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The components of the illiquidity premium: An empirical analysis of US stocks 1927–2010

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ABSTRACT

This paper implements a conditional version of the liquidity adjusted CAPM (LCAPM). The conditional LCAPM allows for a time-varying decomposition of the total illiquidity premium into a level component and three risk components. The estimated average annual total illiquidity premium for US stocks 1927–2010 is 1.74–2.08%, which is substantially lower than in most previous studies. The contributions from illiquidity level and illiquidity risk are 1.25–1.28% and 0.46–0.83%, respectively. Of the three illiquidity risk components, risk related to the hedging of wealth shocks is the most important, while commonality risk is the least important. The illiquidity premia are clearly time-varying, with peaks in downturns and crises, but with no general tendency to decrease over time. The level premium and the risk premium are significantly positively correlated, at around 0.35; indicating that in periods of turbulence both illiquidity cost and illiquidity risk premia tend to be high.

1. Introduction

A large empirical and theoretical literature suggests that both the illiquidity level and the illiquidity risk influence asset prices. The conclusions of the empirical studies diverge, both with respect to the magnitude of level and risk premia, and with respect to their relative importance. The liquidity adjusted capital asset pricing model (LCAPM) by Acharya and Pedersen (2005) provides a unified theoretical framework in which both the illiquidity level and different types of illiquidity risk affect asset prices. The LCAPM is a conditional model, implying that both illiquidity betas and illiquidity risk premia potentially vary over time. Earlier empirical implementations of this model assume constant risk premia, yielding unconditional versions of the LCAPM (Acharya and Pedersen, 2005; Lee, 2011). This study is the first that empirically implements the conditional LCAPM.

The seminal paper by Amihud and Mendelson (1986) proposes that the long-term investor benefits from investment in illiquid securities. 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). Investors engaging in illiquid investment however also need to monitor their illiquidity risk. The Economist (February 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 illiquid investors found themselves forced to fire sales. In this paper, we use the LCAPM to understand to what extent stock markets price illiquidity risk, as well as to investigate its variation over time.

The LCAPM suggests that there are three types of illiquidity risk. Firstly, there is the covariance of individual asset illiquidity with market-wide illiquidity, studied by, e.g., Chordia et al. (2000). Such commonality in illiquidity is documented for all major equity markets (Brockman et al., 2009; Karolyi et al., 2012). For the US stock markets, Acharya and Pedersen (2005) find that this is the least important of the three types of illiquidity risk. Secondly, there is the covariance between individual asset return and market-wide illiquidity. This type of illiquidity risk is extensively studied. Pástor and Stambaugh (2003), Liu (2006), Watanabe and Watanabe (2008), Korajczyk and Sadka (2008), and Lou and Sadka (2011) all show that this illiquidity risk is priced in US stock markets, but Hasbrouck (2009) and Asparouhova et al. (2010) reach the opposite conclusion. Finally, there is the covariance between individual asset illiquidity and market return, which Acharya and Pedersen (2005) identify as the most important of the different illiquidity risks. Wagner (2011) argues theoretically that this risk is

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realized when investors simultaneously need to liquidate their positions. Brunnermeier and Pedersen (2009) show that such scenarios materialize when investors simultaneously hit their funding constraints and are forced to sell assets. To our knowledge, the only studies investigating all three illiquidity risks are Acharya and Pedersen (2005) and Lee (2011), who both consider 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 study contrasts that of Acharya and Pedersen (2005) in three important ways. Firstly, we do not assume constant conditional covariances, instead we estimate a conditional LCAPM with time-varying illiquidity risk. A conditional model implies that 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), which is a proxy for the effective spread. Adjusted for expected holding period, the effective spread is a measure that corresponds closely to the definition of trading cost in the LCAPM. This cost measure is arguably more suitable for the LCAPM than the transformed illiquidity ratio used by Acharya and Pedersen (2005). Finally, our investigation spans 84 years (1927–2010), which is much longer than the sample period in Acharya and Pedersen (2005). A long time-span gives credibility 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. We find that there is substantial time-variation in average holding period, and that it hence is important to account for in illiquidity asset pricing models.

The results show that there is considerable time-variation in illiquidity risk and illiquidity risk premia, supporting our conditional implementation of the LCAPM. Illiquidity risk premia are highest in periods of market turmoil, with magnitudes many times higher than in tranquil periods. The order of importance of different types of illiquidity risk in a liquidity-oriented trading strategy is the same as concluded by Acharya and Pedersen (2005). The dominating illiquidity risk is the covariance of individual asset illiquidity and market return, while commonality risk is the least important. Overall, our average estimated premia are lower than in Acharya and Pedersen (2005), and we argue that this is due to the more appropriate illiquidity cost measure used in this study. The estimated illiquidity level premium is 1.25–1.28% per year, whereas the illiquidity risk premia together reaches 0.46–0.83%, giving a total annual illiquidity premium of 1.74–2.08%. We also find that illiquidity level and illiquidity risk have a positive correlation of around 0.35, suggesting that both illiquidity cost and illiquidity risk are high in periods of market turmoil and crises.

This paper contains five sections. The next section reviews the theoretical framework of the conditional LCAPM. The third section outlines the empirical setting and includes five subsections. The first subsection discusses the econometric specification and the second subsection gives a detailed account of our estimation strategy. The remaining three subsections describe the data, the illiquidity measure and the formation of illiquidity sorted portfolios. The fourth section gives the results, starting with a subsection reporting model diagnostics and continuing with two subsections giving the main results of the paper. The final section provides a summary and conclusions.

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. The model generates 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, potentially correlated with the stochastic dividend process. Thus, the gross return r_t^i is composed of the price change plus the stochastic dividend, and the net return is the gross return minus the relative illiquidity cost c_t^i. CAPM holds for expected net return: $E_t[r_{t+1}^i - c_{t+1}^i]$, and as a result, in equilibrium the conditional expected gross return of security i is:

$$E_t[r_{t+1}^i] = r^f + E_t[c_{t+1}^i] + \frac{cov_t(r_{t+1}^i - c_{t+1}^i, r_{t+1}^m - c_{t+1}^m)}{var_t(r_{t+1}^m - c_{t+1}^m)} E_t[r_{t+1}^m - c_{t+1}^m - r^f] \quad (1)$$

$$= r^f + E_t[c_{t+1}^i] + \delta_t cov_t(r_{t+1}^i - c_{t+1}^i, r_{t+1}^m - c_{t+1}^m), \quad (2)$$

where δ_t is the time-varying price of risk defined as:

$$\delta_t \equiv \frac{E_t[r_{t+1}^m - c_{t+1}^m - r^f]}{var_t(r_{t+1}^m - c_{t+1}^m)}. \quad (3)$$

Expanding the covariance term, an equivalent formulation of Eq. (2) is:

$$E_t[r_{t+1}^i] = r^f + E_t[c_{t+1}^i] + \delta_t cov_t(r_{t+1}^i, r_{t+1}^m) + \delta_t cov_t(c_{t+1}^i, c_{t+1}^m) - \delta_t cov_t(r_{t+1}^i, c_{t+1}^m) - \delta_t cov_t(c_{t+1}^i, r_{t+1}^m). \quad (4)$$

Notice the model-implied restrictions of a single risk price δ_t.

Besides the traditional market risk, $cov_t(r_{t+1}^i, r_{t+1}^m)$, there are three additional sources of risk that are interpreted as different forms of illiquidity risk. The term $cov_t(c_{t+1}^i, c_{t+1}^m)$ represents commonality in illiquidity (Chordia et al., 2000), and it gives rise to a premium for holding a security that becomes illiquid when the market in general becomes illiquid. The term $cov_t(r_{t+1}^i, c_{t+1}^m)$ represents return sensitivity to market illiquidity, i.e., the risk of holding an asset with a low return in times of market illiquidity. An asset for which this covariance is positive is a hedge to c^m (Pástor and Stambaugh, 2003), or illiquidity shocks. The term $cov_t(c_{t+1}^i, r_{t+1}^m)$ represents illiquidity sensitivity to market return and it leads to a discount for holding an asset that is liquid in bad states of the market. 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 the LCAPM. Using the estimated model, they decompose the total compensation for illiquidity (*TP*) into a compensation for the level of illiquidity (*LP*) and a compensation for risk related to illiquidity (*RP*). The level premium is the ratio of the expected illiquidity cost and the expected holding period. The illiquidity risk premium is the product of the risk price and the sum of the three illiquidity risks (covariances). Thus, *RP* can be decomposed into three risk premium components corresponding to three separate types of illiquidity risk, $RP = RP_1 + RP_2 + RP_3$. Our analysis evolves largely around these different types of illiquidity premia, estimated using the conditional version of Acharya and Pedersen's (2005) model outlined above, allowing for time-variation in all risk premia.

3. Empirical framework

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

3.1. Econometric specification of LCAPM

We suggest to parameterize the conditional LCAPM as a quadvariate GARCH (1,1)-in-mean model. 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. We specify an AR (2) process both for illiquidity dynamics and for residual dynamics in the asset pricing equations.[1] Our joint parameterization of the mean equations and the variances-covariances in the conditional LCAPM are:

$$c_t^p = \phi_0^p + \phi_1^p c_{t-1}^p + \phi_2^p c_{t-2}^p + \eta_t^p \tag{5}$$

$$c_t^m = \phi_0^m + \phi_1^m c_{t-1}^m + \phi_2^m c_{t-2}^m + \eta_t^m \tag{6}$$

$$\begin{aligned} r_t^p = {} & \alpha_0^p + r_t^f + \gamma_t^p + \delta h_t^{r_p r_m} + \delta h_t^{c_p c_m} - \delta h_t^{r_p c_m} - \delta h_t^{c_p r_m} + g_1^p \varepsilon_{t-1}^p \\ & + g_2^p \varepsilon_{t-2}^p + \varepsilon_t^p \end{aligned} \tag{7}$$

$$\begin{aligned} r_t^m = {} & \alpha_0^m + r_t^f + \gamma_t^m + \delta h_t^{r_m r_m} + \delta h_t^{c_m c_m} - 2\delta h_t^{r_m c_m} + g_1^m \varepsilon_{t-1}^m \\ & + g_2^m \varepsilon_{t-2}^m + \varepsilon_t^m, \end{aligned} \tag{8}$$

where γ_t^p and γ_t^m denote, respectively, the expected illiquidity cost per period for the individual portfolio and the market portfolio. The definition of expected illiquidity cost is:

$$\gamma_t^k \equiv \kappa_t\left(\phi_0^k + \phi_1^k c_{t-1}^k + \phi_2^k c_{t-2}^k\right); \quad k = p, m, \tag{9}$$

where κ_t is the reciprocal of the expected holding period. The theoretical model assumes a one-period investment horizon, implying $\gamma_t^k = E_{t-1}[c_t^k]$. In our empirical setting, there are three modifications of the theoretical model. Firstly, the investment horizon can differ from one period. Expected illiquidity is a cost, measured in dollars per dollar invested, and therefore does not scale with sampling frequency. Secondly, the investment horizon can vary over time, which we motivate by the observation that average holding period indeed varies over time (see Section 3.4). Finally, the constants in the return equations, α_0^p and α_0^m, are zero according to the theoretical model. In the empirical model, we allow for a non-zero intercept for the individual portfolio, but we require the model to price the market portfolio with no systematic pricing error.

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

$$H_t = \begin{pmatrix} h_t^{c_p c_p} & h_t^{c_p c_m} & h_t^{c_p r_p} & h_t^{c_p r_m} \\ & h_t^{c_m c_m} & h_t^{c_m r_p} & h_t^{c_m r_m} \\ & & h_t^{r_p r_p} & h_t^{r_p r_m} \\ & & & h_t^{r_m r_m} \end{pmatrix}. \tag{10}$$

We assume that the variance–covariance matrix follows a quadvariate GARCH process of BEKK type developed by Engle and Kroner (1995) and Kroner and Ng (1998):

$$H_t = C'C + A'e_{t-1}e_{t-1}'A + B'H_{t-1}B + D'\xi_{t-1}\xi_{t-1}'D, \tag{11}$$

where $e_{t-1}e_{t-1} = (\eta_{t-1}^p, \eta_{t-1}^m, \varepsilon_{t-1}^p, \varepsilon_{t-1}^m)'$ is the vector of error terms and $\xi_{t-1} = (\max[\eta_{t-1}^p, 0], \max[\eta_{t-1}^m, 0], \min[\varepsilon_{t-1}^p, 0], \min[\varepsilon_{t-1}^m, 0])'$ is the vector of asymmetric error terms.[2] The specification of the matrix C is such that $C'C$ is guaranteed to be positive semi-definite and A, B, and D are symmetric matrices. McAleer et al. (2008), Proposition 1, provide theoretical foundation for the BEKK specification. Their Proposition 1 states that the BEKK specification is a special case of a vector random coefficient autoregressive process. They argue, "In conjunction with the theoretical results in Comte and Lieberman (2003), Proposition 1 provides strong justification for using BEKK to model the conditional covariances directly" (p. 1559). The BEKK specification also allows us to incorporate the required covariance feedback terms in the return equations as postulated by the LCAPM. Finally, specifications that are more general naturally allow for richer variance–covariance dynamics. We estimate four different versions of the BEKK specification of increasing complexity: diagonal symmetric, diagonal asymmetric, nondiagonal symmetric and nondiagonal asymmetric.[3]

The only liquidity study we are aware of using a similar econometric framework is Gibson and Mougeot (2004), estimating a bivariate BEKK specification focusing solely on market portfolio illiquidity risk. An alternative approach to model a time varying illiquidity risk premium is taken by Watanabe and Watanabe (2008) using a Markov regime-switching model to identify high and low liquidity-beta periods in the sample. This approach implies that they allow for only two different values of the illiquidity risk premium ("high" and "low"). Furthermore, Gibson and Mougeot (2004) and Watanabe and Watanabe (2008) do not consider the decomposition of the illiquidity risk premium and do not allow for an illiquidity level premium. We therefore regard our empirical model as an important step forward.

3.2. Estimation

The parameters in the econometric models are estimated using quasi-maximum likelihood with the log-likelihood function under conditional normality given by:

$$\begin{aligned} \ln L(\theta) = {} & -\frac{NT}{2}\ln(2\pi) - \frac{1}{2}\sum_{t=1}^{T}\ln|H_t(\theta)| \\ & -\frac{1}{2}\sum_{t=1}^{T} e_t'(\theta)H_t^{-1}(\theta)e_t(\theta), \end{aligned} \tag{12}$$

where N is the number of cross-sectional dimensions and T is the number of time-series observations. In the present application $N = 4$ and $T = 1008$. Initial values for residuals are set equal to zero and initial values for conditional variances and covariances are set equal to their sample counterparts. Due to the autoregressive structures, all estimations are conditional on the first two time-series observations. The parameter vector θ contains the autoregressive parameters, the constant in the portfolio return equation, the risk price and the parameters in the variance–covariance matrices. The total number of parameters in the four different specifications is: 30 (diagonal symmetric), 34 (diagonal asymmetric), 42 (nondiagonal symmetric) and 52 (nondiagonal asymmetric).

Conventional algorithms for various reasons have difficulties converging to the global optimum (if they converge at all) when the number of parameters increases. To resolve this problem, our estimation strategy is to replace the standard gradient based hill climbing algorithms with simulated annealing, a derivative-free stochastic search algorithm. The algorithm has its roots in physics, while Goffe et al. (1994) provide an econometric perspective. Simulated annealing is in theory able to escape from local optima and is therefore not sensitive to parameter starting values. To further increase the likelihood of identifying the global optimum, we implement a sequential estimation strategy and use the optimal

[1] Many papers postulate an AR (2) specification for illiquidity dynamics, e.g., Amihud (2002), Pástor and Stambaugh (2003), Acharya and Pedersen (2005) and Korajczyk and Sadka (2008). We adhere to this assumption. The AR (2) specification for residual dynamics in asset pricing equations is designed to remove remaining residual autocorrelation. Subsection 4.1 reports specification tests.

[2] When the parameter matrix D is diagonal, the definition of the asymmetric error term implies that a positive own illiquidity shock and a negative own return shock increase the variance of illiquidity and return (all other things being equal). When D is nondiagonal, there are in addition asymmetric variance effects across equations.

[3] The word "diagonal" indicates that the parameter matrices A, B, and D are all diagonal and the word "nondiagonal" that they are all nondiagonal. The word "asymmetric" indicates that the estimation includes the asymmetric term. Subsection 4.1 reports specification tests.

parameter values for simpler specifications as starting values for the more complex models. In addition, we estimate each specification ten times, each estimation using different quasi-random paths through the parameter space.[4] The estimation strategy outlined above is clearly very computer intensive. Estimation of a single model takes approximately between 72 and 120 h. We therefore execute all optimizations on a high performance computer cluster.

3.3. Data

We investigate the pricing of illiquidity in US equity markets for the period 1927–2010. For illiquidity measurement, we use stock prices from the Centre for Research in Security Prices (CRSP) daily database, and for portfolio return calculation, we use stock returns from the CRSP monthly files. Given the sample period, our investigation is limited to stocks traded at the New York Stock Exchange (NYSE) and the American Stock Exchange (AMEX). To estimate the expected holding period, we retrieve yearly data on average stock turnover from the NYSE homepage.

3.4. Illiquidity measure and average holding period

The relative illiquidity cost measure in the LCAPM corresponds closely to the relative effective spread. The relative effective spread is twice the difference between the actual trade price and the market quote at the time of order entry, divided by the actual trade price. The effective spread thereby 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). As intraday data are unavailable for many markets and in particular for long time series, several approximations of the effective spread utilizing daily data are available. Goyenko et al. (2009) implement a horserace between different proxies and conclude that the effective tick proxy by Holden (2009) and the effective cost proxy by Hasbrouck (2009) are preferable to other proxies. Both proxies are highly correlated with the effective spread and they reflect the level of the true spread, for periods when intraday data are available. As Hasbrouck's (2009) measure is available only at an annual frequency, we use Holden's (2009) effective tick proxy in this study.

Holden's (2009) measure of illiquidity builds on the empirical observation that trade prices tend to cluster around specific numbers, so called 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 assumes that trade is conducted in two steps. First, in order to minimize negotiation costs traders decide what price cluster to use on a particular day. Then, traders negotiate a particular price from the chosen price cluster. This proxy for the effective spread thereby relies on the assumption that the effective spread on a particular day equals the price increment of the price cluster used that day.[5]

The fact that the effective tick is a direct measure of trading costs is a non-trivial advantage compared to the illiquidity ratio of Amihud (2002) applied by Acharya and Pedersen (2005), as LCAPM by construction requires illiquidity to be measured as a trading cost. By using the effective tick, we therefore circumvent the transformation employed by Acharya and Pedersen (2005) to convert Amihud's illiquidity ratio into a cost measure. In conjunction with our presentation of results below, we discuss in detail what implications the choice of illiquidity measure may have for estimates of illiquidity premia (see Section 4.2).

It is important to consider how often trading costs are incurred when accounting for illiquidity costs in asset pricing models. We observe that the average holding period is not constant over time and considering this time-variation can therefore potentially improve the fit of the conditional LCAPM. The average holding period is reciprocal to the average turnover rate and we use annual NYSE turnover rates to estimate the average holding period.[6]

Fig. 1 shows time-series of the effective tick for the equal weighted market portfolio (Panel a), c_t^m, the reciprocal of the average holding period (in months; Panel b), κ_t, and their product, which is an estimate of the monthly average realized illiquidity cost (Panel c). The general message from the graphs is that both effective tick and average holding period vary over the sample. Effective tick is at its highest during the great depression in the first years of the 1930s, with maximum over 5%, and with a tendency to decrease over time to its current value of about 0.25% (with a peak during the financial crisis at the end of 2008). At the same time, there is a tendency for average holding period to decrease over time from its high in the first years of the 1940s, implying that illiquidity cost *per period* is not falling as much as suggested by the decrease in effective tick. In fact, illiquidity cost per month is currently around 1%, a decrease compared to the period 1980–2000, but similar to the period 1950–1970. These observations suggest that not taking time-variation in the expected investment horizon into account would lead to overestimation of monthly illiquidity costs during some periods, and underestimation of monthly illiquidity costs during other periods.

3.5. Illiquidity sorted portfolios

To construct illiquidity sorted portfolios we follow a procedure similar to previous literature. 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 used by for example Amihud (2002), Pástor and Stambaugh (2003) and Acharya and Pedersen (2005). To include a stock we also require that price data is available at least 100 days in a particular year. For all stocks included, we calculate the effective tick 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), sorting by the annual estimated illiquidity for individual stocks in the previous year. We sort stocks into 25 portfolios and repeat the procedure for each year, 1927–2010. 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.

For each portfolio, we calculate equal weighted monthly return (r_t^p) and monthly illiquidity cost (c_t^p) for the twelve months

[4] For the diagonal symmetric, diagonal asymmetric and nondiagonal symmetric model specifications, the optimization algorithm finds the same optimum in all 10 estimations. For the nondiagonal asymmetric model specification, the optimization algorithm identifies two different optima with likelihood values very close to each other (we report results only for the best optimum).

[5] For the NYSE and AMEX stock used in this study, the we definie the possible price clusters (price increments) as: \$1/8, \$1/4, \$1/2 and \$1 before July 1997, \$1/16, \$1/8, \$1/4, \$1/2 and \$1 from July 1997 up to January 2001, and \$0.01, \$0.05, \$0.10, \$0.25 and \$1 after January 2001.

[6] 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.

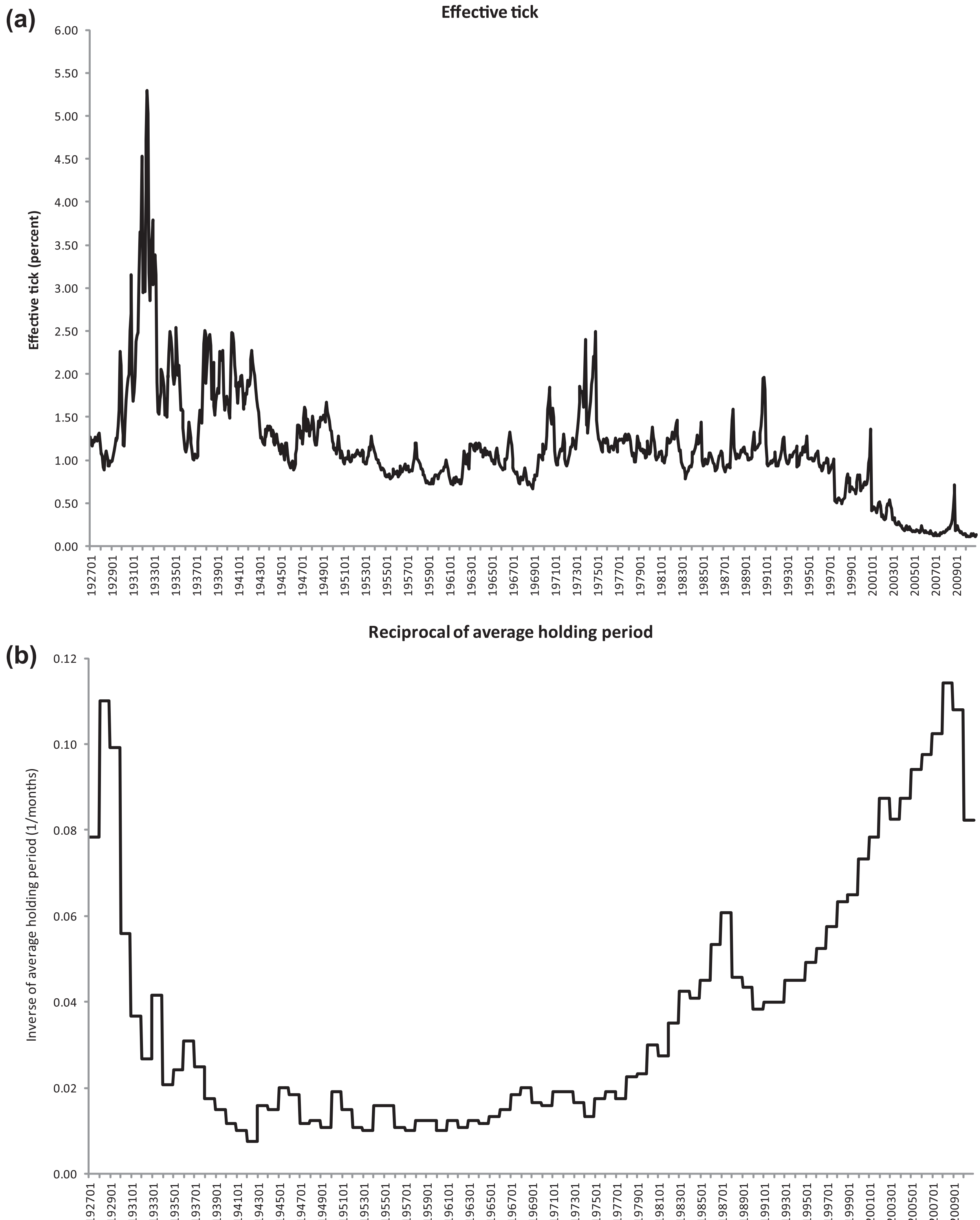

Fig. 1. (a) The effective tick for the market portfolio. (b) The reciprocal of the average holding period for the market portfolio. (c) The realized illiquidity cost for the market portfolio, defined as the product of the effective tick and the reciprocal of the average holding period.

following the portfolio formation date. Similarly, we calculate monthly market portfolio return (r_t^m) and monthly market illiquidity cost (c_t^m) as equal weighted averages of all eligible stocks. As an alternative to equal weighted test portfolios, it is common in the literature to use portfolio weights based on market capitalization. Imposing such a weighting scheme on the stocks, however, after sorting them into portfolios, is an unnecessary distortion of the original sorting (see Hasbrouck, 2009). Thus, we focus on equal weighted test portfolios throughout our analysis. Acharya and Pedersen (2005) and Hasbrouck (2009) argue that a value weighted market portfolio understates the illiquidity of the true market portfolio, due to the obvious dominance of large liquid

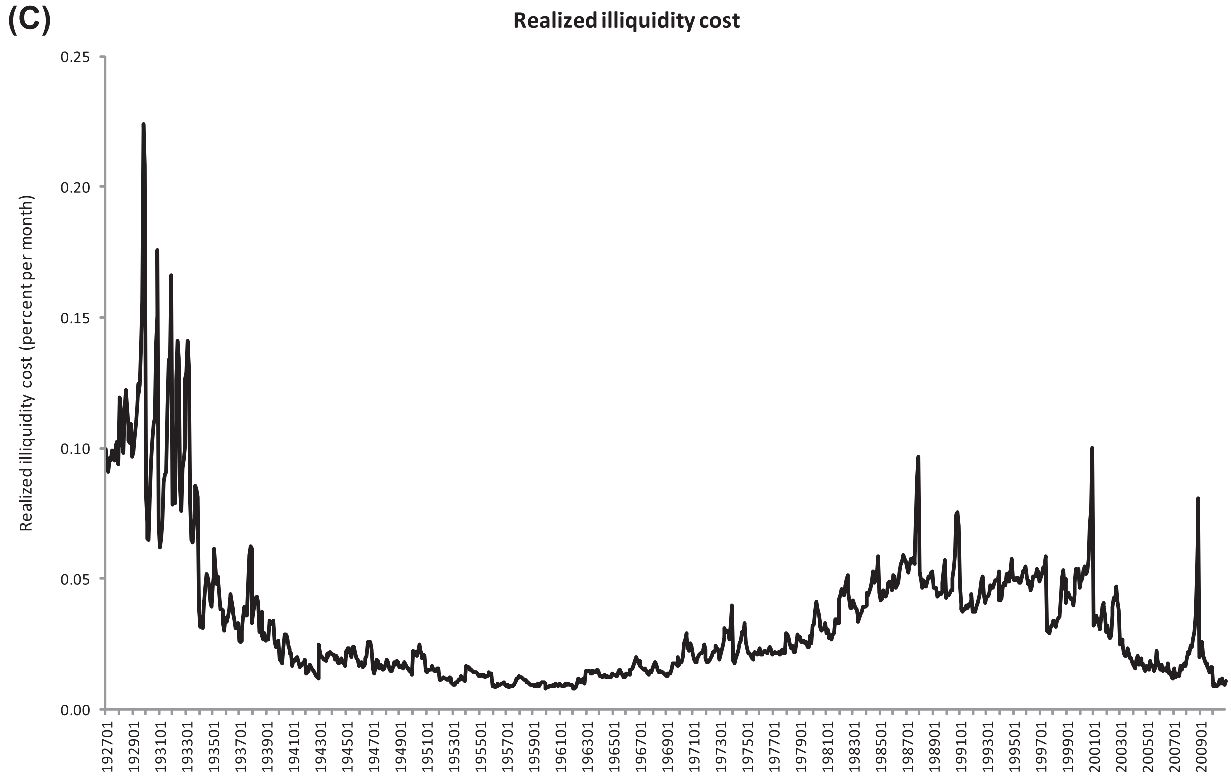

Fig. 1. (*continued*)

stocks. We therefore use an equal weighted market portfolio. As value weighted portfolios are common in the literature, however, we repeat the analysis using value weighted portfolios. The results, which are available upon request from the authors, are qualitatively the same as for equal weighted portfolios.

Following Shumway (1997), we set the delisting stock 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.[7] Asparouhova et al. (2010) argue that microstructure noise in security prices causes an upward bias in calculated returns. In a simple model of measurement errors, they quantify the size of this bias to $S^2/3$, where S is the relative effective spread. Our illiquidity measure by definition is a proxy for the effective spread, and we incorporate this correction directly in all returns for individual stocks used in the calculation of portfolio returns (excluding delisting returns). Table 1 presents post-formation characteristics of the illiquidity sorted portfolios.

We find that portfolio P25 has the highest average illiquidity and the highest average return. It also has the highest average illiquidity variability and among the highest average return variability. Portfolio P01 has the lowest average illiquidity and the second lowest average return. It also has the lowest average illiquidity variability and the lowest average return variability. The fact that the ex post portfolio ranking is identical to the ex ante ranking strongly suggests that illiquidity is a persistent characteristic of individual stocks. The portfolio properties also indicate that illiquidity is priced by the market in the sense that illiquid stocks are rewarded a higher return than are liquid stocks. In order to analyze the illiquidity premium, our estimations of conditional LCAPM naturally focus on the illiquidity portfolio, P25–P01 (the most illiquid portfolio minus the most liquid portfolio).

[7] We assign a delisting return of −30% 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).

4. Results

This section presents estimation results for the conditional LCAPM. As the estimation strategy is a core contribution of this

Table 1
Ex post characteristics of equal weighted illiquidity sorted portfolios. The columns show average portfolio illiquidity, standard deviation of portfolio illiquidity, average portfolio return and standard deviation of portfolio return. Averages and standard deviations are monthly and expressed in percentage terms. P01 is the most liquid portfolio and P25 is the most illiquid portfolio.

	Portfolio characteristics			
	$\mu(c^p)$	$\sigma(c^p)$	$\mu(r^p)$	$\sigma(r^p)$
P01	0.284	0.134	0.919	5.626
P02	0.373	0.170	0.877	5.874
P03	0.433	0.206	0.926	5.866
P04	0.484	0.237	0.969	6.050
P05	0.528	0.269	1.002	6.502
P06	0.579	0.300	0.949	6.283
P07	0.622	0.338	1.022	6.460
P08	0.665	0.375	1.127	6.613
P09	0.712	0.394	1.113	6.704
P10	0.768	0.448	1.011	6.519
P11	0.813	0.451	1.094	6.472
P12	0.864	0.499	1.115	6.736
P13	0.922	0.635	1.214	7.092
P14	0.990	0.606	1.174	6.890
P15	1.066	0.628	1.189	6.922
P16	1.157	0.757	1.124	7.549
P17	1.224	0.713	1.224	7.379
P18	1.321	0.774	1.238	7.135
P19	1.455	0.833	1.249	7.429
P20	1.608	0.979	1.289	7.640
P21	1.754	0.968	1.145	7.773
P22	1.932	1.105	1.333	7.813
P23	2.191	1.282	1.240	7.978
P24	2.527	1.294	1.231	7.666
P25	3.331	1.668	1.359	7.667

paper, we begin with reporting parameter estimates and test results for our four alternative model specifications. We then present our economic results and benchmark them to the previous literature. We first focus on estimated average level and risk illiquidity premia and then on the time-variation in estimated premia.

4.1. Model diagnostics

Table 2 reports parameter estimates and log-likelihood values for the estimated models. We find that standard LR-tests reject the symmetric models against their asymmetric counterparts at very high confidence levels.[8] LR-tests also reject both diagonal models against their nondiagonal counterparts.[9] These results clearly indicate that both asymmetric effects and spillover effects are important features of the data. The large number of significant conditional variance parameters (matrices *A*, *B* and *D*) further manifests this conclusion. For the diagonal symmetric model all 8 parameters are significant, for the diagonal asymmetric model 11 out of 12 parameters are significant, for the nondiagonal symmetric model 14 out of 20 parameters are significant, and for the nondiagonal asymmetric model 21 out of 30 of these parameters are significant. The price of risk (δ) in the asset pricing equations is significant and estimated at an economically reasonable value in all four model specifications. Furthermore, the portfolio alpha (α_0^p) is insignificant in all specifications. These results suggest that the conditional LCAPM performs well from an economic perspective and that illiquidity is a priced source of risk.

Following the generic procedures in Wooldridge (1991) we implement robust versions of regression based LM-tests of residual autocorrelation, ARCH effects, and the Engle and Ng (1993) sign/size bias test. Altogether we perform 48 residual based tests; four model specifications with four equations in each specification and three different tests. Table 3 reports the residual diagnostics results. Firstly, with a single exception there is no remaining autocorrelation in residuals. Secondly, again with only one exception, there is no evidence of remaining ARCH effects. Thirdly, for three of the model specifications there are indications of sign or size bias in the market return equation, but not in the other three equations. Finally, we note that the nondiagonal asymmetric model passes all three tests for all four equations.

The model diagnostics discussed above suggest that we may regard the nondiagonal asymmetric specification as our preferred econometric model. However, encouraged by the overall good model performance, and in particular for reasons of comparison and robustness, we choose to present our main economic results for all four specifications in the next two subsections of the paper.

4.2. Average illiquidity premia

Table 4 presents annualized illiquidity premia as calculated using the estimates of the risk price and covariances. The first row of the table shows the results for *TP*, taking values in the range of 1.74–2.08%, depending on model specification. Comparing this total illiquidity premium to similar studies, Pástor and Stambaugh (2003) find an annual premium of 7.5% and Acharya and Pedersen (2005) report a *TP* of 4.6%. Pástor and Stambaugh (2003) do not rely on an underlying asset pricing model and do not consider the illiquidity level. They also sort their portfolios based on systematic illiquidity risk [$cov(r^i,c^m)$] rather than illiquidity level, making a detailed comparison to our study difficult. The methodology of Acharya and Pedersen (2005) also differ in many dimensions to our study, but as we have the same asset pricing model as starting point, we give a detailed analysis of the differences in results.

An important difference between the study by Acharya and Pedersen (2005) and our paper is that we analyze a much longer sample period. To make the comparison to their results more useful, we calculate illiquidity premia for the subsample corresponding to their sample period, 1964–1999. For brevity, we perform this comparison for the nondiagonal asymmetric specification only. Our *TP* for the sample period in question is 1.44%, which decomposed into level and risk premia is *LP* = 1.08% and *RP* = 0.36%. Both premia are substantially smaller than those reported by Acharya and Pedersen (2005). The largest difference is for the level premium *LP*, which is 3.5% in their study, more than three times higher than our estimate. Given that we have the same data sources (CRSP and NYSE), the same limitation to NYSE and AMEX stocks (albeit with slight differences in data filtering), and that we follow the same portfolio formation methodology, the liquidity level premium difference should be due to either the definition of holding period (κ) or the liquidity measure used. The fact that we allow κ to vary over time, whereas Acharya and Pedersen (2005) hold it constant, may induce differences in *LP* in certain periods, but can only to a limited extent explain differences in the average for the whole subsample period. Thus, the main source of the difference in *LP* is the choice of liquidity measure.

As discussed in Subsection 3.4, we measure illiquidity using Holden's (2009) effective tick because it is the most reliable effective spread approximation available using low frequency (daily) data. As the effective tick measure was not yet available at their time of writing, Acharya and Pedersen (2005) designed their transformation of Amihud's (2002) illiquidity ratio to make its level and variance correspond to an effective spread measure. A weakness of the transformation is that the illiquidity ratio does not only differ from effective spreads in mean and variance, it also has much higher (positive) skewness and kurtosis. According to Hasbrouck (2009), skewness and kurtosis of effective spreads are 4.6 and 54.7, respectively, whereas the corresponding metrics for the illiquidity ratio are 16.6 and 395.8. The third and fourth moments thus imply that the illiquidity ratio has a much higher propensity to large outliers than the effective spread. Acharya and Pedersen (2005) address this problem by capping their liquidity measure at 30%. Still, the transformed measure in Acharya and Pedersen (2005) indicates that their most illiquid portfolio is about three times as illiquid as the most illiquid portfolio in this study. Their most liquid portfolio has about the same illiquidity as the most liquid portfolio in our study. Hence, their difference in illiquidity between P25 and P01 is about three times larger in their study, and this difference feeds directly through to the estimate of the illiquidity level premium.

According to our results, about two thirds of the total illiquidity premium are due to illiquidity level compensation. The remaining third is the illiquidity risk premium. The full sample estimates of *LP* and *RP* are 1.25–1.28% and 0.46–0.83%, respectively. This distribution of the illiquidity premium between *LP* and *RP* is roughly the same as in Acharya and Pedersen (2005). The total illiquidity risk premium, *RP*, is about a third of that reported by Acharya and Pedersen (2005). This difference again originates mainly from the measurement of illiquidity since the components of *RP* are directly proportional to the covariances with illiquidity. Even though other methodological differences may be important, our results suggest that the illiquidity premium in US equity markets is smaller than previously thought. In the next section, we show that the magnitudes of *LP* and *RP* vary substantially over time and that the relative importance of *LP* and *RP* varies with market conditions, highlighting the advantages of a conditional model.

[8] The test statistics are 406.87 (diagonal symmetric against diagonal asymmetric) and 476.56 (nondiagonal symmetric against nondiagonal asymmetric). The critical values at the 95% confidence level are 9.49 and 18.31, respectively.

[9] The test statistics are 134.76 (diagonal symmetric against nondiagonal symmetric) and 204.45 (diagonal asymmetric against nondiagonal asymmetric). The critical values at the 95% confidence level are 21.03 and 28.87, respectively.

Table 2
Parameter estimates, absolute *t*-values and log-likelihood values for the four different model specifications of the conditional LCAPM: diagonal symmetric, diagonal asymmetric, nondiagonal symmetric, and nondiagonal asymmetric. Calculation of robust standard errors follows Bollerslev and Wooldridge (1992).

	Model specifications							
	Diagonal symmetric		Diagonal asymmetric		Nondiagonal symmetric		Nondiagonal asymmetric	
	Coeff.	|*t*-Stat.|	Coeff.	|*t*-Stat.|	Coeff.	|*t*-Stat.|	Coeff.	|*t*-Stat.|
Liquidity cost equations parameters								
ϕ_0^p	0.139	2.52	0.148	3.82	0.148	2.96	0.165	4.14
ϕ_1^p	0.665	18.33	0.699	22.96	0.657	19.68	0.679	22.53
ϕ_2^p	0.276	8.34	0.252	8.80	0.275	9.05	0.263	9.68
ϕ_0^m	0.010	2.51	0.011	3.20	0.011	3.09	0.017	5.34
ϕ_1^m	0.774	20.53	0.880	30.39	0.776	21.46	0.862	33.53
ϕ_2^m	0.210	5.50	0.113	4.02	0.205	5.60	0.125	5.01
Return equations parameters								
α_0^p	0.098	0.63	−0.108	0.75	0.258	1.84	−0.149	1.05
δ	2.917	5.01	2.419	5.07	3.255	6.19	2.720	5.82
g_1^p	0.067	1.98	0.076	2.39	0.061	1.86	0.076	2.68
g_2^p	0.028	0.90	0.031	1.06	0.020	0.66	0.052	1.89
g_1^m	−0.174	5.10	−0.142	4.45	−0.150	4.43	−0.115	3.57
g_2^m	0.088	2.10	0.074	2.69	0.058	1.75	0.072	2.80
A matrix								
a_{11}	0.493	10.52	−0.022	0.49	0.341	8.41	0.243	6.21
a_{22}	0.593	14.76	0.083	2.17	0.593	8.63	−0.022	0.60
a_{33}	0.181	6.40	0.202	4.49	0.200	6.71	0.223	6.73
a_{44}	0.243	9.06	0.292	8.76	0.251	7.57	0.242	7.94
a_{12}					0.003	0.27	−0.025	3.02
a_{13}					−0.005	1.51	−0.010	2.88
a_{14}					−0.016	3.16	−0.003	0.69
a_{23}					−0.001	1.14	−0.001	1.69
a_{24}					−0.001	0.75	−0.002	3.09
a_{34}					−0.050	2.44	0.116	5.56
B matrix								
b_{11}	0.843	33.55	0.914	65.25	0.875	37.05	0.821	30.16
b_{22}	0.824	54.32	0.873	51.71	0.755	22.76	0.795	29.44
b_{33}	0.977	146.39	0.964	72.99	0.957	81.32	0.940	72.40
b_{44}	0.952	151.09	0.914	72.23	0.943	91.68	0.919	76.95
b_{12}					0.005	0.48	0.004	0.51
b_{13}					−0.006	2.16	−0.011	4.02
b_{14}					0.005	2.48	0.006	3.14
b_{23}					−0.002	2.81	−0.001	1.87
b_{24}					−0.001	0.98	−0.001	2.52
b_{34}					0.030	3.42	0.049	5.32
D matrix								
d_{11}			0.492	10.66			0.454	5.99
d_{22}			0.716	13.04			0.617	6.65
d_{33}			0.204	3.97			0.055	0.99
d_{44}			0.250	5.41			0.255	6.49
d_{12}							0.011	0.83
d_{13}							0.018	2.81
d_{14}							−0.026	5.64
d_{23}							−0.002	2.15
d_{24}							−0.001	1.07
d_{34}							0.002	0.06
$\ln L(\theta)$	−5470.96		−5267.53		−5403.58		−5165.30	

The decomposition of *RP* shows that all three sources of illiquidity risk on average contribute positively to the illiquidity risk premium. The covariance of asset illiquidity and market return (RP_3) related to the hedging of wealth shocks is by far the most important illiquidity risk. The annualized estimated premium is 0.38–0.68%, depending on model specification (for the full sample). Compensation is low for the risks of being illiquid (RP_1) or having low returns (RP_2) when the market as a whole is illiquid: 0.02–0.04% and 0.06–0.12% per year. This distribution of average illiquidity risk premia across the three risk types is very similar to the findings of Acharya and Pedersen (2005).

In spite of the finding that RP_3 is much higher than RP_1 and RP_2, little research is dedicated to this type of illiquidity 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 demand of selling 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.

4.3. Time-variation in illiquidity premia

Our empirical models of the conditional LCAPM model constrain the risk price (δ) to a constant value across periods, but allows for time-varying illiquidity risk. The product of the risk price and the illiquidity risk provides us with time-series of monthly illiquidity premia for each model. Table 5 presents

Table 3
Tests against 10th order autocorrelation in residuals (AC), 10th order autocorrelation in squared residuals (ARCH), and sign/size bias in the conditional variance equations (Engle and Ng, 1993) for the four different model specifications of the conditional LCAPM; diagonal symmetric, diagonal asymmetric, nondiagonal symmetric and nondiagonal asymmetric. We implement robust versions of all tests following Wooldridge (1991). The columns for each model specification show test statistics and *p*-values. Critical values at the 95% confidence level for the AC and ARCH tests are 18.31 and for the sign/size bias test 7.82.

	Diagonal symmetric		Diagonal asymmetric		Nondiagonal symmetric		Nondiagonal asymmetric	
	χ^2-stat	*p*-Value	χ^2-stat	*p*-Value	χ^2-stat	*p*-Value	χ^2-stat	*p*-Value
AC								
c^p	6.48	0.773	8.03	0.626	6.19	0.799	10.28	0.417
c^m	9.97	0.443	8.70	0.561	9.97	0.443	9.47	0.488
r^p	10.71	0.381	12.94	0.227	18.52	0.047	15.76	0.107
r^m	11.36	0.330	7.62	0.666	9.06	0.526	8.11	0.618
ARCH								
c^p	13.76	0.184	13.94	0.176	14.49	0.152	12.09	0.279
c^m	21.92	0.016	14.74	0.142	15.42	0.117	14.68	0.144
r^p	10.63	0.387	6.97	0.728	10.67	0.384	9.80	0.458
r^m	12.74	0.239	14.25	0.162	12.83	0.233	11.37	0.329
SIGN/SIZE								
c^p	2.83	0.419	0.28	0.963	4.45	0.216	1.45	0.695
c^m	4.25	0.236	6.92	0.074	6.54	0.088	6.63	0.085
r^p	0.99	0.804	1.20	0.754	1.04	0.792	1.18	0.758
r^m	16.36	0.001	12.43	0.006	8.08	0.044	5.61	0.132

Table 4
Annualized estimated time-series averages of risk premia for each of the four different model specifications of the conditional LCAPM: diagonal symmetric, diagonal asymmetric, nondiagonal symmetric, and nondiagonal asymmetric. The first three rows 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 rows show RP_1, which is the compensation for comovement of portfolio illiquidity and market illiquidity (commonality risk); RP_2, which is compensation for comovement of portfolio return and market illiquidity; and RP_3, which is compensation for comovement of portfolio illiquidity and market return. By definition $RP = RP_1 + RP_2 + RP_3$.

	Model specifications			
	Diagonal symmetric	Diagonal asymmetric	Nondiagonal symmetric	Nondiagonal asymmetric
TP	1.886	1.735	2.083	1.893
LP	1.262	1.277	1.254	1.274
RP	0.626	0.458	0.828	0.618
RP_1	0.030	0.020	0.036	0.023
RP_2	0.082	0.060	0.116	0.083
RP_3	0.512	0.378	0.676	0.511

Table 5
Risk premia correlations. Panel A shows time-series Pearson correlations between the risk premium (*RP*) as estimated in four different model specifications of the conditional LCAPM: diagonal symmetric, diagonal asymmetric, nondiagonal symmetric, and nondiagonal asymmetric. Panel B shows, for each model specification, time-series correlations between the level premium (*LP*) and the risk premium (*RP*) as estimated within the same model specification.[a]

RP/*RP*	Model specifications			
	Diagonal symmetric	Diagonal asymmetric	Nondiagonal symmetric	Nondiagonal asymmetric
Panel A: Risk premium correlations across model specifications				
Diagonal symmetric	1			
Diagonal asymmetric	0.909	1		
Nondiagonal symmetric	0.975	0.915	1	
Nondiagonal asymmetric	0.831	0.939	0.839	1
Panel B: Correlations between level and risk premia within model specifications				
LP/*RP*				
Diagonal symmetric	0.321			
Diagonal asymmetric		0.404		
Nondiagonal symmetric			0.287	
Nondiagonal asymmetric				0.372

[a] All correlations are statistically significant at the 5% level.

correlations between illiquidity risk premia (*RP*) estimated in different empirical specifications (Panel A), and correlations between the level premium and the risk premium within each specification (Panel B). We find that *RP* is highly correlated across the four models. In particular, the two symmetric specifications record a correlation of 0.98, and the two asymmetric model specifications have a risk premium correlation of 0.94. Furthermore, the correlations among the components of *RP*, i.e., RP_1, RP_2 and RP_3, are also high (not tabulated). Across symmetric models these correlations are in the range [0.94, 0.98] and across asymmetric models in the range [0.80, 0.97]. Motivated by the high correlations, we present time series plots of each illiquidity premium for the nondiagonal asymmetric specification only.

Fig. 2 shows time-variation in *TP* (Panel a), the time-variation in *LP* and *RP* (Panel b), and the decomposition of the illiquidity risk premium over time into its three components (Panel c). *TP* takes its highest values in the first 15 years of the sample. It decreases steadily until around 1960, when it is less than 0.4% per year.

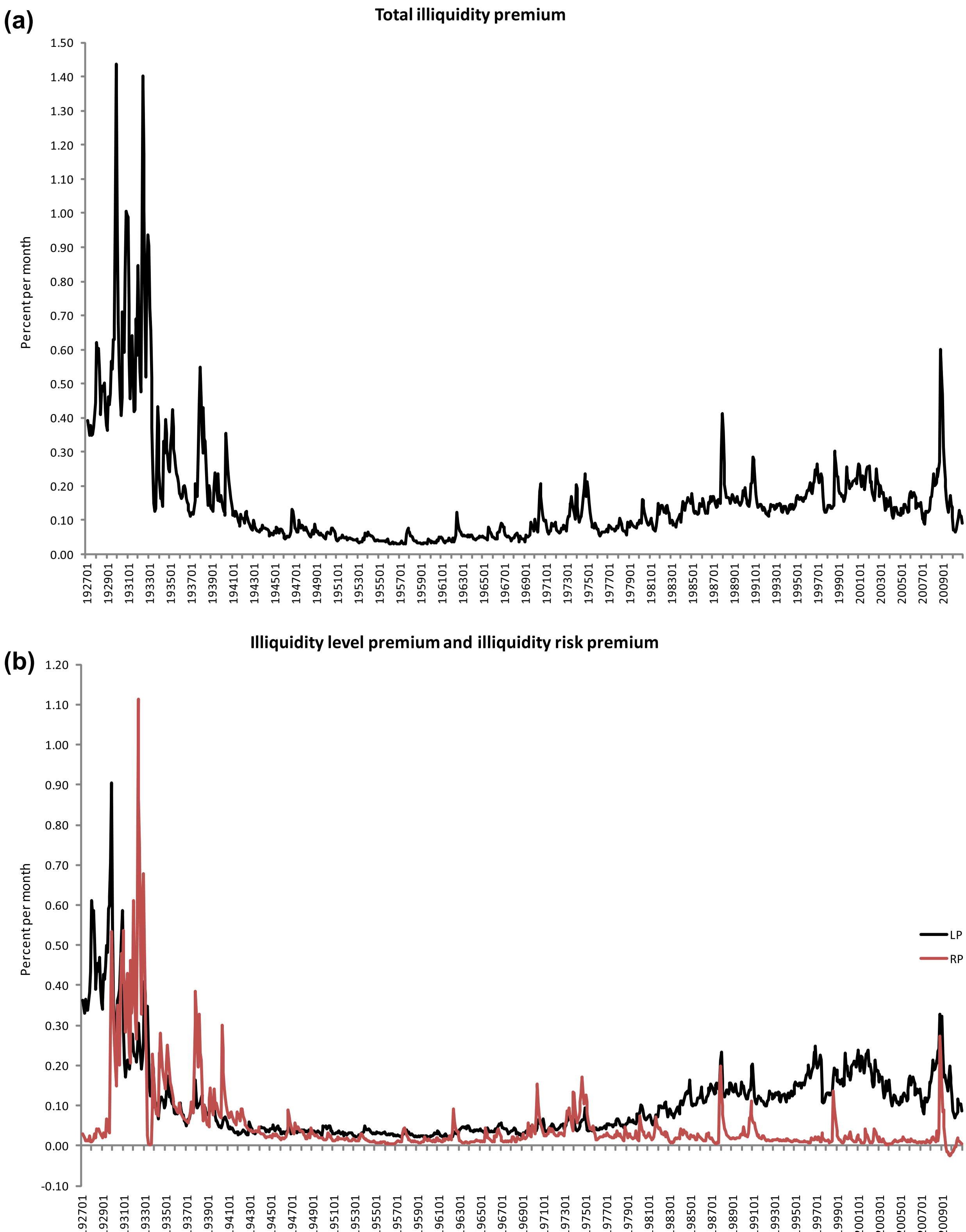

Fig. 2. (a) The total illiquidity premium. (b) The decomposition of the total illiquidity premium into a level premium and a risk premium. (c) The decomposition of the illiquidity risk premium into its three components.

The total illiquidity premium then increases until the end of the sample, when it is around 1.1% annually. Panel (b) in Fig. 2 reveals that the relative importance of the illiquidity level premium (*LP*) and the illiquidity risk premium (*RP*) is changing over time. In most times, *LP* is many times higher than *RP*, in particular in the second half of the sample. The difference between the two is much smaller, however, at time of financial distress, such as the oil crises of 1973 and 1979, the October 1987 crash, the LTCM bankruptcy in 1998, and the Lehman Brothers bankruptcy in 2008. The correlation between *LP* and *RP* is positive and significantly different from

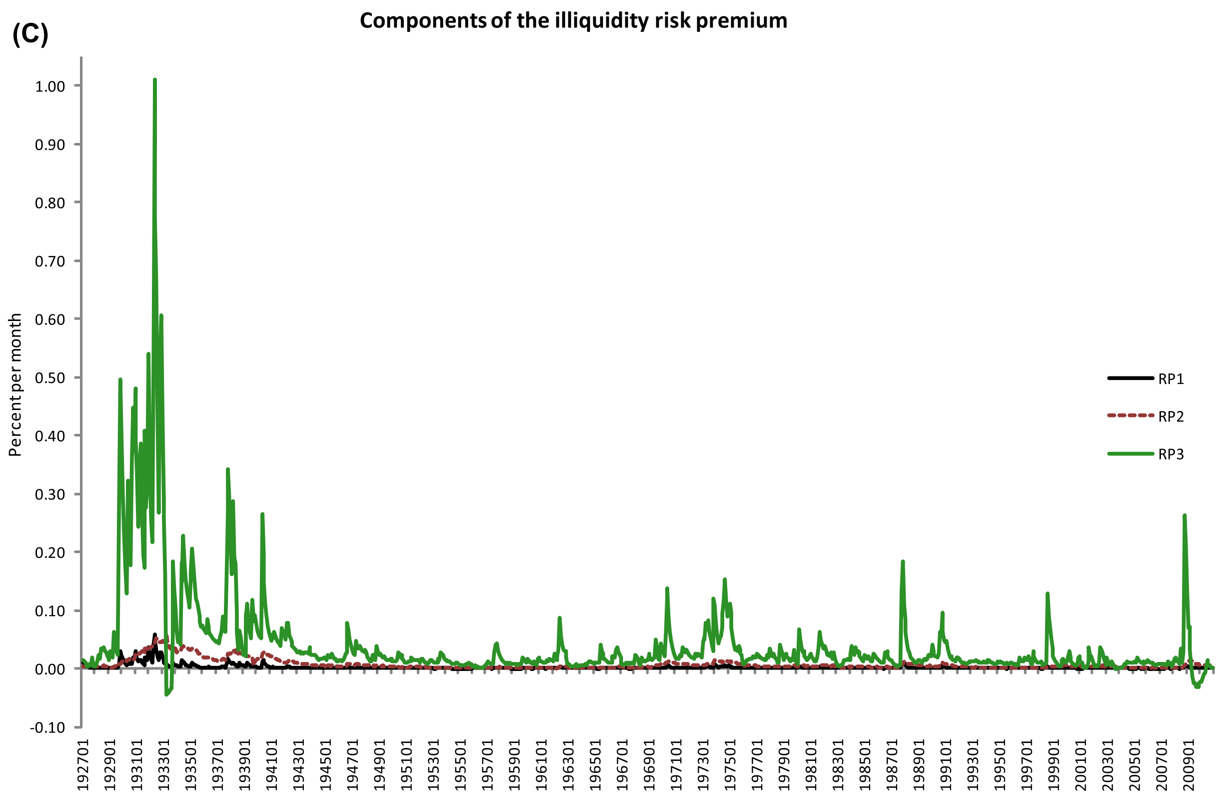

Fig. 2. (*continued*)

Table 6
Time-series Pearson correlations between components of the illiquidity premium for the nondiagonal asymmetric specification. The rows in the correlation matrix are the illiquidity level premium (*LP*), the total illiquidity risk premium (*RP*), compensation for comovement of portfolio illiquidity and market illiquidity (RP_1), compensation for comovement of portfolio return and market illiquidity (RP_2) and compensation for comovement of portfolio illiquidity and market return (RP_3).[a]

	Illiquidity premium component				
	LP	*RP*	RP_1	RP_2	RP_3
LP	1				
RP	0.372	1			
RP_1	0.383	0.955	1		
RP_2	0.216	0.738	0.696	1	
RP_3	0.376	0.997	0.949	0.688	1

[a] All correlations are statistically significant at the 5% level.

zero, varying between 0.29 and 0.40 (see Table 5, Panel B). The high illiquidity premia (*LP* as well as *RP*) from 1930 to 1940, relative to the rest of the sample, is important to keep in mind when comparing our results to studies based on shorter samples.

The substantial inter-temporal variation in illiquidity risk gives merit to the conditional version of LCAPM. Watanabe and Watanabe (2008) propose another conditional liquidity asset pricing model. 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, supports their findings. During these periods, visual inspection of Fig. 2 (Panel b) also tells us that the risk premium is more volatile than the level premium.

In a recent study, Ben-Rephael et al. (2010) investigate the time-variation in the illiquidity level premium. They show that the influence on US equity return associated with an inflation adjusted version of Amihud's (2002) illiquidity ratio has decreased over time. As the illiquidity ratio is not a cost measure, they have to estimate the level premium. This is an important difference to the LCAPM, where the expected illiquidity cost per period (γ in our model) is a cost measure that is directly deductible from the returns. Another difference between the level premium reported by Ben-Rephael et al. (2010) and our *LP* is that their estimated premium reflects the return effect of the illiquidity ratio as well as the effect of other variables correlated with the illiquidity ratio, such as illiquidity risk. Hence, their premium is a hybrid of the level and risk premia, and of other variables correlated with the illiquidity ratio, and is not comparable to *LP* in a straightforward way.

Fig. 2 (Panel c) shows the time-variation in the different types of illiquidity risk premia. The graphs strongly suggest that the dominance of RP_3 prevails over time. The three time-series are highly correlated. Table 6 presents correlation coefficients between the illiquidity premia for the nondiagonal asymmetric model. The correlations between the three types of illiquidity risk premia are between 0.69 and 0.95. The lower panel of Fig. 2 also illustrates the high correlations, as all three series seem to peak simultaneously in times of financial distress. Finally, looking at correlations between the level premium and the different risk premia, all correlation coefficients are positive and significant, with values between 0.21 and 0.38. This result is in line with our previous finding of a positive and significant correlation between the level premium and the total risk premium.

5. Summary and conclusions

The liquidity adjusted conditional capital asset pricing model (LCAPM) developed by Acharya and Pedersen (2005) shows that both the level and the risk in illiquidity are determinants of expected asset returns. The LCAPM provides an integrated view of three types of illiquidity risk; the covariance of asset illiquidity with market-wide illiquidity, the covariance of asset return and market-wide illiquidity and the covariance of asset illiquidity and market return.

In this paper, we estimate the LCAPM for stocks traded on NYSE and AMEX. Our empirical model differs in several ways from that of Acharya and Pedersen (2005). We estimate a conditional version of the model in which both illiquidity level premia and illiquidity risk premia are time-varying. We estimate illiquidity using the effective tick measure by Holden (2009), which is a proxy for the cost of trading and therefore directly suitable for the LCAPM. Finally, we consider a long sample period covering 84 years of data, from 1927 to 2010. For robustness and comparison, we estimate four different specifications of our empirical model. The model specifications differ in terms of the complexity in the parameterization of the covariance dynamics. We find that differences in covariance specifications have no noteworthy implications for our economic conclusions. Both the magnitude of the illiquidity premia and the variation of premia over time are qualitatively unaffected by changes in model complexity.

We find that the total illiquidity premium, i.e., the sum of the illiquidity level premium and the illiquidity risk premium, is on average 1.74–2.08% annually, depending on model specification. This is markedly lower than in most previous studies of US equity markets. Further, our results show that illiquidity risk varies substantially over time, which highlights the advantage of a conditional modeling approach. Consistent with the findings of Acharya and Pedersen (2005), the most important type of illiquidity risk, in terms of illiquidity risk premia, is the asset illiquidity covariance with market return. This covariance describes the risk of asset illiquidity to increase when markets are in distress. Wagner (2011) analyzes this type of illiquidity risk from a theoretical perspective, but it deserves more attention in future empirical asset pricing research. Finally, our results show that the magnitude of the illiquidity level premium relative to illiquidity risk premia has increased steadily since the 1970s. The influence of illiquidity risk, however, becomes material in times of financial distress, such as the oil crises of 1973 and 1979, the October 1987 crash, the LTCM bankruptcy in 1998, and the Lehman Brothers bankruptcy in 2008.

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