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# The components of the illiquidity premium: An empirical analysis of U.S. stocks 1927-2010

Björn Hagströmer, Björn Hansson and Birger Nilsson<sup>\*†</sup>

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**Abstract:** This paper estimates a conditional version of the liquidity adjusted CAPM by Acharya and Pedersen (2005) using NYSE and AMEX data from 1927 to 2010 to study the illiquidity premium and its variation over time. The components of the illiquidity premium is in this model derived as the level of expected illiquidity together with three types of illiquidity risks. We measure illiquidity of individual stocks by the efficient spread proxy developed in Holden (2009) and employ illiquidity sorted portfolios as test assets. The average annual illiquidity premium is estimated to 1.55%, the respective contributions from illiquidity level being 1.15% and from the three different illiquidity risks 0.40%. Results also indicate that commonality risk is the least important component in the illiquidity risk premium, while a component related to the hedging of wealth shocks is the most important. The illiquidity premium varies substantially over time, with peaks in downturns and crises, but with no general tendency to decrease over time.

**Keywords:** illiquidity level premium; illiquidity risk premium; conditional LCAPM; effective tick

**JEL codes:** G12; G11; C22

## 1 Introduction

The liquidity-adjusted capital asset pricing model (LCAPM) by Acharya and Pedersen (2005) shows that asset prices are potentially influenced by both the level of illiquidity and different types of illiquidity risk. A large empirical literature, reviewed briefly below, has attempted to empirically estimate the magnitude of such illiquidity premia. The conclusions of these studies are divergent, both with respect to the magnitude of premia and with respect

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to the distribution of premia between level and risk in illiquidity. The LCAPM is conditional, meaning that both illiquidity betas and illiquidity risk premia are allowed to vary over time. Earlier empirical assessments of this model have assumed constant conditional covariances (or constant risk premia), yielding unconditional versions of LCAPM (Acharya and Pedersen, 2005; Lee, 2011). This is the first study to empirically estimate the conditional LCAPM.

That long-term investors benefit from investment in illiquid securities was established in the academic literature by Amihud and Mendelson (1986), and is widely accepted in the financial industry. Swensen (2000) states that *"Because market players routinely overpay for liquidity, serious investors benefit by avoiding overpriced liquid securities and locating bargains in less followed, less liquid market segments."* (p.56) But investors engaging in illiquid investment also need to monitor their illiquidity risk. *The Economist* (Feb. 11, 2010) writes that in the financial crisis in 2007-2009, illiquidity risk was neglected: *"With markets awash with cash and hedge funds, private-equity firms and sovereign-wealth funds all keen to invest in assets, there seemed little prospect of a liquidity crisis."* When liquidity evaporated as confidence fell, many illiquidity investors found themselves forced to fire sales. The purpose of the LCAPM model and of this paper is to better understand illiquidity risk and to what extent it is priced in the market.

The LCAPM shows that there are three types of illiquidity risk. Firstly, there is the covariance of illiquidity with market-wide illiquidity, studied by, e.g., Chordia, Roll, and Subrahmanyam (2000). Such commonality in illiquidity is documented for all major equity markets (Brockman, Chung and Perignon, 2009; Karolyi, Lee, and van Dijk, 2011) and for all major asset classes. Acharya and Pedersen (2005) find that this is the least important of the three types of illiquidity risks. Secondly, there is the covariance between asset returns and market-wide illiquidity, which has been studied extensively Pástor and Stambaugh (2003), Liu (2006 and 2009), Watanabe and Watanabe (2007), Korajczyk and Sadka (2008), and Lou and Sadka (2011) all show that this risk is priced in US stock markets, but Hasbrouck (2009) and Asparouhova, Bessembinder and Kalcheva (2010) reach the opposite conclusion. Finally, there is the covariance between asset illiquidity and market returns, which Acharya and Pedersen (2005) identify as the most important of the illiquidity risks. Wagner (2011) argues theoretically that this risk is realized when investors simultaneously need to liquidate their positions. Brunnermeier and Pedersen (2009) show that such scenarios are created when investors simultaneously hit their funding constraints and are forced to sell assets.

As there are few studies of the first and third types of risk, and a clear divergence in

results for the second type of risk, more research is needed. To our knowledge, the only studies investigating all three illiquidity risks simultaneous to the impact of level illiquidity are Acharya and Pedersen (2005) and Lee (2011), who are both considering unconditional versions of the LCAPM.

The purpose of this paper is to investigate the pricing of illiquidity level and illiquidity risk in US equity markets. Our investigation contrasts that of Acharya and Pedersen (2005) in three important ways. Firstly, we do not assume constant conditional covariances, i.e., we estimate the conditional LCAPM with time-varying illiquidity risk. Since the model is conditional we are able to study how the illiquidity premia as well as their economic significance change over time. Secondly, we use the recently developed illiquidity measure in Holden (2009). As this measure is an estimate of the cost of trading, it is more suitable for the LCAPM than the measure developed by Amihud (2002) and used by Acharya and Pedersen (2005). Finally, our investigation spans 85 years of data (1926-2010), which is much longer than the data set applied by Acharya and Pedersen (2005) and most other studies of illiquidity premia. A long time span gives credit to the estimates of risk premia, but it also requires careful methods for dealing with time-varying features of the economy. One such feature is the time-varying nature of the average investor's expected holding period, which determines how often investors incur illiquidity costs. Using historical NYSE data, we show that the time-variation in average holding period is substantial and hence important to account for in illiquidity asset pricing models. We then show how this can be implemented in the conditional LCAPM.

Our investigation shows that the relative order of importance of illiquidity risks is the same as concluded by Acharya and Pedersen (2005): the dominating illiquidity risk is the covariance of asset illiquidity and market returns. Overall, the magnitudes of our premia are smaller than what was found by Acharya and Pedersen (2005). The illiquidity level premium is estimated at 1.15% per year, whereas the illiquidity risk premia together reaches 0.40%, giving a total illiquidity premium of 1.55%. Acharya and Pedersen (2005) estimated these numbers to 3.5%, 1.1% and 4.6%, respectively. We find substantial time variation in illiquidity risk, indicating the advantage of allowing time-varying covariances in LCAPM. The time-varying illiquidity risk premium also lends support to the regime-switching approach by Watanabe and Watanabe (2007).

In the next section we review the theoretical framework of the conditional LCAPM. The empirical framework for our study is presented in Section 3, beginning by outlining the econometric specification allowing for estimation of the conditional LCAPM. We then turn to methodological

issues specific to our empirical setting, presenting the data that we use, the illiquidity measure that we apply, our method for estimating average holding periods, and, finally, our method for portfolio formation. Results of our investigation are given in Section 4, along with various checks for robustness. Section 5 concludes.

## 2 Theoretical model

Acharya and Pedersen (2005) start with an overlapping generations economy where risk-averse agents trade securities whose liquidity varies randomly over time. Their liquidity-adjusted capital asset pricing model is similar to CAPM in the sense that risk averse agents maximize expected utility in a one-period framework (an overlapping generations economy). They generate a liquidity risk by assuming a stochastic illiquidity cost that is the per-share cost of selling a security. In the original economy there are frictions represented by stochastic illiquidity costs that might be correlated with the stochastic dividend process. Thus, the return is composed of the price change plus the stochastic dividend, the gross return  $r_t^i$ , minus the relative illiquidity cost,  $c_t^i$ , and CAPM holds for the gross returns net of illiquidity cost. As a result, in equilibrium the conditional expected gross return of security  $i$  is

$$\begin{aligned} E_t[r_{t+1}^i] &= r^f + E_t[c_{t+1}^i] + \frac{\text{cov}_t(r_{t+1}^i - c_{t+1}^i, r_{t+1}^m - c_{t+1}^m)}{\text{var}_t(r_{t+1}^m - c_{t+1}^m)} E_t[r_{t+1}^m - c_{t+1}^m - r^f] \\ &= r^f + E_t[c_{t+1}^i] + \delta_t \text{cov}_t(r_{t+1}^i - c_{t+1}^i, r_{t+1}^m - c_{t+1}^m), \end{aligned} \quad (1)$$

where  $\delta_t$  is the time-varying price of risk defined as

$$\delta_t \equiv \frac{E_t[r_{t+1}^m - c_{t+1}^m - r^f]}{\text{var}_t(r_{t+1}^m - c_{t+1}^m)}. \quad (2)$$

Equivalently, the formula in eq. (1) can be written

$$\begin{aligned} E_t[r_{t+1}^i] &= r^f + E_t[c_{t+1}^i] + \delta_t \text{cov}_t(r_{t+1}^i, r_{t+1}^m) \\ &\quad + \delta_t \text{cov}_t(c_{t+1}^i, c_{t+1}^m) - \delta_t \text{cov}_t(r_{t+1}^i, c_{t+1}^m) - \delta_t \text{cov}_t(c_{t+1}^i, r_{t+1}^m). \end{aligned} \quad (3)$$

Notice the model-implied restrictions of a single risk price  $\delta_t$ .

Besides the traditional market risk,  $\text{cov}_t(r_{t+1}^i, r_{t+1}^m)$ , there are three additional sources of risk that are interpreted as different forms of liquidity risk. The term  $\text{cov}_t(c_{t+1}^i, c_{t+1}^m)$  represents commonality in liquidity (Chordia, Roll and Subrahmanyam, 2000), and it gives rise to a premium for holding a security that becomes illiquid when the market in general becomes illiquid. The term  $\text{cov}_t(r_{t+1}^i, c_{t+1}^m)$  represents return sensitivity to market liquidity i.e. the

risk of holding an asset with a low return in times of market illiquidity. An asset where this covariance is positive can be seen as a hedge to  $c^m$  (Pástor and Stambaugh, 2003). The term  $cov_t(c_{t+1}^i, r_{t+1}^m)$  represents liquidity sensitivity to market returns and it leads to a discount for holding an asset that is liquid in bad states for the market i.e. such an asset is a hedge to  $r^m$  or wealth shocks.

In their empirical investigation Acharya and Pedersen (2005) estimate an unconditional version of this model. However, we will estimate a conditional model that is presented below.

### 3 Empirical framework for conditional LCAPM

Below we provide an econometric specification that allows for empirical estimation of the conditional LCAPM. After that we turn to issues that are specific to our empirical setting, including data availability, illiquidity measurement, average holding period measurement, and portfolio formation.

#### 3.1 Econometric specification of LCAPM

We suggest to parameterize the theoretical model by Acharya and Pedersen as a quad-variate GARCH(1,1)-in-mean model, thereby allowing us to directly model conditional variances and covariances of interest in the asset pricing equations. The four dependent variables in our model are illiquidity of the individual portfolio,  $c_t^p$ , illiquidity of the market portfolio,  $c_t^m$ , return on the individual portfolio,  $r_t^p$ , and return on the market portfolio,  $r_t^m$ . Following Pástor and Stambaugh (2003), Acharya and Pedersen (2005) and Sadka and Korajczyk (2008), we assume AR(2)-processes for liquidity of individual portfolios and market portfolio. Our joint parameterization of the mean equations and the variances-covariances in the conditional version of the Acharya and Pedersen (2005) can be written:

$$c_t^p = a_0^p + a_1^p c_{t-1}^p + a_2^p c_{t-2}^p + \eta_t^p \quad (4)$$

$$c_t^m = a_0^m + a_1^m c_{t-1}^m + a_2^m c_{t-2}^m + \eta_t^m \quad (5)$$

$$r_t^p = \alpha_0^p + r_t^f + \gamma_t^p + \delta h_t^{r_p r_m} + \delta h_t^{c_p c_m} - \delta h_t^{r_p c_m} - \delta h_t^{c_p r_m} + \varepsilon_t^p \quad (6)$$

$$r_t^m = \alpha_0^m + r_t^f + \gamma_t^m + \delta h_t^{r_m r_m} + \delta h_t^{c_m c_m} - 2\delta h_t^{r_m c_m} + \varepsilon_t^m, \quad (7)$$

where  $\gamma_t^p$  and  $\gamma_t^m$  denote the expected illiquidity cost per time period for the illiquidity portfolio and the market portfolio respectively. These are defined as  $\gamma_t^p = \kappa_t (a_0^p + a_1^p c_{t-1}^p + a_2^p c_{t-2}^p)$

and  $\gamma_t^m = \kappa_t (a_0^m + a_1^m c_{t-1}^m + a_2^m c_{t-2}^m)$ , where  $\kappa_t$  is the inverse of the expected holding period. The theoretical model assumes a one-period holding period, implying  $\gamma_t^p = E_{t-1}[c_t^p]$  and  $\gamma_t^m = E_{t-1}[c_t^m]$ . In our empirical setting, the expected holding period is allowed to differ from one period and also to vary over time. The former deviation from the theoretical model is motivated by the fact that expected illiquidity is a cost, measured in dollars per dollar invested, and therefore does not scale with sampling frequency. The latter deviation is motivated by the observation that average holding period actually seems to vary over time. The constants in the return equations,  $\alpha_0^p$  and  $\alpha_0^m$ , are zero according to the theoretical model, but we allow for a non-zero intercept in the empirical model for the illiquidity portfolio, but require the model to price the market portfolio with no systematic pricing error. Finally, our empirical specification imposes the theoretical model restriction of an equal price of market risk and the prices of illiquidity risks. According to Acharya and Pedersen (2005) this restriction is not likely to hold empirically. However, in our econometric framework, we are unable to find evidence for this claim. We estimate models with different risk prices for market risk and illiquidity risk, but find no statistical support this specification.

The upper portion of the conditional variance-covariance matrix is by definition:

$$H_t = \begin{pmatrix} h_t^{c_p c_p} & h_t^{c_p c_m} & h_t^{c_p r_p} & h_t^{c_p r_m} \\ & h_t^{c_m c_m} & h_t^{c_m r_p} & h_t^{c_m r_m} \\ & & h_t^{r_p r_p} & h_t^{r_p r_m} \\ & & & h_t^{r_m r_m} \end{pmatrix}. \quad (8)$$

This variance-covariance matrix is assumed to follow a quad-variate GARCH process of BEKK type developed by Engle and Kroner (1995) and Kroner and Ng (1998):

$$H_t = C'C + A'e_{t-1}e_{t-1}'A + B'H_{t-1}B + D'\xi_{t-1}\xi_{t-1}'D, \quad (9)$$

where  $e_{t-1}$  is the vector of innovations in illiquidity and return:  $e_{t-1} = (\eta_{t-1}^p, \eta_{t-1}^m, \varepsilon_{t-1}^p, \varepsilon_{t-1}^m)'$  and the asymmetric residual  $\xi_{t-1} = (\max[\eta_{t-1}^p, 0], \max[\eta_{t-1}^m, 0], \min[\varepsilon_{t-1}^p, 0], \min[\varepsilon_{t-1}^m, 0])'$ . This specification of the asymmetric residual imply that the variance of illiquidity increase when illiquidity shocks are positive (increased illiquidity), and that the variance of return increase when return shocks are negative. The direction of the asymmetric effect on the covariances depends on the signs of the corresponding parameters. The specification of the matrix  $C$  is such that  $C'C$  is guaranteed to be positive semi-definite and the matrices  $A$ ,  $B$  and  $D$  are either diagonal or non-diagonal. More general specifications naturally allow for richer variance-covariance dynamics. The diagonality assumption implies that there are no interactions between

variance processes of different dependent variables. This may be regarded as a strong restriction and hence we estimate the model both with and without the diagonality restriction on the parameter matrices. Taken together we estimate four different specifications of the GARCH model: symmetric diagonal, asymmetric diagonal, symmetric non-diagonal and asymmetric non-diagonal. We note that both asymmetric effects and variance spillover effects are important features of the data. This is especially true when the two effects are combined in the asymmetric non-diagonal specification. This parameterization is therefore our preferred variance-covariance specification and is used throughout the empirical parts of the paper.

Assuming conditional normality, the log-likelihood function is:

$$\ln L(\theta) = -\frac{NT}{2} \ln(2\pi) - \frac{1}{2} \sum_{t=1}^T \ln |H_t(\theta)| - \frac{1}{2} \sum_{t=1}^T e_t'(\theta) H_t^{-1}(\theta) e_t(\theta), \quad (10)$$

where  $N$  is the number of cross-sectional dimensions  $T$  is the number of time-series observations. The parameter vector  $\theta$  contains the autoregressive parameters, the constant in the portfolio return equation, the risk price and the parameters in the variance-covariance equations. The models are estimated using quasi-maximum likelihood with time-zero values for residuals equal to zero and for conditional variances and covariances equal to their unconditional sample counterparts. Robust  $t$ -statistics for parameters are calculated using the method proposed by Bollerslev and Wooldridge (1992).

### 3.2 Data

We investigate the pricing of illiquidity in US equity markets using data for the time interval 1926:01-2010:12. For illiquidity measurement we use stock prices from the CRSP daily database, and for portfolio formation and return calculation we use stock prices stock market capitalization from the CRSP monthly files. Given the time interval, our investigation is limited to stocks traded at the New York Stock Exchange (NYSE) and the American Stock Exchange (Amex). To estimate the average holding period, we retrieve data on stock turnover from the NYSE homepage (<http://www.nyxdata.com/nyxdata/NYSE/FactsFigures/tabid/115/Default.aspx>).

### 3.3 Illiquidity measure

The Holden (2009) pure price clustering measure of illiquidity builds on the empirical observation that trade prices tend to cluster around specific numbers, i.e. what is usually labeled rounder numbers (Harris, 1991, Christie and Schultz 1994). On a decimal price grid, whole dollars are rounder than quarters, which are rounder than dimes, which are rounder than nickels,



which are rounder than pennies. Harris (1991) gives a theoretical explanation for such price clustering. He argues that price clustering reduces negotiation costs between two potential traders by avoiding trivial price changes and by reducing the amount of information exchanged. To derive his measure Holden (2009) assumes that trade is conducted in two steps. 1) In order to minimize negotiation costs traders decide what price cluster to use on a particular day. 2) Traders negotiate a particular price from the chosen price cluster. His proxy for the effective spread, i.e. the *effective tick*, thereby relies on the assumption that the effective spread on a particular day equals the price increment of the price cluster used that day.<sup>1</sup>

To decide which price cluster is used for a specific stock on a particular day (assuming daily data), the observed closing price that day is classified as a *special price* for one of the price clusters. A special price is defined as a price that could not be generated on any *higher* price cluster. Indexing the  $J$  possible price clusters with  $j$ , where  $j = 1$  is defined as the lowest cluster (penny prices on a decimal price grid), the number of observed special prices,  $N_j$ , for each price cluster is counted over the time period considered. The empirical frequency,  $F_j$ , of special prices corresponding to the  $j$ th spread can then be calculated. In this paper, we also use the information contained in bid-ask averages (when no closing prices are available). Similar to closing prices, the number of special bid-ask averages,  $N_{J+j}$ , is counted and the empirical frequency,  $F_{J+j}$ , of special bid-ask averages corresponding to the  $j$ th spread can be calculated:

$$F_j = \frac{N_j}{\sum_{j=1}^J N_j} \text{ (closing prices)} \quad (11)$$

$$F_{J+j} = \frac{N_{J+j}}{\sum_{j=1}^J N_{J+j}} \text{ (bid-ask averages)}. \quad (12)$$

Under the additional assumption that prices are uniformly distributed across each given price cluster, the unconstrained probabilities of the different spreads are:

$$U_j = \begin{cases} \frac{A_j}{B_j} F_j + \frac{A_{J+j}}{B_{J+j}} F_{J+j} & j = 1 \\ \frac{A_j}{B_j} F_j - \sum_{k=1}^{j-1} \frac{D_{jk}}{B_k} F_k + \frac{A_{J+j}}{B_{J+j}} F_{J+j} - \sum_{k=1}^{j-1} \frac{D_{J+j, J+k}}{B_{J+k}} F_{J+k} & j = 2, \dots, J \end{cases} \quad (13)$$

Here,  $A_j$  is the *total* number of prices corresponding to the  $j$ th spread,  $B_j$  is the number of *special* prices corresponding to the  $j$ th spread and  $D_{jk}$  with  $j > k$  is the number of price

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<sup>1</sup>The effective spread captures the cost of a round-trip order by including both price movement (dealers coming in to execute orders at a better price than previously quoted) and market impact (spread widening due to the size of the order itself). Effective spread is defined as twice the difference between the actual trade price and the market quote at the time of order entry, divided by the actual trade price. For the NYSE and AMEX stock used in this study, the possible prices are at \$1/8, \$1/4, \$1/2 and \$1 before July 1997, at \$1/16, \$1/8, \$1/4, \$1/2 and \$1 from July 1997 up to January 2001, and at \$0.01, \$0.05, \$0.10, \$0.25 and \$1 after January 2001.

increments for the  $j$ th spread that *overlap* with the price increments of the  $k$ th spread and do *not overlap* the price increments of any spread between the  $j$ th and the  $k$ th spread. Intuitively, these corrections of the empirical frequencies are performed to avoid double counting; there is an overlapping pattern between different price clusters, i.e. observed prices can be generated on more than one price cluster.

Finally, a non-linear transformation is applied to the unconstrained probabilities to obtain constrained probabilities that are by definition bounded by zero and one:

$$\pi_j = \begin{cases} \min[\max(U_j, 0), 1] & j = 1 \\ \min[\max(U_j, 0), 1 - \sum_{k=1}^{j-1} \pi_k] & j = 2, \dots, J \end{cases} \quad (14)$$

As can be seen in eq. (13), the price clustering model of Holden (2009) is based on the assumption that trade prices are more likely to be on rounder price increments (and similarly for bid-ask averages). The motivation for the non-linear transformation is that unconstrained probabilities are not necessarily bounded by zero and one because lower frequencies at rounder increments may be observed in small samples.

The effective tick illiquidity measure is defined as the probability weighted average of the possible spreads,  $s_j$ , relative to the average price of the stock,  $\bar{P}$ , calculated over the time period in question:

$$c = \sum_{j=1}^J \frac{\pi_j s_j}{\bar{P}}. \quad (15)$$

Goyenko, Holden and Trzcinka (2009) show that the effective tick is highly correlated with the effective spread and also reflects the level of the true spread, for periods when high frequency data are available. Our notation  $c$  for the effective tick indicates that this is a measure of trading costs. The fact that effective tick is a cost measure is a substantial advantage compared to the *ILLIQ* measure (Amihud, 2002) applied by Acharya and Pedersen (2005), as it fits directly in the framework of the liquidity-adjusted CAPM. By using the effective tick measure we therefore also circumvent the (rather arbitrary) transformation of the *ILLIQ* measure in Acharya and Pedersen (2005).

### 3.4 Average holding period and its influence on $\gamma$

When accounting for illiquidity costs in asset pricing models, it is important to consider how often such costs are incurred. In their empirical application, Acharya and Pedersen (2005) use the average holding period in their sample to calculate  $\kappa$ . As the average holding period across stocks and time in their sample equals 29 months, they set  $\kappa = 0.034$ . We note that the average

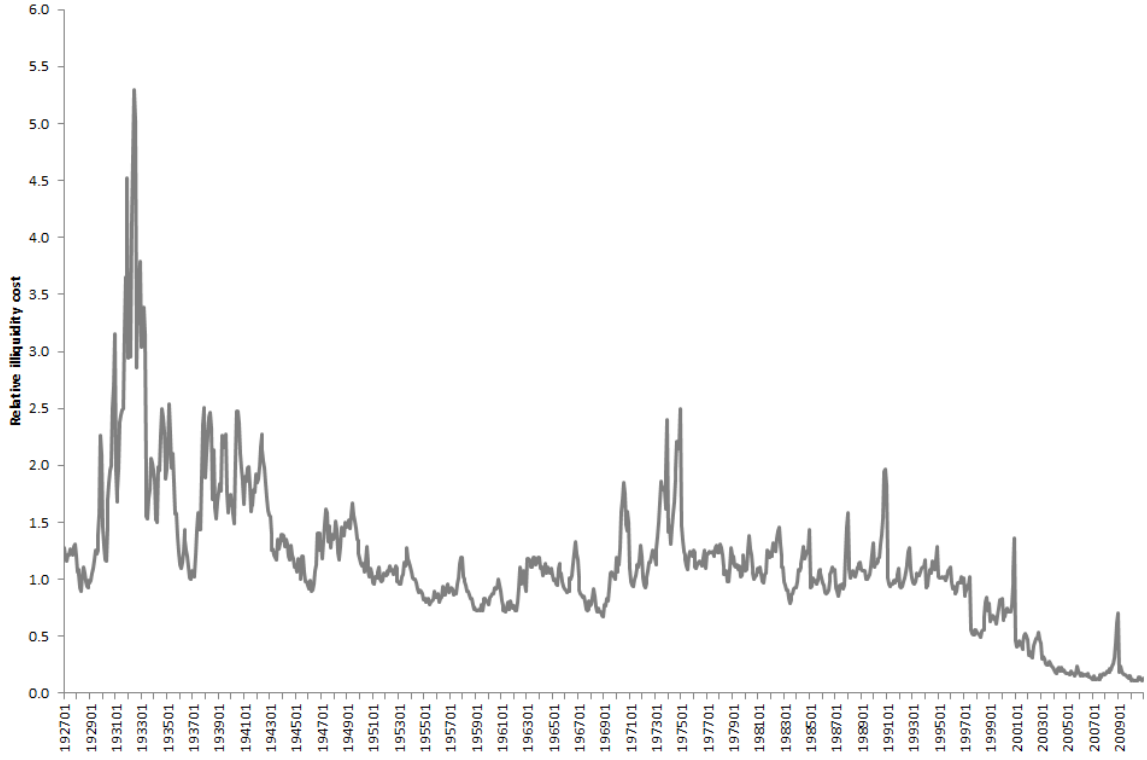
holding period is not constant over our long sample period and accounting for time-variation in  $\kappa$  can therefore potentially improve the fit of the conditional LCAPM. As the average holding period equals the reciprocal of the average turnover rate, we approximate  $\kappa_t$  with annual NYSE turnover rate divided by twelve.<sup>2</sup>

Figure 1 shows time series of the equal-weighted average effective tick,  $c_t^m$  [Panel (a)], the inverse of the average holding period,  $\kappa_t$  [Panel (b)], and their product, which is the an estimate of the monthly average realized illiquidity cost [Panel (c)]. We observe that the effective spread peaks during the great depression, and that it features spikes at events associated with economic distress, such as the oil crises in the 1970's and the October 1987 crash. The financial crisis in 2007-2009 shows relatively low illiquidity costs. The inverse of the average holding period displays a long period of low values (i.e., long holding periods) from the end of the 1930's until the end of 1970's. After that, average holding period gradually decreases. The decreasing effective spreads and decreasing average holding periods since the 1970's counteract each other in determining the illiquidity cost. The latter measure grows gradually until the October 1987 crash, where it has its highest value since 1934. It is relatively stable over the 1990's, and then decreases gradually and quite dramatically until the summer of 2007.

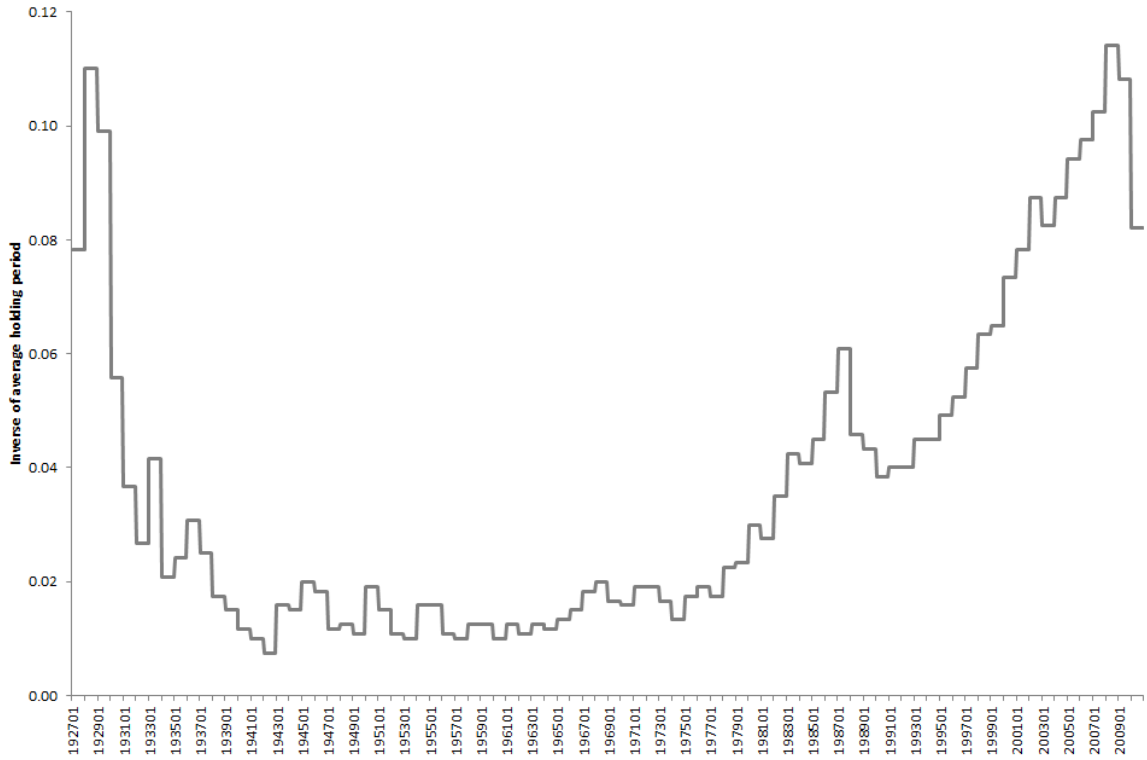
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<sup>2</sup>We use the turnover rate from the current year and not the previous year. This means we assume that investors know their investment horizon, i.e. investment horizon is not a stochastic variable with an uncertain outcome in the future. Therefore, the econometrician can observe the average investment horizon for the current year ex post, using data from the same year, without introducing look-ahead bias.

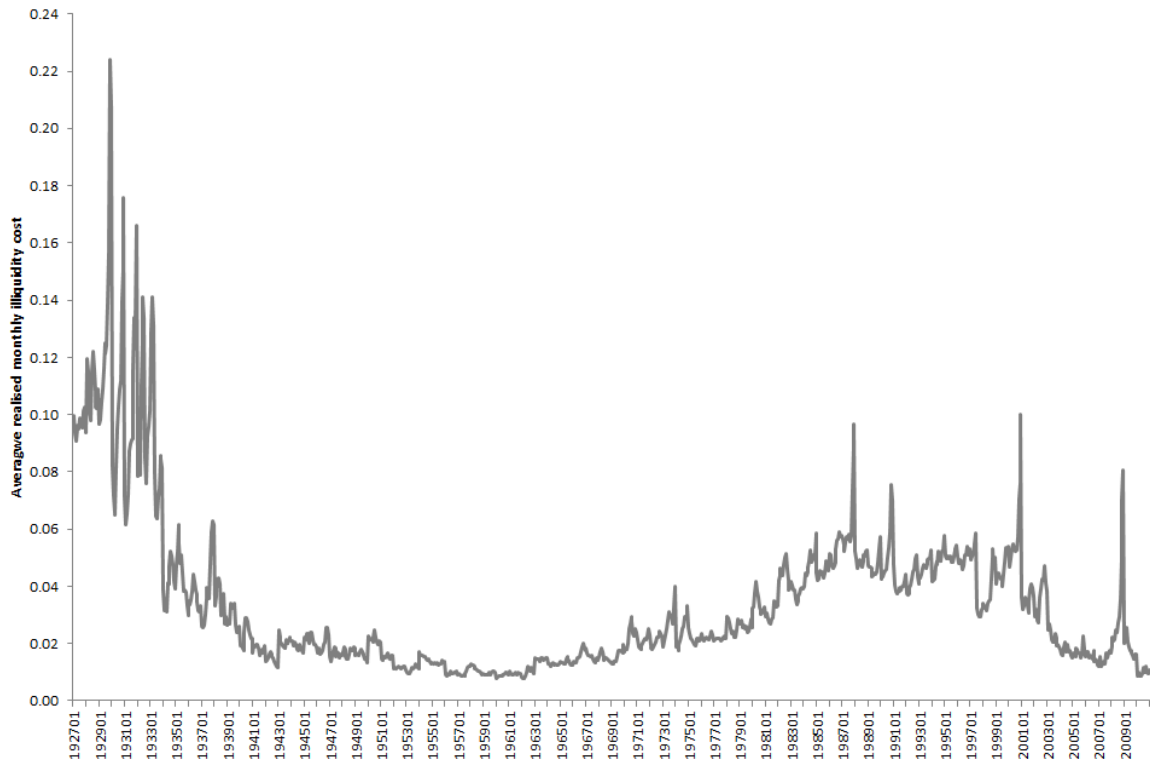
Figure 1: Market illiquidity, average holding period and realized illiquidity cost



(a) Average effective spread ( $c_t^m$ )



(b) Inverse of average holding period ( $\kappa_t$ )



(c) Average monthly realized illiquidity cost

### 3.5 Illiquidity sorted portfolios

To construct illiquidity sorted portfolios we follow a procedure similar to Acharya and Pedersen (2005). A daily stock price observation is included in the portfolio formation process if the stock price observation is at least \$5. This price limit corresponds to the notion of a penny-stock defined in Security Exchange Act Rule 3a51-1 and is also used by for example Amihud (2002), Pástor and Stambaugh (2003) and Acharya and Pedersen (2005).<sup>3</sup> To include a stock we also require that price data is available at least 100 days in a particular year. For each stock included, the effective tick is calculated each year from daily price data. The portfolio formation is annual in the sense that portfolio formation takes place once a year (in the beginning of each year), using the annual estimated illiquidity for individual stocks in the previous year. Included stocks are then sorted into 25 illiquidity portfolios. The procedure is repeated for each year. This portfolio formation process therefore implies that the stocks in a particular portfolio are the same throughout a given year, but potentially varies from year to year.

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<sup>3</sup>As the upper limit of the nominal effective tick measure throughout our sample is \$1, this restriction implies a cap on the effective tick measure at 20%. This can be compared to the 30% cap that Acharya & Pedersen (2005) use on their transformed illiquidity cost measure.

For each illiquidity portfolio and the market portfolio, both equal weighted and value weighted monthly illiquidity,  $c_t^p$ , and monthly return,  $r_t^p$ , are calculated for the twelve months following the portfolio formation date:

$$c_t^p = \sum_{i \text{ in } p} \omega_t^i c_t^i \quad (16)$$

$$r_t^p = \sum_{i \text{ in } p} \omega_t^i r_t^i, \quad (17)$$

where  $c_t^i$  is the effective tick for stock  $i$ ,  $r_t^i$  is the return for stock  $i$  and  $\omega_t^i$  are either equal weights or value weights based on the market value of stock  $i$  in the beginning of month  $t$ . It is often argued that a value weighted stock market portfolio understates the illiquidity of the market portfolio due to the dominance of large liquid stock (see e.g. Acharya and Pedersen, 2005). We therefore focus our analysis on an equal weighted stock market portfolio as a proxy for the market portfolio, but use as test assets both equal and value weighted illiquidity sorted portfolios. The proxy for the market portfolio is taken as the union of the individual portfolios. Following Shumway (1997), we set the delisting return to  $-30\%$  to avoid survivorship bias in portfolio returns and we set the associated "delisting illiquidity" to the maximum value of 20 cents per dollar invested.<sup>4</sup> Asparouhova, Bessembinder and Kalcheva (2010) argue that microstructure noise in security prices cause an upward bias in returns (see also Blume and Stambaugh, 1983). In a simple model of measurement errors they quantify the size of this bias to  $S^2/3$ , where  $S$  is the effective spread. Our illiquidity measure by definition is a proxy for the effective spread, and we incorporate this correction in all returns for individual stocks used in the calculation of portfolio returns (excluding delisting returns). Some characteristics of the monthly illiquidity sorted portfolios can be found in Table I.

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<sup>4</sup> A delisting return of  $-30\%$  is assigned if the delisting code in CRSP is 500 (reason unavailable), 520 (went to OTC), 551–573 and 580 (various reasons), 574 (bankruptcy), and 584 (does not meet exchange financial guidelines).

**Table I: Portfolio characteristics**

The table reports average portfolio illiquidity, standard deviation of portfolio illiquidity, average portfolio return and standard deviation of portfolio return. Averages and standard deviations are calculated on a monthly basis and are expressed in percentage terms.

	Equal weighted				Value weighted			
	$\mu(c^p)$	$\sigma(c^p)$	$\mu(r^p)$	$\sigma(r^p)$	$\mu(c^p)$	$\sigma(c^p)$	$\mu(r^p)$	$\sigma(r^p)$
P01	0.284	0.134	0.919	5.626	0.228	0.087	0.865	4.952
P02	0.373	0.170	0.877	5.874	0.341	0.154	0.818	5.496
P03	0.433	0.206	0.926	5.866	0.395	0.183	0.899	5.390
P04	0.484	0.237	0.969	6.050	0.442	0.208	0.879	5.358
P05	0.528	0.269	1.002	6.502	0.478	0.239	1.024	6.129
P06	0.579	0.300	0.949	6.283	0.520	0.259	1.009	5.840
P07	0.622	0.338	1.022	6.460	0.571	0.309	0.906	5.949
P08	0.665	0.375	1.127	6.613	0.595	0.315	1.055	6.315
P09	0.712	0.394	1.113	6.704	0.649	0.356	1.046	6.239
P10	0.768	0.448	1.011	6.519	0.695	0.370	0.992	6.072
P11	0.813	0.451	1.094	6.472	0.736	0.403	0.977	5.929
P12	0.864	0.499	1.115	6.736	0.779	0.437	1.091	6.224
P13	0.922	0.635	1.214	7.092	0.834	0.523	1.123	6.818
P14	0.990	0.606	1.174	6.890	0.894	0.531	1.090	6.579
P15	1.066	0.628	1.189	6.922	0.947	0.545	1.049	6.178
P16	1.157	0.757	1.124	7.549	1.011	0.625	1.138	7.199
P17	1.224	0.713	1.224	7.379	1.100	0.653	1.087	7.067
P18	1.321	0.774	1.238	7.135	1.155	0.674	1.311	6.881
P19	1.455	0.833	1.249	7.429	1.279	0.703	1.279	7.136
P20	1.608	0.979	1.289	7.640	1.380	0.824	1.304	7.276
P21	1.754	0.968	1.145	7.773	1.509	0.795	1.160	7.748
P22	1.932	1.105	1.333	7.813	1.725	1.073	1.291	8.010
P23	2.191	1.282	1.240	7.978	1.889	1.072	1.157	7.939
P24	2.527	1.294	1.231	7.666	2.175	1.130	1.050	7.392
P25	3.331	1.668	1.359	7.667	2.846	1.470	1.273	7.599

The average illiquidity is monotonically increasing, showing that illiquidity is a persistent characteristic of individual stocks as the pre-ranking of portfolios is the same as the post-ranking. A more detailed examination reveals that over time there are reasonably few cross overs in illiquidity between adjacent portfolios and virtually no cross overs between portfolios farther away from each other. We also note that there is an increasing relation between portfolio illiquidity and portfolio return, i.e. a higher average illiquidity is in general associated with a higher average return. This pattern is slightly stronger for equal weighted portfolios. Since the portfolios are otherwise identical, this is a consequence of imposing value weights on the stocks after sorting them into portfolios. This may be seen as a unnecessary distortion of the original sorting, but since forming value weighted portfolios is very common in the literature, we use both equal weighted and value weighted test portfolios in the subsequent analysis. A similar increasing relation is found between the volatility of illiquidity and the volatility of return.

## 4 Results

In the next subsections, we use our estimated models to analyze the size and time-variation in the illiquidity premium. We focus in particular on the difference between the illiquid portfolio and the liquid portfolio (P25–P01), which can be used to identify the illiquidity premium under the restrictions of the theoretical model. As previously mentioned, allowing the price of market risk to differ from the price of illiquidity risk does not produce any significant increase in likelihood value. The focus in the subsequent analysis is therefore on the empirical model with equal risk prices and the preferred asymmetric non-diagonal variance-covariance specification. Parameter estimates in asset pricing equations are reported in Table II.

**Table II: Conditional LCAPM estimates**

The table reports estimated intercepts and risk prices for all 50 test portfolios and the difference portfolio P25–P01. Test portfolios are either equal weighted or value weighted. The last row shows the average risk price calculated over the 50 test portfolios. The asymmetric non-diagonal conditional variance-covariance specification (preferred GARCH model) is used in all estimations. Intercepts are expressed in percentage units (per month). Robust  $t$ -statistics calculated according to Bollerslev and Wooldridge (1992) are in parentheses (absolute values).

	Conditional LCAPM			
	Equal weighted		Value weighted	
	$\alpha_0^p$	$\delta$	$\alpha_0^p$	$\delta$
P01	0.080 (1.343)	2.595 (4.769)	0.064 (0.954)	3.127 (5.868)
P02	0.011 (0.201)	3.265 (5.594)	0.010 (0.162)	3.510 (6.191)
P03	0.031 (0.691)	3.162 (5.207)	0.011 (0.179)	3.146 (5.749)
P04	0.028 (0.619)	3.001 (6.161)	0.010 (0.175)	3.753 (7.073)
P05	0.009 (0.200)	4.006 (7.249)	0.093 (1.544)	3.280 (6.679)
P06	0.005 (0.114)	3.091 (5.899)	0.077 (1.223)	3.402 (6.113)
P07	−0.045 (0.854)	2.801 (5.390)	−0.079 (1.245)	3.331 (5.666)
P08	0.076 (1.711)	2.654 (4.861)	0.036 (0.613)	3.753 (7.028)
P09	0.028 (0.684)	3.227 (6.186)	−0.041 (0.697)	2.797 (5.484)
P10	−0.056 (1.453)	3.030 (6.264)	−0.027 (0.485)	2.789 (5.291)
P11	−0.024 (0.618)	3.565 (6.927)	−0.080 (1.422)	2.701 (5.814)
P12	0.019 (0.492)	4.144 (8.177)	0.050 (0.781)	2.820 (5.230)
P13	0.049 (1.234)	3.178 (5.997)	0.051 (0.947)	2.899 (5.411)
P14	0.033 (0.856)	3.362 (6.768)	0.081 (1.418)	2.175 (5.282)
P15	−0.018 (0.410)	3.543 (6.688)	0.033 (0.558)	3.436 (5.913)
P16	0.017 (0.342)	4.325 (8.418)	0.174 (3.029)	2.224 (5.005)
P17	0.012 (0.262)	2.607 (5.438)	−0.025 (0.426)	2.896 (5.599)
P18	0.002 (0.044)	3.007 (5.759)	0.064 (1.042)	3.221 (5.961)
P19	−0.034 (0.643)	4.138 (7.926)	0.028 (0.457)	3.443 (5.934)
P20	−0.005 (0.097)	3.391 (7.096)	0.068 (1.057)	2.533 (4.981)
P21	−0.107 (1.898)	3.495 (7.390)	0.046 (0.497)	2.939 (5.981)
P22	−0.016 (0.247)	3.841 (7.913)	0.054 (0.704)	3.302 (6.697)
P23	−0.068 (0.924)	3.429 (6.309)	−0.071 (0.812)	2.412 (4.745)
P24	−0.098 (1.305)	3.157 (6.283)	−0.062 (0.661)	3.263 (6.147)
P25	0.082 (0.947)	3.033 (6.108)	−0.013 (0.120)	3.157 (6.806)
P25–P01	0.140 (1.123)	3.031 (5.733)	−0.127 (0.825)	3.603 (5.288)
Average risk price	3.201			

Estimated risk prices are highly significant for all 50 portfolios. The average estimated risk price is 3.201 and the average  $t$ -statistic is 6.171. Alphas for individual portfolios are mostly



insignificant with an average absolute value of 0.048% per month and an average  $t$ -statistic of 0.820. The finding of insignificant alphas also partly explains why we statistically reject the specification with different risk prices for market and illiquidity risks. Our estimation results suggest that the conditional LCAPM performs reasonably well and that illiquidity is a priced source of risk. These conclusions are in line with Acharya and Pedersen (2005) in their unconditional setting. We also argue that using an asset pricing model and not an ad hoc regression based approach strengthens our results. However, in our econometric framework based on equation by equation estimation, we are not able to simultaneously price multiple portfolios, which is the preferred way of test an asset pricing model’s capabilities. A more rigorous test of the conditional LCAPM is an interesting venue for future research.

#### 4.1 Illiquidity premium

The portfolio defined by difference between the most illiquid portfolio (P25) and the most liquid portfolio (P01) can be used to study illiquidity premia. The illiquidity level premium for that portfolio,  $LP$ , is according to the empirical model given by the ratio of the expected illiquidity cost and the expected holding period. The illiquidity risk premium,  $RP$ , is given by the product of the risk price and the sum of the three illiquidity risks (covariances).  $RP$  can be decomposed to three risk premia corresponding to the three separate types of illiquidity risk,  $RP = RP_1 + RP_2 + RP_3$ . The sum of the illiquidity level and risk premia is referred to as the total illiquidity premium,  $TP$ .

**Table III: Average illiquidity premium**

The table reports annualized estimated time-series averages of risk premia. Estimated risk price refers to a calculation of risk premia using the point estimate of risk price from the model for P25–P01. Average risk price refers to a calculation of risk premia using the average estimated risk price calculated over all 50 individual test portfolios. The first three columns show the total illiquidity premium ( $TP$ ), the illiquidity level premium ( $LP$ ) and the total illiquidity risk premium ( $RP$ ) with  $TP = LP + RP$ . The next three columns show  $RP_1$  related to the covariability between portfolio illiquidity and market illiquidity (the commonality risk premium),  $RP_2$  is related to the covariability between portfolio return and market illiquidity and  $RP_3$  is related to the covariability between portfolio illiquidity and market return. By definition  $RP = RP_1 + RP_2 + RP_3$ .

		$TP$	$LP$	$RP$	$RP_1$	$RP_2$	$RP_3$
Estimated risk price	Equal weighted	1.719	1.276	0.443	0.021	0.077	0.345
	Value weighted	1.439	1.013	0.426	0.014	0.065	0.347
Average risk price	Equal weighted	1.720	1.282	0.438	0.022	0.059	0.357
	Value weighted	1.337	1.024	0.313	0.014	0.065	0.234
Column average		1.554	1.149	0.405	0.018	0.067	0.321

Table III presents annualized illiquidity premia as calculated using the P25–P01 portfolio estimates of the risk price and covariances. The first row of the table shows results for the equal-weighted portfolio, for which we find an annual  $TP$  of 1.72%. This is smaller than the 4.6%

observed by Acharya and Pedersen (2005) and the 7.5% observed by Pástor and Stambaugh (2003). The study by Pástor and Stambaugh (2003) uses a non asset-pricing regression model that does not take the illiquidity level into account and sort their portfolios based on  $RP_2$  rather than illiquidity level. An important difference in Acharya and Pedersen (2005) is that they use a transformed version of the Amihud (2002) illiquidity measure. Their transformation of the measure is designed to make the level and variance correspond to an effective cost measure, and it caps extreme values at 30%. The transformed measure in Acharya & Pedersen (2005) indicates a much higher illiquidity for the most illiquid portfolio (about three times higher) than the most illiquid portfolio in this study. This may be due to sample differences or the fact that Amihud's (2002) measure is more prone to have extreme values (has higher kurtosis) than effective cost measures. As different studies differ widely in, e.g., sample selection, model specification, and portfolio formation, it is difficult to pin down the exact reason for any observed differences. Still, our result is a clear indication that the illiquidity premium in US equity markets may be smaller than previously thought.

About three quarters of the  $TP$  is due to illiquidity level compensation and the residual quarter is the illiquidity risk premium. This distribution of the illiquidity premium between  $LP$  and  $RP$  is roughly the same as in Acharya and Pedersen (2005). It is, however, important to note that portfolios in their study as well as ours are sorted by illiquidity level, not illiquidity risk. This inherently creates large differences in illiquidity level between the most illiquid and the most liquid portfolio and hence a large  $LP$ . This should not be taken as evidence of that compensation for the level of illiquidity level in general dominates the compensation for illiquidity risk. Furthermore, we show in Sections 4.2 and 4.3 that the relative importance of  $LP$  and  $RP$  varies substantially both across portfolios and over time.

The decomposition of  $RP$  shows that all three sources of illiquidity risk on average contribute positively to the illiquidity risk premium. The covariance between asset illiquidity and market return ( $RP_3$ ), related to the hedging of wealth shocks, is by far the most important illiquidity risk, with an annualized premium of 0.40%. Compensation for the risks of being illiquid ( $RP_1$ ) or having low returns ( $RP_2$ ) when the market as a whole is illiquid, is low, 0.02% and 0.08% per year, respectively. This distribution of illiquidity risk premia mirrors the results of Acharya and Pedersen (2005) almost exactly. In spite of the finding that  $RP_3$  is much higher than  $RP_1$  and  $RP_2$ , little research has since been dedicated to this type of risk. An exception is Wagner (2011), who provides a theoretical model where the ability to liquidate assets in times of distress is a main theme. He argues that as markets fall sharply, illiquidity is created as investors are

forced to liquidate their holdings simultaneously (due to e.g., funding constraints, as argued by Brunnermeier and Pedersen, 2009). Accordingly, investors with an expected high need of liquidation in times of distress should allocate their portfolios to assets with a low risk of being illiquid in such times. Our results show that this property is indeed valued in the market.

The second row of Table III shows the results for a value-weighted P25–P01 portfolio. The value-weighted portfolio has a lower  $TP$  than its equal-weighted equivalent. That difference is almost entirely due to a difference in  $LP$  between the two portfolios, which in turn is probably due to that the relatively illiquid stocks also tend to have relatively small market capitalization. The third and fourth rows of Table III show illiquidity premia as calculated using the average risk price of all portfolio models ( $\delta = 3.201$ , see Table II). The results are virtually the same as when the P25–P01 risk price estimate is applied, showing that the illiquidity premia discussed above are robust to variations in the sample of portfolios used for risk price estimation.

## 4.2 Illiquidity compensation for individual portfolios

Table IV presents illiquidity compensation for all portfolios under investigation. We note here that  $LP$  is monotonically increasing with portfolio number, both for equal-weighted and value-weighted portfolios. This is due to that the portfolios are monotonically increasing in illiquidity level and that all portfolios are subject to the same expected holding period. The illiquidity risk premium also tends to increase with portfolio numbers, indicating the well-known fact that illiquidity risk is correlated with illiquidity level (see, e.g., Acharya and Pedersen, 2005). As mentioned above, the relative importance of  $LP$  and  $RP$  varies across portfolios. In many cases in the upper half of the table,  $RP$  exceeds  $LP$ , whereas in P25 the level premium is more than double the risk premium. This implies that investors holding relatively liquid assets are more concerned with the risk of the liquidity changing than the current liquidity cost. To investors of the most illiquid assets, on the other hand, the expected level illiquid cost is more important than its potential covariation with market-wide return and illiquidity.

**Table IV: Average illiquidity compensation for individual portfolios**

The table reports annualized estimated time-series averages of compensation for illiquidity for individual portfolios. The column  $TP$  shows the total illiquidity compensation,  $LP$  the compensation for illiquidity level and  $RP$  the compensation for illiquidity risk. By definition  $TP = LP + RP$ .

	Equal weighted			Value weighted		
	$TP$	$LP$	$RP$	$TP$	$LP$	$RP$
P01	0.217	0.098	0.119	0.189	0.079	0.110
P02	0.300	0.123	0.177	0.276	0.112	0.164
P03	0.315	0.143	0.172	0.258	0.127	0.131
P04	0.343	0.157	0.186	0.330	0.144	0.186
P05	0.429	0.173	0.256	0.329	0.154	0.175
P06	0.375	0.191	0.184	0.338	0.167	0.170
P07	0.401	0.205	0.196	0.346	0.182	0.164
P08	0.411	0.223	0.188	0.402	0.192	0.210
P09	0.485	0.237	0.248	0.367	0.209	0.158
P10	0.452	0.253	0.199	0.389	0.227	0.162
P11	0.567	0.273	0.294	0.396	0.243	0.153
P12	0.652	0.289	0.363	0.526	0.256	0.270
P13	0.592	0.311	0.281	0.480	0.274	0.206
P14	0.622	0.337	0.285	0.432	0.295	0.137
P15	0.703	0.360	0.343	0.547	0.315	0.232
P16	0.972	0.402	0.570	0.472	0.338	0.134
P17	0.701	0.426	0.275	0.582	0.364	0.218
P18	0.893	0.464	0.429	0.593	0.385	0.208
P19	1.001	0.516	0.485	0.670	0.438	0.232
P20	1.069	0.575	0.494	0.704	0.473	0.231
P21	1.131	0.640	0.491	0.940	0.518	0.422
P22	1.376	0.713	0.663	1.188	0.602	0.586
P23	1.348	0.821	0.527	0.960	0.674	0.286
P24	1.516	0.984	0.532	1.205	0.809	0.396
P25	1.935	1.380	0.554	1.523	1.102	0.421

### 4.3 Time variation in illiquidity premium

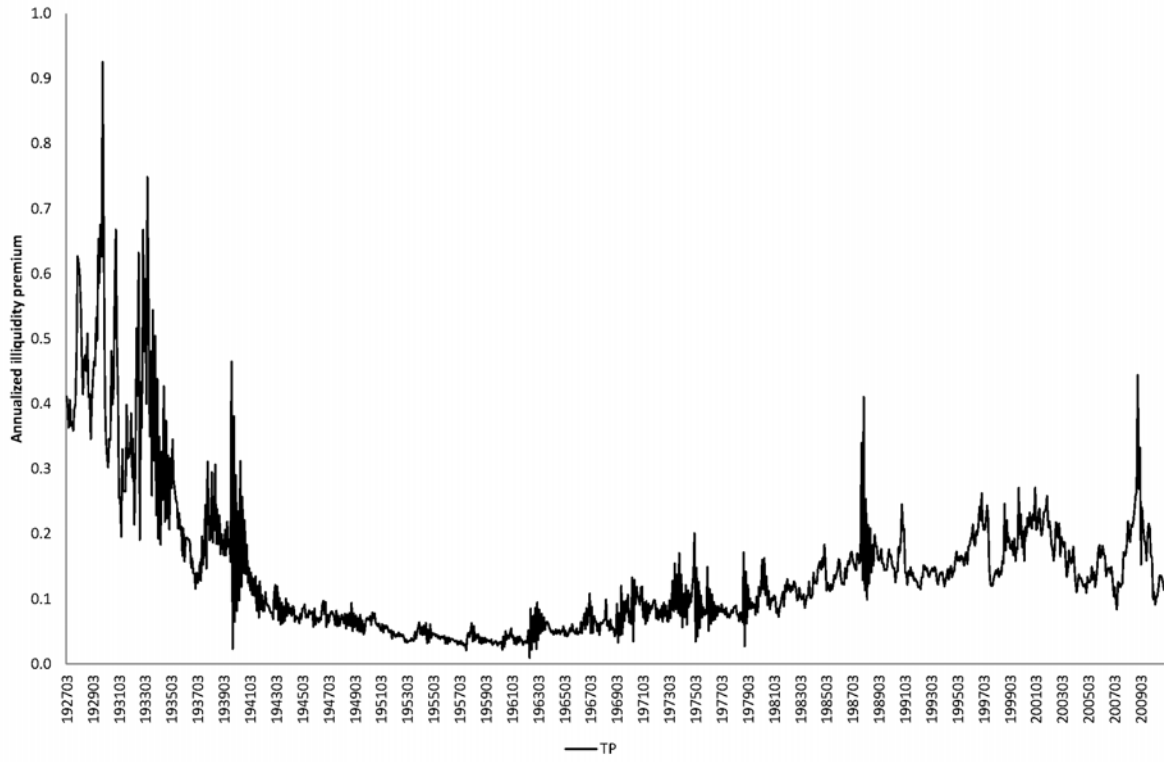
Our estimation of the conditional LCAPM model constrains the risk price ( $\delta$ ) to be constant across periods, but allows the illiquidity risks to be time-varying. The product of the risk price and the illiquidity risks provide us with time series of illiquidity premia, presented in Fig. 2 (for the equal-weighted version of the P25–P01- portfolio). Panel (a) displays time variation in  $TP$ , Panel (b) shows the same for  $LP$  and  $RP$ , and Panel (c) shows the decomposition of the illiquidity risk premium. As seen in Panel (b), the importance of the illiquidity level premium ( $LP$ ) relative to the total illiquidity risk premium ( $RP$ ) is consistent throughout our sample. The pattern in  $LP$  is similar to that of Panel (c) in Fig. 1, and we do not repeat the comments on that here.  $RP$  is high in the beginning of the 1930's and then follows a falling trend until around 1965, with exception for peaks during World War II. The relatively high illiquidity risk premium during this period, relative to the rest of the sample, should be kept in mind when comparing the results to studies based on shorter samples. During the period

1965-1975 the illiquidity risk premium appears to follow an increasing trend, and after that it is gradually decreasing. Well-known periods of distress, including the oil crises of 1973 and 1979, the October 1987 crash, the LTCM bankruptcy in 1998, and the Lehman Brothers bankruptcy in 2008, are marked by peaks and high volatility in illiquidity risk.

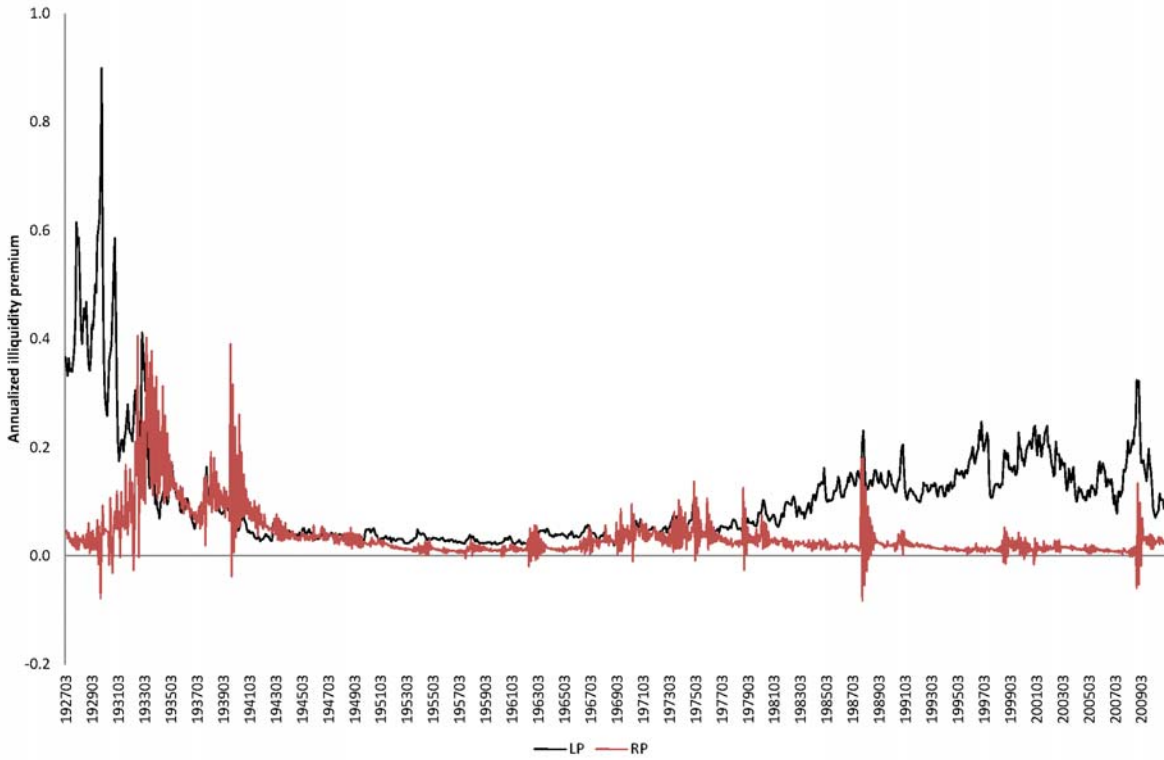
The substantial inter-temporal variation in illiquidity risks gives merit to the conditional version of LCAPM. The fact that our specification allows for time-varying illiquidity risk is a strong advantage to unconditional LCAPM specifications that allow for time variation in  $LP$ , but hold  $RP$  constant. Another conditional liquidity asset pricing model is proposed by Watanabe and Watanabe (2008). They show that illiquidity risk follows a regime-switching pattern, and that pricing of illiquidity risk is significant only when the economy is in a high illiquidity risk state. Our evidence, with short periods of high illiquidity risk around the times of financial distress, is in line with their findings. Time variation in  $LP$  has earlier been studied by Jensen and Moorman (2010). They identify links between the illiquidity premium and monetary conditions. We find that the correlation between  $LP$  and  $RP$  is not significantly different from zero (0.07). This motivates future research on determinants of the illiquidity risk premium. Visual inspection of Panel (b) also tells us that the risk premium is more volatile than the level premium.

Panel (b) of Fig. 2 shows the time variation in the different types of illiquidity risk premia. The plot shows that the dominance of  $RP_3$  is consistent over time. As discussed by Acharya and Pedersen (2005), the three time series are significantly correlated (Pearson's correlation coefficients range between 0.42 and 0.54). This is also seen in times of financial distress, where all three series seem to peak simultaneously. Looking at correlations to  $LP$  and  $RP$  (complete results not shown), we see that  $RP_3$  has a close to perfect correlation to  $RP$  (0.98), and that  $RP_1$  is the only illiquidity risk that is significantly correlated to  $LP$  (0.38).

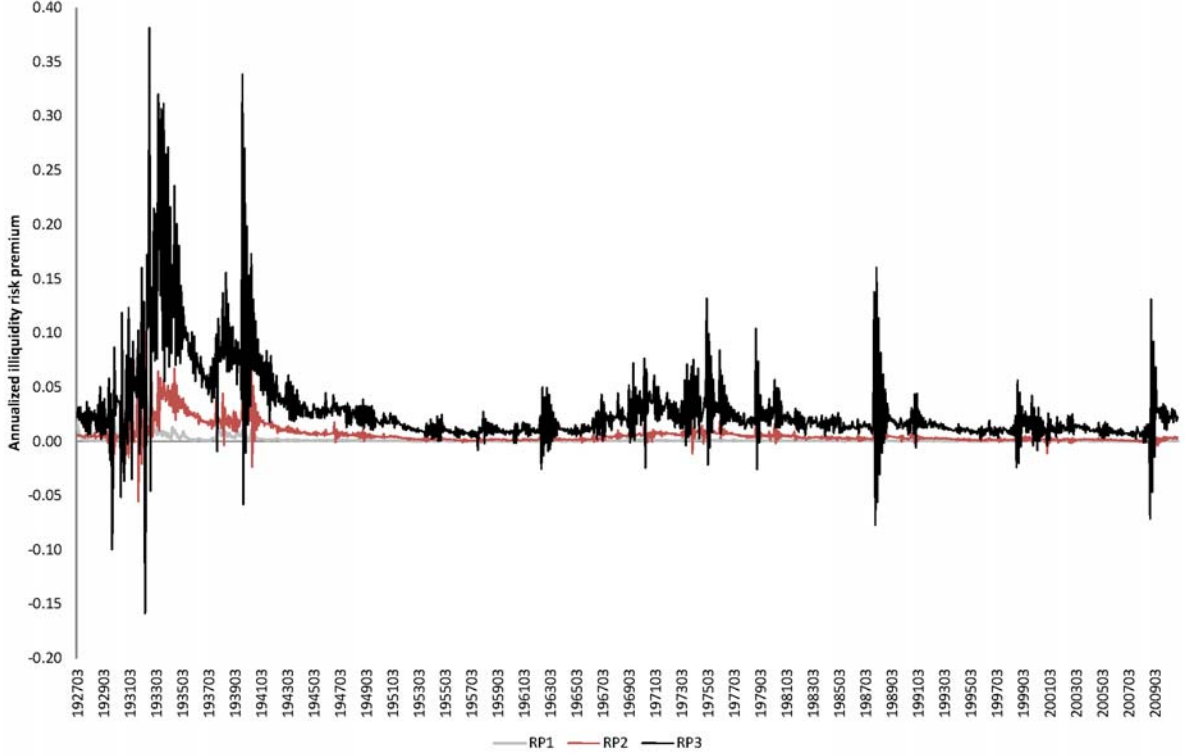
Figure 2: Time variation in illiquidity premia



(a) Total illiquidity premium



(b) Illiquidity level premium and illiquidity risk premium



(c) Decomposition of illiquidity risk premium

## 5 Conclusion

The liquidity-adjusted conditional capital asset pricing model (LCAPM) developed by Acharya and Pedersen (2005) takes into consideration that the expected asset return are determined by the level of illiquidity as well as the variation in illiquidity, i.e., the illiquidity risk. LCAPM provides an integrated view of three types of illiquidity risk: the covariance of illiquidity with market-wide illiquidity, the covariance between asset returns and market-wide illiquidity and the covariance between asset illiquidity and market returns.

In this paper we estimate LCAPM using NYSE and AMEX data from 1926 to 2010. Our empirical model differs in several ways from that of Acharya and Pedersen (2005). We estimate a conditional model where covariances are time varying while Acharya and Pedersen used constant covariances. Our monthly illiquidity measures is based on Holden (2009), which is an estimate of the cost of trading and therefore more suitable for the LCAPM than the measure used by Acharya and Pedersen (2005). Our time period is also much longer than the period studied by Acharya and Pedersen (2005): 1926-2009 vs. 1962-1999.

Our results show the following:

- Illiquidity risk varies substantially over time. The ability of our estimation to capture such time variation is a strong advantage compared to unconditional approaches.
- The total illiquidity premium, i.e., the sum of the illiquidity level premium and the illiquidity risk premium, to be 1.55%. This is markedly smaller than what has been found in previous studies of US equity markets.
- The most important type of illiquidity risk, in terms of illiquidity risk premia, is the asset illiquidity exposure to market returns. This result mirrors the findings of Acharya and Pedersen (2005). This covariance describes the risk of asset illiquidity to increase when markets are in distress. This type of illiquidity risk is discussed by Wagner (2011) but deserves more attention in future asset pricing research.

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