Working Paper
WP-749
April, 2008

EXPECTED RETURNS AND LIQUIDITY RISK: DOES ENTREPRENEURIAL INCOME MATTER?

Pedro A. C. Saffi[1]

[1] Profesor of Financial Management, IESE

IESE Business School – University of Navarra
Av. Pearson, 21 – 08034 Barcelona, Spain. Phone: (+34) 93 253 42 00 Fax: (+34) 93 253 43 43
Camino del Cerro del Águila, 3 (Ctra. de Castilla, km 5,180) – 28023 Madrid, Spain. Phone: (+34) 91 357 08 09 Fax: (+34) 91 357 29 13

Expected Returns and Liquidity Risk: Does Entrepreneurial Income Matter?

Pedro A. C. Saffi *†

November 10th, 2007

Abstract

This paper studies the effects of jointly incorporating liquidity risk and non-tradeable wealth in a single asset pricing equation. First, I propose an overlapping-generations model with random endowment shocks and liquidity risk, evaluating their joint impact on expected returns. The model presents a single-factor asset pricing equation with a new term capturing the covariance between assets' liquidities and non-tradeable wealth. In this economy, assets with higher liquidity or returns when non-tradeable wealth is low command lower expected returns.

Second, I investigate if risks associated with liquidity are priced after including non-tradeable wealth due to entrepreneurial income. I test the model on equally and value-weighted portfolios sorted by illiquidity levels, illiquidity variation and size, using U.S. stock data from January 1962 to December 2004. The extra terms due to entrepreneurial income reduce liquidity risk *premium* by almost 40%, with an impact of -0.45% per year on expected returns of value-weighted illiquidity-sorted portfolios. Overall, liquidity risk as a whole has an yearly premium equal to 1.06%. However, liquidity levels are much more important and have a premium of 6.14% per year, contributing to most of the explanatory gains of the model.

1 Introduction

This paper studies the effects of liquidity risk and non-tradeable wealth on stock returns. First, I extend the model in Acharya and Pedersen (2005) to include random endowment shocks that capture non-tradeable wealth. I evaluate how these shocks affect expected returns in the presence of liquidity risk, deriving a single-factor asset

*This paper has benefited from conversations with Lauren Cohen, Gregory Connor, Andrew Jackson, Marcelo Fernandes, Francisco Gomes, Anna Pavlova, Astrid Schornick, Kari Sigurdsson and seminar participants at the Trans-Atlantic PhD Conference, the 3rd Portuguese Finance Network meeting, the 2004 meeting of the Brazilian Finance Society and the Economics PhD students' seminar at UCL. I'm immensely indebted to Tim Johnson and Viral Acharya for their time and guidance throughout this project. I also thank the financial support provided by London Business School. All errors are obviously mine. This paper was previously circulated as "Expected Returns and Liquidity Risk: Does Labor Income Matter?"

†Finance PhD programme, London Business School. Email: psaffi@london.edu Web: http://phd.london.edu/psaffi/

pricing equation adjusted for liquidity and non-tradeable wealth that motivates the empirical analysis. In this economy, assets with higher liquidity or returns when non-tradeable wealth is low, command lower expected returns in equilibrium. Most importantly, it is the ratio between non-tradeable and tradeable wealth that matters for agents instead of the returns from non-tradeable asset.

Second, I investigate if risks associated with liquidity are priced after including non-tradeable wealth due to entrepreneurial income. I test an unconditional version of the model on equally and value-weighted portfolios sorted by illiquidity levels, illiquidity variation and size, using U.S. stock data from January 1962 to December 2004. The extra terms due to entrepreneurial income reduces liquidity risk premium by almost 40%, having an impact of -0.45% per year on expected returns of value-weighted illiquidity-sorted portfolios. Overall, liquidity risk has an yearly premium equal to 1.06% but, similar to previous papers (e.g. Acharya and Pedersen (2005) and Korajczyk and Sadka (2007)), I find that liquidity levels are much more important to explain differences in stock returns, with a premium of 6.14% per year that contributes with most of the explanatory gains of the model relative to the standard CAPM.

Liquidity can be broadly defined as the ability to quickly and cheaply trade assets at fair prices. Standard models do not take into account the fact that the degree of liquidity an asset possess can also affect its expected return. For example, because it is generally harder to sell a house than sell a share of IBM, agents require higher expected returns when investing in a house, an effect that is not considered by the CAPM. One obvious extension is to allow liquidity to change over time (hence the liquidity risk terminology), allowing assets to have different degrees of marketability over time. Many authors have shown the impact of liquidity risk, both in theoretical [Acharya and Pedersen (2005)] and empirical settings [Acharya and Pedersen (2005), Fujimoto and Watanabe (2003), Pastor and Stambaugh (2003), Sadka (2003), Wang (2003) and Korajczyk and Sadka (2007)]. In the presence of time-varying liquidity, expected returns are affected not only by the covariance of returns with state variables, but also by how liquidity moves together with them (like the market portfolio in the standard CAPM or consumption in the C-CAPM).

However, none of the papers mentioned above study the effect of jointly incorporating liquidity risk and non-tradeable income in a single asset-pricing equation. More specifically, I focus on human capital as the source of non-tradeable wealth and entrepreneurial income as its proxy. Thus, the economic significance of liquidity risk could be due to an "omitted variable" problem, caused by excluding the impact from systematic movements of returns and liquidity with entrepreneurial income. During periods of relatively lower entrepreneurial income, it is important not only to own assets that provide high returns, but also ones that can be easily sold. For example, suppose that an investor suddenly becomes unemployed and his only asset is a house worth $1 million that cannot be easily sold due to a "cold" real-estate market. He would happily agree to own a more easily marketable asset, say IBM shares worth $1 million dollars, even if it gives him smaller expected returns. Therefore, systematic fluctuations of liquidity and returns with non-tradeable income might be priced in the cross-section of expected returns.

Although there are several different sources of non-tradeable income, like human capital (Jagannathan and

Wang (1996) and Heaton and Lucas (2000)) or real estate investments (Lustig and Nieuwerburgh (2005)), in this paper I chose to focus only on effects caused by labor income on traded assets. Labor income comprises the largest part of households' income (in 1989, wages comprise 78.4% of total income versus 3.1% due to personal dividend income). In particular, I focus on the income due to entrepreneurial ventures, which has been shown to comprise a significant component of income to investors with significant stock holdings.

The rest of the paper proceeds as follows. Section 2 surveys the literature, Section 3 describes the model linking non-tradeable wealth and liquidity risk. Section 4 describes the data used to test the model. Section 5 reports the empirical results. Section 6 concludes.

2 Literature Review

Asset pricing models show how a set of state variables influences expected returns through their effect on investors' utilities, using variables like aggregate stock market returns, consumption or dividend-yields to explain returns of financial securities. The basic version of the Capital Asset Pricing model (CAPM) (see Sharpe (1964), Lintner (1965) and Black (1972)), uses the market portfolio return as the state variable to derive a formula that expresses expected excess returns of an asset as a function of the covariance of its returns with the market portfolio. However, as pointed by Roll (1977), the market portfolio cannot be observed and rejection of the model in empirical studies may occur due to the use of improper proxies for this portfolio and not because the model itself is a poor representation of reality. Mayers (1973) extends the results of the basic CAPM to include human capital in the wealth portfolio, but Fama and Schwert (1977) do not find any significant empirical differences between the two models' results.

Trying to tackle Roll's critique, Jagannathan and Wang (1996) estimate a conditional version of the CAPM with human capital returns, finding a large increase in the explanatory power of the model after their proxy for human capital is added to the market portfolio. Following their evidence, the correlation between stock markets and labor income returns shows the practical relevance of models that take into account not only how assets move with stock returns, but also how these assets vary with human capital.

Another strand of the asset pricing literature tries to measure the impact of liquidity, broadly defined as the ability to quickly and cheaply trade assets at fair prices, on securities returns. Standard models do not take into account the fact that the degree of liquidity an asset possess can also affect their expected returns. One obvious extension is to allow liquidity to change over time (hence the liquidity risk terminology), allowing assets to have different degrees of marketability over time. Many authors have shown the impact of liquidity risk, both in theoretical [Acharya and Pedersen (2005)] and empirical settings [Acharya and Pedersen (2005), Pastor and Stambaugh (2003), Sadka (2003) and Wang (2003)].

3 Model

The setup is similar to Acharya and Pedersen (2005): an overlapping generations economy in which N new agents (indexed by n), with a life span of two periods, are born at time t and trade in periods t and $t+1$. Agents derive utility from expected consumption at $t+1$ and have CARA utility functions with constant absolute risk aversion coefficient given by A_n. Thus, the n-th agent has preferences given by $E_t\left(-e^{-A_n W_{t+1}}\right)$ and chooses her stock holdings at time t (given by the vector y_n) to maximize her utility function.

The economy has I securities, with a given stock i having a supply of S_i shares. At time t this stock has an ex-dividend price P_t^i, pays dividend D_t^i and has a liquidity cost C_t^i. This cost is paid whenever an agent sells the stock and is meant to capture all costs arising due to liquidity issues. The fact that this cost only applies to sales is not problematic, since agents trade only once and C_t^i can then be seen as a round-trip cost of trading. Furthermore, it is assumed that agents can freely borrow and lend at an exogenous risk-free rate $r_f > 1$. The inclusion of a random endowment shock at time $t+1$, represented by L_{t+1}, is used to capture the impact of non-tradeable wealth on asset prices. In the empirical section, I focus on aggregate entrepreneurial income as the only source of non-tradeable wealth.

The maximization problem of agent n is given by:

$$\underset{y_n}{Max}\ E_t[W_{t+1}] - \frac{A_n}{2} Var_t[W_{t+1}] \tag{1}$$

where

$$W_{t+1} = \left(P_{t+1} + D_{t+1} - C_{t+1}\right)^T y_n + r_f(e_t - P_t^T y_n) + L_{t+1} \tag{2}$$

The processes followed by D_{t+1}, C_{t+1} and L_{t+1} are given by the mean-reverting equations:

$$\begin{aligned} D_{t+1} &= \overline{D} + \gamma(D_t - \overline{D}) + \epsilon_{t+1} \\ C_{t+1} &= \overline{C} + \gamma(C_t - \overline{C}) + \eta_{t+1} \\ L_{t+1} &= \overline{L} + \gamma(L_t - \overline{L}) + v_{t+1} \end{aligned} \tag{3}$$

with

$$\begin{bmatrix} \epsilon_{t+1} \\ \eta_{t+1} \\ v_{t+1} \end{bmatrix} \sim N\left(\begin{bmatrix} 0 \\ 0 \\ 0 \end{bmatrix}, \begin{bmatrix} \Sigma^D & \Sigma^{DC} & \Sigma^{DL} \\ \Sigma^{CD} & \Sigma^C & \Sigma^{CL} \\ \Sigma^{LD} & \Sigma^{LC} & \Sigma^L \end{bmatrix}\right) \tag{4}$$

and $\overline{D_i} > \overline{C_i}\ \forall\ i = 1, \ldots, I$. Also $\Sigma^D, \Sigma^C, \Sigma^{DC}$ and Σ^{CD} are $I \times I$ symmetric matrices, Σ^{DL} and Σ^{CL} are $I \times 1$ vectors and Σ^L a scalar. The covariance matrices are assumed constant over time. The parameter capturing mean-reversion is assumed equal for D_{t+1}, C_{t+1} and L_{t+1} for tractability reasons. In order to ensure stationarity, I also assume that $|\gamma| < 1$.

The FOC, imply:

$$\begin{aligned} y_n = &\ \frac{1}{A_n} Var_t\left(P_{t+1} + D_{t+1} - C_{t+1}\right)^{-1} E_t[(P_{t+1} + D_{t+1} - C_{t+1}) - r_f P_t] \\ &- Var_t\left(P_{t+1} + D_{t+1} - C_{t+1}\right)^{-1} Cov_t\left[\left(P_{t+1} + D_{t+1} - C_{t+1}\right), L_{t+1}\right] \end{aligned} \tag{5}$$

Finally, prices are found through the market clearing condition $\sum_n y_n = S$ and are given by:

$$P_t = \frac{1}{r_f}\left[\begin{array}{c} E_t\left(P_{t+1}+D_{t+1}-C_{t+1}\right)-AVar_t\left(P_{t+1}+D_{t+1}-C_{t+1}\right)S \\ -NACov_t\left(P_{t+1}+D_{t+1}-C_{t+1},L_{t+1}\right)\end{array}\right], \tag{6}$$

with$A = \left[\sum_n \left(\frac{1}{A_n}\right)\right]^{-1}$.

The resulting linear equilibrium prices are:

$$P_t = \frac{1}{r_f-1}\frac{r_f}{r_f-\gamma}\left[(1-\gamma)\left(\overline{D}-\overline{C}\right)-\frac{A}{r_f-\gamma}\Gamma S - NA\left(\Sigma^{DL}-\Sigma^{CL}\right)\right]+\frac{\gamma}{r_f-\gamma}(D_t-C_t) \tag{7}$$

with $\Gamma = Var_t(\epsilon_t-\eta_t) = \Sigma^D+\Sigma^C-\Sigma^{DC}-\Sigma^{CD}$.

Comparing the equation above with the one in Acharya and Pedersen (2005), we can observe that extending the model to include random labor income affects prices only by adding an extra term, $NA\left(\Sigma^{DL}-\Sigma^{CL}\right)$. It is related to the covariance between net dividends and non-tradeable wealth and shows that assets for which net dividends are higher whenever entrepreneurial income is also high, will have lower equilibrium prices.

Solving for y_n allow me to obtain the number of shares purchased by agent n in equilibrium:

$$y_n = \frac{A}{A_n}S+\frac{1}{A_n}\left(\frac{r_f-\gamma}{r_f}\right)(NA-A_n)\Gamma^{-1}\left(\Sigma^{DL}-\Sigma^{CL}\right) \tag{8}$$

If future income is deterministic or uncorrelated to net dividends $\left(\Sigma^{DL}-\Sigma^{CL}=0\right)$, all investors hold a positive fraction $\frac{A}{A_n}$ of the market portfolio S. Thus, no short sales take place and the standard CAPM holds for net returns.

Effects of adding random endowments to the model arise when $\Gamma^{-1}\left(\Sigma^{DL}-\Sigma^{CL}\right)$ is different from zero. An increase in the correlation of net dividends with non-tradeable wealth leads to a fall in stock holdings by agent n if $A_n > NA$, i.e., when she is more risk-averse than a measure of aggregate risk aversion.

The expected return on a portfolio with weights given by $q = [q_1,\ldots,q_I]^T$ is:[1]

$$E_t\left(r^q_{t+1}\right) = \frac{B+r_f(1-\gamma)\overline{D^q}+r_f\gamma D^q_t-\gamma(1-\gamma)\overline{C^q}-\gamma^2C^q_t}{B+\gamma\left(D^q_t-C^q_t\right)} \tag{9}$$

where

$$B = \frac{r_f}{r_f-1}q^T\left[(1-\gamma)\left(\overline{D}-\overline{C}\right)-A\left(\frac{r_f}{r_f-\gamma}\right)\Gamma S-NA\left(\Sigma^{DL}-\Sigma^{CL}\right)\right] \tag{10}$$

Empirical tests require a representation in terms of the market price of risk. From equation (6) we have:

$$\begin{aligned} r^f P_t &= E_t\left(P_{t+1}+D_{t+1}-C_{t+1}\right)-AVar_t\left(P_{t+1}+D_{t+1}-C_{t+1}\right)S \\ &\quad -NACov_t\left(P_{t+1}+D_{t+1}-C_{t+1},L_{t+1}\right)\end{aligned} \tag{11}$$

[1]The notation used to express portfolio's characteristics is the following: for any variable X_t we have $X^q = q^TX_t$. For example, gross returns are given by: $r^q_{t+1} = \frac{q^T\left[P_{t+1}+D_{t+1}\right]}{q^TP_t} = \frac{P^q_{t+1}+D^q_{t+1}}{P^q_t}$.

Multiplying by S^T yields the market value on the left-hand side:

$$r^f P_t^M = E_t\left(P_{t+1}^M + D_{t+1}^M - C_{t+1}^M\right) - AVar_t\left(P_{t+1}^M + D_{t+1}^M - C_{t+1}^M\right)P_t^M \quad (12)$$
$$-NACov_t\left(P_{t+1}^M + D_{t+1}^M - C_{t+1}^M, L_{t+1}\right)$$

Dividing by P_t^M, I obtain A as a function of returns:

$$A = \frac{E_t\left(r_{t+1}^M - c_{t+1}^M - r^f\right)}{Var_t\left(r_{t+1}^M - c_{t+1}^M\right)P_t^M + NCov_t\left(r_{t+1}^M - c_{t+1}^M, L_{t+1}\right)} \quad (13)$$

Going back to the pricing equation (11), for any asset i we have:

$$r^f P_t^i = E_t\left(P_{t+1}^i + D_{t+1}^i - C_{t+1}^i\right) - NACov_t\left[P_{t+1}^i + D_{t+1}^i - C_{t+1}^i, L_{t+1}\right] \quad (14)$$
$$-A\sum_{j=1}^{L} Cov(P_{t+1}^i + D_{t+1}^i - C_{t+1}^i, P_{t+1}^j + D_{t+1}^j - C_{t+1}^j)S_j$$

Dividing by P_t^i and rearranging terms inside the covariances leads to:

$$r^f = E_t\left(r_{t+1}^i - c_{t+1}^i\right) - ACov(r_{t+1}^i - c_{t+1}^i, r_{t+1}^M - c_{t+1}^M)P_t^M - NACov_t\left(r_{t+1}^i - c_{t+1}^i, L_{t+1}\right) \Rightarrow$$

$$E_t\left(r_{t+1}^i - c_{t+1}^i - r^f\right) = A\left[Cov(r_{t+1}^i - c_{t+1}^i, r_{t+1}^M - c_{t+1}^M)P_t^M + NCov_t\left(r_{t+1}^i - c_{t+1}^i, L_{t+1}\right)\right] \quad (15)$$

Replacing A by the result in equation (13) and dividing above and below by P_t^M, I finally obtain:

$$E_t\left(r_{t+1}^i - c_{t+1}^i - r_f\right) = \left[\frac{E_t\left(r_{t+1}^M - c_{t+1}^M - r_f\right)}{Var_t\left(r_{t+1}^M - c_{t+1}^M\right) + NCov_t\left(r_{t+1}^M - c_{t+1}^M, \frac{L_{t+1}}{P_t^M}\right)}\right] * \quad (16)$$
$$\left[Cov_t(r_{t+1}^i - c_{t+1}^i, r_{t+1}^M - c_{t+1}^M) + NCov_t\left(r_{t+1}^i - c_{t+1}^i, \frac{L_{t+1}}{P_t^M}\right)\right]$$

The equation above is solely a function of observed variables and can be used to test the model's implications. Under the assumption that covariances are constant over time, the unconditional version of the model is given by:[2]

$$E\left(r_{t+1}^i - r_f\right) = E\left(c_{t+1}^i\right) + \lambda\left(\beta_{mkt}^i + \beta_2^i - \beta_3^i - \beta_4^i - \beta_{liq,lab}^i + \beta_{labor}^i\right) \quad (17)$$

[2]This assumption is made for tractability. A conditional CAPM approach like the one in Acharya and Pedersen (2005) is also possible.

with $\lambda = E(\lambda_t) = E\left(r^M_{t+1} - c^M_{t+1} - r_f\right)$ and

$$\begin{aligned}
\beta^i_{mkt} &= \frac{Cov\left(r^i_{t+1}, r^M_{t+1}\right)}{Var\left[r^M_{t+1} - c^M_{t+1}\right] + Cov\left[r^M_{t+1} - c^M_{t+1}, \frac{NL_{t+1}}{P^M_t}\right]} \\
\beta^i_{2} &= \frac{Cov\left(c^i_{t+1}, c^M_{t+1}\right)}{Var\left[r^M_{t+1} - c^M_{t+1}\right] + Cov\left[r^M_{t+1} - c^M_{t+1}, \frac{NL_{t+1}}{P^M_t}\right]} \\
\beta^i_{3} &= \frac{Cov\left(r^i_{t+1}, c^M_{t+1}\right)}{Var\left[r^M_{t+1} - c^M_{t+1}\right] + Cov\left[r^M_{t+1} - c^M_{t+1}, \frac{NL_{t+1}}{P^M_t}\right]} \\
\beta^i_{4} &= \frac{Cov\left(c^i_{t+1}, r^M_{t+1}\right)}{Var\left[r^M_{t+1} - c^M_{t+1}\right] + Cov\left[r^M_{t+1} - c^M_{t+1}, \frac{NL_{t+1}}{P^M_t}\right]} \\
\beta^i_{liq,lab} &= \frac{Cov\left(c^i_{t+1}, \frac{NL_{t+1}}{P^M_t}\right)}{Var\left[r^M_{t+1} - c^M_{t+1}\right] + Cov\left[r^M_{t+1} - c^M_{t+1}, \frac{NL_{t+1}}{P^M_t}\right]} \\
\beta^i_{labor} &= \frac{Cov\left(r^i_{t+1}, \frac{NL_{t+1}}{P^M_t}\right)}{Var\left[r^M_{t+1} - c^M_{t+1}\right] + Cov\left[r^M_{t+1} - c^M_{t+1}, \frac{NL_{t+1}}{P^M_t}\right]}
\end{aligned} \tag{18}$$

There are two main differences between equation (17) and the one derived in Acharya and Pedersen (2005). The inclusion of non-tradeable wealth adds two new covariance terms: $\beta_{liq,lab}$ and β_{labor}, which account for the covariance between net returns and liquidity and the covariance between non-tradeable-to-tradeable wealth ratio. It also affects the other betas via the denominator, which contains the variance of net market returns plus this extra covariance term of net returns with $\left(\frac{NL_{t+1}}{P^M_t}\right)$. Thus, any variable that provides individuals with additional (risky) income in the future will affect expected returns of tradeable assets, as agents can only hedge this extra source of risk by investing in stocks, giving a theoretical explanation for why variables like proprietary income [Heaton and Lucas (2000)] are priced in the cross-section.

Looking at equation (18), we can observe how betas of the market portfolio add up to one, i.e., $\sum_i \left(\beta^i_{mkt} + \beta^i_2 - \beta^i_3 - \beta^i_4 - \beta^i_{l}\right.$ $= 1$. This expression is similar to the result obtained by Mayers (1973), but now adjusted for liquidity risk.

In total there are four terms related to liquidity risk: β_2, β_3, β_4 and $\beta_{liq,lab}$. I summarize the impact of the correlation between non-tradeable wealth and liquidity changes with the following proposition:

Proposition 1 *Consider a portfolio with weights $q \in \mathbb{R}^I$ such that* ***net*** *returns are given by $r^{q,net}_{t+1} = \frac{P^q_{t+1} + D^q_{t+1} - C^q_{t+1}}{P^q_t}$. A marginal increase in the covariance between net dividends and non-tradeable income increases conditional expected returns whenever $(D^q_t - C^q_t) > 0$.*

Proof 1 $\frac{\partial E_t\left(r^{q,net}_{t+1}\right)}{\partial q^T(\Sigma^{DL} - \Sigma^{CL})} = \frac{NA}{(r_f-1)(r_f-\gamma)^2(P^q_t)^2}\left[r_f(1+\gamma)\left(\overline{D}^q - \overline{C}^q\right) + \gamma\left(r_f - 1\right)\left(D^q_t - C^q_t\right)\right]$

Thus, $(D^q_t - C^q_t) > 0 \Longrightarrow \frac{\partial E_t\left(r^{q}_{t+1}\right)}{\partial q^T(\Sigma^{DL} - \Sigma^{CL})} > 0.$

3.1 The Four Liquidity "Betas"

This subsection further develops the underlying mechanisms through which expected returns are affected by liquidity risk, describing the economic intuition behind the betas shown in equation (17).

1. $\beta_2^i : Cov\left(c_{t+1}^i, c_{t+1}^M\right)$: This term compensates investors for holding stocks that become more illiquid as the stock market becomes more illiquid. This effect is known in the literature as the "commonality-in-liquidity" effect. It has been documented by Chordia, Roll, and Subrahmanyam (2000), Hasbrouck and Seppi (2001) and Huberman and Halka (2001) and its impact on prices first is objectively estimated by Acharya and Pedersen (2005). In terms of the model, if illiquidity increases for the market as a whole, investors optimally prefer to sell assets whose illiquidities didn't go up as much. *Ceteris paribus*, net dividends for these assets are higher, increasing the price paid for stocks with illiquidities that don't vary much with market illiquidity.

2. $\beta_3^i : Cov\left(r_{t+1}^i, c_{t+1}^M\right)$: This effect is due to the covariance between asset's returns and market illiquidity and works in the same manner as the previous one. If market illiquidity goes up, investors would pay a premium for stocks that have higher dividends, as it is another way to keep *net* dividends constant. This effect is studied by Pastor and Stambaugh (2003), Fujimoto and Watanabe (2003), Sadka (2003) and Wang (2003).

3. $\beta_4^i : Cov\left(c_{t+1}^i, r_{t+1}^M\right)$: As market returns increase, investors have more appetite for less liquid assets, accepting smaller expected returns. Alternatively, during periods of low market returns, agents are particularly interested in assets that are more liquid, since they could sell their holdings at a lower cost. The impact of this effect on asset prices is analyzed by Acharya and Pedersen (2005), who show that this term is by far the most important of the liquidity risk terms, with a premium of approximately 0.8% a year .

4. $\beta_{liq,lab}^i : Cov_t\left(c_{t+1}^i, \frac{NL_{t+1}}{P_t^M}\right)$: This term summarizes the contribution of this paper to the liquidity literature. It shows that agents prefer assets that can be more easily sold during times when the non-tradeable to tradeable wealth ratio is low. Investors are specially dissatisfied with stocks that have higher transaction costs when larger shares of wealth come from marketable assets, i.e., periods in which they are unemployed. At those times, most of their consumption comes from tradeable assets and to hold relatively more illiquid securities, they require a premium.

4 Data

4.1 Stocks

The monthly sample uses data for the period January 1962-December 2004. It includes NYSE and AMEX common stocks (CRPS's SHRCD values 10 or 11).[3] The daily data used to compute the illiquidity measure are based on CRSP's returns and volume data from January 1st, 1962 to December 31st, 2004. Book-to-market ratios (B/M) are computed with the procedure described in Daniel and Titman (2003) and use Compustat data for book values.

Sorted portfolios only include stocks that in the previous year had prices between \$5 and \$1000 dollars and data for at least 100 days. These requirements are imposed to reduce estimation problems due to infrequent trading and are similar to the ones used by Acharya and Pedersen (2005) and Pastor and Stambaugh (2003) and have the purpose of reducing measurement error in illiquidity series. In order to adjust for delisting bias, I use the suggestion of Shumway (1997) and assign a -30% return to delisting returns for stocks delisted due to “poor performance”.[4] I construct portfolios using equal and value-weighted returns to make the conclusions more robust to the sorting procedure.

The sort on illiquidity levels in year t uses average illiquidity of eligible stocks in year $t-1$ to form 25 portfolios from January 1962 to December 2004. I then track these stocks until the last month of year t, when they are rebalanced and new portfolios are formed. Sorts on illiquidity variation are based on the standard deviation of daily illiquidity calculated in year $t-1$. Finally, size-sorted portfolios are based on December of year $t-1$ values. The market portfolio in month t is constructed based on equal-weighting all stocks with prices, at the end of year $t-1$, between 5 and 1000, and data for at least 15 days. Equally weighted stocks are used as a way to reduce the over-representation of large stocks in my proxy of the “true” market portfolio.

The return of a portfolio i in month t is given by:

$$r_t^i = \sum_{s \text{ in } i} w_t^s r_t^s, \tag{19}$$

with w_t^s being the weights of stocks that fulfill data requirements and r_t^s the return of stock s on month t.

Similarly, their normalized illiquidity is given by:

$$c_t^i = \sum_{s \text{ in } i} w_t^s c_t^s, \tag{20}$$

[3] Nasdaq stocks are excluded from empirical tests because they only have daily data available starting in 1982. This ensures consistency of the illiquidity estimates detailed below.

[4] Shumway (1997) shows how missing delisting returns could lead to biases in asset pricing models' tests. In particular, stocks delisted due to what he broadly classifies as “poor performance” reasons (CRSP codes 500, 520, 551-574, 580 and 584) are found to have an average corrected delisting return equal to -30% from data collected outside CRSP. Following this evidence, I assign a -30% to all delisting returns that have the delisting codes mentioned above.

4.2 Liquidity Measure

In a perfect world, agents would be able to freely move their holdings without paying any transaction costs. In real life though, a liquid market is one where these costs are minimized. They not only include explicit costs like commissions and taxes, but also implicit ones arising due to asymmetric information [Glosten and Milgrom (1985) and Easley and O'Hara (1987)].

The literature suggests many alternative measures to capture these costs, such as the bid-ask spread, amortized spread, volume or turnover [see Aitken and Comerton-Forde (2003) for a survey]. Unfortunately, many of these measures require intra-day data that are unavailable for the long time periods required by asset pricing tests. Amihud (2002) proposes a measure of illiquidity based on daily data shown to be related to price impacts of trading and transaction costs. The daily frequency of this measure allows calculation for the larger number of observations required by tests of asset pricing models and has been extensively used in the literature [Acharya and Pedersen (2005), Fujimoto and Watanabe (2003), Pastor and Stambaugh (2003), Sadka (2003) and Wang (2003)]. This measure is given by:

$$ILLIQ_t^i = \frac{1}{Days_t^i} \sum_{d=1}^{Days_t^i} \frac{\left|R_{t,d}^i\right|}{Volume_{t,d}^i} * 10^6, \tag{21}$$

with $R_{t,d}^i$ and $Volume_{t,d}^i$ denoting the return and dollar volume on day d in month t of stock i, and $Days_t^i$ represents the number of valid data points for stock i in month t. $ILLIQ$ measures the absolute price change per dollar of trading volume, with large values representing highly illiquid stocks. For example, stocks with large swings in prices but low volume are considered illiquid under this measure.

There are two major problems in directly using $ILLIQ$ in regressions to estimate the risk premium: first, it is not stationary, as the inflationary component in dollar volume makes it drift towards zero over time. Second, it is not an explicit measure of trading costs like effective spreads. In order to mitigate these issues, regressions use a normalized measure of illiquidity:

$$c_t^i = min\left(0.28 + 0.3 * ILLIQ_t^i * X_{t-1}^M, 30\right), \tag{22}$$

where X_{t-1}^M is the ratio of market capitalizations at the end of month $t-1$ and July 1962. The ratio X_{t-1}^M is used to turn c_t^i into a measure of the cost of trading relative to stock price. This scaling also has the additional advantage of making $ILLIQ$ relatively stationary.

The two coefficients (0.28 and 0.3) are calibrated so that c_t^i has mean and variance approximately equal to the effective spreads of the size-sorted portfolios measured by Chalmers and Kadlec (1998). Their paper reports that these portfolios have effective-spread mean and standard deviation of respectively 1.19% and 0.97%, with values ranging from 0.29% to 3.41%. As for c_t^i, it has a mean of 1.39% and standard deviation of 1.67%, with values ranging from 0.29% to 5.56% for identically-formed portfolios using data from January 1962 to December 1999.

Also, it is often the case that, for stocks with low trading volume, $ILLIQ$ is very high, yielding unreasonable values for c_t^i. In order to prevent exclusion of these firms from the sample, stocks with c_t^i greater than 30% are truncated to ensure that results are unaffected by outliers $ILLIQ$ due to high return-low volume days. Without the truncation, some stocks would have a value of c_t^i greater than 100%, which is clearly not possible. Overall, this calibration allows me to interpret c_t^i as a measure of percentage cost per trade.

As agents already factor out expected components of time series in their calculations, I use the unexpected component of illiquidity for estimating betas. The specification used is based on an AR(2) specification, similar to Pastor and Stambaugh (2003) and Acharya and Pedersen (2005):

$$\begin{aligned} 0.28 + 0.3 * \overline{ILLIQ_t^i} * X_{t-1}^M &= a_0 + a_1 \left(0.28 + 0.3 * \overline{ILLIQ_{t-1}^i} * X_{t-1}^M\right) \\ &\quad + a_2 \left(0.28 + 0.3 * \overline{ILLIQ_{t-2}^i} * X_{t-1}^M\right) + u_t^i, \end{aligned} \tag{23}$$

with $\overline{ILLIQ_t^i} = min\left(ILLIQ_t^i, \frac{30-0.28}{0.3*X_{t-1}^M}\right)$.

This specification is used for two reasons: first, the expression for c_t^i in equation (22) involves X_{t-1}^M and estimating the model with lags of c_t^i might capture innovations due to changes in P_{t-1}^M and not those only due to illiquidity. Hence, I use a truncated measure of $ILLIQ$ while keeping X_{t-1}^M fixed, making them free of innovations due to market capitalization increases. All other references to illiquidity throughout the paper though, refer to c_t^i. Table 1 shows estimated coefficients of the AR(2) model for the market portfolio. The adjusted R^2 of the equation is 91% and generate residuals free of serial correlation.

The estimated correlations between normalized illiquidity shocks of the market portfolio (c_t^m) and, respectively, Acharya and Pedersen (2005) and Pastor and Stambaugh (2003)'s measures of market illiquidity shocks are equal to 0.56 and -0.35 and are shown in Table 2.[5] Figure 1 exhibits estimated illiquidity levels and residuals for the market portfolio. On average, market illiquidity has fluctuated around 3.19%, with the latest levels in December 2004 being close to this average after the spike seen during the Internet bubble. The residual series show that $ILLIQ$ is able to capture periods usually associated to illiquid market conditions, like the oil crisis in 1973, the market crash in October 1987, or the LTCM crisis in October 1998. The apparent increase in illiquidity levels over time (especially during the Internet bubble period) can be explained by the higher number of thinly traded stocks entering the equal-weighted market portfolio during those years.

The residual u_t^i of equation (23) is taken as the innovation in illiquidity used to calculate liquidity betas in equation (17):

$$c_t^i - E_{t-1}\left(c_t^i\right) \equiv u_t^i \tag{24}$$

4.3 Non-tradeable Wealth and Entrepreneurial Income

Ideally, we would like to have a measure of aggregate non-tradeable wealth over time. In this paper, I'm most interested in looking at a component of wealth that captures changes related to human capital, which is a source of capital that cannot usually be used - if at all - as collateral to smooth consumption. In this way, income derived from labor is the first proxy that comes to mind. Heaton and Lucas (2000) has shown that the return from

[5] Pastor and Stambaugh (2003) measure liquidity instead of *il*liquidity, which explains the negative correlation. I kindly thank both sets of authors for providing their data on illiquidity innovations.

entrepreneurial ventures constitutes an important fraction of income in households that also have large stock ownership. They report that this proprietary income is more volatile and correlated to stock returns than when the variation in real aggregate wages are used (correlation with the CRSP value-weighted market returns equals 0.14, versus -0.07 when using real aggregate wages)and able to improve the performance of asset pricing models over similar models that only includes wage income. Other forms of non-tradeable illiquid wealth, like real estate assets, are also expected to affect the expected returns of stocks, but the lack of long-term time-series makes it difficult to measure their impact as sources of return variation.

I measure this source of income with data on non-farm proprietors' income, defined as income of sole proprietorships and partnerships and of tax-exempt cooperatives, excluding any dividends and interest received by non-financial businesses and rental incomes received by persons not primarily engaged in the real estate business. Essentially, they measure aggregate income of entrepreneurs, whose private enterprizes' income are hard to diversify (like income from a small shop, for example). Hence, any systematic risk from this source of income can only be hedged via stock holdings, leading to a potential impact on expected stock returns. I also perform tests using alternative measures of labor income (Jagannathan and Wang (1996), Lustig and Nieuwerburgh (2005)) and show that my results are even stronger when more aggregated measures are used.

Given the static set-up of the model, all shocks to labor income are permanent and I cannot distinguish income – a flow variable – from wealth. Empirically, there are two possible variables that could be used to test it, but I implicitly assume a constant growth rate of income and focus on current income only, similar to Jagannathan and Wang (1996) and Heaton and Lucas (2000).

Note that the model proposes a measure different than usually seen in the literature [see for example, Jagannathan and Wang (1996), Heaton and Lucas (2000) and Palacios-Huerta (2003)], which use proxies of *returns* on human capital. Here, the relevant variable is the ratio given by $\left(\frac{NL_{t+1}}{P_t^M}\right)$, corresponding to aggregate non-tradeable wealth at time $t+1$ of a cohort born at time t divided by the aggregate stock market wealth at time t. As mentioned before, I estimate NL_{t+1} using aggregate non-farm proprietors' income from Table 2.8 in the *National Income and Product Accounts of the USA*.[6] Since labor income data are usually published with a one-month delay, I lag values to better capture the information set available to investors. Also, because analysis of $\left(\frac{NL_t}{P_t^M}\right)$ produces strong evidence of non-stationarity, I use first differences when testing the model and use them as shocks to entrepreneurial income. As another robustness test, I replace the non-tradeable to tradeable wealth ratio proposed by the structural model with returns on labor income measures, finding that results are actually even stronger.

In Figure 2, I plot both the wealth ratio, $\frac{NL_{t+1}}{P_t^M}$, and its first differences over time. Entrepreneurial income corresponds on average to 12% of total market capitalization on and exhibits a negative trend since 1960, although it increased a little during the past 5 years. For comparison, the average value of aggregate labor income corresponds to roughly 133% of the aggregate stock market value. In Table 2 I show correlations among different illiquidity measures, market returns and the wealth ratio. We can observe how the wealth ratio is highly corre-

[6] Data on earnings are published by the Bureau of Economic Analysis, US Department of Commerce and can be found at: http://www.bea.doc.gov/bea/dn/nipaweb/index.asp.

lated to illiquidity shocks and that market illiquidity measures are more correlated with differences in $\frac{NL_{t+1}}{P_t^M}$ than market returns. However, we'll later see that because $Cov(c_t^M, \frac{NL_{t+1}}{P_t^M})$ is much smaller in magnitude than $Cov(r_t^M, \frac{NL_{t+1}}{P_t^M})$, the overall impact on expected returns is larger for the former rather than the latter. We can also observe the negative correlation between market illiquidity and market returns, i.e., periods of bad returns are also associated with greater illiquidity, reinforcing the intuition of a liquidity risk premium in stocks.

4.4 Liquidity Risk

This subsection provides the description of risk associated to liquidity as measured by β_2, β_3, β_4 and $\beta_{liq,lab}$ in equation (17). First, I calculate monthly returns and illiquidity of an equal-weighted market portfolio and of yearly-formed portfolios sorted according to illiquidity, size or B/M ratios using data from January 1962 to December 2004. Since illiquidity measures and the wealth ratio are all very persistent, I use the unexpected component of these variables (instead of levels) to avoid any possible correlation between expected illiquidity and expected returns that have already been incorporated by agents into prices. I then estimate innovations in illiquidity implied by the model in equation (23) and use these shocks, together with the first difference of the wealth ratio, to calculate the betas shown in equation (16). Market return innovations are estimated from shocks using an AR(1) process to remove first-order autocorrelation.

Given betas derived in Equation (18), I cannot use the standard practice of estimating time-series regressions for each portfolio's returns series to obtain them. Instead, I take the moment conditions implied by equation Equation (18) and compute betas via GMM estimation using Hansen's optimal weighting matrix. Then, in a second stage, I use these calculated betas as inputs to Equation (23) and estimate the risk premium implied by the data.

Table 3 exhibits the correlation among expected illiquidity levels and betas for each sorted portfolio. The liquidity betas are not only highly correlated among themselves, but also to illiquidity levels ($E\left(c_t^i\right)$) across all portfolio sorts. This correlation remains high even when betas are aggregated betas according to Equation (17). This collinearity explains why it is so problematic to pin-down individual liquidity risk premia, motivating the calibration of the parameter associated to illiquidity levels, trying to disentangle premia arising from individual liquidity risk components from ones due to liquidity levels.

As shown by Acharya and Pedersen (2005), less liquid portfolios also tend to have higher illiquidity betas (β_2, β_3 and β_4). However, these portfolios also tend to have positive $\beta_{liq,lab}$ and negative β_{labor}. Thus, whenever entrepreneurial income is relatively high, portfolio *il*liquidities are high while portfolio returns are low. Given a positive risk premium, these betas reduce expected returns and counterbalance the liquidity risk premium estimated by Acharya and Pedersen (2005), reducing the overall size of the risk associated to time-varying liquidity. Portfolios that have lower liquidity costs or higher returns when entrepreneurial income is low are desired by investors, decreasing their expected returns in equilibrium.

5 Liquidity Risk *Premia*

5.1 Cross-sectional Regressions

This section discusses the economic significance of the estimated risk premia. I run regressions of excess returns on betas estimated by equation (17) with portfolios sorted by illiquidity levels, illiquidity standard deviations and size.[7] I consider different cases of the following regression:

$$E\left(r_t^i - r_f\right) = \alpha + kE\left(c_t^i\right) + \lambda_{mkt}\beta_{mkt}^i + \lambda_{liq}\beta_{liq}^i + \lambda_{labor}\beta_{labor}^i + \lambda_{Net}\beta_{Net}^i, \tag{25}$$

with $\beta_{liq}^i = \beta_2^i - \beta_3^i - \beta_4^i - \beta_{liq,lab}^i$, $\beta_{Net}^i = \beta_{mkt}^i + \beta_2^i - \beta_3^i - \beta_4^i - \beta_{liq,lab}^i + \beta_{labor}^i$.

The liquidity-adjusted CAPM derived in this paper has only one risk-factor (λ_{Net}), but I also estimate regressions relaxing the restriction that all types of liquidity risk factors face the same risk premium, trying to pin-down individual estimates for each liquidity component. The β_{liq} parameter subsumes all liquidity risk-related effects and allows me to test whether the entrepreneurial income-related betas, $\beta_{liq,lab}$ and β_{labor}, have any explanatory power above and beyond the impacts of liquidity levels ($E\left(c_t^i\right)$) and liquidity risk (β_{liq}). The coefficient k is used to adjust for the difference between the estimation period and the holding period of investors: since $E\left(c_t^i\right)$ is not scaled by time, as holding periods increase, costs of transacting are spread over more periods, reducing the monthly premium for illiquidity levels required to hold an asset. Also, because of collinearity between expected illiquidity and the liquidity betas, I run equations in which $k \cdot E\left(c_t^i\right)$ is calibrated. Here, I choose k to be the average turnover of the 25 portfolios used to test the model. For illiquidity-levels sorted portfolios, it equals 4.44% per month, implying an average holding period of 22.5 months.[8] Thus, the total monthly effect of illiquidity *levels* on expected returns is given by $k \cdot E\left(c_t^i\right)$.

Table 4 presents the descriptive statistics of value-weighted illiquidity-sorted portfolios. We can observe that sorting on illiquidity *levels* generate portfolios that also sort stocks by their illiquidity *risks* (measured by β_2, β_3, β_4 and $\beta_{liq,lab}$). Entrepreneurial income betas become more negative with illiquidity, implying smaller expected returns. As expected, portfolios with higher illiquidity also tend to have higher returns, risk and B/M ratios, but smaller sizes and turnover.

Table 5 contains estimated parameters using sorts on illiquidity levels with value-weighted returns. The first three equations estimate factor premia without adjusting for differences in illiquidity levels. In Row 1, the standard CAPM is rejected and have a low R^2, as it tends to underestimate actual returns. Row 2 has β_{labor} added to the model and its high statistical significance is a consequence of collinearity with omitted liquidity betas. In other specifications, I cannot reject the null that $\lambda_{labor} = 0$ when liquidity terms are added.

The main regression implied by the model appears in Row 5 and has statistically significant premium and intercept statistically not different from zero. The model adds explanatory power by making an adjustment for liquidity and non-tradeable wealth to the usual CAPM, but it still has only one risk factor. The risk premium

[7] This two-stage procedure implicitly assumes away any estimation error in betas.

[8] The dependent variable in this case becomes $r_t^i - r_t^f - kc_t^i$.

associated to illiquidity levels is significant in most regressions, but as different risk premia are allowed, the impact of collinearity becomes stronger and liquidity betas' coefficients are no longer individually significant. However, the point estimates associated to market returns (β_1 in column 3) and liquidity parameters (β_{liq} in column 4) seem stable regardless of whether I calibrate the coefficient on liquidity levels (rows 4-5), use value or equal-weighted returns (Table 5 or Table 7) or sort portfolios on illiquidity variation (Table 9).

5.2 Economic Interpretation

In order to get an estimate of the return premium associated to liquidity risk, I use the risk premium $\lambda = 1.37$ estimated in Row 5 of Table 5, which is significant at the 1% confidence level. The annualized return difference that can be attributed to liquidity risk is:

$$\lambda \cdot \left[\left(\beta_{liq}^{25}\right) - \left(\beta_{liq}^{1}\right)\right] \cdot 12 = 1.06\% \; p.a.$$

The 95% confidence interval is (0.22%, 1.89%). The most important liquidity risk factor is β_4, which captures the covariance between asset illiquidity and market returns and contributes with more than 80% of the estimated annualized return difference due to liquidity risk, for an actual contribution of 0.88% a year. This value is similar to the one Acharya and Pedersen (2005) find using a similar sample of stock returns ending in December 1999.

The premium due to covariance between illiquidity and the wealth ratio, $\beta_{liq,lab}$, is given by:

$$\lambda \cdot \left[\left(\beta_{liq,lab}^{25}\right) - \left(\beta_{liq,lab}^{1}\right)\right] \cdot 12 = -0.11\% \; p.a.$$

This extra term alone generates a decrease in liquidity risk of almost 10% when compared to models that only include traded assets in agents' budget constraints. Furthermore, when we add the impact from the covariance between portfolio returns and entrepreneurial income, the difference in expected returns between the least and most liquid portfolios that is not due to illiquidity levels or stock market betas falls to 0.72% per year. This represents a decrease of almost 40% to the case where time-varying liquidity, but not non-tradeable wealth, is considered.

The effect from $k \cdot \left[E\left(c_t^{25}\right) - E\left(c_t^{1}\right)\right]$ provides an estimate of how liquidity levels affect expected returns. This is by far the most relevant variable and amounts to an expected return difference of 6.15%. In total, the overall effect of liquidity on asset returns is 7.21% per year, with 95% confidence interval [6.37%, 8.04%].

In Figure 6, I plot realized and fitted monthly returns of illiquidity-sorted portfolios. The upper panel shows returns estimated by the standard CAPM model, while the bottom panel has estimates for the liquidity-adjusted CAPM. We can observe that most of the failure of the standard CAPM lies on the less liquid portfolios, exactly because it does not take into account these portfolios' higher liquidity costs. For example, the return of most illiquid portfolio (labelled 25 in the graph) is greatly underestimated by the standard CAPM. However, as soon as liquidity is taken into account, the expected larger transaction costs enable the model to price portfolios much better than before.

5.3 Robustness Checks

On Table 7, I also show results for equal-weighted portfolios sorted on illiquidity. These portfolios have characteristics, shown in Table 6, that are very close to value-weighted portfolios. The overall liquidity risk effect is close to the one found for VW portfolios and equals 0.89% per year.

As further robustness checks, I also estimate the risk premium using sorts on illiquidity-variability and size portfolios. Table 8 and Table 9 have descriptive statistics and estimates for value-weighted size-sorted portfolios and Table 10 and Table 11 do the same for size-sorted portfolios.[9]

Estimates based on illiquidity-variability result in the same conclusions as sorting on illiquidity levels and lead to similar premium estimates. Estimates using size-sorted portfolios are not statistically significant, although point-estimates are similar to those obtained for illiquidity sorts using the model specified in rows 4-5 or when I calibrate parameters for illiquidity levels (k). The expected liquidity risk effect on returns has the correct sign and equals 0.63% per year.

The risk premia computed above is based on spreads computed from sorting stocks into 25 portfolios. This compares the top 4% with the bottom 4% of stocks, which might too aggressive. In Table 12 and Table 13 I repeat the analysis on stocks over illiquidity deciles instead. The differences in illiquidity (and expected returns are lower than when I use 25 portfolios (the annualized illiquidity spread goes from 6.31% p.a. to 4.68%, while the spread in returns goes from 9.94% p.a. to 9.30%), but the results remain the same. Using the parameters estimated in regression (5) in Table 13, the risk premium due to differences in liquidity levels is equal to 4.52% p.a. (compared to 6.15% when using spreads based on 25 portfolios). The premium due to the liquidity labor income beta decreases from -0.1% p.a. to -0.06% p.a. Finally, the overall liquidity premium falls from 7.21% to 5.39%, mainly due to the smaller spread in liquidity levels. Thus, results are not being driven simply by an extreme sort of stocks.

An important decision is the choice of labor income used to capture the impact on non-tradeable wealth on expected returns of traded assets. Although I use entrepreneurial income as Heaton and Lucas (2000), it is likely that broader measures of labor income also affect returns. In Table 14 I repeat tests on deciles of illiquidity-sorted portfolios using two alternative measures previously used in the literature to compute the non-tradeable to tradeable wealth ratios. I follow Jagannathan and Wang (1996) and use the difference between total personal income and dividend income, which encompasses not only entrepreneurial income but also gross wage compensation and net interest payments. I also compute labor income as Lustig and Nieuwerburgh (2005), which take labor income as the sum of wage and salary disbursements, other labor income (Column 6 in NIPA Table 2.6), and proprietors' income with inventory valuation and capital consumption adjustments. This measure excludes taxes and is closer to a measure of disposable income. Furthermore, I also replace the non-tradeable to tradeable wealth ratios inside the betas derived in equation 18 directly with return measures. Thus, instead of computing covariances of stock returns or stock illiquidities with the $\frac{NL_{t+1}}{P_t^M}$ ratio, I replace the non-tradeable to tradeable wealth ratio directly with the one-month change in labor income measures.

[9] The results for equal-weighted portfolios are similar to value-weighted ones and can be obtained upon request.

In Panel A of Table 14 we can see that results of cross-sectional regressions are robust across labor income measures. The estimated factor premia λnet are still significant, while the null hypothesis that $\alpha = 0$ cannot be statistically rejected. Parameters are more stable for Labor Income returns than for Wealth ratios, which is also reflected on the return differences for each type of liquidity measure shown in the second part of the table. In Panel B, decompose the return difference between the highest and lowest decile portfolios than can be attributed to each component of liquidity. The difference due to liquidity levels remains the most important component, similar to results found by Acharya and Pedersen (2005) and Korajczyk and Sadka (2007), ranging from 4.52% p.a. for proprietary income to 8.11% when using Jagannathan and Wang (1996)'s measure. The importance of the labor income-liquidity risk beta is even greater for the alternative measures. While for proprietary income it amounts to -6.9% of the total return differences implied by the Acharya and Pedersen (2005) liquidity betas, a much bigger effect is found for the two other alternative measures (closer to 70%), going from -0.06% p.a. to about 1.1% p.a. These estimates imply that the covariance between liquidity and non-tradeable wealth is more important than either the betas capturing the covariance of aggregate illiquidity with either stock returns or stock illiquidity derived in the Acharya and Pedersen (2005) model, but less important than the beta capturing the covariance between stock illiquidity and market returns. Also note that when the wealth ratio are based on Jagannathan and Wang (1996) or Lustig and Nieuwerburgh (2005)'s measures, the aggregate liquidity risk premia is close to zero. Overall, the results are even stronger when broader measures of labor income are used.

I also test whether results are significant because illiquidity captures effects due to size and/or book-to-market ratios. Therefore, I run additional tests including log(size) and B/M ratios as explanatory variables. Although for value-weighted illiquidity-sorted portfolios the estimated premium is still significant regardless of size or B/M effects, for other types of return-weighting and sorting procedures parameters are not individually significant and don't have the correct signal. In Table 15, I provide results of these robustness regressions for illiquidity-level sorts.

6 Conclusion

This paper proposes a new relationship between asset prices and non-tradeable wealth: the effect of the fluctuations between an asset's liquidity and the ratio of non-tradeable-to-tradeable wealth. In this economy, assets with higher liquidity or returns when non-tradeable wealth is lower have lower expected returns. I extend the model in Acharya and Pedersen (2005) and show how returns are affected by the addition of a random endowment shock.

Empirically, I calculate monthly returns and illiquidity of an equally-weighted market portfolio and yearly-formed portfolios sorted by illiquidity levels, illiquidity variation and size, using U.S. stock data from January 1962 to December 2004. The extra terms due to entrepreneurial income reduces liquidity risk premium by almost 40%, having an impact of -0.45% per year on expected returns of value-weighted illiquidity-sorted portfolios. Overall, liquidity risk as a whole has an yearly premium equal to 1.06%. However, liquidity levels are much more important and have a premium of 6.14% per year, contributing to most of the explanatory gains of the model.

The high level of collinearity between liquidity factors makes it difficult to pin-down the influence of each liquidity risk component and is a feature of the data that must be tackled by future work. Another question of interest is how to model labor market's illiquidity and its impact to on assets' expected returns. Given the economic significance of aggregate measures of liquidity to explain assets' expected returns differences [e.g., Brennan and Subrahmanyam (1996), Huberman and Halka (2001), Pastor and Stambaugh (2003) and Fujimoto and Watanabe (2003)], construction of a measure of human capital liquidity and derivation of its theoretical impact on expected returns would also benefit the literature. This is in a direct analogy to the addition of human capital to the standard CAPM, like papers by Jagannathan and Wang (1996), Heaton and Lucas (2000) and Viceira (2001), resulting in better understanding about how expected returns are related to systematic changes in liquidity and human capital.

References

Acharya, Viral, and Lasse Pedersen, 2005, Asset pricing with liquidity risk, *Journal of Financial Economics* 77, 375–410.

Aitken, Michael, and Carole Comerton-Forde, 2003, How should liquidity be measured?, *Pacific-Basin Finance Journal* 11, 45–59.

Amihud, Yakov, 2002, Illiquidity and stock returns: Cross-section and time-series effects, *Journal of Financial Markets* 5, 31–56.

Black, Fischer, 1972, Capital market equilibrium with restricted borrowing, *Journal of Business* 45, 444–455.

Brennan, Michael J., and Avanidhar Subrahmanyam, 1996, Market microstructure and asset pricing: On the compensation for illiquidity in stock returns, *Journal of Financial Economics* 41, 441–464.

Chalmers, John M.R., and Gregory B. Kadlec, 1998, An empirical examination of the amortized spread, *Jounal of Financial Economics* 48, 159–188.

Chordia, Tarun, Richard Roll, and Avanidhar Subrahmanyam, 2000, Commonality in liquidity, *Jounal of Financial Economics* 56, 3–28.

Daniel, Kent, and Sheridan Titman, 2003, Market reactions to tangible and intangible information, *Working Paper* Kellogg School of Management, Northwester University.

Easley, David, and Maureen O'Hara, 1987, Price, trade size, and information in securities markets, *Journal of Financial Economics* 19, 69–90.

Fama, Eugene F., and G. William Schwert, 1977, Human capital and capital market equilibrium, *Journal of Financial Economics* 4, 95–125.

Fujimoto, Akiko, and Masahiro Watanabe, 2003, Liquidity and conditional heteroscedasticity in conditional returns, *Working Paper* Department of Economics, Yale University.

Glosten, Lawrence R., and Paul R. Milgrom, 1985, Bid, ask and transaction prices in a specialist market with heterogeneously informed traders, *Journal of Financial Economics* 14, 71–100.

Hasbrouck, Joel, and Duane J. Seppi, 2001, Common factors in prices, order flows, and liquidity, *Jounal of Financial Economics* 59, 383–411.

Heaton, John, and Deborah Lucas, 2000, Portfolio choice and asset prices: The importance of entrepreneurial risk, *Journal of Finance* 55, 1163–1198.

Huberman, Gur, and Dominika Halka, 2001, Systematic liquidity, *Journal of Financial Research* 24, 161–178.

Jagannathan, Ravi, and Zhenyu Wang, 1996, The capm is alive and well, *Journal of Finance* 51, 3–53.

Korajczyk, Robert A., and Ronnie Sadka, 2007, Pricing the commonality across alternative measures of liquidity, *Forthcoming Journal of Financial Economics*.

Lintner, John, 1965, The valuation of risk assets and the selection of risky investments in stock portfolios and capital budgets, *Review of Economic and Statistics* 47, 13–37.

Lustig, Hanno N., and Stijn G. Van Nieuwerburgh, 2005, Housing collateral, consumption insurance, and risk premia: An empirical perspective, *Journal of Finance* 60, 1167–1219.

Mayers, David, 1973, Nonmarketable assets and the determination of capital asset prices in the absence of a riskless asset, *Journal of Business* 46, 258–267.

Newey, Whitney K., and Kenneth D. West, 1987, A simple, positive semi-definite, heteroskedasticity and autocorrelation consistent covariance matrix, *Econometrica* 55, 703–708.

Palacios-Huerta, Ignacio, 2003, The robustness of the conditional capm with human capital, *Journal of Financial Econometrics* 1, 272–289.

Pastor, Lubos, and Robert Stambaugh, 2003, Liquidity risk and expected stock returns, *Journal of Political Economy* 111, 642–685.

Roll, Richard W., 1977, A critique of the asset pricing theory's tests, *Journal of Financial Economics* 4, 129–176.

Sadka, Ronnie, 2003, Liquidity risk and asset pricing, *Working Paper* Kellogg School of Management, Northwestern University.

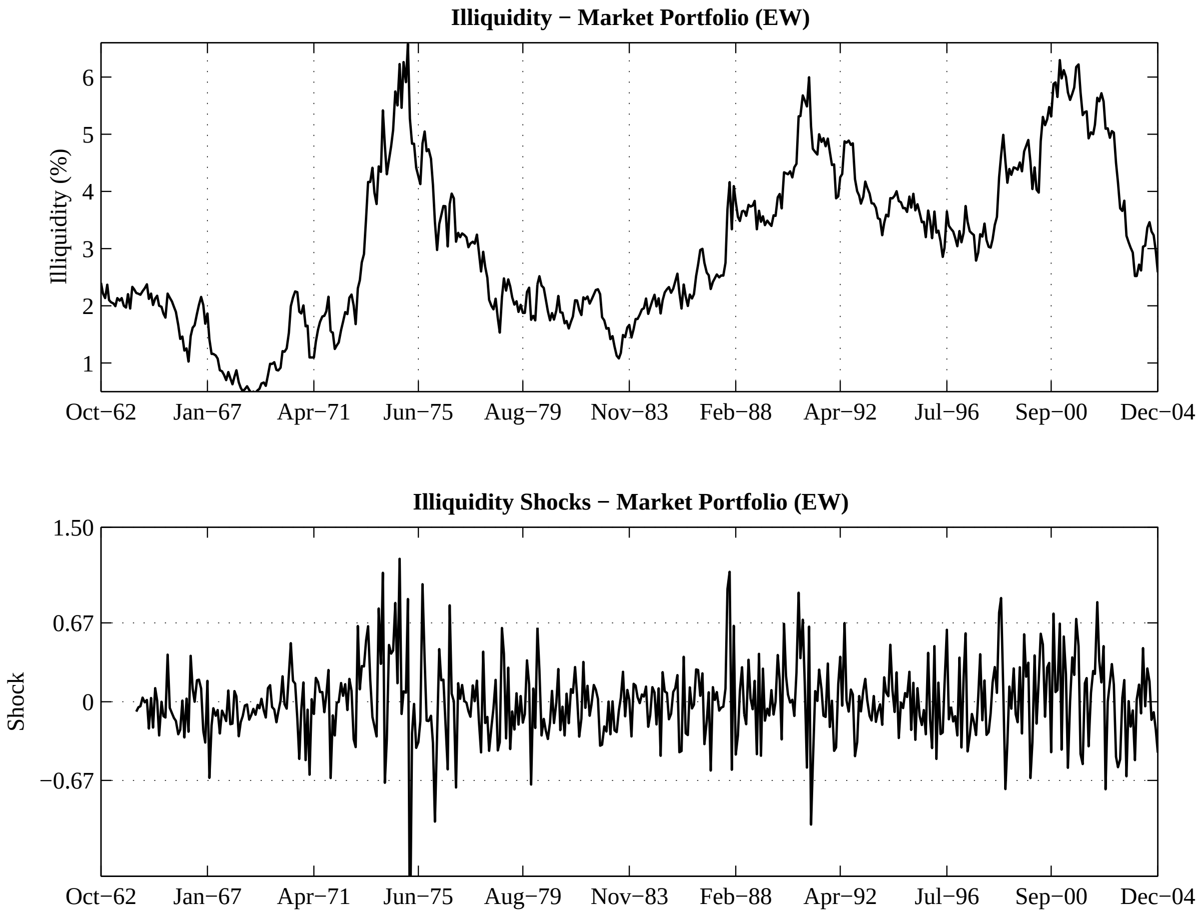
Sharpe, William F., 1964, Capital asset prices: A theory of market equilibrium under conditions of risk, *Journal of Finance* 19, 425–442.

Shumway, Tyler, 1997, The delisting bias in CRSP data, *Journal of Finance* 52, 327–340.

Viceira, Luis M., 2001, Optimal portfolio choice for long-horizon investors with nontradable labor income, *Journal of Finance* 56, 433–478.

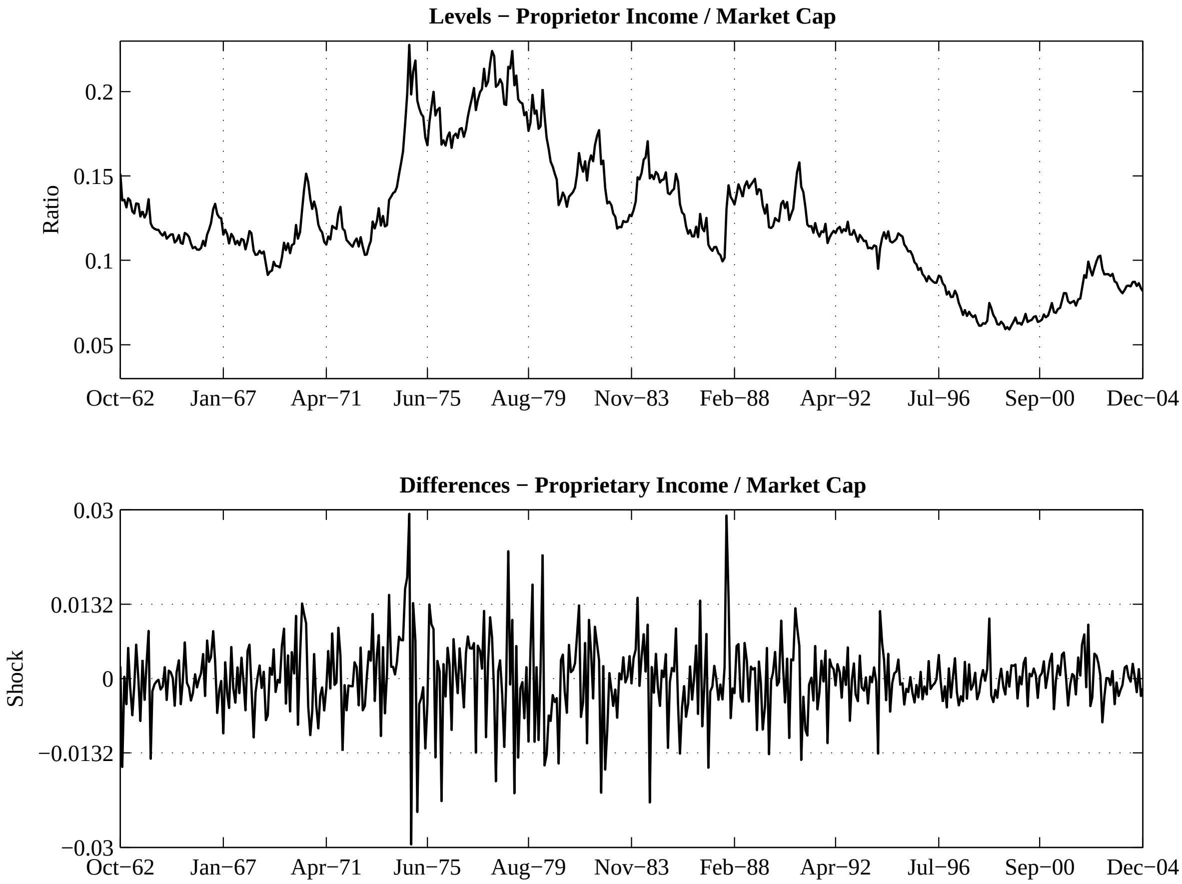
Wang, Ashley W., 2003, Institutional equity flows, liquidity risk and asset pricing, *Working Paper* Anderson School of Management, UCLA.

Figure 1: Market Portfolio Illiquidity Series



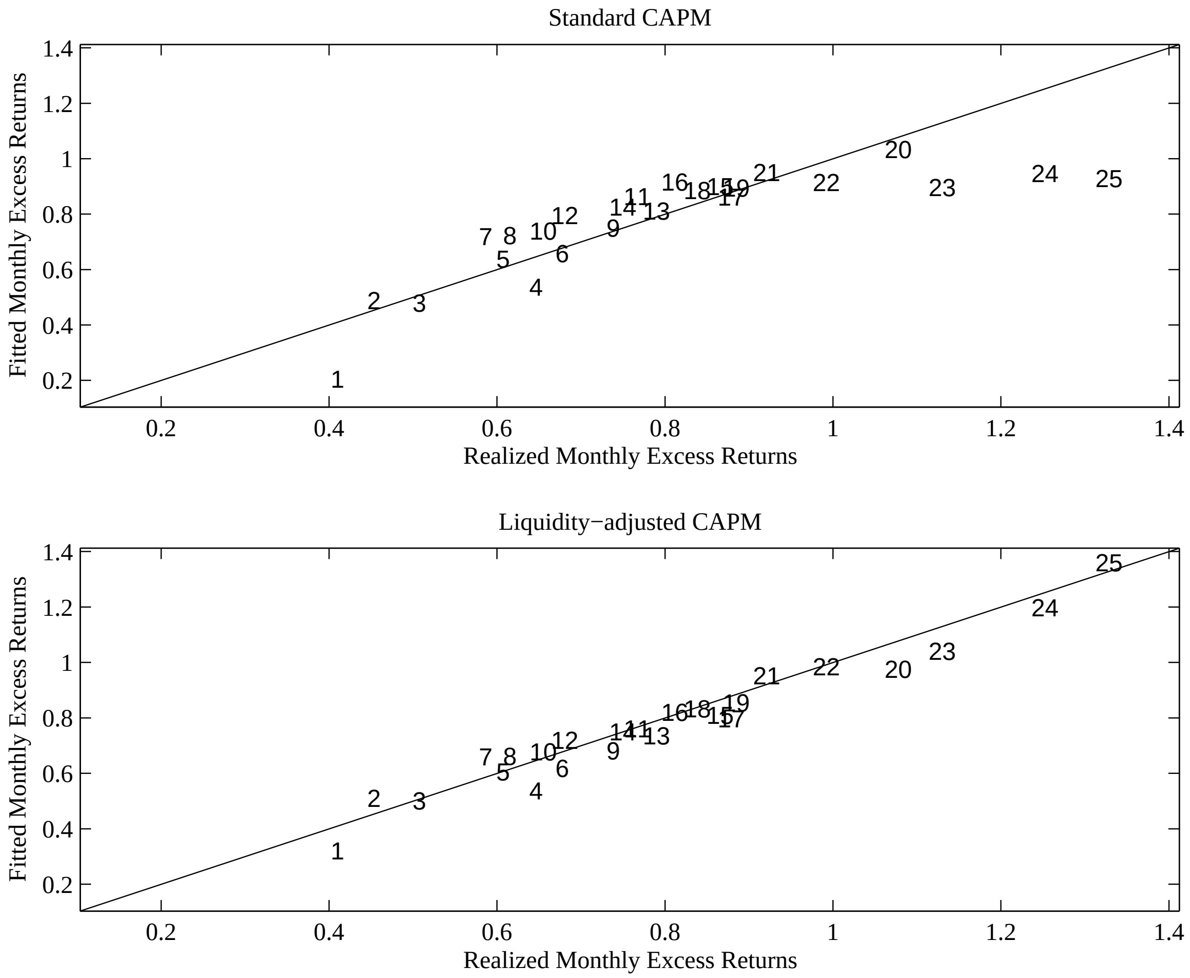
This figure show the illiquidity of the aggregate US stock market from October 1962 to December 2004. Illiquidity is based on the ILLIQ measure (Amihud (2002)) and normalized using the procedure outlined by Acharya and Pedersen (2005). Illiquidity shocks shown are the normalized residual after estimating an AR(2) model.

Figure 2: Proprietor’s Income / Market Capitalization Series - Levels and First Differences



This figure shows levels and first-differences of the ratio between proprietor’s income and the previous year’s stock market capitalization, from October 1962 to December 2004. Proprietor’s income is defined as aggregate non-farm proprietors’ income from Table 2.8 in the NIPA tables published by the US Department of Commerce. Stock market capitalization is the aggregate value of all NYSE and AMEX common stocks with prices between 5 and 1,000 dollars and at least 15 days of data in a given month.

Figure 3: Illiquidity Portfolios - Fitted vs. Actual Returns



This figure plots realized vs. fitted returns of illiquidity-sorted VW portfolios using monthly data from March 1964 to December 2004 for two different specifications. The upper graph has fitted returns using the standard CAPM. The lower graph uses fitted values from the liquidity-adjusted CAPM. Portfolios are numbered 1 (most liquid) to 25 (least liquid).

Table 1: Illiquidity Regression Results - Market Portfolio

This table reports the estimated coefficients of the equal-weighted market portfolio illiquidity using an AR(2) process given by:

$$
\begin{aligned}
0.28 + 0.3 * \overline{ILLIQ_t^i} * X_{t-1}^M \quad &= \quad a_0 + a_1 \left(0.28 + 0.3 * \overline{ILLIQ_{t-1}^i} * X_{t-1}^M\right) \\
&\quad + a_2 \left(0.28 + 0.3 * \overline{ILLIQ_{t-2}^i} * X_{t-1}^M\right) + u_t^i,
\end{aligned}
$$

$\overline{ILLIQ}$ is a normalized measure of liquidity calibrated to match effective spreads, while X_{t-1}^M is the ratio of market capitalizations at the end of month $t-1$ and July 1962. The regression uses monthly data between March 1964-December 2004 for the equal-weighted market portfolio. AIC reports the Akaike Information Criterion and SIC reports the Schwarz Information Criterion.

	Coefficient	Std. Error	t-stat	p-value
a^0	0.096	0.037	2.594	0.010
a^1	1.095	0.045	24.195	0.000
a^2	-0.130	0.045	-2.912	0.004
R^2	0.942		AIC	0.681
Adj. R^2	0.942		SIC	0.707

Table 2: Aggregate Illiquidity Measures, Returns and Proprietor's Income Correlations

This table reports the correlations among aggregate market illiquidity measures and proprietor's income from 1964 to 2004. $Illiq$ corresponds to Amihud's (2002) measure calibrated to match effective-spread's moments, $Illiq_{PS}$ are the liquidity innovations shown in Pastor and Stambaugh (2003), $Illiq_{AP}$ is the illiquidity measure innovations provided by Acharya and Pedersen (2005), r_M are the equal-weight market returns. $\frac{NL_{t+1}}{P_t}$ corresponds to ratio between proprietor's income and stock market capitalization, lagged one period to match the date that this information becomes available to agents.

Corr(↓,⟶)	$Illiq$	$Illiq_{PS}$	$Illiq_{AP}$	r_M	$\frac{NL_{t+1}}{P_t}$	$\Delta(\frac{NL_{t+1}}{P_t})$
$Illiq$	1.000	-0.352	0.562	-0.431	0.377	0.450
$Illiq_{PS}$		1.000	-0.326	0.361	-0.350	-0.187
$Illiq_{AP}$			1.000	-0.511	0.383	0.247
r_M				1.000	-0.796	-0.137
$\frac{NL_{t+1}}{P_t}$					1.000	0.014
$\delta(\frac{NL_{t+1}}{P_t})$						1.000

Table 3: Beta Correlations - Sorted Portfolios (VW)

This table reports the correlations among expected illiquidity ($E(c_t)$), six estimated covariances β_1^i, β_2^i, β_3^i, β_4^i, $\beta_{liq,lab}^i$, β_{labor}^i, and the combined betas β_{net}^i and β_{liq} for 25 portfolios sorted yearly from January 1964 to December 2004. The illiquidity innovations used to compute betas are based on an AR(2) process. Panel A is based on sorting stocks according to illiquidity levels, Panel B on the standard deviation of the illiquidity innovati and Panel C on sorts based on market capitalization.

Panel A: Illiquidity Levels

Cov(↓,⟶)	$E(c_t)$	β_{mkt}	β_2	β_3	β_4	$\beta_{liq,labor}$	β_{labor}	β_{net}	β_{liq}
$E(c_t)$	1.000	0.468	0.988	-0.560	-0.951	0.978	-0.713	0.398	0.906
β_{mkt}		1.000	0.530	-0.948	-0.605	0.522	-0.872	0.975	0.724
β_2			1.000	-0.623	-0.974	0.996	-0.778	0.451	0.947
β_3				1.000	0.690	-0.618	0.943	-0.938	-0.808
β_4					1.000	-0.959	0.837	-0.508	-0.980
$\beta_{liq,lab}$						1.000	-0.771	0.449	0.939
β_{labor}							1.000	-0.824	-0.916
β_{net}								1.000	0.645
β_{liq}									1.000

Panel B: Illiquidity Variation

Cov(↓,⟶)	$E(c_t)$	β_{mkt}	β_2	β_3	β_4	$\beta_{liq,labor}$	β_{labor}	β_{net}	β_{liq}
$E(c_t)$	1.000	0.481	0.984	-0.564	-0.954	0.993	-0.700	0.397	0.892
β_{mkt}		1.000	0.545	-0.947	-0.609	0.524	-0.871	0.980	0.735
β_2			1.000	-0.635	-0.981	0.995	-0.779	0.445	0.937
β_3				1.000	0.678	-0.611	0.941	-0.922	-0.793
β_4					1.000	-0.969	0.824	-0.514	-0.978
$\beta_{liq,lab}$						1.000	-0.750	0.430	0.918
β_{labor}							1.000	-0.811	-0.905
β_{net}								1.000	0.652
β_{liq}									1.000

Panel C: Size

Cov(↓,⟶)	$E(c_t)$	β_{mkt}	β_2	β_3	β_4	$\beta_{liq,labor}$	β_{labor}	β_{net}	β_{liq}
$E(c_t)$	1.000	0.298	0.967	-0.409	-0.945	0.980	-0.746	0.381	0.898
β_{mkt}		1.000	0.425	-0.978	-0.457	0.389	-0.823	0.992	0.596
β_2			1.000	-0.540	-0.991	0.994	-0.842	0.514	0.971
β_3				1.000	0.564	-0.501	0.897	-0.989	-0.695
β_4					1.000	-0.983	0.859	-0.546	-0.985
$\beta_{liq,lab}$						1.000	-0.821	0.475	0.954
β_{labor}							1.000	-0.875	-0.930
β_{net}								1.000	0.678
β_{liq}									1.000

Table 4: Descriptive Statistics - Illiquidity Portfolios - Value-Weighted

This table reports the properties of odd-numbered illiquidity-sorted portfolios formed yearly during 1964-2004 using VW weights. The six estimated covariances (x 100) β^i_{mkt}, β^i_2, β^i_3, β^i_4, $\beta^i_{liq,lab}$, β^i_{labor} are computed via GMM estimation using using all monthly illiquidity shocks and returns of a portfolio and an equal-weighted market portfolio. T-statistics for each coefficient are shown in brackets. Illiquidity shocks are calculated using an AR(2) process, while unexpected market returns use an AR(1) specification. Average excess returns appear in column E(ret). I also report standard deviations of returns ($\sigma_(ret)$), average illiquidity (E(c)), standard deviation of illiquidity ($\sigma(c)$), size in billions of dollars (Size), average percentage turnover (Trv) and book-to-market ratios (B/M) for each portfolio.

	β^i_{mkt}	β^i_2	β^i_3	β^i_4	$\beta^i_{liq,lab}$	β^i_{labor}	E(ret)	$\sigma(ret)$	E(c)	$\sigma(c)$	Size	Trv	B/M
1	52.89	0.00	-1.37	-0.01	0.00	0.14	0.39	4.22	0.28	0.00	38.72	3.89	0.56
	(14.47)	(2.00)	(-5.29)	(-2.17)	(1.42)	(.28)							
3	65.81	0.00	-1.65	-0.03	0.00	-0.01	0.49	4.63	0.29	0.01	4.11	5.35	0.82
	(17.89)	(3.42)	(-5.84)	(-5.17)	(3.14)	(-0.02)							
5	73.25	0.00	-1.92	-0.07	0.00	-0.26	0.59	4.96	0.31	0.02	2.13	5.66	0.79
	(20.87)	(3.19)	(-5.81)	(-5.23)	(2.74)	(-0.40)							
7	77.05	0.01	-1.97	-0.12	0.01	-0.34	0.57	5.12	0.33	0.04	1.31	5.56	0.79
	(20.19)	(4.42)	(-5.32)	(-5.42)	(3.56)	(-0.52)							
9	78.48	0.01	-2.03	-0.23	0.01	-0.59	0.72	5.14	0.36	0.07	0.91	5.21	0.81
	(29.13)	(3.47)	(-5.92)	(-4.48)	(3.22)	(-0.94)							
11	83.77	0.01	-2.19	-0.43	0.02	-0.80	0.75	5.42	0.41	0.11	0.68	5.08	0.83
	(26.84)	(3.60)	(-5.34)	(-4.42)	(3.54)	(-1.17)							
13	81.38	0.02	-2.28	-0.50	0.03	-0.83	0.77	5.27	0.48	0.14	0.52	4.55	0.83
	(22.79)	(3.48)	(-5.81)	(-4.70)	(3.09)	(-1.34)							
15	85.49	0.04	-2.53	-0.81	0.04	-0.88	0.85	5.50	0.61	0.21	0.37	4.34	0.88
	(26.00)	(4.54)	(-6.39)	(-5.52)	(2.45)	(-1.25)							
17	83.69	0.06	-2.47	-1.19	0.07	-1.44	0.86	5.38	0.80	0.31	0.31	3.87	0.97
	(24.84)	(4.47)	(-5.31)	(-6.06)	(3.30)	(-1.98)							
19	85.21	0.12	-2.39	-1.64	0.16	-1.26	0.87	5.51	1.16	0.49	0.23	3.57	0.95
	(23.60)	(5.15)	(-5.27)	(-4.56)	(4.40)	(-1.74)							
21	87.88	0.17	-2.70	-2.59	0.26	-1.70	0.90	5.81	1.79	0.78	0.20	3.39	0.98
	(25.45)	(4.43)	(-5.63)	(-5.52)	(4.38)	(-2.31)							
23	85.30	0.27	-2.56	-4.01	0.34	-1.85	1.11	5.76	3.13	1.53	0.12	3.07	1.12
	(18.49)	(4.82)	(-5.90)	(-6.20)	(4.54)	(-2.26)							
25	86.80	0.50	-2.61	-5.34	0.67	-1.90	1.31	6.15	6.60	3.66	0.07	3.36	1.18
	(17.32)	(5.03)	(-5.64)	(-4.98)	(6.54)	(-2.17)							

Table 5: Regression Results - Illiquidity Portfolios - Value-Weighted

This table reports coefficients from the illiquidity and labor returns-adjusted CAPM using data from March 1964-December 2004 using 25 value-weighted illiquidity-sorted portfolios. The estimates are based on a GMM framework setting where regressions are alternative cases of the relation:

$$\begin{aligned} E\left(r_t^i - r_f\right) &= \alpha + kE\left(c_t^i\right) + \lambda_{mkt}\beta_{mkt}^i + \lambda_{liq}\beta_{liq}^i + \lambda_{labor}\beta_{labor}^i + \lambda_{Net}\beta_{Net}^i, \text{ where} \\ \beta_{liq}^i &= \beta_2^i - \beta_3^i - \beta_4^i - \beta_{liq,lab}^i \\ \beta_{Net}^i &= \beta_{mkt}^i + \beta_2^i - \beta_3^i - \beta_4^i - \beta_{liq,lab}^i + \beta_{labor}^i \end{aligned}$$

The coefficient k adjusts for the difference between the estimation period and the typical holding period of investors. Coefficients are followed by t-statistics adjusted for serial correlation using 5 lags (Newey and West (1987)). The adjusted R^2 reported in each row is computed from a single cross-sectional regression using average portfolio returns. The factors are estimated with 25 portfolios times 490 months = 12,250 observations.

	α	k	λ_{mkt}	λ_{liq}	λ_{labor}	λ_{net}	Adj.R^2
1	-0.927		2.136				0.468
	(-2.110)		(3.182)				
2	0.368		0.148		-31.732		0.820
	(1.118)		(0.290)		(-3.035)		
3	-0.244		0.929	7.255			0.943
	(-0.706)		(1.626)	(1.286)			
4	-0.674	0.044				1.700	0.834
	(-1.561)					(2.666)	
5	-0.451	0.081				1.376	0.948
	(-1.211)	(3.703)				(2.487)	
6	-0.437	0.044	1.253	6.323			0.834
	(-1.177)		(2.327)	(2.060)			
7	-0.437	0.043	1.250	6.522			0.943
	(-1.180)	(0.876)	(2.249)	(0.987)			
8	-0.263	0.044	1.010	5.199	-0.170		0.915
	(-0.773)		(1.935)	(1.871)	(-0.017)		
9	-0.261	0.040	0.996	5.760	0.280		0.948
	(-0.762)	(0.794)	(1.776)	(0.910)	(0.026)		

Table 6: Descriptive Statistics - Illiquidity Portfolios - Equal-Weighted

This table reports the properties of odd-numbered illiquidity-sorted portfolios formed yearly during 1964-2004 using EW weights. The six estimated covariances (x 100) β^i_{mkt}, β^i_2, β^i_3, β^i_4, $\beta^i_{liq,lab}$, β^i_{labor} are computed via GMM estimation using using all monthly illiquidity shocks and returns of a portfolio and an equal-weighted market portfolio. T-statistics for each coefficient are shown in brackets. Illiquidity shocks are calculated using an AR(2) process, while unexpected market returns use an AR(1) specification. Average excess returns appear in column E(ret). I also report standard deviations of returns ($\sigma_(ret)$), average illiquidity (E(c)), standard deviation of illiquidity ($\sigma(c)$), size in billions of dollars (Size), average percentage turnover (Trv) and book-to-market ratios (B/M) for each portfolio.

	β^i_{mkt}	β^i_2	β^i_3	β^i_4	$\beta^i_{liq,lab}$	β^i_{labor}	E(ret)	$\sigma(ret)$	E(c)	$\sigma(c)$	Size	Trv	B/M
1	62.63	0.00	-1.53	-0.01	0.00	0.05	0.41	4.63	0.28	0.00	20.63	5.40	0.62
	(15.61)	(-0.35)	(-5.36)	(-1.59)	(.28)	(.09)							
3	72.76	0.00	-1.76	-0.04	0.00	-0.19	0.52	4.94	0.29	0.01	3.36	6.45	0.86
	(19.72)	(3.57)	(-5.65)	(-5.61)	(3.24)	(-0.30)							
5	81.02	0.00	-2.09	-0.10	0.00	-0.46	0.60	5.32	0.31	0.02	1.70	7.03	0.84
	(23.05)	(2.65)	(-5.86)	(-4.69)	(2.62)	(-0.69)							
7	86.66	0.01	-2.19	-0.18	0.01	-0.57	0.52	5.60	0.34	0.04	1.00	7.00	0.86
	(22.71)	(3.39)	(-5.42)	(-4.33)	(3.19)	(-0.84)							
9	86.11	0.01	-2.20	-0.25	0.01	-0.69	0.73	5.51	0.37	0.07	0.66	6.57	0.89
	(29.23)	(3.76)	(-6.09)	(-4.98)	(3.25)	(-1.04)							
11	92.71	0.02	-2.37	-0.55	0.03	-0.95	0.75	5.87	0.43	0.11	0.47	6.32	0.91
	(29.66)	(2.72)	(-5.52)	(-4.54)	(2.82)	(-1.31)							
13	91.68	0.03	-2.49	-0.67	0.04	-1.10	0.78	5.78	0.53	0.14	0.34	5.76	0.91
	(24.31)	(3.68)	(-5.87)	(-5.30)	(3.08)	(-1.68)							
15	94.42	0.05	-2.70	-1.04	0.05	-1.08	0.77	5.97	0.68	0.21	0.24	5.60	0.93
	(29.14)	(4.00)	(-6.01)	(-5.37)	(2.00)	(-1.46)							
17	90.58	0.07	-2.62	-1.55	0.09	-1.60	0.81	5.74	0.92	0.31	0.18	4.87	1.05
	(24.51)	(3.89)	(-5.56)	(-5.17)	(3.28)	(-2.11)							
19	91.32	0.12	-2.56	-2.18	0.16	-1.38	0.80	5.82	1.34	0.49	0.13	4.44	1.03
	(26.95)	(4.44)	(-5.72)	(-4.94)	(4.05)	(-1.83)							
21	92.08	0.19	-2.76	-3.31	0.27	-1.77	0.95	5.92	2.05	0.78	0.08	4.12	1.06
	(27.22)	(3.80)	(-5.58)	(-5.73)	(4.17)	(-2.28)							
23	87.09	0.29	-2.54	-4.40	0.39	-2.12	1.13	5.77	3.55	1.53	0.05	3.45	1.20
	(17.60)	(3.99)	(-5.79)	(-5.57)	(4.55)	(-2.62)							
25	90.46	0.48	-2.61	-6.16	0.72	-2.01	1.40	6.18	7.83	3.66	0.03	3.64	1.40
	(15.16)	(4.49)	(-5.58)	(-5.63)	(6.17)	(-2.17)							

Table 7: Regression Results - Illiquidity Portfolios - Equal-Weighted

This table reports coefficients from the illiquidity and labor returns-adjusted CAPM using data from March 1964-December 2004 using 25 equal-weighted illiquidity-sorted portfolios. The estimates are based on a GMM framework setting where regressions are alternative cases of the relation:

$$\begin{aligned} E\left(r_t^i - r_f\right) &= \alpha + kE\left(c_t^i\right) + \lambda_{mkt}\beta_{mkt}^i + \lambda_{liq}\beta_{liq}^i + \lambda_{labor}\beta_{labor}^i + \lambda_{Net}\beta_{Net}^i, \text{ where} \\ \beta_{liq}^i &= \beta_2^i - \beta_3^i - \beta_4^i - \beta_{liq,lab}^i \\ \beta_{Net}^i &= \beta_{mkt}^i + \beta_2^i - \beta_3^i - \beta_4^i - \beta_{liq,lab}^i + \beta_{labor}^i \end{aligned}$$

The coefficient k adjusts for the difference between the estimation period and the typical holding period of investors. Coefficients are followed by t-statistics adjusted for serial correlation using 5 lags (Newey and West (1987)). The adjusted R^2 reported in each row is computed from a single cross-sectional regression using average portfolio returns. The factors are estimated with 25 portfolios times 490 months = 12,250 observations.

	α	k	λ_{mkt}	λ_{liq}	λ_{labor}	λ_{net}	Adj.R^2
1	-0.693		1.692				0.303
	(-1.448)		(2.489)				
2	0.892		-0.600		-37.908		0.782
	(2.664)		(-1.240)		(-3.795)		
3	-0.254		0.746	13.589			0.911
	(-0.619)		(1.375)	(4.177)			
4	-0.561	0.055				1.410	0.616
	(-1.123)					(2.083)	
5	-0.307	0.097				1.065	0.930
	(-0.721)	(4.567)				(1.825)	
6	-0.266	0.055	0.894	6.831			0.616
	(-0.647)		(1.648)	(2.100)			
7	-0.267	0.059	0.906	6.303			0.911
	(-0.650)	(2.005)	(1.684)	(1.238)			
8	0.015	0.055	0.542	4.490	-4.035		0.853
	(0.041)		(1.044)	(1.623)	(-0.457)		
9	0.025	0.064	0.552	3.254	-5.622		0.935
	(0.066)	(2.197)	(1.061)	(0.717)	(-0.596)		

Table 8: Descriptive Statistics - Illiquidity Variability Portfolios - Value-Weighted

This table reports the properties of odd-numbered illiquidity variability-sorted portfolios formed yearly during 1964-2004 using EW weights. The six estimated covariances (x 100) β^i_{mkt}, β^i_2, β^i_3, β^i_4, $\beta^i_{liq,lab}$, β^i_{labor} are computed via GMM estimation using all monthly illiquidity shocks and returns of a portfolio and an equal-weighted market portfolio. T-statistics for each coefficient are shown in brackets. Illiquidity shocks are calculated using an AR(2) process, while unexpected market returns use an AR(1) specification. Average excess returns appear in column E(ret). I also report standard deviations of returns ($\sigma_(ret)$), average illiquidity (E(c)), standard deviation of illiquidity ($\sigma(c)$), size in billions of dollars (Size), average percentage turnover (Trv) and book-to-market ratios (B/M) for each portfolio.

	β^i_{mkt}	β^i_2	β^i_3	β^i_4	$\beta^i_{liq,lab}$	β^i_{labor}	E(ret)	$\sigma(ret)$	E(c)	$\sigma(c)$	Size	Trv	B/M
1	53.15	0.00	-1.38	-0.01	0.00	0.14	0.40	4.24	0.28	0.00	38.65	3.89	0.56
	(14.46)	(2.06)	(-5.33)	(-2.17)	(1.44)	(.28)							
3	66.97	0.00	-1.64	-0.03	0.00	-0.11	0.50	4.66	0.29	0.01	4.42	5.43	0.83
	(19.75)	(3.57)	(-5.31)	(-5.56)	(3.48)	(-0.20)							
5	71.79	0.00	-1.89	-0.07	0.00	-0.21	0.57	4.92	0.30	0.02	2.18	5.65	0.78
	(20.40)	(3.48)	(-5.99)	(-5.71)	(3.09)	(-0.33)							
7	77.69	0.00	-2.01	-0.12	0.01	-0.36	0.55	5.19	0.33	0.03	1.29	5.59	0.80
	(22.31)	(4.61)	(-5.43)	(-4.92)	(3.97)	(-0.54)							
9	78.73	0.01	-2.08	-0.20	0.01	-0.78	0.68	5.16	0.36	0.06	0.91	5.22	0.79
	(28.11)	(3.90)	(-5.59)	(-5.66)	(2.83)	(-1.26)							
11	79.92	0.01	-2.17	-0.36	0.03	-0.62	0.71	5.24	0.41	0.09	0.71	5.16	0.82
	(24.36)	(4.35)	(-5.60)	(-5.32)	(3.72)	(-1.00)							
13	82.38	0.02	-2.24	-0.48	0.03	-0.77	0.69	5.34	0.48	0.14	0.56	4.61	0.83
	(24.41)	(4.67)	(-5.65)	(-5.05)	(2.28)	(-1.20)							
15	83.11	0.03	-2.48	-0.60	0.04	-0.90	0.85	5.35	0.59	0.17	0.42	4.37	0.83
	(28.32)	(5.13)	(-5.90)	(-5.65)	(3.56)	(-1.22)							
17	85.68	0.07	-2.55	-1.13	0.08	-1.32	0.85	5.49	0.78	0.29	0.30	4.03	0.91
	(26.80)	(4.85)	(-5.63)	(-6.30)	(4.22)	(-1.83)							
19	87.94	0.09	-2.55	-1.75	0.12	-1.30	0.90	5.67	1.13	0.48	0.25	3.68	0.97
	(27.18)	(4.38)	(-5.65)	(-4.70)	(4.01)	(-1.81)							
21	88.89	0.13	-2.44	-2.56	0.16	-1.43	0.90	5.80	1.80	0.83	0.21	3.50	1.01
	(26.91)	(4.30)	(-4.94)	(-5.75)	(3.80)	(-1.92)							
23	84.96	0.27	-2.71	-3.88	0.33	-2.11	1.14	5.82	3.12	1.49	0.14	3.15	1.08
	(19.07)	(4.86)	(-6.58)	(-6.35)	(4.61)	(-2.68)							
25	86.79	0.42	-2.70	-4.82	0.60	-1.79	1.30	6.17	5.88	3.40	0.10	3.77	1.12
	(17.15)	(4.80)	(-5.67)	(-5.13)	(6.23)	(-2.06)							

Table 9: Regression Results - Illiquidity Variability Portfolios - Value-Weighted

This table reports coefficients from the illiquidity and labor returns-adjusted CAPM using data from March 1964-December 2004 using 25 value-weighted illiquidity variability-sorted portfolios. The estimates are based on a GMM framework setting where regressions are alternative cases of the relation:

$$\begin{aligned} E\left(r_t^i - r_f\right) &= \alpha + kE\left(c_t^i\right) + \lambda_{mkt}\beta_{mkt}^i + \lambda_{liq}\beta_{liq}^i + \lambda_{labor}\beta_{labor}^i + \lambda_{Net}\beta_{Net}^i, \text{ where} \\ \beta_{liq}^i &= \beta_2^i - \beta_3^i - \beta_4^i - \beta_{liq,lab}^i \\ \beta_{Net}^i &= \beta_{mkt}^i + \beta_2^i - \beta_3^i - \beta_4^i - \beta_{liq,lab}^i + \beta_{labor}^i \end{aligned}$$

The coefficient k adjusts for the difference between the estimation period and the typical holding period of investors. Coefficients are followed by t-statistics adjusted for serial correlation using 5 lags (Newey and West (1987)). The adjusted R^2 reported in each row is computed from a single cross-sectional regression using average portfolio returns. The factors are estimated with 25 portfolios times 490 months = 12,250 observations.

	α	k	λ_{mkt}	λ_{liq}	λ_{labor}	λ_{net}	Adj.R^2
1	-0.893		2.097				0.565
	(-2.023)		(3.119)				
2	0.479		-0.009		-33.083		0.756
	(1.356)		(-0.017)		(-3.722)		
3	-0.353		0.955	14.671			0.940
	(-0.891)		(1.641)	(4.589)			
4	-0.673	0.045				1.703	0.739
	(-1.562)					(2.679)	
5	-0.333	0.105				1.207	0.939
	(-0.837)	(4.444)				(2.052)	
6	-0.327	0.045	1.031	9.223			0.739
	(-0.826)		(1.770)	(2.885)			
7	-0.335	0.031	1.006	10.982			0.940
	(-0.840)	(0.464)	(1.696)	(1.240)			
8	-0.171	0.045	0.812	8.229	3.581		0.903
	(-0.486)		(1.586)	(2.576)	(0.383)		
9	-0.174	0.028	0.774	10.244	5.397		0.940
	(-0.496)	(0.417)	(1.390)	(1.208)	(0.523)		

Table 10: Descriptive Statistics - Size Portfolios - Value-Weighted

This table reports the properties of odd-numbered size-sorted portfolios formed yearly during 1964-2004 using VW weights. The six estimated covariances (x 100) β^i_{mkt}, β^i_2, β^i_3, β^i_4, $\beta^i_{liq,lab}$, β^i_{labor} are computed via GMM estimation using using all monthly illiquidity shocks and returns of a portfolio and an equal-weighted market portfolio. T-statistics for each coefficient are shown in brackets. Illiquidity shocks are calculated using an AR(2) process, while unexpected market returns use an AR(1) specification. Average excess percentage returns appear in column E(ret). I also report standard deviations of returns ($\sigma(ret)$), average illiquidity (E(c)), standard deviation of illiquidity ($\sigma(c)$), size in billions of dollars (Size), average percentage turnover (Trv) and book-to-market ratios (B/M) for each portfolio.

	β^i_{mkt}	β^i_2	β^i_3	β^i_4	$\beta^i_{liq,lab}$	β^i_{labor}	E(ret)	$\sigma(ret)$	E(c)	$\sigma(c)$	Size	Trv	B/M
1	85.13	0.41	-2.46	-5.89	0.62	-2.07	1.33	5.93	7.10	4.10	0.01	4.02	1.44
	(13.48)	(4.06)	(-6.22)	(-5.20)	(4.94)	(-2.43)							
3	93.37	0.33	-2.75	-5.78	0.48	-2.30	0.90	6.17	3.84	1.95	0.03	4.13	1.19
	(23.71)	(3.62)	(-5.60)	(-5.09)	(5.22)	(-2.83)							
5	100.50	0.22	-2.97	-3.47	0.23	-1.84	0.92	6.46	2.29	1.10	0.06	4.97	1.16
	(21.44)	(4.50)	(-6.28)	(-6.00)	(3.39)	(-2.03)							
7	96.62	0.13	-2.68	-2.20	0.15	-1.59	0.96	6.15	1.50	0.65	0.09	5.19	1.08
	(27.05)	(5.47)	(-5.53)	(-6.73)	(3.18)	(-1.89)							
9	94.99	0.09	-2.77	-1.27	0.10	-1.57	0.88	6.04	0.99	0.41	0.14	5.85	0.97
	(25.60)	(4.62)	(-5.80)	(-5.28)	(3.94)	(-2.05)							
11	95.48	0.06	-2.62	-1.07	0.08	-1.26	0.80	6.04	0.75	0.28	0.20	5.94	0.98
	(26.68)	(5.09)	(-5.90)	(-5.76)	(3.68)	(-1.59)							
13	92.79	0.04	-2.56	-0.68	0.06	-1.09	0.80	5.85	0.58	0.22	0.29	6.24	0.88
	(25.83)	(4.34)	(-5.88)	(-3.94)	(4.28)	(-1.50)							
15	88.11	0.03	-2.37	-0.42	0.04	-0.80	0.79	5.65	0.48	0.13	0.41	6.16	0.85
	(24.55)	(5.27)	(-5.97)	(-4.79)	(4.49)	(-1.14)							
17	84.16	0.02	-2.27	-0.29	0.03	-0.72	0.73	5.39	0.42	0.10	0.60	6.22	0.84
	(30.04)	(5.40)	(-5.87)	(-4.93)	(3.66)	(-1.07)							
19	80.42	0.01	-2.17	-0.17	0.01	-0.63	0.70	5.22	0.36	0.06	0.92	6.19	0.80
	(27.81)	(5.22)	(-5.84)	(-5.41)	(4.17)	(-0.94)							
21	78.43	0.00	-1.95	-0.11	0.01	-0.35	0.63	5.14	0.32	0.03	1.56	6.10	0.81
	(24.61)	(4.32)	(-5.82)	(-4.45)	(3.51)	(-0.57)							
23	68.05	0.00	-1.77	-0.04	0.00	-0.25	0.54	4.69	0.30	0.02	3.07	5.41	0.80
	(20.01)	(3.27)	(-6.14)	(-4.28)	(3.23)	(-0.45)							
25	52.49	0.00	-1.39	0.00	0.00	0.18	0.40	4.22	0.28	0.00	36.02	3.65	0.56
	(14.07)	(4.30)	(-5.39)	(-6.27)	(3.48)	(.36)							

Table 11: Regression Results - Size Portfolios - Value-Weighted

This table reports coefficients from the illiquidity and labor returns-adjusted CAPM using data from March 1964-December 2004 using 25 value-weighted size-sorted portfolios. The estimates are based on a GMM framework setting where regressions are alternative cases of the relation:

$$\begin{aligned} E\left(r_t^i - r_f\right) &= \alpha + kE\left(c_t^i\right) + \lambda_{mkt}\beta_{mkt}^i + \lambda_{liq}\beta_{liq}^i + \lambda_{labor}\beta_{labor}^i + \lambda_{Net}\beta_{Net}^i, \text{ where} \\ \beta_{liq}^i &= \beta_2^i - \beta_3^i - \beta_4^i - \beta_{liq,lab}^i \\ \beta_{Net}^i &= \beta_{mkt}^i + \beta_2^i - \beta_3^i - \beta_4^i - \beta_{liq,lab}^i + \beta_{labor}^i \end{aligned}$$

The coefficient k adjusts for the difference between the estimation period and the typical holding period of investors. Coefficients are followed by t-statistics adjusted for serial correlation using 5 lags (Newey and West (1987)). The adjusted R^2 reported in each row is computed from a single cross-sectional regression using average portfolio returns. The factors are estimated with 25 portfolios times 490 months = 12,250 observations.

	α	k	λ_{mkt}	λ_{liq}	λ_{labor}	λ_{net}	Adj.R^2
1	-0.199		1.135				0.482
	(-0.543)		(1.979)				
2	0.606		-0.133		-26.540		0.783
	(2.283)		(-0.313)		(-2.680)		
3	-0.030		0.694	7.579			0.767
	(-0.094)		(1.463)	(2.590)			
4	-0.058	0.055				0.858	0.736
	(-0.156)					(1.538)	
5	-0.008	0.070				0.779	0.954
	(-0.024)	(3.205)				(1.559)	
6	-0.043	0.055	0.826	1.322			0.736
	(-0.133)		(1.741)	(0.452)			
7	-0.065	0.151	1.058	-9.715			0.767
	(-0.201)	(5.366)	(2.166)	(-2.629)			
8	0.289	0.055	0.392	-2.486	-16.217		0.734
	(0.839)		(0.804)	(-0.803)	(-1.319)		
9	-0.023	0.149	1.000	-10.043	-11.794		0.952
	(-0.064)	(5.240)	(1.957)	(-2.637)	(-0.966)		

Table 12: Descriptive Statistics - Illiquidity Decile Portfolios - Value-Weighted

This table reports the properties of illiquidity-sorted decile portfolios formed yearly during 1964-2004 using VW weights. The six estimated covariances (x 100) β^i_{mkt}, β^i_2, β^i_3, β^i_4, $\beta^i_{liq,lab}$, β^i_{labor} are computed via GMM estimation using using all monthly illiquidity shocks and returns of a portfolio and an equal-weighted market portfolio. T-statistics for each coefficient are shown in brackets. Illiquidity shocks are calculated using an AR(2) process, while unexpected market returns use an AR(1) specification. Average excess returns appear in column E(ret). I also report standard deviations of returns ($\sigma_(ret)$), average illiquidity (E(c)), standard deviation of illiquidity ($\sigma(c)$), size in billions of dollars (Size), average percentage turnover (Trv) and book-to-market ratios (B/M) for each portfolio.

	β^i_{mkt}	β^i_2	β^i_3	β^i_4	$\beta^i_{liq,lab}$	β^i_{labor}	E(ret)	$\sigma(ret)$	E(c)	$\sigma(c)$	Size	Trv	B/M
1	55.51	0.00	0.12	-0.01	0.00	0.13	0.39	4.23	0.28	0.00	30.17	4.28	0.61
	(18.67)	(1.32)	(0.24)	(-5.85)	(2.86)	(0.31)							
3	72.67	0.01	0.10	-0.11	0.01	-0.35	0.58	4.75	0.32	0.03	1.44	5.48	0.78
	(30.73)	(2.83)	(0.18)	(-5.91)	(3.33)	(-0.71)							
5	79.13	0.03	-0.05	-0.42	0.03	-0.74	0.68	5.02	0.44	0.12	0.61	4.88	0.83
	(35.44)	(3.12)	(-0.08)	(-5.93)	(3.94)	(-1.40)							
7	81.05	0.11	-0.33	-1.11	0.08	-1.34	0.79	5.08	0.79	0.29	0.30	4.06	0.94
	(37.11)	(4.32)	(-0.58)	(-7.64)	(4.75)	(-2.44)							
10	80.02	0.95	0.10	-4.98	0.41	-1.79	1.17	5.43	4.97	2.52	0.14	3.14	1.13
	(21.04)	(4.68)	(0.17)	(-5.91)	(5.07)	(-2.86)							

Table 13: Regression Results - Illiquidity Decile Portfolios - Value-Weighted

This table reports coefficients from the illiquidity and labor returns-adjusted CAPM using data from March 1964-December 2004 using 10 value-weighted illiquidity-sorted portfolios. The estimates are based on a GMM framework setting where regressions are alternative cases of the relation:

$$\begin{aligned} E\left(r_t^i - r_f\right) &= \alpha + kE\left(c_t^i\right) + \lambda_{mkt}\beta_{mkt}^i + \lambda_{liq}\beta_{liq}^i + \lambda_{labor}\beta_{labor}^i + \lambda_{Net}\beta_{Net}^i, \text{ where} \\ \beta_{liq}^i &= \beta_2^i - \beta_3^i - \beta_4^i - \beta_{liq,lab}^i \\ \beta_{Net}^i &= \beta_{mkt}^i + \beta_2^i - \beta_3^i - \beta_4^i - \beta_{liq,lab}^i + \beta_{labor}^i \end{aligned}$$

The coefficient k adjusts for the difference between the estimation period and the typical holding period of investors. Coefficients are followed by t-statistics adjusted for serial correlation using 5 lags (Newey and West (1987)). The adjusted R^2 reported in each row is computed from a single cross-sectional regression using average portfolio returns. The factors are estimated with 10 portfolios times 490 months = 4,900 observations.

	α	k	λ_{mkt}	λ_{liq}	λ_{labor}	λ_{net}	Adj.R^2
1	-0.745		1.929				0.561
	(-1.668)		(2.760)				
2	0.558		-0.170		-32.913		0.876
	(1.417)		(-0.277)		(-2.994)		
3	-0.371		1.370	10.091			0.971
	(-0.954)		(2.250)	(3.338)			
4	-0.567	0.044				1.616	0.855
	(-1.278)					(2.353)	
5	-0.374	0.080				1.308	0.979
	(-0.952)	(3.233)				(2.148)	
6	-0.373	0.044	1.336	5.318			0.855
	(-0.957)		(2.194)	(1.759)			
7	-0.374	0.079	1.309	1.489			0.971
	(-0.959)	(0.902)	(2.112)	(0.145)			
8	-0.322	0.044	1.253	4.906	3.242		0.958
	(-0.654)		(1.569)	(1.405)	(0.216)		
9	-0.249	0.087	1.097	-0.437	-4.543		0.975
	(-0.536)	(1.072)	(1.463)	(-0.048)	(-0.311)		

Table 14: Alternative Labor Income Proxies - Cross-sectional regressions and Annual Risk Premia

This table reports coefficients from the illiquidity and labor returns-adjusted CAPM using alternative definitions of labor income. Returns of 25 value-weighted portfolios sorted on illiquidity are computed from March 1964 to December 2004. The estimates are based on a GMM framework setting where regressions have the following specification:

$$
\begin{aligned}
E\left(r_t^i - r_f\right) &= \alpha + kE\left(c_t^i\right) + \lambda_{Net}\beta_{Net}^i, \\
\text{where } \beta_{Net}^i &= \beta_{mkt}^i + \beta_2^i - \beta_3^i - \beta_4^i - \beta_{liq,lab}^i + \beta_{labor}^i
\end{aligned}
$$

Three alternative labor income measures are used: Prop. denotes entrepreneurial income (Heaton and Lucas (2000)), JW uses aggregate labor income used by Jagannathan and Wang (1996) and Lustig uses using disposable labor income as used by Lustig and Nieuwerburgh (2005). In Panel A, I report parameters estimated using either the non-tradeable to tradeable wealth ratio or labor income returns. Coefficients are followed by t-statistics adjusted for serial correlation using 5 lags (Newey and West (1987)). In Panel B we report the liquidity premia for the alternative measures of labor income. $\Delta(.)$ denotes the difference between the highest and the lowest portfolio sorted on illiquidity. Liquidity levels is the difference in the calibrated transaction costs, Liquidity Betas denote the three liquidity betas – β_2^i, β_3^i and β_4^i – proposed by Acharya and Pedersen (2005) and Labor-Liq represents the labor income - liquidity beta, $\beta_{liq,lab}$ shown in Equation 18. Values with "*" are significant at the 1% level.

Panel A - Cross-sectional Regressions

	Wealth Ratios			Labor Income returns		
Parameters	Prop.	JW	Lustig	Prop.	JW	Lustig
α	-0.374	-0.846	-0.808	-0.320	-0.332	-0.336
$t(\alpha)$	(-0.952)	(-1.424)	(-1.409)	(-0.863)	(-0.881)	(-0.890)
k	0.080	0.144	0.135	0.077	0.076	0.076
$t(k)$	(3.233)	(3.410)	(3.453)	(3.147)	(3.124)	(3.126)
λ_{net}	1.308	2.046	2.003	1.170	1.193	1.200
$t(\lambda_{net})$	(2.140)	(2.146)	(2.153)	(2.152)	(2.147)	(2.149)

Panel B - Annualized Liquidity Premia

		Wealth Ratios			Labor Income returns		
		Prop.	JW	Lustig	Prop.	JW	Lustig
	Δ(Illiquidity Levels) (% p.a.)	4.68*	4.68*	4.68*	4.68*	4.68*	4.68*
(i)	Liquidity Level Premium (% p.a.)	4.52	8.11	7.57	4.33	4.29	4.29
	Δ(Liquidity Betas)*100	5.95*	6.01*	6.05*	5.91*	5.95*	5.93*
(ii)	Total Liquidity Risk (% p.a.)	0.93	1.48	1.46	0.83	0.85	0.85
	Δ(Labor-Liq Betas)*100	0.41*	4.70*	4.41*	0.97*	0.93*	0.85*
(iii)	Labor-Liq Risk (% p.a.)	-0.06	-1.15	-1.06	-0.14	-0.13	-0.12
(i) + (ii) + (iii)	Total Liquidity Premium (% p.a.)	5.39	8.44	7.97	5.02	5.01	5.02
(iii)÷(ii)	Labor-Liq Fraction	-6.88%	-78.08%	-72.93%	-16.45%	-15.58%	-14.37%

Table 15: Robustness Checks - Impact of size and B/M ratios

This table reports coefficients from the illiquidity and labor returns-adjusted CAPM using data from March 1964-December 2004 using 25 value-weighted illiquidity-sorted portfolios and including size and B/M as controls. The estimates are based on a GMM framework setting where regressions are alternative cases of the relation:

$$\begin{aligned} E\left(r_t^i - r_f\right) &= \alpha + kE\left(c_t^i\right) + \lambda_{mkt}\beta_{mkt}^i + \lambda_{liq}\beta_{liq}^i + \lambda_{labor}\beta_{labor}^i + \lambda_{Net}\beta_{Net}^i, \text{ where} \\ \beta_{liq}^i &= \beta_2^i - \beta_3^i - \beta_4^i - \beta_{liq,lab}^i \\ \beta_{Net}^i &= \beta_{mkt}^i + \beta_2^i - \beta_3^i - \beta_4^i - \beta_{liq,lab}^i + \beta_{labor}^i \end{aligned}$$

The coefficient k adjusts for the difference between the estimation period and the typical holding period of investors. Coefficients are followed by t-statistics adjusted for serial correlation using 5 lags (Newey and West (1987)). The adjusted R^2 reported in each row is computed from a single cross-sectional regression using average portfolio returns. The factors are estimated with 25 portfolios times 490 months = 12,250

Illiquidity Portfolios - Value Weighted

	α	k	λ_{net}	ln(size)	B/M	Adj.R^2
1	0.368	0.044	0.760	-0.065		0.842
	(0.436)		(1.038)	(-0.963)		
2	-0.385	0.081	1.319	-0.004		0.767
	(-0.434)	(3.557)	(1.660)	(-0.064)		
3	-1.154	0.044	1.291	0.036	0.752	0.902
	(-1.053)		(1.647)	(0.473)	(1.879)	
4	-0.953	0.064	1.378	0.028	0.455	0.898
	(-0.899)	(2.586)	(1.714)	(0.377)	(1.271)	

Illiquidity Portfolios - Equal Weighted

	α	k	λ_{net}	ln(size)	B/M	Adj.R^2
1	1.477	0.055	-0.427	-0.109		0.882
	(2.127)		(-0.680)	(-2.083)		
2	1.327	0.060	-0.305	-0.099		0.898
	(1.775)	(3.034)	(-0.473)	(-1.696)		
3	1.253	0.055	-0.323	-0.095	0.086	0.876
	(1.070)		(-0.435)	(-1.206)	(0.233)	
4	1.278	0.059	-0.291	-0.096	0.028	0.915
	(1.084)	(2.646)	(-0.397)	(-1.214)	(0.073)	