line with the model prediction.

I carry out further examination by controlling the transaction costs. Specifically, I run the following regression:

$$R_{i,t} - R_{f,t} = \gamma_0 + \gamma_1 tc_{i,t} + \gamma_2 \beta_{i,t-1,c} + \gamma_3 \beta_{i,t-1,tc} + e_{i,t}, \tag{4.27}$$

where $R_{i,t} - R_{f,t}$ is the return of portfolio i in excess of the risk free rate, $E(tc_{i,t})$ is the average transaction costs of portfolio i, $\beta_{i,t-1,c}$ is the consumption beta, and $\beta_{i,t-1,tc}$ is the liquidity beta. Panels A and B of Table 4.17 continue to show that investors require higher expected returns for bearing higher liquidity risk stocks after controlling transaction costs. The coefficient on the liquidity risk loading shows significant return association at the 5% level for each set of test portfolio in Panel A and the 20 MV-

sorted portfolios ($t = 2.30$), 20 B/M-sorted portfolios ($t = 1.99$), and 20 $CSspread$-sorted portfolios ($t = 2.65$) in Panel B. Moreover, the coefficient on transaction costs is insignificant at the 10% level for each set of test portfolio regardless of the transaction costs measures. It indicates that liquidity risk (γ_3) matters over liquidity level (γ_1), which is consistent with Acharya and Pedersen (2005) and Liu (2010).

4.8.5 Risk aversion estimates with 12-month portfolio holding period

Tables 4.18 and 4.19 report the estimated risk aversion based on consumption growth over horizons of S ($S = 0, 1, 2...11$).[37] For each set of test portfolio, I calculate the risk aversion coefficients using $\gamma = \frac{E[R_{i,t}-R_{f,t}]+\frac{\sigma_i^2}{2}}{\sigma_{i,\Delta C^S}}$ for the CCAPM and $\gamma = \frac{E[R_{itc,t}-R_{f,t}]+\frac{\sigma_{itc}^2}{2}}{\sigma_{itc,\Delta C^S}}$ for my liquidity-adjusted model, where $R_{i,t}$ and $R_{itc,t}$ are the cross-sectional average values for each set of portfolios. Test portfolios are: the 20 MV-sorted portfolios, 20 B/M-sorted portfolios, 5×4 $MV\&B/M$-sorted portfolios, 20 DV-sorted portfolios, 20 RV-sorted portfolios, 20 LM-sorted portfolios, 20 $cGibbs$-sorted portfolios, and 20 $CSspread$-sorted portfolios.

My results show that the risk aversion estimates are less plausible based on the CCAPM, consistent with the equity premium puzzle. While the risk version estimates for my liquidity-adjusted model are lower than those of the CCAPM. In particular, for the transaction costs measure of Corwin and Schultz (2012) with $S = 7$, the risk aversion estimate for my model is around 10, the maximum level considered plausible

[37]The consumption growth over horizons of S ($S = 0, 1, 2...11$) is calculated by $\Delta C_t^S = \frac{C_{t+S}}{C_{t-1}} - 1$.

by Mehra and Prescott (1985). While the corresponding risk aversion for the CCAPM is at least above 45. Thus, high R-squares and more plausible risk aversion coefficients lend favorable support to my model.

4.8.6 Robustness on cross-sectional R-squares with 12-month portfolio holding period

- *Other testing portfolios*

  I carry out further tests on the traditional CCAPM and my liquidity-adjusted model using 17 and 30 industry portfolios. Moreover, Lewellen, Nagel, and Shanken (2010) argue that the tight factor structure of size and book-to-market portfolios tends to be less powerful in rejecting misspecified asset pricing models and results in high R-squares in cross-sectional tests. They advocate that asset pricing tests should incorporate other sets of portfolios to disintegrate the structure of size and book-to-market portfolios. Following their study, I augment each set of test portfolios (the 20 MV-sorted portfolios, 20 B/M-sorted portfolios, 5×4 $MV\&B/M$-sorted portfolios, 20 DV-sorted portfolios, 20 RV-sorted portfolios, 20 LM-sorted portfolios, 20 $cGibbs$-sorted portfolios, and 20 $CSspread$-sorted portfolios.) with 10 industry portfolios, respectively. The 10, 17, and 30 industry classification is based on the Fama-French's industry classification.[38] Panel A of Tables 4.20 and 4.21 show that a greater proportion of cross-sectional variation in asset returns can be explained by my liquidity-adjusted model than the CCAPM regardless of the test portfolios

[38]http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/.

and transaction costs measures. For example, for the 17 industry portfolios, the cross-sectional R-squares increase to 42.44% with *cGibbs* costs and 20.03% with *CSspread* costs from 0.16% with *cGibbs* costs and 0.39% with *CSspread* costs. Take the 20 *cGibbs*-sorted portfolios plus 10 industry portfolios for another example. My model can explain 75.89% (with *cGibbs* costs) and 68.84% (with *CSspread* costs) cross-sectional return variations while the CCAPM can explain only 17.53% (with *cGibbs* costs) and 16.39% (with *CSspread* costs) of the variations.

- *Other model specifications*

The ultimate consumption model of Parker and Julliard (2005) measures the systematic risk as the sensitivity of returns to future and contemporaneous consumption. The ultimate consumption risk takes slow consumption adjustment into account. Following Parker and Julliard (2005), I measure consumption risk using the consumption growth of nondurable goods with the horizon ($S = 11$) to test the ultimate consumption model and my corresponding liquidity-adjusted model. Consistent with Parker and Julliard (2005), the CCAPM with $S = 11$ consumption growth ($R^2 = 69.67\%$ with *cGibbs* costs and $R^2 = 68.48\%$ with *CSspread* costs) is more powerful than the traditional CCAPM ($R^2 = 36.64\%$ with *cGibbs* costs and $R^2 = 37.90\%$ with *CSspread* costs) in explaining return variations across the 5×4 $MV\&B/M$-sorted portfolios. Despite this, Panel B of Tables 4.20 and 4.21 illustrate that for various test portfolios, my liquidity-adjusted model (with $S = 11$ consumption growth) does a better job than the CCAPM (with $S = 11$ consumption growth) in explaining cross-sectional return variations. For instance, Panel B of Table 4.20 shows that the CCAPM (with $S = 11$ consumption growth) is less powerful in explaining expected returns across the B/M-sorted portfolios (50.38%) and across the DV-sorted portfolios (66.76%), while my liquidity-adjusted model (with $S = 11$ consumption growth) apparently explains larger proportions of return variations (69.95% for the B/M-sorted portfolios and 85.57% for the DV-sorted portfolios).

Yogo (2006) emphasizes the role of durable consumption in explaining the cross-sectional and time-varying expected returns. I thus substitute total consumption growth for the consumption growth of nondurable goods and services. Panel C of Tables 4.20 and 4.21 indicate that total consumption risk helps explain return variation across different sets of test portfolios. Moreover, my liquidity-adjusted model (with total consumption growth) again performs better than the CCAPM (with total consumption growth). Specifically, when *cGibbs* costs are employed, my model explains 79.10%, 54.50%, 79.19%, 72.79%, 73.70%, 40.21%, 88.44%, and 19.55% return variations across the 20 MV-sorted portfolios, 20 B/M-sorted portfolios, 5×4 $MV\&B/M$-sorted portfolios, 20 DV-sorted portfolios, 20 RV-sorted portfolios, 20 LM-sorted portfolios, 20 *cGibbs*-sorted portfolios, and 20 $CSspread$-sorted portfolios, while the CCAPM explains 70.86%, 50.80%, 73.52%, 37.26%, 57.99%, 0.46%, 79.81%, and 1.85% return variations across the respective portfolios. Similar results can be found when using $CSspread$ costs measure.

Further, Jagannathan and Wang (2007) find that using fourth to fourth quarter consumption growth possesses higher explanatory power in cross-sectional return variations due to the fact that investors are more prone to reappraise consumption and investment decisions during the fourth quarter. I use only the Q4 ($4th$ quarter) data to estimate consumption beta and liquidity beta. Similar to the results for the ultimate consumption risk and total consumption risk, Panel D of Tables 4.20 and 4.21 report that my liquidity-adjusted model explains more return variations than the traditional CCAPM.

4.8.7 Robustness on implied risk aversion with 12-month portfolio holding period

My GMM regression results again show that the risk version estimates for my model are lower compared to those for the CCAPM, generally mirroring the findings shown in Tables 4.18 and 4.19. Specifically, with $S = 7$, risk aversion estimates decline to 25.71 (with *cGibbs* costs) and 10.64 (with $CSspread$ costs) for my liquidity-adjusted model from 40.68 (with *cGibbs* costs) and 40.73 (with $CSspread$ costs) for the CCAPM.

In addition, I carry out the GMM estimates based on some calibrated transaction costs. In particular, I assume that the other transaction costs are 0.5%, 1%, and 1.5% for each quarter. This is similar to Liu and Strong (2008) who assume some levels of transaction costs to calculate transaction-cost-adjusted returns. The risk aversion estimate from my model is all lower than that from the CCAPM. For example, with $S = 7$ and *cGibbs* costs, my model delivers the risk aversion values around 26.84 for

0.5% transaction costs, 18.04 for 1% transaction costs, and 11.55 for 1.5% transaction costs to match the data.

4.9 Conclusion

Motivated by recent studies showing the importance of liquidity in asset pricing, I propose a liquidity adjustment to the consumption-based capital asset pricing model (CCAPM). In addition to the traditional CCAPM risk (i.e., the covariance between asset return and consumption growth), the liquidity-adjusted model suggests that expected return is also associated with transaction costs and liquidity risk (the covariance between transaction costs and consumption growth). This is because high sensitivity of transaction costs to fluctuations in consumption implies the difficulty to convert investment into cash for consumption. Investors, therefore, demand high expected return to compensate for high liquidity risk. My model suggests that neglecting transaction costs and liquidity risk would lead to inaccurate estimate of expected return.

Empirically, I find that the average stock positively exposes to liquidity risk, indicating that the traditional CCAPM underestimates risk and expected return on average. This also potentially explains why the performance of the CCAPM is empirically poor. In contrast, I show that the liquidity-adjusted CCAPM explains a larger fraction of the cross-sectional return variations. I extend the literature that highlights the pricing of various systematic risks associated with consumption (e.g., Lettau and Ludvigson (2001), Bansal and Yaron (2004), Parker and Julliard (2005), Yogo (2006), Jagannathan and Wang (2007), Savov (2011), and Boguth and Kuehn (2013)) by showing the positive relation between stock returns and the sensitivity of transaction costs to consumption growth. My time-varying liquidity-risk explanation to the value premium lend further supports to Watanabe and Watanabe (2008) and Akbas, Boehmer, Genc, and Petkova (2010) that show the importance of time-varying liquidity risk.

I also estimate the risk aversion coefficient with the liquidity-adjusted model, which complements Lagos (2010) that shows the importance of liquidity in explaining the equity premium puzzle by using calibration exercises. Further, unlike other advances of consumption-based asset pricing studies (e.g., Parker and Julliard (2005), Yogo (2006), and Jagannathan and Wang (2007)),[39] I highlight the importance of liquidity in understanding the empirical failure of the CCAPM and the equity premium puzzle.

While I explicitly model the liquidity effects as transaction costs in this chapter, I attempt to summarize the communal features of liquidity in the next chapter. Moveover, by generalizing the liquidity effects, I can not only investigate whether the liquidity risk factor is priced or not but also test whether it is an important contributor to the model's performance.

[39] See Ludvigson (2010) for a review of the advances of consumption-based asset pricing.

Table 4.1: Descriptive statistics

Panel A of this table reports descriptive statistics and correlations for the following market variables:

MV(\$*m*): market capitalization measured in millions of dollars;

B/M: book-to-market ratio;

DV(\$000): the average daily dollar volume measured in thousands over the prior 12 months, where daily dollar volume is the number of shares traded on a day times the closing price on that day;

RV(10^6): daily ratio of the absolute return on a day to the dollar volume on that day averaged over the prior 12 months;

LM: standardized turnover-adjusted number of zero daily trading volumes over the prior 12 months;

cGibbs(%): Hasbrouck's (2009) effective transaction costs measure, which is estimated using daily closing prices in the prior 12 months (at least 60 reported trading prices);

CSspread(%): the bid-ask spread estimates from daily high and low prices by Corwin and Schultz (2012).

The *B/M*-related results are determined based on positive *B/M* stocks. The calculations of *DV* and *LM* require no missing daily trading volumes in the prior 12 months. The calculation of *RV* requires that there are at least 80% non-missing daily trading volumes available in the prior 12 months. Note that the calculation of *RV* excludes zero trading volumes over the prior 12 months. At the end of each month from January 1950 to December 2009, cross-sectional averages for each variable are calculated over NYSE/AMEX stocks. The reported mean and standard deviation are based on these time-series cross-sectional averages. Likewise, at the end of each month from January 1950 to December 2009, the cross-sectional Spearman rank correlations are computed, and the time-series average of those correlations are reported.
Panel B of this table reports the various consumption growth measures in percentage form and the estimated individual consumption beta and liquidity beta. ΔC is the consumption growth of nondurable goods and services. ΔC^S is the consumption growth of nondurable goods over 11 quarters ($S = 11$). The consumption growth over a horizon of S quarters is calculated as $\Delta C_t^S = \frac{C_{t+S}}{C_{t-1}} - 1$. ΔC^T is the total consumption growth. ΔC^{Q4} is the fourth-to-fourth (Q4-Q4) consumption growth based on nondurable goods and services. I calculate the Q4-Q4 annual consumption growth using the fourth quarter consumption data. I use two linear functions of the nondurable goods and services consumption growth to estimate the consumption beta and liquidity beta:

$$R_{i,t} - R_{f,t} = \alpha_c + \beta_c \Delta C_t + \epsilon_{1,t};$$
$$-u_{i,t} = \alpha_{tc} + \beta_{tc} \Delta C_t + \epsilon_{2,t},$$

where $R_{i,\,t} - R_{f,\,t}$ is the return in quarter t of stock i in excess of the risk-free rate, ΔC is the consumption growth of nondurable goods and services, and $u_{i,t}$ is the residual of the following regression:

$$tc_{i,t} = \alpha_0 + \alpha_1 tc_{i,t-1} + u_{i,t},$$

where tc is either *cGibbs* or *CSspread*.

Panel A: market variables							
	MV(\$m)	B/M	DV(\$000)	RV(10^6)	LM	cGibbs(%)	CSspread(%)
Descriptive statistics							
Mean	1636.576	1.066	7389.917	4.770	10.352	0.782	1.300
SD	9540.065	5.273	45820.669	34.176	26.028	0.999	2.291

[Cont.]

(continued)

	MV($m)	B/M	DV($000)	RV(10^6)	LM	cGibbs(%)	CSspread(%)
Spearman rank correlation							
B/M	-0.359	1					
DV	0.899	-0.343	1				
RV	-0.940	0.317	-0.967	1			
LM	-0.506	0.205	-0.735	0.655	1		
cGibbs	-0.680	0.207	-0.611	0.691	0.252	1	
CSspread	-0.627	0.244	-0.529	0.605	0.188	0.705	1
Panel B: consumption growth, consumption beta, and liquidity beta							
	$\Delta C(\%)$	$\Delta C^S(\%)$	$\Delta C^T(\%)$	$\Delta C^{Q4}(\%)$	β_c	β_{tc}^{cGibbs}	$\beta_{tc}^{CSspread}$
Descriptive statistics							
Mean	0.511	4.138	0.545	2.065	3.908	0.107	0.396
SD	0.498	3.255	0.860	1.417	23.589	0.674	2.721
Correlation between β_{tc}^{cGibbs} and $\beta_{tc}^{CSspread}$							
0.187							

Table 4.2: Regressions on the transaction costs, consumption beta, and liquidity beta

This table reports the coefficients by regressing the expected portfolio returns on the transaction costs, consumption beta, and liquidity beta. Test portfolios are the 20 MV-sorted, 20 B/M-sorted, 4×5 $MV\&B/M$-sorted, 20 DV-sorted, 20 RV-sorted, 20 LM-sorted, 20 *cGibbs*-sorted, and 20 $CSspread$-sorted portfolios, respectively. I run the pooled GLS regression on the following equation:

$$R_{i,\,t} - R_{f,\,t} = \gamma_0 + \gamma_1 tc_i + \gamma_2 \beta_{i,t-1,c} + \gamma_3 \beta_{i,t-1,tc} + e_{i,t},$$

where $R_{i,\,t} - R_{f,\,t}$ is the return of portfolio i in excess of the risk free rate, $tc_{i,\,t}$ is the transaction costs of portfolio i, $\beta_{i,t-1,c}$ is the historical consumption beta, and $\beta_{i,t-1,tc}$ is the historical liquidity beta. I estimate the historical consumption beta and liquidity beta for each of the test portfolios using prior 3-year observations. Transaction costs are calculated using the *cGibbs* estimates of Hasbrouck (2009) in Panel A and the $CSspread$ estimates of Corwin and Schultz (2012) in Panel B. t statistics are shown in parentheses. The 1%, 5%, and 10% significance levels are denoted with ***, **, and *, respectively.

Panel A: *cGibbs* as a measure of transaction costs			
20 MV-sorted portfolios	$\hat{\gamma_1} = 0.140$ (0.64)	$\hat{\gamma_2} = 0.060\%^{***}$ (2.91),	$\hat{\gamma_3} = 3.005\%^{***}$ (7.87)
20 BM-sorted portfolios	$\hat{\gamma_1} = 0.811^{*}$ (1.79)	$\hat{\gamma_2} = 0.052\%^{**}$, (2.36),	$\hat{\gamma_3} = 2.037\%^{***}$ (5.75)
4×5 $MV\&B/M$-sorted portfolios	$\hat{\gamma_1} = 0.055$ (0.27)	$\hat{\gamma_2} = 0.043\%^{**}$, (2.11),	$\hat{\gamma_3} = 2.566\%^{***}$ (6.72)
20 DV-sorted portfolios	$\hat{\gamma_1} = 0.319$ (1.51)	$\hat{\gamma_2} = 0.056\%^{***}$, (2.64),	$\hat{\gamma_3} = 2.885\%^{***}$ (7.16)
20 RV-sorted portfolios	$\hat{\gamma_1} = 0.217$ (1.04)	$\hat{\gamma_2} = 0.060\%^{***}$, (2.88),	$\hat{\gamma_3} = 2.958\%^{***}$ (7.41)
20 LM-sorted portfolios	$\hat{\gamma_1} = 0.258$ (0.88)	$\hat{\gamma_2} = 0.051\%^{**}$, (2.35),	$\hat{\gamma_3} = 2.610\%^{***}$ (6.96)
20 *cGibbs*-sorted portfolios	$\hat{\gamma_1} = 0.013$ (0.08)	$\hat{\gamma_2} = 0.087\%^{***}$, (4.07),	$\hat{\gamma_3} = 3.214\%^{***}$ (8.08)
20 $CSspread$-sorted portfolios	$\hat{\gamma_1} = -0.191$ (-0.98)	$\hat{\gamma_2} = 0.080\%^{***}$, (3.72),	$\hat{\gamma_3} = 2.934\%^{***}$ (7.87)
Panel B: $CSspread$ as a measure of transaction costs			
20 MV-sorted portfolios	$\hat{\gamma_1} = -0.003$ (-0.02)	$\hat{\gamma_2} = 0.040\%^{*}$, (1.93),	$\hat{\gamma_3} = 1.355\%^{***}$ (4.98)
20 BM-sorted portfolios	$\hat{\gamma_1} = 0.307^{*}$, (1.66)	$\hat{\gamma_2} = 0.034$ (1.51),	$\hat{\gamma_3} = 1.019\%^{***}$ (4.83)
4×5 $MV\&B/M$-sorted portfolios	$\hat{\gamma_1} = -0.006$ (-0.05)	$\hat{\gamma_2} = 0.024$ (1.16),	$\hat{\gamma_3} = 1.189\%^{***}$ (4.55)
20 DV-sorted portfolios	$\hat{\gamma_1} = 0.085$ (0.70)	$\hat{\gamma_2} = 0.034$ (1.58),	$\hat{\gamma_3} = 1.336\%^{***}$ (5.07)
20 RV-sorted portfolios	$\hat{\gamma_1} = 0.035$ (0.29)	$\hat{\gamma_2} = 0.039\%^{*}$, (1.82),	$\hat{\gamma_3} = 1.313\%^{***}$ (4.94)
20 LM-sorted portfolios	$\hat{\gamma_1} = 0.046$ (0.32)	$\hat{\gamma_2} = 0.033$ (1.47),	$\hat{\gamma_3} = 1.149\%^{***}$ (4.98)
20 *cGibbs*-sorted portfolios	$\hat{\gamma_1} = -0.053$ (-0.49)	$\hat{\gamma_2} = 0.055\%^{**}$, (2.52),	$\hat{\gamma_3} = 1.663\%^{***}$ (6.08)
20 $CSspread$-sorted portfolios	$\hat{\gamma_1} = -0.170$ (-1.64)	$\hat{\gamma_2} = 0.058\%^{***}$, (2.67),	$\hat{\gamma_3} = 1.451\%^{***}$ (5.56)

Table 4.3: Pricing errors: *cGibbs* costs

This table reports the pricing errors (in percent) for the traditional CCAPM and the liquidity-adjusted model. The pricing errors are the differences between the fitted returns and realized returns. The realized average returns are the time-series average returns in excess of the risk-free rate. The fitted expected returns for the CCAPM are calculated as the fitted value from $E[R_{i,t} - R_{f,t}] = \gamma_0 + \gamma_1 \beta_{i,c}$. The fitted expected returns for the liquidity-adjusted CCAPM are calculated as the fitted value from $E[R_{i,t} - R_{f,t}] = \gamma_0 + \gamma_1 E[tc_{i,t}] + \gamma_2 \beta_{i,c} + \gamma_3 \beta_{i,tc}$. Transaction costs are calculated using the *cGibbs* estimates of Hasbrouck (2009). Test portfolios are: the 20 MV-sorted portfolios, 20 B/M-sorted portfolios, 4×5 $MV\&B/M$-sorted portfolios, 20 DV-sorted portfolios, 20 RV-sorted portfolios, 20 LM-sorted portfolios, 20 *cGibbs*-sorted portfolios, and 20 *CSspread*-sorted portfolios. $MV1$ ($B/M1$, $DV1$, $RV1$, $LM1$, *cGibbs*1, and *CSspread*1) denotes the smallest (lowest) MV (B/M, DV, RV, LM, *cGibbs*, and *CSspread*) portfolio and $MV20$ ($B/M20$, $DV20$, $RV20$, $LM20$, *cGibbs*20, and *CSspread*20) denotes the biggest (highest) MV (B/M, DV, RV, LM, *cGibbs*, and *CSspread*) portfolio. For the 4×5 $MV\&B/M$-sorted portfolios, the digit after S denotes the size quintile (1 representing the smallest and 4 the largest), and the digit after B denotes the book-to-market quartile (1 representing the lowest and 5 the highest). The variable explanations refer to Table 4.1.

Panel A: MV-sorted portfolios										
	MV1	MV2	MV3	MV4	MV5	MV6	MV7	MV8	MV9	MV10
Traditional CCAPM	-0.045	-0.106	0.072	-0.055	-0.203	0.347	0.175	-0.070	0.189	0.056
Liquidity-adjusted CCAPM	-0.006	-0.281	0.227	-0.215	0.015	0.198	0.093	-0.123	0.080	0.056
	MV11	MV12	MV13	MV14	MV15	MV16	MV17	MV18	MV19	MV20
Traditional CCAPM	0.134	0.266	0.095	0.130	-0.003	-0.034	0.006	0.029	-0.349	-0.634
Liquidity-adjusted CCAPM	0.173	0.154	-0.027	0.181	0.057	0.106	-0.037	-0.001	-0.339	-0.313
Panel B: B/M-sorted portfolios										
	B/M1	B/M2	B/M3	B/M4	B/M5	B/M6	B/M7	B/M8	B/M9	B/M10
Traditional CCAPM	-0.019	-0.679	-0.182	-0.394	-0.381	-0.298	-0.101	-0.363	-0.351	-0.309
Liquidity-adjusted CCAPM	0.013	-0.224	0.155	-0.124	-0.132	-0.032	0.121	-0.157	-0.175	-0.064
	B/M11	B/M12	B/M13	B/M14	B/M15	B/M16	B/M17	B/M18	B/M19	B/M20
Traditional CCAPM	-0.167	-0.316	0.284	0.138	-0.315	0.388	0.436	0.584	0.741	1.305
Liquidity-adjusted CCAPM	-0.038	-0.216	0.301	0.184	-0.206	0.291	0.291	0.209	0.061	-0.257
Panel C: 4×5 $MV\&B/M$ portfolios										
	S1B1	S1B2	S1B3	S1B4	S1B5	S2B1	S2B2	S2B3	S2B4	S2B5
Traditional CCAPM	-0.656	-0.012	0.317	0.474	1.043	-0.384	-0.119	0.155	0.555	0.406
Liquidity-adjusted CCAPM	-0.494	-0.046	-0.098	0.166	0.081	-0.064	0.306	0.440	0.598	0.310
	S3B1	S3B2	S3B3	S3B4	S3B5	S4B1	S4B2	S4B3	S4B4	S4B5
Traditional CCAPM	-0.344	-0.431	-0.178	0.327	0.614	-0.753	-0.706	-0.501	-0.057	0.249
Liquidity-adjusted CCAPM	-0.087	-0.283	-0.168	0.343	0.681	-0.561	-0.555	-0.623	-0.251	0.306

[Cont.]

(continued)

Panel D: *DV*-sorted portfolios										
	DV1	DV2	DV3	DV4	DV5	DV6	DV7	DV8	DV9	DV10
Traditional CCAPM	0.862	0.349	0.076	0.262	0.422	-0.059	0.592	0.224	0.024	0.002
Liquidity-adjusted CCAPM	-0.095	0.083	-0.011	0.046	0.408	-0.348	0.176	0.184	-0.172	-0.054
	DV11	DV12	DV13	DV14	DV15	DV16	DV17	DV18	DV19	DV20
Traditional CCAPM	-0.277	-0.020	-0.045	-0.030	0.037	-0.236	-0.065	-0.394	-0.413	-1.314
Liquidity-adjusted CCAPM	-0.284	-0.031	-0.079	0.191	0.084	-0.088	0.153	-0.090	0.135	-0.207
Panel E: *RV*-sorted portfolios										
	RV1	RV2	RV3	RV4	RV5	RV6	RV7	RV8	RV9	RV10
Traditional CCAPM	-0.979	-0.538	-0.323	-0.366	-0.010	0.264	-0.367	0.283	0.162	-0.074
Liquidity-adjusted CCAPM	-0.211	-0.149	-0.155	-0.046	0.110	0.184	-0.251	0.169	-0.243	-0.116
	RV11	RV12	RV13	RV14	RV15	RV16	RV17	RV18	RV19	RV20
Traditional CCAPM	0.240	0.023	-0.060	0.167	0.002	0.199	0.407	0.514	0.029	0.427
Liquidity-adjusted CCAPM	0.109	0.056	-0.301	0.239	0.033	0.329	0.108	0.150	0.202	-0.216
Panel F: *LM*-sorted portfolios										
	LM1	LM2	LM3	LM4	LM5	LM6	LM7	LM8	LM9	LM10
Traditional CCAPM	-1.351	-0.489	-0.239	0.188	-0.246	-0.056	-0.017	-0.073	-0.201	-0.212
Liquidity-adjusted CCAPM	-0.848	-0.106	0.201	0.357	-0.018	0.242	0.058	0.014	-0.130	-0.084
	LM11	LM12	LM13	LM14	LM15	LM16	LM17	LM18	LM19	LM20
Traditional CCAPM	-0.312	-0.170	0.183	0.099	-0.018	0.327	0.349	0.564	0.750	0.923
Liquidity-adjusted CCAPM	-0.332	-0.201	0.451	0.016	-0.235	0.121	0.342	0.130	0.276	-0.252
Panel G: *cGibbs*-sorted portfolios										
	cGibbs1	cGibbs2	cGibbs3	cGibbs4	cGibbs5	cGibbs6	cGibbs7	cGibbs8	cGibbs9	cGibbs10
Traditional CCAPM	-0.101	-0.183	-0.154	0.067	0.088	-0.091	0.001	-0.202	0.086	-0.142
Liquidity-adjusted CCAPM	-0.158	0.018	-0.039	0.090	-0.062	0.077	0.063	-0.109	0.176	-0.189
	cGibbs11	cGibbs12	cGibbs13	cGibbs14	cGibbs15	cGibbs16	cGibbs17	cGibbs18	cGibbs19	cGibbs20
Traditional CCAPM	0.138	-0.162	-0.159	-0.468	0.379	0.434	0.104	0.062	0.083	0.220
Liquidity-adjusted CCAPM	-0.016	-0.159	-0.009	-0.086	0.008	0.228	0.120	0.071	0.070	-0.093
Panel H: *CSspread*-sorted portfolios										
	CSspread1	CSspread2	CSspread3	CSspread4	CSspread5	CSspread6	CSspread7	CSspread8	CSspread9	CSspread10
Traditional CCAPM	-0.097	0.125	-0.007	0.011	-0.150	0.064	0.033	-0.121	0.116	-0.144
Liquidity-adjusted CCAPM	-0.059	0.130	-0.000	-0.010	-0.170	0.034	0.050	-0.117	0.101	-0.132
	CSspread11	CSspread12	CSspread13	CSspread14	CSspread15	CSspread16	CSspread17	CSspread18	CSspread19	CSspread20
Traditional CCAPM	0.046	0.057	0.100	0.014	0.026	-0.084	0.021	0.187	-0.247	0.052
Liquidity-adjusted CCAPM	0.005	0.056	0.080	-0.045	0.051	-0.091	0.047	0.235	-0.162	-0.001

Table 4.4: Pricing errors: $CSspread$ costs

This table reports the pricing errors (in percent) for the traditional CCAPM and the liquidity-adjusted model. The pricing errors are the differences between the fitted returns and realized returns. The realized average returns are the time-series average returns in excess of the risk-free rate. The fitted expected returns for the CCAPM are calculated as the fitted value from $E[R_{i,t} - R_{f,t}] = \gamma_0 + \gamma_1 \beta_{i,c}$. The fitted expected returns for the liquidity-adjusted CCAPM are calculated as the fitted value from $E[R_{i,t} - R_{f,t}] = \gamma_0 + \gamma_1 E[tc_{i,t}] + \gamma_2 \beta_{i,c} + \gamma_3 \beta_{i,tc}$. Transaction costs are calculated using the $CSspread$ estimates of Corwin and Schultz (2012). Test portfolios are: the 20 MV-sorted portfolios, 20 B/M-sorted portfolios, 4×5 $MV\&B/M$-sorted portfolios, 20 DV-sorted portfolios, 20 RV-sorted portfolios, 20 LM-sorted portfolios, 20 *cGibbs*-sorted portfolios, and 20 $CSspread$-sorted portfolios. $MV1$ ($B/M1$, $DV1$, $RV1$, $LM1$, *cGibbs*1, and $CSspread1$) denotes the smallest (lowest) MV (B/M, DV, RV, LM, *cGibbs*, and $CSspread$) vigintiles portfolio and $MV20$ ($B/M20$, $DV20$, $RV20$, $LM20$, *cGibbs*20, and $CSspread20$) denotes the biggest (highest) MV (B/M, DV, RV, LM, *cGibbs*, and $CSspread$) portfolio. For the 4×5 $MV\&B/M$-sorted portfolios, the digit after S denotes the size quintile (1 representing the smallest and 4 the largest), and the digit after B denotes the book-to-market quartile (1 representing the lowest and 5 the highest). The variable explanations refer to Table 4.1.

Panel A: MV-sorted portfolios										
	MV1	MV2	MV3	MV4	MV5	MV6	MV7	MV8	MV9	MV10
Traditional CCAPM	0.006	-0.115	0.031	-0.108	-0.207	0.338	0.138	-0.020	0.156	0.070
Liquidity-adjusted CCAPM	0.016	-0.157	-0.070	-0.077	-0.192	0.270	0.152	-0.030	0.210	0.079
	MV11	MV12	MV13	MV14	MV15	MV16	MV17	MV18	MV19	MV20
Traditional CCAPM	0.082	0.294	0.095	0.176	0.008	-0.018	-0.021	0.054	-0.340	-0.618
Liquidity-adjusted CCAPM	0.085	0.311	0.102	0.186	0.041	0.000	-0.023	0.033	-0.346	-0.592
Panel B: B/M-sorted portfolios										
	B/M1	B/M2	B/M3	B/M4	B/M5	B/M6	B/M7	B/M8	B/M9	B/M10
Traditional CCAPM	0.018	-0.641	-0.132	-0.394	-0.365	-0.295	-0.061	-0.401	-0.373	-0.344
Liquidity-adjusted CCAPM	0.002	-0.533	0.157	-0.028	-0.016	-0.090	0.028	-0.078	-0.052	-0.182
	B/M11	B/M12	B/M13	B/M14	B/M15	B/M16	B/M17	B/M18	B/M19	B/M20
Traditional CCAPM	-0.233	-0.330	0.294	0.126	-0.367	0.369	0.406	0.546	0.828	1.349
Liquidity-adjusted CCAPM	0.054	-0.090	0.284	0.156	-0.258	0.345	0.148	0.285	0.075	-0.209
Panel C: 4×5 $MV\&B/M$ portfolios										
	S1B1	S1B2	S1B3	S1B4	S1B5	S2B1	S2B2	S2B3	S2B4	S2B5
Traditional CCAPM	-0.687	-0.005	0.312	0.466	1.130	-0.399	-0.115	0.158	0.561	0.405
Liquidity-adjusted CCAPM	-0.657	0.251	0.498	-0.060	0.015	-0.071	0.211	0.332	0.301	-0.177
	S3B1	S3B2	S3B3	S3B4	S3B5	S4B1	S4B2	S4B3	S4B4	S4B5
Traditional CCAPM	-0.350	-0.437	-0.184	0.327	0.616	-0.762	-0.709	-0.507	-0.062	0.241
Liquidity-adjusted CCAPM	0.105	-0.239	-0.062	0.435	0.323	-0.249	-0.394	-0.439	-0.294	0.171

[Cont.]

(continued)

Panel D: *DV*-sorted portfolios										
	DV1	DV2	DV3	DV4	DV5	DV6	DV7	DV8	DV9	DV10
Traditional CCAPM	0.888	0.372	0.088	0.263	0.431	-0.053	0.591	0.215	0.026	0.007
Liquidity-adjusted CCAPM	-0.151	0.286	0.036	0.158	0.208	-0.363	0.305	0.256	-0.266	-0.008
	DV11	DV12	DV13	DV14	DV15	DV16	DV17	DV18	DV19	DV20
Traditional CCAPM	-0.281	-0.027	-0.036	-0.037	0.035	-0.246	-0.076	-0.411	-0.423	-1.326
Liquidity-adjusted CCAPM	-0.330	0.215	0.035	0.300	-0.045	-0.129	-0.044	-0.163	-0.021	-0.278
Panel E: *RV*-sorted portfolios										
	RV1	RV2	RV3	RV4	RV5	RV6	RV7	RV8	RV9	RV10
Traditional CCAPM	-0.999	-0.549	-0.328	-0.379	-0.009	0.276	-0.388	0.291	0.175	-0.071
Liquidity-adjusted CCAPM	-0.332	-0.233	-0.336	0.050	0.068	0.092	-0.034	0.252	0.006	0.097
	RV11	RV12	RV13	RV14	RV15	RV16	RV17	RV18	RV19	RV20
Traditional CCAPM	0.247	0.019	-0.049	0.158	-0.008	0.187	0.409	0.500	0.050	0.467
Liquidity-adjusted CCAPM	0.094	0.177	-0.298	0.209	-0.176	0.372	-0.165	0.335	-0.112	-0.065
Panel F: *LM*-sorted portfolios										
	LM1	LM2	LM3	LM4	LM5	LM6	LM7	LM8	LM9	LM10
Traditional CCAPM	-1.331	-0.511	-0.260	0.175	-0.251	-0.064	0.003	-0.062	-0.196	-0.217
Liquidity-adjusted CCAPM	-0.978	-0.245	0.097	0.334	-0.012	0.190	-0.002	0.027	-0.284	-0.226
	LM11	LM12	LM13	LM14	LM15	LM16	LM17	LM18	LM19	LM20
Traditional CCAPM	-0.306	-0.156	0.171	0.111	-0.008	0.331	0.336	0.578	0.746	0.912
Liquidity-adjusted CCAPM	-0.195	-0.312	0.299	0.002	0.186	0.250	0.376	0.162	0.596	-0.264
Panel G: *cGibbs*-sorted portfolios										
	cGibbs1	cGibbs2	cGibbs3	cGibbs4	cGibbs5	cGibbs6	cGibbs7	cGibbs8	cGibbs9	cGibbs10
Traditional CCAPM	-0.085	-0.189	-0.172	0.064	0.114	-0.099	-0.018	-0.218	0.090	-0.144
Liquidity-adjusted CCAPM	-0.111	0.033	-0.018	0.078	0.013	0.088	0.083	-0.154	0.092	-0.194
	cGibbs11	cGibbs12	cGibbs13	cGibbs14	cGibbs15	cGibbs16	cGibbs17	cGibbs18	cGibbs19	cGibbs20
Traditional CCAPM	0.134	-0.151	-0.172	-0.492	0.409	0.440	0.080	0.053	0.117	0.240
Liquidity-adjusted CCAPM	-0.033	-0.184	-0.013	-0.123	-0.050	0.295	0.143	0.071	0.036	-0.054
Panel H: *CSspread*-sorted portfolios										
	CSspread1	CSspread2	CSspread3	CSspread4	CSspread5	CSspread6	CSspread7	CSspread8	CSspread9	CSspread10
Traditional CCAPM	-0.066	0.125	0.016	-0.014	-0.110	0.055	0.034	-0.119	0.100	-0.139
Liquidity-adjusted CCAPM	-0.083	0.113	0.005	-0.016	-0.127	0.046	0.030	-0.115	0.081	-0.145
	CSspread11	CSspread12	CSspread13	CSspread14	CSspread15	CSspread16	CSspread17	CSspread18	CSspread19	CSspread20
Traditional CCAPM	0.039	0.045	0.087	-0.004	0.007	-0.087	-0.007	0.159	-0.279	0.159
Liquidity-adjusted CCAPM	0.039	0.050	0.083	-0.006	0.016	-0.082	0.071	0.218	-0.184	0.007

Table 4.5: The consumption beta and liquidity beta: *cGibbs* costs

This table reports the patterns of the consumption beta and liquidity beta. Consumption beta is estimated through a time-series regression of returns in excess of the risk-free rate on consumption growth for each portfolio. Liquidity beta is estimated through a time-series regression of liquidity innovations on consumption growth for each portfolio. Transaction costs are calculated using the *cGibbs* estimates of Hasbrouck (2009). Test portfolios are: the 20 MV-sorted portfolios, 20 B/M-sorted portfolios, 4×5 $MV\&B/M$-sorted portfolios, 20 DV-sorted portfolios, 20 RV-sorted portfolios, 20 LM-sorted portfolios, 20 *cGibbs*-sorted portfolios, and 20 $CSspread$-sorted portfolios. $MV1$ ($B/M1$, $DV1$, $RV1$, $LM1$, *cGibbs*1, and $CSspread1$) denotes the smallest (lowest) MV (B/M, DV, RV, LM, *cGibbs*, and $CSspread$) portfolio and $MV20$ ($B/M20$, $DV20$, $RV20$, $LM20$, *cGibbs*20, and $CSspread20$) denotes the biggest (highest) MV (B/M, DV, RV, LM, *cGibbs*, and $CSspread$) portfolio. For the 4×5 $MV\&B/M$-sorted portfolios, the digit after S denotes the size quintile (1 representing the smallest and 4 the largest), and the digit after B denotes the book-to-market quartile (1 representing the lowest and 5 the highest). The variable explanations refer to Table 4.1.

				Panel A: MV-sorted portfolios						
	MV1	MV2	MV3	MV4	MV5	MV6	MV7	MV8	MV9	MV10
β_c	4.251	3.542	3.167	3.540	3.791	3.010	3.154	3.158	3.224	3.109
β_{tc}	0.371	0.145	0.181	0.069	0.096	0.075	0.065	0.061	0.038	0.058
	MV11	MV12	MV13	MV14	MV15	MV16	MV17	MV18	MV19	MV20
β_c	2.970	2.659	2.651	2.700	2.756	2.833	2.414	2.273	2.311	2.733
β_{tc}	0.067	0.056	0.049	0.069	0.065	0.068	0.058	0.065	0.063	0.074
				Panel B: B/M-sorted portfolios						
	B/M1	B/M2	B/M3	B/M4	B/M5	B/M6	B/M7	B/M8	B/M9	B/M10
β_c	4.272	3.356	3.620	3.606	3.416	3.458	3.670	3.090	3.082	2.731
β_{tc}	0.087	0.100	0.044	-0.009	0.003	0.032	0.023	0.009	0.012	0.053
	B/M11	B/M12	B/M13	B/M14	B/M15	B/M16	B/M17	B/M18	B/M19	B/M20
β_c	2.793	3.077	3.589	2.919	2.310	2.998	3.093	2.553	2.859	3.690
β_{tc}	0.008	0.032	0.010	0.050	0.099	0.084	0.151	0.136	0.190	0.289
				Panel C: 4×5 $MV\&B/M$ portfolios						
	S1B1	S1B2	S1B3	S1B4	S1B5	S2B1	S2B2	S2B3	S2B4	S2B5
β_c	5.371	4.394	3.547	3.968	3.455	3.310	3.692	3.127	2.386	2.503
β_{tc}	0.147	0.139	0.156	0.161	0.219	0.057	0.064	0.056	0.052	0.078
	S3B1	S3B2	S3B3	S3B4	S3B5	S4B1	S4B2	S4B3	S4B4	S4B5
β_c	3.076	2.503	2.410	2.234	3.152	2.781	2.606	1.898	1.936	2.986
β_{tc}	0.064	0.050	0.066	0.055	0.097	0.064	0.061	0.064	0.078	0.097

[Cont.]

(continued)

Panel D: *DV*-sorted portfolios										
	DV1	DV2	DV3	DV4	DV5	DV6	DV7	DV8	DV9	DV10
β_c	4.201	3.767	3.623	3.298	3.324	2.772	2.358	2.999	2.593	2.783
β_{tc}	0.279	0.120	0.119	0.055	0.096	0.053	0.053	0.043	0.042	0.039
	DV11	DV12	DV13	DV14	DV15	DV16	DV17	DV18	DV19	DV20
β_c	2.727	2.744	2.601	3.007	2.490	2.612	2.642	2.755	3.098	4.095
β_{tc}	0.058	0.034	0.038	0.040	0.065	0.061	0.068	0.065	0.077	0.075
Panel E: *RV*-sorted portfolios										
	RV1	RV2	RV3	RV4	RV5	RV6	RV7	RV8	RV9	RV10
β_c	3.247	2.864	2.432	3.038	2.610	2.339	2.988	2.496	2.205	2.909
β_{tc}	0.073	0.062	0.078	0.050	0.067	0.066	0.042	0.058	0.047	0.042
	RV11	RV12	RV13	RV14	RV15	RV16	RV17	RV18	RV19	RV20
β_c	2.676	3.086	2.730	3.226	3.151	3.336	2.559	2.898	3.656	4.398
β_{tc}	0.056	0.053	0.051	0.064	0.076	0.091	0.118	0.104	0.172	0.317
Panel F: *LM*-sorted portfolios										
	LM1	LM2	LM3	LM4	LM5	LM6	LM7	LM8	LM9	LM10
β_c	4.244	3.992	4.037	3.222	3.291	3.186	2.505	2.569	2.311	2.515
β_{tc}	0.060	0.006	0.004	-0.002	-0.005	0.053	0.034	0.015	0.060	0.046
	LM11	LM12	LM13	LM14	LM15	LM16	LM17	LM18	LM19	LM20
β_c	2.311	2.207	3.077	2.362	2.676	3.047	3.759	3.098	3.812	3.999
β_{tc}	0.008	0.059	0.091	0.090	0.014	0.049	0.082	0.114	0.132	0.244
Panel G: *cGibbs*-sorted portfolios										
	cGibbs1	cGibbs2	cGibbs3	cGibbs4	cGibbs5	cGibbs6	cGibbs7	cGibbs8	cGibbs9	cGibbs10
β_c	2.626	2.983	2.890	2.796	2.597	2.993	2.873	2.943	2.938	2.782
β_{tc}	0.051	0.057	0.057	0.060	0.061	0.058	0.059	0.065	0.061	0.061
	cGibbs11	cGibbs12	cGibbs13	cGibbs14	cGibbs15	cGibbs16	cGibbs17	cGibbs18	cGibbs19	cGibbs20
β_c	2.694	2.881	3.100	3.427	2.544	2.811	3.207	3.394	3.762	4.534
β_{tc}	0.070	0.063	0.069	0.075	0.082	0.092	0.116	0.155	0.237	0.401
Panel H: *CSspread*-sorted portfolios										
	CSspread1	CSspread2	CSspread3	CSspread4	CSspread5	CSspread6	CSspread7	CSspread8	CSspread9	CSspread10
β_c	2.366	2.182	2.464	2.557	2.509	2.460	2.960	3.286	2.789	3.287
β_{tc}	0.071	0.067	0.062	0.047	0.052	0.053	0.066	0.050	0.062	0.064
	CSspread11	CSspread12	CSspread13	CSspread14	CSspread15	CSspread16	CSspread17	CSspread18	CSspread19	CSspread20
β_c	2.823	3.242	3.214	3.307	3.364	3.919	3.622	3.654	3.230	4.228
β_{tc}	0.057	0.070	0.067	0.050	0.108	0.082	0.134	0.176	0.274	0.433

Table 4.6: The consumption beta and liquidity beta: $CSspread$ costs

This table reports the patterns of the consumption beta and liquidity beta. Consumption beta is estimated through a time-series regression of returns in excess of the risk-free rate on consumption growth for each portfolio. Liquidity beta is estimated through a time-series regression of liquidity innovations on consumption growth for each portfolio. Transaction costs are calculated using the $CSspread$ estimates of Corwin and Schultz (2012). Test portfolios are: the 20 MV-sorted portfolios, 20 B/M-sorted portfolios, 4×5 $MV\&B/M$-sorted portfolios, 20 DV-sorted portfolios, 20 RV-sorted portfolios, 20 LM-sorted portfolios, 20 *cGibbs*-sorted portfolios, and 20 $CSspread$-sorted portfolios. $MV1$ ($B/M1$, $DV1$, $RV1$, $LM1$, *cGibbs*1, and $CSspread1$) denotes the smallest (lowest) MV (B/M, DV, RV, LM, *cGibbs*, and $CSspread$) vigintiles portfolio and $MV20$ ($B/M20$, $DV20$, $RV20$, $LM20$, *cGibbs*20, and $CSspread20$) denotes the biggest (highest) MV (B/M, DV, RV, LM, *cGibbs*, and $CSspread$) portfolio. For the 4×5 $MV\&B/M$-sorted portfolios, the digit after S denotes the size quintile (1 representing the smallest and 4 the largest), and the digit after B denotes the book-to-market quartile (1 representing the lowest and 5 the highest). The variable explanations refer to Table 4.1.

Panel A: MV-sorted portfolios										
	MV1	MV2	MV3	MV4	MV5	MV6	MV7	MV8	MV9	MV10
β_c	4.262	3.512	3.214	3.511	3.775	3.046	3.180	3.152	3.246	3.118
β_{tc}	0.984	0.473	0.411	0.318	0.314	0.293	0.246	0.248	0.208	0.216
	MV11	MV12	MV13	MV14	MV15	MV16	MV17	MV18	MV19	MV20
β_c	3.005	2.634	2.659	2.681	2.733	2.825	2.467	2.267	2.309	2.733
β_{tc}	0.202	0.166	0.166	0.160	0.148	0.160	0.144	0.135	0.127	0.130
Panel B: B/M-sorted portfolios										
	B/M1	B/M2	B/M3	B/M4	B/M5	B/M6	B/M7	B/M8	B/M9	B/M10
β_c	4.276	3.397	3.659	3.609	3.448	3.431	3.698	3.060	3.075	2.744
β_{tc}	0.283	0.322	0.186	0.143	0.159	0.254	0.303	0.199	0.191	0.315
	B/M11	B/M12	B/M13	B/M14	B/M15	B/M16	B/M17	B/M18	B/M19	B/M20
β_c	2.795	3.079	3.597	2.957	2.334	3.018	3.094	2.571	2.958	3.478
β_{tc}	0.222	0.219	0.342	0.352	0.338	0.347	0.462	0.449	0.643	0.847
Panel C: 4×5 $MV\&B/M$ portfolios										
	S1B1	S1B2	S1B3	S1B4	S1B5	S2B1	S2B2	S2B3	S2B4	S2B5
β_c	5.317	4.314	3.556	3.998	3.433	3.342	3.750	3.134	2.410	2.511
β_{tc}	0.555	0.406	0.361	0.512	0.676	0.220	0.240	0.220	0.241	0.317
	S3B1	S3B2	S3B3	S3B4	S3B5	S4B1	S4B2	S4B3	S4B4	S4B5
β_c	3.079	2.513	2.392	2.237	3.154	2.790	2.604	1.907	1.934	2.992
β_{tc}	0.157	0.157	0.161	0.154	0.295	0.118	0.136	0.129	0.179	0.231

[Cont.]

(continued)

Panel D: DV-sorted portfolios										
	DV1	DV2	DV3	DV4	DV5	DV6	DV7	DV8	DV9	DV10
β_c	4.176	3.731	3.624	3.311	3.284	2.773	2.353	3.002	2.580	2.775
β_{tc}	0.828	0.434	0.400	0.355	0.385	0.313	0.225	0.248	0.270	0.222
	DV11	DV12	DV13	DV14	DV15	DV16	DV17	DV18	DV19	DV20
β_c	2.727	2.738	2.588	2.996	2.500	2.618	2.647	2.762	3.102	4.093
β_{tc}	0.223	0.136	0.159	0.155	0.188	0.150	0.181	0.137	0.155	0.146
Panel E: RV-sorted portfolios										
	RV1	RV2	RV3	RV4	RV5	RV6	RV7	RV8	RV9	RV10
β_c	3.248	2.865	2.446	3.036	2.616	2.332	2.995	2.489	2.204	2.885
β_{tc}	0.098	0.129	0.148	0.131	0.156	0.178	0.149	0.171	0.168	0.182
	RV11	RV12	RV13	RV14	RV15	RV16	RV17	RV18	RV19	RV20
β_c	2.670	3.089	2.729	3.237	3.149	3.340	2.555	2.891	3.611	4.362
β_{tc}	0.227	0.219	0.265	0.272	0.314	0.279	0.360	0.346	0.476	1.034
Panel F: LM-sorted portfolios										
	LM1	LM2	LM3	LM4	LM5	LM6	LM7	LM8	LM9	LM10
β_c	4.169	4.002	4.036	3.231	3.260	3.175	2.506	2.553	2.313	2.507
β_{tc}	0.221	0.260	0.224	0.222	0.187	0.170	0.221	0.180	0.243	0.227
	LM11	LM12	LM13	LM14	LM15	LM16	LM17	LM18	LM19	LM20
β_c	2.321	2.210	3.066	2.370	2.682	3.063	3.764	3.141	3.796	3.961
β_{tc}	0.136	0.262	0.228	0.247	0.118	0.299	0.321	0.448	0.353	0.720
Panel G: $cGibbs$-sorted portfolios										
	cGibbs1	cGibbs2	cGibbs3	cGibbs4	cGibbs5	cGibbs6	cGibbs7	cGibbs8	cGibbs9	cGibbs10
β_c	2.619	2.987	2.902	2.803	2.576	2.989	2.889	2.950	2.924	2.790
β_{tc}	0.114	0.142	0.143	0.173	0.141	0.166	0.169	0.212	0.234	0.207
	cGibbs11	cGibbs12	cGibbs13	cGibbs14	cGibbs15	cGibbs16	cGibbs17	cGibbs18	cGibbs19	cGibbs20
β_c	2.702	2.875	3.100	3.421	2.535	2.812	3.209	3.379	3.703	4.547
β_{tc}	0.230	0.236	0.233	0.262	0.315	0.276	0.339	0.438	0.636	1.194
Panel H: $CSspread$-sorted portfolios										
	CSspread1	CSspread2	CSspread3	CSspread4	CSspread5	CSspread6	CSspread7	CSspread8	CSspread9	CSspread10
β_c	2.392	2.161	2.437	2.575	2.550	2.474	2.933	3.276	2.814	3.346
β_{tc}	0.097	0.123	0.133	0.154	0.141	0.159	0.172	0.190	0.171	0.195
	CSspread11	CSspread12	CSspread13	CSspread14	CSspread15	CSspread16	CSspread17	CSspread18	CSspread19	CSspread20
	2.827	3.300	3.222	3.344	3.339	3.909	3.689	3.641	3.244	4.078
	0.213	0.230	0.232	0.249	0.285	0.304	0.433	0.472	0.661	1.267

Table 4.7: Regressions on consumption beta and liquidity beta

This table reports the regression coefficients of the expected portfolio returns on the consumption beta and liquidity beta. Test portfolios are the 20 MV-sorted, 20 B/M-sorted, 4×5 $MV\&B/M$-sorted, 20 DV-sorted, 20 RV-sorted, 20 LM-sorted, 20 *cGibbs*-sorted, and 20 $CSspread$-sorted portfolios, respectively. I run the following Fama and MacBeth (1973) cross-sectional regression:

$$R_{i,\,t} - R_{f,\,t} = \gamma_0 + \gamma_1\beta_{i,c} + \gamma_2\beta_{i,tc} + e_{i,t},$$

where $R_{i,\,t} - R_{f,\,t}$ is the quarterly return of portfolio i in excess of the risk-free rate, $\beta_{i,c}$ is the consumption beta and $\beta_{i,tc}$ is the liquidity beta. Consumption beta is estimated through a time-series regression of return in excess of the risk-free rate on consumption growth. Liquidity beta is estimated through a time-series regression of liquidity innovations on consumption growth. Transaction costs are calculated using the *cGibbs* estimates of Hasbrouck (2009) in Panel A and the $CSspread$ estimates of Corwin and Schultz (2012) in Panel B. Numbers in parentheses are t statistics. The 1%, 5%, and 10% significance levels are denoted with ***, **, and *, respectively.

Panel A: *cGibbs* as a measure of transaction costs
20 MV-sorted portfolios $\hat{\gamma_1} = 0.653\%^{*}$ (1.92), $\hat{\gamma_2} = -0.528\%$ (-0.36)
20 BM-sorted portfolios $\hat{\gamma_1} = -0.659\%^{***}$ (-3.39), $\hat{\gamma_2} = 5.165\%^{**}$ (2.06)
4×5 $MV\&B/M$-sorted portfolios $\hat{\gamma_1} = -0.335\%^{*}$ (-1.81), $\hat{\gamma_2} = 8.221\%^{**}$ (2.36)
20 DV-sorted portfolios $\hat{\gamma_1} = -0.295\%^{***}$ (-2.63), $\hat{\gamma_2} = 7.177\%^{***}$ (3.29)
20 RV-sorted portfolios $\hat{\gamma_1} = -0.079\%$ (-0.84), $\hat{\gamma_2} = 4.727\%^{**}$ (2.06)
20 LM-sorted portfolios $\hat{\gamma_1} = -0.219\%$ (-1.09), $\hat{\gamma_2} = 5.441\%^{***}$ (3.49)
20 *cGibbs*-sorted portfolios $\hat{\gamma_1} = -0.142\%$ (-0.89), $\hat{\gamma_2} = 4.908\%^{**}$ (2.09)
20 $CSspread$-sorted portfolios $\hat{\gamma_1} = 0.168\%$ (0.81), $\hat{\gamma_2} = -0.080\%$ (-0.04)
Panel B: $CSspread$ as a measure of transaction costs
20 MV-sorted portfolios $\hat{\gamma_1} = 0.578\%^{*}$ (1.84), $\hat{\gamma_2} = 0.124\%$ (0.16)
20 BM-sorted portfolios $\hat{\gamma_1} = -0.651\%^{***}$ (-3.27), $\hat{\gamma_2} = 2.656\%^{**}$ (2.27)
4×5 $MV\&B/M$-sorted portfolios $\hat{\gamma_1} = -0.509\%^{**}$ (-2.42), $\hat{\gamma_2} = 3.494\%^{**}$ (2.42)
20 DV-sorted portfolios $\hat{\gamma_1} = -0.392\%^{**}$ (-2.57), $\hat{\gamma_2} = 3.152\%^{***}$ (2.87)
20 RV-sorted portfolios $\hat{\gamma_1} = -0.254\%^{**}$ (-2.25), $\hat{\gamma_2} = 2.110\%^{**}$ (2.34)
20 LM-sorted portfolios $\hat{\gamma_1} = -0.299\%$ (-1.44), $\hat{\gamma_2} = 2.804\%^{***}$ (3.94)
20 *cGibbs*-sorted portfolios $\hat{\gamma_1} = -0.096\%$ (-0.68), $\hat{\gamma_2} = 1.723\%^{**}$ (1.98)
20 $CSspread$-sorted portfolios $\hat{\gamma_1} = 0.129\%$ (0.70), $\hat{\gamma_2} = 0.105\%$ (0.14)

Table 4.8: Regressions on historical consumption beta and liquidity beta

This table reports the regression coefficients of the expected portfolio returns on the consumption beta and liquidity beta. Test portfolios are the 20 MV-sorted, 20 B/M-sorted, 4×5 $MV\&B/M$-sorted, 20 DV-sorted, 20 RV-sorted, 20 LM-sorted, 20 *cGibbs*-sorted, and 20 *CSspread*-sorted portfolios, respectively. I run the following Fama-MacBeth (1973) cross-sectional regression:

$$R_{i,\,t} - R_{f,\,t} = \gamma_0 + \gamma_1 \beta_{i,t-1,c} + \gamma_2 \beta_{i,t-1,tc} + e_{i,t},$$

where $R_{i,\,t} - R_{f,\,t}$ is the one-month ahead return of portfolio i in excess of the risk-free rate, $\beta_{i,t-1,c}$ is the historical consumption beta, and $\beta_{i,t-1,tc}$ is the historical liquidity beta. I estimate the historical consumption beta and liquidity beta for each set of the 20 test portfolios using prior 10-year observations. Transaction costs are calculated using the *cGibbs* estimates of Hasbrouck (2009) in Panel A and the *CSspread* estimates of Corwin and Schultz (2012) in Panel B. Numbers in parentheses are t statistics. The 1%, 5%, and 10% significance levels are denoted with ***, **, and *, respectively.

Panel A: *cGibbs* as a measure of transaction costs		
20 MV-sorted portfolios	$\hat{\gamma_1} = 0.079\%$ (0.98),	$\hat{\gamma_2} = 3.320\%^{***}$ (4.72)
20 BM-sorted portfolios	$\hat{\gamma_1} = 0.078\%$ (1.43),	$\hat{\gamma_2} = 2.203\%^{***}$ (2.62)
4×5 $MV\&B/M$-sorted portfolios	$\hat{\gamma_1} = 0.063\%$ (0.96),	$\hat{\gamma_2} = 1.175\%$ (1.16)
20 DV-sorted portfolios	$\hat{\gamma_1} = 0.057\%$ (1.08),	$\hat{\gamma_2} = 1.421\%$ (1.42)
20 RV-sorted portfolios	$\hat{\gamma_1} = 0.098\%$ (1.62),	$\hat{\gamma_2} = 1.897\%^{**}$ (2.16)
20 LM-sorted portfolios	$\hat{\gamma_1} = -0.032\%$ (-0.51),	$\hat{\gamma_2} = 0.656\%$ (1.28)
20 *cGibbs*-sorted portfolios	$\hat{\gamma_1} = 0.072\%$ (1.49),	$\hat{\gamma_2} = 2.990\%^{*}$ (1.93)
20 *CSspread*-sorted portfolios	$\hat{\gamma_1} = 0.088\%$ (1.43),	$\hat{\gamma_2} = 2.071\%^{**}$ (2.11)
Panel B: *CSspread* as a measure of transaction costs		
20 MV-sorted portfolios	$\hat{\gamma_1} = -0.009\%$ (-0.13),	$\hat{\gamma_2} = 1.595\%^{***}$ (3.70)
20 BM-sorted portfolios	$\hat{\gamma_1} = 0.041\%$ (0.81),	$\hat{\gamma_2} = 1.411\%^{***}$ (2.79)
4×5 $MV\&B/M$-sorted portfolios	$\hat{\gamma_1} = 0.013\%$ (0.20),	$\hat{\gamma_2} = 1.074\%^{**}$ (2.31)
20 DV-sorted portfolios	$\hat{\gamma_1} = 0.019\%$ (0.38),	$\hat{\gamma_2} = 1.800\%^{***}$ (4.05)
20 RV-sorted portfolios	$\hat{\gamma_1} = 0.070\%$ (1.23),	$\hat{\gamma_2} = 1.084\%^{***}$ (2.52)
20 LM-sorted portfolios	$\hat{\gamma_1} = -0.056\%$ (-0.94),	$\hat{\gamma_2} = 0.586\%^{***}$ (2.70)
20 *cGibbs*-sorted portfolios	$\hat{\gamma_1} = 0.068\%$ (1.54),	$\hat{\gamma_2} = 1.415\%^{***}$ (3.25)
20 *CSspread*-sorted portfolios	$\hat{\gamma_1} = 0.038\%$ (0.74),	$\hat{\gamma_2} = 1.530\%^{***}$ (2.99)

Table 4.9: Risk aversion estimates

This table reports the estimated risk aversion based on nondurable goods and services consumption growth over a horizon of S ($S = 0, 1, 2, ..., 11$) quarters, which is calculated as $\Delta C_t^S = \frac{C_{t+S}}{C_{t-1}} - 1$. Test portfolios are the 20 MV-sorted, 20 B/M-sorted, 4×5 $MV\&B/M$-sorted, 20 DV-sorted, 20 RV-sorted, 20 LM-sorted, 20 *cGibbs*-sorted, and 20 $CSspread$-sorted portfolios, respectively. For each set of the 20 test portfolios, I calculate the risk aversion coefficient using $\gamma = \frac{E[R_{i,t} - R_{f,t}] + \frac{\sigma_i^2}{2}}{\sigma_{i,\Delta C^S}}$ for the CCAPM and $\gamma = \frac{E[R_{itc,t} - R_{f,t}] + \frac{\sigma_{itc}^2}{2}}{\sigma_{itc,\Delta C^S}}$ for the liquidity-adjusted model. The reported values of risk aversion are mean values of the 20 test portfolios involved. $R_{itc,t} = R_{i,t} - tc_{i,t}$, $\sigma_{i,\Delta C^S} = Cov(R_{i,t}, \Delta C_t^S)$, $\sigma_{itc,\Delta C^S} = Cov(R_{itc,t}, \Delta C_t^S)$, and ΔC^S is the consumption growth over the horizon of S quarters. Transaction costs are calculated using the *cGibbs* estimates of Hasbrouck (2009) in Panel A and the $CSspread$ estimates of Corwin and Schultz (2012) in Panel B.

Panel A: *cGibbs* as a measure of transaction costs												
HORIZONS	S0	S1	S2	S3	S4	S5	S6	S7	S8	S9	S10	S11
20 MV-sorted portfolios												
Traditional CCAPM	284.37	117.66	91.27	75.92	59.51	57.89	54.34	52.99	63.85	66.76	63.19	64.46
Liquidity-adjusted CCAPM	227.16	94.70	72.29	62.06	48.45	47.87	45.26	44.41	55.20	58.68	55.02	56.53
20 B/M-sorted portfolios												
Traditional CCAPM	286.22	119.73	93.02	75.34	59.46	56.94	53.01	51.30	61.24	63.52	60.66	62.19
Liquidity-adjusted CCAPM	173.49	73.92	57.61	47.69	37.62	36.50	34.16	33.18	40.93	42.81	40.75	42.12
4×5 $MV\&B/M$-sorted portfolios												
Traditional CCAPM	299.38	122.85	94.00	77.72	61.28	58.92	54.99	53.31	63.92	66.81	62.83	63.98
Liquidity-adjusted CCAPM	233.90	95.71	71.88	61.40	48.18	46.88	43.99	42.72	52.75	56.03	51.88	53.03
20 DV-sorted portfolios												
Traditional CCAPM	278.88	113.43	88.96	72.90	56.95	55.04	51.54	50.06	60.69	63.40	60.18	61.95
Liquidity-adjusted CCAPM	209.38	85.19	66.36	56.01	43.50	42.76	40.41	39.53	50.01	53.41	50.44	52.82
20 RV-sorted portfolios												
Traditional CCAPM	285.26	116.24	90.56	74.83	58.44	56.47	52.84	51.21	61.76	64.45	61.04	62.53
Liquidity-adjusted CCAPM	226.49	93.09	71.52	60.95	47.31	46.35	43.67	42.52	52.97	56.20	52.91	54.88

[Cont.]

(continued)

20 LM-sorted portfolios												
Traditional CCAPM	288.26	117.52	91.60	75.49	58.94	56.68	52.96	51.13	61.02	63.00	59.52	60.32
Liquidity-adjusted CCAPM	195.85	79.19	61.94	52.66	40.90	39.99	37.72	36.61	45.79	48.09	45.12	46.20
20 $cGibbs$-sorted portfolios												
Traditional CCAPM	280.37	116.82	90.66	74.76	58.57	56.53	53.01	51.46	61.91	64.81	61.52	63.19
Liquidity-adjusted CCAPM	224.85	94.30	71.84	61.59	47.87	46.75	44.30	43.11	53.19	56.52	53.05	54.94
20 $CSspread$-sorted portfolios												
Traditional CCAPM	301.41	126.45	96.88	80.47	62.89	60.86	57.04	55.43	66.26	68.89	65.01	66.27
Liquidity-adjusted CCAPM	240.00	101.67	76.50	65.78	51.02	50.05	47.30	46.04	56.49	59.30	55.17	56.46
Panel B: $CSspread$ as a measure of transaction costs												
HORIZONS	S0	S1	S2	S3	S4	S5	S6	S7	S8	S9	S10	S11
20 MV-sorted portfolios												
Traditional CCAPM	283.90	117.73	91.42	76.01	59.55	57.99	54.42	53.10	64.07	67.01	63.40	64.69
Liquidity-adjusted CCAPM	102.08	42.84	31.60	27.16	21.12	20.61	19.34	18.81	22.37	23.35	21.52	21.52
20 B/M-sorted portfolios												
Traditional CCAPM	286.84	120.30	93.49	75.77	59.81	57.28	53.32	51.62	61.62	63.90	61.02	62.57
Liquidity-adjusted CCAPM	26.48	11.83	8.98	7.60	5.99	5.81	5.44	5.29	6.46	6.64	6.27	6.38
4×5 $MV\&B/M$-sorted portfolios												
Traditional CCAPM	299.81	123.19	94.28	78.00	61.50	59.17	55.23	53.57	64.26	67.18	63.17	64.35
Liquidity-adjusted CCAPM	98.48	40.03	28.83	24.93	19.47	18.70	17.41	16.65	19.49	20.21	18.30	18.11

[Cont.]

(continued)

						20 DV-sorted portfolios						
Traditional CCAPM	280.82	114.23	89.57	73.43	57.34	55.42	51.90	50.41	61.11	63.82	60.57	62.34
Liquidity-adjusted CCAPM	79.76	31.95	24.03	20.38	15.66	15.24	14.34	13.85	16.91	17.85	16.62	17.02
						20 RV-sorted portfolios						
Traditional CCAPM	286.83	116.89	91.09	75.28	58.77	56.79	53.14	51.50	62.12	64.80	61.36	62.86
Liquidity-adjusted CCAPM	98.84	40.76	30.25	25.81	19.94	19.26	18.02	17.37	20.76	21.66	20.12	20.37
						20 LM-sorted portfolios						
Traditional CCAPM	290.17	118.41	92.26	76.05	59.37	57.09	53.34	51.49	61.42	63.40	59.90	60.73
Liquidity-adjusted CCAPM	49.89	19.31	14.52	12.58	9.61	9.22	8.65	8.20	9.83	10.12	9.32	9.22
						20 $cGibbs$-sorted portfolios						
Traditional CCAPM	282.40	117.63	91.30	75.31	58.98	56.94	53.42	51.86	62.43	65.37	62.06	63.77
Liquidity-adjusted CCAPM	90.94	38.08	28.00	24.28	18.73	18.05	17.10	16.47	19.56	20.51	18.86	19.07
						20 $CSspread$-sorted portfolios						
Traditional CCAPM	301.86	126.87	97.32	80.73	63.09	61.10	57.27	55.69	66.70	69.38	65.45	66.77
Liquidity-adjusted CCAPM	131.31	55.45	40.56	34.91	26.93	26.15	24.63	23.78	28.36	29.38	26.97	27.06

Table 4.10: Robustness tests on R^2

This table reports the cross-sectional R-squares obtained from several robustness tests. For the liquidity-adjusted CCAPM, I use two transaction costs measures: one is the *cGibbs* estimates of Hasbrouck (2009) and the other one is *CSspread*, the bid-ask spread estimate of Corwin and Schultz (2012). Test portfolios are the 20 MV-sorted, 20 B/M-sorted, 4×5 $MV\&B/M$-sorted, 20 DV-sorted, 20 RV-sorted, 20 LM-sorted, 20 *cGibbs*-sorted, and 20 *CSspread*-sorted portfolios, respectively, except Panel A. In Panel A, I augment each set of the 20 test portfolios with 10 industry portfolios. The classification of the 10 industries is based on Fama and French (1997). In Panels B, C and D, I take into account the long run consumption growth (Parker and Julliard (2005)), the total consumption growth (Yogo (2006)) and the fourth quarter consumption growth (Jagannathan and Wang (2007)), respectively. Specifically, in Panel B, I measure consumption risk using the 11-quarter consumption growth of nondurable goods. In Panel C, I use the total consumption growth. Following Breeden, Gibbons, and Litzenberger (1989) and Jagannathan and Wang (2007), in Panel D, I construct a mimicking consumption growth factor using the maximum-correlation portfolio (MCP) approach. I run regression of the demeaned fourth-to-fourth quarter consumption growth on annual excess returns of the 10 value-weighted industry portfolios to obtain the MCP weights. I replace the consumption growth of nondurable goods and services with the MCP. The portfolio data are annualized values in Panel D.

	cGibbs as a measure of transaction costs		*CSspread* as a measure of transaction costs	
	Traditional CCAPM	Liquidity-adjusted CCAPM	Traditional CCAPM	Liquidity-adjusted CCAPM
Panel A: Plus 10 industry portfolios				
20 MV-sorted portfolios	$R^2 = 38.63\%$	$R^2 = 52.45\%$	$R^2 = 37.83\%$	$R^2 = 50.98\%$
20 B/M-sorted portfolios	$R^2 = 0.00\%$	$R^2 = 59.24\%$	$R^2 = 0.02\%$	$R^2 = 56.38\%$
4×5 $MV\&B/M$-sorted portfolios	$R^2 = 3.21\%$	$R^2 = 38.81\%$	$R^2 = 3.01\%$	$R^2 = 20.11\%$
20 DV-sorted portfolios	$R^2 = 16.05\%$	$R^2 = 63.02\%$	$R^2 = 15.09\%$	$R^2 = 52.79\%$
20 RV-sorted portfolios	$R^2 = 24.42\%$	$R^2 = 57.64\%$	$R^2 = 23.68\%$	$R^2 = 49.96\%$
20 LM-sorted portfolios	$R^2 = 3.59\%$	$R^2 = 47.03\%$	$R^2 = 3.96\%$	$R^2 = 30.31\%$
20 *cGibbs*-sorted portfolios	$R^2 = 37.24\%$	$R^2 = 79.72\%$	$R^2 = 36.07\%$	$R^2 = 69.81\%$
20 *CSspread*-sorted portfolios	$R^2 = 34.62\%$	$R^2 = 46.33\%$	$R^2 = 33.52\%$	$R^2 = 44.80\%$
Panel B: Consumption growth over 11 quarters				
20 MV-sorted portfolios	$R^2 = 79.74\%$	$R^2 = 91.66\%$	$R^2 = 80.03\%$	$R^2 = 84.76\%$
20 B/M-sorted portfolios	$R^2 = 71.27\%$	$R^2 = 72.19\%$	$R^2 = 75.94\%$	$R^2 = 78.11\%$
4×5 $MV\&B/M$-sorted portfolios	$R^2 = 51.21\%$	$R^2 = 57.96\%$	$R^2 = 3.01\%$	$R^2 = 20.11\%$
20 DV-sorted portfolios	$R^2 = 71.03\%$	$R^2 = 80.20\%$	$R^2 = 15.09\%$	$R^2 = 52.79\%$
20 RV-sorted portfolios	$R^2 = 75.78\%$	$R^2 = 82.39\%$	$R^2 = 23.68\%$	$R^2 = 49.96\%$
20 LM-sorted portfolios	$R^2 = 9.14\%$	$R^2 = 56.60\%$	$R^2 = 9.80\%$	$R^2 = 37.87\%$
20 *cGibbs*-sorted portfolios	$R^2 = 73.12\%$	$R^2 = 90.53\%$	$R^2 = 74.45\%$	$R^2 = 91.38\%$
20 *CSspread*-sorted portfolios	$R^2 = 38.18\%$	$R^2 = 53.45\%$	$R^2 = 43.06\%$	$R^2 = 60.98\%$

[Cont.]

(continued)

	cGibbs as a measure of transaction costs		*CSspread* as a measure of transaction costs	
	Traditional CCAPM	Liquidity-adjusted CCAPM	Traditional CCAPM	Liquidity-adjusted CCAPM
Panel C: Total consumption growth				
20 MV-sorted portfolios	$R^2 = 76.61\%$	$R^2 = 83.66\%$	$R^2 = 76.97\%$	$R^2 = 81.75\%$
20 B/M-sorted portfolios	$R^2 = 55.92\%$	$R^2 = 67.50\%$	$R^2 = 62.33\%$	$R^2 = 69.44\%$
4×5 $MV\&B/M$-sorted portfolios	$R^2 = 19.97\%$	$R^2 = 55.64\%$	$R^2 = 20.74\%$	$R^2 = 58.97\%$
20 DV-sorted portfolios	$R^2 = 43.40\%$	$R^2 = 81.84\%$	$R^2 = 15.09\%$	$R^2 = 52.79\%$
20 RV-sorted portfolios	$R^2 = 58.90\%$	$R^2 = 75.79\%$	$R^2 = 61.07\%$	$R^2 = 74.59\%$
20 LM-sorted portfolios	$R^2 = 1.41\%$	$R^2 = 57.96\%$	$R^2 = 2.37\%$	$R^2 = 48.66\%$
20 *cGibbs*-sorted portfolios	$R^2 = 78.17\%$	$R^2 = 90.27\%$	$R^2 = 79.74\%$	$R^2 = 90.02\%$
20 $CSspread$-sorted portfolios	$R^2 = 40.08\%$	$R^2 = 47.79\%$	$R^2 = 43.06\%$	$R^2 = 60.98\%$
Panel D: Q4-Q4 consumption growth				
20 MV-sorted portfolios	$R^2 = 81.87\%$	$R^2 = 83.71\%$	$R^2 = 83.17\%$	$R^2 = 84.15\%$
20 B/M-sorted portfolios	$R^2 = 52.37\%$	$R^2 = 78.44\%$	$R^2 = 57.29\%$	$R^2 = 75.18\%$
4×5 $MV\&B/M$-sorted portfolios	$R^2 = 33.48\%$	$R^2 = 43.79\%$	$R^2 = 35.25\%$	$R^2 = 51.03\%$
20 DV-sorted portfolios	$R^2 = 80.43\%$	$R^2 = 83.64\%$	$R^2 = 80.76\%$	$R^2 = 87.04\%$
20 RV-sorted portfolios	$R^2 = 82.08\%$	$R^2 = 83.59\%$	$R^2 = 83.59\%$	$R^2 = 85.43\%$
20 LM-sorted portfolios	$R^2 = 8.86\%$	$R^2 = 63.19\%$	$R^2 = 9.12\%$	$R^2 = 49.18\%$
20 *cGibbs*-sorted portfolios	$R^2 = 88.29\%$	$R^2 = 90.85\%$	$R^2 = 89.23\%$	$R^2 = 91.88\%$
20 $CSspread$-sorted portfolios	$R^2 = 59.09\%$	$R^2 = 65.50\%$	$R^2 = 60.70\%$	$R^2 = 76.75\%$

Table 4.11: GMM estimates

This table reports the estimated risk aversion using a generalized method of moments (GMM) based on nondurable goods and services consumption growth over a horizon of S ($S = 0, 1, 2, ..., 11$) quarters, which is calculated as $\Delta C_t^S = \frac{C_{t+S}}{C_{t-1}} - 1$. I follow Yogo (2006) and apply a two-step GMM method. I also use the Newey and West (1987) adjustment to take into account heteroscedasticity and auto-correlation. Estimates are based on the equally-weighted market portfolio together with *cGibbs* as the transaction costs proxy in Panel A and with *CSspread* as the transaction costs proxy in Panel B. Similar to Liu and Strong (2008), I assume the transaction costs to be 0.5%, 1%, or 1.5% each quarter. I use the empirical moment function $E[M_t^S(R_t - R_{f,t})z_t] = 0$ for the CCAPM and $E[M_t^S(R_t - R_{f,t} - tc_t)z_t] = 0$ for my liquidity-adjusted CCAPM, where $M_t^S = \beta(\frac{C_{t+S}}{C_{t-1}})^{-\gamma}$, β is the subjective discount factor, γ is the coefficient of risk aversion, $R_{m,t} - R_{f,t}$ is the market return in excess of the risk-free rate, $tc_{m,t}$ is the aggregate transaction costs, and z_t is a 2×1 vector of instrumental variables. I fix $\beta = 0.95$. The instrument variables are the three-time-period-lagged risk-free rate and excess return of the market portfolio.

HORIZONS	S0	S1	S2	S3	S4	S5	S6	S7	S8	S9	S10	S11
Panel A: Equal-weighted market portfolios (*cGibbscosts*)												
Traditional CCAPM	159.67	81.49	65.93	57.99	49.11	46.95	45.36	44.36	46.70	46.25	43.90	44.18
Liquidity-adjusted CCAPM: *cGibbs*	38.54	24.78	20.04	18.12	15.69	14.93	15.08	14.02	15.84	17.44	16.72	16.60
Liquidity-adjusted CCAPM: 0.5%	117.48	50.75	40.79	35.61	30.21	29.12	28.04	27.67	31.23	31.71	30.27	30.58
Liquidity-adjusted CCAPM: 1%	72.26	32.75	26.44	23.09	19.61	18.72	18.28	17.43	19.66	20.64	19.81	19.67
Liquidity-adjusted CCAPM: 1.5%	28.83	18.08	15.24	14.05	12.12	11.88	12.06	11.35	13.23	14.43	13.86	13.92
Panel B: Equal-weighted market portfolios (*CSspread* costs)												
Traditional CCAPM	134.95	86.11	67.71	60.53	51.15	49.64	47.88	49.47	54.45	52.57	51.41	50.49
Liquidity-adjusted CCAPM: *CSspread*	32.56	16.20	2.91	9.61	8.34	28.32	30.80	31.39	32.87	44.15	43.48	43.96
Liquidity-adjusted CCAPM: 0.5%	97.42	54.82	43.58	38.60	32.95	32.49	31.78	33.47	39.70	38.56	38.55	38.76
Liquidity-adjusted CCAPM: 1%	66.62	35.60	29.38	26.42	22.50	22.38	22.41	21.78	24.96	25.56	26.20	26.69
Liquidity-adjusted CCAPM: 1.5%	29.00	20.94	18.70	18.52	16.26	17.20	18.25	17.44	19.61	21.71	22.21	23.30

Table 4.12: Pricing errors with 12-month portfolio holding period: *cGibbs* costs

This table reports the pricing errors (in percent) for the traditional CCAPM and the liquidity-adjusted model. The pricing errors are the differences between the fitted returns and realized returns. The realized average returns are the time-series average returns in excess of the risk-free rate. The fitted expected returns for the CCAPM are calculated as the fitted value from $E[R_{i,t} - R_{f,t}] = \gamma_0 + \gamma_1\beta_{i,c}$. The fitted expected returns for the liquidity-adjusted CCAPM are calculated as the fitted value from $E[R_{i,t} - R_{f,t}] = \gamma_0 + \gamma_1 E[tc_{i,t}] + \gamma_2\beta_{i,c} + \gamma_3\beta_{i,tc}$. Transaction costs are calculated using the *cGibbs* estimates of Hasbrouck (2009). Test portfolios are: the 20 MV-sorted portfolios, 20 B/M-sorted portfolios, 4×5 $MV\&B/M$-sorted portfolios, 20 DV-sorted portfolios, 20 RV-sorted portfolios, 20 LM-sorted portfolios, 20 *cGibbs*-sorted portfolios, and 20 *CSspread*-sorted portfolios. $MV1$ ($B/M1$, $DV1$, $RV1$, $LM1$, *cGibbs*1, and *CSspread*1) denotes the smallest (lowest) MV (B/M, DV, RV, LM, *cGibbs*, and *CSspread*) portfolio and $MV20$ ($B/M20$, $DV20$, $RV20$, $LM20$, *cGibbs*20, and *CSspread*20) denotes the biggest (highest) MV (B/M, DV, RV, LM, *cGibbs*, and *CSspread*) portfolio. For the 4×5 $MV\&B/M$-sorted portfolios, the digit after S denotes the size quintile (1 representing the smallest and 4 the largest), and the digit after B denotes the book-to-market quartile (1 representing the lowest and 5 the highest). The variable explanations refer to Table 4.1.

Panel A: MV-sorted portfolios										
	MV1	MV2	MV3	MV4	MV5	MV6	MV7	MV8	MV9	MV10
Traditional CCAPM	-0.143	-0.265	0.219	-0.341	0.348	0.038	0.128	0.050	0.285	0.293
Liquidity-adjusted CCAPM	-0.125	-0.124	0.404	-0.271	0.369	-0.137	0.068	-0.121	0.131	0.129
	MV11	MV12	MV13	MV14	MV15	MV16	MV17	MV18	MV19	MV20
Traditional CCAPM	0.211	0.086	-0.048	0.100	-0.096	0.103	0.072	-0.022	-0.477	-0.541
Liquidity-adjusted CCAPM	0.122	0.010	-0.182	0.010	-0.073	0.204	0.178	0.108	-0.385	-0.313
Panel B: B/M-sorted portfolios										
	B/M1	B/M2	B/M3	B/M4	B/M5	B/M6	B/M7	B/M8	B/M9	B/M10
Traditional CCAPM	-0.439	-0.456	-0.337	-0.425	-0.343	-0.367	-0.359	0.005	-0.113	0.106
Liquidity-adjusted CCAPM	-0.179	-0.140	-0.159	-0.067	-0.028	-0.091	-0.060	0.098	-0.204	0.007
	B/M11	B/M12	B/M13	B/M14	B/M15	B/M16	B/M17	B/M18	B/M19	B/M20
Traditional CCAPM	0.019	-0.038	0.248	0.320	0.262	0.600	0.502	0.564	0.423	-0.171
Liquidity-adjusted CCAPM	-0.055	-0.001	0.193	-0.125	0.095	0.199	0.571	-0.081	0.453	-0.427
Panel C: 4×5 $MV\&B/M$ portfolios										
	S1B1	S1B2	S1B3	S1B4	S1B5	S2B1	S2B2	S2B3	S2B4	S2B5
Traditional CCAPM	0.456	-0.328	-0.205	-0.338	-0.624	-0.282	0.087	-0.018	-0.226	-0.380
Liquidity-adjusted CCAPM	-0.014	-0.320	-0.140	-0.281	-0.500	-0.322	0.109	-0.082	-0.232	-0.345
	S3B1	S3B2	S3B3	S3B4	S3B5	S4B1	S4B2	S4B3	S4B4	S4B5
Traditional CCAPM	-0.038	0.281	0.277	0.277	-0.122	0.006	0.155	0.504	0.300	0.218
Liquidity-adjusted CCAPM	0.112	0.225	0.175	0.245	-0.072	0.022	0.143	0.472	0.412	0.394

[Cont.]

(continued)

Panel D: *DV*-sorted portfolios										
	DV1	DV2	DV3	DV4	DV5	DV6	DV7	DV8	DV9	DV10
Traditional CCAPM	0.400	0.352	0.068	0.212	0.343	0.297	0.328	0.341	0.078	0.242
Liquidity-adjusted CCAPM	-0.166	-0.139	0.171	0.225	0.155	0.127	0.139	0.230	-0.037	-0.062
	DV11	DV12	DV13	DV14	DV15	DV16	DV17	DV18	DV19	DV20
Traditional CCAPM	-0.253	0.044	-0.077	0.032	0.081	-0.304	-0.077	-0.352	-0.548	-1.207
Liquidity-adjusted CCAPM	-0.278	-0.106	-0.154	0.076	0.099	-0.050	-0.106	-0.046	0.134	-0.211
Panel E: *RV*-sorted portfolios										
	RV1	RV2	RV3	RV4	RV5	RV6	RV7	RV8	RV9	RV10
Traditional CCAPM	-0.870	-0.485	-0.298	0.039	-0.090	0.082	-0.319	0.387	-0.011	0.163
Liquidity-adjusted CCAPM	-0.487	-0.194	-0.185	0.112	-0.008	0.144	-0.250	0.155	-0.281	0.119
	RV11	RV12	RV13	RV14	RV15	RV16	RV17	RV18	RV19	RV20
Traditional CCAPM	0.143	0.248	0.253	0.106	0.095	0.183	0.432	-0.030	0.003	-0.030
Liquidity-adjusted CCAPM	-0.001	0.055	-0.020	0.081	0.107	0.151	0.521	0.141	0.212	-0.370
Panel F: *LM*-sorted portfolios										
	LM1	LM2	LM3	LM4	LM5	LM6	LM7	LM8	LM9	LM10
Traditional CCAPM	-0.662	-0.242	-0.147	0.309	-0.186	0.095	0.062	-0.062	-0.304	-0.410
Liquidity-adjusted CCAPM	-0.372	-0.229	-0.010	0.260	-0.066	0.345	0.114	0.196	-0.049	-0.398
	LM11	LM12	LM13	LM14	LM15	LM16	LM17	LM18	LM19	LM20
Traditional CCAPM	-0.265	-0.247	0.058	0.023	0.136	0.366	0.301	0.335	0.499	0.341
Liquidity-adjusted CCAPM	-0.238	-0.199	0.174	0.024	-0.079	0.306	0.114	0.163	0.132	-0.191
Panel G: *cGibbs*-sorted portfolios										
	cGibbs1	cGibbs2	cGibbs3	cGibbs4	cGibbs5	cGibbs6	cGibbs7	cGibbs8	cGibbs9	cGibbs10
Traditional CCAPM	-0.051	-0.336	-0.199	-0.032	0.161	-0.320	-0.367	-0.381	0.012	-0.191
Liquidity-adjusted CCAPM	-0.180	0.011	-0.092	-0.006	0.057	0.002	0.003	-0.096	0.061	-0.176
	cGibbs11	cGibbs12	cGibbs13	cGibbs14	cGibbs15	cGibbs16	cGibbs17	cGibbs18	cGibbs19	cGibbs20
Traditional CCAPM	0.404	-0.115	-0.144	-0.652	0.176	0.593	0.242	-0.035	0.724	0.510
Liquidity-adjusted CCAPM	-0.070	-0.210	0.078	-0.131	0.146	0.342	0.356	-0.101	0.233	-0.229
Panel H: *CSspread*-sorted portfolios										
	CSspread1	CSspread2	CSspread3	CSspread4	CSspread5	CSspread6	CSspread7	CSspread8	CSspread9	CSspread10
Traditional CCAPM	-0.199	0.089	-0.002	0.017	-0.181	-0.075	-0.149	0.118	0.041	-0.045
Liquidity-adjusted CCAPM	-0.157	0.122	0.052	0.039	-0.167	-0.111	-0.147	0.147	-0.019	-0.068
	CSspread11	CSspread12	CSspread13	CSspread14	CSspread15	CSspread16	CSspread17	CSspread18	CSspread19	CSspread20
Traditional CCAPM	0.053	0.034	-0.066	0.280	0.090	0.140	-0.117	0.340	-0.256	-0.113
Liquidity-adjusted CCAPM	0.066	-0.017	-0.087	0.179	0.109	0.045	-0.174	0.382	-0.148	-0.046

Table 4.13: Pricing errors: *CSspread* costs

This table reports the pricing errors (in percent) for the traditional CCAPM and the liquidity-adjusted model. The pricing errors are the differences between the fitted returns and realized returns. The realized average returns are the time-series average returns in excess of the risk-free rate. The fitted expected returns for the CCAPM are calculated as the fitted value from $E[R_{i,t} - R_{f,t}] = \gamma_0 + \gamma_1 \beta_{i,c}$. The fitted expected returns for the liquidity-adjusted CCAPM are calculated as the fitted value from $E[R_{i,t} - R_{f,t}] = \gamma_0 + \gamma_1 E[tc_{i,t}] + \gamma_2 \beta_{i,c} + \gamma_3 \beta_{i,tc}$. Transaction costs are calculated using the *CSspread* estimates of Corwin and Schultz (2012). Test portfolios are: the 20 MV-sorted portfolios, 20 B/M-sorted portfolios, 4×5 $MV\&B/M$-sorted portfolios, 20 DV-sorted portfolios, 20 RV-sorted portfolios, 20 LM-sorted portfolios, 20 *cGibbs*-sorted portfolios, and 20 *CSspread*-sorted portfolios. $MV1$ ($B/M1$, $DV1$, $RV1$, $LM1$, *cGibbs*1, and *CSspread*1) denotes the smallest (lowest) MV (B/M, DV, RV, LM, *cGibbs*, and *CSspread*) vigintiles portfolio and $MV20$ ($B/M20$, $DV20$, $RV20$, $LM20$, *cGibbs*20, and *CSspread*20) denotes the biggest (highest) MV (B/M, DV, RV, LM, *cGibbs*, and *CSspread*) portfolio. For the 4×5 $MV\&B/M$-sorted portfolios, the digit after S denotes the size quintile (1 representing the smallest and 4 the largest), and the digit after B denotes the book-to-market quartile (1 representing the lowest and 5 the highest). The variable explanations refer to Table 4.1.

Panel A: MV-sorted portfolios										
	MV1	MV2	MV3	MV4	MV5	MV6	MV7	MV8	MV9	MV10
Traditional CCAPM	-0.144	-0.243	0.213	-0.379	0.362	0.021	0.139	0.078	0.293	0.270
Liquidity-adjusted CCAPM	0.017	-0.286	0.215	-0.423	0.321	-0.029	0.075	0.083	0.273	0.244
	MV11	MV12	MV13	MV14	MV15	MV16	MV17	MV18	MV19	MV20
Traditional CCAPM	0.222	0.060	-0.058	0.116	-0.102	0.113	0.068	-0.022	-0.476	-0.533
Liquidity-adjusted CCAPM	0.241	0.062	-0.053	0.086	-0.110	0.134	0.107	0.019	-0.451	-0.523
Panel B: B/M-sorted portfolios										
	B/M1	B/M2	B/M3	B/M4	B/M5	B/M6	B/M7	B/M8	B/M9	B/M10
Traditional CCAPM	-0.437	-0.464	-0.353	-0.437	-0.346	-0.354	-0.361	-0.004	-0.098	0.116
Liquidity-adjusted CCAPM	-0.277	-0.370	-0.138	-0.096	-0.150	0.096	0.038	-0.022	-0.025	0.471
	B/M11	B/M12	B/M13	B/M14	B/M15	B/M16	B/M17	B/M18	B/M19	B/M20
Traditional CCAPM	0.021	-0.026	0.255	0.317	0.257	0.614	0.490	0.560	0.410	-0.161
Liquidity-adjusted CCAPM	-0.316	-0.073	0.012	-0.110	0.172	0.320	0.252	0.148	0.363	-0.295
Panel C: 4×5 $MV\&B/M$ portfolios										
	S1B1	S1B2	S1B3	S1B4	S1B5	S2B1	S2B2	S2B3	S2B4	S2B5
Traditional CCAPM	0.415	-0.339	-0.216	-0.340	-0.629	-0.274	0.096	-0.015	-0.221	-0.367
Liquidity-adjusted CCAPM	0.169	-0.351	-0.152	-0.247	-0.566	-0.186	0.132	0.034	-0.161	-0.343
	S3B1	S3B2	S3B3	S3B4	S3B5	S4B1	S4B2	S4B3	S4B4	S4B5
Traditional CCAPM	-0.043	0.275	0.281	0.277	-0.121	0.021	0.162	0.510	0.314	0.214
Liquidity-adjusted CCAPM	-0.318	0.295	0.335	0.281	-0.155	-0.009	0.228	0.466	0.389	0.160

[Cont.]

(continued)

Panel D: *DV*-sorted portfolios										
	DV1	DV2	DV3	DV4	DV5	DV6	DV7	DV8	DV9	DV10
Traditional CCAPM	0.387	0.363	0.070	0.211	0.353	0.293	0.328	0.347	0.083	0.246
Liquidity-adjusted CCAPM	-0.275	0.222	0.139	0.223	0.589	0.243	-0.042	0.207	0.008	-0.008
	DV11	DV12	DV13	DV14	DV15	DV16	DV17	DV18	DV19	DV20
Traditional CCAPM	-0.241	0.053	-0.084	0.028	0.086	-0.309	-0.081	-0.359	-0.556	-1.219
Liquidity-adjusted CCAPM	-0.116	-0.090	0.020	0.103	0.169	-0.152	-0.422	-0.236	-0.051	-0.531
Panel E: *RV*-sorted portfolios										
	RV1	RV2	RV3	RV4	RV5	RV6	RV7	RV8	RV9	RV10
Traditional CCAPM	-0.876	-0.487	-0.307	0.047	-0.092	0.084	-0.332	0.395	-0.003	0.176
Liquidity-adjusted CCAPM	-0.763	-0.451	-0.271	0.049	-0.046	0.052	-0.333	0.327	-0.003	0.191
	RV11	RV12	RV13	RV14	RV15	RV16	RV17	RV18	RV19	RV20
Traditional CCAPM	0.148	0.261	0.246	0.117	0.077	0.188	0.418	-0.057	0.015	-0.020
Liquidity-adjusted CCAPM	0.124	0.233	0.133	0.036	0.014	0.157	0.425	0.099	0.295	-0.268
Panel F: *LM*-sorted portfolios										
	LM1	LM2	LM3	LM4	LM5	LM6	LM7	LM8	LM9	LM10
Traditional CCAPM	-0.663	-0.268	-0.153	0.310	-0.187	0.090	0.063	-0.067	-0.301	-0.415
Liquidity-adjusted CCAPM	-0.580	-0.178	-0.087	0.360	-0.111	0.189	0.085	0.024	-0.272	-0.432
	LM11	LM12	LM13	LM14	LM15	LM16	LM17	LM18	LM19	LM20
Traditional CCAPM	-0.255	-0.248	0.049	0.017	0.141	0.380	0.307	0.377	0.507	0.318
Liquidity-adjusted CCAPM	-0.295	-0.240	0.129	0.025	0.094	0.427	0.304	0.371	0.327	-0.140
Panel G: *cGibbs*-sorted portfolios										
	cGibbs1	cGibbs2	cGibbs3	cGibbs4	cGibbs5	cGibbs6	cGibbs7	cGibbs8	cGibbs9	cGibbs10
Traditional CCAPM	-0.053	-0.333	-0.209	-0.043	0.170	-0.332	-0.410	-0.402	0.011	-0.199
Liquidity-adjusted CCAPM	-0.139	0.016	-0.148	-0.035	-0.082	-0.120	-0.097	-0.068	0.315	-0.114
	cGibbs11	cGibbs12	cGibbs13	cGibbs14	cGibbs15	cGibbs16	cGibbs17	cGibbs18	cGibbs19	cGibbs20
Traditional CCAPM	0.387	-0.106	-0.166	-0.677	0.181	0.587	0.216	-0.047	0.837	0.588
Liquidity-adjusted CCAPM	-0.065	-0.149	0.126	-0.183	0.123	0.350	0.394	-0.173	0.189	-0.140
Panel H: *CSspread*-sorted portfolios										
	CSspread1	CSspread2	CSspread3	CSspread4	CSspread5	CSspread6	CSspread7	CSspread8	CSspread9	CSspread10
Traditional CCAPM	-0.192	0.100	-0.001	0.014	-0.169	-0.084	-0.144	0.106	0.041	-0.043
Liquidity-adjusted CCAPM	-0.187	0.090	-0.000	0.020	-0.186	-0.094	-0.115	0.105	0.029	-0.051
	CSspread11	CSspread12	CSspread13	CSspread14	CSspread15	CSspread16	CSspread17	CSspread18	CSspread19	CSspread20
Traditional CCAPM	0.045	0.042	-0.090	0.284	0.085	0.135	-0.131	0.328	-0.257	-0.070
Liquidity-adjusted CCAPM	0.036	0.092	-0.143	0.260	0.108	0.064	-0.178	0.342	-0.172	-0.020

Table 4.14: Consumption beta and liquidity beta with 12-month portfolio holding period: *cGibbs* costs

This table reports the patterns of the consumption beta and the liquidity beta which are estimated from a single multiple time-series regression for each portfolio. Transaction costs are calculated using the *cGibbs* estimates of Hasbrouck (2009). Test portfolios are: the 20 MV-sorted portfolios, 20 B/M-sorted portfolios, 5×4 MV&B/M-sorted portfolios, 20 DV-sorted portfolios, 20 RV-sorted portfolios, 20 LM-sorted portfolios, 20 *cGibbs*-sorted portfolios and 20 *CSspread*-sorted portfolios. $MV1$ ($B/M1$, $DV1$, $RV1$, $LM1$, *cGibbs*1, and *CSspread*1) denotes the smallest (lowest) MV (B/M, DV, RV, LM, *cGibbs*, and *CSspread*) portfolio and $MV20$ ($B/M20$, $DV20$, $RV20$, $LM20$, *cGibbs*20, and *CSspread*20) denotes the biggest (highest) MV (B/M, DV, RV, LM, *cGibbs*, and *CSspread*) portfolio. For the 5×4 MV&B/M-sorted portfolios, the digit after S denotes the size quintile (1 representing the smallest and 5 the largest), and the digit after B denotes the book-to-market quartile (1 representing the lowest and 4 the highest). The variable explanations refer to Table 4.1.

					Panel A: MV-sorted portfolios					
	MV1	MV2	MV3	MV4	MV5	MV6	MV7	MV8	MV9	MV10
β_c	5.622	5.412	4.365	4.511	4.301	4.192	4.236	3.444	3.643	3.639
β_{tc}	0.300	0.199	0.165	0.130	0.111	0.074	0.083	0.058	0.057	0.052
	MV11	MV12	MV13	MV14	MV15	MV16	MV17	MV18	MV19	MV20
β_c	3.087	3.203	3.160	3.599	3.241	2.957	2.729	2.629	2.788	2.946
β_{tc}	0.053	0.052	0.041	0.046	0.056	0.062	0.056	0.055	0.047	0.059
					Panel B: BM-sorted portfolios					
	B/M1	B/M2	B/M3	B/M4	B/M5	B/M6	B/M7	B/M8	B/M9	B/M10
β_c	3.533	3.424	3.238	3.405	3.690	3.666	3.840	3.387	3.205	3.411
β_{tc}	0.066	0.051	0.057	0.063	0.067	0.050	0.050	0.071	0.057	0.032
	B/M11	B/M12	B/M13	B/M14	B/M15	B/M16	B/M17	B/M18	B/M19	B/M20
β_c	3.192	3.568	3.351	2.921	3.468	3.258	4.170	3.405	4.996	6.167
β_{tc}	0.075	0.063	0.076	0.076	0.076	0.080	0.098	0.079	0.138	0.211
					Panel C: 5×4 MV&B/M portfolios					
	S1B1	S2B1	S3B1	S4B1	S5B1	S1B2	S2B2	S3B2	S4B2	S5B2
β_c	3.302	4.012	3.674	3.363	2.964	5.023	3.876	3.457	3.096	2.599
β_{tc}	0.148	0.084	0.070	0.054	0.059	0.137	0.080	0.043	0.046	0.046
	S1B3	S2B3	S3B3	S4B3	S5B3	S1B4	S2B4	S3B4	S4B4	S5B4
β_c	4.302	3.834	3.126	2.757	2.402	5.505	4.403	3.278	3.885	2.730
β_{tc}	0.194	0.060	0.041	0.049	0.054	0.182	0.075	0.063	0.056	0.077

[Cont.]

(continued)

Panel D: DV-sorted portfolios										
	DV1	DV2	DV3	DV4	DV5	DV6	DV7	DV8	DV9	DV10
β_c	5.361	3.973	4.425	4.309	3.899	3.705	3.330	3.518	3.585	3.022
β_{tc}	0.280	0.168	0.163	0.117	0.086	0.085	0.096	0.073	0.049	0.057
	DV11	DV12	DV13	DV14	DV15	DV16	DV17	DV18	DV19	DV20
β_c	3.712	3.222	3.225	3.399	3.258	3.505	2.882	3.350	3.929	4.312
β_{tc}	0.037	0.050	0.054	0.050	0.046	0.056	0.055	0.062	0.064	0.068
Panel E: RV-sorted portfolios										
	RV1	RV2	RV3	RV4	RV5	RV6	RV7	RV8	RV9	RV10
β_c	3.584	3.296	2.982	2.978	3.363	3.185	3.505	2.560	3.117	3.360
β_{tc}	0.057	0.060	0.050	0.051	0.051	0.056	0.057	0.038	0.031	0.057
	RV11	RV12	RV13	RV14	RV15	RV16	RV17	RV18	RV19	RV20
β_c	3.659	3.618	3.064	3.911	4.352	4.269	3.774	4.350	5.224	5.709
β_{tc}	0.046	0.047	0.052	0.074	0.083	0.091	0.128	0.165	0.201	0.315
Panel F: LM-sorted portfolios										
	LM1	LM2	LM3	LM4	LM5	LM6	LM7	LM8	LM9	LM10
β_c	5.214	4.733	4.537	3.892	3.953	4.019	3.084	3.594	2.850	2.841
β_{tc}	0.089	0.046	0.055	0.036	0.059	0.063	0.046	0.067	0.094	0.052
	LM11	LM12	LM13	LM14	LM15	LM16	LM17	LM18	LM19	LM20
β_c	2.597	2.828	3.536	3.373	3.067	3.806	3.539	3.813	3.874	4.388
β_{tc}	0.062	0.068	0.071	0.076	0.070	0.102	0.118	0.135	0.164	0.233
Panel G: $cGibbs$-sorted portfolios										
	cGibbs1	cGibbs2	cGibbs3	cGibbs4	cGibbs5	cGibbs6	cGibbs7	cGibbs8	cGibbs9	cGibbs10
β_c	2.635	3.166	2.942	2.879	2.769	3.230	3.302	3.244	3.022	3.018
β_{tc}	-0.030	-0.026	-0.024	-0.023	-0.020	-0.019	-0.016	-0.012	-0.011	-0.006
	cGibbs11	cGibbs12	cGibbs13	cGibbs14	cGibbs15	cGibbs16	cGibbs17	cGibbs18	cGibbs19	cGibbs20
β_c	2.543	2.964	3.334	3.683	3.160	3.020	3.493	3.497	3.398	4.143
β_{tc}	-0.003	-0.002	0.005	0.008	0.010	0.030	0.043	0.089	0.166	0.282
Panel H: $CSspread$-sorted portfolios										
	CSspread1	CSspread2	CSspread3	CSspread4	CSspread5	CSspread6	CSspread7	CSspread8	CSspread9	CSspread10
β_c	3.094	2.838	2.769	2.921	3.190	3.106	2.855	3.102	3.196	3.550
β_{tc}	0.050	0.050	0.058	0.054	0.055	0.042	0.055	0.067	0.044	0.060
	CSspread11	CSspread12	CSspread13	CSspread14	CSspread15	CSspread16	CSspread17	CSspread18	CSspread19	CSspread20
β_c	3.283	2.865	3.981	4.358	3.429	4.972	5.069	4.567	5.259	5.593
β_{tc}	0.073	0.056	0.075	0.059	0.096	0.078	0.103	0.150	0.214	0.348

Table 4.15: Consumption beta and liquidity beta with 12-month portfolio holding period: $CSspread$ costs

This table reports the patterns of the consumption beta and the liquidity beta which are estimated from a single multiple time-series regression for each portfolio. Transaction costs are calculated using the $CSspread$ estimates of Corwin and Schultz (2012). Test portfolios are: the 20 MV-sorted portfolios, 20 B/M-sorted portfolios, 5×4 $MV\&B/M$-sorted portfolios, 20 DV-sorted portfolios, 20 RV-sorted portfolios, 20 LM-sorted portfolios, 20 $cGibbs$-sorted portfolios and 20 $CSspread$-sorted portfolios. $MV1$ ($B/M1$, $DV1$, $RV1$, $LM1$, $cGibbs1$, and $CSspread1$) denotes the smallest (lowest) MV (B/M, DV, RV, LM, $cGibbs$, and $CSspread$) portfolio and $MV20$ ($B/M20$, $DV20$, $RV20$, $LM20$, $cGibbs20$, and $CSspread20$) denotes the biggest (highest) MV (B/M, DV, RV, LM, $cGibbs$, and $CSspread$) portfolio. For the 5×4 $MV\&B/M$-sorted portfolios, the digit after S denotes the size quintile (1 representing the smallest and 5 the largest), and the digit after B denotes the book-to-market quartile (1 representing the lowest and 4 the highest). The variable explanations refer to Table 4.1.

Panel A: MV-sorted portfolios										
	MV1	MV2	MV3	MV4	MV5	MV6	MV7	MV8	MV9	MV10
β_c	5.750	5.371	4.333	4.528	4.312	4.219	4.301	3.452	3.616	3.697
β_{tc}	1.216	0.658	0.497	0.411	0.370	0.306	0.280	0.252	0.211	0.230
	MV11	MV12	MV13	MV14	MV15	MV16	MV17	MV18	MV19	MV20
β_c	3.098	3.257	3.163	3.565	3.229	2.962	2.742	2.656	2.791	2.951
β_{tc}	0.199	0.183	0.162	0.181	0.137	0.170	0.163	0.143	0.125	0.130
Panel B: BM-sorted portfolios										
	B/M1	B/M2	B/M3	B/M4	B/M5	B/M6	B/M7	B/M8	B/M9	B/M10
β_c	3.527	3.453	3.260	3.410	3.700	3.641	3.838	3.391	3.213	3.413
β_{tc}	0.232	0.232	0.186	0.180	0.244	0.189	0.224	0.246	0.209	0.183
	B/M11	B/M12	B/M13	B/M14	B/M15	B/M16	B/M17	B/M18	B/M19	B/M20
β_c	3.179	3.593	3.350	2.932	3.475	3.239	4.204	3.426	4.997	6.197
β_{tc}	0.283	0.278	0.285	0.272	0.274	0.287	0.393	0.336	0.467	0.657
Panel C: 5×4 $MV\&B/M$ portfolios										
	S1B1	S2B1	S3B1	S4B1	S5B1	S1B2	S2B2	S3B2	S4B2	S5B2
β_c	3.258	4.012	3.742	3.357	2.978	5.040	3.849	3.479	3.090	2.595
β_{tc}	0.601	0.325	0.217	0.147	0.130	0.420	0.261	0.200	0.147	0.127
	S1B3	S2B3	S3B3	S4B3	S5B3	S1B4	S2B4	S3B4	S4B4	S5B4
β_c	4.310	3.861	3.128	2.760	2.405	5.531	4.423	3.276	3.856	2.734
β_{tc}	0.630	0.272	0.166	0.165	0.156	0.620	0.308	0.267	0.208	0.201

[Cont.]

(continued)

Panel D: DV-sorted portfolios										
	DV1	DV2	DV3	DV4	DV5	DV6	DV7	DV8	DV9	DV10
β_c	5.400	3.978	4.448	4.318	3.918	3.722	3.329	3.507	3.604	3.011
β_{tc}	1.257	0.525	0.469	0.417	0.306	0.315	0.307	0.270	0.265	0.216
	DV11	DV12	DV13	DV14	DV15	DV16	DV17	DV18	DV19	DV20
β_c	3.685	3.190	3.232	3.395	3.259	3.509	2.879	3.362	3.930	4.313
β_{tc}	0.224	0.209	0.162	0.181	0.160	0.170	0.188	0.156	0.151	0.157
Panel E: RV-sorted portfolios										
	RV1	RV2	RV3	RV4	RV5	RV6	RV7	RV8	RV9	RV10
β_c	3.585	3.292	3.003	2.967	3.373	3.182	3.513	2.564	3.085	3.325
β_{tc}	0.131	0.146	0.132	0.146	0.160	0.179	0.194	0.157	0.180	0.190
	RV11	RV12	RV13	RV14	RV15	RV16	RV17	RV18	RV19	RV20
β_c	3.647	3.608	3.099	3.905	4.357	4.265	3.803	4.365	5.162	5.827
β_{tc}	0.235	0.243	0.254	0.297	0.344	0.348	0.348	0.406	0.521	1.348
Panel F: LM-sorted portfolios										
	LM1	LM2	LM3	LM4	LM5	LM6	LM7	LM8	LM9	LM10
β_c	5.196	4.734	4.552	3.905	3.929	4.009	3.084	3.592	2.836	2.840
β_{tc}	0.304	0.303	0.215	0.253	0.300	0.256	0.232	0.279	0.291	0.217
	LM11	LM12	LM13	LM14	LM15	LM16	LM17	LM18	LM19	LM20
β_c	2.613	2.830	3.549	3.356	3.084	3.834	3.542	3.876	3.852	4.412
β_{tc}	0.211	0.237	0.286	0.214	0.190	0.325	0.414	0.420	0.343	1.317
Panel G: $cGibbs$-sorted portfolios										
	cGibbs1	cGibbs2	cGibbs3	cGibbs4	cGibbs5	cGibbs6	cGibbs7	cGibbs8	cGibbs9	cGibbs10
β_c	2.641	3.164	2.949	2.893	2.756	3.230	3.328	3.256	3.017	3.031
β_{tc}	0.045	0.066	0.070	0.081	0.074	0.092	0.103	0.126	0.161	0.142
	cGibbs11	cGibbs12	cGibbs13	cGibbs14	cGibbs15	cGibbs16	cGibbs17	cGibbs18	cGibbs19	cGibbs20
β_c	2.558	2.957	3.342	3.683	3.148	3.024	3.500	3.496	3.321	4.145
β_{tc}	0.144	0.166	0.179	0.187	0.204	0.226	0.286	0.330	0.476	1.319
Panel H: $CSspread$-sorted portfolios										
	CSspread1	CSspread2	CSspread3	CSspread4	CSspread5	CSspread6	CSspread7	CSspread8	CSspread9	CSspread10
β_c	3.105	2.819	2.776	2.911	3.196	3.090	2.858	3.099	3.184	3.572
β_{tc}	0.127	0.120	0.132	0.148	0.151	0.157	0.177	0.175	0.180	0.203
	CSspread11	CSspread12	CSspread13	CSspread14	CSspread15	CSspread16	CSspread17	CSspread18	CSspread19	CSspread20
β_c	3.291	2.908	4.018	4.356	3.421	5.009	5.189	4.534	5.217	5.717
β_{tc}	0.200	0.230	0.229	0.266	0.275	0.304	0.358	0.424	0.629	1.300

Table 4.16: Regressions on consumption beta and liquidity beta with 12-month portfolio holding period

This table reports the coefficients by regressing expected returns on the consumption beta and liquidity beta. Test portfolios are: the 20 MV-sorted portfolios, 20 B/M-sorted portfolios, 5×4 $MV\&B/M$-sorted portfolios, 20 DV-sorted portfolios, 20 RV-sorted portfolios, 20 LM-sorted portfolios, 20 *cGibbs*-sorted portfolios and 20 $CSspread$-sorted portfolios. I run the pooled GLS regression on the following equation:

$$R_{i,\,t} - R_{f,\,t} = \gamma_0 + \gamma_1 \beta_{i,t-1,c} + \gamma_2 \beta_{i,t-1,tc} + e_{i,t},$$

where $R_{i,\,t} - R_{f,\,t}$ is the returns of portfolio i in excess of the risk free rate, $\beta_{i,t-1,c}$ is the consumption beta and $\beta_{i,t-1,tc}$ is the liquidity beta. I estimate the historical risk loadings for each portfolio using prior 3-year observations. Transaction costs are calculated using the *cGibbs* estimates of Hasbrouck (2009) in Panel A and the $CSspread$ estimates of Corwin and Schultz (2012) in Panel B, respectively. The 1%, 5%, and 10% significance levels are denoted with ***, **, and *, respectively.

Panel A: *cGibbs* costs		
20 MV-sorted portfolios	$\hat{\gamma_1} = 0.064\%^{***}$ (3.29),	$\hat{\gamma_2} = 2.366\%^{***}$ (6.28)
20 BM-sorted portfolios	$\hat{\gamma_1} = 0.077\%^{***}$ (3.81),	$\hat{\gamma_2} = 2.263\%^{***}$ (5.94)
5×4 $MV\&B/M$ portfolios	$\hat{\gamma_1} = 0.056\%^{***}$ (2.88),	$\hat{\gamma_2} = 2.175\%^{***}$ (5.70)
20 DV-sorted portfolios	$\hat{\gamma_1} = 0.065\%^{***}$ (3.24),	$\hat{\gamma_2} = 2.293\%^{***}$ (6.00)
20 RV-sorted portfolios	$\hat{\gamma_1} = 0.064\%^{***}$ (3.23),	$\hat{\gamma_2} = 2.413\%^{***}$ (6.35)
20 LM-sorted portfolios	$\hat{\gamma_1} = 0.080\%^{***}$ (3.96),	$\hat{\gamma_2} = 2.103\%^{***}$ (5.63)
20 *cGibbs*-sorted portfolios	$\hat{\gamma_1} = 0.077\%^{***}$ (3.67),	$\hat{\gamma_2} = 3.309\%^{***}$ (8.35)
20 $CSspread$-sorted portfolios	$\hat{\gamma_1} = 0.071\%^{***}$ (3.57),	$\hat{\gamma_2} = 2.457\%^{***}$ (6.63)
Panel B: $CSspread$ costs		
20 MV-sorted portfolios	$\hat{\gamma_1} = 0.055\%^{***}$ (2.77),	$\hat{\gamma_2} = 0.566\%^{**}$ (2.48)
20 BM-sorted portfolios	$\hat{\gamma_1} = 0.071\%^{***}$ (3.48),	$\hat{\gamma_2} = 0.507\%^{**}$ (2.08)
5×4 $MV\&B/M$ portfolios	$\hat{\gamma_1} = 0.055\%^{***}$ (2.77),	$\hat{\gamma_2} = 0.206\%$ (1.01)
20 DV-sorted portfolios	$\hat{\gamma_1} = 0.060\%^{***}$ (2.95),	$\hat{\gamma_2} = 0.304\%$ (1.51)
20 RV-sorted portfolios	$\hat{\gamma_1} = 0.057\%^{***}$ (2.85),	$\hat{\gamma_2} = 0.383\%^{*}$ (1.73)
20 LM-sorted portfolios	$\hat{\gamma_1} = 0.075\%^{***}$ (3.70),	$\hat{\gamma_2} = 0.139\%$ (0.82)
20 *cGibbs*-sorted portfolios	$\hat{\gamma_1} = 0.059\%^{***}$ (2.75),	$\hat{\gamma_2} = 0.898\%^{***}$ (4.25)
20 $CSspread$-sorted portfolios	$\hat{\gamma_1} = 0.060\%^{***}$ (2.94),	$\hat{\gamma_2} = 0.608\%^{**}$ (2.43)

Table 4.17: Regressions on transaction costs, consumption beta, and liquidity beta with 12-month portfolio holding period

This table reports the coefficients by regressing expected returns on transaction costs, consumption risk and liquidity risk. Test portfolios are: the 20 MV-sorted portfolios, 20 B/M-sorted portfolios, 5×4 $MV\&B/M$-sorted portfolios, 20 DV-sorted portfolios, 20 RV-sorted portfolios, 20 LM-sorted portfolios, 20 *cGibbs*-sorted portfolios and 20 *CSspread*-sorted portfolios. I run the pooled GLS regression on the following equation:

$$R_{i,\,t} - R_{f,\,t} = \gamma_0 + \gamma_1 E(tc_i) + \gamma_2 \beta_{i,t-1,c} + \gamma_3 \beta_{i,t-1,tc} + e_{i,t},$$

where $R_{i,\,t} - R_{f,\,t}$ is the returns of portfolio i in excess of the risk free rate, $E(tc_i)$ is the average transaction costs of portfolio i, $\beta_{i,t-1,c}$ is the consumption beta and $\beta_{i,t-1,tc}$ is the liquidity beta. I estimate the historical risk loadings for each portfolio using prior 3-year observations. Transaction costs are calculated using the *cGibbs* estimates of Hasbrouck (2009) in Panel A and the *CSspread* estimates of Corwin and Schultz (2012) in Panel B, respectively. The 1%, 5%, and 10% significance levels are denoted with ***, **, and *, respectively.

Panel A: *cGibbs* costs			
20 MV-sorted portfolios	$\hat{\gamma_1} = 0.233$ (1.04)	$\hat{\gamma_2} = 0.061\%^{***}$ (3.05),	$\hat{\gamma_3} = 2.338\%^{***}$ (6.20)
20 BM-sorted portfolios	$\hat{\gamma_1} = 0.526$ (1.00)	$\hat{\gamma_2} = 0.076\%^{***}$ (3.72),	$\hat{\gamma_3} = 2.249\%^{***}$ (5.90)
20 $MV\&B/M$ portfolios	$\hat{\gamma_1} = 0.253$ (0.98)	$\hat{\gamma_2} = 0.053\%^{***}$ (2.68),	$\hat{\gamma_3} = 2.156\%^{***}$ (5.65)
20 DV-sorted portfolios	$\hat{\gamma_1} = 0.308$ (1.37)	$\hat{\gamma_2} = 0.062\%^{***}$ (3.05),	$\hat{\gamma_3} = 2.255\%^{***}$ (5.89)
20 RV-sorted portfolios	$\hat{\gamma_1} = 0.193$ (0.94)	$\hat{\gamma_2} = 0.061\%^{***}$ (3.04),	$\hat{\gamma_3} = 2.379\%^{***}$ (6.23)
20 LM-sorted portfolios	$\hat{\gamma_1} = 0.205$ (0.43)	$\hat{\gamma_2} = 0.079\%^{***}$ (3.90),	$\hat{\gamma_3} = 2.094\%^{***}$ (5.59)
20 *cGibbs*-sorted portfolios	$\hat{\gamma_1} = 0.209$ (1.11)	$\hat{\gamma_2} = 0.074\%^{***}$ (3.48),	$\hat{\gamma_3} = 3.268\%^{***}$ (8.22)
20 *CSspread*-sorted portfolios	$\hat{\gamma_1} = -0.228$ (-1.06)	$\hat{\gamma_2} = 0.073\%^{***}$ (3.70),	$\hat{\gamma_3} = 2.485\%^{***}$ (6.69)
Panel B: *CSspread* costs			
20 MV-sorted portfolios	$\hat{\gamma_1} = 0.079$ (0.65)	$\hat{\gamma_2} = 0.054\%^{***}$ (2.67),	$\hat{\gamma_3} = 0.536\%^{**}$ (2.30)
20 BM-sorted portfolios	$\hat{\gamma_1} = 0.191$ (0.71)	$\hat{\gamma_2} = 0.070\%^{***}$ (3.42),	$\hat{\gamma_3} = 0.489\%^{**}$ (1.99)
20 $MV\&B/M$ portfolios	$\hat{\gamma_1} = 0.163$ (0.96)	$\hat{\gamma_2} = 0.052\%^{***}$ (2.61),	$\hat{\gamma_3} = 0.174\%$ (0.84)
20 DV-sorted portfolios	$\hat{\gamma_1} = 0.120$ (1.02)	$\hat{\gamma_2} = 0.058\%^{***}$ (2.84),	$\hat{\gamma_3} = 0.255\%$ (1.24)
20 RV-sorted portfolios	$\hat{\gamma_1} = 0.095$ (0.82)	$\hat{\gamma_2} = 0.056\%^{***}$ (2.73),	$\hat{\gamma_3} = 0.342\%$ (1.51)
20 LM-sorted portfolios	$\hat{\gamma_1} = 0.023$ (0.16)	$\hat{\gamma_2} = 0.075\%^{***}$ (3.67),	$\hat{\gamma_3} = 0.136\%$ (0.80)
20 *cGibbs*-sorted portfolios	$\hat{\gamma_1} = 0.124$ (0.85)	$\hat{\gamma_2} = 0.057\%^{***}$ (2.64),	$\hat{\gamma_3} = 0.855\%^{***}$ (3.96)
20 *CSspread*-sorted portfolios	$\hat{\gamma_1} = -0.135$ (-1.18)	$\hat{\gamma_2} = 0.063\%^{***}$ (3.06),	$\hat{\gamma_3} = 0.681\%^{***}$ (2.65)

Table 4.18: Risk aversion estimates with 12-month portfolio holding period: *cGibbs* costs

This table reports the estimated risk aversion based on consumption growth over horizons of S ($S = 0, 1, 2...11$), which is calculated by $\Delta C_t^S = \frac{C_{t+S}}{C_{t-1}} - 1$. Transaction costs are calculated using the *cGibbs* estimates of Hasbrouck (2009). For each set of test portfolios, I calculate the risk aversion coefficients using $\gamma = \frac{E[R_{i,t}-R_{f,t}]+\frac{\sigma_i^2}{2}}{\sigma_{i,\Delta C^S}}$ for traditional CCAPM and $\gamma = \frac{E[R_{itc,t}-R_{f,t}]+\frac{\sigma_{itc}^2}{2}}{\sigma_{itc,\Delta C^S}}$ for my liquidity-adjusted model. $R_{i,t}$ and $R_{itc,t}$ are cross-sectional mean values for each set of portfolios. $R_{itc,t} = R_{i,t} - tc_{i,t}$; $\sigma_{i,\Delta C^S}$ denotes the covariance of innovations $Cov(R_{i,t} - E[R_{i,t}], \Delta C_t^S - E[\Delta C_t^S])$; $\sigma_{itc,\Delta C^S}$ denotes the covariance of innovations $Cov(R_{itc,t} - E[R_{itc,t}], \Delta C_t^S - E[\Delta C_t^S])$; ΔC^S denotes the consumption growth over period S. Test portfolios are: the 20 MV-sorted portfolios, 20 B/M-sorted portfolios, 5×4 $MV\&B/M$-sorted portfolios, 20 DV-sorted portfolios, 20 RV-sorted portfolios, 20 LM-sorted portfolios, 20 *cGibbs*-sorted portfolios and 20 $CSspread$-sorted portfolios.

HORIZONS	S0	S1	S2	S3	S4	S5	S6	S7	S8	S9	S10	S11
20 MV-sorted portfolios												
Traditional CCAPM	244.28	106.11	83.31	69.35	54.97	52.91	49.14	46.58	53.26	53.94	50.62	50.73
Liquidity-adjusted CCAPM	175.19	76.10	59.75	49.74	39.42	37.95	35.24	33.40	38.20	38.69	36.31	36.38
20 B/M-sorted portfolios												
Traditional CCAPM	246.63	106.90	83.75	69.61	55.31	53.12	49.34	46.74	53.32	53.94	50.65	50.76
Liquidity-adjusted CCAPM	182.67	79.18	62.03	51.56	40.97	39.35	36.54	34.62	39.49	39.95	37.51	37.60
5×4 $MV\&B/M$-sorted portfolios												
Traditional CCAPM	256.30	110.18	86.25	71.34	56.64	54.21	50.07	47.26	53.63	53.95	50.61	50.70
Liquidity-adjusted CCAPM	189.15	81.32	63.66	52.65	41.80	40.01	36.95	34.88	39.58	39.82	37.35	37.42
20 DV-sorted portfolios												
Traditional CCAPM	240.68	104.70	82.12	68.34	54.33	52.19	48.45	45.86	52.24	52.78	49.44	49.47
Liquidity-adjusted CCAPM	170.80	74.30	58.28	48.49	38.55	37.04	34.38	32.55	37.07	37.45	35.09	35.11
20 RV-sorted portfolios												
Traditional CCAPM	241.72	105.06	82.43	68.59	54.48	52.34	48.56	45.96	52.35	52.88	49.55	49.57
Liquidity-adjusted CCAPM	171.75	74.64	58.57	48.73	38.71	37.19	34.50	32.65	37.19	37.57	35.20	35.22
20 LM-sorted portfolios												
Traditional CCAPM	240.95	104.64	81.99	68.12	54.13	51.99	48.25	45.69	52.16	52.77	49.51	49.63
Liquidity-adjusted CCAPM	170.06	73.85	57.87	48.08	38.20	36.69	34.05	32.25	36.81	37.24	34.95	35.03
20 *cGibbs*-sorted portfolios												
Traditional CCAPM	300.13	123.87	98.49	81.25	63.69	61.01	56.90	55.97	67.37	70.39	66.15	66.24
Liquidity-adjusted CCAPM	220.87	91.16	72.48	59.79	46.87	44.90	41.88	41.19	49.58	51.80	48.68	48.75
20 $CSspread$-sorted portfolios												
Traditional CCAPM	243.33	105.75	83.10	69.17	54.89	52.84	49.06	46.48	53.12	53.78	50.44	50.53
Liquidity-adjusted CCAPM	174.44	75.81	59.58	49.59	39.35	37.88	35.17	33.32	38.08	38.56	36.16	36.22

Table 4.19: Risk aversion estimates with 12-month portfolio holding period: $CSspread$ costs

This table reports the estimated risk aversion based on consumption growth over horizons of S ($S = 0, 1, 2...11$), which is calculated by $\Delta C_t^S = \frac{C_{t+S}}{C_{t-1}} - 1$. Transaction costs are calculated using the $CSspread$ estimates of Corwin and Schultz (2012). For each set of test portfolios, I calculate the risk aversion coefficients using $\gamma = \frac{E[R_{i,t} - R_{f,t}] + \frac{\sigma_i^2}{2}}{\sigma_{i,\Delta C^S}}$ for traditional CCAPM and $\gamma = \frac{E[R_{itc,t} - R_{f,t}] + \frac{\sigma_{itc}^2}{2}}{\sigma_{itc,\Delta C^S}}$ for my liquidity-adjusted model. $R_{i,t}$ and $R_{itc,t}$ are cross-sectional mean values for each set of portfolios. $R_{itc,t} = R_{i,t} - tc_{i,t}$; $\sigma_{i,\Delta C^S}$ denotes the covariance of innovations $Cov(R_{i,t} - E[R_{i,t}], \Delta C_t^S - E[\Delta C_t^S])$; $\sigma_{itc,\Delta C^S}$ denotes the covariance of innovations $Cov(R_{itc,t} - E[R_{itc,t}], \Delta C_t^S - E[\Delta C_t^S])$; ΔC^S denotes the consumption growth over period S. Test portfolios are: the 20 MV-sorted portfolios, 20 B/M-sorted portfolios, 5×4 $MV\&B/M$-sorted portfolios, 20 DV-sorted portfolios, 20 RV-sorted portfolios, 20 LM-sorted portfolios, 20 $cGibbs$-sorted portfolios and 20 $CSspread$-sorted portfolios.

HORIZONS	S0	S1	S2	S3	S4	S5	S6	S7	S8	S9	S10	S11
20 MV-sorted portfolios												
Traditional CCAPM	244.22	106.35	83.55	69.63	55.19	53.18	49.39	46.84	53.60	54.27	50.90	51.01
Liquidity-adjusted CCAPM	61.61	26.83	21.08	17.57	13.92	13.42	12.46	11.82	13.52	13.69	12.84	12.87
20 B/M-sorted portfolios												
Traditional CCAPM	246.88	107.17	83.97	69.89	55.53	53.36	49.56	46.96	53.56	54.18	50.87	50.98
Liquidity-adjusted CCAPM	78.76	34.19	26.79	22.30	17.71	17.02	15.81	14.98	17.09	17.28	16.23	16.26
5×4 $MV\&B/M$-sorted portfolios												
Traditional CCAPM	256.36	110.35	86.38	71.50	56.76	54.36	50.22	47.43	53.83	54.13	50.76	50.86
Liquidity-adjusted CCAPM	84.63	36.43	28.52	23.60	18.74	17.95	16.58	15.66	17.77	17.87	16.76	16.79
20 DV-sorted portfolios												
Traditional CCAPM	241.63	105.22	82.49	68.68	54.58	52.44	48.67	46.07	52.46	52.99	49.64	49.67
Liquidity-adjusted CCAPM	56.91	24.78	19.43	16.18	12.86	12.35	11.46	10.85	12.36	12.48	11.69	11.70
20 RV-sorted portfolios												
Traditional CCAPM	242.73	105.63	82.86	68.97	54.76	52.61	48.80	46.18	52.58	53.10	49.74	49.78
Liquidity-adjusted CCAPM	58.69	25.54	20.03	16.67	13.24	12.72	11.80	11.17	12.71	12.84	12.03	12.04
20 LM-sorted portfolios												
Traditional CCAPM	241.91	105.15	82.37	68.48	54.39	52.24	48.48	45.90	52.39	52.99	49.72	49.84
Liquidity-adjusted CCAPM	52.79	22.95	17.98	14.94	11.87	11.40	10.58	10.02	11.43	11.56	10.85	10.88
20 $cGibbs$-sorted portfolios												
Traditional CCAPM	301.82	124.58	99.02	81.74	64.04	61.37	57.23	56.31	67.79	70.84	66.56	66.64
Liquidity-adjusted CCAPM	96.30	39.75	31.59	26.08	20.43	19.58	18.26	17.96	21.63	22.60	21.24	21.26
20 $CSspread$-sorted portfolios												
Traditional CCAPM	243.53	106.13	83.47	69.53	55.19	53.18	49.37	46.79	53.53	54.17	50.78	50.87
Liquidity-adjusted CCAPM	63.52	27.68	21.77	18.14	14.40	13.87	12.88	12.21	13.96	14.13	13.24	13.27

Table 4.20: Summary of R^2 for robustness tests with 12-month portfolio holding period: *cGibbs* costs

This table reports the cross-sectional R-squares obtained from several robustness tests. Transaction costs are calculated using the *cGibbs* estimates of Hasbrouck (2009). Test portfolios are: the 20 MV-sorted portfolios, 20 B/M-sorted portfolios, 5×4 $MV\&B/M$-sorted portfolios, 20 DV-sorted portfolios, 20 RV-sorted portfolios, 20 LM-sorted portfolios, 20 *cGibbs*-sorted portfolios and 20 *CSspread*-sorted portfolios except Panel A. In Panel A, I test 17 industry portfolios and 30 industry portfolios. I also augment each set of test portfolios (the 20 MV-sorted portfolios, 20 B/M-sorted portfolios, 5×4 $MV\&B/M$-sorted portfolios, 20 DV-sorted portfolios, 20 RV-sorted portfolios, 20 LM-sorted portfolios, 20 *cGibbs*-sorted portfolios and 20 *CSspread*-sorted portfolios.) with 10 industry portfolios, respectively. The 10, 17 and 30 industry classification is based on Fama-French's industry classification. In Panel B, C and D, I take into account the long run consumption growth (Parker and Julliard (2005)), the total consumption growth (Yogo (2006)) and the fourth quarter consumption growth (Jagannathan and Wang (2007)), respectively. Specifically, in Panel B, I measure consumption risk using the consumption growth of nondurable goods with the horizon ($S = 11$). In Panel C, I substitute total consumption growth for the consumption growth of nondurable goods and services. In Panel D, I use only the Q4 ($4th$ quarter) data to estimate consumption beta and liquidity beta. I calculated R-squares using the method as in Figure 4.2.

	Traditional CCAPM	Liquidity risk adjusted CCAPM
Panel A: Other testing portfolios		
17 industry portfolios	$R^2 = 0.16\%$	$R^2 = 42.44\%$
30 industry portfolios	$R^2 = 0.19\%$	$R^2 = 7.53\%$
20 MV-sorted portfolios	$R^2 = 31.06\%$	$R^2 = 39.36\%$
20 BM-sorted portfolios	$R^2 = 8.95\%$	$R^2 = 32.77\%$
20 $MV\&B/M$-sorted portfolios	$R^2 = 19.26\%$	$R^2 = 29.42\%$
20 DV-sorted portfolios	$R^2 = 6.67\%$	$R^2 = 42.94\%$
20 RV-sorted portfolios	$R^2 = 20.50\%$	$R^2 = 36.95\%$
20 LM-sorted portfolios	$R^2 = 0.40\%$	$R^2 = 26.26\%$
20 *cGibbs*-sorted portfolios	$R^2 = 17.53\%$	$R^2 = 75.89\%$
20 *CSspread*-sorted portfolios	$R^2 = 1.71\%$	$R^2 = 18.88\%$
Panel B: Ultimate consumption risk (S11 consumption growth)		
20 MV-sorted portfolios	$R^2 = 68.71\%$	$R^2 = 79.82\%$
20 BM-sorted portfolios	$R^2 = 50.38\%$	$R^2 = 69.95\%$
20 $MV\&B/M$-sorted portfolios	$R^2 = 69.67\%$	$R^2 = 77.81\%$
20 DV-sorted portfolios	$R^2 = 66.76\%$	$R^2 = 85.57\%$
20 RV-sorted portfolios	$R^2 = 69.60\%$	$R^2 = 83.64\%$
20 LM-sorted portfolios	$R^2 = 3.59\%$	$R^2 = 26.53\%$
20 *cGibbs*-sorted portfolios	$R^2 = 75.65\%$	$R^2 = 88.74\%$
20 *CSspread*-sorted portfolios	$R^2 = 2.05\%$	$R^2 = 16.73\%$
Panel C: Total consumption growth		
20 MV-sorted portfolios	$R^2 = 70.86\%$	$R^2 = 79.10\%$
20 BM-sorted portfolios	$R^2 = 50.80\%$	$R^2 = 54.50\%$
20 $MV\&B/M$-sorted portfolios	$R^2 = 73.52\%$	$R^2 = 79.19\%$
20 DV-sorted portfolios	$R^2 = 37.26\%$	$R^2 = 72.79\%$
20 RV-sorted portfolios	$R^2 = 57.99\%$	$R^2 = 73.70\%$
20 LM-sorted portfolios	$R^2 = 0.46\%$	$R^2 = 40.21\%$
20 *cGibbs*-sorted portfolios	$R^2 = 79.81\%$	$R^2 = 88.44\%$
20 *CSspread*-sorted portfolios	$R^2 = 1.85\%$	$R^2 = 19.55\%$
Panel D: Q4 ($4th$ quarter) consumption growth		
20 MV-sorted portfolios	$R^2 = 74.94\%$	$R^2 = 82.03\%$
20 BM-sorted portfolios	$R^2 = 32.94\%$	$R^2 = 55.64\%$
20 $MV\&B/M$-sorted portfolios	$R^2 = 48.87\%$	$R^2 = 74.12\%$
20 DV-sorted portfolios	$R^2 = 41.81\%$	$R^2 = 79.57\%$
20 RV-sorted portfolios	$R^2 = 64.76\%$	$R^2 = 80.55\%$
20 LM-sorted portfolios	$R^2 = 2.16\%$	$R^2 = 55.10\%$
20 *cGibbs*-sorted portfolios	$R^2 = 81.17\%$	$R^2 = 88.84\%$
20 *CSspread*-sorted portfolios	$R^2 = 3.47\%$	$R^2 = 12.65\%$

Table 4.21: Summary of R^2 for robustness tests with 12-month portfolio holding period: $CSspread$ costs

This table reports the cross-sectional R-squares obtained from several robustness tests. Transaction costs are calculated using the $CSspread$ estimates of Corwin and Schultz (2012). Test portfolios are: the 20 MV-sorted portfolios, 20 B/M-sorted portfolios, 5×4 $MV\&B/M$-sorted portfolios, 20 DV-sorted portfolios, 20 RV-sorted portfolios, 20 LM-sorted portfolios, 20 *cGibbs*-sorted portfolios and 20 $CSspread$-sorted portfolios except Panel A. In Panel A, I test 17 industry portfolios and 30 industry portfolios. I also augment each set of test portfolios (the 20 MV-sorted portfolios, 20 B/M-sorted portfolios, 5×4 $MV\&B/M$-sorted portfolios, 20 DV-sorted portfolios, 20 RV-sorted portfolios, 20 LM-sorted portfolios, 20 *cGibbs*-sorted portfolios and 20 $CSspread$-sorted portfolios.) with 10 industry portfolios, respectively. The 10, 17 and 30 industry classification is based on Fama-French's industry classification. In Panel B, C and D, I take into account the long run consumption growth (Parker and Julliard (2005)), the total consumption growth (Yogo (2006)) and the fourth quarter consumption growth (Jagannathan and Wang (2007)), respectively. Specifically, in Panel B, I measure consumption risk using the consumption growth of nondurable goods with the horizon ($S = 11$). In Panel C, I substitute total consumption growth for the consumption growth of nondurable goods and services. In Panel D, I use only the Q4 ($4th$ quarter) data to estimate consumption beta and liquidity beta. I calculated R-squares using the method as in Figure 4.2.

	Traditional CCAPM	Liquidity risk adjusted CCAPM
Panel A: Other testing portfolios		
17 industry portfolios	$R^2 = 0.39\%$	$R^2 = 20.03\%$
30 industry portfolios	$R^2 = 0.12\%$	$R^2 = 7.89\%$
20 MV-sorted portfolios	$R^2 = 32.05\%$	$R^2 = 38.95\%$
20 BM-sorted portfolios	$R^2 = 10.02\%$	$R^2 = 22.64\%$
20 $MV\&B/M$-sorted portfolios	$R^2 = 20.13\%$	$R^2 = 31.25\%$
20 DV-sorted portfolios	$R^2 = 7.13\%$	$R^2 = 30.72\%$
20 RV-sorted portfolios	$R^2 = 21.76\%$	$R^2 = 34.08\%$
20 LM-sorted portfolios	$R^2 = 0.53\%$	$R^2 = 5.07\%$
20 *cGibbs*-sorted portfolios	$R^2 = 16.39\%$	$R^2 = 68.84\%$
20 $CSspread$-sorted portfolios	$R^2 = 2.27\%$	$R^2 = 15.13\%$
Panel B: Ultimate consumption risk (S11 consumption growth)		
20 MV-sorted portfolios	$R^2 = 67.41\%$	$R^2 = 70.35\%$
20 BM-sorted portfolios	$R^2 = 53.73\%$	$R^2 = 58.13\%$
20 $MV\&B/M$-sorted portfolios	$R^2 = 68.48\%$	$R^2 = 76.15\%$
20 DV-sorted portfolios	$R^2 = 67.24\%$	$R^2 = 69.45\%$
20 RV-sorted portfolios	$R^2 = 70.86\%$	$R^2 = 71.40\%$
20 LM-sorted portfolios	$R^2 = 4.59\%$	$R^2 = 11.60\%$
20 *cGibbs*-sorted portfolios	$R^2 = 76.19\%$	$R^2 = 88.07\%$
20 $CSspread$-sorted portfolios	$R^2 = 0.50\%$	$R^2 = 17.00\%$
Panel C: Total consumption growth		
20 MV-sorted portfolios	$R^2 = 70.59\%$	$R^2 = 76.34\%$
20 BM-sorted portfolios	$R^2 = 54.36\%$	$R^2 = 62.13\%$
20 $MV\&B/M$-sorted portfolios	$R^2 = 74.47\%$	$R^2 = 76.99\%$
20 DV-sorted portfolios	$R^2 = 38.55\%$	$R^2 = 48.93\%$
20 RV-sorted portfolios	$R^2 = 59.62\%$	$R^2 = 62.82\%$
20 LM-sorted portfolios	$R^2 = 0.15\%$	$R^2 = 12.44\%$
20 *cGibbs*-sorted portfolios	$R^2 = 80.09\%$	$R^2 = 87.26\%$
20 $CSspread$-sorted portfolios	$R^2 = 0.66\%$	$R^2 = 3.09\%$
Panel D: Q4 ($4th$ quarter) consumption growth		
20 MV-sorted portfolios	$R^2 = 75.51\%$	$R^2 = 78.88\%$
20 BM-sorted portfolios	$R^2 = 36.85\%$	$R^2 = 57.65\%$
20 $MV\&B/M$-sorted portfolios	$R^2 = 49.32\%$	$R^2 = 74.27\%$
20 DV-sorted portfolios	$R^2 = 43.00\%$	$R^2 = 57.83\%$
20 RV-sorted portfolios	$R^2 = 66.15\%$	$R^2 = 72.00\%$
20 LM-sorted portfolios	$R^2 = 1.84\%$	$R^2 = 24.95\%$
20 *cGibbs*-sorted portfolios	$R^2 = 82.09\%$	$R^2 = 89.72\%$
20 $CSspread$-sorted portfolios	$R^2 = 1.28\%$	$R^2 = 5.68\%$

Table 4.22: GMM estimates with 12-month portfolio holding period

This table reports the estimated risk aversion using a generalized method of moments (GMM) estimate with an optimal weighting matrix method. I test the equal-weighted market portfolios formed with *cGibbs* estimates of Hasbrouck (2009) in Panel A and *CSspread* costs estimates of Corwin and Schultz (2012) in Panel B. I use the empirical moment function $E[M_t^S(R_t - R_{f,t})z_t] = 0$ for the CCAPM and $E[M_t^S(R_t - R_{f,t} - tc_t)z_t] = 0$ for my liquidity risk-adjusted CCAPM, where R_t^e denote the market returns in excess of the risk free rate, tc_t denote the transaction costs, z_t denote a $M \times 1$ vector of instrumental variables, and $M_t^S = \beta(\frac{C_{t+S}}{C_{t-1}})^{-\gamma}$. I fix $\beta = 0.95$. The instrument variables are the risk-free rate and the excess return of market portfolio with two lags.

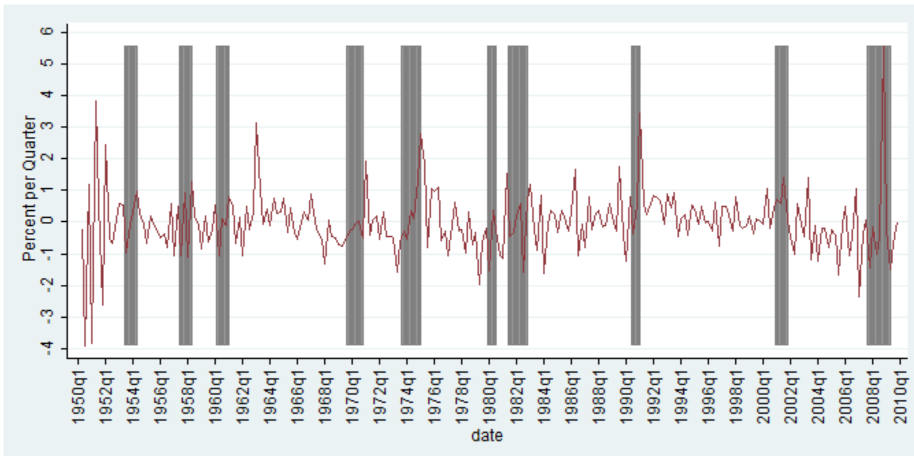
HORIZONS	S0	S1	S2	S3	S4	S5	S6	S7	S8	S9	S10	S11
Panel A: Equal-weighted market portfolios (*cGibbscosts*)												
Traditional CCAPM	136.38	71.37	57.74	52.02	44.26	43.75	41.70	40.68	41.32	39.94	38.93	38.90
Liquidity-adjusted CCAPM: *cGibbs*	81.36	39.00	31.62	28.56	25.24	25.39	25.48	25.71	26.78	26.64	25.65	25.83
Liquidity-adjusted CCAPM: 0.5%	94.75	44.07	35.66	31.84	27.58	27.47	26.94	26.84	28.23	27.64	26.73	26.90
Liquidity-adjusted CCAPM: 1%	32.64	26.82	22.09	19.76	17.71	17.68	17.95	18.04	18.92	18.91	18.20	18.06
Liquidity-adjusted CCAPM: 1.5%	21.00	10.39	9.37	9.27	9.13	9.71	10.98	11.55	12.64	13.13	12.81	13.07
Panel B: Equal-weighted market portfolios (*CSspread* costs)												
Traditional CCAPM	136.22	71.26	57.73	52.02	44.26	43.78	41.74	40.73	41.38	40.02	39.02	38.99
Liquidity-adjusted CCAPM: *CSspread*	15.21	8.24	7.67	8.11	8.10	8.75	10.06	10.64	11.97	12.10	11.78	12.12
Liquidity-adjusted CCAPM: 0.5%	94.77	44.13	35.74	31.90	27.64	27.54	27.01	26.90	28.27	27.71	26.79	26.94
Liquidity-adjusted CCAPM: 1%	63.53	26.96	22.22	19.86	17.80	17.77	18.04	18.13	18.98	19.00	18.28	18.12
Liquidity-adjusted CCAPM: 1.5%	21.50	10.64	9.57	9.44	9.28	9.88	11.13	11.70	12.76	13.26	12.92	13.17

Figure 4.1: Time series plots of liquidity innovations

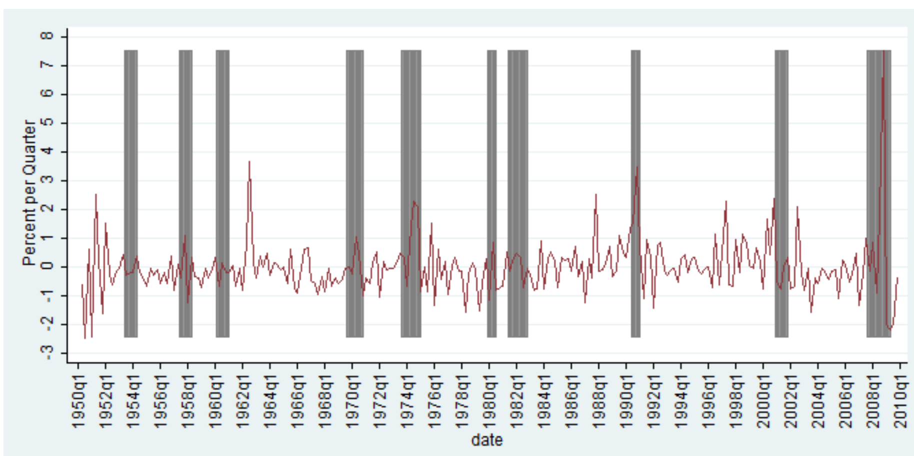
These figures plot the standardized liquidity innovations. The shaded regions are recessions defined by the National Bureau of Economic Research (NBER). The liquidity innovation (u_t) is the residual of the following regression:

$$tc_t = \alpha_0 + \alpha_1 tc_{t-1} + u_t,$$

where tc_t denotes the average of the transaction costs measures over the sample stocks in quarter t. The time series of liquidity innovation are scaled to have zero mean and unit standard deviation. Transaction costs are calculated using the *cGibbs* estimates of Hasbrouck (2009) in Panel A and the *CSspread* estimates of Corwin and Schultz (2012) in Panel B.



Panel A: *cGibbs* as a measure of transaction costs



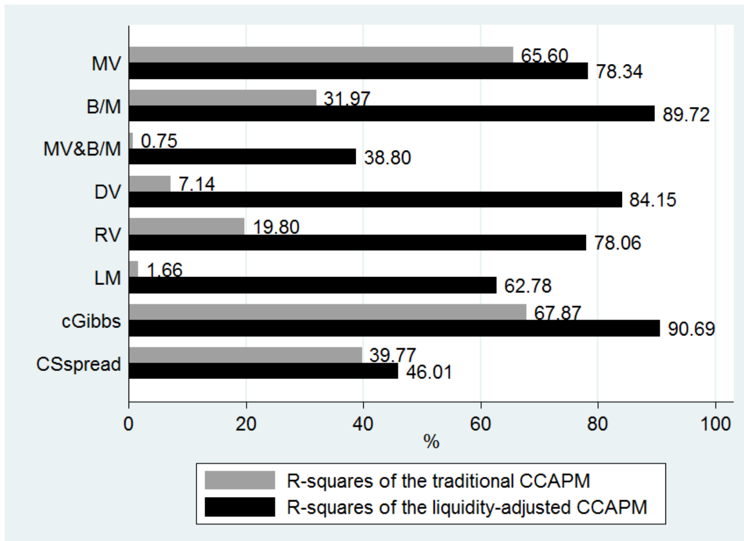
Panel B: *CSspread* as a measure of transaction costs

Figure 4.2: R-square comparisons

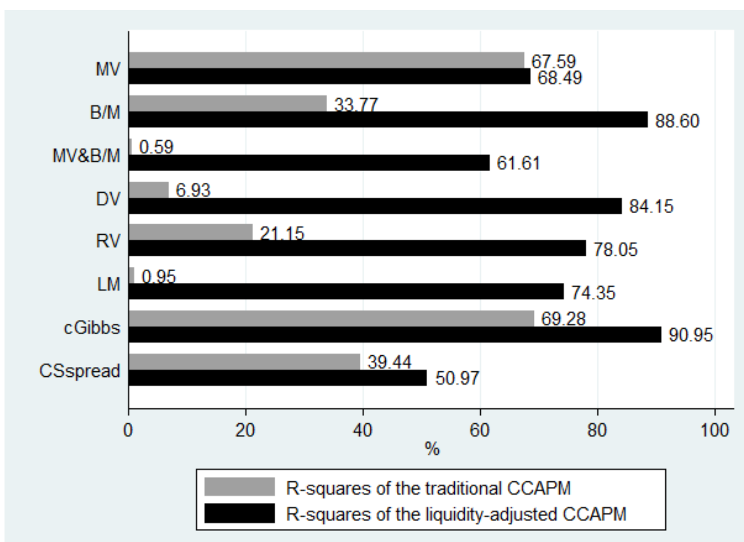
These figures plot the R-squares for the traditional CCAPM and the liquidity-adjusted model. Test portfolios are the 20 MV-sorted, 20 B/M-sorted, 4×5 $MV\&B/M$-sorted, 20 DV-sorted, 20 RV-sorted, 20 LM-sorted, 20 *cGibbs*-sorted, and 20 $CSspread$-sorted portfolios, respectively. Following Jagannathan and Wang (1996) and Lettau and Ludvigson (2001), I employ the Fama-MacBeth (1973) procedure to calculate the cross-sectional R-square, which has the following form:

$$R^2 = \frac{[Var_c(\bar{R}_i^e) - Var_c(\bar{\epsilon}_i)]}{Var_c(\bar{R}_i^e)},$$

where $\bar{R}_i^e$ is the time-series average of returns in excess of the risk-free rate for portfolio i, $\bar{\epsilon}_i$ is the time-series average of residuals for portfolio i, and Var_c is the cross-sectional variance. Transaction costs are calculated using the *cGibbs* estimates of Hasbrouck (2009) in Panel A and the $CSspread$ estimates of Corwin and Schultz (2012) in Panel B.



Panel A: *cGibbs* as a measure of transaction costs

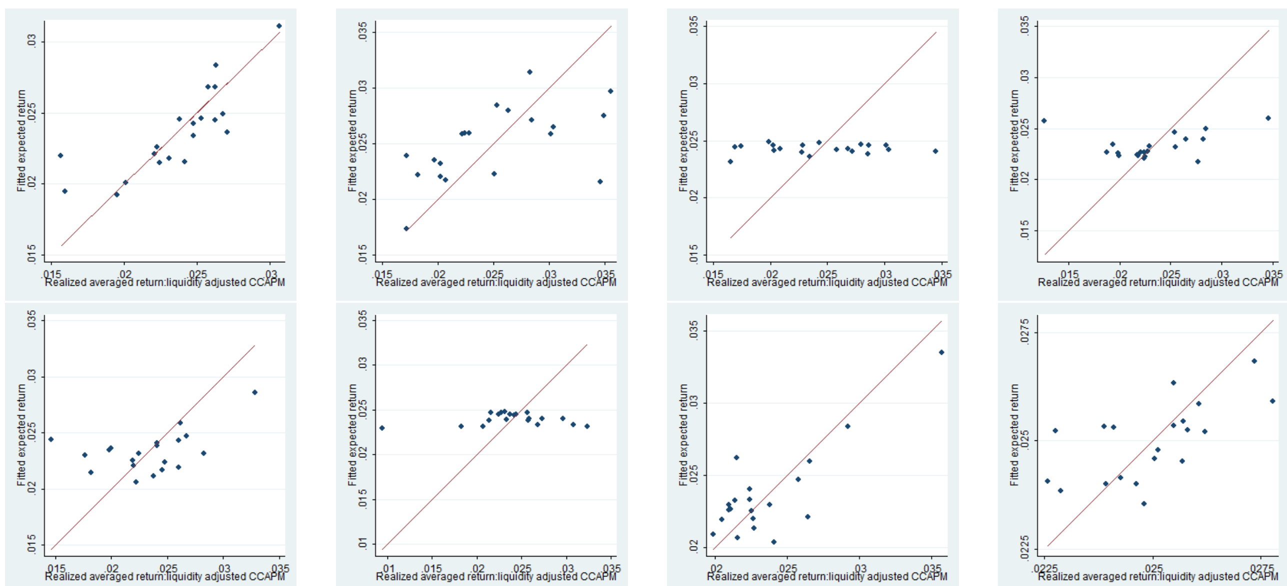


Panel B: $CSspread$ as a measure of transaction costs

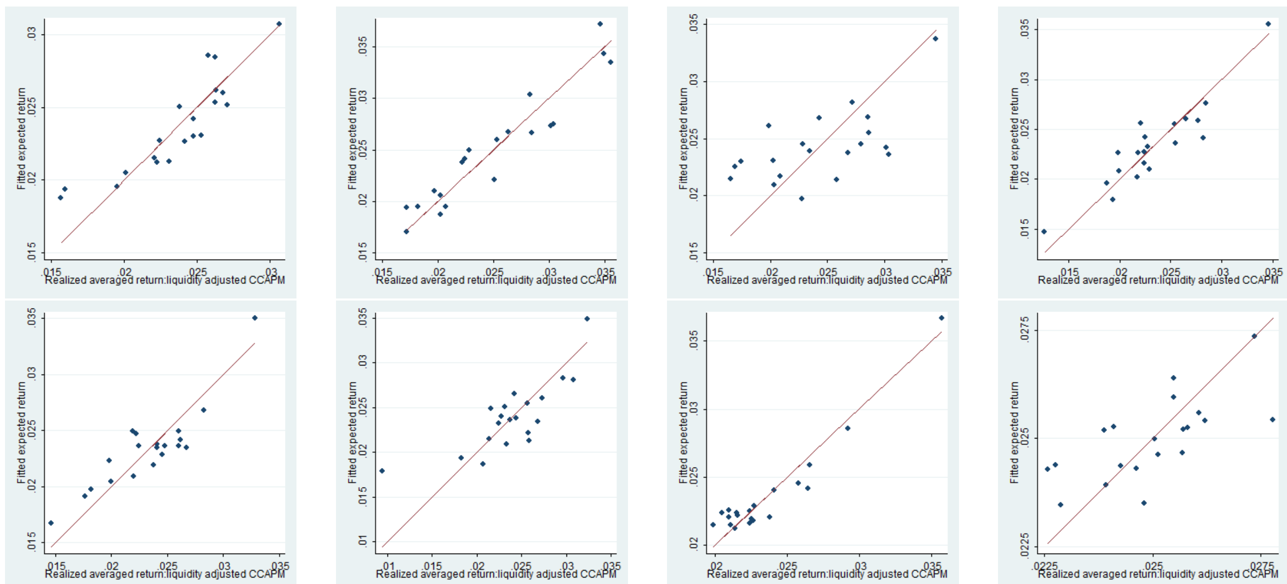
Figure 4.3: Fitted versus realized returns

These figures plot the fitted returns versus realized returns. The horizonal axis shows the realized average excess return and the vertical axis shows the excess return fitted by model. Test portfolios from left to right are the 20 MV-sorted, 20 B/M-sorted, 4×5 $MV\&B/M$-sorted, 20 DV-sorted, 20 RV-sorted, 20 LM-sorted, 20 *cGibbs*-sorted, and 20 *CSspread*-sorted portfolios, respectively. The realized average returns are the time-series average returns in excess of the risk-free rate. The fitted expected returns for the CCAPM are calculated as the fitted value from $E[R_{i,\,t} - R_{f,\,t}] = \gamma_0 + \gamma_1 \beta_{i,c}$. The fitted expected returns for the liquidity-adjusted CCAPM are calculated as the fitted value from $E[R_{i,\,t} - R_{f,\,t}] = \gamma_0 + \gamma_1 E[tc_{i,\,t}] + \gamma_2 \beta_{i,c} + \gamma_3 \beta_{i,tc}$. Transaction costs are calculated using the *cGibbs* estimates of Hasbrouck (2009) in Panel A and the *CSspread* estimates of Corwin and Schultz (2012) in Panel B.

Panel A: *cGibbs* as a measure of transaction costs

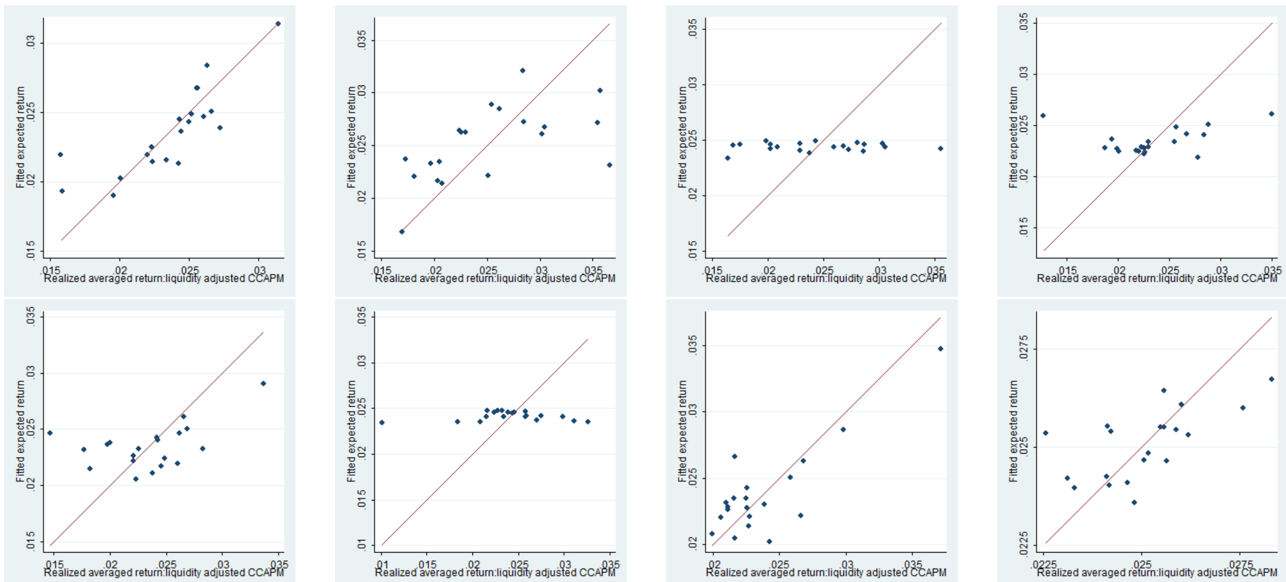


The traditional CCAPM

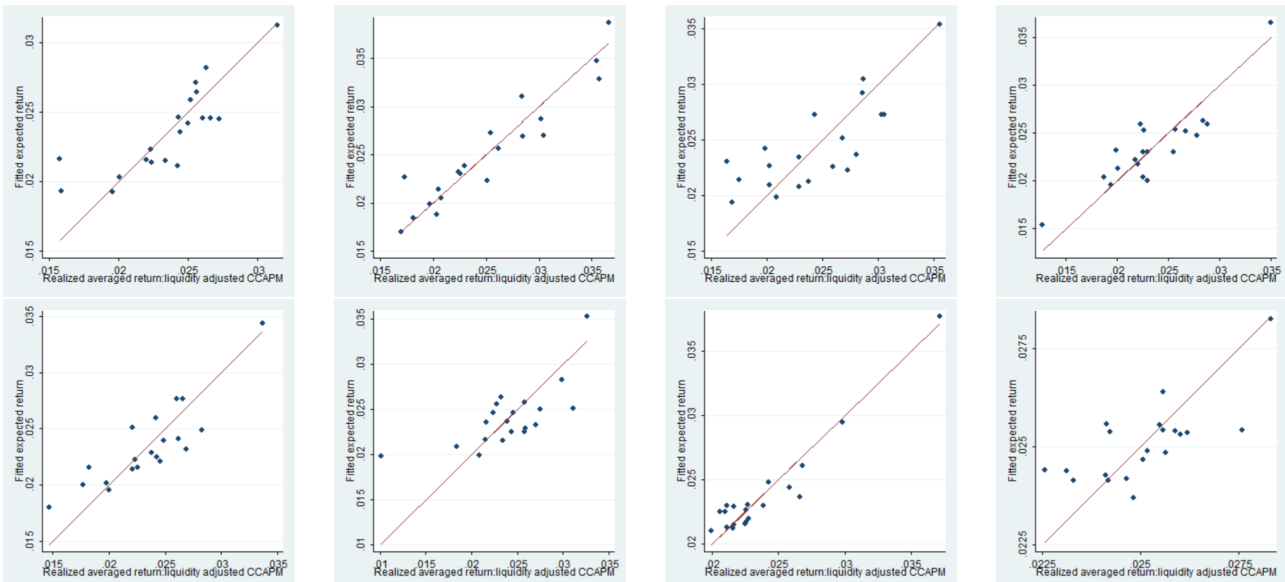


The liquidity-adjusted CCAPM

Panel B: $CSspread$ as a measure of transaction costs



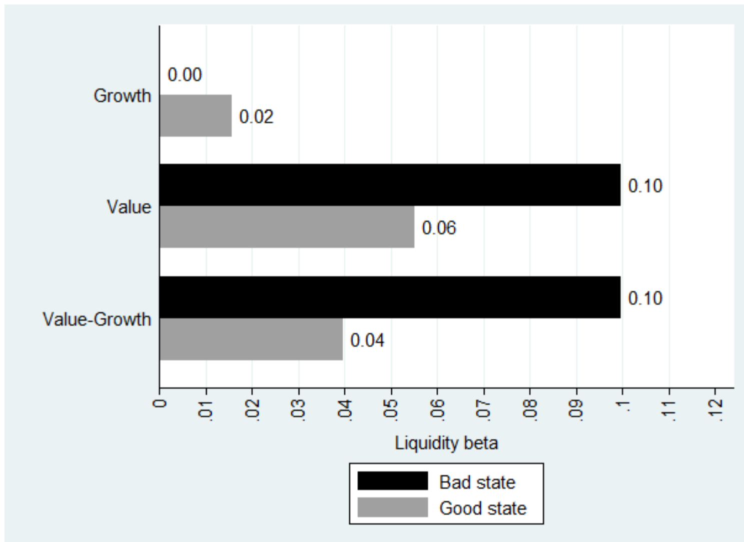
The traditional CCAPM



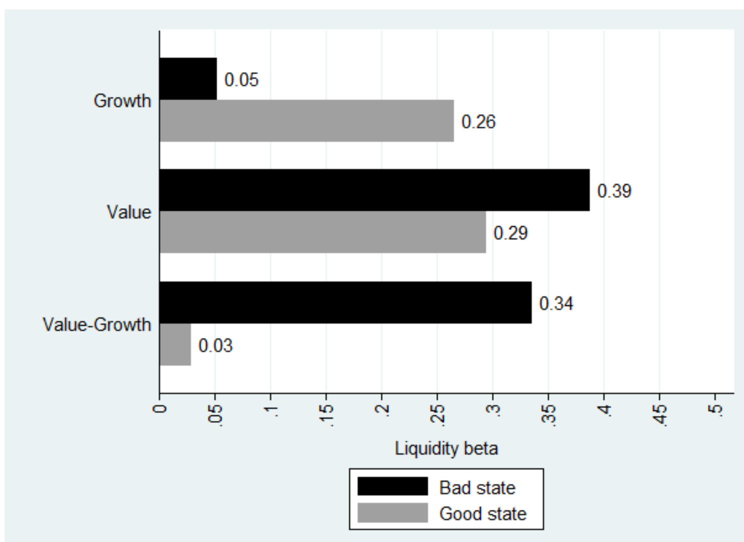
The liquidity-adjusted CCAPM

Figure 4.4: Bad time betas and good time betas

These figures plot the average rolling liquidity betas for growth and value stocks in bad states and good states. The rolling liquidity betas for each stock are estimated from the 10-year rolling regressions based on Eqs. (4.11) and (4.12). Then the estimated liquidity betas are allocated into the 20 B/M portfolios. The plotted rolling liquidity betas are the cross-sectional time-series averages for the lowest (growth) and highest (value) B/M portfolios. I use NBER recession periods to identify bad states and expansion periods to identify good states. Transaction costs are calculated using the *cGibbs* estimates of Hasbrouck (2009) in Panel A and the $CSspread$ estimates of Corwin and Schultz (2012) in Panel B.



Panel A: *cGibbs* as a measure of transaction costs



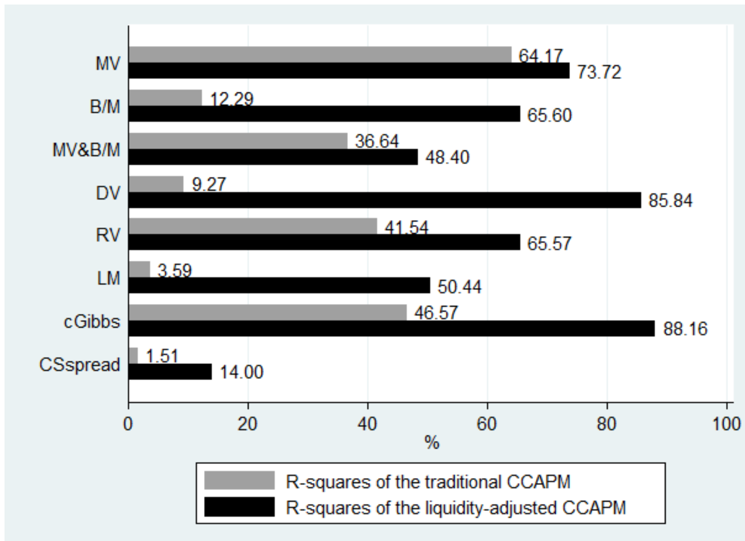
Panel B: $CSspread$ as a measure of transaction costs

Figure 4.5: R-square comparisons with 12-month portfolio holding period

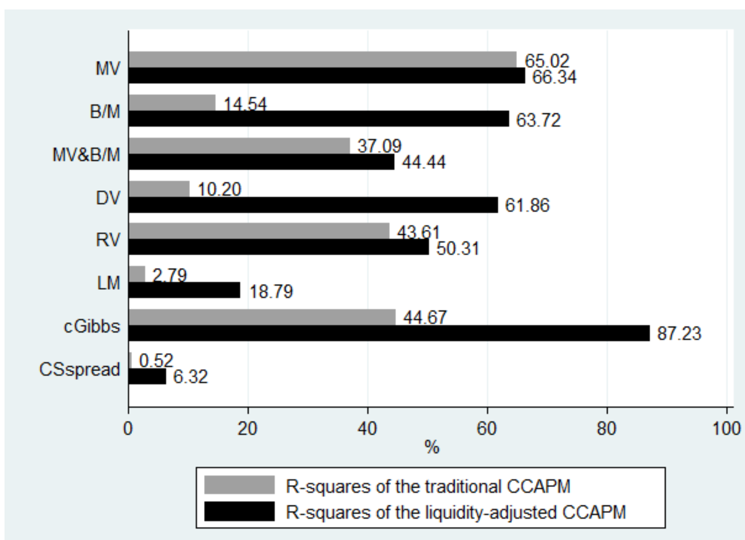
These figures plot the R-squares for the traditional CCAPM and the liquidity-adjusted model. Test portfolios are the 20 MV-sorted, 20 B/M-sorted, 4×5 $MV\&B/M$-sorted, 20 DV-sorted, 20 RV-sorted, 20 LM-sorted, 20 *cGibbs*-sorted, and 20 *CSspread*-sorted portfolios, respectively. Following Jagannathan and Wang (1996) and Lettau and Ludvigson (2001), I employ the Fama-MacBeth (1973) procedure to calculate the cross-sectional R-square, which has the following form:

$$R^2 = \frac{[Var_c(\bar{R}_i^e) - Var_c(\bar{\epsilon}_i)]}{Var_c(\bar{R}_i^e)},$$

where $\bar{R}_i^e$ is the time-series average of returns in excess of the risk-free rate for portfolio i, $\bar{\epsilon}_i$ is the time-series average of residuals for portfolio i, and Var_c is the cross-sectional variance. Transaction costs are calculated using the *cGibbs* estimates of Hasbrouck (2009) in Panel A and the *CSspread* estimates of Corwin and Schultz (2012) in Panel B.



Panel A: *cGibbs* as a measure of transaction costs

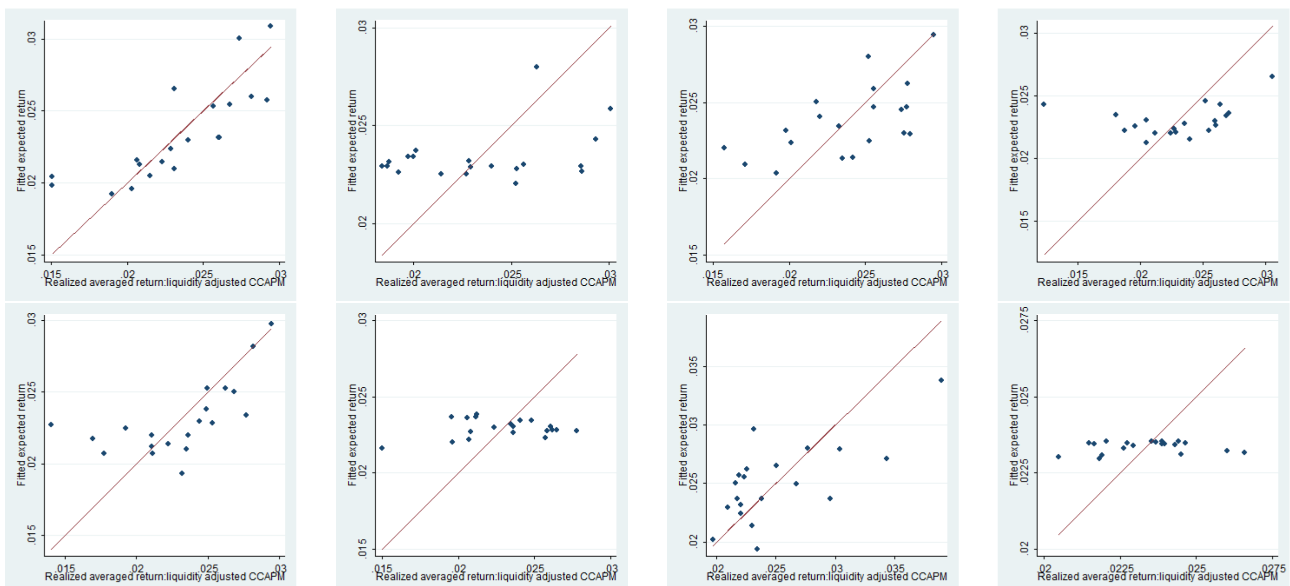


Panel B: *CSspread* as a measure of transaction costs

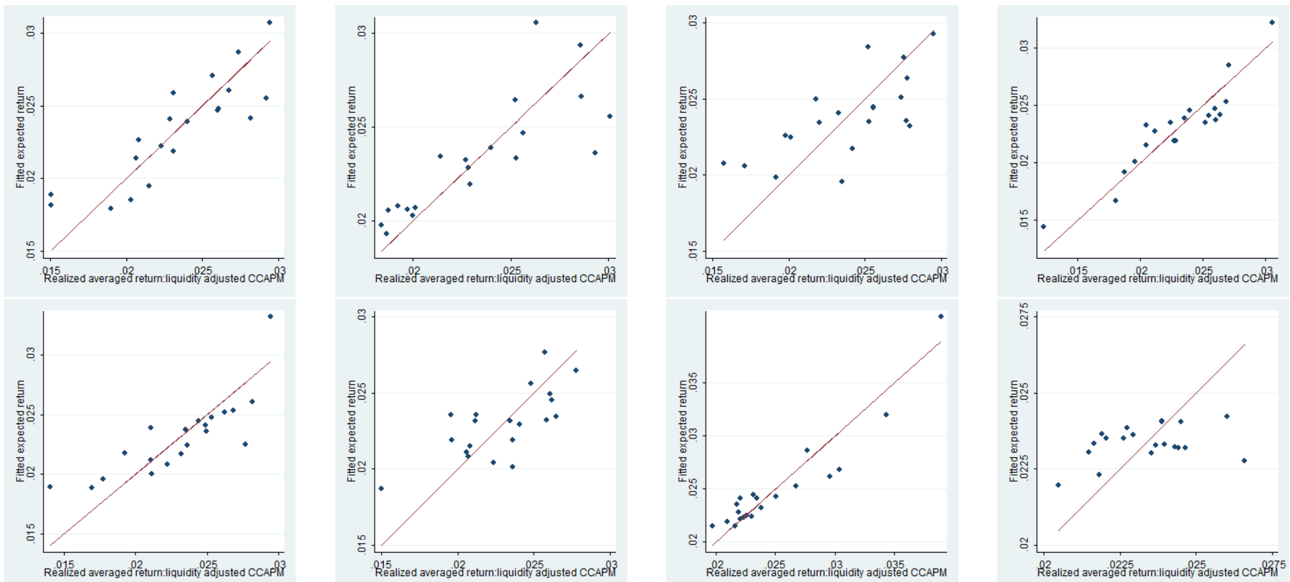
Figure 4.6: Fitted versus realized returns with 12-month portfolio holding period

These figures plot the fitted returns versus realized returns. The horizonal axis shows the realized average excess return and the vertical axis shows the excess return fitted by model. Test portfolios from left to right are the 20 MV-sorted, 20 B/M-sorted, 4×5 $MV\&B/M$-sorted, 20 DV-sorted, 20 RV-sorted, 20 LM-sorted, 20 *cGibbs*-sorted, and 20 *CSspread*-sorted portfolios, respectively. The realized average returns are the time-series average returns in excess of the risk-free rate. The fitted expected returns for the CCAPM are calculated as the fitted value from $E[R_{i,\,t} - R_{f,\,t}] = \gamma_0 + \gamma_1\beta_{i,c}$. The fitted expected returns for the liquidity-adjusted CCAPM are calculated as the fitted value from $E[R_{i,\,t} - R_{f,\,t}] = \gamma_0 + \gamma_1 E[tc_{i,\,t}] + \gamma_2\beta_{i,c} + \gamma_3\beta_{i,tc}$. Transaction costs are calculated using the *cGibbs* estimates of Hasbrouck (2009) in Panel A and the *CSspread* estimates of Corwin and Schultz (2012) in Panel B.

Panel A: *cGibbs* as a measure of transaction costs

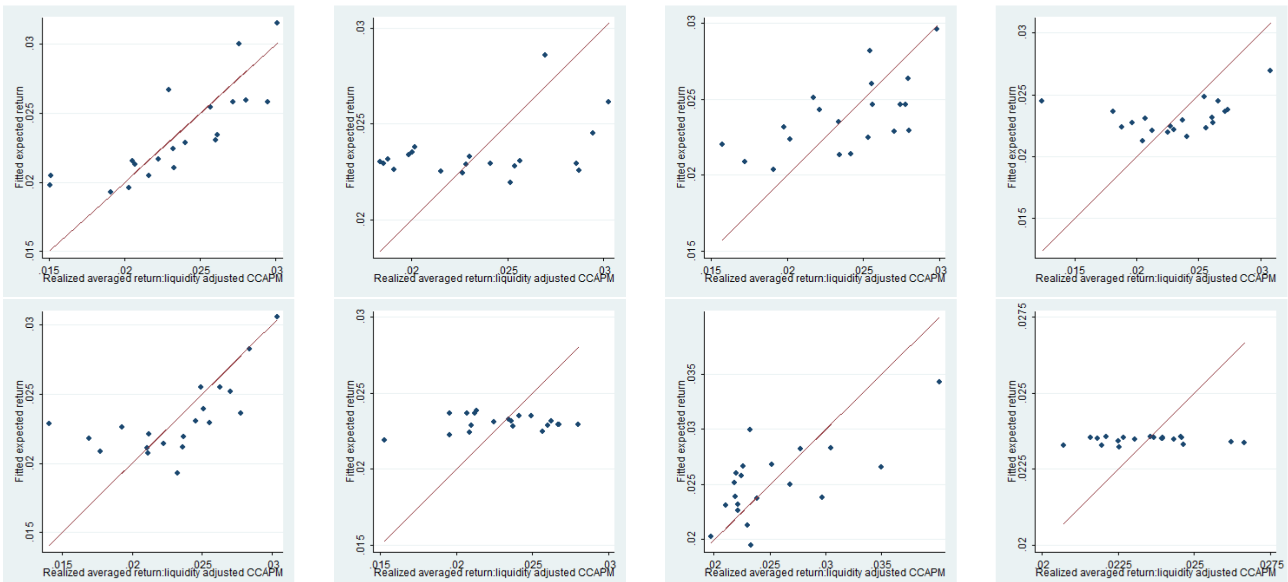


The traditional CCAPM

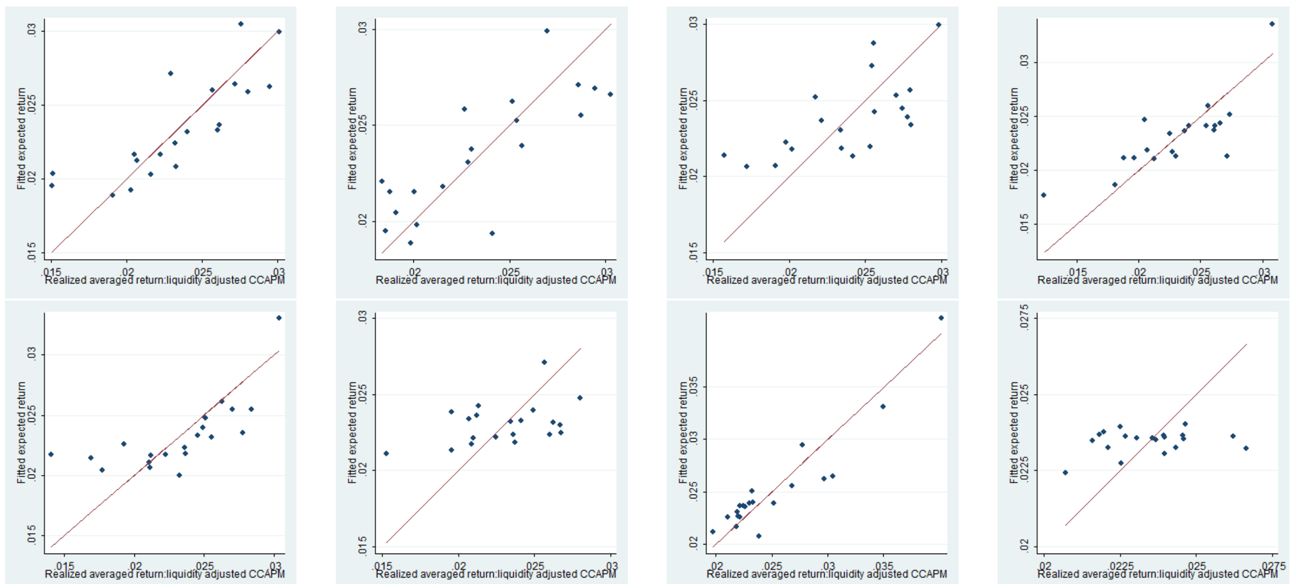


The liquidity-adjusted CCAPM

Panel B: *CSspread* as a measure of transaction costs



The traditional CCAPM



The liquidity-adjusted CCAPM

Chapter 5

The Liquidity Risk Adjusted Epstein-Zin Model

5.1 Introduction

Recent studies in asset pricing suggest that liquidity plays a significant role in investors' consumption and investment decision-making.[1] In this chapter, I extend the Epstein and Zin (1989, 1991) model by incorporating liquidity risk and show that consumption risk, market risk, and liquidity risk jointly determine expected returns. Specifically, using the liquidity risk factors of Pastor and Stambaugh (2003), Liu (2006), and Sadka (2006), I show that the liquidity risk is significantly priced, suggesting that investors do care about the sensitivity of stock returns to market liquidity variations and demand high compensation for stocks with large exposure to liquidity

[1] For instance, Parker and Julliard (2005) suggest that concerns of liquidity are perhaps imperative components neglected by consumption risk alone. Liu (2010) and Chien and Lustig (2010) argue that liquidity risk may originate from consumption and solvency constraints. Næs, Skjeltorp, and Ødegaard (2011) find that stock market liquidity can predict consumption growth. Lynch and Tan (2011) show that transaction costs can generate a first-order effect when they add return predictability, wealth shocks, and state-dependent costs to the traditional consuming and investing problems.

risk. This evidence is consistent with recent literature that highlights the importance of liquidity in asset pricing (e.g., Chordia, Roll, and Subrahmanyam (2000), Amihud (2002), Pastor and Stambaugh (2003), Acharya and Pedersen (2005), Liu (2006), Sadka (2006), and Bekaert, Harvey, and Lundblad (2007)).

Kan, Robotti, and Shanken (2013) argue that examining whether a factor makes an incremental contribution to a multi-factor model's goodness-of-fit is different from testing whether the factor is priced.[2] They argue that, in a multi-factor model, it is important to test the significance of covariance risk (the covariance between return and a risk factor). If the coefficient of the covariance is significantly different from zero, then the factor makes an incremental contribution to the model's overall explanatory power. They show that although the book-to-market factor (Fama and French, 1993) is priced in the conventional test, it is insignificant in terms of covariance risk. Thus, although liquidity risk is priced in the model, it may not add any explanatory power to it.

Given prior studies were largely focusing on examining whether liquidity risk is priced or not, the main objective of this study is to assess the liquidity factor's incremental contribution to the model's performance. Following Lewellen, Nagel, and Shanken (2010) and Kan, Robotti, and Shanken (2013),[3] I perform both the ordinary least squares (OLS) and generalized least squares (GLS) regressions in my analysis. I

[2] Cochrane (2005, Chapter 13) discusses a related issue in the stochastic discount factor (SDF) framework.

[3] Lewellen, Nagel, and Shanken (2010) suggest that it is important to implement the GLS estimates besides OLS. Kan, Robotti, and Shanken (2013) argue that the OLS regression emphasizes more on the returns for a particular set of test portfolios, while the GLS may be potentially more interesting from an investment point of view.

find that the coefficient of the covariance between return and the liquidity risk factor is significant, indicating an improved model. Further, the liquidity-augmented Epstein-Zin model explains up to 70% of the cross-sectional expected returns on the 25 Fama and French (1993) value-weighted size and book-to-market portfolios, a substantial improvement comparing to previous studies.[4]

Acharya and Pedersen (2005) and Sadka (2006) show that incorporating liquidity risk into the traditional CAPM or the Fama-French three-factor model accounts for a large proportion of cross-sectional return variations. It is, however, not clear whether the differences of the R^2 between the models are significant or not. Applying the equality test of cross-sectional R^2 (Kan, Robotti, and Shanken (2013)), the equality of R^2 is rejected under both OLS and GLS estimates, indicating that the liquidity-augmented model is more successful in explaining the cross-sectional expected returns than the traditional consumption-based capital asset pricing model (CCAPM) of Rubinstein (1976), Lucas (1978), Breeden (1979), and the Epstein-Zin (1989, 1991) model.

To further evaluate the model performance, I use Hansen and Jagannathan (1997) distance (HJ distance hereafter) as an alternative measure of a model's goodness-of-fit. I show that, compared to the traditional CCAPM and the Epstein-Zin model, my liquidity-augmented model generates a smaller HJ distance estimate. The null hypothesis that the squared HJ distances are equal is rejected in general based on

[4] Lettau and Ludvigson (2001) show that the traditional CCAPM explains only 16% of the cross-sectional return variations based on quarterly data. Jagannathan and Wang (2007) find that the CCAPM has almost no explanatory power based on monthly data.

the tests of Kan and Robotti (2009).

Lewellen, Nagel, and Shanken (2010) argue that it is important for asset pricing tests to include other sets of portfolios (e.g., industry portfolios) to break down the structure of size and book-to-market portfolios.[5] Recent studies also highlight the importance of the consumption-to-wealth ratio (Lettau and Ludvigson (2001)), long-run consumption risk (Parker and Julliard (2005) and Malloy, Moskowitz, and Vissing-Jørgensen (2009)), and durable goods (Yogo (2006) and Gomes, Kogan, and Yogo (2009)) in consumption-based asset pricing. In my robustness tests, I take these issues into account and find that both the liquidity risk premium and the coefficient of the covariance risk between return and liquidity risk factor are significant. Again, my liquidity-augmented Epstein-Zin model is more successful in explaining expected returns than the CCAPM and the Epstein-Zin model based on the equality tests of cross-sectional R^2 and the HJ distance.

One study relates to mine is Márquez, Nieto, and Rubio (2014) where the authors build a liquidity-adjusted stochastic discount factor. The differences between their model and mine are, however, that they assume a market illiquidity shock to consumption while I focus on liquidity costs following Pastor and Stambaugh (2003), Acharya and Pedersen (2005), Liu (2006), and Sadka (2006). Further, they show that liquidity risk is priced under ultimate consumption risk, while I perform a more comprehensive set of tests by taking into account contemporaneous consumption growth,

[5] Recent studies of Savov (2011) and Kan, Robotti, and Shanken (2013) also incorporate industry portfolios. They use the 25 Fama-French (1993) size and book-to-market portfolios plus industry portfolios as test portfolios.

consumption-to-wealth ratio, long-run consumption growth, and durable consumption growth. Most importantly, my focus is on assessing the liquidity factor's incremental contribution to the model's performance, which itself is new to the literature.

The remainder of the chapter proceeds as follows. Section 5.2 develops the liquidity-augmented Epstein-Zin model. Section 5.3 describes the data. Section 5.4 presents the empirical results. Section 5.5 carries out robustness tests. Section 5.6 conducts alternative tests using quarterly data. Section 5.7 concludes the chapter.

5.2 The model

In this section, I embed stock liquidity, my key element, into the Epstein and Zin (1989, 1991) model to develop the liquidity-adjusted model.

5.2.1 The economy and utility function

The economy in this section is the same as that in section 2.3 of chapter 2. I assume that the representative consumer's utility follows the Epstein and Zin (1989, 1991) recursive function as in chapter two. I later show that the recursive utility allows us to take into account the excess market returns in my liquidity-augmented model, which is in line with Pastor and Stambaugh (2003), Liu (2006), and Sadka (2006).

5.2.2 The liquidity effect

The return of risky asset i after netting out liquidity costs is,

$$
\begin{aligned}
R^n_{i,t+1} &= \frac{D_{i,t+1} + P_{i,t+1} - LC_{i,t+1}}{P_{i,t}} \\
&= R_{i,t+1} - lc_{i,t+1},
\end{aligned}
\tag{5.1}
$$

where $P_{i,t+1}$ is the ex-dividend stock i's price at $t+1$, $D_{i,t+1}$ is the dividend per share, $LC_{i,t+1}$ is the per-share cost of selling stock i,[6] $R_{i,t+1}$ is the return before liquidity costs, $R^n_{i,t+1}$ is the net return, and $lc_{i,t+1}$ is the relative time-varying liquidity costs. In the spirit of Acharya and Pedersen (2005), investors can buy stock i at $P_{i,t+1}$ but have to sell it at $P_{i,t+1} - LC_{i,t+1}$.

Liquidity cost here is a general term, which can stem from transaction costs,[7] thin and infrequent trading, and price impact. For thinly and infrequently traded securities, liquidity traders may have to lower the price to sell and raise the price to buy. For stocks with high price impact, selling (buying) can result in large price decrease (increase). I use liquidity costs to generalize the communal feature of liquidity on price. Following Acharya and Pedersen (2005), I assume that liquidity costs, $lc_{i,t}$, are time-varying, which allows us to examine the liquidity effects on dynamic wealth.

Let the representative consumer's portfolio weight of the risky asset i be $\omega_{i,t}$ ($i = 1, 2, ..., n$), the weight of the risk-free asset is then $1 - \sum_{i=1}^{n} \omega_{i,t}$. Suppose the representative consumer closes her position at $t+1$. According to Eq. (5.1), I can

[6]Following Acharya and Pedersen (2005) model $D_{i,t+1}$ and $LC_{i,t+1}$ are the first-order autoregressive processes.

[7]While transaction costs are not taken into account by the traditional CCAPM, they are the subject currently generating much research interests. See, for example, Amihud and Mendelson (1986), Jacoby, Fowler, and Gottesman (2000), Lo, MacKinlay, and Wang (2004), Acharya and Pedersen (2005), Jang, Koo, Liu, and Loewenstein (2007), and Lynch and Tan (2011).

have the following inequality constraint:

$$W_{t+1} \leq (W_t - C_t)(R_{f,\,t+1} + \sum_{i=1}^{n} \omega_{i,t}(R_{i,\,t+1} - R_{f,\,t+1})). \tag{5.2}$$

where C_t denotes consumption at t, W_t denotes wealth at t, and $R_{f,\,t+1}$ denotes the risk-free rate from t to $t+1$. I assume that trading on the liquid risk-free asset incurs no liquidity costs.

The economic meaning behind Inequality (5.2) is that returns are partially distorted due to liquidity issues, since the representative consumer is exposed to the market in which net returns are obtained after adjusting for liquidity costs. Specifically, the distortion generated by liquidity costs is fairly intuitive. According to Eq. (5.1), as long as the costs are bigger than zero, the net return ($R_{i,\,n}$) will be less than the unadjusted return (R_i). Let L_{t+1} ($0 \leq L_{t+1} \leq 1$) denote the Lagrange multiplier associated with the inequality constraint above.[8] The Lagrange formulation of the dynamic wealth has the form:

$$W_{t+1} = (1 - L_{t+1})(W_t + y_t - C_t)\Big[R_{f,\,t+1} + \sum_{i=1}^{n} \omega_{it}(R_{i,\,t+1} - R_{f,\,t+1})\Big]. \tag{5.3}$$

The effects of liquidity on optimal consumption and investment decisions are consistent with Lynch and Tan (2011) and Márquez, Nieto, and Rubio (2014). For

[8] Using the Lagrange multiplier associated with Inequality (5.2) in a dynamic model is similar to Gomes, Yaron, and Zhang (2006) and Whited and Wu (2006). They study the Lagrange multiplier associated with financial constraints in firms' optimal investment decisions.

example, Eq. (5.3) is similar to Eq. (3) in Lynch and Tan (2011), which also take into account the transaction costs in the dynamic wealth.

If Inequality (5.2) is binding, the effect of liquidity shows up in $1-L_{t+1}$. Chordia, Roll, and Subrahmanyam (2000), Hasbrouck and Seppi (2001), and Acharya and Pedersen (2005) show that individual stock liquidity tends to co-move with market liquidity. As the representative consumer holds a portfolio of the risky asset, $1-L_{t+1}$ captures the aggregate liquidity shocks on the budget constraints over time, i.e., the aggregate distortion due to liquidity costs on the dynamic wealth. In the absence of liquidity costs, L_{t+1} is equal to zero, then liquidity costs have no effect on the budget constraints.

Márquez, Nieto, and Rubio (2014) examine the role of market illiquidity shocks in affecting consumption behavior. In the rest of this sub-section, I examine how the level of market liquidity affects consumption. I assume a simple one-period wealth dynamic without labor income. Let W_0 and C_0 be the representative consumers wealth and consumption at time 0 (the beginning of the period). Also, she is assumed to consume all of her wealth, C_1, at time 1 (the end of the period). Then the Lagrange formulation of the one-period dynamic wealth has the form:

$$C_1 = (1-L_1)(W_0-C_0)\Big[R_{f,1} + \sum_{i=1}^{n} \omega_i (R_{i,1} - R_{f,1})\Big]. \tag{5.4}$$

where $1-L_{t+1}$ can be interpreted as the percentage change in net wealth (W_0-C_0) as a result of the liquidity shock from holding a portfolio of risky assets. According to Eq. (5.4), the consumption at time 1 is negatively affected when the market is less liquid (higher L_1), consistent with Næs, Skjeltorp, and Ødegaard (2011). That is, the same stock payoff at time 1 will have a higher value today in terms of consumption at time 1 when the market liquidity is low.

5.2.3 The liquidity-augmented Epstein-Zin model

The representative consumer maximizes her life-time utility function as follows:

$$\max_{C_s, \omega_{i,s}, \forall s, i} E_t \left[\sum_{s=t}^{T-1} U(C_s) + B(W_T) \right], \tag{5.5}$$

where $U(C_s)$ is the utility from consumption at time s, $B(W_T)$ is the ending bequest function that is monotonically increasing and strictly concave, and $E_t[\ ]$ is the expectation function conditional on information at time t.

Eq. (5.5) indicates that the representative consumer makes decisions with variables C_s and $\omega_{i,s}$ $(i = 1, 2, ..., n)$ so as to maximize the expected value of the lifetime utility. The optimization problem of Eq. (5.5) is subject to the constraint condition of Eq. (5.3). Based on Eq. (5.3), I can use stochastic dynamic programming to obtain the following first-order condition (FOC) of the optimal choice problem in Eq. (5.5):

$$E_t \left[\frac{U_C(C^*_{t+1}, t+1)}{U_C(C^*_t, t)} (1 - L_{t+1})(R_{i,t+1} - R_{f,t+1}) \right] = 0. \tag{5.6}$$

where U_C denotes the partial differentiation with respect to the consumption, C.

According to Epstein and Zin (1989, 1991), I can have:

$$\frac{U_C(C^*_{t+1}, t+1)}{U_C(C^*_t, t)} = \beta^{\frac{1-\theta}{1-\rho}} (\frac{C_{t+1}}{C_t})^{-\rho\frac{1-\theta}{1-\rho}} R_{W,t+1}^{\frac{\rho-\theta}{1-\rho}}. \tag{5.7}$$

where $R_{W,t+1}$ is the return to wealth from date t to date $t+1$. Without the liquidity effect, the asset pricing implication of Epstein-Zin model is a two factor model that mixes the traditional CAPM (Sharpe (1964) and Lintner (1965)) with the traditional CCAPM (Rubinstein (1976), Lucas (1978), and Breeden (1979)).

According to Eqs. (5.6) and (5.7), the Euler equation of my liquidity-augmented model in the specific form is

$$E_t\left[\beta^{\frac{1-\theta}{1-\rho}} (\frac{C_{t+1}}{C_t})^{-\rho\frac{1-\theta}{1-\rho}} R_{W,t+1}^{\frac{\rho-\theta}{1-\rho}} (1-L_{t+1})(R_{i,t+1}-R_{f,t+1})\right] = 0. \tag{5.8}$$

According to Cochrane (2005),[9] the beta representation of Eq. (5.8) has the form:

$$E[R_i - R_f] = \gamma_{cg}\beta_{i,cg} + \gamma_{mkt}\beta_{i,R_W} + \gamma_{liq}\beta_{i,liq}, \tag{5.9}$$

where $\beta_{i,cg}$ denotes the consumption beta, β_{i,R_W} denotes the return to wealth beta, and $\beta_{i,liq}$ denotes the liquidity beta; γ_{cg}, γ_{mkt}, and γ_{liq} are the prices of consumption risk, market risk, and liquidity risk.[10] Eq. (5.9) forms the liquidity-augmented Epstein-Zin model.

This model is in line with recent studies which support the important role of liq-

[9] See Cochrane (2005), Chapter 9.

[10] For detailed derivation of Eq. (5.9), see Appendix D.

uidity risk in asset pricing. Based on the framework of Merton's (1973) intertemporal CAPM (ICAPM), many studies find that liquidity is a priced state variable (e.g., Pastor and Stambaugh (2003), Liu (2006), and Sadka (2006)). Further, they show that augmenting the traditional CAPM or the Fama-French three-factor model with a liquidity factor improves the performance of these models.

The economic meaning on incorporating the liquidity risk into the consumption-based asset pricing model is straight-forward. When the economy is uncertain, impacting consumption and squeezing liquidity, individual investors may unwillingly switch from their stocks to cash to smooth out consumption; institutional investors may reluctantly exchange their holdings for cash to fulfill their obligations. Under these circumstances, stocks whose returns are less sensitive to market liquidity comfort investors from states of low consumption. On the contrary, stocks with high liquidity risk impair investors' abilities to cushion the deterioration in consumption. As a result, investors require high compensation for holding high liquidity-risk stocks.

5.3 Data

There is a large literature proposing various liquidity measures together with several measures of liquidity risk factors. To empirically test the liquidity-augmented Epstein-Zin model, I use three alternative proxies for the liquidity risk factor. The first is the aggregate liquidity innovation of Pastor and Stambaugh (2003), where liquidity is measured as the price reversal caused by the temporary price impact of trading volume.[11] The second is Liu's (2006) mimicking liquidity factor constructed based on the trading discontinuity measure of liquidity, the standardized turnover-adjusted number of zero daily trading volumes. The third is Sadka's (2006) aggregate liquidity innovation constructed based on the variable component of price impact.[12]

I measure the aggregate consumption growth as the percentage change from preceding period (one month) of per capita real personal consumption expenditures on nondurable goods and services. I obtain consumption expenditures, population numbers, and price deflator series from the National Income and Product Accounts (NIPA).[13] I use the "end of period" time convention to match the aggregate consumption growth to stock returns.[14] In addition, for robustness tests I also use the consumption-to-wealth ratio (*cay*) of Lettau and Ludvigson (2001), consumption growth of nondurable goods over a long horizon of 36 months ($cg36$) of Parker and Julliard (2005), and durable consumption growth (*cgd*) of Yogo (2006).[15]

My main test portfolios are the 25 Fama-French value-weighted size and book-to-market portfolios. I also add the 5 value-weighted industry portfolios onto the 25 main test portfolios in the robustness tests, following Lewellen, Nagel, and Shanken

[11] I thank Professor Lubos Pastor for providing his liquidity factor data on his website: http://faculty.chicagobooth.edu/lubos.pastor/research/.

[12] I thank Professor Ronnie Sadka for providing his liquidity factor data on his website: https://www2.bc.edu/ sadka/.

[13] http://www.bea.gov/iTable/.

[14] Under the "end of period" time convention, I assume that the consumption data measures consumption at the end of the month. An alternative convention is the "beginning of period" as in Campbell (2003).

[15] I obtain the consumption-to-wealth ratio from Sydney Ludvigson's website. I thank Prof. Sydney Ludvigson for providing the *cay* data on her website: http://www.econ.nyu.edu/user/ludvigsons/. Since *cay* data are quarterly, I linearly interpolate the quarterly values to the monthly values following Vissing-Jørgensen and Attanasio (2003). I calculate the consumption growth over 36 months by $cg36_t = \frac{C_{t+36}}{C_{t-1}} - 1$, where *cg* denotes the consumption growth of nondurable goods. The consumption data of nondurable and durable goods are from NIPA.

(2010). To empirically test the liquidity-augmented model, I use the excess return of the value-weighted NYSE/AMEX/NASDAQ index to proxy for the return to wealth factor (R_W), following Epstein and Zin (1991) and Yogo (2006). I use the one-month treasury bill rate as the risk-free rate. I download the monthly portfolio returns, excess market returns, and treasury bill rate from Kenneth French's website.[16]

My sample period is from 1962 to 2009 for the Pastor and Stambaugh (2003) liquidity factor,[17] from 1959 to 2009 for the Liu (2006) liquidity factor,[18] and from 1983 to 2009 for the Sadka (2006) liquidity factor.[19]

Table 5.1 provides descriptive statistics for the main variables. Consumption growth (cg) is positively correlated with the market factor (mkt). However, cg is virtually uncorrelated with all three liquidity risk factors. In addition, the correlation between the liquidity risk factors are low, indicating that they capture different information and thus are useful for testing the robustness of the liquidity-augmented Epstein-Zin model.

[16] I thank Prof. Kenneth French for providing the 25 Fama-French value-weighted size and book-to-market classified portfolio returns, excess market returns, and one-month treasure bill rate data on his website: http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/.

[17] The innovations in aggregate liquidity (Eq. (8) in Pastor and Stambaugh (2003)) begin from 1962. The sample ends in 2009.

[18] The monthly consumption data begin from 1959.

[19] The Sadka (2006) liquidity factor data based on the variable component of price impact begin from 1983.

5.4 Cross-sectional regressions

5.4.1 Risk premium

In this sub-section I test whether liquidity risk is priced in the cross-sectional regressions. I run the Fama-MacBeth (1973) cross-sectional regressions on the following equation:

$$R_{i,t} = \gamma_0 + \gamma_{cg}\beta_{i,cg} + \gamma_{mkt}\beta_{i,mkt} + \gamma_{liq}\beta_{i,liq} + e_{i,t}, \tag{5.10}$$

where $\beta_{i,cg}$ denotes the consumption beta, $\beta_{i,mkt}$ denotes the market beta, and $\beta_{i,liq}$ denotes the liquidity beta. The consumption, market, and liquidity betas are estimated from a single multiple time-series regression for each testing portfolio using the entire sample.[20] I use the 25 Fama-French value-weighted size and book-to-market portfolios as test portfolios.

Table 5.2 reports the estimated risk premium (γ) under both the ordinary least squares (OLS) and generalized least squares (GLS) regressions, recommended by Lewellen, Nagel, and Shanken (2010) and Kan, Robotti, and Shanken (2013). I use the alternative t-ratios to test the significance of γ: the FM t-ratio of Fama and MacBeth (1973), the SH t-ratio of Shanken (1992) with errors-in-variables adjustment, the JW t-ratio of Jagannathan and Wang (1996), and the KRS t-ratio of Kan, Robotti, and Shanken (2013) under potentially misspecified models.[21]

[20] I estimate the consumption, market, and liquidity betas using the entire sample as in Lettau and Ludvigson (2001), Acharya and Pedersen (2005), and Sadka (2006), throughout the paper.

[21] Kan and Robotti (2008, 2009) and Balduzzi and Robotti (2010) also highlight the potential model misspecification problem in the statistical inference of the estimated risk premium.

For the OLS estimates, I find that the liquidity risk (β_{liq}) is positively priced in the cross-sectional analysis, consistent with the model's prediction. The γ estimate is significantly different from zero with all t-ratios at the 5% level, except for the Sadka (2006) liquidity factor.[22] For the GLS estimates, the coefficient on $\beta_{liq,i}$ is significantly positive, regardless of the liquidity factors and t-ratios used. It suggests that investors do care about the liquidity risk and require a high compensation for bearing it. In contrast, for both OLS and GLS estimates, the coefficient on consumption risk (β_{cg}) is generally insignificant at the conventional level, though consumption risk is positively priced. This is consistent with previous studies (e.g., Lettau and Ludvigson (2001) and Lustig and Nieuwerburgh (2005)) that the CCAPM does a poor job in explaining cross-sectional stock returns. Also, consistent with early studies such as Fama and French (1992), market beta has difficulties in depicting returns. It is even negatively related to returns when the Pastor-Stambaugh factor loading or the Sadka factor loading is involved in the cross-section regressions.

5.4.2 Price of covariance risk

Kan, Robotti, and Shanken (2013) argue that the price of covariance risk is related to the rise of explanatory power to the cross-sectional return variations in a multi-factor model. It is, therefore, important to test whether the coefficient of covariance risk relating to a particular factor is significantly different from zero. Following their study, I run the following cross-sectional regression:

[22] The coefficient on the liquidity beta estimated with the Sadka (2006) liquidity factor is significant at the 10% level according to the FM t-ratio.

$$R_{i,t} = \lambda_0 + \lambda_{cg} Cov(R_i, cg) + \lambda_{mkt} Cov(R_i, mkt) + \lambda_{liq} Cov(R_i, liq) + e_{i,t}, \qquad (5.11)$$

where $Cov(R_i, cg)$ denotes the covariance of returns and consumption growth, $Cov(R_i, mkt)$ denotes the covariance of returns and excess value-weighted market returns, and $Cov(R_i, liq)$ denotes the covariance of returns and the liquidity factor. These covariances are estimated for each testing portfolio using the entire sample.

Table 5.3 reports the parameter (λ) estimates of the OLS and GLS regressions of portfolio returns on the three covariances. The results are similar to the ones presented in Table 5.2. For the OLS estimates, the coefficient of the covariance between return and market liquidity is significantly positive at the 5% level for all t-ratios except for the Sadka (2006) liquidity factor.[23] Under the GLS estimates, λ_{liq} is significantly positive, regardless of the liquidity factors and t-ratios used. Overall, Table 5.3 shows that, according to Kan, Robotti, and Shanken (2013), the liquidity adjustment adds significant explanatory power to the model.

5.4.3 Model performance

In this sub-section, I compare the model performance between the liquidity-augmented model and other consumption pricing models. Table 5.4 reports the sample cross-sectional R^2, calculated as in Kandel and Stambaugh (1995). Specifically, for the

[23] The coefficient on the covariance of portfolio returns with the Sadka (2006) liquidity factor is significant at the 10% level according to the FM t-ratio.

25 Fama-French value-weighted size and book-to-market portfolios, the fraction of cross-sectional return variations explained by my liquidity-augmented model is 60.5%, 67.8%, and 69.8% (26.6%, 23.9%, and 46.8%) under the OLS (GLS) regressions, using the Pastor and Stambaugh (2003), Liu (2006), and Sadka (2006) liquidity factors, respectively. In contrast, the traditional CCAPM and the Epstein-Zin model explain a much smaller proportion of return variations. For example, the corresponding figures relative to the original Epstein-Zin model are 33.6%, 41.0%, and 57.3% (11.1%, 13.7%, and 23.7%) under the OLS (GLS) regressions.

Kan, Robotti, and Shanken (2013) argue that it is important to test whether the seemingly better performance of one model over another is statistically significant. I thus test whether the differences of the cross-sectional R^2 between my model and the traditional CCAPM or the Epstein-Zin model are statistically significant. Following Kan, Robotti, and Shanken (2013), I estimate the p value under the null hypothesis that the cross-sectional R^2 of two competing models are equal.

Table 5.4 shows that, under the OLS (GLS) estimates, my model offers 55.3% (23.9%) to 67.7% (46.1%) additional explanatory power compared to the traditional CCAPM. Further, the null hypothesis that the equality of cross-sectional R^2 is rejected at the 5% level, regardless of the estimation methods and liquidity factors used. Similarly, the liquidity-augmented model also significantly explains a larger fraction of return variations than the Epstein-Zin model, expect for the Sadka (2006) liquidity factor under the OLS estimates.

While the cross-sectional R^2 is aimed at explaining expected returns, the HJ distance of Hansen and Jagannathan (1997) is oriented towards measuring a model's power in explaining asset prices (Kan, Robotti, and Shanken (2013)). Smaller HJ distance indicates smaller pricing errors. Following Kan and Robotti (2009), I conduct tests of equality of squared HJ distances. Table 5.4 presents the results of the tests of equality of squared HJ distances between alternative models. Similar to the cross-sectional R^2 tests, the liquidity-augmented model produces smaller HJ distance than the CCAPM and the Epstein-Zin model. The null hypothesis that the squared HJ distances of two competing models are equal is rejected at the 5% level under both Liu (2006) and Sadka (2006) liquidity factor. Following Kan and Robotti (2009), the tests of equality of squared HJ distances are based on the Proposition 2 for nested models and Proposition 6 for nonnested models. They show that the asymptotic distribution of the sample squared HJ distances is related to the asymptotic variance of estimated coefficients on factor risk loadings. The variance of the estimated coefficients on factor risk loadings is adjusted by potential model misspecification. In this chapter, I focus on the comparisons of nested models. For example, the liquidity-augmented model nests the original Epstein-Zin model. The extra factor is the liquidity risk factor. Therefore, the asymptotic distribution for the test of equality of squared HJ distances is associated with the asymptotic variance of estimated coefficients on liquidity risk. The variance of the estimated coefficients on liquidity risk is adjusted by potential model misspecification.

5.4.4 Fitted versus realized returns

Figure 5.1 plots the realized average portfolio returns and the fitted portfolio returns. With the traditional CCAPM, the fitted expected returns are calculated as $E[R_{i,t}] = \gamma_0 + \gamma_{cg}\beta_{cg}$. The Epstein-Zin model based expected returns are calculated as $E[R_{i,t}] = \gamma_0 + \gamma_{cg}\beta_{cg} + \gamma_{mkt}\beta_{mkt}$. The fitted expected returns under the liquidity-augmented Epstein-Zin model are calculated as $E[R_{i,t}] = \gamma_0 + \gamma_{cg}\beta_{cg} + \gamma_{mkt}\beta_{mkt} + \gamma_{liq}\beta_{liq}$.

Each two-digit number in Figure 5.1 indicates one portfolio. The first digit denotes the size quintile (1 representing the smallest and 5 the largest), and the second denotes the book-to-market quintile (1 representing the lowest and 5 the highest). The vertical distance of these points to the 45 degree line represents the pricing errors. Figure 1 shows that, overall, the pricing errors associated with the liquidity-augmented Epstein-Zin model are smaller than those associated with either the traditional CCAPM or the original Epstein-Zin model. Specifically, the CCAPM or the Epstein-Zin model has difficulties in explaining the expected returns of book-to-market portfolios for a given size quintile. For instance, the small growth portfolio (portfolio 11) and the small value portfolio (portfolio 15) are poorly priced. In contrast, there is substantial improvement in nearly all the size and book-to-market portfolios for the liquidity-augmented model. It especially shortens the vertical distance of small value portfolios to the 45-degree line.

5.5 Robustness tests

In this section, I first test the robustness of my results by examining the estimated risk premium and the price of covariance risk under various adjustments and by adding industry portfolios to the main test portfolios. I then test the robustness of the model performance under these new settings.

5.5.1 Robustness on risk premium and price of covariance risk

Lettau and Ludvigson (2001) show that the traditional CCAPM conditional on the consumption-to-wealth ratio (*cay*) explains the expected return variations as well as the Fama-French (1993) three-factor model does. I embed *cay* into the liquidity-augmented Epstein-Zin model to test the robustness of my results.[24] Panel A of Table 5.5 shows that, after controlling for *cay*, the estimated risk premium and the price of covariance risk for the liquidity factors are significantly positive at the 5% level, except for the Sadka (2006) liquidity factor under the OLS estimates.[25]

Bansal and Yaron (2004), Parker and Julliard (2005), Da (2009), Malloy, Moskowitz, and Vissing-Jørgensen (2009), and Favilukis and Lin (2013) highlight the importance of long-run consumption risk in explaining the cross-sectional variations of expected returns. Following Parker and Julliard (2005), I measure consumption risk by using the consumption growth of nondurable goods over 36 months ($cg36$) to test the

[24]Embedding *cay* into the liquidity-augmented model yields a 4-factor model.

[25]The coefficient on the liquidity beta based on the Sadka (2006) liquidity factor is significant at the 10% level according to the FM t-ratio under the OLS estimates. The coefficient on the covariance between portfolio return and the Sadka (2006) liquidity factor is significant at the 5% (10%) level according to the FM (SH) t-ratio under the OLS estimates.

liquidity-augmented model. Panel B shows that, in general, liquidity risk is significantly priced and the covariance risk of liquidity contributes significantly to the model's explanatory power.

Recent studies point out that when utility is nonseparable in nondurable and durable consumption, the durable goods plays an important role in determining expected returns (Yogo (2006) and Gomes, Kogan, and Yogo (2009)). Following Yogo (2006), I incorporate the durable consumption growth (*cgd*) into my model.[26] Panel C shows that, for the Pastor and Stambaugh (2003) liquidity factor, the coefficients of the liquidity risk (γ_{liq}) and the covariance risk related to liquidity (λ_{liq}) are statistically significant with the FM t-ratio (FM, SH, and JW t-ratios) under the OLS (GLS) estimates. For the Liu (2006) factor, γ_{liq} significantly differs from zero at the 1% level. For the Sadka (2006) factor, γ_{liq} and λ_{liq} are significantly different from zero at the 5% level, except for the KRS t-ratio under the OLS estimates.

Lewellen, Nagel, and Shanken (2010) argue that the tight factor structure of size and book-to-market portfolios tends to be less powerful in rejecting misspecified asset pricing models and results in high R^2 in cross-sectional tests. They advocate that asset pricing tests should incorporate other sets of portfolios (e.g., industry portfolios) to disintegrate the structure of size and book-to-market portfolios. To address this concern, I expand the 25 Fama-French value-weighted size and book-to-market portfolios with five value-weighted industry portfolios of Gomes, Kogan, and Yogo (2009). Panel D reports the results for the 30 test portfolios. Results are similar

[26] Incorporating *cgd* into the liquidity-augmented model yields a 4-factor model.

to previous ones, i.e., the estimated liquidity risk premium and the price of covariance risk relating to liquidity are, in general, significant under the 30 test portfolios.

5.5.2 Robustness on cross-sectional R^2 and HJ distance

Based on the above adjustments, I conduct further robustness tests on the model's goodness-of-fit. Specifically, following Lettau and Ludvigson (2001) and Yogo (2006), I incorporate *cay* and *cgd* into the CCAPM, the Epstein-Zin model, and the liquidity-augmented Epstein-Zin model to take into account consumption-to-wealth ratio and durable goods.[27] I follow Parker and Julliard (2005) and measure consumption growth over a horizon of 36 months ($cg36$) to test the above models. I use the 25 Fama-French size and book-to-market portfolios plus five industry portfolios of Gomes, Kogan, and Yogo (2009) as the alternative test portfolios to examine the performance of these models.

Panels A and B of Table 5.6 report the results on the differences of cross-sectional R^2 and HJ distance between the liquidity-augmented Epstein-Zin model and the traditional CCAPM and the Epstein-Zin model. It shows that the liquidity-augmented model, in general, significantly outperforms the CCAPM and the Epstein-Zin model after adjusting for consumption-to-wealth ratio, long-run consumption risk, durable consumption growth, and industry portfolios.

[27] Incorporating *cay* (*cgd*) into the CCAPM and the Epstein-Zin model yields a 2-factor model and a 3-factor model.

5.6 Alternative tests with quarterly data

While I use monthly data in the above tests, I conduct alternative tests using quarterly data in the following sub-sections. Many studies use quarterly data in their empirical tests, e.g., Lettau and Ludvigson (2001), Parker and Julliard (2005), and Yogo (2006). In addition, I also construct the aggregate liquidity factors based on a variety of liquidity measures.

5.6.1 The liquidity measure and mimicking liquidity factor with quarterly data

Liu (2006) highlights four dimensions of liquidity: trading quantity, trading speed, trading costs, and impact of trading on price. I use the following liquidity proxies with each capturing a different dimension:

(i) The dollar volume measure of Brennan, Chordia, and Subrahmanyam (1998), DV, which is defined as the average daily dollar volume over the prior 12 months.

(ii) The proportion of daily zero returns of Lesmond, Ogden, and Trzcinka (1999), $P0R$, which is defined as the proportion of daily zero returns over the prior 12 months. This measure is related to both the quoted bid-ask spread and Roll (1984)'s measure of the effective spread (Lesmond, Ogden, and Trzcinka (1999)). Bekaert, Harvey, and Lundblad (2007) adopt the proportion of zero returns as a liquidity measure.

(iii) The price impact measure of Amihud (2002), RV, which is defined as the daily absolute-return-to-dollar-volume ratio averaged over the prior 12 months. Goyenko, Holden, and Trzcinka (2009) show that these this liquidity proxy relates closely to price impact measures estimated from high frequency TAQ and Rule 605 data.

(iv) The trading discontinuity measure of Liu (2006), LM, which is defined as the standardized turnover-adjusted number of zero daily trading volumes over the prior 12 months. The LM proxy measures the probability of no trading. Large LM (i.e., high infrequent trading) indicates slow trading speed (or low liquidity).[28]

One ideal candidate for a liquidity risk factor may be innovations in market liquidity as in Pastor and Stambaugh (2003). However, Liu (2010) argues that there are empirical issues of constructing a volume-based liquidity measure since some stocks appear to be thinly traded. Further, Kan, Robotti, and Shanken (2013) show that, for traded-factors (e.g., the size and book-to-market factors in the Fama-French three-factor model), the impact of model misspecification on the variance of risk premia can potentially be small. Hence, to measure the market liquidity (liq) in Eq. (5.9), I construct four mimicking liquidity factors liq^{DV}, liq^{P0R}, liq^{RV}, and liq^{LM}, based on the above liquidity proxies, following Fama and French (1993) and Liu (2006).

[28]Similar to Amihud (2002), the calculation of RV requires that there are at least 80% non-missing daily trading volumes available in the prior 12 months. Note also that the calculation of RV excludes zero trading volumes over the prior 12 months. Constructions of DV, $P0R$, and LM require no missing daily trading volumes in the prior 12 months.

I form two portfolios, low liquidity (LL) and high liquidity (HL), at the end of June in each year for each liquidity measure (DV, $P0R$, RV, and LM) and hold them for the subsequent 12 months. LL contains the lowest liquidity stocks based on a 30% NYSE breakpoint. HL contains the highest liquidity stocks based on a 30% NYSE breakpoint. The two portfolios are equally weighted and held for one year. The monthly values of mimicking liquidity factor are the monthly profits of longing \$1 of LL and shorting \$1 of HL. I decompose the buy-and-hold portfolio return over the 12-month holding period into monthly returns based on Liu and Strong (2008).

5.6.2 Returns and consumption with quarterly data

I examine the 25 Fama-French equally-weighted size and book-to-market classified portfolios. To test the liquidity-augmented model (Eq. 5.9), I need an empirical proxy for the return to wealth (R_W). Following Epstein and Zin (1991) and Yogo (2006), I use the market factor (mkt) as in the Fama-French three-factor model to proxy R_W. I use the one-month Treasury bill rate as the risk-free rate. I download the monthly portfolio returns, market factor, and Treasury bill rate from Kenneth French's website.[29]

For aggregate consumption growth, I use the percentage change from preceding period of real (chain-weighted) personal consumption expenditures on nondurable goods and services obtained from Sydney Ludvigson's website.[30] In matching the

[29] I thank Prof. Kenneth French for providing the 25 Fama-French equally-weighted size and book-to-market classified portfolios returns, market factor and one-month treasure bill rate data on his website: http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/

[30] I thank Prof. Sydney Ludvigson for providing the consumption and consumption-to-wealth ratio (cay) data on her website: http://www.econ.nyu.edu/user/ludvigsons/.

consumption growth to return data, I use the "beginning of period" convention, following Campbell (2003) and Yogo (2006).[31] Since consumption data is with quarterly frequency, I first compound monthly portfolio returns, the market factor, and the mimicking liquidity factors to quarterly values. Then I use the price deflator series from National Income and Product Account (NIPA) published by the Bureau of Economic Analysis to convert quarterly values to real terms.

Following a growing literature of the consumption-based asset pricing models, I also use other macroeconomic variables such as the consumption-to-wealth ratio (*cay*) of Lettau and Ludvigson (2001), consumption growth of nondurable goods over a horizon of 11 quarters ($cg11$) of Parker and Julliard (2005), and durable consumption growth (*cgd*) of Yogo (2006).[32] These variables are found to be important in determining the cross-sectional return variations.

My sample period is from 1952 to 2009, which covers both NYSE and AMEX ordinary common stocks.[33] I exclude NASDAQ stocks since its trading volume data only become available from 1983 and are inflated compared with NYSE/AMEX stocks.[34]

Table 5.7 provides descriptive statistics for the main variables. The mean of the

[31]Under the "beginning of period" timing convention, I assume that the consumption data measures consumption at the beginning of the quarter.

[32]I obtain the consumption-to-wealth ratio from Sydney Ludvigson's website. I thank Prof. Sydney Ludvigson for providing the *cay* data on her website: http://www.econ.nyu.edu/user/ludvigsons/. I calculate the consumption growth over 11 quarters by $cg11_{t-1} = \frac{C_{t+11}}{C_{t-1}} - 1$, where C denotes the nondurable goods consumption. Following Gomes, Kogan, and Yogo (2009), durable consumption is the properly chain-weighted sum of real personal consumption expenditures on durable goods and real private residential fixed investment. I download the consumption of nondurable and durable goods from National Income and Product Account (NIPA).

[33]The consumption data on Prof. Sydney Ludvigson's Website begins from 1952. The sample ends in 2009 due to the use of the long run consumption growth. I identify ordinary common stocks as those with CRSP share code 10 and 11.

[34]For example, Brennan, Chordia, and Subrahmanyam (1998), Pastor and Stambaugh (2003), and Acharya and Pedersen (2005).

mimicking liquidity factor constructed by LM is 1.126% per quarter, higher than that of the mimicking liquidity factor constructed by DV, $P0R$, and RV. That is, the trading speed discontinuity premium is more pronounced compared with the dollar volume premium, the transaction costs premium, and the price impact premium. The correlation between the market factor and the mimicking liquidity factor or its one-period lag is generally negative.[35] It indicates that high liquidity premium is associated with poor market performance, consistent with Pastor and Stambaugh (2003), Acharya and Pedersen (2005), and Liu (2006). To further explore the relation between liquidity premia and economic conditions, Figure 5.2 shows time-series plots of liquidity premium related to the four liquidity measures. The shaded regions are recessions defined by the National Bureau of Economic Research (NBER). As the figure shows, liquidity premium generally rises during recessions and falls during booms, consistent with the above numerical correlation.

5.6.3 Risk premium and price of covariance risk with quarterly data

In this subsection, I ask two questions: (1) Is liquidity risk priced in the cross-sectional regressions? (2) Is the liquidity factor helpful in accounting for the cross-sectional return variations? To answer the first question, I run the Fama-MacBeth (1973) cross-sectional regressions on the following equation:

[35] Liu (2006) find that the time-series pattern of the market factor and the shock of the aggregate liquidity is to move either simultaneously or with a time lag.

$$R_{i,t} - R_{f,t} = \gamma_0 + \gamma_{cg}\beta_{cg} + \gamma_{mkt}\beta_{mkt} + \gamma_{liq}\beta_{liq} + \varepsilon_{i,t}, \tag{5.12}$$

where β_{cg} denotes the consumption beta, β_{mkt} denotes the market beta, and β_{liq} denotes the liquidity beta. The consumption betas, market betas, and liquidity betas are estimated from a single multiple time-series regression for each portfolio using the entire sample as in Lettau and Ludvigson (2001). I use the 25 Fama-French equally-weighted size and book-to-market classified portfolios as test portfolios.

Kan, Robotti, and Shanken (2013) argue that the price of covariance risk is related to the gain of explanatory power to the cross-sectional return variations in a multi-beta model. Hence, it is necessary to test whether the coefficient of covariance risk related to a particular factor (simple regression beta) significantly differs from zero. Following their study, I run the Fama-MacBeth cross-sectional regressions on the following equation:

$$R_{i,t} - R_{f,t} = \lambda_0 + \lambda_{cg}Cov(R_i, cg) + \lambda_{mkt}Cov(R_i, mkt) + \lambda_{liq}Cov(R_i, liq) + \varepsilon_{i,t}, \tag{5.13}$$

where $Cov(R_i, cg)$ denotes the covariance of portfolio returns and consumption growth, $Cov(R_i, mkt)$ denotes the covariance of portfolio returns and excess value-weighted market returns, and $Cov(R_i, liq)$ denotes the covariance of portfolio returns and the mimicking liquidity factor.

Table 5.8 presents the estimated risk premium and price of covariance risk in percentage form. I use both the ordinary least squares (OLS) and generalized least squares (GLS) regressions, consistent with the suggestions of Lewellen, Nagel, and Shanken (2010) and Kan, Robotti, and Shanken (2013). I report the following t-ratios: the FM t-ratio of Fama and MacBeth (1973), the SH t-ratio of Shanken (1992) with errors-in-variables adjustment, the JW t-ratio of Jagannathan and Wang (1996), and the KRS t-ratio of Kan, Robotti, and Shanken (2013) t-ratio under potentially misspecified models. For various liquidity measures, I find that, under both the OLS and GLS estimates, liquidity risk (β_{liq}) is positively priced in the cross-sectional analysis, consistent with my model expectation. The coefficient on the liquidity beta is also significantly different from zero with the FM , SH, JW, and KRS t-ratios at the 1% level. It indicates that investors care about liquidity risk and require a compensation for bearing it. Consumption risk (β_{cg}) is positively priced while it is statistically insignificant. Market risk (β_{mkt}) is generally negatively priced and insignificant at the conventional level with the KRS t-ratio.[36] In terms of the price of covariance risk, under both the OLS and GLS estimates, I find that $\hat{\lambda}_{liq}$ is positive and significantly different from zero at the 5% level according to the FM , SH, JW, and KRS t-ratios. Hence, the mimicking liquidity factor is significantly useful in explaining the cross-sectional return variations.

[36] Many studies find that market risk premium is negative, such as Fama and French (1992), Lettau and Ludvigson (2001), and Petkova (2006).

5.6.4 Consumption risk, market risk, and liquidity risk with quarterly data

In this sub-section, I study the patterns of the consumption beta, market beta, and liquidity beta which are estimated from a single multiple time-series regression for each portfolio using the entire sample as in Lettau and Ludvigson (2001). In particular, the risk loadings are calculated according to the following equation:

$$R_{i,t} - R_{f,t} = \alpha_i + \beta_{cg,i} f_{cg,t} + \beta_{mkt,i} f_{mkt,t} + \beta_{liq,i} f_{liq,t} + \varepsilon_{i,t}, \tag{5.14}$$

where $f_{cg,t}$ denotes the consumption growth on nondurable goods and services, $f_{mkt,t}$ denotes excess value-weighted excess returns, and $f_{liq,t}$ denotes the mimicking liquidity factor. In fact, the estimation of factor loadings corresponds to the first-step of the Fama-MacBeth procedure. I calculate the covariance matrices using the Newey-West (1987) estimator with two lags to take into account heteroscedasticity and autocorrelation.

Table 5.9 shows that, broadly speaking, liquidity betas are related to size and value effects, no matter which mimicking liquidity factor (liq^{DV}, liq^{P0R}, liq^{RV}, or liq^{LM}) is used. Within each book-to-market quintile, the liquidity beta is low for big stocks and high for small stocks. Similarly, the liquidity beta increases in book-to-market ratio for a given size equity quintile. In addition, untabulated results show that loadings on the aggregate consumption growth are generally insignificant at the conventional level, similar to the findings of Parker and Julliard (2005).[37] With regard to loadings on the market factor, they are statistically significantly different from zero at the conventional level. However, the pattern of the market beta is inconsistent with the value effect. In particular, glamor stocks exhibit high market risk while value stocks display low market risk.[38]

5.6.5 Pricing power with quarterly data

In this subsection, I focus on the pricing power of my liquidity-augmented model. Using both the OLS and GLS estimates, Columns 1 and 4 of Table 5.10 present the sample cross-sectional R^2, which is calculated according to Kandel and Stambaugh (1995). The covariance matrices are calculated using the Newey-West estimator with two lags to take into account heteroscedasticity and autocorrelation. For the 25 Fama-French equally-weighted size and book-to-market classified portfolios, the fraction of cross-sectional return variations explained by my liquidity-augmented model is about 80% under the OLS regressions and up to about 30% under the GLS regressions. For both the OLS and GLS results, R^2 test with the hypothesis that $R^2 = 0$ can be rejected at the 5% level.

Shanken (1985) develops a cross-sectional regression test, which has a quadratic form of the sample mean of the pricing errors.

[37] Results are available upon request. In Table 4 of Parker and Julliard (2005), they regress the Fama-French size factor (*smb*) and the book-to-market factor (*hml*) on log consumption growth, respectively. They find that, by and large, the coefficients on log consumption growth are insignificant at the 10% level.

[38] This is similar to the findings in Table IV of Petkova (2006).

$$Q = T\bar{\epsilon}_i{}'\hat{\Sigma^{-1}}\bar{\epsilon}_i, \tag{5.15}$$

where T is the number of time-series observations; $\bar{\epsilon}_i$ is the time-series average of residuals for portfolio i calculated from the procedure as in Lettau and Ludvigson (2001); $\hat{\Sigma}$ is the estimated covariance matrix of the sample pricing errors. Columns 2 and 5 of Table 5.10 present the cross-sectional regression test (CSRT), $\hat{Q}_c$, using both the OLS and GLS regressions. Following Kan, Robotti, and Shanken (2013), $p(Q_c = 0)$ is the $p-value$ with the approximate F-distribution for the test of the hypothesis that the Q_c is equal to zero. The $p-value$ is at least about 8% for both the OLS and GLS results, which means that the null of zero pricing errors cannot be rejected.

Kan, Robotti, and Shanken (2013) suggest that it is important to test whether the better performance of one model over another is statistically significant. According to my results in Table 5.8, the mimicking liquidity factor contributes significantly to the gain of explanatory power to the cross-sectional return variations. In addition, my model differs from the Epstein and Zin's model by taking the liquidity factor into account. To further examine the important role of liquidity, I test whether the different performance in terms of R^2 between my model and the Epstein-Zin model is statistically significant. I estimate the $p-value$ under potentially misspecified models with the hypothesis that the cross-sectional R^2 of the two competing models are equal. Columns 3 and 6 of Table 5.10 show that even though the liquidity-augmented model is developed from the recursive utility of Epstein and Zin (1991), my model provides between 17% and 25% additional explanatory power. Moreover, the null hypothesis is that the equality of cross-sectional R^2 can be rejected at the 5% level, regardless of the different estimation methods (OLS and GLS) and mimicking liquidity factors (liq^{DV}, liq^{P0R}, liq^{RV}, and liq^{LM}).

While the cross-sectional R^2 aims to explain expected returns, the HJ-distance (Hansen and Jagannathan (1997)) is oriented towards a model's power to explain asset prices (Kan, Robotti, and Shanken (2013)). To further evaluate the performance of my model, I also conduct tests of equality of squared HJ distances, following Kan and Robotti (2009). Column 7 of Table 5.10 presents the test of equality of squared HJ distances. Similar to the cross-sectional R^2 comparison tests, my liquidity-augmented model gives smaller HJ-distance estimates than the Epstein and Zin (1991) model. Moreover, the null hypothesis that the squared HJ-distances of two competing models are equal is rejected at the 5% level. Overall, my model exhibits significant better performance than the Epstein-Zin model with regard to the cross-sectional R^2 and HJ distance.

5.6.6 Other model specifications and test portfolios with quarterly data

Lettau and Ludvigson (2001) show that the traditional CCAPM conditional on the consumption-to-wealth ratio (*cay*) explains well the expected return variations across the Fama-French 25 size and book-to-market portfolios. I embed *cay* into the Epstein-

Zin model and my liquidity-augmented model to test robustness. Panel A of Table 5.11 shows that after controlling *cay*, the estimated risk premium and price of covariance risk for different mimicking liquidity factors are significantly positive at the 5% level, consistent with my previous findings. Moreover, Panel A of Table 5.12 shows that the cross-sectional R^2 of my model exceeds that of the Epstein-Zin model by 19.3 (OLS) and 18.7 (GLS) percentage points and is statistically significant at the 5% level. Similarly, the HJ distance of my model is significantly smaller than that of the Epstein-Zin model at the 1% level.

Parker and Julliard (2005) and Malloy, Moskowitz, and Vissing-Jørgensen (2009) highlight the importance of long-run consumption risk in explaining the cross-sectional variations of expected return. Following Parker and Julliard (2005), I substitute the consumption growth of nondurable goods and services (cg) for the consumption growth of nondurable goods over 11 quarters ($cg11$). Panel B of Table 5.11 again shows that, in general, liquidity risk is significantly priced and the covariance risk of liquidity contributes significantly to the increase of cross-sectional R^2 at the 5% level. To a lesser extent, with the DV and RV liquidity measures, the coefficients on the covariance risk of liquidity under the OLS estimates are significant at the 10% level. Moreover, compared with the Epstein and Zin's model, my model exhibits significantly better fit for the cross-sectional return variations at least at the 6% level according to the results of Panel B of Table 5.12. In terms of the HJ distance, my model has significantly smaller pricing errors at the 1% level.

When utility is nonseparable in nondurable and durable consumption, the durable goods play an important role in affecting expected returns (Yogo (2006) and Gomes, Kogan, and Yogo (2009)). I incorporate the durable consumption growth (*cgd*) into the Epstein-Zin model, which is equivalent to the model of Yogo (2006), and my model. Panel C of Table 5.11 shows that the coefficients of the risk loading and the covariance risk related to market liquidity are statistically significant at the 5% level. Also, Panel C of Table 5.12 shows that my model is significantly more successful in pricing the 25 Fama-French equally-weighted size and book-to-market classified portfolios at the 5% level.

Lewellen, Nagel, and Shanken (2010) argue that the tight factor structure of size and book-to-market portfolios tends to be less powerful in rejecting misspecified asset pricing models and result in high R-squares in cross-sectional tests. They further advocate that asset pricing tests should incorporate other sets of portfolios (e.g. industry portfolios) to disintegrate the structure of size and book-to-market portfolios. I augment the 25 Fama-French equally-weighted size and book-to-market classified portfolios with 5 equally-weighted industry portfolios. Panel D of Tables 5.11 and 5.12 shows results similar to the above findings. Thus, even if I test another set of portfolios, the estimated risk premium and price of covariance risk related to the mimicking liquidity factors are significant at the 5% level. Furthermore, the differences of the cross-sectional R^2 and the squared HJ distance are significant at the 5% level. One exception is the difference of the cross-sectional R^2 under GLS with LM measure, which has a p-value of 5.1%

5.6.7 Portfolio characteristics and conditional information with quarterly data

My focus in this subsection is on (1) whether portfolio characteristics play a significant role in determining the cross-sectional expected returns and (2) whether conditional variables contribute significantly to the gain of extra explanatory power in my model.

Jagannathan and Wang (1998) suggest that it is necessary to detect model misspecification by including portfolio characteristics. I accommodate portfolio size and book-to-market ratio after log transformation in the second-stage of the cross-sectional regressions. Specifically, I run the regressions on the following equation:

$$R_{i,t} - R_{f,t} = \gamma_0 + \gamma_{cg}\beta_{cg} + \gamma_{mkt}\beta_{mkt} + \gamma_{liq}\beta_{liq} + \gamma_Z Z + \varepsilon_{i,t}, \tag{5.16}$$

where β_{cg} denotes the consumption beta, β_{mkt} denotes the market beta, β_{liq} denotes the liquidity beta, and Z denotes the log of portfolio characteristic, either size ($ln(Size)$) or book-to-market ratio ($ln(B/M)$). The risk loadings are estimated from a single multiple time-series regression for each portfolio using the entire sample. I report the estimated coefficients in percentage form.

Panels A and B of Table 5.13 present the cross-sectional regression results in the presence of size or book-to-market ratio. Untabulated results show that size and book-to-market ratio are statistically significant when added to the Fama-French three-factor model in the cross-sectional regression, consistent with Daniel and Titman

(1997) (among others).[39] However, the residual size and book-to-market effects are eliminated in my liquidity-augmented model. The coefficient on neither size nor book-to-market ratio is statistically significant at the 5% level under both the FM t-ratio and SH t-ratio. Further, high liquidity risk is still related to high expected returns in the presence of book-to-market ratio. Liquidity risk estimated by the mimicking liquidity factor (liq^{LM}) is even significantly priced after controlling for size.

Ferson and Harvey (1999) and Petkova (2006) (among others) find that the Fama-French three-factor model has difficulty in capturing the lagged instrument variables. Following their studies, I use the lagged 1-month Treasure bill yield (RF) and the lagged difference between Moody's Baa and Aaa corporate bond yields ($JUNK$) as conditional variables. Monthly values are compounded to obtain the corresponding quarterly values. To include conditional variables, I run the following regressions,

$$R_{i,t} - R_{f,t} = \gamma_0 + \gamma_{cg}\beta_{cg} + \gamma_{mkt}\beta_{mkt} + \gamma_{liq}\beta_{liq} + \gamma_\delta\delta + \varepsilon_{i,t}, \tag{5.17}$$

where β_{cg} denotes the consumption beta, β_{mkt} denotes the market beta, and β_{liq} denotes the liquidity beta. The loadings on cg, mkt, and liq are estimated from a single multiple time-series regression for each portfolio using the entire sample. δ denotes the loading on one-period lagged RF or $JUNK$, which is estimated from a univariate time-series regression for each portfolio using the entire sample.

Panels C and D of Table 5.13 report the cross-sectional regression results in the

[39] I also do not reports the regression results of $\hat{\gamma}_0$, $\hat{\gamma}_{cg}$, and $\hat{\gamma}_{mkt}$ to save space. The results are available upon request.

presence of the one-period lagged RF or $JUNK$. Untabulated results uncover similar findings to those of Ferson and Harvey (1999) and Petkova (2006). Specifically, for the Fama-French three-factor model, the coefficients on loadings of lagged RF or $JUNK$ are significantly different from zero at the 5% level even after the Shanken (1992) errors-in-variables adjustment.[40] However, for my liquidity-augmented model, I find that the null hypothesis that $\hat{\lambda}_{JUNK} = 0$ and $\hat{\lambda}_{RF} = 0$ cannot be rejected at the 5% level after the Shanken (1992) errors-in-variables adjustment. Therefore, my model does not leave out common time-varying patterns associated with cross-sectional difference in covariance with conditional variables. That is, lagged RF or $JUNK$ does not provide significant improvement on the power of my model to explain cross section of returns. Moreover, I find that the loading on liquidity is significantly priced at the 5% level after controlling for lagged RF. The coefficient on liquidity risk estimated by the mimicking liquidity factor ($liq^L M$) significantly differs from zero even after controlling for lagged $JUNK$.

5.7 Conclusion

Liquidity costs, which are generally related to transaction costs, thin or infrequent trading, and the impact of trading on price, affect investors' investment return and consumption. Recently, a series of papers (Pastor and Stambaugh (2003), Liu (2006), and Sadka (2006)) highlight the importance of liquidity in asset pricing. While existing studies appear to make adjustment to the CAPM or the Fama-French three-factor

[40] I also do not reports the regression results of $\hat{\gamma}_0$, $\hat{\gamma}_{cg}$, and $\hat{\gamma}_{mkt}$ to save space. The results are available upon request.

model with liquidity risk and show that models with liquidity adjustment reveal significantly increased explanatory power, there are few studies incorporating liquidity risk into consumption based pricing models. In this chapter, I develop a liquidity-augmented Epstein-Zin model under the setting that after taking into account liquidity costs, individuals maximize their life-time utility of consumption. My model reveals that in addition to the consumption and market risks, expected stock return is also determined by liquidity risk.

Applying a number of newly developed procedures in testing asset pricing models, I empirically evaluate my three-beta pricing model against the traditional CCAPM and the Epstein-Zin two-beta model. I find that the liquidity risk is fairly priced and the liquidity factor makes a significant contribution to explain cross-sectional expected returns.

In terms of both the cross-sectional R^2 and the Hansen and Jagannathan (1997) distance, the results show that my model performs better than the traditional CCAPM and the Epstein-Zin model based on the equality tests of the cross-sectional R^2 (Kan, Robotti, and Shanken (2013)) and the HJ distance (Kan and Robotti (2009)). Thus, my results not only support the extension of liquidity risk to asset pricing, but the extension also helps to explain why the empirical performance of the CCAPM and the Epstein-Zin model is less successful.

Li and Zhang (2010) and Lam and Wei (2011) argue that investment frictions (e.g., asset size proxy) from the firms' side and transaction frictions (e.g., trading volumes proxy) from the investors' side are less likely to be mutually exclusive. While I link stock liquidity to investors' consumption and investment decisions in the above two chapters, in the next chapter, I attempt to link stock liquidity to firms' investment costs.

Table 5.1: Descriptive statistics

This table reports the mean, standard deviation (SD), and correlation of the excess market returns (mkt), consumption growth of nondurables and services (cg), consumption to aggregate wealth ratio (cay), consumption growth of nondurable goods over 36 months ($cg36$), durable consumption growth (cgd), and three liquidity risk factors. The notation liq^{PS}, liq^{LM}, and liq^{Sadka} stand for the aggregate liquidity innovation of Pastor and Stambaugh (2003) from 1962 to 2009, Liu's (2006) mimicking liquidity risk factor from 1959 to 2009, and Sadka's (2006) aggregate liquidity innovation based on the variable component of price impact from 1983 to 2009.

	mkt	cg	cay	$cg36$	cgd	liq^{PS}	liq^{LM}	liq^{Sadka}
Descriptive statistics								
Mean	0.432	0.166	0.125	4.331	0.373	-0.001	0.599	-0.000
SD	4.458	0.346	1.717	3.591	2.746	0.057	3.473	0.006
Correlation								
cg	0.159	1						
cay	-0.015	0.005	1					
$cg36$	0.086	0.193	0.298	1				
cgd	0.013	0.228	-0.004	0.095	1			
liq^{PS}	0.342	0.063	0.083	0.051	0.082	1		
liq^{LM}	-0.635	-0.087	0.070	0.047	0.053	-0.122	1	
liq^{Sadka}	0.166	0.098	-0.091	-0.000	0.076	0.235	0.021	1

Table 5.2: Risk premium

This table reports the cross-sectional regressions using the monthly portfolio returns on the 25 Fama-French value-weighted size and book-to-market portfolios. To estimate the risk premium, I run the following regression:

$$R_{i,t} = \gamma_0 + \gamma_{cg}\beta_{i,cg} + \gamma_{mkt}\beta_{i,mkt} + \gamma_{liq}\beta_{i,liq} + e_{i,t},$$

where $\beta_{i,cg}$ denotes the consumption beta, $\beta_{i,mkt}$ denotes the market beta, and $\beta_{i,liq}$ denotes the liquidity beta. These betas are estimated from a single multiple time-series regression for each testing portfolio using the entire sample. I report the estimated risk premium using both the ordinary least squares (OLS) and generalized least squares (GLS) regressions. The estimated coefficients are in percentage. For robustness, I report different t-statistics: the FM t-ratio of Fama and MacBeth (1973), the SH t-ratio of Shanken (1992) with errors-in-variables adjustment, the JW t-ratio of Jagannathan and Wang (1996), and the KRS t-ratio of Kan, Robotti, and Shanken (2013) under potentially misspecified models. The test uses three alternative liquidity risk factors: the aggregate liquidity innovation of Pastor and Stambaugh (2003) from 1962 to 2009 in Panel A, Liu's (2006) mimicking liquidity risk factor from 1959 to 2009 in Panel B, and Sadka's (2006) aggregate liquidity innovation based on the variable component of price impact from 1983 to 2009 in Panel C. The 1%, 5%, and 10% significance levels are denoted with ***, **, and *, respectively.

	OLS				GLS			
	$\hat{\gamma}_0$	$\hat{\gamma}_{cg}$	$\hat{\gamma}_{mkt}$	$\hat{\gamma}_{liq}$	$\hat{\gamma}_0$	$\hat{\gamma}_{cg}$	$\hat{\gamma}_{mkt}$	$\hat{\gamma}_{liq}$
Panel A: Pastor and Stambaugh (2003) liquidity factor								
Estimates	1.44	0.12	-0.79	5.35	1.42	0.02	-0.83	2.48
FM t-ratio	4.01***	1.63	-2.00**	4.47***	6.70***	0.45	-2.92***	2.96***
SH t-ratio	2.63***	1.08	-1.41	2.97***	5.82***	0.40	-2.69***	2.60***
JW t-ratio	2.02**	0.81	-1.14	2.31**	5.06***	0.35	-2.43**	2.51**
KRS t-ratio	1.90*	0.52	-1.07	2.11**	4.68***	0.26	-2.25**	1.84*
Panel B: Liu (2006) liquidity factor								
Estimates	0.48	0.17	0.15	0.92	0.86	0.08	-0.29	0.74
FM t-ratio	1.01	2.23**	0.30	4.11***	3.11***	1.37	-0.87	4.04***
SH t-ratio	0.87	1.92*	0.26	3.72***	2.95***	1.30	-0.84	3.95***
JW t-ratio	0.83	1.89*	0.25	3.69***	2.84***	1.23	-0.81	3.96***
KRS t-ratio	0.73	1.07	0.22	3.73***	2.35**	0.77	-0.70	3.74***
Panel C: Sadka (2006) liquidity factor								
Estimates	1.70	0.06	-1.01	0.34	2.17	0.06	-1.47	0.44
FM t-ratio	3.03***	0.84	-1.68*	1.79*	8.93***	1.29	-4.19***	4.20***
SH t-ratio	2.54**	0.71	-1.44	1.51	6.82***	1.01	-3.61***	3.29***
JW t-ratio	2.55**	0.75	-1.46	1.30	6.47***	1.07	-3.39***	3.47***
KRS t-ratio	2.42**	0.49	-1.39	1.12	5.76***	0.72	-3.06***	2.66***

Table 5.3: Price of covariance risk

This table reports the cross-sectional regressions using the monthly portfolio returns on the 25 Fama-French value-weighted size and book-to-market portfolios. To estimate the price of covariance risk, I run the following regression:

$$R_{i,t} = \lambda_0 + \lambda_{cg}Cov(R_i, cg) + \lambda_{mkt}Cov(R_i, mkt) + \lambda_{liq}Cov(R_i, liq) + e_{i,t},$$

where $Cov(R_i, cg)$ stands for the covariance between portfolio i's return and consumption growth, $Cov(R_i, mkt)$ for the covariance between portfolio i's return and excess value-weighted market return, and $Cov(R_i, liq)$ for the covariance between portfolio i's return and the liquidity factor. These covariances are estimated for each testing portfolio using the entire sample. I report the estimated price of covariance risk using both the ordinary least squares (OLS) and generalized least squares (GLS) regressions. The estimated coefficients are in percentage. For robustness, I apply different t-statistics: the FM t-ratio of Fama and MacBeth (1973), the SH t-ratio of Shanken (1992) with errors-in-variables adjustment, the JW t-ratio of Jagannathan and Wang (1996), and the KRS t-ratio of Kan, Robotti, and Shanken (2013) under potentially misspecified models. My test uses three alternative liquidity risk factors: the aggregate liquidity innovation of Pastor and Stambaugh (2003) from 1962 to 2009 in Panel A, Liu's (2006) mimicking liquidity risk factor from 1959 to 2009 in Panel B, and Sadka's (2006) aggregate liquidity innovation based on the variable component of price impact from 1983 to 2009 in Panel C. The 1%, 5%, and 10% significance levels are denoted with ***, **, and *, respectively.

	OLS				GLS			
	$\hat{\lambda}_0$	$\hat{\lambda}_{cg}$	$\hat{\lambda}_{mkt}$	$\hat{\lambda}_{liq}$	$\hat{\lambda}_0$	$\hat{\lambda}_{cg}$	$\hat{\lambda}_{mkt}$	$\hat{\lambda}_{liq}$
Panel A: Pastor and Stambaugh (2003) liquidity factor								
Estimates	1.44	11740.71	-1413.42	1977.74	1.42	3034.29	-879.74	987.55
FM t-ratio	4.01***	1.81*	-4.81***	4.75***	6.70***	0.67	-4.35***	3.42***
SH t-ratio	2.63***	1.19	-3.14***	3.10***	5.82***	0.58	-3.73***	2.95***
JW t-ratio	2.02**	0.88	-2.44**	2.32**	5.06***	0.50	-3.19***	2.65***
KRS t-ratio	1.90*	0.56	-2.70***	2.18**	4.68***	0.38	-2.67***	1.98**
Panel B: Liu (2006) liquidity factor								
Estimates	0.48	14080.13	532.65	1311.83	0.86	6864.45	158.49	803.65
FM t-ratio	1.01	2.21**	1.32	3.29***	3.11***	1.40	0.56	2.76***
SH t-ratio	0.87	1.89*	1.13	2.80***	2.95***	1.33	0.54	2.60***
JW t-ratio	0.83	1.82*	1.05	2.69***	2.84***	1.24	0.53	2.69***
KRS t-ratio	0.73	1.01	0.81	2.42**	2.35**	0.78	0.42	2.28**
Panel C: Sadka (2006) liquidity factor								
Estimates	1.70	7078.25	-768.88	8824.29	2.17	7158.79	-1055.59	11541.55
FM t-ratio	3.03***	0.84	-2.81***	1.94*	8.93***	1.23	-5.49***	4.49***
SH t-ratio	2.54**	0.70	-2.33**	1.62	6.82***	0.94	-4.08***	3.37***
JW t-ratio	2.55**	0.70	-2.45**	1.42	6.47***	0.91	-3.92***	3.63***
KRS t-ratio	2.42**	0.45	-2.20**	1.19	5.76***	0.64	-3.63***	2.71***

Table 5.4: Cross-sectional R^2 and HJ distance

This table reports the sample cross-sectional R^2, the test of equality of cross-sectional R^2 as in Kan, Robotti, and Shanken (2013), and the test of equality of HJ distance (Hansen and Jagannathan (1997)) as in Kan and Robotti (2009). I examine three consumption-based asset pricing models: the traditional CCAPM, the Epstein-Zin model and the liquidity-augmented model. dR^2 is the R^2 of the liquidity-augmented model minus that of the CCAPM or Epstein-Zin model. The numbers in parentheses (after dR^2) calculated under potentially misspecified models are the p-values associated with the hypothesis that the cross-sectional R^2 of two competing models are equal. dHJ is the squared HJ distance of CCAPM or Epstein-Zin model minus that of liquidity-augmented model. The numbers in parentheses (after dHJ) calculated under potentially misspecified models are the p-values associated with the hypothesis that the squared HJ distances of two competing models are equal. Test portfolios are the 25 Fama-French value-weighted size and book-to-market portfolios. I report the results using both the ordinary least squares (OLS) and generalized least squares (GLS) estimates. I apply three alternative liquidity risk factors to the tests: the aggregate liquidity innovation of Pastor and Stambaugh (2003) from 1962 to 2009 in Panel A, Liu's (2006) mimicking liquidity risk factor from 1959 to 2009 in Panel B, and Sadka's (2006) aggregate liquidity innovation based on the variable component of price impact from 1983 to 2009 in Panel C. The 1%, 5%, and 10% significance levels are denoted with ***, **, and *, respectively.

	Traditional CCAPM	Epstein-Zin model	Liquidity-augmented model	Tests of equality	
				Traditional CCAPM	Epstein-Zin model
			Panel A: Pastor and Stambaugh (2003) liquidity factor		
R^2 (OLS)	$R^2 = 0.4\%$	$R^2 = 33.6\%$	$R^2 = 60.5\%$	$dR^2 = 60.1\%^{**}$ (0.013)	$dR^2 = 26.9\%^{**}$ (0.029)
R^2 (GLS)	$R^2 = 0.6\%$	$R^2 = 11.1\%$	$R^2 = 26.6\%$	$dR^2 = 26.0\%^{**}$ (0.025)	$dR^2 = 15.4\%^{**}$ (0.047)
HJ distance	$HJ = 0.438$	$HJ = 0.429$	$HJ = 0.408$	$dHJ = 0.026$ (0.119)	$dHJ = 0.018$ (0.105)
			Panel B: Liu (2006) liquidity factor		
R^2 (OLS)	$R^2 = 0.1\%$	$R^2 = 41.0\%$	$R^2 = 67.8\%$	$dR^2 = 67.7\%^{***}$ (0.000)	$dR^2 = 26.8\%^{**}$ (0.015)
R^2 (GLS)	$R^2 = 0.00\%$	$R^2 = 13.7\%$	$R^2 = 23.9\%$	$dR^2 = 23.9\%^{***}$ (0.001)	$dR^2 = 10.3\%^{**}$ (0.022)
HJ distance	$HJ = 0.410$	$HJ = 0.405$	$HJ = 0.323$	$dHJ = 0.062^{***}$ (0.000)	$dHJ = 0.060^{***}$ (0.000)
			Panel C: Sadka (2006) liquidity factor		
R^2 (OLS)	$R^2 = 14.5\%$	$R^2 = 57.3\%$	$R^2 = 69.8\%$	$dR^2 = 55.3\%^{**}$ (0.031)	$dR^2 = 12.4\%$ (0.232)
R^2 (GLS)	$R^2 = 0.7\%$	$R^2 = 23.7\%$	$R^2 = 46.8\%$	$dR^2 = 46.1\%^{***}$ (0.000)	$dR^2 = 23.1\%^{***}$ (0.005)
HJ distance	$HJ = 0.685$	$HJ = 0.673$	$HJ = 0.599$	$dHJ = 0.110^{**}$ (0.029)	$dHJ = 0.094^{**}$ (0.022)

Table 5.5: Robustness on risk premium and the price of covariance risk

With different settings for robustness tests, this table reports the estimated risk premium (γ_{liq}) and the price of covariance risk (λ_{liq}) with respect to the three alternative liquidity risk factors. Test portfolios are the 25 Fama-French value-weighted size and book-to-market portfolios, expect in Panel D. In Panels A and C, I incorporate the consumption-to-wealth ratio (cay) of Lettau and Ludvigson (2001) and durable consumption growth (cgd) of Yogo (2006) into the liquidity-augmented consumption model. In Panel B, I follow Parker and Julliard (2005) and measure consumption growth based on nondurable goods over 36 months ($cg36$). In Panel D, I expand the 25 Fama-French value-weighted size and book-to-market portfolios with five value-weighted industry portfolios. The classification of the five industries is based on Gomes, Kogan, and Yogo (2009). I report the estimated risk premium and price of covariance risk using both the ordinary least squares (OLS) and generalized least squares (GLS) regressions. The estimated coefficients are in percentage. For robustness, I report different t-statistics: the FM t-ratio of Fama and MacBeth (1973), the SH t-ratio of Shanken (1992) with errors-in-variables adjustment, the JW t-ratio of Jagannathan and Wang (1996), and the KRS t-ratio of Kan, Robotti, and Shanken (2013) under potentially misspecified models. The three alternative liquidity risk factors are the aggregate liquidity innovation of Pastor and Stambaugh (2003) from 1962 to 2009, Liu's (2006) mimicking liquidity risk factor from 1959 to 2009, and Sadka's (2006) aggregate liquidity innovation based on the variable component of price impact from 1983 to 2009. The 1%, 5%, and 10% significance levels are denoted with ***, **, and *, respectively.

	OLS		GLS		OLS		GLS		OLS		GLS	
	$\hat{\gamma}_{liq}$	$\hat{\lambda}_{liq}$	$\hat{\gamma}_{liq}$	$\hat{\lambda}_{liq}$	$\hat{\gamma}_{liq}$	$\hat{\lambda}_{liq}$	$\hat{\gamma}_{liq}$	$\hat{\lambda}_{liq}$	$\hat{\gamma}_{liq}$	$\hat{\lambda}_{liq}$	$\hat{\gamma}_{liq}$	$\hat{\lambda}_{liq}$
	Pastor and Stambaugh (2003) liquidity factor				Liu (2006) liquidity factor				Sadka (2006) liquidity factor			
Panel A: cay (Lettau and Ludvigson (2001))												
Estimates	4.88	1991.67	2.50	985.64	0.94	1345.88	0.76	824.56	0.35	8968.80	0.45	11682.33
FM t-ratio	4.36***	4.75***	2.95***	3.41***	4.47***	3.42***	4.08***	2.80***	1.87*	2.08**	4.21***	4.47***
SH t-ratio	2.68***	2.86***	2.58***	2.93***	4.05***	2.87***	3.96***	2.61***	1.57	1.73*	3.29***	3.35***
JW t-ratio	2.30**	2.35**	2.51**	2.63***	4.01***	2.74***	3.99***	2.70***	1.33	1.47	3.43***	3.47***
KRS t-ratio	2.13**	2.32**	1.83*	1.97**	3.60***	2.39**	3.67***	2.25**	1.14	1.23	2.63***	2.62***
Panel B: $cg36$ (Parker and Julliard (2005))												
Estimates	3.77	1312.08	2.52	968.99	0.85	1358.19	0.72	773.40	0.49	12507.99	0.42	11139.71
FM t-ratio	3.55***	3.61***	3.00***	3.35***	3.66***	2.81***	3.85***	2.19**	2.81***	2.95***	3.82***	4.16***
SH t-ratio	2.40**	2.39**	2.55**	2.79***	3.45***	2.56**	3.81***	2.13**	2.15**	2.21**	3.08***	3.23***
JW t-ratio	2.30**	2.24**	2.50**	2.56**	3.31***	2.53**	3.78***	2.13**	1.99**	2.11**	3.41***	3.66***
KRS t-ratio	1.94*	1.82*	1.85*	1.91*	2.56**	1.30	3.43***	1.49	1.41	1.49	2.40**	2.56**

[Cont.]

(continued)

	OLS		GLS		OLS		GLS		OLS		GLS	
	$\hat{\gamma}_{liq}$	$\hat{\lambda}_{liq}$	$\hat{\gamma}_{liq}$	$\hat{\lambda}_{liq}$	$\hat{\gamma}_{liq}$	$\hat{\lambda}_{liq}$	$\hat{\gamma}_{liq}$	$\hat{\lambda}_{liq}$	$\hat{\gamma}_{liq}$	$\hat{\lambda}_{liq}$	$\hat{\gamma}_{liq}$	$\hat{\lambda}_{liq}$
	Pastor and Stambaugh (2003) liquidity factor				Liu (2006) liquidity factor				Sadka (2006) liquidity factor			
Panel C: *cgd* (Yogo (2006))												
Estimates	2.13	808.80	2.07	809.81	0.86	305.65	0.70	434.69	0.38	9796.25	0.47	12214.39
FM t-ratio	1.85*	1.90*	2.38**	2.66***	3.76***	0.68	3.74***	1.20	2.68***	2.65***	4.27***	4.52***
SH t-ratio	1.35	1.38	2.06**	2.27**	3.20***	0.54	3.60***	1.10	2.20**	2.13**	3.26***	3.31***
JW t-ratio	1.36	1.34	2.02**	2.09**	3.40***	0.58	3.70***	1.13	1.98**	1.99**	3.21***	3.25***
KRS t-ratio	0.93	0.96	1.40	1.47	3.17***	0.30	3.40***	0.78	1.27	1.29	2.55**	2.55**
Panel D: FF25+5 industry (Lewellen, Nagel, and Shanken (2010))												
Estimates	4.92	1780.08	2.05	838.95	0.79	1298.77	0.70	680.50	0.20	5208.50	0.25	6712.09
FM t-ratio	4.00***	4.16***	2.69***	3.20***	3.67***	3.42***	4.02***	2.46**	1.12	1.21	2.63***	2.86***
SH t-ratio	2.90***	2.96***	2.44**	2.85***	3.49***	3.11***	3.97***	2.37**	1.04	1.12	2.31**	2.44**
JW t-ratio	2.16**	2.09**	2.29**	2.52**	3.48***	3.02***	4.01***	2.38**	0.96	1.05	2.45**	2.78***
KRS t-ratio	2.11**	2.06**	1.76*	1.91*	3.49***	2.89***	3.78***	1.98**	0.73	0.76	1.65*	1.85*

Table 5.6: Robustness on cross-sectional R^2 and HJ distance

This table reports the test of equality of cross-sectional R^2 and HJ distance obtained from several robustness tests. My tests are based on the 25 Fama-French value-weighted size and book-to-market portfolios, unless otherwise stated. In Panels A and B, I respectively evaluate my model relative to the CCAPM and the Epstein-Zin model. I incorporate the consumption-to-wealth ratio (cay) of Lettau and Ludvigson (2001) and durable consumption growth (cgd) of Yogo (2006) into the CCAPM, the Epstein-Zin model, and the liquidity-augmented model. I also follow Parker and Julliard (2005) and measure consumption growth based on nondurable goods over 36 months ($cg36$). In addition, I expand the 25 Fama-French value-weighted size and book-to-market portfolios with five value-weighted industry portfolios. The classification of the five industries is based on Gomes, Kogan, and Yogo (2009). I use these 30 testing portfolios to compare my model with the CCAPM and the Epstein-Zin model. The symbol dR^2 is the R^2 of the liquidity-augmented model (with different specifications) minus that of the CCAPM (with different specifications) in Panel A and Epstein-Zin model (with different specifications) in Panel B, $p(dR^2)$ (in parenthesis) calculated under potentially misspecified models is associated with the hypothesis that the cross-sectional R^2 of two competing models are equal, dHJ is the squared HJ distance of CCAPM (with different specifications) in Panel A and Epstein-Zin model (with different specifications) in Panel B minus that of the liquidity-augmented model (with different specifications), and $p(dHJ)$ (in parentheses) calculated under potentially misspecified models is associated with the hypothesis that the squared HJ distances of two competing models are equal. I report the results using both the ordinary least squares (OLS) and generalized least squares (GLS) estimates. My tests are based on three alternative liquidity risk factors: the aggregate liquidity innovation of Pastor and Stambaugh (2003) from 1962 to 2009 in columns 1, 2, and 3; Liu's (2006) mimicking liquidity risk factor from 1959 to 2009 in columns 4, 5, and 6; and Sadka's (2006) aggregate liquidity innovation based on the variable component of price impact from 1983 to 2009 in columns 7, 8, and 9. The 1%, 5%, and 10% significance levels are denoted with ***, **, and *, respectively.

Panel A: the traditional CCAPM and the liquidity-augmented model								
Pastor and Stambaugh (2003) liquidity factor			Liu (2006) liquidity factor			Sadka (2006) liquidity factor		
1	2	3	4	5	6	7	8	9
dR^2 (OLS)	dR^2 (GLS)	dHJ	dR^2 (OLS)	dR^2 (GLS)	dHJ	dR^2 (OLS)	dR^2 (GLS)	dHJ
$p(dR^2)$	$p(dR^2)$	$p(dHJ)$	$p(dR^2)$	$p(dR^2)$	$p(dHJ)$	$p(dR^2)$	$p(dR^2)$	$p(dHJ)$
cay: Lettau and Ludvigson (2001)								
0.644**	0.245**	0.021	0.676***	0.227***	0.053***	0.447*	0.453***	0.127**
(0.024)	(0.032)	(0.119)	(0.000)	(0.000)	(0.000)	(0.067)	(0.000)	(0.028)

[Cont.]

(continued)

*cg*36: Parker and Julliard (2005)								
0.230	0.263**	0.019	0.189	0.176***	0.045***	0.515	0.424***	0.071*
(0.115)	(0.014)	(0.188)	(0.214)	(0.007)	(0.001)	(0.189)	(0.000)	(0.094)
cgd: Yogo (2006)								
0.228	0.217**	0.023	0.191	0.170**	0.060***	0.397*	0.452***	0.120**
(0.104)	(0.034)	(0.162)	(0.114)	(0.019)	(0.000)	(0.072)	(0.000)	(0.020)
FF25+5 industry: Lewellen, Nagel, and Shanken (2010)								
0.510**	0.212**	0.022	0.631***	0.189***	0.069***	0.410*	0.266***	0.072**
(0.041)	(0.019)	(0.121)	(0.000)	(0.001)	(0.000)	(0.098)	(0.002)	(0.045)
Panel B: the Epstein-Zin model and the liquidity-augmented model								
Pastor and Stambaugh (2003) liquidity factor			Liu (2006) liquidity factor			Sadka (2006) liquidity factor		
1	2	3	4	5	6	7	8	9
dR^2 (OLS)	dR^2 (GLS)	dHJ	dR^2 (OLS)	dR^2 (GLS)	dHJ	dR^2 (OLS)	dR^2 (GLS)	dHJ
$p(dR^2)$	$p(dR^2)$	$p(dHJ)$	$p(dR^2)$	$p(dR^2)$	$p(dHJ)$	$p(dR^2)$	$p(dR^2)$	$p(dHJ)$
cay: Lettau and Ludvigson (2001)								
0.273**	0.153**	0.017	0.228**	0.106**	0.050***	0.116	0.229***	0.108**
(0.019)	(0.048)	(0.120)	(0.017)	(0.024)	(0.000)	(0.220)	(0.007)	(0.016)

[Cont.]

(continued)

Pastor and Stambaugh (2003) liquidity factor			Liu (2006) liquidity factor			Sadka (2006) liquidity factor		
1	2	3	4	5	6	7	8	9
dR^2 (OLS)	dR^2 (GLS)	dHJ	dR^2 (OLS)	dR^2 (GLS)	dHJ	dR^2 (OLS)	dR^2 (GLS)	dHJ
$p(dR^2)$	$p(dR^2)$	$p(dHJ)$	$p(dR^2)$	$p(dR^2)$	$p(dHJ)$	$p(dR^2)$	$p(dR^2)$	$p(dHJ)$
			$cg36$: Parker and Julliard (2005)					
0.101^{*}	0.149^{*}	0.017	0.073	0.065	0.042^{***}	0.128	0.199^{***}	0.066^{*}
(0.067)	(0.054)	(0.110)	(0.194)	(0.137)	(0.000)	(0.139)	(0.010)	(0.058)
			cgd: Yogo (2006)					
0.029	0.093	0.014	0.003	0.019	0.055^{***}	0.082	0.235^{***}	0.106^{**}
(0.336)	(0.141)	(0.158)	(0.763)	(0.436)	(0.000)	(0.196)	(0.009)	(0.013)
			FF25+5 industry: Lewellen, Nagel, and Shanken (2010)					
0.244^{**}	0.114^{*}	0.015	0.333^{***}	0.067^{**}	0.065^{***}	0.049	0.081^{*}	0.057^{**}
(0.038)	(0.054)	(0.113)	(0.004)	(0.046)	(0.000)	(0.450)	(0.061)	(0.040)

Table 5.7: Descriptive statistics with quarterly data

This table reports the mean, standard deviation, and correlation of the excess market returns, consumption growth of nondurables and services (cg), consumption to aggregate wealth ratio (cay), consumption growth of nondurable goods over 11 quarter ($cg11$), durable consumption growth (cgd), and four mimicking liquidity factors. The notation liq^{DV}, liq^{P0R}, liq^{RV}, and liq^{LM} stands for various mimicking liquidity factors constructed from the dollar volumes measure of Brennan, Chordia, and Subrahmanyam (1998), proportion of daily zero returns measure of Lesmond, Ogden, and Trzcinka (1999), price impact measure of Amihud (2002), and trading speed discontinuity measure of Liu (2006). DV is the average daily dollar volume measured in thousands over the prior 12 months. $P0R$ is the proportion of daily zero returns over the prior 12 months. RV is the daily absolute return-to-dollar-volume ratio averaged over the prior 12 months. LM is the standardized turnover-adjusted number of zero daily trading volumes over the prior 12 months. The mimicking liquidity factors are constructed as follows. I form two portfolios, low liquidity (LL) and high liquidity (HL), at the end of June in each year for each liquidity measure and hold them for the subsequent 12 months. LL contains the lowest liquidity stocks based on a 30% NYSE breakpoint. HL contains the highest liquidity stocks based on a 30% NYSE breakpoint. The two portfolios are equally weighted and held for one year. The monthly values of mimicking liquidity factor are the monthly profits of longing \$1 of LL and shorting \$1 of HL.

	mkt	cg	cay	$cg11$	cgd	liq^{DV}	liq^{P0R}	liq^{RV}	liq^{LM}
Descriptive statistics									
Mean	1.658	0.470	0.090	4.111	0.530	0.916	1.004	0.796	1.126
SD	8.347	0.476	1.636	3.323	3.695	6.323	6.913	6.959	5.218
Correlation									
cg	0.273	1							
cay	-0.014	0.009	1						
$cg11$	0.118	0.315	0.344	1					
cgd	0.415	0.415	0.104	0.320	1				
liq^{DV}	0.078	0.082	-0.090	0.101	0.158	1			
$L.liq^{DV}$	(-0.116)	(-0.003)	(-0.085)	(0.067)	(0.039)				
liq^{P0R}	-0.098	0.052	-0.094	0.097	0.065	0.877	1		
$L.liq^{P0R}$	(-0.136)	(0.003)	(-0.097)	(0.083)	(0.029)				
liq^{RV}	0.215	0.110	-0.104	0.101	0.196	0.978	0.815	1	
$L.liq^{RV}$	(-0.112)	(-0.012)	(-0.091)	(0.050)	(0.054)				
liq^{LM}	-0.618	-0.059	0.095	0.065	-0.069	0.296	0.452	0.126	1
$L.liq^{LM}$	(-0.025)	(0.023)	(0.051)	(0.098)	(-0.045)				

Table 5.8: Risk premium and price of covariance risk with quarterly data

This table reports the Fama-MacBeth cross-sectional regressions using the quarterly excess returns on the 25 Fama-French equally-weighted size and book-to-market classified portfolios. In Panel A, I run the regressions on the following equation,

$$R_{i,t} - R_{f,t} = \gamma_0 + \gamma_{cg}\beta_{cg} + \gamma_{mkt}\beta_{mkt} + \gamma_{liq}\beta_{liq} + \varepsilon_{i,t},$$

where β_{cg} denotes the consumption beta, β_{mkt} denotes the market beta, and β_{liq} denotes the liquidity beta. The consumption betas, market betas, and liquidity betas are estimated from a single multiple time-series regression for each portfolio using the entire sample. I report the estimated coefficients in percentage form.

In Panel B, I run the regressions on the following equation,

$$R_{i,t} - R_{f,t} = \lambda_0 + \lambda_{cg}Cov(R_i, cg) + \lambda_{mkt}Cov(R_i, mkt) + \lambda_{liq}Cov(R_i, liq) + \varepsilon_{i,t},$$

where $Cov(R_i, cg)$ denotes the covariance of portfolio returns and consumption growth, $Cov(R_i, mkt)$ denotes the covariance of portfolio returns and excess value-weighted market returns, and $Cov(R_i, liq)$ denotes the covariance of portfolio returns and the mimicking liquidity factor.

I present the estimated risk premium and price of covariance risk using both the ordinary least squares (OLS) and generalized least squares (GLS) regressions. The estimated coefficients are in percentage form. I report the following t-ratios: the FM t-ratio of Fama and MacBeth (1973), the SH t-ratio of Shanken (1992) with errors-in-variables adjustment, the JW t-ratio of Jagannathan and Wang (1996), and the KRS t-ratio of Kan, Robotti, and Shanken (2013) t-ratio under potentially misspecified models. The construction of the mimicking liquidity factor is described in Table 5.7. The 1%, 5%, and 10% significance levels are denoted with ***, **, and *, respectively.

	OLS							GLS						
	Risk premium				Price of covariance risk			Risk premiuma				Price of covariance risk		
	$\hat{\gamma}_0$	$\hat{\gamma}_{cg}$	$\hat{\gamma}_{mkt}$	$\hat{\gamma}_{liq}$	$\hat{\lambda}_{cg}$	$\hat{\lambda}_{mkt}$	$\hat{\lambda}_{liq}$	$\hat{\gamma}_0$	$\hat{\gamma}_{cg}$	$\hat{\gamma}_{mkt}$	$\hat{\gamma}_{liq}$	$\hat{\lambda}_{cg}$	$\hat{\lambda}_{mkt}$	$\hat{\lambda}_{liq}$
Panel A: DV as a measure of liquidity														
Estimates	4.36	0.26	-2.17	1.61	14000.15	-561.56	378.04	3.20	0.08	-1.19	1.81	4478.30	-273.36	470.08
FM t-ratio	5.17***	1.74*	-2.34**	3.59***	1.88*	-2.92***	3.13***	5.34***	0.86	-1.47	4.17***	0.95	-2.00**	4.04***
SH t-ratio	4.15***	1.41	-2.01**	3.42***	1.44	-2.31**	2.64***	4.96***	0.81	-1.42	4.13***	0.89	-1.85*	3.65***
JW t-ratio	3.91***	1.21	-1.83*	3.36***	1.25	-2.08**	2.86***	4.88***	0.79	-1.37	4.25***	0.86	-1.80*	3.98***
KRS t-ratio	2.92***	0.73	-1.36	3.32***	0.82	-2.07**	2.07**	3.76***	0.49	-1.18	4.13***	0.53	-1.39	3.69***

[Cont.]

(continued)

	OLS							GLS						
	Risk premium				Price of covariance risk			Risk premiuma				Price of covariance risk		
	$\hat{\gamma}_0$	$\hat{\gamma}_{cg}$	$\hat{\gamma}_{mkt}$	$\hat{\gamma}_{liq}$	$\hat{\lambda}_{cg}$	$\hat{\lambda}_{mkt}$	$\hat{\lambda}_{liq}$	$\hat{\gamma}_0$	$\hat{\gamma}_{cg}$	$\hat{\gamma}_{mkt}$	$\hat{\gamma}_{liq}$	$\hat{\lambda}_{cg}$	$\hat{\lambda}_{mkt}$	$\hat{\lambda}_{liq}$
Panel B: $P0R$ as a measure of liquidity														
Estimates	3.95	0.13	-1.89	2.29	6991.81	-352.77	427.17	3.01	0.05	-0.98	2.64	2504.04	-142.18	547.95
FM t-ratio	4.38***	0.91	-1.95*	4.19***	1.01	-1.78*	3.38***	5.06***	0.53	-1.22	5.02***	0.53	-1.03	4.65***
SH t-ratio	3.91***	0.82	-1.80*	4.02***	0.90	-1.58	2.96***	4.67***	0.49	-1.17	4.90***	0.49	-0.95	4.13***
JW t-ratio	3.63***	0.80	-1.66*	3.96***	0.87	-1.48	3.19***	4.49***	0.50	-1.14	5.11***	0.49	-0.93	4.52***
KRS t-ratio	2.99***	0.34	-1.31	3.77***	0.40	-1.30	2.28**	3.59***	0.31	-1.00	4.80***	0.30	-0.73	4.14***
Panel C: RV as a measure of liquidity														
Estimates	4.45	0.28	-2.26	1.39	15006.90	-627.68	338.10	3.27	0.09	-1.26	1.70	5069.06	-337.82	411.33
FM t-ratio	5.29***	1.87*	-2.43**	2.89***	2.03**	-3.26***	3.08***	5.42***	0.96	-1.56	3.61***	1.09	-2.44**	3.88***
SH t-ratio	4.17***	1.48	-2.06**	2.77***	1.59	-2.53**	2.40**	5.03***	0.89	-1.49	3.59***	1.01	-2.24**	3.50***
JW t-ratio	3.94***	1.27	-1.88*	2.74***	1.36	-2.28**	2.57**	4.97***	0.88	-1.45	3.65***	0.97	-2.19**	3.80***
KRS t-ratio	2.90***	0.77	-1.38	2.72***	0.88	-2.29**	2.01**	3.78***	0.54	-1.23	3.59***	0.60	-1.70*	3.51***
Panel D: LM as a measure of liquidity														
Estimates	0.70	0.04	1.60	2.76	-2190.08	988.17	1979.95	1.39	0.04	0.69	2.12	-937.27	623.33	1393.04
FM t-ratio	0.54	0.27	1.15	4.89***	-0.27	2.53**	4.42***	2.06**	0.36	0.80	4.48***	-0.19	2.66***	4.58***
SH t-ratio	0.41	0.21	0.91	4.07***	-0.21	1.93*	3.32***	1.78*	0.32	0.73	4.15***	-0.16	2.28**	3.84***
JW t-ratio	0.40	0.21	0.91	4.16***	-0.22	1.93*	3.25***	1.71*	0.32	0.72	4.20***	-0.16	2.21**	3.73***
KRS t-ratio	0.40	0.12	0.91	3.81***	-0.12	1.44	2.57**	1.34	0.19	0.60	3.95***	-0.09	1.63	3.18***

Table 5.9: Liquidity betas estimated from time-series regressions with quarterly data

This table reports the patterns of consumption risk, market risk, and liquidity risk. Risk loadings are estimated from a single multiple time-series regression on the 25 Fama-French equally-weighted size and book-to-market classified portfolios using the entire sample. In particular, the risk loadings are calculated according to the following equation:

$$R_{i,t} - R_{f,t} = \alpha_i + \beta_{cg,i} f_{cg,t} + \beta_{mkt,i} f_{mkt,t} + \beta_{liq,i} f_{liq,t} + \varepsilon_{i,t},$$

where $f_{cg,t}$ denotes the consumption growth on nondurable goods and services, $f_{mkt,t}$ denotes excess value-weighted excess returns, and $f_{liq,t}$ denotes the mimicking liquidity factor. The t-ratio is calculated to take into account heteroscedasticity and autocorrelation using the Newey-West (1987) estimator with two lags. The construction of the mimicking liquidity factor is described in Table 5.7. The 1%, 5%, and 10% significance levels are denoted with ***, **, and *, respectively.

	Low	2	3	4	High	Low	2	3	4	High
			β_{liq}^{DV}					t_{liq}^{DV}		
Small	1.222***	1.123***	1.123***	1.107***	1.333***	(10.30)	(14.83)	(22.53)	(27.72)	(27.76)
2	0.541***	0.591***	0.566***	0.568***	0.776***	(7.71)	(10.07)	(10.90)	(11.79)	(12.44)
3	0.326***	0.354***	0.352***	0.404***	0.561***	(5.61)	(7.67)	(7.80)	(6.63)	(8.40)
4	0.085***	0.177***	0.199***	0.244***	0.403***	(1.86)	(3.97)	(4.16)	(4.35)	(4.89)
Big	-0.144***	-0.033	-0.041	0.056	0.059	(-5.25)	(-1.06)	(-1.13)	(1.24)	(0.88)
			β_{liq}^{P0R}					t_{liq}^{P0R}		
Small	0.828***	0.819***	0.863***	0.859***	1.082***	(6.33)	(8.21)	(11.54)	(11.65)	(15.30)
2	0.330***	0.430***	0.445***	0.500***	0.719***	(3.89)	(6.12)	(8.40)	(10.00)	(13.45)
3	0.140***	0.251***	0.291***	0.383***	0.553***	(2.11)	(4.89)	(6.64)	(7.27)	(9.45)
4	-0.017***	0.122***	0.187***	0.265***	0.417***	(-0.36)	(2.79)	(4.46)	(5.69)	(5.80)
Big	-0.175***	-0.016	-0.006	0.103***	0.134**	(-7.02)	(-0.54)	(-0.19)	(2.67)	(2.43)
			β_{liq}^{RV}					t_{liq}^{RV}		
Small	1.211***	1.098***	1.073***	1.057***	1.262***	(11.47)	(16.44)	(22.94)	(28.99)	(29.92)
2	0.563***	0.584***	0.544***	0.535***	0.731***	(8.72)	(10.44)	(11.23)	(11.37)	(12.51)
3	0.345***	0.341***	0.342***	0.375***	0.539***	(6.32)	(7.89)	(8.05)	(6.43)	(8.45)
4	0.111***	0.172***	0.183***	0.227***	0.389***	(2.58)	(4.05)	(4.16)	(4.27)	(5.04)
Big	-0.125***	-0.037	-0.041	0.047	0.064	(-4.78)	(-1.27)	(-1.14)	(1.09)	(1.04)
			β_{liq}^{LM}					t_{liq}^{LM}		
Small	-0.312	0.032	0.240	0.328*	0.462**	(-1.41)	(0.16)	(1.37)	(1.92)	(2.20)
2	-0.489***	-0.151	0.062	0.171	0.188	(-2.95)	(-1.10)	(0.53)	(1.41)	(1.14)
3	-0.403***	-0.098	-0.022	0.193*	0.113	(-3.23)	(-1.03)	(-0.22)	(1.87)	(0.73)
4	-0.393***	-0.087	0.012	0.068	0.112	(-4.29)	(-1.06)	(0.17)	(0.84)	(0.73)
Big	-0.187***	-0.028	-0.064	0.096	-0.029	(-4.31)	(-0.52)	(-1.16)	(1.47)	(-0.28)

Table 5.10: Specification tests of the model with quarterly data

This table reports the sample cross-section R^2, the generalized cross-sectional regression test (CSRT), Q^2, of Shanken (1985), the test of equality of cross-sectional R^2 as in Kan, Robotti, and Shanken (2013), and the test of equality of HJ distance (Hansen and Jagannathan (1997)) as in Kan and Robotti (2009). $p(R^2)$ (in parenthesis) is the $p-value$ for the test of the hypothesis that the R^2 is equal to zero. $p(Q^2)$ (in parentheses) is the $p - value$ with the approximate F-distribution for the test of the hypothesis that the Q^2 is equal to zero. dR^2 is the R^2 of the liquidity-augmented model minus that of the Epstein and Zin's model. $p(dR^2)$ (in parenthesis) calculated under potentially misspecified models is associated with the hypothesis that the cross-sectional R^2 of two competing models are equal. dHJ is the squared HJ distance of Epstein and Zin's model minus that of the liquidity-augmented model. $p(dHJ)$ (in parentheses) calculated under potentially misspecified models is associated with the hypothesis that the squared HJ distances of two competing models are equal. Test portfolios are the quarterly excess returns on the 25 Fama-French equally-weighted size and book-to-market classified portfolios. I present results using both the ordinary least squares (OLS) and generalized least squares (GLS) estimates. I calculate the covariance matrices using the Newey-West (1987) estimator with two lags to take into account heteroscedasticity and autocorrelation. The construction of the mimicking liquidity factor is described in Table 5.7. The 1%, 5%, and 10% significance levels are denoted with ***, **, and *, respectively.

OLS			GLS			HJ
1	2	3	4	5	6	7
R^2	Q^2	dR^2	R^2	Q^2	dR^2	dHJ
$p(R^2)$	$p(Q^2)$	$p(dR^2)$	$p(R^2)$	$p(Q^2)$	$p(dR^2)$	$p(dHJ)$
Panel A: DV as a measure of liquidity						
0.803**	0.134	0.182**	0.231**	0.147*	0.185***	0.047***
(0.012)	(0.161)	(0.023)	(0.038)	(0.096)	(0.000)	(0.002)
Panel B: $P0R$ as a measure of liquidity						
0.823***	0.136	0.201**	0.291**	0.131	0.245***	0.082***
(0.009)	(0.151)	(0.016)	(0.011)	(0.181)	(0.000)	(0.000)
Panel C: RV as a measure of liquidity						
0.798**	0.133	0.177**	0.216**	0.152*	0.171***	0.038***
(0.013)	(0.164)	(0.027)	(0.048)	(0.079)	(0.000)	(0.006)
Panel D: LM as a measure of liquidity						
0.874**	0.099	0.253***	0.284**	0.116	0.238***	0.171***
(0.018)	(0.490)	(0.008)	(0.031)	(0.302)	(0.001)	(0.000)

Table 5.11: Robustness on risk premium and price of covariance risk with quarterly data

This table reports the risk premia ($\hat{\gamma}_{liq}$) and prices of covariance risk ($\hat{\lambda}_{liq}$) of the mimicking liquidity factors by conducting other model specifications and test portfolios. In Panels A and C, I incorporate the consumption-to-wealth ratio (cay) and durable consumption growth (cgd) into my model. In Panel B, I replace the consumption growth of nondurable goods and services with the long run consumption growth ($cg11$). In Panel D, I augment the 25 Fama-French equally-weighted size and book-to-market classified portfolios with the 5 equally-weighted industry portfolios.
I present the estimated risk premium and price of covariance risk using both the ordinary least squares (OLS) and generalized least squares (GLS) regressions. The estimated coefficients are in percentage form. I report the following t-ratios: the FM t-ratio of Fama and MacBeth (1973), the SH t-ratio of Shanken (1992) with errors-in-variables adjustment, the JW t-ratio of Jagannathan and Wang (1996), and the KRS t-ratio of Kan, Robotti, and Shanken (2013) t-ratio under potentially misspecified models. The construction of the mimicking liquidity factor is described in Table 5.7. The 1%, 5%, and 10% significance levels are denoted with ***, **, and *, respectively.

	OLS		GLS		OLS		GLS	
	$\hat{\gamma}_{liq}$	$\hat{\lambda}_{liq}$	$\hat{\gamma}_{liq}$	$\hat{\lambda}_{liq}$	$\hat{\gamma}_{liq}$	$\hat{\lambda}_{liq}$	$\hat{\gamma}_{liq}$	$\hat{\lambda}_{liq}$
	Panel A: cay				Panel B: $cg11$			
	DV as a measure of liquidity							
Estimates	1.51	391.84	1.79	473.75	1.56	366.97	1.79	496.37
FM t-ratio	3.26***	3.22***	4.09***	4.06***	3.48***	2.81***	4.12***	4.10***
SH t-ratio	2.98***	2.33**	4.05***	3.67***	3.40***	2.44**	4.09***	3.76***
JW t-ratio	2.89***	2.68***	4.14***	4.09***	3.54***	2.80***	4.25***	4.07***
KRS t-ratio	2.72***	2.14**	3.87***	3.81***	3.37***	1.89*	4.10***	3.58***
	$P0R$ as a measure of liquidity							
Estimates	2.00	459.68	2.59	554.79	2.33	466.67	2.69	602.12
FM t-ratio	3.49***	3.59***	4.84***	4.68***	4.18***	3.41***	5.07***	4.83***
SH t-ratio	3.07***	2.69***	4.71***	4.16***	4.05***	3.09***	4.93***	4.25***
JW t-ratio	3.00***	3.06***	4.85***	4.65***	4.10***	3.28***	5.16***	4.44***
KRS t-ratio	2.71***	2.36**	4.32***	4.27***	3.46***	2.18**	4.61***	3.81***
	RV as a measure of liquidity							
Estimates	1.30	352.43	1.68	415.66	1.35	318.89	1.67	427.93
FM t-ratio	2.65***	3.19***	3.56***	3.90***	2.80***	2.73***	3.56***	3.90***
SH t-ratio	2.47**	2.26**	3.53***	3.53***	2.74***	2.33**	3.54***	3.60***
JW t-ratio	2.39**	2.59***	3.58***	3.91***	2.79***	2.68***	3.62***	3.93***
KRS t-ratio	2.34**	2.09**	3.45***	3.65***	2.77***	1.83*	3.55***	3.47***
	LM as a measure of liquidity							
Estimates	2.76	1980.94	2.15	1423.96	3.01	2234.91	2.18	1494.10
FM t-ratio	4.90***	4.29***	4.52***	4.62***	5.42***	5.48***	4.56***	4.81***
SH t-ratio	4.08***	3.22***	4.18***	3.86***	4.37***	3.88***	4.19***	3.96***
JW t-ratio	4.17***	3.11***	4.25***	3.70***	4.21***	3.34***	4.20***	3.51***
KRS t-ratio	3.83***	2.41**	4.03***	3.22***	3.94***	3.21***	3.89***	3.25***

[Cont.]

(continued)

	OLS		GLS		OLS		GLS	
	$\hat{\gamma}_{liq}$	$\hat{\lambda}_{liq}$	$\hat{\gamma}_{liq}$	$\hat{\lambda}_{liq}$	$\hat{\gamma}_{liq}$	$\hat{\lambda}_{liq}$	$\hat{\gamma}_{liq}$	$\hat{\lambda}_{liq}$
	Panel C: *cgd*				Panel D: FF25+5 industry			
	DV as a measure of liquidity							
Estimates	1.68	498.65	1.82	511.31	1.41	414.22	1.52	412.00
FM t-ratio	3.77***	3.82***	4.19***	4.12***	3.15***	3.49***	3.52***	3.62***
SH t-ratio	3.48***	2.65***	4.14***	3.64***	3.12***	3.2***2	3.50***	3.38***
JW t-ratio	3.41***	2.73***	4.23***	3.89***	3.24***	3.51***	3.61***	3.72***
KRS t-ratio	3.32***	2.20***	4.10***	3.43***	2.60***	2.26**	2.79***	3.25***
	P0R as a measure of liquidity							
Estimates	2.58	541.05	2.70	578.86	2.01	476.96	2.15	453.59
FM t-ratio	4.70***	4.11***	5.09***	4.70***	3.70***	3.90***	4.17***	4.01***
SH t-ratio	4.32***	3.24***	4.94***	4.12***	3.54***	3.35***	4.11***	3.69***
JW t-ratio	4.29***	3.65***	5.14***	4.68***	3.77***	3.82***	4.30***	4.20***
KRS t-ratio	4.09***	3.00***	4.73***	4.22***	3.42***	2.53**	3.69***	3.80***
	RV as a measure of liquidity							
Estimates	1.42	444.30	1.70	443.02	1.26	368.68	1.36	348.76
FM t-ratio	2.94***	3.75***	3.60***	3.94***	2.63***	3.39***	2.90***	3.35***
SH t-ratio	2.76***	2.56**	3.57***	3.49***	2.61***	3.15***	2.89***	3.15***
JW t-ratio	2.70***	2.62***	3.62***	3.70***	2.65***	3.39***	2.93***	3.41***
KRS t-ratio	2.66***	2.10**	3.57***	3.23***	2.60***	2.26**	2.79***	3.25***
	LM as a measure of liquidity							
Estimates	2.95	2339.62	2.21	1565.31	2.21	1905.43	1.60	1003.51
FM t-ratio	5.27***	5.52***	4.63***	4.75***	3.99***	4.70***	3.54***	3.60***
SH t-ratio	4.18***	3.84***	4.23***	3.89***	3.24***	3.39***	3.41***	3.25***
JW t-ratio	4.14***	3.52***	4.16***	3.76***	3.63***	3.39***	3.45***	3.31***
KRS t-ratio	4.03***	3.32***	3.80***	7.17***	3.25***	3.02***	2.97***	2.12**

Table 5.12: Robustness on cross-sectional R^2 and HJ distance with quarterly data

This table reports the test of equality of cross-sectional R^2 and the test of equality of HJ distance by conducting other model specifications and test portfolios. In Panels A and C, I incorporate the consumption-to-wealth ratio (cay) and durable consumption growth (cgd) into my model. In Panel B, I replace the consumption growth of nondurable goods and services with the long run consumption growth ($cg11$). In Panel D, I augment the 25 Fama-French equally-weighted size and book-to-market classified portfolios with the 5 equally-weighted industry portfolios.
dR^2 is the R^2 of the liquidity-augmented model (with different specifications in Panels A, B, C, and D) minus that of Epstein and Zin's model (with different specifications in Panels A, B, C, and D). $p(dR^2)$ (in parentheses) calculated under potentially misspecified models is associated with the hypothesis that the cross-sectional R^2 of two competing models are equal. dHJ is the squared HJ distance of Epstein and Zin's model (with different specifications in Panels A, B, C, and D) minus that of the liquidity-augmented model (with different specifications in Panels A, B, C, and D). $p(dHJ)$ (in parentheses) calculated under potentially misspecified models is associated with the hypothesis that the squared HJ distances of two competing models are equal. I present results using both the ordinary least squares (OLS) and generalized least squares (GLS) estimates. I calculate the covariance matrices using the Newey-West (1987) estimator with two lags to take into account heteroscedasticity and autocorrelation. The construction of the mimicking liquidity factor is described in Table 5.7. The 1%, 5%, and 10% significance levels are denoted with ***, **, and *, respectively.

Panel A: cay			Panel B: $cg11$			Panel C: cgd			Panel D: FF25+5 industry		
OLS	GLS	HJ	OLS	GLS	HJ	OLS	GLS	HJ	OLS	GLS	HJ
dR^2	dR^2	dHJ	dR^2	dR^2	dHJ	dR^2	dR^2	dHJ	dR^2	dR^2	dHJ
$p(dR^2)$	$p(dR^2)$	$p(dHJ)$	$p(dR^2)$	$p(dR^2)$	$p(dHJ)$	$p(dR^2)$	$p(dR^2)$	$p(dHJ)$	$p(dR^2)$	$p(dR^2)$	$p(dHJ)$
DV as a measure of liquidity											
0.193**	0.187***	0.057***	0.086**	0.190***	0.038***	0.156**	0.193***	0.035**	0.286***	0.087***	0.038***
(0.030)	(0.000)	(0.003)	(0.049)	(0.000)	(0.003)	(0.030)	(0.000)	(0.011)	(0.010)	(0.000)	(0.002)
$P0R$ as a measure of liquidity											
0.224**	0.249***	0.093***	0.113**	0.264***	0.067***	0.174***	0.251***	0.068***	0.344***	0.107***	0.061***
(0.024)	(0.000)	(0.000)	(0.024)	(0.000)	(0.001)	(0.006)	(0.000)	(0.001)	(0.008)	(0.000)	(0.000)
RV as a measure of liquidity											
0.189**	0.173***	0.049***	0.081*	0.173***	0.030***	0.150**	0.176***	0.028**	0.269**	0.074***	0.027***
(0.033)	(0.000)	(0.008)	(0.059)	(0.000)	(0.007)	(0.037)	(0.001)	(0.011)	(0.015)	(0.001)	(0.009)
LM as a measure of liquidity											
0.246**	0.242***	0.149***	0.173***	0.263***	0.154***	0.223***	0.256***	0.158***	0.396***	0.086*	0.124***
(0.015)	(0.001)	(0.000)	(0.001)	(0.001)	(0.000)	(0.002)	(0.001)	(0.000)	(0.001)	(0.051)	(0.002)

Table 5.13: Portfolio characteristics and conditional variables with quarterly data

This table reports Fama-MacBeth cross-sectional regressions on the liquidity-augmented model by taking into account portfolio characteristics and conditional variables. In Panels A and B, I accommodate portfolio size and book-to-market ratio after log transformation in the second-stage of the cross-sectional regressions. Specifically, I run the regressions on the following equation,

$$R_{i,t} - R_{f,t} = \gamma_0 + \gamma_{cg}\beta_{cg} + \gamma_{mkt}\beta_{mkt} + \gamma_{liq}\beta_{liq} + \gamma_Z Z + \varepsilon_{i,t},$$

where β_{cg} denotes the consumption beta, β_{mkt} denotes the market beta, and β_{liq} denotes the liquidity beta, and Z denotes the log of portfolio characteristic (size ($ln(Size)$) in Panel A and book-to-market ratio ($ln(B/M)$) in Panel B). The risk loadings are estimated from a single multiple time-series regression for each portfolio using the entire sample.

In Panels C and D, I augment the liquidity-augmented model with one-period lagged RF or $JUNK$. RF denotes the 1-month Treasure bill yield. $JUNK$ denotes the difference between Moody's Baa and Aaa corporate bond yields. These values are compounded to quarterly values. Specifically, I run the regressions on the following equation,

$$R_{i,t} - R_{f,t} = \gamma_0 + \gamma_{cg}\beta_{cg} + \gamma_{mkt}\beta_{mkt} + \gamma_{liq}\beta_{liq} + \gamma_\delta \delta + \varepsilon_{i,t},$$

where β_{cg} denotes the consumption beta, β_{mkt} denotes the market beta, β_{liq} denotes the liquidity beta. The loadings on cg, mkt, and liq are estimated from a single multiple time-series regression for each portfolio using the entire sample. δ denotes the loading on one-period lagged RF (Panel C) or $JUNK$ (Panel D), estimated from a univariate time-series regression for each portfolio using the entire sample.

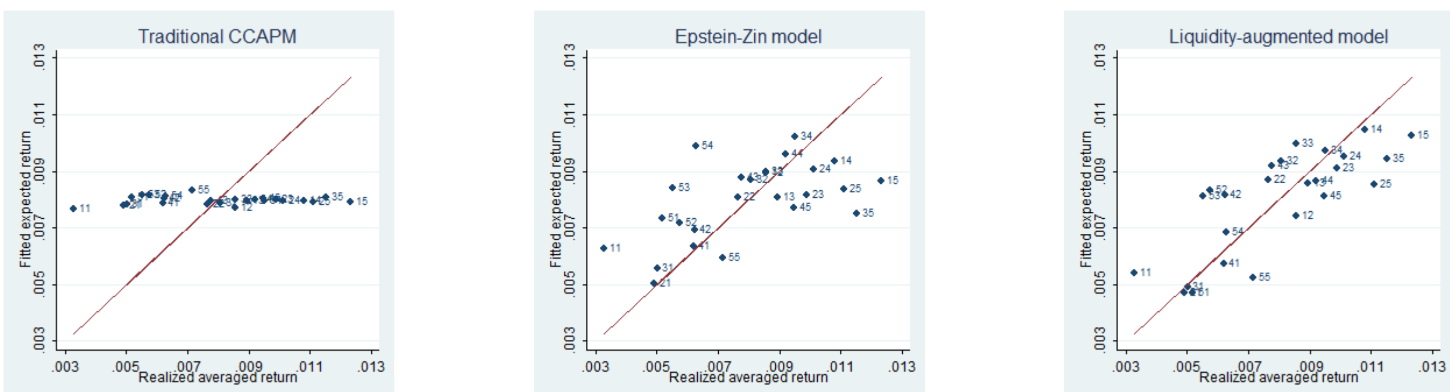
I present results using the ordinary least squares (OLS) regressions. The estimated coefficients are in percentage form. The FM t-ratio represents the Fama-Macbeth estimate. The SH t-ratio represents the Shanken (1992) t-ratio. The construction of the mimicking liquidity factor is described in Table 5.7. The 1%, 5%, and 10% significance levels are denoted with ***, **, and *, respectively.

	$\hat{\gamma}_{liq}$	$\hat{\gamma}_{ln(Size)}$	$\hat{\gamma}_{liq}$	$\hat{\gamma}_{ln(BM)}$	$\hat{\gamma}_{liq}$	$\hat{\gamma}_{RF}$	$\hat{\gamma}_{liq}$	$\hat{\gamma}_{JUNK}$
	DV as a measure of liquidity							
Estimates	0.76	-0.23	1.18	0.50	1.90	0.57	0.71	1.57
FM t-ratio	1.07	-1.70*	2.40**	1.89*	4.19***	2.48**	1.37	2.95***
SH t-ratio	0.98	-1.23	2.37**	1.82*	3.71***	1.62	1.06	1.82*
	$P0R$ as a measure of liquidity							
Estimates	1.58	-0.17	1.77	0.34	2.47	0.71	1.38	1.42
FM t-ratio	2.06**	-1.43	2.56**	1.15	4.53***	3.21***	2.32**	2.85***
SH t-ratio	1.86*	-1.23	2.50**	1.10	3.58***	1.93*	1.83*	1.90*
	RV as a measure of liquidity							
Estimates	0.42	-0.24	1.08	0.51	1.87	0.57	0.34	1.63
FM t-ratio	0.55	-1.82*	2.11**	1.91*	3.66***	2.49**	0.58	3.05***
SH t-ratio	0.45	-1.39	2.09**	1.82*	3.17***	1.61	0.44	1.85*
	LM as a measure of liquidity							
Estimates	2.47	-0.13	1.97	0.42	2.66	0.07	2.43	1.03
FM t-ratio	4.39***	-1.45	3.28***	1.59	4.00***	0.29	4.69***	1.97**
SH t-ratio	3.94***	-1.23	2.69***	1.21	3.28***	0.23	3.96***	1.53

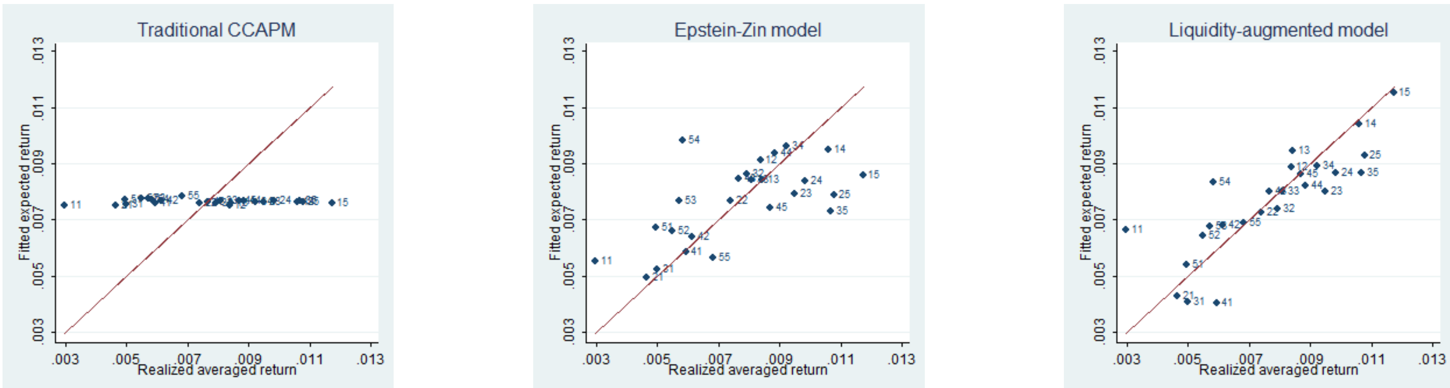
Figure 5.1: Fitted versus realized returns

These figures plot the fitted returns versus realized returns using the OLS estimates. The horizonal axis shows the realized average portfolio return and the vertical axis shows the portfolio return fitted by different models. The straight line is the 45-degree line from the origin. Test portfolios are the 25 Fama-French value-weighted size and book-to-market portfolios. The realized average returns are the time-series average returns. The fitted expected returns for the traditional CCAPM are calculated with $E[R_{i,\,t}] = \gamma_0 + \gamma_{cg}\beta_{i,cg}$. The fitted expected returns for the Epstein-Zin model are calculated with $E[R_i] = \gamma_0 + \gamma_{cg}\beta_{i,cg} + \gamma_{mkt}\beta_{i,mkt}$. The fitted expected returns for the liquidity-augmented model are calculated with $E[R_i] = \gamma_0 + \gamma_{cg}\beta_{i,cg} + \gamma_{mkt}\beta_{i,mkt} + \gamma_{liq}\beta_{i,liq}$. The consumption betas, market betas, and liquidity betas are estimated from a single multiple time-series regression for each portfolio using the entire sample. Each two-digit number in the figure indicates one portfolio. The first digit denotes the size quintile (1 representing the smallest and 5 the largest), and the second digit denotes the book-to-market quintile (1 representing the lowest and 5 the highest). I use three alternative liquidity risk factors: the aggregate liquidity innovation of Pastor and Stambaugh (2003) from 1962 to 2009 in Panel A, Liu's (2006) mimicking liquidity risk factor from 1959 to 2009 in Panel B, and Sadka's (2006) aggregate liquidity innovation based on the variable component of price impact from 1983 to 2009 in Panel C.

Panel A: Pastor and Stambaugh (2003) liquidity factor



Panel B: Liu (2006) liquidity factor



Panel C: Sadka (2006) liquidity factor

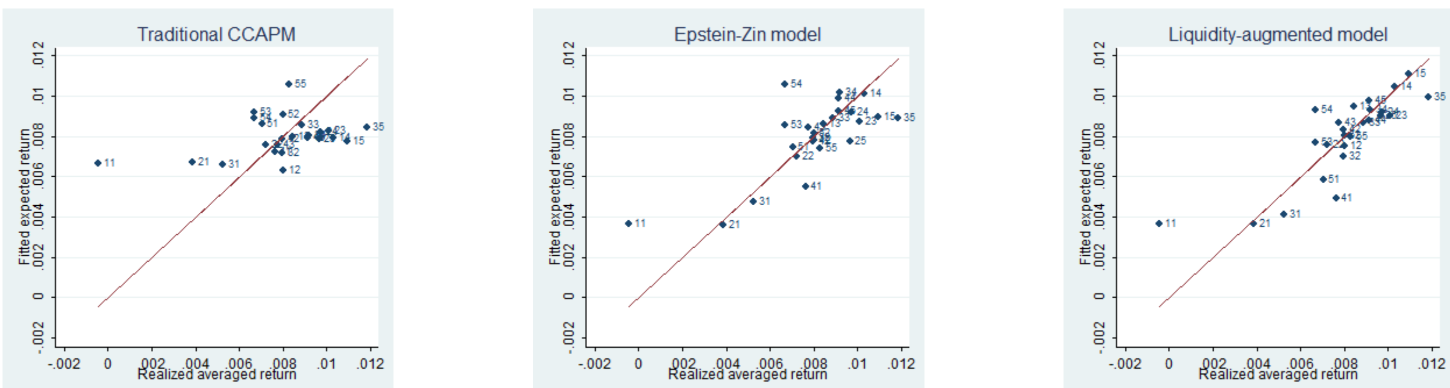
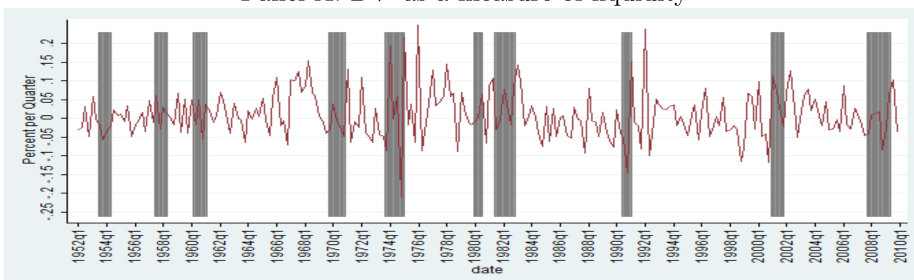


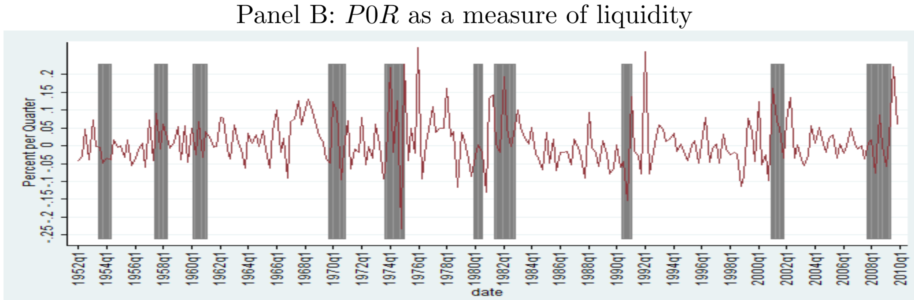
Figure 5.2: Time series plots of mimicking liquidity factors

These figures are the time-series plots of the four mimicking liquidity factors (liq^{DV}, liq^{P0R}, liq^{RV}, and liq^{LM}). They are constructed from the dollar volume measure, DV, in Panel A, the proportion of daily zero returns measure, $P0R$, in Panel B, the absolute return-to-dollar-volume ratio measure, RV, in Panel C, and the standardized turnover-adjusted number of zero daily trading volumes measure, LM, in Panel D. The shaded regions are recessions defined by the National Bureau of Economic Research (NBER). The construction of the mimicking liquidity factor is described in Table 5.7.

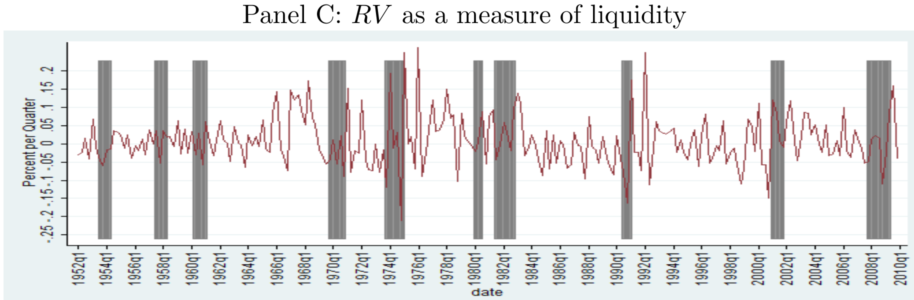
Panel A: DV as a measure of liquidity



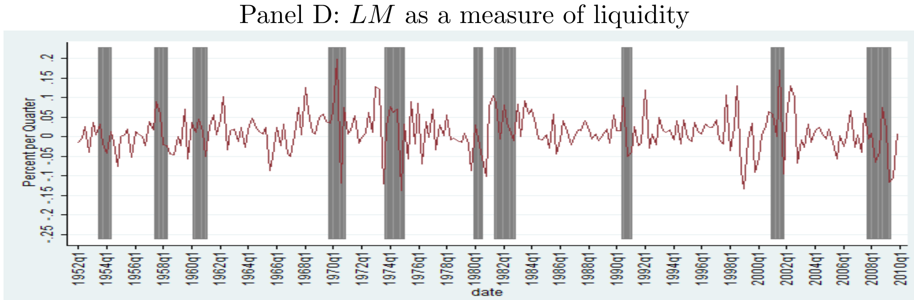
Panel B: $P0R$ as a measure of liquidity



Panel C: RV as a measure of liquidity



Panel D: LM as a measure of liquidity



Chapter 6

Financial Constraints, Stock Liquidity, and Stock Returns

6.1 Introduction

The relation between financial constraints and stock returns has received increasing attention in the financial literature and the empirical findings appear to be mixed. For example, Lamont, Polk, and Saa-Requejo (2001) find that financially constrained firms generate lower returns than unconstrained firms. On the contrary, Whited and Wu (2006), Livdan, Sapriza, and Zhang (2009), and Li (2011) report that financially constrained firms are more risky and earn higher returns. By definition, financial constraints mean the inability of a firm to access to low-cost external finance to fund investment due to financial frictions (Lamont, Polk, and Saa-Requejo, 2001). Hahn and Lee (2009) provide evidence that debt capacity is a significant determinant of the cross-section of stock returns for financially constrained firms, but it is insignificant for unconstrained firms. Equity finance as another source of external finance, Li and Zhang (2010) and Lam and Wei (2011) find that investment frictions measured by financial constraints are highly related to stock markets trading frictions. They use bid-ask spread, price impact, and dollar trading volume as the proxies for trading frictions. They are also the most widely used measures of stock liquidity. However, to my knowledge, none of existing studies explore the role of liquidity in determining the cross-section of stock returns of financially constrained and unconstrained firms. To fill this gap, this study examines the impact of stock liquidity on the stock returns across financially constrained and unconstrained firms. It also investigate the possible reasons for the mixed relation between financial constraint and stock returns in existing studies.

I hypothesize that liquidity has different impacts on the cross-section of stock returns between financially constrained and unconstrained firms. Specifically, I expect that financially constrained firms earn high returns because they have low liquidity and high liquidity risk, namely, high transaction costs and low trading quantities; while unconstrained firms yield low returns since they have high liquidity and low liquidity risk, that is, low transaction costs and high trading quantities. Moreover, the stock returns of financially constrained firms are highly sensitive to liquidity, but those of unconstrained firms are less sensitive to liquidity.

Three strands of the literature provide motivations for my hypotheses. First, early studies of Akerlof (1970), Myers and Majluf (1984), and Greenwald, Stiglitz, and Weiss (1984) show that asymmetric information can increase the cost of external funds since potential buyers with limited information are unwilling to pay high price. Fazzari, Hubbard, and Petersen (1988) and Morellec and Schürhoff (2011) extend these studies and demonstrate that the effects of information asymmetry are even stronger for financially constrained firms than unconstrained firms. Second, the relations between asymmetric information, asset prices and liquidity have been extensively studied. On the one hand, several models have been developed to capture the impact of asymmetric information on asset prices.[1] They show that investors require a higher return for holding stocks with more private information. Kelly and Ljungqvist (2012) further report that liquidity is the major link between information asymmetry and share prices. On the other hand, a group of studies suggests that asymmetric information in the marketplace can lead to high liquidity costs due to the adverse selection costs, which can be captured by price impact and trading volume.[2] In particular, Diamond and Verrecchia (1991) theoretically show that disclosing information to public can reduce information asymmetry and attract more demand from institutional investors, thereby increasing a security's liquidity and mitigating the firm's cost of capital. Empirically, Ng (2011), Lang and Maffett (2011), and Sadka (2011) provide evidence that firms with higher information quality experience lower liquidity risk, which, in turn, leads to a lower cost of capital. Finally, a large body of literature reports that investors require a premium to compensate for holding illiquid

[1]Related papers include Grossman and Stiglitz (1980), Admati (1985), Wang (1993), Easley, Hvidkjær and O'Hara (2002), Easley and O'Hara (2004), and Gârleanu and Pedersen (2004).

[2]See, for example, Glosten and Milgrom (1985), Kyle (1985), Easley and O'Hara (1987), Glosten and Harris (1988), Admati and Pfeiderer (1988), and Brennan and Subrahmanyan (1995).

securities. Amihud and Mendelson (1986) and Brenna and Subrahmanyam (1996) find that stocks with large bid-ask spreads or high price impacts yield high returns. Acharya and Pedersen (2005) argue that asset prices are not only affected by liquidity level, but also affected by three forms of liquidity risks, including: commonality in liquidity, stock return sensitivity to the market liquidity, and stock liquidity sensitivity to market returns. Further, Li and Zhang (2010) and Lam and Wei (2011) argue that investment frictions (e.g., asset size proxy) from firms' side and transaction frictions (e.g., trading volumes proxy) from investors' side are less likely to mutually exclusive. When the economy is haunted by uncertainties, squeezing market liquidity, firms are more difficult to raise funds and thus more likely to be financially constraints. Similarly, holding everything else constant, more financially constrained firms are less liquid since investors are less interested in holding these firms' shares (Liu (2006)).

Intuitionally, financially constrained firms are likely to be small and illiquid firms with higher asymmetric information; their prices are very sensitive to their information quality because higher asymmetric information can make financially constrained firms less attractive in the market, and results to lower demand and higher liquidity risk. Therefore, investors require a premium to compensate for holding financially constrained firms. On the other hand, unconstrained firms are likely to be large and liquid firms with less asymmetric information; as a result, their liquidity and liquidity risk have less impact on their returns.

In this chapter, I use four proxies for financial constraints, including asset size, dividend payout ratio, bond rating, and commercial paper rating.[3] Firms with small asset, low payout ratios and unrated long-term and short-term public debts are classified as financially constrained firms. While firms with big asset, high payout ratios and rated long-term and short-term public debts are classified as unconstrained firms. I compute three liquidity measures: bid-ask spread (Amihud and Mendelson 1986), return-to-volume ratio (price impact measure, Amihud 2002), and turnover (Datar, Naik, and Radcliffe 1998). Stocks with high bid-ask spread, high return-to-volume ratio, and low turnover are less liquid than stocks with low bid-ask spread, low return-to-volume ratio and high turnover. Following Ng (2011), I also estimate the information quality measures using earnings precision and accruals quality to capture information asymmetry.

Consistent with my conjectures, I find that financial constraints are highly correlated with information quality, liquidity, and liquidity risk. Specifically, financially constrained firms are typical of small firms with lower information quality and higher liquidity risk. They are traded on the market with high transaction costs, large price impacts, and low trading quantities. On the contrary, unconstrained firms are large firms with higher information quality, higher liquidity, and lower liquidity risk. In line with Almeida, Campello, and Weisbach (2004), Faulkender and Wang (2006), and Denis and Sibilkov (2010), I find that financially constrained firms have more investment opportunities and hold higher level of cash. The possible reason for this finding

[3]I also computed other two financial constraints measures: Whited-Wu (WW) index of and SA index of Hadlock and Pierce (2010). The results were even stronger than above four financial constraints measures. As WW index and SA index are highly correlated to asset size, I therefore did not report them.

is because external financing is costly for financially constrained firms; therefore, they are more likely to rely on internal funds. This appears to support the prediction of Myers and Majluf (1984). While unconstrained firms are profitable firms with more tangible assets, less investment opportunities, and tend to have higher leverage, suggesting that unconstrained firms face less costs of financial distress and borrow more debt to exploit the benefit of tax on interest payments. This is consistent with the prediction of the trade-off model.

Using the Fama and MacBeth (1973) cross-sectional regression, I find that the average coefficients of liquidity measures are significant for financially constrained firms even after controlling for size, book-to-market ratio, and momentum effects, whereas they are insignificant for unconstrained firms. The results are robust to the estimates across the four financial constraints classification criteria under the three stock liquidity measures. In addition, they are also robust to the estimates using the Litzenberger and Ramaswamy (1979) cross-sectional regression.

I further investigate whether the strong positive relation between liquidity and returns of constrained firms is due to liquidity risk. Chordia, Roll, and Subrahmanyam (2000) argue that individual trading costs, trading volume, and other liquidity measures are likely to co-move each other, which is defined as commonality in liquidity. Following their study, I examine commonality in liquidity across the financially constrained and unconstrained groups. Liquidities of both individual stocks and portfolios of financially constrained and unconstrained firms exhibit strong co-movements with market liquidity. Moreover, financially constrained firms have greater magnitude of coefficients of commonality in liquidity than unconstrained firms. Chordia, Roll, and Subrahmanyam (2000), Hasbrouck and Seppi (2001), and Acharya and Pedersen (2005) show that commonality in liquidity is associated with systematic liquidity risk. My results indicate that financially constrained firms have higher liquidity risk than unconstrained firms.

Using a two-way portfolio sorts approach based on stock liquidity and financial constraints, I find that holding stock liquidity fixed, constrained-minus-unconstrained portfolios produce the positive Fama and French (1993) abnormal returns in the illiquid groups and the negative abnormal returns in the liquid groups. On the other hand, controlling for financial constraints, the significant liquidity premiums only exist in the constrained groups, and disappear in the unconstrained groups under the most of financial constraints classification criteria and liquidity measures. The results suggest that liquidity premium contains financial constraint premium, but it cannot be subsumed by constraint premium.

This study conducts the first deep examination of the relation between financial constraints and stock liquidity. It highlights the different impacts of stock liquidity on the stock returns between financially constrained and unconstrained firms. My results are consistent with theories of liquidity, information asymmetry, and asset pricing. It also contributes to the financial constraints literature by shedding light on stock liquidity as the main driver of the mixed relation between financial constraints and stock returns in existing studies. I find that constrained firms outperforming unconstrained firms only exists in illiquid stocks, while constrained firms underperforming unconstrained firms concentrates on liquid stocks. In addition, the liquidity premium accounts for the positive constraint premium, but it cannot be subsumed by the constraint premium.

The remainder of this chapter is organized as follows. Section 6.2 describes the data and the measures of financial constraints, liquidity, and information quality employed in this study. Section 6.3 presents the empirical results. Section 6.4 concludes the chapter.

6.2 Data

My sample consists of manufacturing firms (SIC codes between 2000 and 3999) traded on the NYSE, AMEX, and NASDAQ for the period 1974 to 2011. Firm-level accounting data comes from the COMPUSTAT annual files. Calomiris, Himmelberg, and Wachtel (1995) argue that for the commercial paper criterion only the highest quality manufacturing companies obtain access to this market. Moreover, Gilchrist and Himmelberg (1995) argue that manufacturing firms are mainly large firms and linear investment models are less likely to be inadequate. Using the sample of manufacturing firms is also consistent with Lamont, Polk, and Saa-Requejo (2001), Almeida, Campello, and Weisbach (2004), Almeida and Campello (2007), and Hahn and Lee (2009). I use Standard & Poor's ($S\&P$) Long-Term and Short-Term Domestic Issuer Credit Ratings as bond rating and commercial paper rating. Following Hahn and Lee

(2009), the sample of bond and commercial paper ratings begins from 1985. Monthly stock returns and daily data for the estimation of stock liquidity, including stock prices, returns and trading volume are obtained from Center for Research in Security Prices (CRSP). The CRSP delisting returns have been adjusted into my dataset. The monthly return series of Fama-French three factors, including size, book-to-market, and market excess returns, and risk-free rates are from Kenneth French's website.[4]

6.2.1 The financial constraints measures

I use the following four measures to proxy for financial constraints:

(i) Asset size (AT): Small firms are likely to have higher expected costs of financial distress, agency costs and information asymmetry than large firms. Therefore, they should have more difficulty in raising external capital. I measure asset size as the book values of total assets (data item AT). Following a number of existing studies,[5] at the end of June of each year t, I rank all firms into terciles based on their asset size for the fiscal year ending in calendar year $t-1$. I then classify the bottom tercile of the asset size distribution as financially constrained firms and the top tercile as unconstrained firms.

(ii) Payout ratio (PR): Fazzari, Hubbard, and Petersen (1988) show that financially constrained firms pay low dividend. This is due to the fact that dividends and investment use funds competitively and constrained firms cannot produce

[4] http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/.

[5] See for example, Gertler and Gilchrist (1994), Gilchrist and Himmelberg (1995), Erickson and Whited (2000), Almeida, Campello, and Weisbach (2004), Faulkender and Wang (2006), Hahn and Lee (2009), Almeida and Campello (2007), and Li and Zhang (2010).

sufficient internal cash flow to meet their requirements of investment. Hence, they pay low dividend in order to allocate more fund on investment. I use the payout ratio as another measure of financial constraints,[6] which is defined as the ratio of total distributions including dividends paid to preferred stocks (data item DVP), common stocks (data item DVC), and share repurchases (data item $PRSTKC$) divided by operating income before depreciation (data item $OIBDP$).[7] At the end of June of each year t, I rank all firms into terciles by their payout ratios for the fiscal year ending in calendar year $t-1$. I then classify the bottom tercile of the payout distribution as financially constrained firms and the top tercile as financially unconstrained firms.

(iii) Long-term bond rating (BR): Firms with a long-term bond rating can issue public debt and have better access to debt capital, while firms without a rating are unable to access public debt because of their high default risk. As a result, firms with the bond rating face less financial constraints than those without the rating. Following Whited (1992), Kashyap, Lamont, and Stein (1994) and others,[8] I classify firms that have positive debt but without a $S\&P$ long-term bond rating during my sample period as financially constrained firms, and firms that have positive debt with a $S\&P$ long-term bond rating as financially un-

[6]It is also extensively used to proxy for financial constraints by Fazzari, Hubbard, and Petersen (1988), Almeida, Campello, and Weisbach (2004), Faulkender and Wang (2006), Almeida and Campello (2007), Hahn and Lee (2009), and Li and Zhang (2010).

[7]Following Hahn and Lee (2009), when sorting firms based on the payout ratio, I exclude firms with zero payout or negative net income. Then I assign those firms with zero payout or negative net income to the constrained firms.

[8]See for example, Gilchrist and Himmelberg (1995), Almeida, Campello, and Weisbach (2004), Faulkender and Wang (2006), Hahn and Lee (2009), Almeida and Campello (2007), and Li and Zhang (2010).

constrained firms. I then assign the BR equal to one for constrained firms and equal to zero for unconstrained firms.

(iv) Commercial paper rating (CR): Similar to long-term bond rating, firms without a commercial paper rating have higher probability of default than firms with a commercial paper rating, and should face more constraints when they raise external capital.[9] I classify firms that have positive debt but without a $S\&P$ commercial paper rating during my sample period as financially constrained firms, and firms that have positive debt with a $S\&P$ commercial paper rating as financially unconstrained firms. I then assign the CR equal to one for constrained firms and equal to zero for unconstrained firms.

6.2.2 The stock liquidity measures

I use the daily quoted bid-ask spread of Amihud and Mendelson (1986), the price impact of Amihud (2002), and the turnover of Datar, Naik, and Radcliffe (1998) to measure stock liquidity and calculate stock liquidity of each measure as the average daily liquidity measure over the prior 12 months.

(i) Quoted bid-ask spread (BA) measures the difference between the quoted ask price and bid price to the mid-quote. Stocks with higher BA have higher transaction costs and are less liquid.

(ii) Price impact (RV) is defined as the daily absolute return-to-dollar-volume ra-

[9] Calomiris, Himmelberg, and Wachtel (1995) use the presence of commercial paper ratings as a proxy for financial constraints.

tio. It captures the reaction of transaction price to trading volume. Goyenko, Holden, and Trzcinka (2009) report that this liquidity proxy is highly correlated to the price impact measure estimated using high frequency data from the Trade and Quote (TAQ) Database and Securities, Exchange and Commission (SEC) Rule 605. Stocks with higher RV, their transaction prices respond trading volume more and are less liquid.

(iii) Turnover (TO) is the ratio of the number of shares traded to the number of shares outstanding. Turnover captures trading quantity and stocks with higher TO are more liquid.[10]

Table 6.1 provides descriptive statistics and correlations across the measures of financial constraints and stock liquidity. Consistent with Li and Zhang (2010) and Lam and Wei (2011), I find that the stock liquidity measures of bid-ask spread (BA) and price impact (RV) are highly correlated to the proxies of financial constraints. For example, the correlations between bid-ask spread (BA) and asset size (AT), payout ratio (PR), bond rating (BA), and commercial paper rating (CR) are -74.1%, -33.2%, 45.2%, and 38.9%, respectively. Furthermore, asset size (AT) and payout ratio (PR) are negatively correlated with bid-ask spread and price impact, and positively correlated with turnover. While bond rating (BA) and commercial paper rating (CR) are positively correlated with bid-ask spread and price impact, and negatively correlated with turnover. These suggest that stocks with small asset size, low payout

[10]Similar to Amihud (2002), I calculate RV requiring least 80% non-missing daily trading volumes available in the prior 12 months. In addition, I exclude zero trading volumes over the prior 12 months. To construct of BA and TO, I require no missing daily trading volumes in the prior 12 months.

ratio, and without the bond and commercial ratings are illiquid, namely, trading on these stocks incurs high transaction costs, has large price impacts and less trading quantities.

6.3 Empirical results

6.3.1 Descriptive analysis of the financially constrained and unconstrained firms

Table 6.2 presents summary statistics of various firm characteristics for the financially constrained and unconstrained groups under the four financial constraints classification criteria. The letter U represents the financially unconstrained groups and the letter C represents the constrained groups. The detailed description of firm characteristics is provided in Appendix E. Consistent with Hahn and Lee (2009), Livdan, Sapriza, and Zhang (2009), and Hadlock and Pierce (2010), I find that firms classified as financially constrained are generally small size firms, while firms classified as financially unconstrained are large size firms. Moreover, both constrained and unconstrained firms have similar book-to-market ratios (B/M). In line with a number of studies,[11] I also find that financially constrained firms have high Tobin's Q, low book leverage (BL)), low cash flow ratio (CF) and tend to hold more cash (CH), implying that constrained firms have more investment opportunities, but generate low cash flows from operations and face high difficulty in accessing debt capital, therefore,

[11] See, for example, Fazzari, Hubbard, and Petersen (1988), Almeida, Campello, and Weisbach (2004), Faulkender and Wang (2006), and Denis and Sibilkov (2009).

cash is more valuable for them. This is consistent with prediction of the pecking order theory of Myers and Majluf (1984). On the other hand, unconstrained firms generate high cash flow (CF), have more safe tangible assets (TA) and less investment opportunities (Q), they tend to borrow more debt with high leverage (BL) (except for BL in the unconstrained PR group), implying that unconstrained firms have low costs of financial distress and follow the trade-off theory in making capital structure decision.

The first objective of this chapter is to find information asymmetry, liquidity, and liquidity risk for the financially constrained and unconstrained groups. I use information quality to capture information asymmetry. Following Ng (2011), I calculate earnings precision (EP) and accruals quality (AQ) to proxy for information quality. The detailed constructions of EP and AQ are in Appendix E. EP and AQ measure the volatility of earnings and accruals, respectively. The higher EP and AQ, the lower information quality. Panel A of Table 6.3 shows that firms in the constrained groups have higher earnings precision (EP) and accruals quality (AQ) than those in the unconstrained groups across the four financial constraints classifications criteria, suggesting that financially constrained firms have lower information quality and more asymmetric information than unconstrained firms. This appears to support the findings of Fazzari, Hubbard, and Petersen (1988) and Morellec and Schürhoff (2011). In terms of liquidity, Panel B of Table 6.3 exhibits that financially constrained firms are typical of illiquid stocks with high bid-ask spread (BA) and price impact (RV), and low turnover (TO), while unconstrained firms are liquid stocks with low BA and RV, and high TO (except for TO in the CR and PR groups). For example, the bid-ask spread is 5.7% for financially constrained firms and 1.96% for unconstrained firms under the bond rating classification.

Lang and Maffett (2011), Ng (2011), and Sadka (2011) report that information quality is highly correlated with liquidity risk. I therefore estimate liquidity risk, β_{PS}, from the following equation:

$$R_{i,t}-R_{f,t}=\alpha_i+\beta_{i,MKT}(R_{m,t}-R_{f,t})+s_iSMB_t+h_iHML_t+\beta_{i,PS}LIQ_{PS,t}+\varepsilon_{i,t}, \quad (6.1)$$

where $R_{i,t}$ is the return on stock i at time t. $R_{f,t}$ is the one-month T-bill rate and $R_{m,t}$ is the value-weighted market return on all stocks listed on the NYSE, AMEX, and NASDAQ. SMB_t (Small-Minus-Big), HML_t (High-Minus-Low) and $LIQ_{PS,t}$ are the returns on the mimicking portfolios for capturing size, book-to-market equity effects and the liquidity risk factor of Pastor and Stambaugh (2003).

I also estimate liquidity risk, β_{Sadka}, from the following equation:

$$R_{i,t}-R_{f,t}=\alpha_i+\beta_{i,MKT}(R_{m,t}-R_{f,t})+\beta_{i,Sadka}LIQ_{Sadka,t}+\varepsilon_{i,t}, \quad (6.2)$$

where $LIQ_{Sadka,t}$ denotes Sadka's (2006) aggregate liquidity innovation based on the fixed component of price impact.

Panel C of Table 6.3 reveals that financially constrained firms have higher liquidity risk than unconstrained firms regardless of the financial constraints classification criteria. For instance, $\beta_{i,Sadka}$ and $\beta_{i,PS}$ are 4.52 and 0.04 respectively for financially constrained firms in the AT group, and they are 1.96 and 0.00 respectively for unconstrained firms in the same group.

I also examine raw returns and Fama and French (1993) abnormal returns (FF3 alphas). FF3 alphas are estimated from the Fama and French (1993) three-factor model as follows:

$$R_{i,t} - R_{f,t} = \alpha_i + \beta_{i,MKT}(R_{m,t} - R_{f,t}) + s_i SMB_t + h_i HML_t + \varepsilon_{i,t}. \tag{6.3}$$

Panel D of Table 6.3 reports the results of the average monthly returns for financially constrained and unconstrained firms. I find that the return patterns of the constrained and unconstrained groups vary based on the different financial constraints classification criteria. In the asset size (AT) and payout ratio (PR) groups, constrained firms uniformly outperform unconstrained firms even after controlling for the Fama and French (1993) three factors. For example, constrained AT firms earn an average raw return of 1.64% per month and FF3 alpha of 0.38% per month, while unconstrained AT firms generates an average raw return of 1.3% per month and FF3 alpha of -0.03% per month. This is in line with the findings of Whited and Wu (2006) and Li (2011) that constrained firms earns higher returns than unconstrained firms. However, in the bond rating (BR) and commercial paper rating (CR) groups, my results show that unconstrained firms produce higher returns than constrained firms.

6.3.2 Cross-section regressions

To explore the different impacts of liquidity on stock returns between financially constrained and unconstrained firms, I use the Fama-MacBeth (1973) cross-sectional regression. Fama and French (2008) argue that cross-section regression approach provides more accurate estimates for many explanatory variables than portfolio sorts approach. However, estimates from the regression on all stocks could be driven by a small group of stocks that have extreme explanatory variables and returns. To solve this problem, I split my sample into financially constrained firms and unconstrained firms and run two cross-sectional regressions separately. In my first specification, I use lagged stock liquidity as an explanatory variable and in the second specification, I add the Fama and French (1993) size ($ln(MV)$) and book-to-market ratio ($ln(B/M)$) factors, and the momentum (MOM) factor of Jegadeesh and Titman (1993). $ln(MV)$ is the natural logarithm of market capitalization of equity at the end of June of year t, $ln(B/M)$ is the natural logarithm of the ratio of the book value of equity for the fiscal year ending in year $t-1$ divided by market equity at the end of December of year $t-1$. MOM is the cumulative compounded stock returns of the previous 6 months at the end of May of year t. I use the monthly stock liquidity variable at the end of June in year t to May in year $t+1$ to link the cross-sectional monthly returns for July of year t to June of $t+1$, but update $ln(MV)$, $ln(B/M)$, and MOM variables annually. I calculate the t-statistics with the Newey and West (1987) adjustment.[12]

Panels A, B, C, and D of Table 6.4 report the average slope coefficients of stock liquidity and the control variables for the financially constrained and unconstrained groups under the four financial constraints criteria. I find that stock liquidity is a significant explanatory variable of the cross-sectional returns for the financial constrained groups, but it is insignificant for the unconstrained groups. Specifically, in the absence of the control variables of $ln(MV)$, $ln(B/M)$, and MOM, the average slope coefficients are positive for the BA and RV measures and negative for the TO measure in the financially constrained groups regardless of the financial constraints classification criteria. This is consistent with Amihud and Mendelson (1986), Amihud (2002), and Datar, Naik, and Radcliffe (1998). Moreover, all of them are statistically significant at the 5% level. By contrast, in the unconstrained groups, they are statistically insignificant under all of the three stock liquidity measures across the four constraints classifications with only a few exceptions (BA and TO in the CR group and TO in the PR group). For example, in the financially constrained PR group, the average slope coefficients of BA, RV, and TO are 0.079 (t=2.7), 0.032 (t=3.19), and -1.566 (t=-4.3), respectively. While in the unconstrained PR group, the average slope coefficients of BA, RV, and TO are 0.04 (t=1.01), 0.022 (t=1.36), and -0.828 (t=-2.39), respectively.

More importantly, controlling for the $ln(MV)$, $ln(B/M)$, and MOM variables does not largely change the sign and significance (insignificance) of coefficients of

[12] I calculate the t-statistics with the Newey and West (1987) adjustment throughout the chapter.

stock liquidity variables for the financially constrained (unconstrained) groups. For instance, the average slope coefficients of BA, RV, and TO are 0.074, 0.024, and -0.934, with t-statistics of 2.29, 2.88, and -3.48 for the constrained PR group, respectively. While they are 0.03, 0.018, and -0.607 with t-statistics of 0.74, 1.07, and -1.85 for the unconstrained PR group. Interestingly, the coefficients of control variable $ln(B/M)$ are strong and positive for the financially constrained groups across the four financial constraints proxies, but insignificant for the unconstrained BR and CR groups. This indicates that book-to-market equity is another significant determinant of the cross-sectional stock returns of financially constrained firms apart from stock liquidity.

In summary, my results show that stock liquidity has different impacts on the cross-sectional stock returns between financially constrained and unconstrained firms. It is significant for financially constrained firms, but insignificant for financially unconstrained firms, even after controlling for size, book-to-market ratio, and momentum factors.

6.3.3 Robustness tests

To check for the regression results, I use the generalized least squares (GLS) method suggested by Litzenberger and Ramaswamy (1979) to do the robustness test. Specifically, the coefficients γ_k ($k = 0$, 1, 2, 3, 4.) of the independent variables in the Fama and MacBeth (1973) cross-sectional regression have the following form:

$$\tilde{\gamma}_k = \sum_{t=1}^{T} w_{kt}\tilde{\gamma}_{kt}, \tag{6.4}$$

where $\tilde{\gamma}_{kt}$ is the cross-sectional OLS estimate of γ_k in month t, w_{kt} is the weight for $\tilde{\gamma}_{kt}$, and T is the total number of cross-section regressions over the sample period. The variance of $\tilde{\gamma}_k$ is given by the following equation:

$$Var(\tilde{\gamma}_k) = \frac{1}{T(T-1)} \sum_{t=1}^{T} (Tw_{kt}\tilde{\gamma}_{kt} - \tilde{\gamma}_k)^2. \tag{6.5}$$

The Fama and MacBeth (1973) cross-sectional regression estimates coefficients based on the equally-weighted method, i.e., $w_{kt} = 1/T$. While Litzenberger and Ramaswamy (1979) show that an efficient weighting, w_{kt}, can be calculated as $w_{kt} = \frac{1/Var(\tilde{\gamma}_{kt})}{\sum_{t=1}^{T}[1/Var(\tilde{\gamma}_{kt})]}$, where $Var(\tilde{\gamma}_{kt})$ is the variance estimate of $\tilde{\gamma}_{kt}$.

Panels A, B, C, and D of Table 6.5 report the GLS estimates of stock liquidity and the control variables from the Litzenberger and Ramaswamy (1979) cross-sectional regression for the financially constrained and unconstrained groups under the four financial constraints classification criteria. The dependent and independent variables are the same as those in the Fama-MacBeth regression in Table 6.4. Under the efficient weighting method, the results from the Fama-MacBeth regression are robust to those from the Litzenberger and Ramaswamy (1979) cross-sectional regression, which liquidity is the significant determinant of stock returns for financially constrained firms, but insignificant for unconstrained firms regardless of the financial constraints classification criteria.

6.3.4 Liquidity commonality test

My results in Tables 6.4 and 6.5 raise the possibility that the positive relation between liquidity and returns of financially constrained firms might be driven by liquidity risk. An increasing body of work finds that individual stock liquidity co-moves with market liquidity. In addition, stocks whose liquidities are highly sensitive to market liquidity have high systematic liquidity risk and earn high returns.[13] This commonality in liquidity is persistent over time. In this subsection, I explore the difference in liquidity commonality between financially constrained firms and unconstrained firms.

Following Chordia, Roll, and Subrahmanyam (2000), I estimate liquidity commonality from the following time series regression:

$$\Delta LIQ_{i,m} = \alpha + \beta \Delta LIQ_{MKT,m} + \varepsilon_m, \tag{6.6}$$

where $\Delta LIQ_{i,m}$ is the change in a liquidity measure of individual stock or portfolio in the financially unconstrained or constrained groups from month $m-1$ to m. $\Delta LIQ_{MKT,m}$ is the change in the corresponding cross-sectional average of the same liquidity measure of all sample stocks in the corresponding constraints proxy from month $m-1$ to m.

Table 6.6 presents the results of liquidity commonality for the financially constrained and unconstrained groups. Except for the RV measure in the unconstrained CR groups, liquidity commonality is significant and positive at the 5% level under

[13] Related papers include: Chordia, Roll, and Subrahmanyam (2000), Hasbrouck and Seppi (2001), and Acharya and Pedersen (2005).

the BA and TO liquidity measures across the four financial constraints proxies. In particular, financially constrained firms in general have the higher coefficients of commonality in liquidity than unconstrained firms regardless of the liquidity measures. For example, in the constrained AT group, the coefficient under the BA measure is 1.293 (t=8.10) for individual stock and 1.365 (t=4.18) for portfolio; while in the unconstrained AT group, it is 0.331 (t=8.82) for individual stock and 0.399 (t=3.81) for portfolio. Acharya and Pedersen (2005) report that commonality in liquidity is associated with liquidity risk. Whited and Wu (2006), Livdan, Sapriza, and Zhang (2009), and Li (2011) find that financially constrained firms are riskier than unconstrained firms. Thus, my results suggest that the high risk of constrained firms is related to high liquidity risk.

6.3.5 Portfolio return tests

Fama and French (2008) highlight that portfolio sorts approach can simply show the variation of average returns related to another variable. It provides a double check for the estimates from cross-section regression. In order to explore the link between liquidity and financial constraints, I conduct a test using a two-way portfolio sorts approach. Specifically, at the end of June of each year t, I sort stocks into three financial constraints groups, low, median, and high (two groups for BR and CR, low and high) based on their financial constraints proxies for the fiscal year ending in calendar year $t-1$. Within each financial constraints group, I use NYSE breakpoints to sort stocks into two stock liquidity groups based on their one-month lagged stock liquidity measures and hold them for the one subsequent month.[14]

Panels A, B, C, and D of Table 6.7 report the average equal-weighted monthly raw returns and FF3 alphas of portfolios under each of the four financial constraints classifications and the three stock liquidity measures. The letter L stands for liquid portfolio and the letter I stands for illiquid portfolio. I first focus on the difference in returns between constrained and unconstrained portfolios (C-U). Sorting stocks by financial constraints and conditional on stock liquidity, I find that constrained firms generate lower average monthly raw returns than unconstrained firms only in liquid portfolios. While in illiquid portfolios, constrained firms produce higher (lower) average monthly raw returns than unconstrained firms according to the AT and PR (BR and CR) measures. The positive constraints premium is consistent with Whited and Wu (2006). They argue that firms tend to use collateral to borrow capital due to the agency costs. Thus, the value of collateral is related to the firms' ability of financing their investment. When the economy is affected by negative shocks which decrease the value of collateral, financially constrained firms tend to reduce investment more than unconstrained firms. Therefore, financially constrained firms are more risky than unconstrained firms and investors require a premium to hold the stocks of financially constrained firms. On the other hand, the negative constraints premium is in line with Lamont, Polk, and Saa-Requejo (2001). They argue that the negative premium is related to low levels of dividends and low earnings. Further, the

[14] I occasionally find very few firms in some groups. Thus, I sort stocks into two financial constraints groups based on the AT classification with three liquidity measures.

negative premium is consistent with previous studies which find that zero-dividend firms earn negative returns and firms with lower cash flow and earnings have lower returns. My results shed light on the mixed relation between financial constraints and stock returns in previous studies and suggest that the negative relation is driven by liquid stocks and the positive relation is associated with illiquid stocks. More importantly, the results from the Fama and French (1993) three-factor model further confirm this pattern. Specifically, constrained-minus-unconstrained portfolios systematically generate positive FF alphas for illiquid portfolios and negative FF alphas for liquid portfolios regardless of the constraints classifications and the stock liquidity measures. For instance, it is -0.35% (t=-2.38) for liquid portfolio and 0.031% (t=0.16) for illiquid portfolio under the BR financial constraint measure and the BA stock liquidity measure. This suggests that after controlling for the Fama and French (1993) three factors, positive financial constraints premiums only exist in the illiquid groups although they are statistically insignificant, which is in line with the finding of Whited and Wu (2006).

I then look at the liquidity premium (I-L) across the constrained and unconstrained groups. Ranking stocks by liquidity and holding financial constraints fixed, my results exhibit that the monthly raw returns of illiquid-minus-liquid portfolios are positive and significant at the 5% level for the constrained groups, but insignificant for the unconstrained groups under the three liquidity measures with only a few exceptions. For instance, in the constrained PR group, the average monthly raw returns of illiquid-minus-liquid portfolios are 0.388%, 0.564%, and 0.669%, with t-statistics of 2.35, 3.32, and 3.51 for the BA, RV, and TO measures, respectively. However, in the unconstrained PR group, they are 0.119%, 0.178%, and 0.12%, with t-statistics of 0.96, 1.23, and 1.18, respectively. Similar to the raw returns, FF3 alphas of illiquid-minus-liquid portfolios further prove that they are significant for the constrained groups except for the BA measure in the constrained CR group, but insignificant for the unconstrained groups, suggesting that financial constraint and illiquidity are highly correlated each other, and the liquidity premium is much stronger than the financial constraint premium.

Overall, I find that stock liquidity is a main driver of the different relations between financial constraints and stock returns. The positive relation only can be observed in illiquid stocks and the negative relation concentrates on liquid stocks. Moreover, the strong positive liquidity premiums are limited to constrained firms, indicating that illiquidity accounts for the relation between financial constraints and future returns, but the liquidity premium cannot be subsumed by the financial constrained premium.

6.4 Conclusion

This chapter investigates the impact of liquidity on the stock returns across financially constrained firms and unconstrained firms. I hypothesize that the stock returns of constrained firms are highly sensitive to stock liquidity because high asymmetric information and low information quality of constrained firms make them less attractive to investors, in turn, leading to high transaction costs and low trading quantity.

On the other hand, stock returns of unconstrained firms are less sensitive to stock liquidity due to their low information asymmetry.

My empirical findings are consistent with the hypotheses. In particular, I find that constrained firms have lower information quality, lower stock liquidity and higher liquidity risk than unconstrained firms. The results from the Fama-MacBeth (1973) and Litzenberger and Ramaswamy (1979) cross-sectional regressions prove that stock liquidity is the important determinant of the cross-sectional stock returns for constrained firms, but it is insignificant for unconstrained firms even after controlling for size, book-to-market ratios, and momentum factors. I also find that constrained firms have higher systematic liquidity risk than unconstrained firms due to their high commonality of liquidity. Holding stock liquidity fixed, I show that the Fama and French (1993) abnormal returns of constrained-minus-unconstrained portfolios are positive but insignificant for illiquid stocks; while they are negative for liquid stocks. Moreover, the abnormal returns of illiquid-minus-liquid portfolios conditional on financial constraints are generally significant for constrained firms, but insignificant for unconstrained firms. In all, this chapter fills the gaps in understanding of the mixed relation between financial constraints and stock returns in previous studies. It highlights the different relation of liquidity on the stock returns for constrained and unconstrained firms.

Table 6.1: Descriptive statistics

This table reports the mean, standard deviation, minimum, maximum, and correlation of the empirical proxies of financial constraints and stock liquidity. I use the following four financial constraints measures: book value of asset (AT), payout ratio (PR), bond rating (BR), and commercial paper rating (CR). I also use the following three stock liquidity measures: quoted bid-ask spread (BA, %), absolute-return-to-dollar-volume ratio (RV, 10^6), and turnover (TO). I report the mean standard deviation and Spearman rank correlations based on the time-series cross-sectional averages.

	AT	PR	BR	CR	BA	RV	TO
Descriptive statistics							
Mean	1298	0.007	0.625	0.860	5.650	7.338	0.485
SD	8668	33.152	0.484	0.347	8.443	61.933	0.719
Min	0.113	-8089	0.000	0.000	0.021	0.000	0.000
Max	479921	758.100	1.000	1.000	189.824	6749.815	34.413
Spearman rank correlation							
PR	0.469	1.000					
BR	-0.670	-0.306	1.000				
CR	-0.534	-0.367	0.519	1.000			
BA	-0.741	-0.332	0.452	0.389	1.000		
RV	-0.817	-0.367	0.570	0.500	0.880	1.0000	
TO	0.306	-0.052	-0.234	-0.135	-0.533	-0.620	1.000

Table 6.2: Firm characteristics across the financially constrained and unconstrained groups

This table reports summary statistics of firm characteristics across the financially constrained groups (C) and unconstrained groups (U) classified by various financial constraints measures. The variables of firm characteristics are the market value (MV, in millions dollar), book-to-market ratios (B/M), cash flow ratios (CF), cash holdings (CH), book leverage (BL), Tobin's Q (Q), tangible asset (TA), and profitability (PF). See the Appendix E for detailed definitions of firm characteristics. I use the following four financial constraints measures: book value of asset (AT), payout ratio (PR), bond rating (BR), and commercial paper rating (CR). At the end of June of each year t, I sort stocks into three financial constraints groups, low, median, and high, (two groups for BR and CR, low and high) and hold them for the subsequent 12 months. All variables of financial constraints are for the fiscal ending in calendar year $t-1$. The reported means are time-series average of the cross-sectional values.

		Financial Constraints Criteria							
		AT		PR		BR		CR	
		U	C	U	C	U	C	U	C
MV	Mean	4196	39	4072	440	4917	200	10856	408
	SD	17631	88	18850	3699	17733	652	27149	1825
	Min	2.08	0.04	0.27	0.04	1.13	0.16	10.89	0.16
	Max	524352	3870	472519	451211	472519	29606	472519	166948
B/M	Mean	0.88	0.95	0.92	1.00	0.75	0.89	0.58	0.90
	SD	1.32	1.20	0.91	1.38	1.12	1.16	0.89	1.30
	Min	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	Max	97.71	27.37	30.57	61.23	27.90	28.27	27.21	97.71
CF	Mean	0.07	-0.13	0.06	-0.03	0.07	-0.03	0.08	-0.01
	SD	0.07	0.48	0.08	0.35	0.10	0.31	0.07	0.30
	Min	-2.73	-24.00	-2.73	-24.00	-3.65	-10.12	-2.68	-11.12
	Max	0.54	1.71	0.60	1.71	0.67	1.69	0.67	1.69
CH	Mean	0.10	0.24	0.14	0.19	0.10	0.18	0.07	0.17
	SD	0.13	0.26	0.15	0.24	0.14	0.23	0.09	0.21
	Min	-0.00	-0.01	-0.00	-0.01	0.00	-0.00	0.00	-0.01
	Max	0.99	1.00	0.99	1.00	0.97	1.00	0.88	0.99
BL	Mean	0.91	0.56	0.46	1.00	0.92	0.63	0.76	0.65
	SD	48.04	14.46	6.63	41.68	40.90	12.45	11.37	27.28
	Min	-1074.19	-1154.83	-580.76	-1096.63	-2618.35	-1154.83	-466.33	-2618.35
	Max	7329.29	1149.33	232.04	7329.29	3096.64	753.73	347.09	3096.64
Q	Mean	1.56	2.76	1.60	2.20	1.74	2.10	1.83	2.03
	SD	1.25	4.85	1.24	3.71	1.48	2.68	1.32	2.64
	Min	0.18	0.09	0.19	0.09	0.25	0.21	0.25	0.21
	Max	45.31	294.34	23.57	294.34	80.96	82.43	39.81	91.44
TA	Mean	0.31	0.21	0.28	0.24	0.30	0.25	0.32	0.25
	SD	0.17	0.16	0.16	0.17	0.16	0.16	0.16	0.16
	Min	0.00	0.00	0.00	0.00	0.00	0.00	0.02	0.00
	Max	0.92	1.00	0.90	1.00	0.88	0.99	0.85	0.99
PF	Mean	0.15	-0.09	0.15	0.01	0.14	0.02	0.16	0.04
	SD	0.08	0.49	0.10	0.36	0.11	0.34	0.08	0.32
	Min	-0.92	-18.87	0.00	-18.87	-3.08	-18.28	-2.65	-18.28
	Max	1.09	1.83	0.98	1.71	1.39	1.70	0.97	1.70

Table 6.3: Liquidity, information quality, and returns across the financially constrained and unconstrained groups

This table reports the average information quality measures in Panel A, the stock liquidity measures in Panel B, liquidity betas in Panel C, and the stock returns in Panel D across the financially constrained groups (C) and unconstrained groups (U) classified by the four financial constraints measures. The information quality measures are earnings precision (EP) and accruals quality (AQ). Earnings precision (EP) is defined as the standard deviation of earnings before extraordinary items (data item IBC) scaled by average total assets over the most recent five years. The detailed estimation of accrual quality (AQ) can be found in Appendix E. The monthly stock liquidity measures are quoted bid-ask spread (BA, %), absolute-return-to-dollar-volume ratio (RV, 10^6), and turnover (TO). β_{PS} and β_{Sadka} are the measures of liquidity risk of Pastor and Stambaugh (2003) and Sadka (2006), respectively. They are the liquidity risk loadings from a single multiple time-series regression of portfolio returns against the market, size, book-to-market, and Pastor and Stambaugh (2003) liquidity factors and on the market and Sadka (2006) liquidity factors. The monthly stock returns are the raw returns and FF3 alphas. FF3 alphas are the intercepts from the Fama and French (1993) three-factor model. I use the following four financial constraints measures: book value of asset (AT), payout ratio (PR), bond rating (BR), and commercial paper rating (CR). At the end of June of each year t, I sort stocks into three financial constraints groups, low, median, and high, (two groups for BR and CR, low and high) and hold them for the subsequent 12 months. All variables of financial constraints are for the fiscal ending in calendar year $t-1$.

	Financial Constraints Criteria							
	AT		PR		BR		CR	
	U	C	U	C	U	C	U	C
Panel A: Information quality								
EP	0.04	0.16	0.04	0.11	0.05	0.11	0.03	0.10
AQ	0.10	0.16	0.11	0.15	0.12	0.15	0.11	0.14
Panel B: Stock liquidity								
BA	1.61	9.43	3.48	6.63	1.96	5.70	0.92	5.07
RV	0.34	18.98	3.01	10.78	0.93	10.35	0.03	8.50
TO	0.51	0.44	0.36	0.52	0.61	0.50	0.49	0.54
Panel C: Liquidity beta								
β_{PS}	0.00	0.04	-0.01	0.00	0.01	0.02	0.02	0.02
β_{Sadka}	1.96	4.52	2.24	3.85	2.06	3.69	0.75	3.53
Panel D: Stock returns								
Raw Returns(%)	1.30	1.64	1.34	1.49	1.39	1.22	1.32	1.29
FF3 alphas(%)	-0.03	0.38	0.12	0.13	0.19	0.17	0.22	0.19

Table 6.4: Average slopes from Fama-MecBeth cross-sectional regressions for the financially constrained and unconstrained groups

For each month from July of year t to June of year $t+1$, I estimate the average slopes from the Fama and MacBeth cross-sectional regressions of the monthly percent excess returns on the liquidity measure (LIQ) or plus the control variables of size ($ln(MV)$), book-to-market ($ln(B/M)$), and momentum (MOM). $ln(MV)$ is the natural logarithm of market capitalization calculated with information available at the end of June of year t, $ln(B/M)$ is the natural logarithm of the ratio of the book value of equity for the fiscal year ending in year $t-1$ divided by market equity at the end of December of year $t-1$, and $MOM_{i,t}$ is the cumulative compounded stock returns of the previous 6 months at the end of May of year t. I use the following four financial constraints measures: book value of asset (AT), payout ratio (PR), bond rating (BR), and commercial paper rating (CR). I also use the following three stock liquidity measures: quoted bid-ask spread (BA, %), absolute-return-to-dollar-volume ratio (RV, 10^6), and turnover (TO). At the end of June of each year t, I sort stocks into three financial constraints groups, low, median, and high (two groups for BR and CR, low and high) and hold them for the subsequent 12 months. All sorting variables related to the financial constraints proxies are for the fiscal ending in calendar year $t-1$. The liquidity measures are winsorized at the top and bottom 1%. The corresponding t-statistics based on Newey and West (1987) standard errors are in parentheses. The 1%, 5%, and 10% significance levels are denoted with ***, **, and *, respectively.

	Constant	LIQ	ln(MV)	ln(B/M)	MOM	Constant	LIQ	ln(MV)	ln(B/M)	MOM
	Panel A: Asset Size (AT)					Panel B: Payout Ratio (PR)				
	BA as a liquidity measure					BA as a liquidity measure				
Unconstrained	0.837***	0.210				0.845***	0.040			
	(3.12)	(1.63)				(3.43)	(1.01)			
	0.978*	0.093	-0.010	0.209***	0.323	0.975***	0.030	-0.032	0.235***	0.384
	(1.71)	(1.22)	(-0.16)	(2.36)	(1.40)	(2.41)	(0.74)	(-0.69)	(2.60)	(1.56)
Constrained	0.237	0.141***				0.597	0.079***			
	(0.48)	(4.35)				(1.48)	(2.70)			
	1.079	0.069	-0.079	0.363***	-0.088	0.833	0.074***	0.005	0.388***	0.064
	(1.44)	(1.58)	(-0.50)	(3.83)	(-0.39)	(1.31)	(2.29)	(0.06)	(4.56)	(0.39)

[Cont.]

(continued)

	TO as a liquidity measure					*TO* as a liquidity measure				
Unconstrained	0.920***	-0.288				1.070***	-0.828**			
	(3.51)	(-1.01)				(4.49)	(-2.39)			
	1.231**	-0.367	-0.052	0.170**	0.359*	1.207***	-0.607*	-0.049	0.150*	0.441*
	(2.38)	(-1.33)	(-1.10)	(2.12)	(1.74)	(3.30)	(-1.85)	(-1.20)	(1.87)	(1.90)
Constrained	1.756***	-1.686***				1.502***	-1.566***			
	(4.36)	(-3.86)				(4.04)	(-4.30)			
	2.670***	-0.896***	-0.370***	0.273***	-0.152	1.888***	-0.934***	-0.120**	0.346***	0.104
	(5.10)	(-2.58)	(-2.90)	(2.79)	(-0.65)	(3.77)	(-3.48)	(-1.95)	(4.27)	(0.62)
	RV as a liquidity measure					*RV* as a liquidity measure				
Unconstrained	0.841***	0.178				0.846***	0.022			
	(2.98)	(1.60)				(3.42)	(1.36)			
	1.198**	0.117	-0.054*	0.159	0.339	1.040***	0.018	-0.037	0.166**	0.412*
	(2.10)	(0.89)	(-1.10)	(1.89)	(1.48)	(2.75)	(1.07)	(-0.94)	(2.01)	(1.68)
Constrained	0.817**	0.043***				0.818**	0.032***			
	(1.90)	(4.26)				(2.15)	(3.19)			
	1.821***	0.024***	-0.239**	0.290***	-0.217	1.302***	0.024***	-0.064	0.350***	0.065
	(3.91)	(2.59)	(-2.13)	(2.76)	(-0.95)	(2.71)	(2.88)	(-1.25)	(3.98)	(0.37)

[Cont.]

(continued)

	Panel C: Bond Rating (BR)					Panel D: Commercial Paper Rating (CR)				
	BA as a liquidity measure					BA as a liquidity measure				
Unconstrained	0.926***	0.141				0.986***	0.282*			
	(2.62)	(1.50)				(3.18)	(1.89)			
	1.275	0.094	-0.048	0.097	0.610**	2.186***	-0.054	-0.220***	-0.047	1.391***
	(1.59)	(1.07)	(-0.65)	(0.94)	(2.19)	(2.68)	(-0.29)	(-2.86)	(-0.35)	(3.54)
Constrained	0.239	0.110**				0.444	0.094**			
	(0.51)	(2.10)				(0.99)	(1.98)			
	0.415	0.098*	0.077	0.428***	-0.038	0.341	0.116**	0.106	0.391***	-0.018
	(0.42)	(1.78)	(0.52)	(4.60)	(-0.19)	(0.38)	(2.27)	(0.85)	(3.99)	(-0.09)
	RV as a liquidity measure					RV as a liquidity measure				
Unconstrained	1.038***	-0.048				0.977***	0.809			
	(2.85)	(-0.56)				(3.21)	(0.67)			
	1.519**	0.020	-0.085	0.053	0.519**	1.686**	2.608	-0.113**	-0.028	0.940***
	(2.05)	(0.21)	(-1.42)	(0.53)	(2.04)	(2.25)	(1.12)	(-1.97)	(-0.23)	(2.71)
Constrained	0.639	0.047***				0.767*	0.037***			
	(1.50)	(3.10)				(1.81)	(2.79)			
	1.290**	0.039***	-0.076	0.375***	-0.051	1.118*	0.039***	-0.026	0.334***	-0.006
	(2.04)	(2.59)	(-1.03)	(3.88)	(-0.25)	(1.88)	(3.08)	(-0.43)	(3.38)	(-0.03)
	TO as a liquidity measure					TO as a liquidity measure				
Unconstrained	0.983***	0.170				0.708***	0.722**			
	(2.89)	(0.65)				(2.84)	(2.52)			
	1.551**	0.194	-0.099	0.081	0.487**	1.573***	0.639**	-0.125**	-0.042	0.820**
	(2.27)	(0.77)	(-1.64)	(0.87)	(2.00)	(2.66)	(2.40)	(-2.49)	(-0.36)	(2.45)
Constrained	1.352***	-1.035***				1.322***	-0.740***			
	(3.26)	(-3.68)				(3.19)	(-2.97)			
	2.021***	-0.515**	-0.178*	0.361***	-0.058	1.849***	-0.320	-0.133*	0.343***	-0.011
	(3.10)	(-2.13)	(-1.89)	(4.49)	(-0.30)	(2.96)	(-1.39)	(-1.65)	(4.07)	(-0.06)

Table 6.5: Robustness tests

This table reports the coefficients of the Litzenberger and Ramaswamy (1979) cross-sectional regressions for the financially unconstrained and constrained groups. I use the generalized least squares (GLS) method suggested by Litzenberger and Ramaswamy (1979), where the coefficients γ_k ($k = 0$, 1, 2, 3, 4.) of the independent variables in the Fama-MacBeth (1973) regression have the following form: $\tilde{\gamma}_k = \sum_{t=1}^{T} w_{kt}\tilde{\gamma}_{kt}$, where $\tilde{\gamma}_{kt}$ is the cross-sectional OLS estimate of γ_k in month t, T is the total number of cross-section regressions over the sample period and w_{kt} is the weight for $\tilde{\gamma}_{kt}$ as follows: $Var(\tilde{\gamma}_k) = \frac{1}{T(T-1)}\sum_{t=1}^{T}(Tw_{kt}\tilde{\gamma}_{kt} - \tilde{\gamma}_k)^2$. For each month from July of year t to June of year $t+1$, I estimate the average slopes from the Litzenberger and Ramaswamy (1979) cross-sectional regressions of the monthly percent excess returns on a liquidity measure (LIQ) or plus the control variables of size ($ln(MV)$), book-to-market ($ln(B/M)$), and momentum (MOM). $ln(MV)$ is the natural logarithm of market capitalization calculated with information available at the end of June of year t, $ln(B/M)$ is the natural logarithm of the ratio of the book value of equity for the fiscal year ending in year $t-1$ divided by market equity at the end of December of year $t-1$, and $MOM_{i,t}$ is the cumulative compounded stock returns of the previous 6 months at the end of May of year t. I use the following four financial constraints measures: book value of asset (AT), payout ratio (PR), bond rating (BR), and commercial paper rating (CR). I also use the following three stock liquidity measures: quoted bid-ask spread (BA, %), absolute-return-to-dollar-volume ratio (RV, 10^6), and turnover (TO). At the end of June of each year t, I sort stocks into three financial constraints groups, low, median, and high (two groups for BR and CR, low and high) and hold them for the subsequent 12 months. All sorting variables related to the financial constraints proxies are for the fiscal ending in calendar year $t-1$. The liquidity measures are winsorized at the top and bottom 1%. The corresponding t-statistics based on Newey and West (1987) standard errors are in parentheses. The 1%, 5%, and 10% significance levels are denoted with ***, **, and *, respectively.

	Constant	LIQ	ln(MV)	ln(B/M)	MOM	Constant	LIQ	ln(MV)	ln(B/M)	MOM
	Panel A: Asset Size (AT)					Panel B: Payout Ratio (PR)				
	BA as a liquidity measure					BA as a liquidity measure				
Unconstrained	0.527**	-0.039				0.644***	0.312			
	(1.97)	(-1.09)				(3.19)	(1.41)			
	0.358	-0.053*	0.028	0.379**	0.274	0.321	0.018	0.038	0.889**	0.195
	(0.66)	(-1.80)	(0.56)	(1.78)	(1.02)	(0.87)	(1.22)	(0.83)	(2.49)	(0.83)
Constrained	-1.168***	0.047***				0.597	0.079***			
	(-2.91)	(5.43)				(1.48)	(2.70)			
	-0.111	0.022***	-0.082	0.349***	-0.072	-0.467	0.025***	0.118**	0.783***	-0.019
	(-0.24)	(2.71)	(-0.95)	(6.56)	(-0.42)	(-1.15)	(2.99)	(2.30)	(6.42)	(-0.11)

[Cont.]

(continued)

	RV as a liquidity measure					*RV* as a liquidity measure				
Unconstrained	0.411*	0.002				0.366*	0.007			
	(1.81)	(0.23)				(1.76)	(1.32)			
	0.304	-0.032	0.017	0.613**	0.221	0.385	0.001	0.012	1.114**	0.204
	(0.67)	(-1.27)	(0.38)	(2.30)	(1.08)	(1.21)	(0.32)	(0.32)	(2.24)	(0.92)
Constrained	-1.083***	0.016***				-0.437	0.014***			
	(-2.83)	(3.46)				(-1.40)	(3.57)			
	-0.166	0.007*	-0.106	0.473***	-0.175	-0.392	0.009	** 0.078*	1.286***	-0.026
	(-0.41)	(1.71)	(-1.17)	(7.27)	(-0.90)	(-1.04)	(2.52)	(1.71)	(6.63)	(-0.14)
	TO as a liquidity measure					*TO* as a liquidity measure				
Unconstrained	0.591***	-0.389**				0.644***	-0.616***			
	(2.85)	(-2.04)				(3.37)	(-3.64)			
	0.407	-0.298*	0.023	0.530*	0.337**	0.505	-0.498***	0.021	1.024*	0.459**
	(0.96)	(-1.73)	(0.52)	(1.89)	(2.02)	(1.61)	(-2.73)	(0.57)	(1.85)	(2.54)
Constrained	0.119	-1.889***				0.358	-1.181***			
	(0.37)	(-5.02)				(1.23)	(-5.35)			
	0.280	-1.456***	0.050	0.800***	0.519***	0.067	-0.995***	0.116**	1.303***	0.182
	(0.70)	(-4.75)	(0.52)	(7.61)	(4.01)	(0.18)	(-5.54)	(2.38)	(6.24)	(1.55)

[Cont.]

(continued)

	Panel C: Bond Rating (BR)					Panel D: Commercial Paper Rating (CR)				
	BA as a liquidity measure					BA as a liquidity measure				
Unconstrained	0.669**	0.031				0.759***	0.084			
	(2.08)	(1.03)				(2.80)	(1.31)			
	0.584	0.029	-0.011	0.314	0.414	1.531**	0.107	-0.093	0.044	0.702**
	(0.88)	(0.72)	(-0.18)	(1.21)	(1.57)	(2.03)	(1.27)	(-1.46)	(0.19)	(2.09)
Constrained	-0.675*	0.060***				-0.359	0.054***			
	(-1.91)	(3.95)				(-1.03)	(3.57)			
	-0.663	0.044***	0.130*	0.768***	-0.024	-0.646	0.048***	0.149**	0.878***	-0.008
	(-1.25)	(3.09)	(1.82)	(6.19)	(-0.10)	(-1.36)	(3.65)	(2.57)	(5.78)	(-0.04)
	RV as a liquidity measure					RV as a liquidity measure				
Unconstrained	0.619**	0.016*				0.824***	0.016			
	(2.13)	(1.94)				(3.67)	(0.14)			
	0.419	0.019*	0.013	0.361	0.453*	1.404**	0.076	-0.088*	-0.091	0.702**
	(0.77)	(1.90)	(0.29)	(1.03)	(1.82)	(2.56)	(0.97)	(-1.92)	(-0.26)	(2.46)
Constrained	-0.488	0.021***				-0.217	0.021***			
	(-1.37)	(3.93)				(-0.63)	(4.08)			
	-0.342	0.014***	0.095	1.112***	-0.039	-0.337	0.016***	0.115**	1.266***	-0.003
	(-0.71)	(3.05)	(1.46)	(6.22)	(-0.18)	(-0.76)	(3.69)	(2.17)	(5.94)	(-0.01)
	TO as a liquidity measure					TO as a liquidity measure				
Unconstrained	0.734***	-0.290				0.644***	0.312			
	(2.77)	(-1.57)				(3.19)	(1.41)			
	0.569	-0.243	0.007	0.290	0.545***	1.299***	0.317	-0.098**	-0.169	0.649**
	(1.14)	(-1.36)	(0.16)	(0.78)	(2.67)	(2.76)	(1.59)	(-2.40)	(-0.46)	(2.51)
Constrained	0.352	-1.403***				0.470	-1.135***			
	(1.07)	(-5.41)				(1.46)	(-5.05)			
	0.321	-1.111***	0.078	1.236***	0.212	0.296	-0.897***	0.098	1.384***	0.209
	(0.69)	(-5.46)	(1.14)	(6.06)	(1.48)	(0.67)	(-4.99)	(1.65)	(6.02)	(1.55)

Table 6.6: Commonality in liquidity for the financially constrained and unconstrained groups

This table reports the liquidity commonality of individual stocks and portfolios for the financially constrained and unconstrained groups. Specifically, I estimate the regressions as follows:

$$\Delta LIQ_{i,m} = \alpha + \beta \Delta LIQ_{MKT,m} + \varepsilon_m,$$

where $\Delta LIQ_{i,m}$ is the change in a liquidity measure of individual stock or a portfolio in the financially unconstrained or constrained groups from month $m-1$ to m. $\Delta LIQ_{MKT,m}$ is the change in the corresponding liquidity measure of all stocks in the corresponding constraints proxy from month $m-1$ to m. I use the following four financial constraints measures: book value of asset (AT), payout ratio (PR), bond rating (BR), and commercial paper rating (CR). I also use the following three stock liquidity measures: quoted bid-ask spread (BA), absolute-return-to-dollar-volume ratio (RV), and turnover (TO). At the end of June of each year t, I sort stocks into three financial constraints, low, median, and high, (two groups for BR and CR, low and high, and hold them for subsequent 12 months. All sorting variables related to the financial constraints proxies are for the fiscal ending in calendar year $t-1$. The corresponding t-statistics based on Newey and West (1987) standard errors are in parentheses. The 1%, 5%, and 10% significance levels are denoted with ***, **, and *, respectively.

	Individuals			*Portfolios*		
	BA	RV	TO	BA	RV	TO
Panel A: Asset Size (AT) as a financial constraints measure						
Unconstrained	0.331***	0.044***	0.714***	0.399***	0.020*	0.397***
	(8.82)	(3.61)	(5.03)	(3.81)	(1.85)	(4.08)
Constrained	1.293***	7.155**	1.315***	1.365***	2.770***	1.741***
	(8.10)	(2.29)	(10.27)	(4.18)	(21.75)	(13.53)
Panel B: Payout Ratio (PR) as a financial constraints measure						
Unconstrained	0.505***	0.420***	0.978***	0.604***	0.143*	0.529***
	(11.40)	(3.98)	(4.54)	(3.41)	(1.93)	(4.66)
Constrained	0.819	1.690	1.089	1.068	1.472	1.289
	(4.03)	(4.34)	(13.45)	(7.94)	(59.86)	(37.00)
Panel C: Bond Rating (BR) as a financial constraints measure						
Unconstrained	0.570***	0.052***	0.941***	0.789***	0.054***	0.562***
	(9.18)	(4.46)	(3.10)	(8.98)	(3.37)	(6.13)
Constrained	1.111***	2.719***	0.904***	0.788***	1.610***	1.277***
	(13.52)	(3.18)	(5.67)	(4.00)	(68.26)	(19.89)
Panel D: Commercial Paper Rating (CR) as a financial constraints measure						
Unconstrained	0.296***	0.000	0.306***	0.277***	0.000	0.311***
	(2.68)	(1.59)	(4.72)	(2.98)	(0.68)	(3.32)
Constrained	0.877***	1.590***	0.866***	0.850***	1.180***	1.108***
	(9.42)	(3.70)	(7.98)	(7.83)	(321.92)	(66.32)

Table 6.7: Average returns for portfolios formed using sorts on financial constraints and liquidity variables

At the end of June of each year t, I sort stocks into three financial constraints groups, low, median, and high (two groups for BR and CR, low and high). Then within each financial constraints groups I sort stocks into two stock liquidity groups using NYSE breakpoints and hold them for the subsequent one month. All sorting variables related to the financial constraints proxies are for the fiscal ending in calendar year $t-1$, while all sorting variables related to the stock liquidity proxies are for the end of each month before the one-month holding period. I report the average equally-weighted monthly raw returns and FF3 alphas. FF3 alphas are the intercepts from the Fama and French (1993) three-factor model. I use the following four financial constraints measures: book value of asset (AT), payout ratio (PR), bond rating (BR), and commercial paper rating (CR). I also use the following three stock liquidity measures: quoted bid-ask spread (BA, %), absolute-return-to-dollar-volume ratio (RV, 10^6), and turnover (TO). The corresponding t-statistics based on Newey and West (1987) standard errors are in parentheses. The 1%, 5%, and 10% significance levels are denoted with ***, **, and *, respectively.

	BA			RV			TO		
	U	C	C-U	U	C	C-U	U	C	C-U
Panel A: Asset Size (AT) as a financial constraints measure									
Raw returns(%)									
L	1.320***	1.116***	-0.204	1.169***	1.030***	-0.139	1.270***	1.257***	-0.013
	(5.01)	(2.99)	(-1.08)	(4.46)	(2.46)	(-0.56)	(3.95)	(2.82)	(-0.06)
I	1.417***	1.803***	0.386*	1.446***	1.908***	0.462**	1.356***	1.911***	0.555***
	(4.16)	(4.33)	(1.83)	(4.49)	(4.65)	(2.22)	(4.98)	(5.47)	(3.24)
I-L	0.097	0.687***		0.277**	0.878***		0.086	0.653***	
	(0.65)	(3.93)		(2.04)	(4.29)		(0.62)	(2.75)	
FF3 alphas(%)									
L	0.576***	0.310**	-0.266**	0.475***	0.184	-0.290*	0.347***	0.324*	-0.023
	(7.25)	(2.15)	(-2.01)	(6.04)	(1.12)	(-1.85)	(3.84)	(1.74)	(-0.13)
I	0.337***	0.948***	0.610***	0.392***	1.000***	0.608***	0.469***	1.061***	0.592***
	(3.39)	(4.68)	(3.10)	(4.66)	(4.90)	(3.03)	(5.07)	(5.78)	(3.26)
I-L	-0.239***	0.637***		-0.083	0.816***		0.122	0.738***	
	(-2.62)	(3.39)		(-1.23)	(4.14)		(1.15)	(3.72)	

[Cont.]

(continued)

Panel B: Payout Ratio (PR) as a financial constraints measure									
Raw returns(%)									
L	1.319***	1.270***	-0.049	1.228***	1.042***	-0.186	1.268***	1.086***	-0.182
	(6.01)	(3.63)	(-0.25)	(5.54)	(3.01)	(-0.92)	(4.59)	(2.61)	(-0.90)
I	1.438***	1.658***	0.220	1.406***	1.607***	0.201	1.388***	1.755***	0.367**
	(5.02)	(4.05)	(1.24)	(5.08)	(4.03)	(1.16)	(5.88)	(4.84)	(2.13)
I-L	0.119	0.388***		0.178	0.564***		0.120	0.669***	
	(0.96)	(2.35)		(1.23)	(3.32)		(1.18)	(3.51)	
FF3 alphas(%)									
L	0.682***	0.425***	-0.257**	0.624***	0.220**	-0.405***	0.442***	0.109	-0.332**
	(7.99)	(4.07)	(-2.27)	(7.47)	(2.02)	(-3.48)	(4.73)	(0.79)	(-2.51)
I	0.571***	0.709***	0.138	0.540***	0.618***	0.078	0.649***	0.802***	0.153
	(6.34)	(4.27)	(0.98)	(6.49)	(4.15)	(0.58)	(7.85)	(5.21)	(1.12)
I-L	-0.111	0.284*		-0.084	0.398***		0.207**	0.692***	
	(-1.32)	(1.79)		(-1.15)	(2.58)		(2.36)	(4.16)	
Panel C: Bond Rating (BR) as a financial constraints measure									
Raw returns(%)									
L	1.294***	0.923***	-0.371**	1.163***	0.738*	-0.425**	1.436***	0.992**	-0.443**
	(4.16)	(2.51)	(-2.12)	(3.89)	(1.95)	(-2.26)	(3.55)	(2.11)	(-1.99)
I	1.631***	1.355***	-0.275	1.576***	1.384***	-0.192	1.348***	1.483***	0.134
	(3.58)	(2.98)	(-1.33)	(3.68)	(3.09)	(-0.99)	(4.04)	(3.82)	(0.83)
I-L	0.336	0.432**		0.413	0.646***		-0.087	0.490*	
	(1.48)	(2.08)		(2.04)	(2.99)		(-0.57)	(1.75)	

[Cont.]

(continued)

FF3 alphas(%)									
L	0.587***	0.236*	-0.350*	0.468***	0.008	-0.460***	0.513***	0.201	-0.312*
	(4.89)	(1.76)	(-2.38)	(4.44)	(0.06)	(-3.88)	(4.12)	(1.20)	(-1.91)
I	0.615***	0.647***	0.031	0.583***	0.679***	0.096	0.548***	0.821***	0.272
	(3.68)	(3.13)	(0.16)	(4.36)	(3.44)	(0.51)	(4.39)	(4.03)	(1.43)
I-L	0.029	0.410*		0.115	0.671***		0.035	0.619***	
	(0.19)	(1.95)		(1.08)	(3.09)		(0.30)	(2.71)	
Panel D: Commercial Paper Rating (CR) as a financial constraints measure									
Raw returns(%)									
L	1.304***	1.118***	-0.187	1.177***	0.984***	-0.193	1.386***	1.070**	-0.315
	(4.68)	(3.06)	(-0.78)	(4.54)	(2.62)	(-0.85)	(3.72)	(2.32)	(-1.09)
I	1.527***	1.432***	-0.095	1.467***	1.417***	-0.050	1.255***	1.517***	0.262
	(3.77)	(3.12)	(-0.33)	(4.07)	(3.17)	(-0.19)	(5.13)	(3.80)	(0.99)
I-L	0.222	0.314		0.290*	0.433**		-0.130	0.447*	
	(1.00)	(1.60)		(1.80)	(2.32)		(-0.72)	(1.89)	
FF3 alphas(%)									
L	0.681***	0.387***	-0.294*	0.563***	0.213*	-0.350***	0.488***	0.245	-0.243
	(4.28)	(3.57)	(-1.70)	(5.71)	(1.88)	(-3.12)	(3.67)	(1.63)	(-1.40)
I	0.608***	0.669***	0.061	0.550***	0.654***	0.104	0.626***	0.786***	0.160
	(2.68)	(3.41)	(0.25)	(3.75)	(3.70)	(0.51)	(4.62)	(4.34)	(0.72)
I-L	-0.073	0.281		-0.013	0.440**		0.138	0.542***	
	(-0.37)	(1.48)		(-0.14)	(2.43)		(1.04)	(2.85)	

Table 6.8: Average returns for portfolios formed using sorts on financial constraints and liquidity variables with one-year holding period

At the end of June of each year t, I sort stocks into three financial constraints groups, low, median, and high (two groups for BR and CR, low and high). Then within each financial constraints groups I sort stocks into two stock liquidity groups using NYSE breakpoints and hold them for the subsequent one month. All sorting variables related to the financial constraints proxies from July of year $t-1$ to June of year t are for the fiscal ending in calendar year $t-1$, while all sorting variables related to the stock liquidity proxies are for the end of each month before the one-month holding period. I report the average equally-weighted monthly raw returns and FF3 alphas. The FF3 alphas are the intercepts from the Fama and French (1993) three-factor model. I use the following four financial constraints measures: the book value of asset (AT), payout ratio (PR), bond rating (BR), and commercial paper rating (CR). I also use the following three stock liquidity measures: the quoted bid-ask spread (BA, %), absolute-return-to-dollar-volume ratio (RV, 10^6), and turnover (TO). The corresponding t-statistics based on Newey and West (1987) standard errors are in parentheses. The 1%, 5%, and 10% significance levels are denoted with ***, **, and *, respectively.

	BA			RV			TO		
	U	C	C-U	U	C	C-U	U	C	C-U
Panel A: Asset Size (AT) as a financial constraints measure									
Raw returns(%)									
L	1.349***	1.196***	-0.153	1.201***	1.169***	-0.032	1.285***	1.358***	0.073
	(5.06)	(3.13)	(-0.79)	(4.50)	(2.77)	(-0.13)	(3.97)	(3.06)	(0.34)
I	1.399***	1.813***	0.414**	1.440***	1.941***	0.501**	1.353***	1.955***	0.602***
	(4.18)	(4.43)	(1.97)	(4.53)	(4.82)	(2.43)	(5.05)	(5.70)	(3.45)
I-L	0.050	0.617***		0.239*	0.772***		0.068	0.596***	
	(0.34)	(3.79)		(1.78)	(4.02)		(0.49)	(2.73)	
FF3 alphas(%)									
L	0.592***	0.378**	-0.214	0.486***	0.305*	-0.181	0.348***	0.424**	0.076
	(7.19)	(2.49)	(-1.52)	(5.98)	(1.79)	(-1.13)	(3.93)	(2.35)	(0.46)
I	0.326***	0.959***	0.633***	0.395***	1.033***	0.638***	0.478***	1.102***	0.624***
	(3.46)	(4.87)	(3.27)	(4.87)	(5.26)	(3.25)	(5.25)	(6.07)	(3.36)
I-L	-0.267***	0.581***		-0.091	0.728***		0.130	0.678***	
	(-2.98)	(3.33)		(-1.39)	(3.99)		(1.28)	(3.60)	

[Cont.]

(continued)

Panel B: Payout Ratio (PR) as a financial constraints measure									
Raw returns(%)									
L	1.355***	1.271***	-0.083	1.223***	1.115***	-0.108	1.296***	1.153***	-0.144
	(6.01)	(3.60)	(-0.43)	(5.45)	(3.17)	(-0.52)	(4.63)	(2.79)	(-0.74)
I	1.452***	1.660***	0.208	1.419***	1.633***	0.213	1.374***	1.773***	0.400**
	(5.12)	(4.11)	(1.18)	(5.17)	(4.15)	(1.26)	(6.01)	(4.94)	(2.25)
I-L	0.097	0.389**		0.196	0.517***		0.077	0.621***	
	(0.78)	(2.48)		(1.37)	(3.18)		(0.75)	(3.42)	
FF3 alphas(%)									
L	0.703***	0.395***	-0.308***	0.611***	0.254**	-0.357***	0.454***	0.169	-0.285**
	(7.61)	(3.86)	(-2.75)	(6.99)	(2.30)	(-3.00)	(5.24)	(1.25)	(-2.28)
I	0.586***	0.724***	0.137	0.558***	0.649***	0.091	0.659***	0.823***	0.164
	(6.83)	(4.42)	(0.96)	(6.90)	(4.51)	(0.70)	(7.72)	(5.52)	(1.17)
I-L	-0.116	0.329**		-0.053	0.395***		0.205**	0.654***	
	(-1.33)	(2.15)		(-0.72)	(2.73)		(2.47)	(4.10)	
Panel C: Bond Rating (BR) as a financial constraints measure									
Raw returns(%)									
L	1.276***	0.995***	-0.282	1.199***	0.770**	-0.429**	1.414***	0.976**	-0.439**
	(4.07)	(2.68)	(-1.64)	(3.91)	(1.98)	(-2.27)	(3.46)	(2.10)	(-1.97)
I	1.634***	1.371***	-0.263	1.545***	1.397***	-0.148	1.357***	1.539***	0.182
	(3.65)	(3.06)	(-1.23)	(3.67)	(3.18)	(-0.77)	(4.15)	(3.99)	(1.08)
I-L	0.358*	0.376**		0.346*	0.627***		-0.058	0.563**	
	(1.68)	(2.08)		(1.85)	(3.22)		(-0.37)	(2.14)	

[Cont.]

(continued)

FF3 alphas(%)									
L	0.558***	0.278**	-0.280**	0.476***	0.001	-0.475***	0.485***	0.201	-0.283*
	(4.59)	(2.23)	(-2.07)	(4.11)	(0.01)	(-3.93)	(3.78)	(1.24)	(-1.72)
I	0.623***	0.674***	0.051	0.571***	0.705***	0.134	0.567***	0.881***	0.315
	(3.90)	(3.31)	(0.25)	(4.55)	(3.68)	(0.73)	(4.74)	(4.38)	(1.58)
I-L	0.065	0.396**		0.095	0.704***		0.082	0.680***	
	(0.44)	(2.01)		(0.95)	(3.33)		(0.71)	(3.15)	
Panel D: Commercial Paper Rating (CR) as a financial constraints measure									
Raw returns(%)									
L	1.300***	1.135	*** -0.165	1.198***	1.032***	-0.166	1.374***	1.057**	-0.317
	(4.54)	(3.06)	(-0.68)	(4.63)	(2.69)	(-0.74)	(3.73)	(2.29)	(-1.13)
I	1.569***	1.460***	-0.109	1.444***	1.421***	-0.023	1.267***	1.551***	0.284
	(4.05)	(3.22)	(-0.39)	(4.01)	(3.22)	(-0.09)	(5.12)	(3.94)	(1.10)
I-L	0.269	0.325*		0.245	0.389**		-0.108	0.494**	
	(1.32)	(1.83)		(1.52)	(2.20)		(-0.63)	(2.27)	
FF3 alphas(%)									
L	0.667***	0.375***	-0.292*	0.574***	0.230*	-0.344***	0.484***	0.226	-0.258
	(3.92)	(3.40)	(-1.72)	(5.80)	(1.88)	(-3.16)	(3.64)	(1.54)	(-1.56)
I	0.672***	0.710***	0.038	0.539***	0.668***	0.129	0.630***	0.831***	0.202
	(3.59)	(3.70)	(0.17)	(3.65)	(3.87)	(0.64)	(4.80)	(4.76)	(0.92)
I-L	0.006	0.335*		-0.035	0.438**		0.145	0.605***	
	(0.03)	(1.83)		(-0.36)	(2.39)		(1.16)	(3.47)	

Chapter 7

Conclusion

This thesis mainly focuses on several questions in chapters 4, 5, and 6. In chapter 4, I examine the performance of the traditional CCAPM with the transaction costs and liquidity risk adjustments. I investigate whether the liquidity-adjusted CCAPM can account for a larger fraction of cross-sectional return variations than the traditional CCAPM. Moreover, I examine whether the liquidity-adjusted CCAPM helps to understand the equity premium puzzle. In chapter 5, I investigate the performance of the Epstein and Zin (1991) model with the liquidity risk adjustment. I also examine whether liquidity risk plays a role in improving a model's explanatory power. In chapter 6, I explore the relation between liquidity and financial constraints. I further investigate the variations of liquidity risk and liquidity premium for the financially constrained firms and unconstrained firms.

Motivated by recent studies highlighting the importance of liquidity in asset pricing, in this thesis, I examine the importance of stock liquidity in investors' consumption and investment decisions and firms' financing decisions. In the first empirical chapter, I incorporate transaction costs and liquidity risk into the traditional CCAPM. Representative consumers invest in stocks and incur time-varying transaction costs. I show that expected security return is associated with expected transaction cost, consumption risk and liquidity risk. I use the effective trading costs of Hasbrouck (2009) and the high-low spread estimates of Corwin and Schultz (2012) to measure transaction costs. I find that my liquidity risk adjusted CCAPM is more successful in accounting for the cross-sectional expected return variations across portfolios classified by market capitalization, book-to-market ratio, liquidity, and industry. More interestingly, when I use the long run consumption growth, the total consumption growth and the fourth quarter consumption growth to the CCAPM and my model, my model also shows the better goodness-of-fit. Moreover, my model gives a risk aversion estimate around 10 to match the data with the long run risk and Corwin and Schultz (2012)'s transaction costs proxy, whereas the CCAPM delivers risk aversion above 45.

I find that stock returns are related to the sensitivity of transaction costs to the aggregate consumption growth. It indicates that the traditional CCAPM overlooks one source of systematic risk. This can help to understand the empirically poor performance of the traditional CCAPM. The liquidity-adjusted model also implies low risk aversion and our empirical results confirm its prediction, which helps to understand the equity premium puzzle. Our study extends the existing theoretical and empirical support of liquidity in asset pricing.

Motivated by Kan, Robotti, and Shanken (2013) showing the importance of covariance risk, I, in the second empirical chapter, incorporate stock liquidity into the Epstein and Zin (1991) framework to examine whether modeling liquidity as a factor is useful in explaining cross-sectional returns. In addition to the consumption risk and market risk, the liquidity consumption model suggests that expected return is also determined by liquidity risk. This is because high sensitivity of stock return to fluctuations in aggregate liquidity implies the difficulty to convert investment into cash for consumption. Investors, therefore, demand high expected return to compensate for high liquidity risk. My model suggests that neglecting liquidity risk would lead to inaccurate estimate of expected return.

Empirically, I find that not only the price of liquidity risk is positively significant, but the liquidity factor makes a significant contribution to the incremental explanatory power to the cross-sectional variations of expected returns. This potentially explains why the performance of the CCAPM and Epstein and Zin (1991) model is empirically less successful. A liquidity-augmented model also performs better in terms of cross-sectional R^2 and HJ distance, which is statistically significant based on the tests of Kan, Robotti, and Shanken (2013) and Kan and Robotti (2009). My study provides additional supports to the existing theoretical and empirical importance of liquidity in asset pricing.

The second empirical chapter provides further supports to the role of liquidity risk in asset pricing as in Pastor and Stambaugh (2003), Liu (2006), and Sadka (2006). It also highlights the importance of liquidity risk factor in the model's performance, which is new to the literature. Moreover, my findings help to explain why the traditional CCAPM and the Epstein-Zin model have difficulties in accounting for the cross-sectional return variations.

Motivated by Li and Zhang (2010) and Lam and Wei (2011), the third empirical chapter investigates the interaction of financial constraints and stock liquidity on stock returns. I hypothesize that financial constraints are highly correlated with stock liquidity and constrained firms are less liquid than unconstrained firms. Therefore, the stock returns of constrained firms are highly sensitive to stock liquidity because high asymmetric information and low information quality of constrained firms make them less attractive to investors, in turn, leading to high transaction costs and low trading quantity. While stock returns of unconstrained firms are less sensitive to stock liquidity due to their low information asymmetry. Moreover, constrained firms produce a premium over unconstrained firms since they are less liquid, but the constraint premium is weaker than the illiquidity premium.

My empirical findings are consistent with the hypotheses. In particular, I find that constrained firms have lower information quality, lower stock liquidity, and higher liquidity risk than unconstrained firms. The results from the cross-sectional regressions prove that stock liquidity is the important determinant of the cross-sectional stock returns for constrained firms, but it is insignificant for unconstrained firms. In addition, constrained firms have higher liquidity risk than unconstrained firms due to their high commonality of liquidity. Controlling for financial constraints, the liquidity premiums are positive and significant for constrained firms, but insignificant for unconstrained firms. Finally, the third empirical chapter fills the gaps in understanding of the mixed relation between financial constraints and stock returns in previous studies. It finds that the mixed relation is associated with the stock liquidity and different classification criteria of financial constraints.

However, there are some limitations of this thesis. In the first empirical chapter, I follow Acharya and Pedersen (2005) and assume that investors incur transaction costs when selling stocks. In the tests, I do not take into account the transaction costs of buying stocks. Future works could follow Jacoby, Fowler, and Gottesman (2000) to take into account the transaction costs of buying and selling stocks. Empirically, future studies could follow Keim and Madhavan (1997) to calculate the transaction costs of buying and selling stocks.

In the second empirical chapter, I focus on the role of the liquidity risk factor in the consumption-based asset pricing models. Future studies could take into account the non-consumption based asset pricing models, e.g., the traditional CAPM of Sharpe (1964) and Lintner (1965), the Fama-French (1993) three-factor model (FF3), and the Jagannathan and Wang (1996) conditional CAPM (JW). Also, future studies could use the conditional approach to examine the role of liquidity risk factor in the consumption-based asset pricing framework.

In the third empirical chapter, I calculate one of the liquidity measures, bid-ask spread (BA), using the daily CRSP data. To investigate whether this measure could better capture the transaction costs of traders, future studies could use the high-frequency bid and ask data from the trade and quote (TAQ) database.

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APPENDIX A

In this section, I show the detailed derivation of the first-order conditions for Eq. (4.4) using stochastic dynamic programming. Specifically, I solve Eq. (4.4) by exploring the last two-period function and using backward programming. I write the last two-period function of Eq. (4.4) as:

$$
\begin{aligned}
I(W_{T-1}) &= \max_{C_s, \omega_{i,s}, \forall s,i} E_{T-1}\left[U(C_{T-1}) + B(W_T)\right] \\
&= \max_{C_s, \omega_{i,s}, \forall s,i} U(C_{T-1}) + E_{T-1}\left[B(W_T)\right],
\end{aligned}
\tag{A-1}
$$

where $W_T = (W_{T-1} + y_{T-1} - C_{T-1})[R_{f,T} + \sum_{i=1}^{n} \omega_{i,T}(R_{i,T} - tc_{i,T} - R_{f,T})]$.

Differentiating Eq. (A-1) with respect to C_{T-1} and $\omega_{i,T}$, I can obtain the following two first-order conditions:

$$
U_C(C_{T-1}) = E_{T-1}\left[B_W(W_T)\Big[R_{f,T} + \sum_{i=1}^{n} \omega_{i,T}(R_{i,T} - tc_{i,T} - R_{f,T})\Big]\right] \tag{A-2}
$$

and

$$
E_{T-1}\left[B_W(W_T)(R_{i,T} - tc_{i,T} - R_{f,T})\right] = 0, \tag{A-3}
$$

where U_C and B_W are partial differentiation with respect to consumption and wealth, respectively. Using the results in Eq. (A-3), I can rewrite Eq. (A-2) as:

$$U_C(C_{T-1}) = R_{f,T} E_{T-1} \left[B_W(W_T) \right]. \tag{A-4}$$

Substituting the first-order conditions of Eqs. (A-2) and (A-3) into Eq. (A-1) and differentiating it with respect to W_{T-1}, I have

$$\begin{aligned}
I_W &= U_C \frac{\partial C^*_{T-1}}{\partial W_{T-1}} + E_{T-1} \left[B_{W_T} \left(\frac{\partial W_T}{\partial W_{T-1}} + \sum_{i=1}^{n} \frac{\partial W_T}{\partial \omega^*_{i,T-1}} \frac{\partial \omega^*_{i,T-1}}{\partial W_{T-1}} + \frac{\partial W_T}{\partial C^*_{T-1}} \frac{\partial C^*_{T-1}}{\partial W_{T-1}} \right) \right] \\
&= U_C \frac{\partial C^*_{T-1}}{\partial W_{T-1}} + E_{T-1} \Bigg[B_{W_T} \Bigg\{ \sum_{i=1}^{n} (R_{i,T} - tc_{i,T} - R_{f,T})(W_{T-1} + y_{T-1} - C_{T-1}) \frac{\partial \omega^*_{i,T-1}}{\partial W_{T-1}} \\
&+ \left[R_{f,T} + \sum_{i=1}^{n} \omega_{i,T} (R_{i,T} - tc_{i,T} - R_{f,T}) \right] \left(1 - \frac{\partial C^*_{T-1}}{\partial W_{T-1}}\right) \Bigg\} \Bigg],
\end{aligned} \tag{A-5}$$

where C^*_{T-1} and $\omega^*_{i,T-1}$ are the representative consumer's optimal decisions of consumption and investment, respectively.

Using Eqs. (A-2), (A-3), and (A-4), I can simplify Eq. (A-5) as:

$$I_W(W_{T-1}) = U_C(C^*_{T-1}). \tag{A-6}$$

Eq. (A-6) indicates that when the representative consumer optimizes her consumption and investment decisions, the marginal utility of wealth is equal to the marginal utility of current consumption.

Following the principle of optimality (Bellman (1957)), I can write the optimal decisions of time $T-2$ as:

$$
\begin{aligned}
I(W_{T-2}) &= \max_{C_{T-2},\,\omega_{i,\,T-2}} \left\{ U(C_{T-2}) + E_{T-2}\Big[\max_{C_{T-1},\,\omega_{i,\,T-1}} E_{T-1}[U(C_{T-1}) + B(W_T)] \Big] \right\} \\
&= \max_{C_{T-2},\,\omega_{i,\,T-2}} U(C_{T-2}) + E_{T-2}\left[I(W_{T-1}) \right].
\end{aligned}
\tag{A-7}
$$

Note that Eq. (A-7) is similar to Eq. (A-1). Thus, by differentiating Eq. (A-7), I can have the following first-order conditions:

$$
I_W(W_{T-2}) = U_C(C^*_{T-2}) \tag{A-8}
$$

and

$$
R_{f,\,T-1} E_{T-2}\left[I_W(W_{T-1}) \right] = E_{T-2}\left[(R_{i,\,T-1} - tc_{i,\,T-1}) I_W(W_{T-1}) \right]. \tag{A-9}
$$

If I apply the principle of optimality to other time periods, for any $t = 0, 1, ..., T-1$, I can generalize the representative consumer's optimal objective function as:

$$
I(W_t) = \max_{C_t,\,\omega_{i,\,t}} U(C_t) + E_t\left[I(W_{t+1}) \right] \tag{A-10}
$$

Similarly, the first-order conditions are

$$
I_W(W_t) = U_C(C^*_t) \tag{A-11}
$$

and

$$R_{f,\,t+1}E_t\left[I_W(W_{t+1})\right] = E_t\left[(R_{i,\,t+1} - tc_{i,\,t+1})I_W(W_{t+1})\right]. \tag{A-12}$$

Substituting $I_W(W_{t+1}) = U_C(C^*_{t+1})$ into Eq. (A-12) and using Eq. (A-11), I have

$$E_t\left[\frac{U_C(C^*_{t+1})}{U_C(C^*_t)}R_{f,\,t+1}\right] = 1 \tag{A-13}$$

and

$$E_t\left[\frac{U_C(C^*_{t+1})}{U_C(C^*_t)}(R_{i,\,t+1} - tc_{i,\,t+1})\right] = 1. \tag{A-14}$$

Q.E.D.

APPENDIX B

In this section, I use the liquidity-adjusted CCAPM to develop the equilibrium model in Acharya and Pedersen (2005). Following Breeden (1979) and Cochrane (2005), I assume that the return of a market portfolio after netting out aggregate transaction costs is perfectly negatively correlated with the marginal utility of time $t+1$ consumption, i.e., $R_{m,\,t+1} - tc_{m,\,t+1} = -\kappa U_C(C^*_{t+1})$. $R_{m,\,t+1}$ is the returns of market portfolio, $tc_{m,\,t+1}$ is the aggregate transaction costs, C^*_{t+1} is the optimal consumption, and $\kappa > 0$. Hence, I can have

$$Cov[U_C(C^*_{t+1}), R_{m,\,t+1} - tc_{m,\,t+1}] = -\kappa Var(R_{m,\,t+1} - tc_{m,\,t+1}) \tag{B-1}$$

and

$$Cov[U_C(C^*_{t+1}), R_{i,\,t+1} - tc_{i,\,t+1}] = -\kappa Cov(R_{m,\,t+1} - tc_{m,\,t+1}, R_{i,\,t+1} - tc_{i,\,t+1}). \tag{B-2}$$

I can rewrite Eq. (4.7) as:

$$E\left[R_{i,t+1} - tc_{i,\,t+1} - R_{f,\,t+1}\right] = \frac{Cov[U_C(C^*_{t+1}), R_{i,\,t+1} - tc_{i,\,t+1}]}{E[U_C(C^*_{t+1}]}. \tag{B-3}$$

Replacing $R_{i,t+1} - tc_{i,\,t+1}$ with $R_{m,\,t+1} - tc_{m,\,t+1}$ in Eq. (B-3) and using Eq. (B-1), I have

$$E\left[R_{m,t+1} - tc_{m,\,t+1} - R_{f,\,t+1}\right] = -\frac{\kappa Var(R_{m,\,t+1} - tc_{m,\,t+1})}{E[U_C(C^*_{t+1})]}. \tag{B-4}$$

Using Eqs. (B-2), (B-3), and (B-4), I have

$$\frac{E\left[R_{m,t+1} - tc_{m,\,t+1} - R_{f,\,t+1}\right]}{E\left[R_{i,t+1} - tc_{i,\,t+1} - R_{f,\,t+1}\right]} = \frac{\kappa Var(R_{m,\,t+1} - tc_{m,\,t+1})}{\kappa Cov(R_{m,\,t+1} - tc_{m,\,t+1}, R_{i,\,t+1} - tc_{i,\,t+1})}. \tag{B-5}$$

The beta representation of Eq. (B-5) has the form:

$$E\left[R_{i,\,t+1}-R_{f,\,t+1}\right]=E\left[tc_{i,\,t+1}\right]+E\left[R_{m,t+1}-tc_{m,\,t+1}-R_{f,\,t+1}\right](\beta_{i,\,1}+\beta_{i,\,2}+\beta_{i,\,3}+\beta_{i,\,4}), \tag{B-6}$$

where $\beta_{i,\,1}=\frac{cov(R_{i,\,t+1},R_{m,\,t+1})}{Var(R_{m,\,t+1}-tc_{m,\,t+1})}$, $\beta_{i,\,2}=\frac{cov(tc_{i,\,t+1},tc_{m,\,t+1})}{Var(R_{m,\,t+1}-tc_{m,\,t+1})}$, $\beta_{i,\,3}=\frac{cov(-R_{i,\,t+1},tc_{m,\,t+1})}{Var(R_{m,\,t+1}-tc_{m,\,t+1})}$, and $\beta_{i,\,4}=\frac{cov(-tc_{i,\,t+1},tc_{m,\,t+1})}{Var(R_{m,\,t+1}-tc_{m,\,t+1})}$. Eq. (B-6) is the liquidity-adjusted CAPM in Acharya and Pedersen (2005).

Q.E.D.

APPENDIX C

In this section, I derive Eqs. (4.22) and (4.23), which are used to estimate the risk aversion coefficient. Following Campbell (2003), I assume that the joint conditional distribution of asset returns and consumption is lognormal and homoskedastic. I take logs of the following equation:

$$E[M_t R_{i,t}]=1, \tag{C-1}$$

where $M_t=\beta(\frac{C_t}{C_{t-1}})^{-\gamma}$. I can then have

$$E[lnR_{i,t}]+E[lnM_t]+(\frac{1}{2})(\sigma_i^2+\sigma_M^2+2\sigma_{i,M})=0, \tag{C-2}$$

where $lnR_{i,t}=ln(R_{i,t})$, $lnM_t=ln(M_t)$, $\sigma_i^2=Var(lnR_{i,t})$ is the variance of log returns, $\sigma_M^2=Var(lnM_t)$ is the variance of stochastic discount factor, and $\sigma_{i,M}=$

$Cov(lnR_{i,t}, lnM_t)$.

When an asset is a risk-free asset, both the variance σ_f^2 and the covariance $\sigma_{f,M}$ will be equal to zero. Hence, the risk-free asset follows:

$$lnR_{f,t} = -E[lnM_t] - \frac{\sigma_M^2}{2}, \tag{C-3}$$

where $lnR_{f,t} = ln(R_{f,t})$. Substituting Eq. (C-3) into Eq. (C-2), I have

$$E[lnR_{i,t} - lnR_{f,t}] + \frac{\sigma_i^2}{2} = -\sigma_{i,M}. \tag{C-4}$$

Recall that the log stochastic discount factor can be written as $lnM_t = ln(M_t) = ln(\beta) - \gamma\Delta lnC_t$, where $\Delta lnC_t = ln(1 + \Delta C_t)$. Substituting this into Eq. (C-4), I have

$$E[lnR_{i,t} - lnR_{f,t}] + \frac{\sigma_i^2}{2} = \gamma\sigma_{i,\Delta C}, \tag{C-5}$$

where $\sigma_{i,\Delta C} = Cov(lnR_{i,t}, lnC_t)$. Eq. (C-5) is the log form expression of the traditional CCAPM.

Replacing $lnR_{i,t}$ with $lnR_{itc,t}$ ($lnR_{itc,t} = ln(R_{i,t} - tc_{i,t})$), I can write the log form of liquidity-adjusted CCAPM as:

$$E[lnR_{itc,t} - lnR_{f,t}] + \frac{\sigma_{itc}^2}{2} = \gamma\sigma_{itc,\Delta C}, \tag{C-6}$$

where $\sigma_{itc}^2 = Var(lnR_{itc,t})$ is the variance of log net returns and

$\sigma_{itc,\Delta C} = Cov(lnR_{itc,t}, lnC_t)$.

Using the Maclaurin series of natural logarithms and replacing contemporaneous consumption growth with consumption growth over a horizon of S quarters, I can rewrite Eq. (C-5) and Eq. (C-6) as:

$$E[R_{i,t} - R_{f,t}] + \frac{\sigma_i^2}{2} = \gamma\sigma_{i,\Delta C^S}; \tag{C-7}$$

$$E[R_{itc,t} - R_{f,t}] + \frac{\sigma_{itc}^2}{2} = \gamma\sigma_{itc,\Delta C^S}, \tag{C-8}$$

where $R_{itc,t} = R_{i,t} - tc_{i,t}$, $\sigma_{i,\Delta C^S} = Cov(R_{i,t}, \Delta C_t^S)$, $\sigma_{itc,\Delta C^S} = Cov(R_{itc,t}, \Delta C_t^S)$, and ΔC^S is the consumption growth over a horizon of S quarters.

Q.E.D.

APPENDIX D

This appendix gives the detailed derivation of the liquidity-augmented Epstein-Zin model (5.9). From Eq. (5.8), I have

$$M_{t+1} = \beta^{\frac{1-\theta}{1-\rho}} (\frac{C_{t+1}}{C_t})^{-\rho\frac{1-\theta}{1-\rho}} R_{W,\,t+1}^{\frac{\rho-\theta}{1-\rho}} (1 - L_{t+1}). \tag{D-1}$$

This can be rewritten as:

$$E[M_{t+1}(R_{i,\,t+1} - R_{f,\,t+1})] = 0. \tag{D-2}$$

Following Cochrane (2005) and Yogo (2006), I can linearize M_{t+1} in a vector f_t of F underlying factors as follows:

$$-\frac{M_{t+1}}{E[M_{t+1}]} = a + b' f_{t+1}. \tag{D-3}$$

The beta representation of Eq. (D-3) is

$$E[R_{i,t+1} - R_{f,t+1}] = \gamma' \beta_i, \tag{D-4}$$

where $\gamma = \sum_{ff} b$, $\beta_i = \sum_{ff}^{-1} \sum_{fi}$, $\sum_{ff} = E[(f_{t+1} - E[f_{t+1}])(f_{t+1} - E[f_{t+1}])']$, $\sum_{fi} = E[(f_{t+1} - E[f_{t+1}])(R_{i,t+1} - R_{f,t+1})]$.

Taking the log of both sides of Eq. (D-1), I have

$$\begin{aligned} m_{t+1} = {} & \frac{1-\theta}{1-\rho} ln(\beta) - \frac{1-\theta}{1-\rho} \rho \Delta c_{t+1} \\ & + \frac{\rho - \theta}{1-\rho} r_{W,t+1} + ln(1 - L_{t+1}), \end{aligned} \tag{D-5}$$

where lowercase letters denote the log of uppercase letters.

Using Eq. (D-5), I can write the covariance between m_{t+1} and the stock/portfolio return as:

$$\begin{aligned} Cov(m_{t+1}, R_{i,t+1}) = {} & -\frac{1-\theta}{1-\rho} \rho Cov(\Delta c_{t+1}, R_{i,t+1}) \\ & + \frac{\rho - \theta}{1-\rho} Cov(r_{W,t+1}, R_{i,t+1}) + Cov[ln(1 - L_{t+1}), R_{i,t+1}]. \end{aligned} \tag{D-6}$$

According to Yogo (2006), I can approximate M_{t+1} as:

$$
\begin{aligned}
-\frac{M_{t+1}}{E[M_{t+1}]} &= -1 - m_{t+1} + E[m_{t+1}] \\
&= a + b1\Delta c_{t+1} + b2 r_{W,t+1} + b3 ln(1 - L_{t+1}),
\end{aligned}
\tag{D-7}
$$

where $a = -1 - b_1 E[\Delta c_{t+1}] - b_2 E[r_{W,t+1}] - b_3 E[ln(1 - L_{t+1})]$, $b_1 = \frac{1-\theta}{1-\rho}\rho$, $b_2 = \frac{\rho-\theta}{\rho-1}$, and $b_3 = -1$.

Using Eqs. (D-4), (D-5), (D-6), and (D-7), I can write the beta representation as:

$$
E[R_i - R_f] = \gamma_{cg}\beta_{i,cg} + \gamma_{mkt}\beta_{i,R_W} + \gamma_{liq}\beta_{i,liq}, \tag{D-8}
$$

where $\beta_{i,cg}$ denotes the consumption beta, β_{i,R_W} denotes the return to wealth beta, and $\beta_{i,liq}$ denotes the liquidity beta, γ_{cg}, γ_{mkt}, and γ_{liq} are the prices of consumption risk, market risk and liquidity risk.

Q.E.D.

APPENDIX E

(I) Firm characteristics

MV: market capitalization of equity, calculated by shares outstanding times closing price at the end of June of year t from CRSP.

B/M: book-to-market equity, the ratio of the book value of equity to the market value of equity. Following Davis, Fama, and French (2000), the book value of equity is calculated as the stockholders' equity (data item SEQ), plus balance sheet deferred taxes and investment tax credit (data item $TXDITC$) (if available), less book value of preferred stock (in the following order: data item $PSTKRV$ or data item $PSTKL$ or data item $PSTK$) from COMPUSTAT. The B/M ratio of year t is the book value of equity for the fiscal year ending in year $t-1$, divided by market value at the end of December in year $t-1$ from CRSP.

MOM: momentum, computed as the cumulative compounded stock returns of the previous 6 months at the end of May of year t.

BL: book leverage, the ratio of sum of long-term debt (data item $DLTT$) and debt in current liabilities (data item DLC) to the book value of equity.

CF: cash flow, calculated as a ratio of operating income before depreciation (data item $OIBDP$) less the sum of interest expenses (data item $XINT$), income taxes (data item TXT), dividends of preferred shares (data item DVP), and dividends of common shares (data item DVC) to the book value of total assets.

CH: cash holdings, the ratio of cash and short-term investments (data item CHE) to the book value of total asset.

Q: Tobin's Q, calculated as the ratio of market value of assets to the book value of total assets. The market value of assets equal the book value of total assets (data item AT) plus the market value of common equity at the end of December in year t from CRSP less the sum of the book value of common equity (data item CEQ) and balance sheet deferred taxes (data item $TXDB$).

TA: tangible asset, defined as the ratio of net property, plant, and equipment (data item $PPENT$) to the book value of total assets.

PF: profitability, computed as the ratio of the operating income before depreciation (data item $OIBDP$) to the book value of total assets.

(II) Information quality

EP: earnings precision, defined as the standard deviation of earnings before extraordinary items (data item IBC) scaled by average total assets over the most recent five years (Dichev and Tang, 2009). EP measures the volatility of earnings.

AQ: accruals quality, defined as the standard deviation of the residuals estimated from the following cross-sectional regression:

$$\begin{aligned} TCA_{i,t} = \phi_{0,i} + \phi_{1,i}CFO_{i,t-1} + \phi_{2,i}CFO_{i,t} + \phi_{3,i}CFO_{i,t+1} \\ + \phi_{4,i}\Delta Rev_{i,t} + \phi_{5,i}PPE_{i,t} + \upsilon_{i,t}, \end{aligned} \tag{E-1}$$

where $TCA_{i,t} = \Delta CA_{i,t} - \Delta CL_{i,t} - \Delta Cash_{i,t} + \Delta STDebt_{i,t}$ = total current accruals, $CFO_{i,t} = NIBE_{i,t} - TA_{i,t}$ = firm i's cash flow from operations, $NIBE_{i,t}$ = firm i's net income before extraordinary items (COMPUSTAT annual item IB), $TA_{i,t} = (\Delta CA_{i,t} - \Delta CL_{i,t} - \Delta CASH_{i,t} + \Delta STDebt_{i,t} - \Delta DEPN_{i,t})$ = firm i's total accruals, $\Delta CA_{i,t}$ = firm i's change in current assets (item ACT), $\Delta CL_{i,t}$ = firm i's change in current liabilities (item LCT), $\Delta Cash_{i,t}$ = firm i's change in cash (item CHE),

$\Delta STDebt_{i,t}$ = firm i's change in debt in current liabilities (item DCL), $\Delta DEPN_{i,t}$ = firm i's depreciation and amortization expense (item DP), $\Delta Rev_{i,t}$ = firm i's change in revenues (item $SALE$), $\Delta PPE_{i,t}$ = firm i's gross value of plant, property, and equipment (item $PPEGT$). Following Francis, LaFond, Olsson, and Schipper (2005), I estimate Eq. (E-1) for each of the Fama and French (1997) 48 industry groups with at least 20 firms. The standard deviation of the residuals is calculated from year $t-4$ to t.