Future Liquidity, Present Value:
Measuring and Pricing Liquidity Risk

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Abstract

Liquidity costs are not incurred once, but many times over the lifetime of an asset. Changes in forecasts of future liquidity levels impact contemporaneous prices. I derive two extensions of the Campbell (1991) return decomposition and decompose contemporaneous returns into revisions in expectations, or news, about future dividends, liquidity, and net discount rates. The two decompositions consider, respectively, news about future proportional costs and news about future fixed costs. Using the decompositions, I find that (i) both fixed cost and proportional cost news are substantially more volatile than contemporaneous proportional costs, (ii) fixed cost news is an economically important contributor to portfolio volatility and proportional cost news is not, (iii) small and illiquid stocks have more volatile proportional and fixed cost news and low turnover stocks have more volatile proportional cost news risk and less volatile fixed cost news, and (iv) the market price of risk for both fixed and proportional cost news, estimated within the Liquidity-Adjusted CAPM framework of Acharya and Pedersen (2005), is not statistically different than the price of non-liquidity risk.

JEL classification: G0; G1; G12.

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1 Introduction

In their extensive survey of the liquidity literature, Amihud, Mendelson, and Pedersen (2005) write

> "Liquidity varies over time. This means that investors are uncertain what transactions cost they will incur in the future when they need to sell an asset. Further, since liquidity affects the level of prices, liquidity fluctuations can affect the asset price volatility itself."

This paper joins the growing body of research that studies the effect of liquidity risk on expected returns, but it begins with an investigation of the effect of liquidity fluctuations on asset price volatility. Amihud (2002) reports that negative shocks to liquidity lower asset prices. Acharya and Pedersen (2005) report a negative relationship between unexpected market illiquidity and asset returns, and between unexpected asset illiquidity and market returns. How much of an asset's volatility can be attributed to these liquidity fluctuations?

A similar question can be, and has been, asked about dividend fluctuations. Campbell (1991) answers the question by decomposing the unexpected contemporaneous return into two components, new information about the dividend stream and new information about future discount rates. Even though uncertainty about contemporaneous cash flows is relatively low, using the decomposition, Campbell (1991) reports that new information about future cash flows accounts for almost half the variation of contemporaneous returns. I extend the Campbell (1991) return decomposition to include a liquidity component in two ways. The first decomposition considers revisions in expected per share fixed costs and the second decomposition considers new information about proportional costs. Each measure captures the resolved uncertainty about contemporaneous liquidity costs as well as the price impact of new information about future fixed and proportional costs.

I estimate the two decompositions for an equal-weight aggregate portfolio of NYSE and AMEX stocks over the period January 1964 to December 2001 using the proportional cost proxy implemented by Acharya and Pedersen (2005), which is a variation of the Amihud (2002) illiquidity measure. I find that the price impact of new information about future liquidity is a larger source of portfolio risk than uncertainty about contemporaneous proportional costs. Although proportional cost news has roughly 7 times the volatility of contemporaneous proportional costs, its volatility is about 100 times smaller than that of contemporaneous returns. Hence, liquidity risk, from the proportional cost perspective, does not appear to be an economically significant source of portfolio risk. Fixed cost news, on the other hand, is approximately 122 times more volatile than contemporaneous proportional costs and has 17 percent the volatility of contemporaneous returns. I derive an explicit relationship between news about fixed costs, proportional costs, and dividends. The relationship suggests that fixed cost news is primarily driven by new information about future dividends. Positive dividend news leads to a capital gain – if proportional costs do not adjust, the increased price results in higher fixed costs.

In addition to the aggregate portfolio, I study the properties of fixed and proportional cost news across the cross-section by forming quintile-ranked portfolios after sorting assets on market capitalization, illiquidity levels, and turnover. The liquidity news components of these portfolio's returns have similar properties to those of the aggregate portfolio. Proportional cost and fixed cost news are significantly more volatile than contemporaneous proportional costs and fixed cost news is substantially more volatile than proportional cost news. I report that small and illiquid stocks have more volatile proportional and fixed cost news and low turnover stocks have more volatile proportional cost news and less volatile fixed cost news.

There is growing evidence that systematic liquidity risk is priced. Pastor and Stambaugh (2003) report that assets with returns that are sensitive to market liquidity earn a risk premium. Sorting assets by their return sensitivities to the aggregate liquidity measure, the portfolio that is long stocks in the highest decile and short stocks in the lowest decile has annualized returns of 8.5 percent after adjusting for the Fama-French factors. Acharya and Pedersen (2005) derive a Liquidity-Adjusted CAPM (LACAPM) that includes a market beta and three liquidity betas. They report that total liquidity risk premium is approximately 1.1 percent when all sources of portfolio systematic risk are restricted to have the same market price of risk. Allowing the prices of the three liquidity risks to differ from gross return risk, depending on the specification, Acharya and Pedersen (2005) report the estimated price of liquidity risk to be between 6 and 22 times larger than that of gross return risk. Sadka (2006) reports a positive and statistically significant liquidity risk premium using the Fama-French model augmented by a liquidity factor. His liquidity factor is the average permanent market impact coefficient after decomposing a measure of Kyle's λ into permanent and transitory effects. The sensitivity Sadka (2006) measures is similar to that measured by Pastor and

Stambaugh (2003) and is related to one of the three liquidity betas in the Acharya and Pedersen (2005) model.

The second half of the paper explores the relationship between expected returns and liquidity news risk by applying the two net return decompositions to the Acharya and Pedersen (2005) LACAPM. A simple description of LACAPM is that it is CAPM, except the gross return is replaced by the net return. An asset's expected excess net return is its net return beta times the market expected excess net return. The final version of their model is obtained by substituting in the relationship that net return equals gross return minus proportional costs. I estimate the LACAPM using the proportional and fixed cost decompositions. The primary finding is that the explanatory of the LACAPM under the two decompositions investigated in this paper is similar to that of their original specification, but the market price of liquidity news risk is not statistically different than that of non-liquidity news risk. Thus, including the price impact of changes in expected liquidity levels as a component of liquidity risk appears to help resolve the puzzle associated with the large price of liquidity risk reported by the above studies.

The rest of the paper is as follows. The next section provides the decomposition of asset net returns into their three components. Section 3 sets up the vector autoregression and relates the VAR to the variance decomposition provided in section 2. In section 4, I describe the data, the data inclusion requirements, and the construction of the cross-sectional portfolios analyzed in the paper. Section 5 reports the results of the variance decomposition for the aggregate and characteristic-sorted portfolios. Section 6 estimates the price of liquidity news risk. Section 7 concludes and the Appendix includes details on the jackknife resampling technique used in this paper.

2 Decomposing Asset Returns

My decompositions begin with the Campbell (1991) log-linear approximation of unexpected returns:

$$r_t - E_{t-1} r_t \approx \Delta E_t \sum_{i=0}^{\infty} \rho^i \Delta c f_{t+i} - \Delta E_t \sum_{i=1}^{\infty} \rho^i r_{t+i}, \tag{1}$$

where r_t is the log stock return, cf_t is the log cash flow paid by the stock, Δ denotes a one-period change, E_t denotes a rational expectation at time t, and $\rho \equiv P/(P+D)$ is a discount coefficient defined at long-horizon means. Equation (1) is the result of a first-order approximation of an accounting identity and not an economic or behavioral model. It says that a capital gain today requires that expected future cash flow growth be higher, or expected future asset returns be lower, or both.

In the Campbell (1991) model, a stock's cash flows are its dividend stream. The notation is simplified by defining *dividend news* ($\eta_{d,t}$), *discount rate news* ($\eta_{r,t}$), and *unexpected returns* (ν_t) as follows:

$$\eta_{d,t} \equiv \Delta E_t \sum_{i=0}^{\infty} \rho^i \Delta d_{t+i} \qquad \eta_{r,t} \equiv \Delta E_t \sum_{i=1}^{\infty} \rho^i r_{t+i} \qquad \nu_t \equiv r_t - E_{t-1} r_t. \tag{2}$$

Then (1) can be rewritten in compact form as $\nu_t \approx \eta_d - \eta_r$.

I introduce illiquidity by considering the *net* or *spread-adjusted* return in a manner similar to Amihud and Mendelson (1986), Jones (2002), and Acharya and Pedersen (2005):

$$\tilde{R}_t \equiv \frac{P_t + D_t - C_t}{P_{t-1}} = R_t - K_t, \tag{3}$$

where C_t is the contemporaneous per share *fixed cost* incurred each period for holding the illiquid asset and $K_t \equiv C_t/P_{t-1}$ is the contemporaneous *proportional cost.* Amihud, Mendelson, and Pedersen (2005) describe the following four sources of illiquidity: exogenous transactions costs (commissions, taxes, etc.), demand pressure and inventory risk[1], asymmetric information about asset fundamentals or order flow[2], and search frictions[3]. I assume the fixed cost is exogenous and captures the four illiquidity sources. I also assume that the cost is incurred each period regardless

[1]See Stoll (1978), Garman (1976), Amihud and Mendelson (1980), Ho and Stoll (1981), Ho and Stoll (1983), Grossman and Miller (1988), and Brunnermeier and Pedersen (2005b).

[2]Some papers that investigate how information is revealed in prices are Akerlof (1970), Grossman (1976), Grossman and Stiglitz (1980), Hellwig (1980), and Admati (1985). Research on the cost associated with strategic use of information about fundamentals is presented by Bagehot (1971), Copeland and Galai (1983), Glosten and Milgrom (1985), Kyle (1985), and Mendelson and Tunca (2004). Madrigal (1996), Vayanos (2001), Gallmeyer, Hollifield, and Seppi (2004), Attari, Mello, and Ruckes (2005), and Brunnermeier and Pedersen (2005a) investigate the strategic use of information about order flow.

[3]See Longstaff (1995), Hopenhayn and Werner (1996), Longstaff (2001), Duffie, Garleanu, and Pedersen (2002), Vayanos and Wang (2002), Weill (2002), Duffie, Garleanu, and Pedersen (2003), Brunnermeier and Pedersen (2005a), Lagos (2005), Duffie, Garleanu, and Pedersen (2005), and Vayanos and Weill (2005).

of whether a transaction takes place. The per period cost includes the monetized opportunity cost associated with holding the illiquid asset, which may be due to second-best portfolio optimization or the inability to profit from small informational asymmetries. It also amortizes over the holding period the illiquidity cost incurred when the asset is liquidated.

2.1 Fixed Cost Decomposition

To the marginal investor, the realized cash flow at time t is the dividend paid by the stock minus liquidity costs. The log cash flow may be written $cf_t \equiv \log(e^{d_t} - e^{c_t})$. Note that log dividends (d_t) and log costs (c_t) enter (1) nonlinearly through cf_t. A first-order Taylor expansion around long run means gives the following approximation of cash flow growth rates

$$\Delta cf_t \approx \omega_d \Delta d_t - \omega_c \Delta c_t, \tag{4}$$

where ω_d and ω_c are defined to be long run means of the following ratios:

$$\omega_d = \frac{D}{D-C} \qquad \omega_c = \frac{C}{D-C}. \tag{5}$$

Substituting (4) into (1), I obtain[4]

$$\tilde{r}_t - E_{t-1}\tilde{r}_t \approx \omega_d \Delta E_t \sum_{i=0}^{\infty} \rho^i \Delta d_{t+i} - \omega_c \Delta E_t \sum_{i=0}^{\infty} \rho^i \Delta c_{t+i} - \Delta E_t \sum_{i=1}^{\infty} \rho^i \tilde{r}_{t+i}, \tag{6}$$

which may be written in compact form to simplify notation

$$\tilde{\nu}_t \approx \omega_d \eta_{d,t} - \omega_c \eta_{c,t} - \eta_{\tilde{r},t} \tag{7}$$

$$= \ddot{\eta}_{d,t} - \ddot{\eta}_{c,t} - \eta_{\tilde{r},t}, \tag{8}$$

[4] An exact substitution of the log cash flow approximation into the Campbell (1991) decomposition would lead to $\rho = \frac{P}{P+D-C}$. Expanding the price-cash flow ratio in the Campbell and Shiller (1988) approximation around the long run mean price-dividend ratio instead of the price-cash flow ratio leads to $\rho = \frac{P}{P+D}$ as defined in this paper.

where $\ddot{\eta}_{d,t} \equiv \omega_d \eta_{d,t}$, $\ddot{\eta}_{c,t} \equiv \omega_c \eta_{c,t}$, and *fixed cost news* is defined by

$$\eta_{c,t} = \Delta E_t \sum_{i=0}^{\infty} \rho^i \Delta c_{t+i}. \tag{9}$$

Equations (6) through (8) relate the unexpected component of net returns to revisions in expectations about future dividend growth, fixed cost growth, and net discount rates. New information about higher than expected future fixed costs negatively influences contemporaneous prices. News about dividends and discount rates have the same effect on unexpected returns as in the Campbell (1991) model. Dividend and fixed cost news are multiplied by ω_d and ω_c respectively in order to account for their relative importance on prices. The natural assumption that long-run dividends are greater than long-run transactions costs dictates that the coefficient on dividend news is greater than that on fixed cost news. News that future dividends will increase by ten percent is more important than news that future costs will increase by ten percent. Both coefficients increase as the long-run mean of the cost-dividend ratio increases and achieve their minimum values when trading costs are absent. Cross-sectionally, these coefficients are important; for example, small firms tend to have low yields and high trading costs and large firms have high yields and low trading costs.

2.2 Proportional Cost Decomposition

An alternate decomposition considers revisions in expected proportional rather than fixed costs. The log gross return of a stock may be approximated by $r_t \approx \tilde{r}_t + K_t$. Substituting the log gross return approximation into the Campbell (1991) decomposition provided by equation (1), I obtain

$$\tilde{r}_t - E_{t-1}\tilde{r}_t \approx \Delta E_t \sum_{i=0}^{\infty} \rho^i \Delta d_{t+i} - \Delta E_t \sum_{i=0}^{\infty} \rho^i K_{t+i} - \Delta E_t \sum_{i=0}^{\infty} \rho^i \tilde{r}_{t+i} \tag{10}$$

which may be written in compact form to simplify notation

$$\tilde{\nu}_t \approx \eta_{d,t} - \eta_{K,t} - \eta_{\tilde{r},t}, \tag{11}$$

where proportional cost news, $\eta_{K,t}$ is defined as follows:

$$\eta_{K,t} = \Delta E_t \sum_{i=0}^{\infty} \rho^i K_{t+i} = \Delta E_t K_t + \sum_{i=1}^{\infty} \rho^i K_{t+i}. \tag{12}$$

In the proportional cost decomposition, cash flows are the dividend stream so that transactions costs are not double counted. Equations (10) and (11) relate the unexpected net return to changes in expected dividend growth, proportional costs, and net returns. Negative contemporaneous returns occur when proportional cost estimates are revised upwards. From equation (12), we see that proportional cost news includes the unexpected contemporaneous proportional cost, which is the source of liquidity risk identified by Acharya and Pedersen (2005). In addition, proportional cost news also contains the newly acquired information about future proportional costs. This additional component is the price impact of changes in forecasted liquidity levels and is another source of liquidity risk.

Fixed costs and proportional costs are obviously related. Equations (8) and (11) may be combined to relate the two liquidity news terms. Two equivalent forms of the relationship follow

$$\eta_{c,t} = \eta_{d,t} + \ddot{\eta}_{K,t} \tag{13}$$

$$\eta_{K,t} = \omega_c(\eta_{c,t} - \eta_{d,t}), \tag{14}$$

where $\ddot{\eta}_{K,t} \equiv \eta_{K,t}/\omega_c$. Proportional costs link information about dividends to information about fixed costs. If proportional costs are time-invariant or there is no newly acquired information about proportional costs, then $\ddot{\eta}_{K,t} = 0$ and $\eta_{c,t} = \eta_{d,t}$. With no change in proportional costs, a 10 percent increase in dividends implies a 10 percent increase in fixed costs. Proportional cost news is primarily driven by price changes. When expected future fixed costs are higher ($\eta_{c,t} > 0$) or dividends are lower ($\eta_{d,t} < 0$), prices drop and expected proportional costs increase ($\eta_{K,t} > 0$). A similar equation may be derived for yield news:

$$\eta_{Y,t} \equiv \Delta E_t \sum_{i=0}^{\infty} \rho^i Y_{t+i} = \omega_d(\eta_{c,t} - \eta_{d,t}). \tag{15}$$

The contemporaneous yield is defined to be the contemporaneous dividend divided by lag price:

$Y_t \equiv D_t/P_{t-1}$. As is the case for proportional cost news, yield news is also primarily driven by price changes. Positive fixed cost news or negative dividend news lowers price and increases the yield. Yield and proportional cost news are related as follows:

$$\eta_{Y,t} = \frac{\omega_d}{\omega_c}\eta_{K,t} = \frac{D}{C}\eta_{K,t}. \tag{16}$$

Equation (16) predicts that the dividend yield should be more volatile than the proportional cost, a prediction that is consistent with the findings of Jones (2002). Using annual data for the entire twentieth century, Jones (2002) regresses yield on proportional costs and reports that a one unit increase in proportional costs is associated with a 5.3 unit increase in yield. Although the regression does not translate perfectly to the relationship given by equation (16), the estimate suggests that dividends are approximately 5.3 times larger than costs. Chalmers and Kadlec (1998) report that between 1983 and 1992 the equal-weight amortized spread was approximately 0.51 percent per year. The equal-weight yield over the same period was approximately 2.82 percent per year. Hence, the dividend-cost ratio during the ten year period was approximately 5.5. Together, the findings suggest that fixed costs are roughly 18 percent the size of dividends. Ceteris paribus, new information about fixed costs should have $\frac{18}{1.18} = 15.3$ percent the effect on returns as new information about dividends.

Although the three-term decompositions distinguish the three sources of return information and risk, the primary purpose of this paper is to investigate the properties of the liquidity component. In Section 6, I estimate the market prices of fixed cost versus non-fixed cost news risk and of proportion cost versus non-proportional cost news risk. In order to do so, I aggregate the non-liquidity components in each decomposition to provide two-term decompositions that simplify the analysis and exposition considerably. Defining $\eta^\star_{c,t} \equiv \ddot{\eta}_{d,t} - \eta_{\tilde{r},t}$ to be non-fixed cost news and $\eta^\star_{K,t} \equiv \eta_{d,t} - \eta_{\tilde{r},t}$ to be non-proportional cost news, the unexpected component of net returns may be rewritten $\tilde{\nu}_t \approx \eta^\star_{c,t} - \eta_{c,t}$ and $\tilde{\nu}_t \approx \eta^\star_{K,t} - \eta_{K,t}$.

2.3 Decomposing the Net Return Variance

The three-term return decompositions result in six-term variance decompositions:

$$\begin{aligned} \operatorname{var}(\tilde{\nu}_t) =& \operatorname{var}(\ddot{\eta}_{d,t}) + \operatorname{var}(\ddot{\eta}_{c,t}) + \operatorname{var}(\eta_{\tilde{r},t}) \\ & - 2\ \operatorname{cov}(\ddot{\eta}_{d,t}, \ddot{\eta}_{c,t}) - 2\ \operatorname{cov}(\ddot{\eta}_{d,t}, \eta_{\tilde{r},t}) + 2\ \operatorname{cov}(\ddot{\eta}_{c,t}, \eta_{\tilde{r},t}) \end{aligned} \tag{17}$$

for the fixed cost decomposition and

$$\begin{aligned} \operatorname{var}(\tilde{\nu}_t) =& \operatorname{var}(\eta_{d,t}) + \operatorname{var}(\eta_{K,t}) + \operatorname{var}(\eta_{\tilde{r},t}) \\ & - 2\ \operatorname{cov}(\eta_{d,t}, \eta_{K,t}) - 2\ \operatorname{cov}(\eta_{d,t}, \eta_{\tilde{r},t}) + 2\ \operatorname{cov}(\eta_{K,t}, \eta_{\tilde{r},t}) \end{aligned} \tag{18}$$

for the proportional cost decomposition. The goal of the above variance decompositions is to determine liquidity's influence on portfolio volatility. The task is ambiguous because liquidity enters the above variance decompositions in three places, through one variance term and two covariance terms. There are many possible measures that aggregate the variance and covariance terms in different ways in order to capture different aspects of liquidity's influence on return volatility. I report the following three measures for each decomposition. The first measure is the ratio of cost volatility to return volatility: $\ddot{\mathcal{R}}_c \equiv \sigma(\ddot{\eta}_{c,t})/\sigma(\tilde{\nu}_t)$ for fixed costs and $\mathcal{R}_K \equiv \sigma(\eta_{K,t})/\sigma(\tilde{\nu}_t)$ for proportional costs. The measure is a relative measure of liquidity news volatility and does not take into account any relationship between liquidity news and the other two news terms. The relative volatilities of dividend news and discount rate news are similarly defined by $\ddot{\mathcal{R}}_d \equiv \sigma(\ddot{\eta}_{d,t})/\sigma(\tilde{\nu}_t)$ for dividend news in the fixed cost decomposition, $\mathcal{R}_d \equiv \sigma(\eta_{d,t})/\sigma(\tilde{\nu}_t)$ for dividend news in the proportional cost decomposition, and $\mathcal{R}_{\tilde{r}} \equiv \sigma(\eta_{\tilde{r},t})/\sigma(\tilde{\nu}_t)$ for net discount rate news. The second measure I report is the regression coefficient of liquidity news on unexpected contemporaneous returns: $\ddot{\mathcal{B}}_c \equiv \operatorname{cov}(\tilde{\nu}_t, \ddot{\eta}_{c,t})/\operatorname{var}(\tilde{\nu}_t)$ for fixed costs and $\mathcal{B}_K \equiv \operatorname{cov}(\tilde{\nu}_t, \eta_{K,t})/\operatorname{var}(\tilde{\nu}_t)$ for proportional costs. When the measure is positive, unexpected contemporaneous returns are less volatile than non-liquidity news because of the positive comovement between liquidity and non-liquidity news. Similarly, I calculate the regression coefficients for dividend and net return news: $\ddot{\mathcal{B}}_d \equiv \operatorname{cov}(\tilde{\nu}_t, \ddot{\eta}_{d,t})/\operatorname{var}(\tilde{\nu}_t)$, $\mathcal{B}_d \equiv \operatorname{cov}(\tilde{\nu}_t, \eta_{d,t})/\operatorname{var}(\tilde{\nu}_t)$ and $\mathcal{B}_{\tilde{r}} \equiv \operatorname{cov}(\tilde{\nu}_t, \eta_{\tilde{r},t})/\operatorname{var}(\tilde{\nu}_t)$. By definition, $\ddot{\mathcal{B}}_d - \ddot{\mathcal{B}}_c - \mathcal{B}_{\tilde{r}} = 1$ and $\mathcal{B}_d - \mathcal{B}_K - \mathcal{B}_{\tilde{r}} = 1$. These regression coefficients are similarly defined as the measures of dividend and discount rate contribution to portfolio variance reported by Campbell (1991) and can be interpreted as the percentage of conditional return volatility attributable to the respective return component. The final measure is the ratio of cost volatility to contemporaneous proportional cost volatility: $\ddot{\mathcal{P}}_c \equiv \sigma(\ddot{\eta}_{c,t})/\sigma(K_t)$ for proportional costs and $\mathcal{P}_K \equiv \sigma(\eta_{K,t})/\sigma(K_t)$. The measure captures how large the volatility of liquidity news is relative to that of uncertainty about contemporaneous proportional costs, the traditional measure of liquidity risk and may be interpreted as a measure of liquidity's persistence. Campbell and Shiller (1988) report a similar persistence measure of discount rate news, which they provide as evidence of long horizon return predictability.

Equation (13) provides the decomposition of fixed cost news into proportional cost news and dividend news. Using the decomposition, the fixed cost news variance may be written:

$$\mathrm{var}(\eta_{c,t}) = \mathrm{var}(\eta_{d,t}) + \mathrm{var}(\ddot{\eta}_{K,t}) + 2(\eta_{d,t}, \ddot{\eta}_{K,t}) \tag{19}$$

Is new information about future fixed costs primarily due to changes in expected future proportional costs or dividends? In order to determine the relative volatility contributions of the two fixed cost news components, I calculate the following three measures for the above decomposition. The first measure is the relative volatilities of the two components: $\mathcal{R}^*_d \equiv \sigma(\eta_{d,t})/\sigma(\eta_{c,t})$ and $\ddot{\mathcal{R}}^*_K \equiv \sigma(\ddot{\eta}_{K,t})/\sigma(\eta_{c,t})$. The second measure is the respective regression coefficients obtained by regressing dividend and scaled proportional cost news on fixed cost news: $\mathcal{B}^*_d \equiv \mathrm{cov}(\eta_{c,t}, \eta_{d,t})/\mathrm{var}(\eta_{c,t})$ for dividend news and $\ddot{\mathcal{B}}^*_K \equiv \mathrm{cov}(\eta_{c,t}, \ddot{\eta}_{K,t})/\mathrm{var}(\eta_{c,t})$ for proportional cost news.

3 Vector Autoregressions

Campbell and Shiller (1988) show that using a vector autoregression (VAR) is a convenient way to implement the return and return variance decomposition and estimate the news series. I assume that the data are generated by a first-order VAR model,

$$\mathbf{z_t} = \mathbf{a} + \mathbf{\Gamma z_{t-1}} + \mathbf{w_t}, \tag{20}$$

where $\mathbf{z_t}$ is a m-by-1 portfolio-specific vector of state variables describing a portfolio at time t,

$\mathbf{a}$ and $\mathbf{\Gamma}$ are, respectively, an m-by-1 vector and an m-by-m matrix of parameters, and $\mathbf{w_t}$ is an m-by-1 vector of i.i.d. shocks. This formulation is not restrictive and allows for higher-order representation by including additional lags in the vector of state variables. The VAR coefficient matrix may differ across portfolios but is assumed to be time invariant. The error vector $\mathbf{w_t}$ has portfolio dependent covariance matrix $\mathbf{\Sigma}$. Writing the VAR in companion form simplifies forecasting. For example, the change in expectations at time t of the state variables i periods ahead is $E_t[z_{t+i}|z_t] - E_{t-1}[z_{t+i}|z_{t-1}] = \mathbf{\Gamma}^i\mathbf{w_t}$.

The vector of state variables includes the log gross return and proportional cost, which are required for calculating the news components, and additional variables that aid in forecasting. The additional state variables included for their forecasting abilities are described in the next section.

I define $\mathbf{e_j}$ to be the jth row of an appropriately sized identity matrix. The vector $\mathbf{e_j}$ extracts jth variable of the vector z_t. For instance, the unexpected net return at date t is $\tilde{\nu}_t = (\mathbf{e_1} - \mathbf{e_2})\mathbf{w_t}$, the unexpected contemporaneous proportional cost is approximately $\Delta E_t K_t = \mathbf{e_2}\mathbf{w_t}$, and the net discount rate news is calculated as follows:

$$\begin{aligned}
\eta_{\tilde{r},t} = \Delta E_t \sum_{i=1}^{\infty} \rho^i \tilde{r}_{t+i} &= (\mathbf{e_1} - \mathbf{e_2}) \sum_{i=1}^{\infty} \rho^i \mathbf{\Gamma}^i \mathbf{w_t} \\
&= (\mathbf{e_1} - \mathbf{e_2})\mathbf{\Gamma}(\mathbf{I} - \rho\mathbf{\Gamma})^{-1}\mathbf{w_t} \\
&= (\mathbf{e_1} - \mathbf{e_2})\mathbf{\Lambda}\mathbf{w_t},
\end{aligned} \tag{21}$$

where $\mathbf{\Lambda}$ is defined by $\mathbf{\Lambda} \equiv \rho\mathbf{\Gamma}(\mathbf{I} - \rho\mathbf{\Gamma})^{-1}$, a nonlinear function of the VAR coefficients. The term $(\mathbf{I} - \rho\mathbf{\Gamma})^{-1}$, which is equal to $(\mathbf{I} + \mathbf{\Lambda})$, gives more persistent variables a higher weight. The derivation of proportional cost news is similar with the following resulting expression:

$$\eta_{K,t} = \mathbf{e_2}(\mathbf{I} + \mathbf{\Lambda})\mathbf{w_t} \tag{22}$$

$$\ddot{\eta}_{K,t} = \frac{1}{\omega_c}\mathbf{e_2}(\mathbf{I} + \mathbf{\Lambda})\mathbf{w_t}. \tag{23}$$

As is the case in the Campbell (1991) implementation, dividend news is estimated as a residual:

$$\eta_{d,t} = \mathbf{e_1}(\mathbf{I} + \mathbf{\Lambda})\mathbf{w_t} \tag{24}$$

$$\ddot{\eta}_{d,t} = \omega_d \mathbf{e_1}(\mathbf{I} + \mathbf{\Lambda})\mathbf{w_t}. \tag{25}$$

Fixed cost news is estimated using equation (13):

$$\eta_{c,t} = (\mathbf{e_1} + \frac{1}{\omega_c}\mathbf{e_2})(\mathbf{I} + \mathbf{\Lambda})\mathbf{w_t} \tag{26}$$

$$\ddot{\eta}_{c,t} = (\omega_c \mathbf{e_1} + \mathbf{e_2})(\mathbf{I} + \mathbf{\Lambda})\mathbf{w_t}. \tag{27}$$

The above expressions may be used, along with the coefficient matrix $\mathbf{\Gamma}$ and the innovation covariance matrix $\mathbf{\Sigma}$, to estimate the desired news covariance matrix and other statistics of interest. For instance, the three previously introduced measures of fixed cost news's influence on portfolio volatility are calculated using the following equations:

$$\mathcal{R}_c = \sqrt{\frac{(\omega_c \mathbf{e_1} + \mathbf{e_2})(\mathbf{I} + \mathbf{\Lambda})\Sigma(\mathbf{I} + \mathbf{\Lambda})'(\omega_c \mathbf{e_1} + \mathbf{e_2})'}{(\mathbf{e_1} - \mathbf{e_2})\mathbf{\Sigma}(\mathbf{e_1} - \mathbf{e_2})'}} \tag{28}$$

$$\mathcal{B}_c = \frac{(\omega_c \mathbf{e_1} + \mathbf{e_2})(\mathbf{I} + \mathbf{\Lambda})\Sigma(\mathbf{e_1} - \mathbf{e_2})'}{(\mathbf{e_1} - \mathbf{e_2})\mathbf{\Sigma}(\mathbf{e_1} - \mathbf{e_2})'} \tag{29}$$

$$\mathcal{P}_c = \sqrt{\frac{(\omega_c \mathbf{e_1} + \mathbf{e_2})(\mathbf{I} + \mathbf{\Lambda})\Sigma(\mathbf{I} + \mathbf{\Lambda})'(\omega_c \mathbf{e_1} + \mathbf{e_2})'}{\mathbf{e_2}\mathbf{\Sigma}\mathbf{e_2}'}}. \tag{30}$$

The VAR coefficient matrix $\mathbf{\Gamma}$ is estimated using OLS and is reported with its OLS standard errors. Robust standard errors and small-sample bias corrected estimates are obtained for all relevant statistics, such as the news' covariances, using the delete-an-observation jackknife method.[5] The jackknife method was selected over the traditional bootstrap because the random sampling of errors often led to ill-conditioned $(\mathbf{I} - \rho\mathbf{\Gamma})$ matrices.[6] Details on the jackknife bias-correction and the estimation of jackknife standard errors are included in the Appendix.

[5] Vuolteenaho (2002) employs Rogers (1993)'s robust estimation of asymptotic standard errors and Shao and Rao (1993)'s delete-a-crossection jackknife in his panel data estimation. Rogers (1993) and Shao and Rao (1993) simplify to White (1984)'s standard errors and the delete-a-group jackknife in the case of a single series of data.

[6] Ill-conditioned matrices occurred approximately 20 percent of the time. Rather than set an arbitrary rule for removing these outliers, I choose the more structured jackknife approach, which eliminates the problem.

4 State Variables, Data Set, and Illiquidity Proxy

As shown in the previous section, two variables are needed to estimate the three news series: log gross returns and proportional costs. Because the news series are changes in forecasts of their respective variables, variables that aid in forecasting should also be included in the VAR. For this reason, the state vector also includes the log yield and its two lags, lagged proportional costs, and the log first difference of monthly turnover.

The price-dividend's (or its inverse) forecasting ability is well-established in the return forecasting literature. The Campbell and Shiller (1988) log-linear approximation of the price-dividend ratio shows why the log yield would have predictive power for returns. Various forms of the dividend-price ratio are typically included in the return decomposition framework. Campbell (1991) includes the ratio of dividends paid over the previous year to the current stock price. Campbell and Ammer (1993) include the log of of the Campbell (1991) measure. Campbell and Vuolteenaho (2004) choose to include the ratio of earnings paid over the previous year to the current stock price. Chen and Zhao (2006) investigate the robustness of the return decomposition to the choice of the price-earnings vs. price-dividend ratio. They estimate the model with the PE measure employed by Campbell and Vuolteenaho (2004) and a smoothed yield and find that the results of the two specifications differ substantially, which they partially attribute to the fact that the unit root test is rejected for the yield, but not for the PE ratio. In order to avoid the persistence problems associated with smoothed variables, I do not smooth dividends like the above papers. Instead, I include the contemporaneous log yield and 2 additional lags of the log yield to account for the quarterly seasonality in dividend payout.

The proportional cost is a required state variable in my decompositions, but it also helps to forecast returns. Two papers that investigate the time-series return-liquidity relationship, Amihud (2002) and Jones (2002), report that high returns are predicted when liquidity is low. Acharya and Pedersen (2005) and Pastor and Stambaugh (2003) predict illiquidity using an AR(2) specification. In their spirit and because I use the Acharya and Pedersen (2005) proportional cost proxy, I include an additional lag of proportional costs in the state vector.

The final variable included in the state vector is the log first difference of monthly turnover, $\Delta\psi_t =$

$\psi_t - \psi_{t-1}$. Jones (2002) reports that high turnover predicts low returns and low trading costs. Because turnover is persistent, I choose to include its logged first difference instead to ensure stationarity.

The price, return, dividend, and volume data are from the Center for Research in Security Prices (CRSP) tape from July 1, 1962 until December 31, 2002 for all common shares (share codes 10 and 11) listed on the NYSE and AMEX (data with exchange codes 3 and 33 are omitted). The risk-free rate used to calculate excess returns are the one month Treasury-bill returns supplied by Ibbotson Associates. Monthly turnover is calculated as the monthly trading volume divided by the number of shares outstanding at the end of the current month. CRSP reports returns both inclusive and exclusive of dividend payout over the period. The log yield is calculated as the log of the equal-weight average single-period yield of the portfolio assets. The Fama-French factors, which are used to sort portfolios on their respective market factor loadings and idiosyncratic risk levels, are taken from Kenneth French's website.

4.1 A Measure of Trading Costs

Unfortunately, illiquidity is not an observable variable and the data that measures certain aspects of liquidity, such as the bid-ask spread, are limited. For example, CRSP provides bid and ask prices for stocks listed on the NASDAQ only after 1982. As a result, researchers have proposed and investigated a number of liquidity proxies.[7] I choose to proxy for trading costs using the methods of Acharya and Pedersen (2005), which are based on the following Amihud (2002) measure of illiquidity:

$$ILLIQ_t^i = \frac{1}{Days_t^i} \sum_{d=1}^{Days_t^i} \frac{|\tilde{R}_{td}^i|}{V_{td}^i}, \tag{31}$$

where $Days_t^i$ is the number of valid observation days for asset i in month t and V_{td}^i is the dollar volume in millions on day d in month t. Given the specification of $ILLIQ_t^i$, one may be concerned that $ILLIQ_t^i$ is proxying for return volatility. Amihud (2002) shows that the correlation between

[7] See Goyenko, Holden, Lundblad, and Trzcinka (2005) for a comprehensive overview of some of the common proxies for liquidity.

his illiquidity measure and asset volatility is low, approximately 0.22. Also, Acharya and Pedersen (2005) test for this effect as a robustness check and find that including volatility as a state variable in their estimation does not significantly change their results. For a more complete discussion on the merits of using $ILLIQ_t^i$ in this setting, see Acharya and Pedersen (2005).

The Amihud (2002) illiquidity measure cannot be used without modification because $ILLIQ_t^i$ is measured in *percent per dollar* whereas my model requires a proportional measure of transactions costs in terms of *dollar cost per dollar invested*. This problem is addressed by relating $ILLIQ_t^i$ to K_t^i, the proportional monthly trading costs:

$$K_t^i = 0.048 \min \big(0.0025 + 0.0030 ILLIQ_t^i \Lambda_{t-1}, 0.30\big), \tag{32}$$

where Λ_{t-1} is the ratio of the capitalizations of the market portfolio at the end of month $t-1$ and of the market portfolio at the end of July 1962. Acharya and Pedersen (2005) select the coefficients 0.0025 and 0.0030 to match the cross-sectional distribution of K_t^i for size-decile ranked portfolios to the effective half-spread reported by Chalmers and Kadlec (1998)[8]. Because I consider the cost incurred each period rather than that paid specifically at liquidation, I multiply by 0.048, the equal-weight average monthly turnover in my sample, to transform the full effective spread into a monthly amortized measure.[9] Proportional trading costs are capped at 30 percent annually to limit the impact of extreme observations of $ILLIQ_t^i$.

4.2 Inclusion Requirements

My inclusion requirements closely resemble those imposed by Amihud (2002), Pastor and Stambaugh (2003), and Acharya and Pedersen (2005). The following requirements are designed to eliminate stocks whose proportional cost proxies may behave poorly:

1. Stocks with end of previous year share prices of less than \$5 or greater than \$1000 are excluded.

[8]Chalmers and Kadlec (1998) report that the mean effective spread is 1.11%.

[9]Acharya and Pedersen (2005) multiply by 0.034, which is the value-weighted monthly turnover and corresponds to a holding period of 29 months. Because I investigate the equal-weight market portfolio, I use the equal-weighted monthly turnover, which I calculate to be 0.048.

2. Only stocks with more than 15 observations in a given month are included. An exception is made for the month of September 2001 because no stocks meet this requirement due to the six day market closure. For this month, to be included, a stock must have 15 observations.

3. The first and last partial month that a stock appears on the CRSP tape are excluded from the sample.

4. Stocks must have at least 120 observations in the previous year.

The initial CRSP sample of ordinary stocks on the NYSE and AMEX between January 1964 and December 2001 includes 1,009,698 observations. 784,908 observations survive the first three requirements. The fourth requirement is designed to ensure a suitable amount of data is available for calculating market factor loadings used in the cross-sectional portfolio analysis and eliminates an additional 27,056 observations. The resulting data set includes 757,852 observations.

4.3 Portfolio Formation

An equal-weight market portfolio is formed each month from January 1964 to December 2002. Acharya and Pedersen (2005) focus on equal-weighted averages for the market portfolio. They argue persuasively that equal weights compensate for the over-representation of liquid assets in the CRSP sample. Because my sample and investigation is similar to and my results are compared against theirs, I too will focus my empirical work on the equal-weighted market portfolio.

In addition to the market portfolio, for each year-end beginning 1963 and ending 2001, eligible stocks are sorted into 3 portfolios according to criteria listed below. Portfolio characteristics for the 12 post-ranking months are linked across years to form a single time series for each quintile. For the quintile-ranked portfolios, all state variables, $\mathbf{z_t}$, are calculated as value-weighted averages. The breakpoints for the sort are calculated using all eligible stocks so that each portfolio has approximately the same number of stocks when formed. The sort criteria is listed below:

- **Size** – Stocks are sorted by end of year market capitalization.

- **Proportional Cost** – Stocks are sorted by an annualized version of the Amihud (2002) illiquidity measure for each eligible stock where equation (31) is estimated over the entire year.

- **Turnover** – Stocks are sorted by their respective mean daily turnover calculated over the entire year.

The purpose of the above sorts is to investigate how liquidity news properties vary over the cross-section. For example, Stoll and Whaley (1983) report that small-cap stocks tend to be less liquid than large-cap stocks. Do they also have more liquidity risk? Acharya and Pedersen (2005) report that less liquid stocks are associated with higher levels of systematic liquidity risk. Does the finding hold when considering liquidity news risk? The cross-sectional analysis helps to answer these questions.

4.4 Calculating the News Coefficients

In Section 2, I emphasized that the weight applied to liquidity news is important over the cross-section. Recall that the liquidity news term is multiplied by the following coefficient:

$$\omega_c = \frac{1}{D/C - 1}. \tag{33}$$

The coefficient is sensitive to changes in the long-run dividend-cost ratio. To see this, consider the dividend cost ratios of the high and low portfolios ranked by market capitalization (Table 5). The average yield and proportional cost of the high portfolio is respectively 3.5678 and 0.1378 percent. The resulting coefficient is 0.04. The average yield and proportional cost of the low portfolio is respectively 1.8915 and 1.2984 percent. The resulting coefficient is 2.19, 55 times larger than that of the high portfolio.

Using these weights more than likely exaggerates the cross-sectional differences. At the same time, applying the same market weight to all portfolios is also suspect because the important cross-sectional differences are completely ignored. My solution is to average each portfolio's yield and proportional cost with the market value prior to calculating the weight. This is a reasonable compromise and a relative conservative approach that assumes the cost-dividend ratio of individual portfolios converge to that of the market over long horizons. Applying this compromise to the above example, I obtain coefficients of 0.12 and 0.644 for the portfolios. The high portfolio's coefficient is now approximately 5 times smaller than that of the low portfolio.

Because of the sensitivity of the weight to the dividend-cost ratio and the noisiness of the Acharya and Pedersen (2005) proportional cost proxy implemented in this paper, I choose to use an alternative measure of long-term trading costs for calculating the coefficients. Chalmers and Kadlec (1998) report the amortized spread for effective spread decile-ranked portfolios. At the end of each year, I rank stocks by their annual Amihud (2002) illiquidity measure and assign to each stock the amortized spread reported by Chalmers and Kadlec (1998) for its respective decile-ranked portfolio. Each month, I calculate the equal-weighted average proportional cost for each portfolio. Finally, I use the time-series average proportional cost as the long run mean cost-price ratio.

5 Results of the VAR Decompositions

Table 2 reports the coefficient estimates for the VAR model for the equal-weight market portfolio formed over the period January 1964 to December 2001. Each estimate includes OLS standard errors in brackets and robust jackknife standard errors in parentheses. The first column is the intercept and the next seven columns are the coefficient estimates that form the coefficient matrix $\mathbf{\Gamma}$. The final two columns report the R^2 and F-statistic for each regression. The second panel reports the correlation matrix of the regression residuals.

The coefficient estimates are consistent with the return predictability literature. Consistent with the findings of Campbell and Shiller (1988), Campbell (1991), Campbell and Ammer (1993), Vuolteenaho (2002), Jones (2002), and Campbell and Vuolteenaho (2004), high returns and yields forecast high returns. High proportional costs positively predict the market return, consistent with Jones (2002), Amihud (2002), and Bekaert, Harvey, and Lundblad (2006). An increase in turnover forecasts higher returns, a result that is inconsistent with the findings of Jones (2002).[10] The R^2 for the regression is 4.8 percent, which is consistent amongst the return predictability literature.

Proportional costs are persistent and predictable. The R^2 of the regression is 84.7 percent. Acharya

[10]These differences can be attributed to the differences in our samples. Jones (2002) considers annual excess returns and his own constructed measurement of the bid-ask spread for the entire century.

and Pedersen (2005) report an R^2 of 78 percent for the AR(2) regression of proportional costs over the period 1964–2000. Combining the coefficients of two lags of K_t indicates a cumulative persistence of approximately 0.85. Like Jones (2002), I find that high returns predict low proportional costs. An increase in turnover forecasts low costs, a result which is again inconsistent with the findings of Jones (2002).

Tables 3 and 4 report the variance decompositions implied by the VAR coefficients reported in Table 2. In order to implement the decomposition, values for ω_d, ω_c, and ρ are required. Using the time-series mean of the portfolio's monthly yield and Chalmers and Kadlec (1998) costs, the calibrated values are: $\omega_d = 1.242$, $\omega_c = 0.242$, and $\rho = 0.99765$. Panel A reports the covariance and correlation matrix for the relevant news terms. Panel B relates the state vector shocks to the news terms through their correlations and the function that maps the state vector shocks to the individual news components. The functional mappings are normalized by multiplying by the respective state variable shock volatility and dividing by the unexpected contemporaneous net return volatility. The resulting estimate is the impact in standard deviations to contemporaneous returns of a single deviation shock to a particular state variable. Panel C provides the seven measures of liquidity's contribution to portfolio risk. Robust jackknife standard errors are in parenthesis and small-sample bias corrected estimates using the jackknife procedure are in brackets.

5.1 Proportional Cost Decomposition

Table 3 reports the previously described statistics for the proportional cost decomposition. Discount rate news has the largest volatility of the three components, a result that is consistent with the Campbell (1991) decomposition. From $\mathcal{R}_{\tilde{r}}$, we see that discount rate news has approximately 96 percent of the variability of unexpected contemporaneous returns. According to $\mathcal{R}_d$, dividend news is also an important component with 75 percent the variability of unexpected returns. As expected, liquidity's contribution to portfolio volatility is the smallest of the three components; it's volatility is approximately 1 percent of that of contemporaneous returns. The beta coefficients ($\mathcal{B}$) take into account the covariation between the three news terms and paint a similar picture. Discount rate news is the largest contributor to portfolio variability with $\mathcal{B}_{\tilde{r}} = -0.601$. Dividend news has about 2/3 the impact on returns as discount rate news with $\mathcal{B}_d = 0.400$. The covariation of proportional cost news with dividend and discount rate news virtually eliminates its impact on contemporaneous returns with $\mathcal{B}_c = 0.001$.

Although proportional cost news is a small component of unexpected returns, its volatility is an order of magnitude larger than that of contemporaneous proportional costs. The persistence measure $\mathcal{P}_K$ indicates that the revision in expectated present and future proportional costs has approximately 7.2 times the volatility as that of contemporaneous proportional costs. Interestingly, the correlation between shocks to contemporaneous proportional costs and proportional cost news is low. From Panel B, we see that the correlation is 0.074. If the VAR for proportional costs were limited to an AR(2) process, then by definition, the correlation between the contemporaneous shock to the news term would be unity. Apparently, the additional information provided by returns, yields, and turnover is important for forecasting future proportional costs. In fact, contemporaneous liquidity shocks are the least informative of the four state variables.

5.2 Fixed Cost Decomposition

Table 4 reports the statistics for the fixed cost decomposition. By definition, the role of discount rate news is identical in the two decompositions. Fixed cost news has a more significant impact on contemporaneous returns than proportional cost news. The $\ddot{\mathcal{R}}_c$ statistic shows that fixed cost news has approximately 17.5 percent the variability of contemporaneous returns versus the 1 percent for proportional cost news in the previous decomposition. The relationship $\eta_{c,t} = \eta_{d,t} + \ddot{\eta}_{K,t}$ suggests that fixed cost news is primarily driven by new information about dividends. Table 3 shows that $\eta_{d,t}$ is substantially more volatile than $\eta_{K,t}$, even after dividing $\eta_{K,t}$ by $\omega_c = 0.242$. New information about dividends influences prices and when proportional costs are relatively stable, the price change due to dividend news is the primary source of fixed cost news variability. As a measure of liquidity risk, fixed cost news is substantially more volatile than contemporaneous proportional costs: 123 times more volatile according to $\ddot{\mathcal{P}}_c$. The fixed cost decomposition indicates that new information about future liquidity costs is an important source of risk for contemporaneous returns and that liquidity risk, as measured by fixed cost news risk, is significantly more important than the risk associated with unpredicted contemporaneous proportional costs.

5.3 Cross-Sectional Variation in the Variance Decompositions

A number of studies have investigated return predictability using the VAR decomposition initially proposed by Campbell and Shiller (1988). One study by Vuolteenaho (2002) estimates the variance decomposition across the cross-section to investigate how the properties of cash flow news and discount rate news differ across firms. Vuolteenaho (2002) forms ten size-ranked portfolios on an annual basis. Vuolteenaho's approach assumes that all portfolios share the same coefficient matrix and that heterogeneity across portfolios is due to portfolio-specific innovation covariance matrices. This assumption eliminates the complication arising from invalidation of the infinite sum formulas. He notes that a result of the assumption is the possibility that heterogeneity in the decomposition may be an artifact of the imposed constraint. I find that imposing the same restriction is problematic in my sample. For example, some portfolios would have variances conditional on the state vector higher than unconditional variances. I choose to take a different approach and assume at the time of portfolio formation that a stock will always have the same transition matrix going forward. Therefore, I estimate portfolio dependent transition and innovation covariance matrices.

Each set of results for the various sorts are presented with sample statistics, the two variance decompositions, and the decomposition of fixed cost news into dividend and proportional cost news. The portfolio sample statistics include the expected gross returns, variance of gross returns, variance of the unexpected component of net returns, average market capitalization, yield, Chalmers and Kadlec (1998)'s amortized spread, the Acharya and Pedersen (2005) proportional cost measure, and turnover. For the variance decompositions, I include the 14 statistics described earlier. Market capitalization is measured in billions of dollars and the remaining terms are annualized and reported as percentages. The rightmost column reports the estimates for the equal-weight market portfolio for ease of comparison.

5.4 Sort by Market Capitalization

Table 5 presents the results for the portfolios formed after sorting assets by their previous year-end market capitalizations. The sample statistics indicate that sorting by firm size leads to the usual results. Expected returns, return variance, and trading costs decrease with firm size, and the yield increases with firm size. Annual turnover only varies slightly across portfolios.

The same relationship between liquidity risk and firm size occurs under the two decompositions. The relative volatility of proportional cost news decreases with firm size, from 0.0392 for the smallest quintile to 0.0004 for the largest quintile. The relative volatility of fixed cost news also decreases with firm size, from 0.597 for the smallest quintile to 0.113 for the largest. For all five portfolios, fixed cost news appears to be primarily driven by dividend news. Panel D reports that the volatility of fixed cost news is slightly less than that of dividend news for all five portfolios. Proportional cost news's contribution to fixed cost news variability decreases with firm size. For instance, proportional cost news has approximately 6.5 percent the volatility of fixed cost news for the smallest quintile and 0.33 percent the volatility of fixed cost news for the largest quintile.

5.5 Sort by Amihud (2002) Illiquidity Level

Table 6 reports the results for firms sorted by their illiquidity level. Due to the close inverse relationship between firm size and liquidity level, the cross-sectional variation of liquidity sorts almost perfectly mimics that of size sorts, only in the opposite direction. Approximately 67 percent of firms are placed in the same quintile-ranked portfolio when sorting on size or illiquidity level.

Unfortunately, the close relationship between firm size and firm liquidity makes it difficult to determine which firm characteristic contributes to the cross-sectional variation of liquidity news. Panel A shows that firms with high costs have low market capitalization. The variance decomposition and measures of contribution also closely follow the results of the size sort. Like Acharya and Pedersen (2005), who show that illiquid securities tend to have high contemporaneous systematic liquidity risk, I find that illiquid securities also have high liquidity news risk as measured by the two decompositions.

5.6 Sort by Turnover

Table 7 presents the results for turnover sorted portfolios. The Amihud and Mendelson (1986) clientele effect predicts that high turnover stocks are more liquid. The reported annualized proportional costs for the five portfolios are consistent with the prediction. The liquid, high turnover portfolios have lower returns and yields. Although turnover and liquidity are linked and liquidity and market capitalization are related, there does not appear to be a relationship between turnover and size.

The turnover sort leads to an interesting set of results. The relative proportional cost volatility decreases in turnover, but the relative fixed cost volatility increases in turnover. The volatility of fixed and proportional cost news is, respectively, high and low for stocks that turn over most frequently. As Panel D reports, for these stocks, fixed cost news is primarily driven by dividend news. The volatility of fixed and proportional cost news is, respectively, low and high for stocks that turn over least frequently and proportional cost news has approximately half the volatility of fixed cost news. For these stocks, new information about proportional costs is a significant source of information about fixed costs.

6 Pricing Liquidity Risk

The Liquidity-Adjusted Capital Asset Pricing Model (LACAPM) derived by Acharya and Pedersen (2005) is a significant contribution that allows liquidity risk to be priced and asset returns to be explained as a function of their systematic liquidity risk. Their result is the solution to an overlapping generations equilibrium model with risk-averse agents and assets with stochastic liquidity levels. The unconditional expected net return of asset i is

$$E(\tilde{r}_t^i) = E(r_t^f) + \lambda \frac{\mathrm{cov}(\tilde{r}_t^i - E_{t-1}(\tilde{r}_t^i), \tilde{r}_t^m - E_{t-1}(\tilde{r}_t^m))}{\mathrm{var}(\tilde{r}_t^m - E_{t-1}(\tilde{r}_t^m))}. \tag{34}$$

The LACAPM is a natural extension to the CAPM, exchanging the net return that agents care about in a world with liquidity costs for the gross return in the original CAPM. Acharya and Pedersen (2005) substitute in the standard decomposition of net return: $\tilde{r}_t^i \approx r_t^i - K_t^i$, which I refer to as the *contemporaneous decomposition*, and obtain the following model for expected returns:

$$E(r_t^i - r_t^f) = E\left(K_t^i\right) + \lambda\beta_{r,r}^i + \lambda\beta_{c,c}^i - \lambda\beta_{c,r}^i - \lambda\beta_{r,c}^i \tag{35}$$

where

$$\beta^i_{r,r} = \frac{\mathrm{cov}\left(r^i_t - E_{t-1}\left(r^i_t\right), r^m_t - E_{t-1}\left(r^m_t\right)\right)}{\mathrm{var}\left(r^m_t - E_{t-1}\left(r^m_t\right) - \left[K^m_t - E_{t-1}\left(K^m_t\right)\right]\right)} \tag{36}$$

is the systematic risk associated with covariation between an individual asset's gross return with the market gross return,

$$\beta^i_{c,c} = \frac{\mathrm{cov}\left(K^i_t - E_{t-1}\left(K^i_t\right), K^m_t - E_{t-1}\left(K^m_t\right)\right)}{\mathrm{var}\left(r^m_t - E_{t-1}\left(r^m_t\right) - \left[K^m_t - E_{t-1}\left(K^m_t\right)\right]\right)} \tag{37}$$

is the systematic risk due to comovement between an individual asset's contemporaneous proportional liquidity level with that of the aggregate portfolio,

$$\beta^i_{c,r} = \frac{\mathrm{cov}\left(K^i_t - E_{t-1}\left(K^i_t\right), r^m_t - E_{t-1}\left(r^m_t\right)\right)}{\mathrm{var}\left(r^m_t - E_{t-1}\left(r^m_t\right) - \left[K^m_t - E_{t-1}\left(K^m_t\right)\right]\right)} \tag{38}$$

represents the non-diversifiable risk due to an individual asset's proportional liquidity sensitivity to the market return, and

$$\beta^i_{r,c} = \frac{\mathrm{cov}\left(r^i_t - E_{t-1}\left(r^i_t\right), K^m_t - E_{t-1}\left(K^m_t\right)\right)}{\mathrm{var}\left(r^m_t - E_{t-1}\left(r^m_t\right) - \left[K^m_t - E_{t-1}\left(K^m_t\right)\right]\right)} \tag{39}$$

is the systematic risk that results from an individual asset's return covarying with the aggregate proportional liquidity level. In their model, the expected excess net return $\lambda = E(r^m_t - K^m_t - r^f_t)$ is the market risk premium.

This paper emphasizes through the return decomposition approach that the gross return contains a liquidity component and that the net return decomposition may be used to disentangle the liquidity component from gross returns. Note that equation (34) is equivalent to

$$E(\tilde{r}^i_t) = E(r^f_t) + \lambda \frac{\mathrm{cov}(\tilde{\nu}^i_t, \tilde{\nu}^m_t)}{\mathrm{var}(\tilde{\nu}^m_t)} \tag{40}$$

$$= E(r^f_t) + \lambda\tilde{\beta}. \tag{41}$$

The two-way decompositions, $\tilde{\nu}^i_t \approx \eta^{\star i}_{K,t} - \eta^i_{K,t}$ for proportional costs and $\tilde{\nu}^i_t \approx \eta^{\star i}_{c,t} - \ddot{\eta}^i_{c,t}$ for fixed costs, may be substituted into equation (41) to obtain two alternative LACAPMs. For the proportional cost decomposition, the four betas are defined as follows:

$$\beta^i_{r,r} = \frac{\mathrm{cov}(\eta^{\star i}_{K,t}, \eta^{\star m}_{K,t})}{\mathrm{var}(\tilde{\nu}^m_t)} \quad \beta^i_{c,c} = \frac{\mathrm{cov}(\eta^i_{K,t}, \eta^m_{K,t})}{\mathrm{var}(\tilde{\nu}^m_t)} \quad \beta^i_{r,c} = \frac{\mathrm{cov}(\eta^{\star i}_{K,t}, \eta^m_{K,t})}{\mathrm{var}(\tilde{\nu}^m_t)} \quad \beta^i_{c,r} = \frac{\mathrm{cov}(\eta^i_{K,t}, \eta^{\star m}_{K,t})}{\mathrm{var}(\tilde{\nu}^m_t)}. \tag{42}$$

For the fixed cost decomposition, the four betas are defined to be

$$\beta^i_{r,r} = \frac{\mathrm{cov}(\eta^{\star i}_{c,t}, \eta^{\star m}_{c,t})}{\mathrm{var}(\tilde{\nu}^m_t)} \quad \beta^i_{c,c} = \frac{\mathrm{cov}(\ddot{\eta}^i_{c,t}, \ddot{\eta}^m_{c,t})}{\mathrm{var}(\tilde{\nu}^m_t)} \quad \beta^i_{r,c} = \frac{\mathrm{cov}(\eta^{\star i}_{c,t}, \ddot{\eta}^m_{c,t})}{\mathrm{var}(\tilde{\nu}^m_t)} \quad \beta^i_{c,r} = \frac{\mathrm{cov}(\ddot{\eta}^i_{c,t}, \eta^{\star m}_{c,t})}{\mathrm{var}(\tilde{\nu}^m_t)}. \tag{43}$$

6.1 Estimating the Betas

In the contemporaneous decomposition, the four betas are estimated over the asset's holding period, which Acharya and Pedersen (2005) estimate to be 29 months on average, and not over the sampling period as viewed by the econometrician. In their model, the transaction cost is paid every 29 months at asset liquidation and dividends are aggregated over the entire holding period. In order to estimate the betas with the 1 month sampling horizon, Acharya and Pedersen (2005) assume that returns are independent over time and proportional costs follow a martingale. In the Appendix, I show that small deviations from the two assumptions can lead to large differences in estimated betas due to error aggregation over the 29 month period. When returns follow an AR(1) process with coefficient ρ_i for portfolio i and ρ_m for the market portfolio and proportional costs follow an AR(1) process with coefficient ϱ_i for portfolio i and ϱ_m for the market portfolio, the four betas are calculated using the following equations for the relevant covariance terms:

$$\mathrm{cov}_t(K^i_{t+\tau}, K^m_{t+\tau}) = \frac{1-\varrho_i^\tau \varrho_m^\tau}{1-\varrho_i\varrho_m}\mathrm{cov}_t(K^i_{t+1}, K^m_{t+1}) \tag{44}$$

$$\mathrm{cov}_t(r^i_{t,t+\tau}, r^m_{t,t+\tau}) = \frac{\mathrm{cov}_t(r^i_{t+1}, r^m_{t+1})}{(1-\rho_i)(1-\rho_m)}\left(\tau + \rho_i\rho_m\frac{1-\rho_i^\tau\rho_m^\tau}{1-\rho_i\rho_m} - \rho_i\frac{1-\rho_m^\tau}{1-\rho_m} - \rho_m\frac{1-\rho_i^\tau}{1-\rho_i}\right) \tag{45}$$

$$\mathrm{cov}_t(K^i_{t+\tau}, r^m_{t,t+\tau}) = \left(\frac{1}{1-\rho_m}\frac{1-\varrho_i^\tau}{1-\varrho_i} - \frac{\rho_m}{1-\rho_m}\frac{1-\varrho_i^\tau\rho_m^\tau}{1-\varrho_i\rho_m}\right)\mathrm{cov}_t(K^i_{t+1}, r^m_{t+1}) \tag{46}$$

$$\mathrm{cov}_t(r^i_{t,t+\tau}, K^M_{t+\tau}) = \left(\frac{1}{1-\rho_i}\frac{1-\varrho_m^\tau}{1-\varrho_m} - \frac{\rho_i}{1-\rho_i}\frac{1-\varrho_m^\tau\rho_i^\tau}{1-\varrho_m\rho_i}\right)\mathrm{cov}_t(r^i_{t+1}, K^m_{t+1}) \tag{47}$$

$$\begin{aligned}\mathrm{var}_t(r^m_{t,t+\tau} - K^m_{t+\tau}) = {} & \frac{\mathrm{var}_t(r^m_{t+1})}{(1-\rho_m)^2}\left(\tau + \rho_m^2\frac{1-\rho_m^{2\tau}}{1-\rho_m^2} - 2\rho_m\frac{1-\rho_m^\tau}{1-\rho_m}\right) + \frac{1-\varrho_m^{2\tau}}{1-\varrho_m^2}\mathrm{var}_t(K^m_{t+\tau}) \\ & - 2\left(\frac{1}{1-\rho_m}\frac{1-\varrho_m^\tau}{1-\varrho_m} - \frac{\rho_m}{1-\rho_m}\frac{1-\varrho_m^\tau\rho_m^\tau}{1-\varrho_m\rho_m}\right)\mathrm{cov}_t(r^m_{t+1}, K^m_{t+1}),\end{aligned} \tag{48}$$

where $r_{t,t+\tau}$ is the cumulative log return over the τ periods from time t to $t+\tau$. For instance, when returns follow an AR(1) process with coefficient 0.167 and proportional costs follow an AR(1) process with coefficient 0.886, $\beta^i_{c,c}$ is estimated to be 6.3 times larger than its true value and $\beta^i_{c,r}$ and $\beta^i_{r,c}$ are estimated to be 3.08 times larger than their true values. The inflated estimates of systematic liquidity risk likely result in estimates of the market price of liquidity risk that are smaller than the population value.

As detailed in Section 2, I take a different approach for the proportional and fixed cost decompositions. Rather than aggregate dividends to be distributed at the end of the average holding period, I assume that at each sampling period, investors bear a cost for holding illiquid assets. Because, by assumption, costs are incurred and dividends are distributed at the sampling frequency, I am able to estimate the covariances and variances in equations (42) and (43) at the monthly frequency.

Tables 8 through 10 present the descriptive statistics for the odd-numbered value-weighted portfolios after sorting assets into 25 portfolios by their annual Amihud (2002) measures for the contemporaneous, proportional, and fixed cost decompositions respectively. For the contemporaneous decomposition, the four betas are estimated using equations (36) through (39) and (44) through (48). For the proportional and fixed cost decompositions, the betas are computed using equations (42) and (43), and the monthly estimated news series for the 25 portfolios and the aggregate portfolio. In addition to the four betas, the aggregate net return beta ($\beta^{*i} = \beta^i_{r,r} + \beta^i_{c,c} - \beta^i_{r,c} - \beta_{c,r})^i$) is reported for each portfolio. All statistics are estimated over the period 1964 to 1999 so that my sample period matches that of Acharya and Pedersen (2005). The reported estimates are small-sample bias corrected and the standard errors are computed using the jackknife procedure and the pre-estimation of the coefficient matrix and residual covariance matrix are taken into account. For each portfolio, I also report the annualized time-series average proportional cost, net return, turnover, yield, and market capitalization as well as the time-series volatility of the portfolio's proportional cost and net return.

Sorting assets on previous illiquidity levels results in portfolios with monotonically increasing illiquidity, which is further evidence of liquidity's persistence. The characteristics of the portfolios are similar to those of the illiquidity sorted portfolios reported by Acharya and Pedersen (2005) in their Table 1, with the differences attributable to the slight difference in our inclusion requirements. Highly illiquid portfolios have high net returns, a relationship that is well documented in the literature. Yield and market capitalization monotonically increase with liquidity. Aside from portfolios 1 and 25, the inverse relationship between illiquidity and turnover is consistent with the Amihud and Mendelson (1986) clientele effect.

Sorting on past illiquidity levels produces clear trends in the betas. The net return beta increases in illiquidity for all three decompositions. By definition, the net return beta for the fixed and proportional cost decompositions are equal. According to the betas reported in Table 8, taking into account return's momentum and liquidity's mean reversion significantly alters the estimates. Comparing the liquidity betas reported in table 8 to those reported by Acharya and Pedersen (2005), we see that the estimates of $\beta_{c,c}$, $\beta_{c,r}$, and $\beta_{r,c}$ in this paper are, respectively, approximately one-tenth, one-third, and one-fourth the magnitude of the Acharya and Pedersen (2005) estimates.

Tables 9 and 10 provide the same information for the betas calculated after performing the proportional and fixed cost decompositions. The magnitudes of the liquidity betas in the fixed cost decomposition are significantly larger than those obtained in the proportional cost and contemporaneous decompositions, reflecting the larger variability in fixed cost news. In the proportional cost decomposition, the only liquidity beta that is consistently statistically significant is the beta that represents the covariation between the portfolio's liquidity and the market return. For fixed costs, both $\beta_{c,r}$ and $\beta_{c,c}$ are, for the most part, statistically significant. As is the case for the contemporaneous decomposition, the measures of systematic liquidity risk increase in portfolio illiquidity.

6.2 The Liquidity Risk–Return Relationship

I closely follow the methods of Acharya and Pedersen (2005) to estimate the market price of liquidity risk. Again, I report the small-sample bias corrected estimates and standard errors calculated using the jackknife procedure. The reported standard errors take into account the pre-estimation of the betas, VAR coefficient matrix, and residual covariance matrix.

In addition to the 25 value-weighted portfolios formed by ranking stocks by their annual ILLIQ measures, Acharya and Pedersen (2005) also form 25 value-weighted portfolios by ranking stocks on a measure they denote $\sigma(illiquidity)$, which is the volatility of daily ILLIQ values estimated over the previous year. Their reason for forming portfolios in this manner is to consider portfolios that differ in their liquidity attributes. Tables 8 through 10 demonstrate that sorting by liquidity levels generates portfolios that differ in their liquidity attributes. I verify that sorting by $\sigma(illiquidity)$ also produces portfolios that satisfy this requirement.

To estimate the risk premia, I consider the following specification with a variety of restrictions:

$$E(r_t^i - r_t^f) = \alpha + \kappa E[K_t^i] + \lambda\beta^i + \lambda^*\beta^{*i} + \lambda_{r,r}\beta_{r,r}^i + \lambda_{r,c}\beta_{r,c}^i + \lambda_{c,r}\beta_{c,r}^i + \lambda_c\beta_c^i, \tag{49}$$

where α allows for a nonzero intercept, κ is an estimate of the illiquidity premium, β is the CAPM beta, β^* is the net return liquidity-adjusted CAPM beta, and $\beta_c^i \equiv \beta_{c,c}^i - \beta_{c,r}^i - \beta_{r,c}$ is a combined measure of the three components of systematic liquidity risk. The Acharya and Pedersen (2005) LACAPM is equation (49) with the following restrictions: $\alpha = \lambda = \lambda_{r,r} = \lambda_{r,c} = \lambda c, r = \lambda_{c,c} = \lambda_c = 0$ and $\kappa = 1$.

Tables 11 through 12 report the estimated coefficients for both sets of sorted portfolios for the contemporaneous, proportional, and fixed cost decompositions respectively. The results for the illiquidity ranked portfolios are reported in Panel A and for the $\sigma(illiquidity)$ ranked portfolios in Panel B.

Line 1 estimates the standard CAPM with betas calculated conditional on the state vector. The second line estimates the LACAPM with restricted liquidity premium and the third line removes the restriction on the liquidity premium. Lines 4 and 5 estimate the LACAPM allowing the market price of liquidity risk to differ from the market price of non-liquidity risk, but restricts the three sources of liquidity risk to have the same price of risk. The fourth line includes a restriction on the liquidity premium, which the fifth line removes. Finally, lines 6 and 7 remove the restriction that requires the three liquidity betas to share the same market price of risk. Line 6 includes a restricted liquidity premium and line 7 is the completely unrestricted model.

As Acharya and Pedersen (2005) report in their empirical analysis, the restricted form of the LACAPM estimated in the second line provides an improvement in fit over the standard CAPM. Table 11 shows the adjusted R^2 increasing from 53.7 percent for CAPM to 61.3 percent for the restricted LACAPM. The improvement in fit is not quite as substantial in my estimates as that reported by Acharya and Pedersen (2005) because of the difference in how the betas are calculated. Adjusting the betas for return momentum and liquidity mean-reversion reduces the magnitude of the liquidity betas and the explanatory power of the model. For the same regression, they report an adjusted R^2 of 73 percent. Releasing the restriction on the liquidity premium provides a significant improvement in fit with an adjusted R^2 of 97.1 percent and more reasonable parameter estimates. For instance, α is not statistically significant, there is a slight liquidity premium which may correspond to the Amihud and Mendelson (1986) clientele effect, and the market price of risk is approximately 6.8 percent per year. The fourth line, which allows the market price of liquidity risk to differ from that of non-liquidity risk, but includes a restricted liquidity premium provides a substantive improvement in fit over the estimation in which all betas share the same price of risk. However, the market price of non-liquidity risk is not statistically significant and the market price of liquidity risk is 575 percent per year and statistically significant. Lifting the restriction on the liquidity premium yields a slight improvement in fit, but the parameter estimates are almost identical. Like Acharya and Pedersen (2005), I find the multi-collinearity problems to be severe in the unrestricted regressions performed in lines 6 and 7.

Table 12 reports the results of the regressions for the proportional cost decomposition. I find the explanatory power of the proportional cost decomposition to be similar to, but slightly less than that of the contemporaneous decomposition. The primary difference between the two decompositions is in the estimated market prices of risk. For example, line 5 reports that the market price of liquidity risk is not statistically different from that of non-liquidity risk which has a market price of 10.2 percent per year. The adjusted R^2 in line 5 is 96.9 percent compared against 96.8 percent for line 3 in which the four sources of risk are restricted to have the same market price of risk. According to this restricted regression, the shared market price of risk is approximately 8.8 percent per year. As is the case for the contemporaneous decomposition, the multi-collinearity problems appear to be severe in the unrestricted regressions reported in the last 2 lines.

The results of the fixed decomposition are reported in Table 13. By definition, the first three regressions are identical for the fixed and proportional cost decompositions. Similar to the proportional cost decomposition, the model estimated in the fifth line shows the market price of non-liquidity risk to not be statistically different than that of liquidity risk, which has a market price of risk of

9.7 percent per year. For this decomposition, the adjusted R^2 for the LACAPM with unrestricted liquidity premium and restricted market prices of risk is higher than the model in which the market price of liquidity risk is allowed to differ from that of non-liquidity risk.

6.3 Economic Significance

So far, this section has focused on the explanatory power and the estimated market price of risk for the adjusted contemporaneous decomposition and the fixed and proportional cost decomposition within the LACAPM framework. The LACAPM may also be used to estimate how much of the expected return is attributable to each systematic risk component. In order to calculate the premia for the different liquidity components, I use the estimates reported in line 3, where the market price of risk is restricted to be the same for the four betas and the liquidity risk premium is unrestricted. Lines 6 and 7 are not selected because of the multi-collinearity problems and line 3 is selected over lines 4 and 5 because the adjusted R^2 are similar for the two regressions, but the estimates obtained in line 3 have lower standard errors.

The model implied liquidity premium between portfolios 25 and 1 is $\kappa\left(E(K^{25}) - E(K^1)\right)$. For the contemporaneous decomposition, I calculate the liquidity premium to be 11.2 percent and the proportional and fixed decompositions provide a similar estimate at 11.4 percent per year.

The annualized risk premium due to comovement between a portfolio's liquidity news and market liquidity news is $12\lambda^*(\beta^{25}_{c,c} - \beta^{1}_{c,c})$. The return difference for the contemporaneous and proportional cost decompositions is approximately zero and for the fixed decomposition is 0.74 percent.

Comovement between portfolio liquidity news and market non-liquidity news leads to a risk premium of $-12\lambda^*(\beta^{25}_{c,r} - \beta^{1}_{c,r})$. The contemporaneous, proportional cost, and fixed decompositions have risk premia of 0.12, 0.48, and -7.66 percent respectively.

Covariation of the portfolio's non-liquidity component with the market liquidity component results in a risk premium of $-12\lambda^*(\beta^{25}_{r,c} - \beta^{1}_{r,c})$. The resulting premia are estimated to be 0.02, -0.01, and -0.91 percent respectively for the contemporaneous, proportional, and fixed cost decompositions.

Like Acharya and Pedersen (2005), I find that of the three sources of liquidity risk, the comovement of the asset's liquidity component with the market non-liquidity component, which is captured by $\beta_{c,r}$, is the most economically important. The total return contribution of systematic liquidity risk captured by the three betas is 0.14, 0.48, and -6.00 percent for the contemporaneous, proportional, and fixed cost decompositions respectively.

The following quote from Acharya and Pedersen (2005) appears to be relevant when comparing the contemporaneous to the proportional cost decomposition:

> "The collinearity between liquidity and liquidity risk implies that the most robust number is their overall effect. Further, our results suggest that studies that focus on the separate effect of liquidity (or liquidity risk) can possibly be reinterpreted as providing an estimate of the overall effect of liquidity and liquidity risk."

The total return difference attributed to liquidity and liquidity risk is 11.54 and 11.68 percent for the two respective decompositions, which both consider proportional liquidity levels.

Although the liquidity premium is similar under the fixed cost decomposition, the liquidity risk premium is substantially different and negative. For fixed costs, the above quote can be revised to relate the collinearity between fixed cost news and dividend news. Studies that focus on the separate effects of fixed cost risk and dividend risk may be reinterpreted as providing an estimate of their overall effect.

7 Conclusion

I derive two extensions of the Campbell (1991) unexpected return decompositions in order to include a liquidity component and investigate how new information about future liquidity levels influence portfolio volatility. The first extension includes an additional news term that represents changes in expectated future proportional costs. The second extension's additional news term represents changes in expectated future fixed costs.

I estimate the news series for the two decompositions for the aggregate portfolio and across the cross-section. The primary findings are that proportional cost news and fixed cost news have, respectively, 7 and 122 times the volatility of unexpected contemporaneous proportional costs. Fixed cost news has approximately 17 percent the volatility of contemporaneous returns and proportional cost news has approximately 1 percent the volatility of contemporaneous returns. Thus, fixed cost news appears to be an economically significant contributor to portfolio risk. Proportional cost news, on the other hand, is not a significant contributor to portfolio volatility. The impact of liquidity news risk varies over the cross section. Both measures of liquidity news risk have increasing volatilities as firm size decreases and illiquidity increases. Stocks that turn over more frequently have less volatile proportional cost news and more volatile fixed cost news.

I investigate the pricing of the systematic component of fixed and proportional cost news risk by implementing the Liquidity-Adjusted CAPM model proposed by Acharya and Pedersen (2005). I report the explanatory power of the LACAPM using the two decompositions proposed in this paper is similar to that of the original specification investigated by Acharya and Pedersen (2005). The primary finding of the analysis is that, when including the price impact of revisions in future expected liquidity levels as a component of liquidity risk, the estimated market price of liquidity risk under both decompositions is not statistically different than that of non-liquidity risk.

References

Acharya, V. V., and L. H. Pedersen (2005): "Asset Pricing with Liquidity Risk," *Journal of Financial Economics*, 77, 375–410.

Admati, A. R. (1985): "A Noisy Rational Expectations Equilibrium for Multi-Asset Securities markets," *Econometrica*, 53, 629–657.

Akerlof, G. A. (1970): "The Market for Lemons: Quality Uncertainty and the Market Mechanism," *Quarterly Journal of Economics*, 84, 488–500.

Amihud, Y. (2002): "Illiquidity and Stock Returns: Cross-Section and Time-Series Effects," *Journal of Financial Markets*, 5, 31–56.

Amihud, Y., and H. Mendelson (1980): "Dealership Markets: Market Making with Inventory," *Journal of Financial Economics*, 8, 21–53.

——— (1986): "Asset pricing and the Bid-Ask Spread," *Journal of Financial Economics*, 17, 223–249.

Amihud, Y., H. Mendelson, and L. H. Pedersen (2005): "Liquidity and Asset Prices," *Foundations and Trends in Finance*, 1, 269–364.

Attari, M., A. S. Mello, and M. E. Ruckes (2005): "Arbitraging Abritageurs," *Journal of Finance*, 60, 2471.

Bagehot, W. P. (1971): "The Only Game in Town," *Financial Analysts Journal*, 22, 12–14.

Bekaert, G., C. R. Harvey, and C. Lundblad (2006): "Liquidity and Expected Returns: Lessons from Emerging Markets," Working Paper.

Brunnermeier, M., and L. H. Pedersen (2005a): "Market Liquidity and Funding Liquidity," Working Paper, Princeton University.

——— (2005b): "Predatory Trading," *Journal of Finance*, 60, 1825–1863.

Campbell, J. Y. (1991): "A Variance Decomposition for Stock Returns," *The Economic Journal*, 101, 157–179.

Campbell, J. Y., and J. Ammer (1993): "What Moves the Stock and Bond Markets? A Variance Decomposition for Long-Term Asset Returns," *Journal of Finance*, 48, 3–37.

Campbell, J. Y., and R. J. Shiller (1988): "The Dividend-Price Ratio and Expectations of Future Discount Factors," *Review of Financial Studies*, 1, 195–228.

Campbell, J. Y., and T. Vuolteenaho (2004): "Bad Beta, Good Beta," *American Economic Review*, 94, 1249–1275.

Chalmers, J. M. R., and G. B. Kadlec (1998): "An Empirical Examination of the Amortized Spread," *Journal of Financial Economics*, 48, 159–188.

Chen, L., and X. Zhao (2006): "Return Decomposition," Unpublished.

Copeland, T. E., and D. Galai (1983): "Informational Effects on the Bid Ask Spread," *Journal of Finance*, 38, 1457–1469.

Duffie, D., N. Garleanu, and L. H. Pedersen (2002): "Securities Lending, Shorting, and Pricing," *Journal of Financial Economics*, 66, 307–339.

——— (2003): "Valuation in Over-the-Counter Markets," Working Paper, Stanford University.

——— (2005): "Over-the-Counter Markets," *Econometrica*, 73, 1815–1847.

Gallmeyer, M. F., B. Hollifield, and D. J. Seppi (2004): "Liquidity Discovery and Asset Pricing," Working Paper, Carnegie Mellon University.

Garman, M. B. (1976): "Market Microstructure," *Journal of Financial Economics*, 3, 257–275.

Glosten, L. R., and P. R. Milgrom (1985): "Bid, Ask and Transaction Prices in a Specialist Market with Heterogeneously Informed Traders," *Journal of Financial Economics*, 14, 71–100.

Goyenko, R., C. W. Holden, C. T. Lundblad, and C. A. Trzcinka (2005): "Horseraces of Monthly and Annual Liquidity Measures," Unpublished, Indiana University.

Grossman, S. J. (1976): "On the Efficiency of Competitive Stock Markets Where Traders Have Diverse Information," *Journal of Finance*, 31, 573–585.

Grossman, S. J., and M. H. Miller (1988): "Liquidity and Market Microstructure," *Journal of Finance*, 43, 617–633.

Grossman, S. J., and J. E. Stiglitz (1980): "On the Impossibility of Informationally Efficient Markets," *American Economic Review*, 70, 393–408.

Hellwig, M. F. (1980): "On the Aggregation of Information in Competitive Markets," *Journal of Economic Theory*, 22, 477–498.

Ho, T. S. Y., and H. R. Stoll (1981): "Optimal Dealer Pricing Under Transactions and Return Uncertainty," *Journal of Financial Economics*, 9, 47–73.

——— (1983): "The Dynamics of Dealer Markets Under Competition," *Journal of Finance*, 38, 1053–1074.

Hopenhayn, H. A., and I. M. Werner (1996): "Information, Liquidity, and Asset Trading in a Random Matching Game," *Journal of Economic Theory*, 68, 349–379.

Jones, C. (2002): "A Century of Stock Market Liquidity and Trading Costs," Unpublished, Columbia University.

Kyle, A. S. (1985): "Continuous Auctions and Insider Trading," *Econometrica*, 53, 1315–1335.

Lagos, R. (2005): "Asset Pricing and Liquidity in an Exchange Economy," Working Paper, New York University.

Longstaff, F. A. (1995): "How Much Can Marketability Affect Security Values?," *Journal of Finance*, 50, 1767–1774.

——— (2001): "Optimal Portfolio Choice and the Valuation of Illiquid Securities," *Review of Financial Studies*, 14, 407–431.

Madrigal, V. (1996): "Non-Fundamental Speculation," *Journal of Finance*, 51, 553–578.

Mendelson, H., and T. Tunca (2004): "Strategic Trading, Liquidity, and Information Acquisition," *Review of Financial Studies*, 17, 295–337.

Pastor, L., and R. F. Stambaugh (2003): "Liquidity Risk and Expected Stock Returns," *Journal of Political Economy*, 111, 642–685.

Rogers, W. H. (1993): “Analyzing Complex Survey Data,” Memorandum, Santa Monica, CA.

Sadka, R. (2006): “Momentum and Post-Earnings-Announcement Drift Anomalies: The Role of Liquidity Risk,” *Journal of Financial Economics*, 80, 309–349.

Shao, J., and J. N. K. Rao (1993): “Jackknife Inference for Heteroscedastic Linear Regression Models,” *Canadian Journal of Statistics*, 21, 377–385.

Stoll, H. R. (1978): “The Supply of Dealer Services in Securities Markets,” *Journal of Finance*, 33, 1133–1151.

Stoll, H. R., and R. E. Whaley (1983): “Transaction Costs and the Small Firm Effect,” *Journal of Financial Economics*, 12, 57–80.

Vayanos, D. (2001): “Strategic Trading in a Dynamic Noisy Market,” *Journal of Finance*, 56, 131–171.

Vayanos, D., and T. Wang (2002): “Search and Endogenous Concentration of Liquidity in Asset Markets,” Working Paper, MIT.

Vayanos, D., and P. O. Weill (2005): “A Search-Based Theory of the On-The-Run Phenomenon,” Working Paper, LSE.

Vuolteenaho, T. (2002): “What Drives Firm-Level Stock Returns?,” *Journal of Finance*, 57, 233–264.

Weill, P. O. (2002): “The Liquidity Premium in a Dynamic Bargaining Market,” Working Paper, Stanford University.

White, H. (1984): *Asymptotic Theory for Econometricians.* Academic Press.

A The Jackknife

Beginning with the full sample of T observations and their respective lags, T new *resampled* data sets with $T-1$ observations each are created by removing a different single observation from the original dataset. The first resampled data set will have the first observation removed, the second will have the second observation removed, and so on. The VAR is then re-estimated for each resampled data set. For example, the following estimation would be performed for the second resampling:

$$\begin{bmatrix} z_1 \\ z_3 \\ z_4 \\ \vdots \\ z_T \end{bmatrix} = \mathbf{a} + \begin{bmatrix} z_0 \\ z_2 \\ z_3 \\ \vdots \\ z_{T-1} \end{bmatrix} \mathbf{\Gamma_2} + \begin{bmatrix} \mathbf{w_1} \\ \mathbf{w_3} \\ \mathbf{w_4} \\ \vdots \\ \mathbf{w_T} \end{bmatrix}. \tag{50}$$

For any statistic of interest, this procedure yields a total of $T+1$ estimates: the original estimate $f(\Gamma, \Sigma)$ and the T resampled estimates, $f(\Gamma_i, \Sigma_i)$, where Γ_i and Σ_i are the estimates of the parameter matrix and error-covariance matrix for each resampling. The standard error of the statistic, $\sigma(f(\Gamma, \Sigma))$, is calculated according to the formula:

$$\sigma(f(\Gamma, \Sigma)) = \sqrt{T-1} \sum_{i=1}^{T} \left(f(\Gamma_i, \Sigma_i) - \tilde{f}(\Gamma, \Sigma) \right)^2, \tag{51}$$

where $\tilde{f}(\Gamma, \Sigma)$ is calculated according to the formula:

$$\tilde{f}(\Gamma, \Sigma) = T f(\Gamma, \Sigma) - \frac{T-1}{T} \sum_{i=1}^{T} f(\Gamma_i, \Sigma_i). \tag{52}$$

In addition to providing an estimate of robust standard errors, the jackknife may be used to adjust for small-sample bias. The small-sample corrected estimate of a statistic, $\hat{f}(\Gamma, \Sigma)$ is calculated according to the formula:

$$\hat{f}(\Gamma, \Sigma) = \frac{1}{T} \sum_{i=1}^{T} f(\Gamma_i, \Sigma_i). \tag{53}$$

B The Acharya and Pedersen (2005) Betas and Mean Reversion

Let τ denote the holding period of an asset in months and $r^i_{t,t+\tau}$ denote the log gross return for asset i over the τ month period between time t and $t+\tau$:

$$r_{t,t+\tau} = r_t + r_{t+1} + \cdots + r_{t+\tau-1} + r_{t+\tau} \tag{54}$$

The four betas in the Acharya and Pedersen (2005) adjusted CAPM are:

$$\beta_1 = \frac{\mathrm{cov}_t(r^i_{t,t+\tau}, r^m_{t,t+\tau})}{\mathrm{var}_t(r^m_{t,t+\tau} - K^m_{t+\tau})} \qquad \beta_2 = \frac{\mathrm{cov}_t(K^i_{t+\tau}, K^m_{t+\tau})}{\mathrm{var}_t(r^m_{t,t+\tau} - K^m_{t+\tau})}$$

$$\beta_3 = \frac{\mathrm{cov}_t(r^i_{t,t+\tau}, K^m_{t+\tau})}{\mathrm{var}_t(r^m_{t,t+\tau} - K^m_{t+\tau})} \qquad \beta_4 = \frac{\mathrm{cov}_t(K^i_{t+\tau}, r^m_{t,t+\tau})}{\mathrm{var}_t(r^m_{t,t+\tau} - K^m_{t+\tau})}.$$

Acharya and Pedersen (2005) estimate the four betas by assuming that returns are independent over time and that liquidity follows a random walk. Under these two assumptions, the four betas are calculated to be

$$\beta_1 = \frac{\mathrm{cov}_t(r^i_{t+1}, r^m_{t+1})}{\mathrm{var}_t(r^m_{t+1} - K^m_{t+1})} \qquad \beta_2 = \frac{\mathrm{cov}_t(K^i_{t+1}, K^m_{t+1})}{\mathrm{var}_t(r^m_{t+1} - K^m_{t+1})}$$

$$\beta_3 = \frac{\mathrm{cov}_t(r^i_{t+1}, K^m_{t+1})}{\mathrm{var}_t(r^m_{t+1} - K^m_{t+1})} \qquad \beta_4 = \frac{\mathrm{cov}_t(K^i_{t+1}, r^m_{t+1})}{\mathrm{var}_t(r^m_{t+1} - K^m_{t+1})}.$$

Here, I show that small deviations from the two assumptions may have a substantial impact on the estimated betas. Suppose returns and proportional costs are first order autoregressive:

$$\begin{aligned} r^i_t &= \alpha_i + \rho_i r^i_{t-1} + e^i_t \\ K^i_t &= \delta_i + \varrho_i K^i_{t-1} + \epsilon^i_t. \end{aligned}$$

Let $\text{rand}_t(x_{t+\tau})$ denote the stochastic component of $x_{t+\tau}$ conditional on information at time t. Then it can be shown that

$$\text{rand}_t(K^i_{t+\tau}) = \sum_{j=1}^{\tau} \varrho^{\tau-j} \epsilon_{t+j} \tag{55}$$

$$\text{rand}_t(r^i_{t,t+\tau}) = \frac{1}{1-\rho_i} \sum_{j=1}^{\tau} e_{t+j} - \frac{\rho_i}{1-\rho_i} \sum_{j=1}^{\tau} \rho_i^{\tau-j} e_{t+j} \tag{56}$$

The five covariances needed to calculate the four liquidity betas are calculated to be:

$$\begin{aligned}
\text{cov}_t(K^i_{t+\tau}, K^m_{t+\tau}) &= \frac{1-\varrho_i^\tau \varrho_m^\tau}{1-\varrho_i\varrho_m} \text{cov}_t(K^i_{t+1}, K^m_{t+1}) \\
\text{cov}_t(r^i_{t,t+\tau}, r^m_{t,t+\tau}) &= \frac{1}{(1-\rho_i)(1-\rho_m)} \left(\tau + \rho_i\rho_m \frac{1-\rho_i^\tau\rho_m^\tau}{1-\rho_i\rho_m} - \rho_i \frac{1-\rho_m^\tau}{1-\rho_m} - \rho_m \frac{1-\rho_i^\tau}{1-\rho_i} \right) \text{cov}_t(r^i_{t+1}, r^m_{t+1}) \\
\text{cov}_t(K^i_{t+\tau}, r^m_{t,t+\tau}) &= \left(\frac{1}{1-\rho_m} \frac{1-\varrho_i^\tau}{1-\varrho_i} - \frac{\rho_m}{1-\rho_m} \frac{1-\varrho_i^\tau\rho_m^\tau}{1-\varrho_i\rho_m} \right) \text{cov}_t(K^i_{t+1}, r^m_{t+1}) \\
\text{cov}_t(r^i_{t,t+\tau}, K^M_{t+\tau}) &= \left(\frac{1}{1-\rho_i} \frac{1-\varrho_m^\tau}{1-\varrho_m} - \frac{\rho_i}{1-\rho_i} \frac{1-\varrho_m^\tau\rho_i^\tau}{1-\varrho_m\rho_i} \right) \text{cov}_t(r^i_{t+1}, K^m_{t+1}) \\
\text{var}_t(r^m_{t,t+\tau} - K^m_{t+\tau}) &= \frac{1}{(1-\rho_m)^2} \left(\tau + \rho_m^2 \frac{1-\rho_m^{2\tau}}{1-\rho_m^2} - 2\rho_m \frac{1-\rho_m^\tau}{1-\rho_m} \right) \text{var}_t(r^m_{t+1}) + \frac{1-\varrho_m^{2\tau}}{1-\varrho_m^2} \text{var}_t(K^m_{t+\tau}) \\
&\quad - 2 \left(\frac{1}{1-\rho_m} \frac{1-\varrho_m^\tau}{1-\varrho_m} - \frac{\rho_m}{1-\rho_m} \frac{1-\varrho_m^\tau\rho_m^\tau}{1-\varrho_m\rho_m} \right) \text{cov}_t(r^m_{t+1}, K^m_{t+1})
\end{aligned}$$

As an example, I consider the equal-weight market portfolio over the period 1964 – 2002. For the portfolio I estimate the AR(1) coefficients to be $\rho_m = 0.167$ and $\varrho = 0.886$ and the covariance of the residuals to be $\text{var}_t(r^m_{t+1}) = 28.6\%$, $\text{var}_t(K^m_{t+1}) = 0.033\%$, and $\text{cov}_t(r^m_{t+1}, K^m_{t+1}) = -0.397\%$. Letting β_1^*, β_2^*, β_3^*, and β_4^* be the respective betas calculated using the first-order autoregressive assumptions and letting the AR coefficients for the individual portfolio equal that of the market portfolio, I calculate that $\beta_1 = 0.98\beta_1^*$, $\beta_2 = 6.31\beta_2^*$, $\beta_3 = 3.08\beta_3^*$, and $\beta_4 = 3.08\beta_4^*$. For this example, we see that although the calculated return beta β_1 appears to be relatively unaffected but the three liquidity betas are substantially overestimated when not taking into account their autoregressive properties. For instance, the beta that represents the systematic risk due to the comovement of a portfolio's proportional cost with that of the market is overestimated by a factor of 6.3.

These differences are likely to impact the Acharya and Pedersen (2005) empirical analysis in two ways. The first impact is in the regression where all liquidity risk premium are restricted to be equal. Because the magnitude of the three liquidity betas are reduced, the dispersion of the net return betas $\beta_{net} = \beta_1 + \beta_2 - \beta_3 - \beta_4$ due to systematic liquidity risk is also reduced and the net return betas β_{net} are closer to the standard CAPM beta, which is approximated by β_1. Hence, the large improvement in the liquidity adjusted CAPM's explanatory power over standard CAPM is likely to be reduced. The second likely impact is in the regression where the liquidity risk premium is allowed to differ from the market risk premium. Because the adjusted liquidity beta are lower in magnitude, the estimated liquidity risk premium is likely to increase.

Table 1: This table reports the sample statistics for the VAR state variables estimated for the period January 1963 to December 2001 for the equal-weight market portfolio. The included state variables are the log market gross return (r^m), proportional costs (K), log dividend yield (y), the first difference of log monthly turnover ($\Delta\psi$), one lag of proportional costs, and two lags of log dividend yield. The second panel reports the correlation and first-order autocorrelation of the series.

Descriptive Statistics of the VAR State Variables

Variable	Mean	Median	Std. Dev.	Min	Max	Autocorr.
$100 \cdot r^m$	1.030	1.372	5.424	−31.436	20.835	0.167
$100 \cdot K$	0.049	0.045	0.019	0.020	0.136	0.888
y	−3.669	−3.662	0.460	−4.754	−2.642	0.378
$\Delta\psi$	0.003	0.011	0.170	−0.600	0.658	−0.273

Shock Correlation Matrix

Correlations	r^m_{t+1}	K_{t+1}	y_{t+1}	$\Delta\psi_{t+1}$	K_t	y_t	y_{t-1}
r^m_{t+1}	1.000	−0.217	0.048	0.329	0.005	0.113	0.096
K_{t+1}	−0.217	1.000	−0.126	0.019	0.888	−0.177	−0.216
y_{t+1}	0.048	−0.126	1.000	−0.026	−0.127	0.378	0.383
$\Delta\psi_{t+1}$	0.329	0.019	−0.026	1.000	0.031	0.131	0.027
K_t	0.005	0.888	−0.127	0.031	1.000	−0.128	−0.172
y_t	0.113	−0.177	0.378	0.131	−0.128	1.000	0.373
y_{t-1}	0.096	−0.216	0.383	0.027	−0.172	0.373	1.000
r^m_t	0.167	−0.403	0.003	0.075	−0.218	0.052	0.113
K_t	0.005	0.888	−0.127	0.031	1.000	−0.128	−0.172
y_t	0.113	−0.177	0.378	0.131	−0.128	1.000	0.373
$\Delta\psi_t$	0.108	−0.089	−0.059	−0.273	0.025	−0.031	0.136
K_{t-1}	0.024	0.785	−0.092	0.102	0.889	−0.128	−0.123
y_{t-1}	0.096	−0.216	0.383	0.027	−0.172	0.373	1.000
y_{t-2}	0.069	−0.223	0.940	−0.062	−0.216	0.380	0.372

Table 2: This table reports the OLS parameter estimates for the equal-weight market portfolio for a monthly first-order VAR model including a constant, the log market gross return (r^m), proportional cost (K), log dividend yield (y), the first difference of log monthly turnover ($\Delta\psi$), one lag of proportional costs, and two lags of log dividend yield. The first eight columns report coefficients for the appropriate explanatory variable. The final two columns report the R^2 and F statistics. OLS standard errors are in brackets below their respective parameter estimates and robust jackknife standard errors are in parentheses. In addition, the second panel reports the correlation matrix of the shocks with robust jackknife standard errors in parentheses.

VAR Parameter Estimates: Jan 1964 – Dec 2001

	Constant	r_t^m	K_t	y_t	$\Delta\psi_t$	K_{t-1}	y_{t-1}	y_{t-2}	R^2	F-stat
r_t^m	0.066	0.165	0.347	0.011	0.017	−0.186	0.005	0.002	4.8	3.20
	[0.027]	[0.057]	[0.338]	[0.006]	[0.016]	[0.325]	[0.006]	[0.006]		
	(0.030)	(0.057)	(0.364)	(0.006)	(0.016)	(0.298)	(0.007)	(0.007)		
$100 \cdot K_t$	−0.003	−0.088	0.630	−0.002	−0.003	0.215	−0.001	0.000	84.7	353.13
	[0.004]	[0.008]	[0.047]	[0.001]	[0.002]	[0.045]	[0.001]	[0.001]		
	(0.004)	(0.009)	(0.088)	(0.001)	(0.002)	(0.079)	(0.001)	(0.001)		
y_t	−0.049	−0.612	0.457	0.011	−0.187	1.502	0.061	0.940	90.3	592.44
	[0.072]	[0.153]	[0.913]	[0.017]	[0.043]	[0.880]	[0.017]	[0.017]		
	(0.071)	(0.190)	(1.145)	(0.016)	(0.050)	(1.048)	(0.016)	(0.016)		
$\Delta\psi_t$	0.053	0.453	−1.418	0.058	−0.320	2.317	0.020	−0.051	15.0	11.20
	[0.079]	[0.168]	[0.998]	[0.018]	[0.047]	[0.962]	[0.018]	[0.018]		
	(0.080)	(0.203)	(1.487)	(0.018)	(0.055)	(1.639)	(0.020)	(0.020)		

Shock Correlation Matrix

	r_t^m	K_t	y_t	$\Delta\psi_t$
r_t^m	1.000	−0.452	−0.020	0.357
	(0.000)	(0.053)	(0.048)	(0.073)
K_t	−0.452	1.000	−0.014	−0.009
	(0.053)	(0.000)	(0.051)	(0.057)
y_t	−0.020	−0.014	1.000	0.025
	(0.048)	(0.051)	(0.000)	(0.049)
$\Delta\psi_t$	0.357	−0.009	0.025	1.000
	(0.073)	(0.057)	(0.049)	(0.000)

Table 3: **Net Return Variance Decomposition (Proportional Cost)** – This table reports the properties of dividend news (η_d), proportional cost news (η_K), and discount rate news ($\eta_{\tilde{r}}$) implied by the VAR model of Table 2. The first panel reports the annualized covariance matrix of the news terms (multiplied by 100) on the left and the correlation matrix on the right. The second panel reports the correlation of shocks to individual state variables with the three news terms on the left and the functions that map the state-variable shocks to the news terms on the right. The functional mappings are normalized by multiplying the term by its respective state variable shock volatility and dividing by the volatility of unexpected contemporaneous returns. Panel C provides seven measures of liquidity's contribution to portfolio risk. $\mathcal{R}_d$, $\mathcal{R}_K$, and $\mathcal{R}_{\tilde{r}}$ are respectively the ratios of dividend news, proportional cost news, and net discount rate news to that of unexpected contemporaneous returns. $\mathcal{P}_K$ is the ratio of proportional cost news volatility to that of unexpected contemporaneous proportional costs. $\mathcal{B}_d$, $\mathcal{B}_K$, and $\mathcal{B}_{\tilde{r}}$ are the regression coefficients obtained by regressing, respectively, dividend news, proportional cost news, and net discount rate news on unexpected contemporaneous returns. Net returns, proportional costs, log dividend yield, and log turnover growth rates are represented by r^m, K, y, and $\Delta\psi$ respectively. Included in brackets are small-sample bias corrected estimates using the jackknife procedure detailed in the appendix and robust jackknife standard errors are in parentheses.

Panel A: News Covariance and Correlation Matrices

	100 * News Covariance			News Correlations		
	η_d	η_K	$\eta_{\tilde{r}}$	$\hat{\eta}_d$	η_K	$\eta_{\tilde{r}}$
η_d	2.6353	−0.0243	1.5842	1.0	−0.6256	0.4927
	(1.7214)	(−0.0125)	(0.3732)		(−0.6729)	(0.5217)
	[1.2761]	[0.0220]	[2.2429]		[0.2585]	[0.3764]
η_K	−0.0243	0.0006	−0.0338	−0.6256	1.0	−0.7118
	(−0.0125)	(0.0003)	(−0.0162)	(−0.6729)		(−0.7636)
	[0.0220]	[0.0005]	[0.0348]	[0.2585]		[0.2530]
$\eta_{\tilde{r}}$	1.5842	−0.0338	3.9237	0.4927	−0.7118	1.0
	(0.3732)	(−0.0162)	(2.4626)	(0.5217)	(−0.7636)	
	[2.2429]	[0.0348]	[3.2872]	[0.3764]	[0.2530]	

Panel B: Correlations and Shock → News Mappings

	Shock Correlations			Functions		
shock	η_d	η_K	$\eta_{\tilde{r}}$	η_d	η_K	$\eta_{\tilde{r}}$
r^m	0.361	0.202	−0.633	0.603	0.002	−0.399
	(0.418)	(0.203)	(−0.636)	(0.661)	(0.001)	(−0.340)
	[0.428]	[0.267]	[0.088]	[0.228]	[0.003]	[0.231]
K	0.257	0.057	0.629	0.508	0.002	0.508
	(0.262)	(0.074)	(0.619)	(0.461)	(0.003)	(0.460)
	[0.255]	[0.294]	[0.104]	[0.176]	[0.003]	[0.178]
y	0.777	−0.963	0.667	0.708	−0.013	0.721
	(0.882)	(−1.023)	(0.694)	(0.648)	(−0.011)	(0.658)
	[0.189]	[0.076]	[0.113]	[0.333]	[0.005]	[0.335]
$\Delta\psi$	0.131	0.191	−0.225	−0.113	0.002	−0.115
	(0.147)	(0.203)	(−0.230)	(−0.097)	(0.002)	(−0.099)
	[0.189]	[0.096]	[0.071]	[0.074]	[0.001]	[0.075]

Panel C: Measures of Liquidity's Contribution to Portfolio Risk

$\mathcal{P}_K$	$\mathcal{R}_d$	$\mathcal{R}_K$	$\mathcal{R}_{\tilde{r}}$	$\mathcal{B}_D$	$\mathcal{B}_K$	$\mathcal{B}_{\tilde{r}}$
9.364	0.884	0.013	1.079	0.319	0.003	−0.684
[7.219]	[0.745]	[0.010]	[0.957]	[0.400]	[0.001]	[−0.601]
(3.819)	(0.221)	(0.005)	(0.453)	(0.316)	(0.004)	(0.321)

Table 4: **Net Return Variance Decomposition (Fixed Cost)** – This table reports the properties of dividend news ($\ddot{\eta}_d$), fixed cost news ($\ddot{\eta}_c$), and discount rate news ($\eta_{\tilde{r}}$) implied by the VAR model of Table 2. The first panel reports the annualized covariance matrix of the news terms (multiplied by 100) on the left and the correlation matrix on the right. The second panel reports the correlation of shocks to individual state variables with the three news terms on the left and the functions that map the state-variable shocks to the news terms on the right. The functional mappings are normalized by multiplying the term by its respective state variable shock volatility and dividing by the volatility of unexpected contemporaneous returns. Panel C provides seven measures of liquidity's contribution to portfolio risk. $\ddot{\mathcal{R}}_d$, $\ddot{\mathcal{R}}_K$, and $\mathcal{R}_{\tilde{r}}$ are respectively the ratios of dividend news, proportional cost news, and net discount rate news to that of unexpected contemporaneous returns. $\ddot{\mathcal{P}}_c$ is the ratio of proportional cost news volatility to that of unexpected contemporaneous proportional costs. $\ddot{\mathcal{B}}_d$, $\ddot{\mathcal{B}}_c$, and $\mathcal{B}_{\tilde{r}}$ are the regression coefficients obtained by regressing, respectively, dividend news, proportional cost news, and net discount rate news on unexpected contemporaneous returns. Net returns, proportional costs, log dividend yield, and log turnover growth rates are represented by r^m, K, y, and $\Delta\psi$ respectively. Included in brackets are small-sample bias corrected estimates using the jackknife procedure detailed in the appendix and robust jackknife standard errors are in parentheses.

Panel A: News Covariance and Correlation Matrices

	100 * News Covariance			News Correlations		
	$\ddot{\eta}_d$	$\ddot{\eta}_c$	$\eta_{\tilde{r}}$	$\ddot{\eta}_d$	$\ddot{\eta}_c$	$\eta_{\tilde{r}}$
$\ddot{\eta}_d$	4.0616	0.7598	1.9668	1.0	0.9988	0.4927
	(2.6530)	(0.5005)	(0.4635)		(0.9991)	(0.5217)
	[1.9662]	[0.3573]	[2.7842]		[0.0011]	[0.3764]
$\ddot{\eta}_c$	0.7598	0.1425	0.3488	0.9988	1.0	0.4665
	(0.5005)	(0.0946)	(0.0742)	(0.9991)		(0.4942)
	[0.3573]	[0.0649]	[0.5127]	[0.0011]		[0.3900]
$\eta_{\tilde{r}}$	1.9668	0.3488	3.9237	0.4927	0.4665	1.0
	(0.4635)	(0.0742)	(2.4626)	(0.5217)	(0.4942)	
	[2.7842]	[0.5127]	[3.2872]	[0.3764]	[0.3900]	

Panel B: Correlations and Shock → News Mappings

	Shock Correlations			Functions		
shock	$\ddot{\eta}_d$	$\ddot{\eta}_c$	$\eta_{\tilde{r}}$	$\ddot{\eta}_d$	$\ddot{\eta}_c$	$\eta_{\tilde{r}}$
r^m	0.361	0.388	−0.633	0.749	0.148	−0.399
	(0.418)	(0.449)	(−0.636)	(0.821)	(0.161)	(−0.340)
	[0.428]	[0.430]	[0.088]	[0.283]	[0.053]	[0.231]
K	0.257	0.270	0.629	0.631	0.124	0.508
	(0.262)	(0.278)	(0.619)	(0.573)	(0.114)	(0.460)
	[0.255]	[0.258]	[0.104]	[0.218]	[0.041]	[0.178]
y	0.777	0.746	0.667	0.880	0.159	0.721
	(0.882)	(0.853)	(0.694)	(0.804)	(0.146)	(0.658)
	[0.189]	[0.211]	[0.113]	[0.413]	[0.078]	[0.335]
$\Delta\psi$	0.131	0.148	−0.225	−0.140	−0.025	−0.115
	(0.147)	(0.167)	(−0.230)	(−0.121)	(−0.022)	(−0.099)
	[0.189]	[0.192]	[0.071]	[0.092]	[0.017]	[0.075]

Panel C: Measures of Liquidity's Contribution to Portfolio Risk

$\ddot{\mathcal{P}}_c$	$\ddot{\mathcal{R}}_d$	$\ddot{\mathcal{R}}_c$	$\mathcal{R}_{\tilde{r}}$	$\ddot{\mathcal{B}}_d$	$\ddot{\mathcal{B}}_c$	$\mathcal{B}_{\tilde{r}}$
147.662	1.097	0.206	1.079	0.396	0.080	−0.684
[123.318]	0.924]	[0.174]	[0.957]	[0.496]	[0.097]	[−0.601]
(34.746)	0.274)	(0.048)	(0.453)	(0.392)	(0.074)	(0.321)

Table 5: This table reports statistics for quintile-ranked portfolios. At the end of each year, beginning in 1963 and ending 2001, eligible stocks are sorted into five portfolios. The breakpoints are based on all eligible stocks so each portfolio has approximately the same number of stocks at the time of formation. The portfolio characteristics for the 12 post-ranking months are joined across years to form a single time series for each quintile. Panel A reports the annualized sample statistics including the time series average of log net returns, variance of log net returns, variance of the unexpected component of log net returns, market capitalization, yield, proportional illiquidity level, and turnover. Market capitalization is reported in billions of dollars. Everything else is reported in percent per year. Panel B presents the statistics associated with the proportional cost decomposition. $\mathcal{B}_d$, $\mathcal{B}_K$, and $\mathcal{B}_{\tilde{r}}$ are, respectively, the regression coefficients of dividend news, proportion cost news, and net discount rate news on unexpected contemporaneous returns. $\mathcal{R}_K$ and $\mathcal{P}_K$ are the volatility of proportional cost news normalized by the volatility of, respectively, unexpected returns and contemporaneous proportional costs. Panel C presents the statistics associated with the fixed cost decomposition. $\ddot{\mathcal{B}}_d$, $\ddot{\mathcal{B}}_c$, and $\mathcal{B}_{\tilde{r}}$ are, respectively, the regression coefficients of dividend news, fixed cost news, and net discount rate news on unexpected contemporaneous returns. $\ddot{\mathcal{R}}_c$ and $\ddot{\mathcal{P}}_c$ are the volatility of proportional cost news normalized by the volatility of, respectively, unexpected returns and contemporaneous proportional costs. Panel D reports the statistics associated with the decomposition of fixed cost news into dividend news and proportional cost news. $\mathcal{B}^*_d$ and $\mathcal{B}^*_K$ are, respectively, the regression coefficients of dividend news and proportional cost news on fixed cost news. $\mathcal{R}^*_d$ and $\mathcal{R}^*_K$ are, respectively, the relative volatilities of dividend news and proportional cost news normalized by fixed cost news. All estimates reported in Panels B through D are bias-corrected using the small-sample jackknife bias correction procedure detailed in the Appendix. Jackknife standard errors are presented in parenthesis.

Sort by Market Capitalization

Decile	Low	2	3	4	High	Avg
Panel A: Sample Statistics						
$E[r^e_i]$	14.4266	11.8481	12.1374	12.0243	10.6678	12.3581
$\sigma^2(r^i)$	5.0893	4.5117	3.9997	3.2715	2.4852	3.5262
$\sigma^2(\nu)$	4.7403	4.3178	3.8924	3.2541	2.4864	3.4221
Market Capitalization	0.0361	0.1163	0.3028	0.8318	6.2945	1.5852
Yield	1.8915	2.4394	2.8232	3.2206	3.5768	2.8278
Cost (Chalmers and Kadlec)	1.2984	0.7245	0.4422	0.2755	0.1378	0.5500
Cost (Acharya and Pedersen)	1.9520	0.5790	0.2918	0.1951	0.1548	0.5884
Turnover	54.2865	57.4259	60.6741	62.1913	54.9171	58.0115
Panel B: Proportional Cost Decomposition						
$\mathcal{B}_d$	0.5958	0.4535	0.4962	0.6510	0.6920	0.4014
	(0.1891)	(0.2436)	(0.3124)	(0.3186)	(0.2853)	(0.3134)
$\mathcal{B}_K$	−0.0167	−0.0062	−0.0033	−0.0015	−0.0003	0.0009
	(0.0096)	(0.0039)	(0.0042)	(0.0013)	(0.0002)	(0.0045)
$\mathcal{B}_{\tilde{r}}$	−0.3875	−0.5403	−0.5005	−0.3475	−0.3077	−0.5995
	(0.1958)	(0.2463)	(0.3135)	(0.3196)	(0.2861)	(0.3184)
$\mathcal{R}_K$	0.0392	0.0083	0.0039	0.0019	0.0004	0.0102
	(0.0102)	(0.0038)	(0.0048)	(0.0016)	(0.0005)	(0.0052)
$\mathcal{P}_K$	7.9410	5.8176	6.5810	7.9314	4.5523	7.2188
	(2.5190)	(2.9594)	(9.6521)	(6.9548)	(7.4875)	(3.8187)
Panel C: Fixed Cost Decomposition						
$\ddot{\mathcal{B}}_d$	0.9792	0.5982	0.6019	0.7538	0.7752	0.4982
	(0.3112)	(0.3215)	(0.3789)	(0.3690)	(0.3197)	(0.3891)
$\ddot{\mathcal{B}}_c$	0.3667	0.1385	0.1024	0.1013	0.0830	0.0977
	(0.1177)	(0.0781)	(0.0673)	(0.0503)	(0.0344)	(0.0733)
$\mathcal{B}_{\tilde{r}}$	−0.3875	−0.5403	−0.5005	−0.3475	−0.3077	−0.5995
	(0.1958)	(0.2463)	(0.3135)	(0.3196)	(0.2861)	(0.3184)
$\ddot{\mathcal{R}}_c$	0.5970	0.2881	0.1706	0.1312	0.1131	0.1722
	(0.0847)	(0.0574)	(0.0334)	(0.0237)	(0.0239)	(0.0472)
$\ddot{\mathcal{P}}_c$	122.1230	202.9908	307.6094	553.4767	1502.9899	122.2368
	(19.0442)	(42.7242)	(69.8378)	(109.8830)	(390.6869)	(33.8864)
Panel D: Decomposing Fixed Cost News						
$\mathcal{B}^*_d$	1.0425	1.0138	1.0093	1.0052	1.0017	1.0385
	(0.0119)	(0.0098)	(0.0154)	(0.0075)	(0.0024)	(0.0207)
$\mathcal{B}^*_K$	−0.0425	−0.0138	−0.0093	−0.0052	−0.0017	−0.0385
	(0.0122)	(0.0099)	(0.0154)	(0.0075)	(0.0024)	(0.0208)
$\mathcal{R}^*_d$	1.0436	1.0140	1.0092	1.0052	1.0017	1.0394
	(0.0122)	(0.0097)	(0.0151)	(0.0076)	(0.0024)	(0.0206)
$\mathcal{R}^*_K$	0.0652	0.0280	0.0229	0.0143	0.0033	0.0594
	(0.0163)	(0.0142)	(0.0255)	(0.0114)	(0.0041)	(0.0228)

Table 6: This table reports statistics for quintile-ranked portfolios. At the end of each year, beginning in 1963 and ending 2001, eligible stocks are sorted into five portfolios. The breakpoints are based on all eligible stocks so each portfolio has approximately the same number of stocks at the time of formation. The portfolio characteristics for the 12 post-ranking months are joined across years to form a single time series for each quintile. Panel A reports the annualized sample statistics including the time series average of log net returns, variance of log net returns, variance of the unexpected component of log net returns, market capitalization, yield, proportional illiquidity level, and turnover. Market capitalization is reported in billions of dollars. Everything else is reported in percent per year. Panel B presents the statistics associated with the proportional cost decomposition. $\mathcal{B}_d$, $\mathcal{B}_K$, and $\mathcal{B}_{\tilde{r}}$ are, respectively, the regression coefficients of dividend news, proportion cost news, and net discount rate news on unexpected contemporaneous returns. $\mathcal{R}_K$ and $\mathcal{P}_K$ are the volatility of proportional cost news normalized by the volatility of, respectively, unexpected returns and contemporaneous proportional costs. Panel C presents the statistics associated with the fixed cost decomposition. $\ddot{\mathcal{B}}_d$, $\ddot{\mathcal{B}}_c$, and $\mathcal{B}_{\tilde{r}}$ are, respectively, the regression coefficients of dividend news, fixed cost news, and net discount rate news on unexpected contemporaneous returns. $\ddot{\mathcal{R}}_c$ and $\ddot{\mathcal{P}}_c$ are the volatility of proportional cost news normalized by the volatility of, respectively, unexpected returns and contemporaneous proportional costs. Panel D reports the statistics associated with the decomposition of fixed cost news into dividend news and proportional cost news. $\mathcal{B}^*_d$ and $\mathcal{B}^*_K$ are, respectively, the regression coefficients of dividend news and proportional cost news on fixed cost news. $\mathcal{R}^*_d$ and $\mathcal{R}^*_K$ are, respectively, the relative volatilities of dividend news and proportional cost news normalized by fixed cost news. All estimates reported in Panels B through D are bias-corrected using the small-sample jackknife bias correction procedure detailed in the Appendix. Jackknife standard errors are presented in parenthesis.

Sort by Acharya and Pedersen (2005) Illiquidity Levels

Decile	Low	2	3	4	High	Avg
Panel A: Sample Statistics						
$E[r_i^e]$	10.3858	10.9297	11.4324	12.0746	16.9009	12.3581
$\sigma^2(r^i)$	2.7788	3.5594	3.9126	4.1433	4.5932	3.5262
$\sigma^2(\nu)$	2.7805	3.5309	3.8414	3.9934	4.2252	3.4221
Market Capitalization	6.1952	0.8787	0.3406	0.1473	0.0533	1.5852
Yield	3.5127	3.1139	2.7875	2.5003	2.0596	2.8278
Cost (Chalmers and Kadlec)	0.1295	0.2611	0.4331	0.7372	1.3346	0.5500
Cost (Acharya and Pedersen)	0.1523	0.1844	0.2750	0.5746	2.0250	0.5884
Turnover	65.9273	67.8055	60.1151	49.7811	44.0212	58.0115
Panel B: Proportional Cost Decomposition						
$\mathcal{B}_d$	0.6436	0.7386	0.6008	0.5591	0.5193	0.4014
	(0.3397)	(0.2497)	(0.3219)	(0.2525)	(0.1721)	(0.3134)
$\mathcal{B}_K$	−0.0002	−0.0011	−0.0036	−0.0082	−0.0121	0.0009
	(0.0001)	(0.0014)	(0.0043)	(0.0058)	(0.0083)	(0.0045)
$\mathcal{B}_{\tilde{r}}$	−0.3562	−0.2603	−0.3956	−0.4327	−0.4686	−0.5995
	(0.3405)	(0.2505)	(0.3225)	(0.2544)	(0.1795)	(0.3184)
$\mathcal{R}_K$	0.0003	0.0014	0.0041	0.0101	0.0448	0.0102
	(0.0002)	(0.0017)	(0.0052)	(0.0066)	(0.0100)	(0.0052)
$\mathcal{P}_K$	3.4355	5.4496	6.6062	6.1349	8.6115	7.2188
	(3.9694)	(9.6638)	(9.7850)	(4.3310)	(2.1507)	(3.8187)
Panel C: Fixed Cost Decomposition						
$\ddot{\mathcal{B}}_d$	0.7208	0.8553	0.7282	0.7372	0.8451	0.4982
	(0.3805)	(0.2892)	(0.3903)	(0.3331)	(0.2806)	(0.3891)
$\ddot{\mathcal{B}}_c$	0.0770	0.1157	0.1239	0.1699	0.3136	0.0977
	(0.0408)	(0.0394)	(0.0691)	(0.0806)	(0.1043)	(0.0733)
$\mathcal{B}_{\tilde{r}}$	−0.3562	−0.2603	−0.3956	−0.4327	−0.4686	−0.5995
	(0.3405)	(0.2505)	(0.3225)	(0.2544)	(0.1795)	(0.3184)
$\ddot{\mathcal{R}}_c$	0.1046	0.1464	0.1763	0.2989	0.5901	0.1722
	(0.0317)	(0.0231)	(0.0364)	(0.0545)	(0.0979)	(0.0472)
$\ddot{\mathcal{P}}_c$	1388.3653	670.3755	299.6338	183.4209	114.1302	122.2368
	(607.6198)	(130.8353)	(70.9687)	(37.7961)	(18.8655)	(33.8864)
Panel D: Decomposing Fixed Cost News						
$\mathcal{B}^*_d$	1.0014	1.0051	1.0073	1.0113	1.0508	1.0385
	(0.0015)	(0.0057)	(0.0168)	(0.0135)	(0.0121)	(0.0207)
$\mathcal{B}^*_K$	−0.0014	−0.0051	−0.0073	−0.0113	−0.0508	−0.0385
	(0.0015)	(0.0057)	(0.0168)	(0.0135)	(0.0125)	(0.0208)
$\mathcal{R}^*_d$	1.0014	1.0051	1.0072	1.0116	1.0521	1.0394
	(0.0015)	(0.0058)	(0.0166)	(0.0135)	(0.0123)	(0.0206)
$\mathcal{R}^*_K$	0.0025	0.0093	0.0233	0.0329	0.0749	0.0594
	(0.0024)	(0.0113)	(0.0270)	(0.0220)	(0.0165)	(0.0228)

Table 7: This table reports statistics for quintile-ranked portfolios. At the end of each year, beginning in 1963 and ending 2001, eligible stocks are sorted into five portfolios. The breakpoints are based on all eligible stocks so each portfolio has approximately the same number of stocks at the time of formation. The portfolio characteristics for the 12 post-ranking months are joined across years to form a single time series for each quintile. Panel A reports the annualized sample statistics including the time series average of log net returns, variance of log net returns, variance of the unexpected component of log net returns, market capitalization, yield, proportional illiquidity level, and turnover. Market capitalization is reported in billions of dollars. Everything else is reported in percent per year. Panel B presents the statistics associated with the proportional cost decomposition. $\mathcal{B}_d$, $\mathcal{B}_K$, and $\mathcal{B}_{\tilde{r}}$ are, respectively, the regression coefficients of dividend news, proportion cost news, and net discount rate news on unexpected contemporaneous returns. $\mathcal{R}_K$ and $\mathcal{P}_K$ are the volatility of proportional cost news normalized by the volatility of, respectively, unexpected returns and contemporaneous proportional costs. Panel C presents the statistics associated with the fixed cost decomposition. $\ddot{\mathcal{B}}_d$, $\ddot{\mathcal{B}}_c$, and $\mathcal{B}_{\tilde{r}}$ are, respectively, the regression coefficients of dividend news, fixed cost news, and net discount rate news on unexpected contemporaneous returns. $\ddot{\mathcal{R}}_c$ and $\ddot{\mathcal{P}}_c$ are the volatility of proportional cost news normalized by the volatility of, respectively, unexpected returns and contemporaneous proportional costs. Panel D reports the statistics associated with the decomposition of fixed cost news into dividend news and proportional cost news. $\mathcal{B}^*_d$ and $\mathcal{B}^*_K$ are, respectively, the regression coefficients of dividend news and proportional cost news on fixed cost news. $\mathcal{R}^*_d$ and $\mathcal{R}^*_K$ are, respectively, the relative volatilities of dividend news and proportional cost news normalized by fixed cost news. All estimates reported in Panels B through D are bias-corrected using the small-sample jackknife bias correction procedure detailed in the Appendix. Jackknife standard errors are presented in parenthesis.

Sort by Turnover

Decile	Low	2	3	4	High	Avg
Panel A: Sample Statistics						
$E[r_i^e]$	15.5380	14.2306	13.4685	11.8173	6.5014	12.3581
$\sigma^2(r^i)$	2.0977	2.6178	3.3866	4.4511	6.3724	3.5262
$\sigma^2(\nu)$	2.0091	2.5165	3.3044	4.3523	6.2715	3.4221
Market Capitalization	0.8755	2.1017	2.0154	1.7113	1.1325	1.5852
Yield	3.7056	3.5115	3.0512	2.4226	1.5535	2.8278
Cost (Chalmers and Kadlec)	0.7710	0.5742	0.5135	0.4831	0.4359	0.5500
Cost (Acharya and Pedersen)	0.9944	0.6113	0.5187	0.4636	0.4032	0.5884
Turnover	19.6039	35.1631	49.1702	68.4694	113.4548	58.0115
Panel B: Proportional Cost Decomposition						
$\mathcal{B}_d$	0.5865	0.5790	0.5272	0.5712	0.6297	0.4014
	(0.2285)	(0.2563)	(0.2167)	(0.2944)	(0.3237)	(0.3134)
$\mathcal{B}_K$	−0.0013	−0.0039	−0.0047	−0.0039	−0.0023	0.0009
	(0.0233)	(0.0039)	(0.0025)	(0.0037)	(0.0040)	(0.0045)
$\mathcal{B}_{\tilde{r}}$	−0.4123	−0.4171	−0.4681	−0.4249	−0.3680	−0.5995
	(0.2411)	(0.2604)	(0.2197)	(0.2966)	(0.3240)	(0.3184)
$\mathcal{R}_K$	0.0717	0.0141	0.0081	0.0080	0.0059	0.0102
	(0.0883)	(0.0057)	(0.0023)	(0.0030)	(0.0054)	(0.0052)
$\mathcal{P}_K$	20.3402	7.7029	5.0837	5.9036	3.3661	7.2188
	(25.7047)	(3.0561)	(1.7732)	(2.9149)	(6.6645)	(3.8187)
Panel C: Fixed Cost Decomposition						
$\ddot{\mathcal{B}}_d$	0.7350	0.7038	0.6437	0.7111	0.8124	0.4982
	(0.2866)	(0.3116)	(0.2646)	(0.3665)	(0.4179)	(0.3891)
$\ddot{\mathcal{B}}_c$	0.1473	0.1209	0.1117	0.1360	0.1804	0.0977
	(0.0524)	(0.0528)	(0.0472)	(0.0714)	(0.0949)	(0.0733)
$\mathcal{B}_{\tilde{r}}$	−0.4123	−0.4171	−0.4681	−0.4249	−0.3680	−0.5995
	(0.2411)	(0.2604)	(0.2197)	(0.2966)	(0.3240)	(0.3184)
$\ddot{\mathcal{R}}_c$	0.1618	0.1879	0.1821	0.2041	0.2757	0.1722
	(0.0276)	(0.0538)	(0.0281)	(0.0380)	(0.0828)	(0.0472)
$\ddot{\mathcal{P}}_c$	46.1511	102.2716	116.3980	154.0177	207.5717	122.2368
	(8.8545)	(28.8249)	(18.0192)	(30.1835)	(68.7136)	(33.8864)
Panel D: Decomposing Fixed Cost News						
$\mathcal{B}^*_d$	1.3053	1.0532	1.0235	1.0256	1.0132	1.0385
	(0.4374)	(0.0198)	(0.0087)	(0.0098)	(0.0084)	(0.0207)
$\mathcal{B}^*_K$	−0.3053	−0.0532	−0.0235	−0.0256	−0.0132	−0.0385
	(0.4378)	(0.0201)	(0.0089)	(0.0099)	(0.0085)	(0.0208)
$\mathcal{R}^*_d$	1.3577	1.0543	1.0240	1.0259	1.0130	1.0394
	(0.3739)	(0.0200)	(0.0090)	(0.0099)	(0.0087)	(0.0206)
$\mathcal{R}^*_K$	0.4682	0.0736	0.0430	0.0382	0.0188	0.0594
	(0.3799)	(0.0254)	(0.0155)	(0.0170)	(0.0230)	(0.0228)

Table 8: This table reports the properties of the odd-numbered value-weighted portfolios obtained by sorting eligible stocks each year, beginning in 1963 and ending in 1999, according to their annual Amihud (2002) illiquidity measures. The breakpoints are based on eligible stocks so each portfolio has approximately the same number of stocks at formation. The betas are calculated using the decomposed returns of the value-weighted portfolios and an equally-weighted market portfolio. β^* is the portfolio's liquidity-adjusted CAPM beta, $\beta_{r,r}$ is the portfolio's non-liquidity news sensitivity to the market's non-liquidity news, $\beta_{r,c}$ is the portfolio's non-liquidity news sensitivity to the market's liquidity news, $\beta_{c,r}$ is the portfolio's liquidity news sensitivity to the market's non-liquidity news, and $\beta_{c,c}$ is the portfolio's liquidity news sensitivity to the market's liquidity news. The reported betas are small-sample bias corrected using the jackknife procedure. Robust standard errors are reported in parenthesis. In addition, for each portfolio, the average market capitalization, annualized time-series expectation and volatility of proportional transactions costs and net excess returns, turnover, and yield are reported.

Illiquidity-Ranked Portfolios: Contemporaneous Decomposition

	β^*	$\beta_{r,r}$	$\beta_{r,c}$	$\beta_{c,r}$	$\beta_{c,c}$	$E(K)$	$\sigma(K)$	$E(\tilde{r})$	$\sigma(r)$	ψ	y	mktcap
1	53.06	52.88	−0.17	0.00	−0.00	0.15	0.00	4.77	50.55	39.38	3.64	14.48
	(3.57)	(3.55)	(0.10)	(0.00)	(0.00)							
3	68.42	68.22	−0.23	0.03	−0.00	0.15	0.01	4.24	55.51	51.20	3.72	2.73
	(2.87)	(2.85)	(0.12)	(0.04)	(0.00)							
5	76.37	76.08	−0.26	−0.03	0.00	0.16	0.01	5.62	58.33	52.32	3.81	1.48
	(3.01)	(2.99)	(0.13)	(0.01)	(0.00)							
7	79.67	79.35	−0.27	−0.05	0.00	0.17	0.02	6.16	58.78	52.46	3.30	0.91
	(2.68)	(2.68)	(0.13)	(0.01)	(0.00)							
9	85.78	85.38	−0.32	−0.08	0.00	0.19	0.04	6.21	62.47	48.71	3.22	0.60
	(2.62)	(2.61)	(0.14)	(0.03)	(0.00)							
11	88.99	88.54	−0.32	−0.13	0.00	0.21	0.05	5.65	63.02	49.08	3.18	0.41
	(2.47)	(2.48)	(0.16)	(0.04)	(0.00)							
13	91.86	91.35	−0.33	−0.18	0.00	0.24	0.07	7.07	63.95	45.53	2.95	0.28
	(2.88)	(2.90)	(0.15)	(0.07)	(0.00)							
15	94.24	93.68	−0.35	−0.21	0.00	0.30	0.11	7.55	67.28	42.74	2.82	0.21
	(3.40)	(3.38)	(0.16)	(0.10)	(0.00)							
17	94.19	93.46	−0.37	−0.35	0.00	0.39	0.16	8.16	66.61	38.75	2.77	0.15
	(2.68)	(2.71)	(0.15)	(0.12)	(0.00)							
19	96.45	95.56	−0.40	−0.49	0.01	0.53	0.23	8.72	69.33	37.92	2.60	0.11
	(3.69)	(3.73)	(0.16)	(0.16)	(0.00)							
21	102.24	101.12	−0.41	−0.69	0.01	0.84	0.43	10.61	73.45	37.22	2.41	0.07
	(3.20)	(3.21)	(0.17)	(0.32)	(0.01)							
23	106.90	105.49	−0.42	−0.97	0.02	1.39	0.62	11.79	77.71	41.78	2.02	0.04
	(4.61)	(4.65)	(0.16)	(0.24)	(0.00)							
25	104.24	102.01	−0.40	−1.79	0.04	2.92	1.59	18.73	81.99	49.21	1.84	0.02
	(5.55)	(5.51)	(0.18)	(0.52)	(0.01)							

Table 9: This table reports the properties of the odd-numbered value-weighted portfolios obtained by sorting eligible stocks each year, beginning in 1963 and ending in 1999, according to their annual Amihud (2002) illiquidity measures. The breakpoints are based on eligible stocks so each portfolio has approximately the same number of stocks at formation. The betas are calculated using the decomposed returns of the value-weighted portfolios and an equally-weighted market portfolio. β^* is the portfolio's liquidity-adjusted CAPM beta, $\beta_{r,r}$ is the portfolio's non-liquidity news sensitivity to the market's non-liquidity news, $\beta_{r,c}$ is the portfolio's non-liquidity news sensitivity to the market's liquidity news, $\beta_{c,r}$ is the portfolio's liquidity news sensitivity to the market's non-liquidity news, and $\beta_{c,c}$ is the portfolio's liquidity news sensitivity to the market's liquidity news. The reported betas are small-sample bias corrected using the jackknife procedure. Robust standard errors are reported in parenthesis. In addition, for each portfolio, the average market capitalization, annualized time-series expectation and volatility of proportional transactions costs and net excess returns, turnover, and yield are reported.

Illiquidity-Ranked Portfolios: Proportional Cost Decomposition

	β^*	$\beta_{r,r}$	$\beta_{r,c}$	$\beta_{c,r}$	$\beta_{c,c}$	$E(K)$	$\sigma(K)$	$E(\tilde{r})$	$\sigma(r)$	ψ	y	mktcap
1	64.07	64.05	−0.02	0.00	−0.00	0.15	0.00	4.77	50.55	39.38	3.64	14.48
	(2.58)	(2.58)	(0.15)	(0.00)	(0.00)							
3	76.99	77.06	−0.05	0.12	−0.00	0.15	0.01	4.24	55.51	51.20	3.72	2.73
	(2.18)	(2.18)	(0.17)	(0.11)	(0.00)							
5	83.29	83.21	−0.04	−0.04	0.00	0.16	0.01	5.62	58.33	52.32	3.81	1.48
	(1.97)	(1.99)	(0.19)	(0.03)	(0.00)							
7	84.99	84.87	−0.02	−0.10	0.00	0.17	0.02	6.16	58.78	52.46	3.30	0.91
	(2.00)	(2.03)	(0.20)	(0.06)	(0.00)							
9	90.71	90.54	−0.05	−0.12	0.00	0.19	0.04	6.21	62.47	48.71	3.22	0.60
	(1.93)	(1.93)	(0.21)	(0.12)	(0.00)							
11	92.42	92.17	−0.03	−0.22	0.00	0.21	0.05	5.65	63.02	49.08	3.18	0.41
	(1.53)	(1.56)	(0.22)	(0.13)	(0.00)							
13	93.96	93.59	−0.03	−0.34	0.00	0.24	0.07	7.07	63.95	45.53	2.95	0.28
	(1.59)	(1.67)	(0.22)	(0.26)	(0.00)							
15	97.53	97.00	−0.03	−0.50	0.00	0.30	0.11	7.55	67.28	42.74	2.82	0.21
	(1.97)	(2.01)	(0.23)	(0.25)	(0.00)							
17	95.63	94.93	−0.03	−0.67	0.00	0.39	0.16	8.16	66.61	38.75	2.77	0.15
	(1.84)	(1.96)	(0.23)	(0.34)	(0.00)							
19	98.42	97.38	−0.02	−1.02	0.00	0.53	0.23	8.72	69.33	37.92	2.60	0.11
	(2.81)	(2.97)	(0.24)	(0.43)	(0.00)							
21	103.99	102.85	0.03	−1.16	0.00	0.84	0.43	10.61	73.45	37.22	2.41	0.07
	(2.30)	(2.46)	(0.26)	(0.59)	(0.00)							
23	99.99	98.08	−0.01	−1.89	0.01	1.39	0.62	11.79	77.71	41.78	2.02	0.04
	(3.57)	(3.50)	(0.24)	(0.49)	(0.00)							
25	103.94	98.60	0.06	−5.38	0.03	2.92	1.59	18.73	81.99	49.21	1.84	0.02
	(3.56)	(3.90)	(0.26)	(1.87)	(0.02)							

Table 10: This table reports the properties of the odd-numbered value-weighted portfolios obtained by sorting eligible stocks each year, beginning in 1963 and ending in 1999, according to their annual Amihud (2002) illiquidity measures. The breakpoints are based on eligible stocks so each portfolio has approximately the same number of stocks at formation. The betas are calculated using the decomposed returns of the value-weighted portfolios and an equally-weighted market portfolio. β^* is the portfolio's liquidity-adjusted CAPM beta, $\beta_{r,r}$ is the portfolio's non-liquidity news sensitivity to the market's non-liquidity news, $\beta_{r,c}$ is the portfolio's non-liquidity news sensitivity to the market's liquidity news, $\beta_{c,r}$ is the portfolio's liquidity news sensitivity to the market's non-liquidity news, and $\beta_{c,c}$ is the portfolio's liquidity news sensitivity to the market's liquidity news. The reported betas are small-sample bias corrected using the jackknife procedure. Robust standard errors are reported in parenthesis. In addition, for each portfolio, the average market capitalization, annualized time-series expectation and volatility of proportional transactions costs and net excess returns, turnover, and yield are reported.

Illiquidity-Ranked Portfolios: Fixed Cost Decomposition

	β^*	$\beta_{r,r}$	$\beta_{r,c}$	$\beta_{c,r}$	$\beta_{c,c}$	$E(K)$	$\sigma(K)$	$E(\tilde{r})$	$\sigma(r)$	ψ	y	mktcap
1	64.07	77.39	7.76	6.39	0.83	0.15	0.00	4.77	50.55	39.38	3.64	14.48
	(2.58)	(4.85)	(3.62)	(1.11)	(0.26)							
3	76.99	96.64	10.20	10.91	1.46	0.15	0.01	4.24	55.51	51.20	3.72	2.73
	(2.18)	(5.41)	(4.28)	(2.41)	(0.44)							
5	83.29	101.78	10.25	9.32	1.09	0.16	0.01	5.62	58.33	52.32	3.81	1.48
	(1.97)	(6.50)	(4.79)	(3.26)	(0.52)							
7	84.99	106.94	10.39	12.94	1.39	0.17	0.02	6.16	58.78	52.46	3.30	0.91
	(2.00)	(7.33)	(5.17)	(4.19)	(0.69)							
9	90.71	112.42	10.84	12.45	1.59	0.19	0.04	6.21	62.47	48.71	3.22	0.60
	(1.93)	(7.55)	(5.32)	(3.51)	(0.54)							
11	92.42	115.68	11.00	13.86	1.59	0.21	0.05	5.65	63.02	49.08	3.18	0.41
	(1.53)	(7.96)	(5.62)	(4.31)	(0.65)							
13	93.96	119.88	11.49	16.30	1.88	0.24	0.07	7.07	63.95	45.53	2.95	0.28
	(1.59)	(9.38)	(5.72)	(5.86)	(0.77)							
15	97.53	127.82	12.07	20.54	2.32	0.30	0.11	7.55	67.28	42.74	2.82	0.21
	(1.97)	(10.75)	(6.17)	(7.11)	(1.01)							
17	95.63	126.16	11.57	21.41	2.45	0.39	0.16	8.16	66.61	38.75	2.77	0.15
	(1.84)	(9.44)	(6.08)	(5.94)	(0.93)							
19	98.42	132.68	11.78	25.34	2.87	0.53	0.23	8.72	69.33	37.92	2.60	0.11
	(2.81)	(11.03)	(6.55)	(7.48)	(1.14)							
21	103.99	147.83	12.92	34.95	4.03	0.84	0.43	10.61	73.45	37.22	2.41	0.07
	(2.30)	(12.58)	(7.46)	(8.67)	(1.55)							
23	99.99	157.45	14.32	48.11	4.96	1.39	0.62	11.79	77.71	41.78	2.02	0.04
	(3.57)	(14.10)	(7.83)	(9.70)	(2.36)							
25	103.94	205.99	18.12	93.18	9.25	2.92	1.59	18.73	81.99	49.21	1.84	0.02
	(3.56)	(21.89)	(10.53)	(19.16)	(4.67)							

Table 11: **Contemporaneous Decomposition:** This table reports the estimated coefficients from cross-sectional regressions of the liquidity-adjusted CAPM for the *contemporaneous decomposition*. At the end of each year, beginning in 1963 and ending in 1999, eligible stocks are sorted into 25 portfolios according to their annual Amihud (2002) illiquidity measures in Panel A and according to volatility of their daily illiquidity measures in Panel B. The breakpoints are based on eligible stocks so each portfolio has approximately the same number of stocks at formation. The individual portfolios are *value-weighted* and the market portfolio is *equal-weighted*. I report special cases of the following relationship: $E(r_t^i - r_t^f) = \alpha + \kappa E[K_t^i] + \lambda\beta^i + \lambda^*\beta^{*i} + \lambda_{r,r}\beta_{r,r}^i + \lambda_{r,c}\beta_{r,c}^i + \lambda_{c,r}\beta_{c,r}^i + \lambda_c\beta_c^i$,
where β is the portfolio's CAPM beta, β^* is the portfolio's liquidity-adjusted CAPM beta, $\beta_{r,r}$ is the portfolio's non-liquidity news sensitivity to the market's non-liquidity news, $\beta_{r,c}$ is the portfolio's non-liquidity news sensitivity to the market's liquidity news, $\beta_{c,r}$ is the portfolio's liquidity news sensitivity to the market's non-liquidity news, $\beta_{c,c}$ is the portfolio's liquidity news sensitivity to the market's liquidity news, and $\beta_c \equiv \beta_{c,c} - \beta_{c,r} - \beta_{r,c}$ is the aggregate liquidity risk beta as defined by Acharya and Pedersen (2005). The reported estimates are small-sample bias corrected using the jackknife procedure. Robust standard errors are reported in parenthesis. Both jackknife procedures take into account the pre-estimation of the news series and the betas. The R^2 is obtained in a single cross-sectional regression and the adjusted R^2 is in parenthesis.

Panel A: Portfolios Ranked by Proportional Liquidity Levels

	α	$E[K]$	β	β^*	$\beta_{r,r}$	$\beta_{r,c}$	$\beta_{c,r}$	$\beta_{c,c}$	β_c	R^2
1	−1.291		2.108							0.557
	(0.215)		(0.237)							(0.537)
2	−0.569	1.000		1.325						0.629
	(0.128)			(0.143)						(0.613)
3	−0.033	4.045		0.567						0.974
	(0.052)	(0.144)		(0.060)						(0.971)
4	0.315	1.000			−0.050				47.883	0.961
	(0.195)				(0.341)				(12.902)	(0.957)
5	0.289	0.875			−0.027				48.261	0.979
	(0.139)	(1.110)			(0.249)				(15.552)	(0.976)
6	0.237	1.000			0.075	−35.446	−35.587	452.404		0.973
	(0.097)				(0.313)	(78.240)	(16.462)	(706.488)		(0.967)
7	0.468	−11.829			1.146	267.287	−59.602	7013.411		0.983
	(0.154)	(7.156)			(0.319)	(97.854)	(28.318)	(4077.016)		(0.979)

Panel B: Portfolios Ranked by Liquidity Risk

	α	$E[K]$	β	β^*	$\beta_{r,r}$	$\beta_{r,c}$	$\beta_{c,r}$	$\beta_{c,c}$	β_c	R^2
1	−1.167		1.943							0.661
	(0.197)		(0.216)							(0.646)
2	−0.455	1.000		1.174						0.607
	(0.114)			(0.127)						(0.590)
3	0.014	3.997		0.503						0.912
	(0.054)	(0.184)		(0.064)						(0.905)
4	0.733	1.000			−0.728				71.140	0.862
	(0.185)				(0.315)				(15.402)	(0.850)
5	0.437	2.233			−0.241				39.216	0.918
	(0.308)	(2.076)			(0.551)				(38.910)	(0.907)
6	0.492	1.000			2.304	674.338	−242.822	−5693.701		0.887
	(0.272)				(1.154)	(188.416)	(87.041)	(3176.492)		(0.864)
7	0.453	8.892			0.050	116.541	−179.903	−924.823		0.943
	(0.187)	(5.153)			(1.156)	(246.159)	(53.068)	(3276.901)		(0.928)

Table 12: **Proportional Cost Decomposition:** This table reports the estimated coefficients from cross-sectional regressions of the liquidity-adjusted CAPM for the *proportional cost decomposition*. At the end of each year, beginning in 1963 and ending in 1999, eligible stocks are sorted into 25 portfolios according to their annual Amihud (2002) illiquidity measures in Panel A and according to volatility of their daily illiquidity measures in Panel B. The breakpoints are based on eligible stocks so each portfolio has approximately the same number of stocks at formation. The individual portfolios are *value-weighted* and the market portfolio is *equal-weighted*. I report special cases of the following relationship: $E(r_t^i - r_t^f) = \alpha + \kappa E[K_t^i] + \lambda\beta^i + \lambda^*\beta^{*i} + \lambda_{r,r}\beta_{r,r}^i + \lambda_{r,c}\beta_{r,c}^i + \lambda_{c,r}\beta_{c,r}^i + \lambda_c\beta_c^i$,
where β is the portfolio's CAPM beta, β^* is the portfolio's liquidity-adjusted CAPM beta, $\beta_{r,r}$ is the portfolio's non-liquidity news sensitivity to the market's non-liquidity news, $\beta_{r,c}$ is the portfolio's non-liquidity news sensitivity to the market's liquidity news, $\beta_{c,r}$ is the portfolio's liquidity news sensitivity to the market's non-liquidity news, $\beta_{c,c}$ is the portfolio's liquidity news sensitivity to the market's liquidity news, and $\beta_c \equiv \beta_{c,c} - \beta_{c,r} - \beta_{r,c}$ is the aggregate liquidity risk beta as defined by Acharya and Pedersen (2005). The reported estimates are small-sample bias corrected using the jackknife procedure. Robust standard errors are reported in parenthesis. Both jackknife procedures take into account the pre-estimation of the news series and the betas. The R^2 is obtained in a single cross-sectional regression and the adjusted R^2 is in parenthesis.

Panel A: Portfolios Ranked by Proportional Liquidity Levels

	α	$E[K]$	β	β^*	$\beta_{r,r}$	$\beta_{r,c}$	$\beta_{c,r}$	$\beta_{c,c}$	β_c	R^2
1	−1.291		2.108							0.557
	(0.215)		(0.237)							(0.537)
2	−1.028	1.000		1.772						0.601
	(0.178)			(0.195)						(0.584)
3	−0.212	4.110		0.736						0.970
	(0.069)	(0.140)		(0.077)						(0.968)
4	−0.183	1.000			0.733				14.891	0.947
	(0.267)				(0.342)				(5.216)	(0.942)
5	−0.287	3.037			0.846				4.158	0.973
	(0.135)	(1.468)			(0.153)				(8.138)	(0.969)
6	0.196	1.000			0.310	445.643	−25.267	−4883.022		0.957
	(0.410)				(0.679)	(158.539)	(15.012)	(2916.760)		(0.949)
7	0.343	3.854			0.011	319.675	−22.069	−5587.924		0.980
	(0.211)	(2.621)			(0.436)	(99.384)	(12.999)	(2031.381)		(0.974)

Panel B: Portfolios Ranked by Liquidity Risk

	α	$E[K]$	β	β^*	$\beta_{r,r}$	$\beta_{r,c}$	$\beta_{c,r}$	$\beta_{c,c}$	β_c	R^2
1	−1.167		1.943							0.661
	(0.197)		(0.216)							(0.646)
2	−0.907	1.000		1.615						0.673
	(0.162)			(0.177)						(0.659)
3	−0.190	3.809		0.711						0.912
	(0.083)	(0.231)		(0.097)						(0.903)
4	0.400	1.000			0.009				24.375	0.880
	(0.330)				(0.425)				(6.519)	(0.869)
5	0.964	−4.206			−0.670				56.460	0.918
	(0.675)	(6.214)			(0.806)				(40.423)	(0.906)
6	0.510	1.000			−0.130	−97.456	−30.907	−647.621		0.880
	(0.434)				(0.562)	(178.076)	(20.137)	(3564.101)		(0.856)
7	−0.326	13.426			0.749	−172.028	30.998	−3193.662		0.918
	(0.803)	(22.243)			(0.780)	(255.296)	(72.182)	(13583.971)		(0.897)

Table 13: **Fixed Cost Decomposition:** This table reports the estimated coefficients from cross-sectional regressions of the liquidity-adjusted CAPM for the *fixed cost decomposition*. At the end of each year, beginning in 1963 and ending in 1999, eligible stocks are sorted into 25 portfolios according to their annual Amihud (2002) illiquidity measures in Panel A and according to volatility of their daily illiquidity measures in Panel B. The breakpoints are based on eligible stocks so each portfolio has approximately the same number of stocks at formation. The individual portfolios are *value-weighted* and the market portfolio is *equal-weighted*. I report special cases of the following relationship: $E(r_t^i - r_t^f) = \alpha + \kappa E[K_t^i] + \lambda\beta^i + \lambda^*\beta^{*i} + \lambda_{r,r}\beta_{r,r}^i + \lambda_{r,c}\beta_{r,c}^i + \lambda_{c,r}\beta_{c,r}^i + \lambda_c\beta_c^i$,
where β is the portfolio's CAPM beta, β^* is the portfolio's liquidity-adjusted CAPM beta, $\beta_{r,r}$ is the portfolio's non-liquidity news sensitivity to the market's non-liquidity news, $\beta_{r,c}$ is the portfolio's non-liquidity news sensitivity to the market's liquidity news, $\beta_{c,r}$ is the portfolio's liquidity news sensitivity to the market's non-liquidity news, $\beta_{c,c}$ is the portfolio's liquidity news sensitivity to the market's liquidity news, and $\beta_c \equiv \beta_{c,c} - \beta_{c,r} - \beta_{r,c}$ is the aggregate liquidity risk beta as defined by Acharya and Pedersen (2005). The reported estimates are small-sample bias corrected using the jackknife procedure. Robust standard errors are reported in parenthesis. Both jackknife procedures take into account the pre-estimation of the news series and the betas. The R^2 is obtained in a single cross-sectional regression and the adjusted R^2 is in parenthesis.

Panel A: Portfolios Ranked by Proportional Liquidity Levels

	α	$E[K]$	β	β^*	$\beta_{r,r}$	$\beta_{r,c}$	$\beta_{c,r}$	$\beta_{c,c}$	β_c	R^2
1	−1.291		2.108							0.557
	(0.215)		(0.237)							(0.537)
2	−1.028	1.000		1.772						0.601
	(0.178)			(0.195)						(0.584)
3	−0.212	4.110		0.736						0.970
	(0.069)	(0.140)		(0.077)						(0.968)
4	−0.016	1.000			0.337				−0.569	0.941
	(0.161)				(0.248)				(0.383)	(0.936)
5	−0.250	4.600			0.812				0.968	0.970
	(0.113)	(1.618)			(0.208)				(0.672)	(0.966)
6	0.124	1.000			−0.351	4.508	−1.000	25.034		0.966
	(0.152)				(0.383)	(3.902)	(1.645)	(12.792)		(0.960)
7	0.086	2.514			0.072	1.081	−1.276	21.114		0.980
	(0.162)	(2.318)			(0.354)	(3.043)	(1.413)	(10.752)		(0.975)

Panel B: Portfolios Ranked by Liquidity Risk

	α	$E[K]$	β	β^*	$\beta_{r,r}$	$\beta_{r,c}$	$\beta_{c,r}$	$\beta_{c,c}$	β_c	R^2
1	−1.167		1.943							0.661
	(0.197)		(0.216)							(0.646)
2	−0.907	1.000		1.615						0.673
	(0.162)			(0.177)						(0.659)
3	−0.190	3.809		0.711						0.912
	(0.083)	(0.231)		(0.097)						(0.903)
4	−0.048	1.000			0.401				−0.355	0.872
	(0.161)				(0.234)				(0.347)	(0.861)
5	−0.020	−1.673			0.269				−1.086	0.913
	(0.246)	(5.181)			(0.509)				(1.817)	(0.901)
6	−0.120	1.000			0.480	0.099	0.166	−1.958		0.876
	(0.205)				(0.635)	(7.158)	(2.525)	(28.103)		(0.851)
7	−0.200	0.878			0.467	1.207	0.086	−2.756		0.915
	(0.299)	(5.461)			(0.792)	(7.343)	(2.967)	(27.662)		(0.893)