Momentum and Post-Earnings-Announcement Drift Anomalies: The Role of Liquidity Risk*

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Abstract

This paper investigates the components of liquidity risk that are important for asset-pricing anomalies. Firm-level liquidity is decomposed into variable and fixed price effects and estimated using intraday data for the period 1983-2001. Unexpected systematic (market-wide) variations of the variable component rather than the fixed component of liquidity are shown to be priced within the context of momentum and post-earnings-announcement drift (PEAD) portfolio returns. As the variable component is typically associated with private information (e.g., Kyle (1985)), the results suggest that a substantial part of momentum and PEAD returns can be viewed as compensation for the unexpected variations in the aggregate ratio of informed traders to noise traders.

JEL classification: G12; G14

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Introduction

Empirical finance literature has documented the predictability of future stock returns using past returns. Jegadeesh and Titman (1993, 2001) document the price momentum of individual stocks. They show that one can obtain superior returns by holding a zero-cost portfolio that consists of long positions in stocks that have out-performed in the past (*winners*), and short positions in stocks that have under-performed during the same period (*losers*). Momentum strategies exhibit high abnormal returns that to date cannot be explained by measures of risk (see, e.g., Grundy and Martin (2001), and Jegadeesh and Titman (2001)). Therefore, behavioral explanations based on some type of bounded rationality of investors (such as overconfidence or underreaction of investors to information) have been developed to explain momentum continuation (see, e.g., Barberis, Shleifer, and Vishny (1998), Daniel, Hirshleifer, and Subrahmanyam (1998), and Hong and Stein (1999)). The momentum anomaly is recognized as one of the biggest challenges to asset pricing (see, e.g., Fama and French (1996), and Fama (1998)).

The literature has documented not only price-momentum drift but also a price drift after earnings announcements. Beginning with the early work of Ball and Brown (1968), the financial literature has argued that investors tend to underreact to earnings information.[1] This follows empirical evidence that good-news firms, i.e. those with high standardized-unexpected earnings (SUE), outperform bad-news (low-SUE) firms. The results suggest that investors underreact to the information content of earnings, thereby generating return continuation. This is also known as the post-earnings-announcement drift (PEAD) anomaly. Recent studies such as Francis, Lafond, Olsson and Schipper (2004) and Vega (2004) find that the post-earnings-announcement drift of a given firm is related to the amount of private information about that firm. Chordia and Shivakumar (2002) suggest that PEAD can be explained by macroeconomic factors, specifically inflation. Also, Kim and Kim (2003) construct a risk factor related to unexpected earnings surprises and find that a four-factor model, including the new factor, reduces the PEAD anomalous returns.

The persistence of these drift anomalies, namely momentum and PEAD, over the past few decades raises serious doubts about the efficient market hypothesis. In light of a recently growing literature on the limits of arbitrage opportunities, a few studies examine whether strategies con-

[1] Other subsequent works include Jones and Litzenberger (1970), Joy, Litzenberger, and McEnally (1977), Rendleman, Jones, and Latané (1982), Foster, Olsen, and Shevlin (1984), Bernard and Thomas (1989, 1990), and Ball and Bartov (1996).

structed to exploit these anomalies can be profitable after taking into account transactions costs.[2] Generally speaking, momentum and PEAD returns are relatively short-lived, as the extreme momentum and PEAD portfolios, the winners and the losers (momentum) and the good-news firms and the bad-news firms (PEAD), exhibit the strongest abnormal performance during the first few months after they are formed. Therefore, the implementation of such trading strategies involves high portfolio turnover (see, e.g., Moskowitz and Grinblatt (1999) and Grundy and Martin (2001) for the case of momentum strategies). The attempt to exploit potentially profitable momentum and PEAD strategies is therefore likely to involve relatively high transactions costs. In this vein, Lesmond, Schill, and Zhou (2004) examine momentum strategies and find that the standard relative strength strategies require frequent trading in particularly costly securities such that trading costs prevent profitable execution. Korajczyk and Sadka (2004) also note that the typical momentum strategies are less likely to be profitable for large investment funds; however, considerable potential profits may be achieved if one considers liquidity-conscious portfolio construction. Employing the arbitrage-risk measure developed in Wurgler and Zhuravskaya (2002), Mendenhall (2004) shows that trading strategies based on PEAD are subject to high arbitrage costs.

The fact that the profitability of momentum and PEAD strategies is strongly related to transactions costs raises the issue of whether these returns can be related to the time variation of liquidity documented in recent literature (see, e.g., Chordia, Roll, and Subrahmanyam (2000)). If unexpected variations in liquidity have a systematic component, then momentum and PEAD returns could be viewed as compensation for liquidity risk provided they are sensitive to unexpected changes in systematic liquidity. Consistent with this hypothesis, Pástor and Stambaugh (2003) argue that a liquidity risk factor accounts for half of the profits to a winner-loser momentum portfolio.

The purpose of this paper is to investigate the component of liquidity risk that can explain asset-pricing anomalies. The paper decomposes liquidity into variable and fixed components and finds that it is the variable component rather than the fixed component that is priced (with an annual premium of about 6.5 percent) in the context of momentum and PEAD portfolio returns. The results indicate that liquidity risk can explain between 40 and 80 percent of the cross-sectional variation of expected momentum and PEAD portfolio returns. As the variable component of

[2] For example, Knez and Ready (1996) find that size-based strategies are too costly to trade; Mitchell and Pulvino (2001) analyze the profits to risk arbitrage of mergers and acquisitions; and Chen, Stanzl, and Watanabe (2002) examine a variety of strategies based on size, BE/ME, and momentum. For evidence from the mortgage-backed securities market see Gabaix, Krishnamurthy, and Vigneron (2004).

liquidity is typically associated with private information (e.g., Kyle (1985)), the results of this paper suggest that a substantial part of momentum returns can be viewed as compensation for unexpected variations in the aggregate ratio of informed traders to noise traders, and of the quality of information possessed by the informed traders.

It is important to emphasize that the focus of this paper is not on the firm-specific liquidity characteristic (the liquidity level), but rather on the concept of market-wide liquidity as an undiversifiable risk factor (the liquidity risk). Most of the studies that investigate the relation between liquidity and asset prices focus on the level of liquidity as a characteristic of a stock.[3] These studies argue that investors holding illiquid assets are compensated by higher future returns. In contrast, a few recent studies focus on the systematic component of liquidity (liquidity risk) rather than on its actual idiosyncratic level (i.e. liquidity level). This strand of literature begins with studies that document the fact that firm-specific liquidity fluctuates over time, and also that there is a systematic, or market-wide component to these liquidity fluctuations (see, e.g., Chordia, Roll, and Subrahmanyam (2000), Huberman and Halka (2001), Amihud (2002)). Pástor and Stambaugh (2003) show that systematic liquidity risk is a priced risk factor. They develop a measure of aggregate (market-wide) liquidity based on daily price reversals and show that assets whose returns covary highly with this aggregate liquidity measure earn higher expected returns than do assets whose returns exhibit low covariation with aggregate liquidity. Last, Acharya and Pedersen (2004) employ the liquidity measure of Amihud (2002) to show that expected stock returns are a function of several terms: first, expected stock illiquidity and second, some covariances between stock return, stock illiquidity, market return, and market illiquidity. This paper extends the literature on liquidity risk and identifies the component of liquidity risk that is related to existing asset-pricing anomalies.

The liquidity measure used in this paper is defined as the price-impact induced by trades, and it is separated into fixed and variable components. The measure and its components are based on the empirical market microstructure model of Glosten and Harris (1988), along with various empirical findings in the literature (such as adjustments for block trades and possible autocorrelation in the order flow). The Glosten and Harris model enables us to separate price impact into permanent

[3] For example, Amihud and Mendelson (1986) argue that investors demand a premium for relatively low liquidity stocks (measured by using bid-ask spreads). Similarly, Brennan and Subrahmanyam (1996) find that stocks with higher price impacts earn higher future returns. Also, Easley, Hvidjaker, and O'Hara (2002) find that the level of liquidity, measured as the probability of information-based trade (PIN), carries a positive premium in asset prices.

(variable) and transitory (fixed) price effects, and study which price-impact component is important for explaining asset-pricing anomalies. The distinction between fixed and variable components of liquidity is achieved by classifying transaction-price changes into those whose effects persist in the following transaction versus those that vanish. A permanent change in the stock price is associated with a change in its perceived intrinsic value (i.e., informational effect), and is dependent on both the amount of informed trading and the amount of noise trading (see Kyle (1985) and Admati and Pfleiderer (1988)). In contrast, a transitory price change corresponds to market-making costs, such as the costs associated with inventory maintenance and order processing or search (i.e., the non-informational effect). These components of price impacts are estimated monthly, by stock, for the period 1983-2001 using tick-by-tick data, which generally provide hundreds or even thousands of observations per month. These firm-specific estimates are then aggregated to form monthly market-wide estimates of the variable and fixed components of liquidity. Using the time series of these market-wide components, variable and fixed liquidity risk factors are introduced based on shocks to each of the time series.

Although the pricing of liquidity risk applies to the cross-section of assets as a whole, I argue that momentum and PEAD returns provide a natural test ground for the importance of liquidity risk. Not only are these returns relatively short-lived and involve relatively high transactions costs, but they may also be related to differences in the ability of investors to interpret public information (informed versus uninformed traders). This is because price-momentum drift is concentrated in stocks about which new public information has been released (see Chan (2003)), while the post-earnings-announcement drift can be viewed as investors' reactions to public news about earnings. It therefore seems reasonable that the returns of these anomalies would be related to the amount of information asymmetry or the amount of noise trading in the market. This reasoning is consistent with the findings of this paper that it is the variable component of liquidity risk that is important for explaining part of momentum and PEAD anomalies.

The rest of this paper is organized as follows. Section 1 describes the methodology for estimating liquidity and discusses empirical results. Section 2 investigates the pricing of liquidity risk with momentum and PEAD portfolios. Discussion and additional tests follow in Section 3. Section 4 concludes.

1 Estimation of Liquidity

1.1 Methodology

Let m_t denote the market maker's expected value of the security, conditional on the information set available at time t (t represents event time of a trade)

$$m_t = E_t\left[\widetilde{m}_{t+1} | D_t, V_t, y_t\right] \tag{1}$$

where V_t is the order flow, D_t is a binary indicator variable which receives a value of (+1) for a buyer-initiated trade and (-1) for a seller-initiated trade, and y_t is a public information signal. To estimate the sign of a trade, I follow the classification scheme proposed by Lee and Ready (1991), which classifies trades as follows: Prices above the midpoint of the quoted bid and ask are considered buyer initiated; prices below the midpoint are considered seller initiated. Trades whose price equals the midpoint are discarded from the estimation.[4,5]

For the estimation I choose to focus only on NYSE-listed stocks, since NASDAQ uses a different trading mechanism (see discussion in Chordia, Roll, and Subrahmanyam (2001) as well). Following Chordia, Roll, and Subrahmanyam (2001, 2002), only BBO-(best bid or offer) eligible primary market (NYSE) quotes are used. Also, trades out of sequence, trades recorded before the opening or after the closing time, and trades with special settlement conditions are discarded. Negative bid-ask spreads and transaction prices are also eliminated from the dataset. To avoid after hours liquidity effects (see, e.g., Barclay and Hendershott (2004)), the first trade after the opening time is ignored. In addition, only quotes that satisfy the following filter conditions are retained: quotes in which the bid-ask spread is positive and below five dollars; quotes in which the bid-ask spread divided by the midpoint of the quoted bid and ask (henceforth defined as quoted spread) is less than 10% if the midpoint is greater than or equal to \$50; and quotes in which the quoted spread is less than 25% for midpoints less than \$50. These conditions assure the use of reasonable quotes in our analysis.

[4]Due to a delay in the time that bid and offer are quoted, the algorithm of Lee and Ready suggests that the midpoint of the quotes as of five seconds prior to the trade should be used. Therefore for the estimation any quote posted less than five seconds prior to a trade is ignored, and the first quote posted at least five seconds prior to the trade is retained.

[5]Other classification schemes are discussed in the literature. For example, Ellis, Michaely, and O'Hara (2000) discuss trades on NASDAQ. See also Peterson and Sirri (2003) and Odders-White (2000) for comparisons of different classification schemes. All studies predict more than 90% success rate for the Lee and Ready (1991) approach.

The literature distinguishes between the permanent and transitory effects that trades may have on prices. Permanent effects are attributed to the possibility of insiders trading on private information, and transitory effects are associated with the costs of making a market, such as inventory and order processing. Following Glosten and Harris (1988) this paper also assumes that price impacts are characterized by linear functional forms and therefore distinguishes between fixed costs per total trade, which are independent of the order flow, and variable costs per share traded, which depend on the order flow. There are four components of price impacts that are denoted as follows: The fixed effects are Ψ and $\overline{\Psi}$ (permanent and transitory, respectively), and the variable costs are λ and $\overline{\lambda}$ (permanent and transitory, respectively).

To estimate the permanent price effects, I follow the formulation proposed by Glosten and Harris (1988) and assume that m_t takes a linear form such that

$$m_t = m_{t-1} + D_t \left[\Psi + \lambda V_t\right] + y_t \tag{2}$$

where Ψ and λ are the fixed and variable permanent price-impact costs, respectively. Equation (2) describes the innovation in the conditional expectation of the security value through new information, both private (D_t, V_t) and public (y_t). Notice that information induces a permanent impact on expected value.

The formulation in (2) assumes that the market maker revises expectations according to the total order flow observed at time t. However, the literature has documented predictability in the order flow (see, e.g., Hasbrouck (1991a,b), Foster and Viswanathan (1993)). For example, to reduce price impact costs, traders may decide to break up large trades into smaller ones, which creates an autocorrelation in the order flow. Thus, I follow Brennan and Subrahmanyam (1996), Madhavan, Richardson, and Roomans (1997), and Huang and Stoll (1997), and adjust the formulation to account for predictability in the order flow. Specifically, the market maker is assumed to revise the conditional expectation of the security value only according to the *unanticipated* order flow rather than the entire order flow at time t. For simplicity, the signed trade size $D_t V_t$ shall henceforth be denoted DV_t. This adjustment induces the following formulation

$$m_t = m_{t-1} + \Psi \left[D_t - E_{t-1}\left[D_t\right]\right] + \lambda \left[DV_t - E_{t-1}\left[DV_t\right]\right] + y_t \tag{3}$$

where the operator $E_{t-1}\left[\cdot\right]$ denotes the conditional expectation. Notice that there are two conditional means to be estimated: that of the sign of the order flow, and that of the order flow itself.

To estimate the two conditional means, this paper applies a two-step procedure. As explained below, I first use a standard autoregressive process with five lags to describe innovations in the (signed) order flow, and then I estimate the conditional expected sign of the order flow assuming a Markov chain model. As in Brennan and Subrahmanyam (1996), the order flow is assumed to follow the process

$$DV_t = \eta_0 + \sum_{j=1}^{5} \eta_j DV_{t-j} + \varepsilon_{\lambda,t} \tag{4}$$

This model is estimated each month using OLS (with correction for serial autocorrelation of the errors). After computing the estimates $\widehat{\eta}_j$ ($j = 0,...,5$) the conditional expectation of the order flow $E_{t-1}[DV_t]$, is estimated as the fitted value. Once $E_{t-1}[DV_t]$ is obtained, $E_{t-1}[D_t]$ can be estimated as follows.

Define the probability that the next trade would be a "buy" given the expected order flow as $p(D_t = +1|E_{t-1}[DV_t])$. This probability is equal to $p(E_{t-1}[DV_t] > -\varepsilon_t)$. Assuming normality of the shocks to the order flow, ε_t, and denoting its variance σ_ε^2, it is easily shown that the probability is further simplified to $1 - \Phi(-E_{t-1}[DV_t]/\sigma_\varepsilon)$, where $\Phi(\cdot)$ denotes the cumulative density function of the normal distribution. Therefore, the expected sign of the order flow is calculated as

$$E_{t-1}[D_t] = 1 - 2\Phi(-E_{t-1}[DV_t]/\sigma_\varepsilon) \tag{5}$$

Denote the unexpected sign of a trade as $\varepsilon_{\Psi,t}$, where $\varepsilon_{\Psi,t} = D_t - E_{t-1}[D_t]$. Using the above formulations for $\varepsilon_{\Psi,t}$ and $\varepsilon_{\lambda,t}$, Equation (3) translates to

$$\Delta m_t = \Psi\varepsilon_{\Psi,t} + \lambda\varepsilon_{\lambda,t} + y_t \tag{6}$$

Notice that the process m_t is unobservable and cannot be directly estimated from the data.

Transitory price effects are added to the model as in the derivation of Glosten and Harris (1988). Glosten and Harris assume linear transaction costs, denote fixed costs by $\overline{\Psi}$, and variable costs by $\overline{\lambda}$. These costs represent both inventory costs and order processing costs. Glosten and Harris argue that preliminary diagnostics show that Ψ and $\overline{\lambda}$ are unimportant components, and they thus assume $\Psi = \overline{\lambda} = 0$ for the estimation procedure.[6] However, Glosten and Harris use a universe of

[6] Brennan and Subrahmanyam (1996) use this formulation as well. Other studies that focus on investigating the relative magnitude of the adverse selection versus the order processing components of the bid-ask spread essentially assume these components are invariant to trade size; for example: Huang and Stoll (1997), Madhavan, Richardson, and Roomans (1997), and George, Kaul and Nimalendran (1991).

20 firms for specification tests. Since the sample used in this study contains a large cross-section of stocks, all four price-impact components are estimated.

Assuming competitive risk-neutral market makers, the observed transaction price, p_t, can be written as

$$p_t = m_t + D_t \left[\overline{\Psi} + \overline{\lambda} V_t\right] \tag{7}$$

Notice that $\overline{\Psi}$ and $\overline{\lambda}$ are temporary effects by the construction of Equation (7), as they only affect p_t, and are not carried on to p_{t+1}. Also, in contrast to the information-based components of price impact, the entire order flow is included while considering the market making costs, rather than using its unanticipated part (see also Huang and Stoll (1997) and Madhavan, Richardson, and Roomans (1997)). Taking first differences of p_t (Equation (7)) and substituting Δm_t from Equation (6) we have

$$\Delta p_t = \Psi \varepsilon_{\Psi,t} + \lambda \varepsilon_{\lambda,t} + \overline{\Psi} \Delta D_t + \overline{\lambda} \Delta D V_t + y_t \tag{8}$$

where y_t is the unobservable pricing error.[7] The model is estimated per firm per month using OLS (including an intercept) with corrections for serial correlation in the error term.[8] Notice that the estimation of the price-impact components involves only information available that month: first the model in (4) is estimated using all trades of a particular firm in a given month, then the results are used to compute $\varepsilon_{\Psi,t}$ and $\varepsilon_{\lambda,t}$, and finally the model in (8) is estimated.

The model above does not distinguish between small or ordinary trades and large trades. These "block trades," generally considered as trades above 10,000 shares, are usually negotiated at the upstairs market. The literature documents different price effects induced by block trades, suggesting these trades may have different information or inventory characteristics.[9] In light of this, block

[7]The formulation in Equation (8) does not consider the effect of rounding errors (consistent with Brennan and Subrahmanyam (1996)). However, following Madhavan, Richardson, and Roomans (1997) one could account for rounding errors by adding an additional i.i.d. mean zero error term, ξ_t, to Equation (7), which would result in a combined error term $y_t + \Delta \xi_t$ in Equation (8). Notice that although this combined error term is serially correlated, it does not create any bias in the OLS estimates of the price-impact components estimated here. Moreover, since the estimation procedure also accounts for possible serial correlation in the error term, the rounding errors would have no effect on the precision of the price-impact estimates either.

[8]Notice, if D_t and DV_t are i.i.d. with zero mean, then $\Psi \varepsilon_{\Psi,t}$ and $\lambda \varepsilon_{\lambda,t}$ may be replaced by D_t and DV_t, respectively, and Equation (8) simply translates to Equation (5) in Glosten and Harris (1988). This equation is identified in our sample.

[9]For example, Madhavan and Smidt (1991) create four trade-size classes separately for each stock, and show different market making costs for the largest trade size group. Keim and Madhavan (1996) study the price effects of block trades using data on institutional trades, and conclude that once the decision date of executing the trade is taken into account, the permanent effects of such trades are larger than previously estimated. The effects of "shopping the block" are also discussed in Nelling (1996). Last, Huang and Stoll (1997) measure different components of the

trades are separated from smaller trades in the estimation using dummy variables for each of the variables in Equation (8).

1.2 Data

The empirical analysis in this paper utilizes several different databases, starting with intraday data for the estimation of execution costs, and daily/monthly/annual data for asset-pricing analyses. The intraday data for NYSE-listed stocks is obtained from two databases: the Institute for the Study of Securities Markets (ISSM) and the New York Stock Exchange Trades and Automated Quotes (TAQ). The ISSM database includes tick-by-tick data for trades and quotes for the period January 1983 through December 1992, while the TAQ database includes data for the period January 1993 through August 2001.

The CRSP data files are used to retrieve monthly/daily returns; market capitalization (defined as share price multiplied by the number of shares outstanding); volume; and turnover (defined as volume scaled by the number of shares outstanding). Earnings surprises and book-to-market equity (BE/ME)[10] are constructed using the COMPUSTAT quarterly/annual files. Since the trading characteristics of ordinary equities might differ from those of other assets, only tradable assets whose last two CUSIP digits are 10 or 11 are retained; i.e., I discard certificates, ADRs, shares of beneficial interest, units, companies incorporated outside the U.S., Americus Trust components, closed-end funds, preferred stocks and REITs.

After both high- and low-frequency datasets are prepared, they are merged by matching the firms on ISSM with CRSP by their ticker symbols, and firms on TAQ with CRSP by their CUSIPs. As discussed in Hvidkjaer (2001), this approach induces the highest matching rate. The merged sample includes a cross-section of 1,159 firms beginning in January 1983, and gradually increasing to 2,226 in August 2001.[11] In all, 4,082 different firms are used for the estimation of liquidity. The total number of trades used is 645 million, 26 million trades of which are above 10,000 shares. The average number of trades per firm per month is about 1,700, while large firms with very high trading volume often reach over 1,000 trades per day.

bid-ask spread and conclude that their magnitudes vary with trade size. (Trade-size cufoffs are 1,000 and 10,000 shares.)

[10] For a detailed description of the construction of BE/ME see Cohen, Polk, and Vuolteenaho (2003).

[11] An exception is July 1987, in which we observe only 506 firms.

1.3 Empirical Results

1.3.1 The Cross Section of Asset Liquidity

The Estimated Measures. The model in Equation (8) is estimated for each firm in the sample every month, provided there are at least 30 trades in a given month. For identification purposes, if there are no more than three trades of more than 10,000 shares, the model is estimated without the dummy variables that separate out large trades. A close look at the distribution of the estimates reveals several outliers, especially for trades below 10,000 shares. The estimates are therefore truncated at 1 and 99 percentiles, i.e., values below the 1% cutoff are re-valued at the 1% cutoff, and similarly, values above the 99% cutoff are re-valued at the 99% cutoff value. A sensitivity analysis of the outliers percentage cutoff shows that the results in this paper are fairly robust to this choice for cutoff values of up to 5 percent on both sides of the distribution.

The time-series averages of monthly diagnostics are reported in Table 1. The average information/permanent variable cost and average non-information/temporary fixed cost for trades below 10,000 shares provide additional validation for the methodology in Glosten and Harris (1988). These seem to be larger than the average non-information variable cost and the average information fixed cost, respectively. Notice, some of the monthly liquidity estimates are negative, which is indicated by the negative time-series averages of the lowest percentile of the liquidity estimates. As some estimation error is always expected while estimating a model for a large cross-section over a period of 224 months, this is not surprising. It is important to note that for the portfolios used in this paper none of the average liquidity estimates of firms in each portfolio are negative (except for the transitory variable cost; see discussion below). This should therefore not be viewed as a serious problem for the analysis. Also, the cross-sectional averages of the liquidity estimates are positive throughout the entire sample period.

The negative average non-information variable cost seems odd at first glance. However, four comments are noteworthy. First, this indicates that while total costs increase with the size of the trade, the fraction of costs attributed to information asymmetry also increases. Indeed, heavy information-based trading induces higher permanent effects. Second, there is a positive non-information fixed cost along with the negative variable cost which keeps the total non-information cost positive, even up to trades of 10,000 shares. Third, this finding corresponds to the work of Huang and Stoll (1997) showing decreasing fixed costs. Last, it is likely that temporary fixed costs are restricted by the size of the tick. Indeed, when the tick size is reduced in June 1997, temporary fixed costs decrease and temporary variable costs increase.

Statistical Properties. The statistical properties of the estimates are shown in Figure 1. This figure plots the distribution of the t-statistics of some estimates across the pooled cross-section and time-series sample of firms. The t-statistic of the transitory fixed costs ($\overline{\Psi}$) is significant at the 95%-significance level for over 90% of the sample. The t-statistics of the permanent variable costs (λ) exhibit a distribution that resembles a normal distribution, centered above 1. Since they are based on market-wide average effects, the liquidity factors introduced below are likely to be estimated with much greater precision.[12]

Scaled Measures. Following Brennan and Subrahmanyam (1996), each component of price impact is scaled by its stock price at the beginning of the month.[13] Scaling is more appropriate when constructing an aggregate measure of liquidity because it maintains the relative importance of liquidity as a transaction cost for each firm. Scaling converts the fixed components from dollars to returns and the variable components from dollars per share to returns per share. The results show that the relative relation between the different scaled variable measures is similar to that of the unscaled measures discussed above. In contrast, the scaled transitory fixed costs appear to be much higher than the permanent fixed costs. This is because low-priced stocks tend to have relatively high fixed costs of trading.

1.3.2 Comparison with Other Measures of Liquidity

This paper uses measures of price impacts as proxies for liquidity. The financial literature includes other proxies such as market capitalization; volume; turnover (defined as volume scaled by the

[12] A sensitivity analysis of the precision of the estimates as a function of the number of trades used for estimation shows that precision increases with the number of trades. For example, the median t-statistic of the pooled time-series cross-sectional sample of $\overline{\Psi}$ increases from 4.11 to 6.37 to 7.42 as the sample is restricted to 30, 50, and 100 trades per month. Similarly for λ: from 1.03 to 1.40 to 1.52. Restricting the sample to at least 100 trades per month reduces the sample size by roughly 10 percent, which is likely to decrease the precision of our aggregate liquidity factor. Thus, all price-impact estimates based on at least 30 trades per month are retained.

[13] The theoretical motivatation for scaling price impacts appears in the unpublished working paper version of Brennan and Subrahmanyam (1995). They introduce a simple equilibrium model whose first order conditions justify price scaling. Independently, Sadka (2002) develops a portfolio choice model accounting for price-impact costs and finds similar first-order conditions.

number of shares outstanding); and the more recent Amihud (2002) measure, which is defined as the monthly average of absolute value of daily return divided by daily dollar volume.

A comparison of the alternative measures discussed above and the price-impact estimates (scaled) is offered in Table 2. The table reports the time-series averages of cross-sectional pair-wise correlations. Among the measures examined here, size seems to be the most correlated (inversely) with both variable-permanent and fixed-transitory price impact (-0.37 and -0.53, respectively). Perhaps the most counter-intuitive result is that turnover has low correlation with price impacts. The finding that volume may not always proxy for liquidity is also discussed in Chordia, Roll, and Subrahmanyam (2002). Last, the correlation of the measure of Amihud (2002) with the fixed-transitory component of liquidity is 0.36, while its correlation with the variable-permanent component is relatively low at 0.15.[14] In conclusion, the price-impact estimates seem to be correlated with other measures in a manner consistent with the general notion of liquidity.

2 Pricing Liquidity Risk with Momentum and PEAD Portfolios

In this section, several liquidity factors are constructed based on the different price-impact components described above. The goal is to determine which component of liquidity is important for explaining momentum and PEAD anomalies. Although four price-impact measures are estimated, I focus here only on the variable permanent component of price impact (λ from Equation (8)) and the fixed transitory component of price impact ($\overline{\Psi}$ from Equation (8)). For brevity, I shall henceforth refer to these components as variable and fixed, respectively. Consistent with the results of Glosten and Harris (1988), these two measures seem the most important in this sample in that most of the fixed price effects are transitory and most of the variable costs are permanent (see also Brennan and Subrahmanyam (1996)). However, the other two price-impact components, Ψ and $\overline{\lambda}$, may potentially contain information about prices as well. See Section 3.2 below.

2.1 Constructing Liquidity Factors

The liquidity factors studied in this paper are based on economy-wide levels of liquidity as sources of potential undiversifiable risk. Denote the market-average time series of the two liquidity components

[14] The unscaled price-impact measures exhibit lower cross-sectional correlations with the other liquidity proxies than do the scaled measures.

considered here as $\overline{\Psi}_t^M$ and λ_t^M. Following Amihud (2002), Pástor and Stambaugh (2003), and Acharya and Pedersen (2004), these aggregate measures are calculated as equal-weighted averages of the price-impact estimates each month.[15] As discussed in Section 1.3.1, price impacts are scaled by beginning-of-month price.[16] Two additional adjustments are implemented. First, since $\overline{\Psi}_t^M$ and λ_t^M measure illiquidity rather than liquidity, a minus sign is added so that negative shocks to $-\overline{\Psi}_t^M$ and $-\lambda_t^M$ can be interpreted as increasing market illiquidity. Second, for purely expositional purposes, λ_t^M is scaled by an order of 5.

To construct liquidity factors one must use innovations. The importance of using innovations stems from the rationale that shocks rather than predictable changes to a macro-economic variable could be priced (see also Chen, Roll, and Ross (1986)). This is also discussed in Pástor and Stambaugh (2003) and in Acharya and Pedersen (2004). These papers use a (modified) second order autoregression to calculate unexpected innovations of liquidity. Here I use Box-Jenkins methods to determine the appropriate ARIMA model for the time series of each aggregate liquidity measure. An analysis of the partial autocorrelations of each time series shows that $\overline{\Psi}_t^M$ simply follows a random walk (i.e. (0,1,0)) while λ_t^M is best modelled with two autoregression lags, no integration term, and one lag of moving average (i.e. (2,0,1)). The shocks extracted for each time series model seem to be serially uncorrelated. These shocks are the liquidity factors used in this paper: $LIQ_t^{\overline{\Psi}}$ and LIQ_t^{λ}. Note that the construction of these liquidity factors seems robust to other time-series models. For example, applying an AR(2) model (similar to the approach in Pástor and Stambaugh (2003) and in Acharya and Pedersen (2004)) to extract shocks results in liquidity factors that are highly correlated with those here (correlation of above 0.90). As a result, applying the latter factors to the asset-pricing tests below gives virtually identical results. Last, a test for the inclusion of a 12-month seasonal lag to the ARIMA specification chosen above concludes that $LIQ_t^{\overline{\Psi}}$ and LIQ_t^{λ} do not exhibit a significant seasonal pattern.

The time series of $LIQ_t^{\overline{\Psi}}$ and LIQ_t^{λ} are plotted in Figure 2. The average $LIQ_t^{\overline{\Psi}}$ innovation

[15] As argued by Acharya and Pedersen (2004), computing the market illiquidity as an equal-weighted average is perhaps more appropriate than a value-weighted average because liquid firms are over represented in the sample. This is because the sample does not include, for example, corporate bonds, private equity, real estate, and many small firms. A value-weighted average would further worsen this problem because it would heavily represent the largest of firms in the sample.

[16] Although price scaling is theoretically motivated as discussed earlier, it could potentially cause spurious effects in the cross-section. Yet I would like to note that this potential effect is diminished in the aggregate—the aggregate scaled liquidity measures used in this paper are highly correlated with their respective aggregate unscaled measures. Consistently, I find that the results throughout this paper about liquidity risk are fairly robust to price scaling.

is zero, with a standard deviation of 2.58×10^{-3}. The minimum is -0.0126 and the maximum is 0.0128. The average LIQ_t^{λ} innovation is zero, with a standard deviation of 5.75×10^{-3}. The minimum is -0.0354 and the maximum is 0.0160. The correlations of $LIQ_t^{\overline{\Psi}}$ with Fama-French (1993) factors are: MKT_t -0.05, SMB_t 0.10, and HML_t 0.14. The correlations of LIQ_t^{λ} with Fama-French (1993) factors are: MKT_t 0.15, SMB_t 0.07, and HML_t -0.05.[17] The correlation of $LIQ_t^{\overline{\Psi}}$ and LIQ_t^{λ} is 0.20.[18] The low correlation of the non-traded liquidity factors with other known factors is important in justifying its possible inclusion as an orthogonal factor to the return space spanned by the existing factors used by asset-pricing models to date.

Notice that the time series of $LIQ_t^{\overline{\Psi}}$ and LIQ_t^{λ} are consistent with several liquidity events that have occurred during the past few decades. For example, the period around the crash of the stock market in October 1987 is clearly reflected in both time series. Intuitively, to the extent that LIQ_t^{λ} proxies for information asymmetry, we do not expect to observe significant shocks to LIQ_t^{λ} around institutional changes such as the reduction in tick size, because it is likely that such exogenous events would have an effect on the uncertainty about the fundamental value of stocks. However, these changes may have a significant impact on spreads and thus inventory costs. In the same vein, Figure 2 shows that significant patterns of the fixed component are found around June 24, 1997, when the NYSE reduced the tick size from one eighth to one sixteenth. Similarly, the decimalization process that began in January 2001 has mostly affected transitory costs. Last, the crash of LTCM during September 1998 is also associated with a negative LIQ_t^{λ} shock and a slightly negative $LIQ_t^{\overline{\Psi}}$ shock, indicating relatively high information-based trading activity, or low noise trading activity during that period.

[17] I thank Ken French for providing these risk factors on his web site: http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html.

[18] I also find some asymmetries between the correlations in up and down markets. Conditioning on the event $[MKT_t \geq 0]$ the correlations are: MKT_t -0.19, SMB_t 0.10, and HML_t 0.16 for $LIQ_t^{\overline{\Psi}}$ and MKT_t -0.16, SMB_t 0, and HML_t 0.01 for LIQ_t^{λ}; and for $[MKT_t < 0]$: MKT_t 0.10, SMB_t 0.11, HML_t 0.11, and MKT_t 0.41, SMB_t 0.15, HML_t -0.06, for $LIQ_t^{\overline{\Psi}}$ and LIQ_t^{λ}, respectively. The correlation between $LIQ_t^{\overline{\Psi}}$ and LIQ_t^{λ} is 0.08 in up markets and 0.33 in down markets.

2.2 Momentum and PEAD Portfolios

Two sets of 25 portfolios are constructed from the sample:[19] 25 momentum portfolios (MOM), and 25 portfolios sorted by standardized unexpected earnings (SUE). The first set of momentum portfolios is formed based on past 12-month cumulative returns (excluding the last month's return). The stocks in each portfolio are equally weighted and the portfolios are rebalanced every month. To form the second set of portfolios, the measure of SUE is introduced. This measure is based on a model of seasonal random walk with a drift. Specifically, SUE for stock i in month t is defined as

$$SUE_{i,t} = \frac{E_{i,q} - E_{i,q-4} - c_{i,t}}{\sigma_{i,t}} \tag{9}$$

where $E_{i,q}$ is the most recent quarterly earnings announced as of month t for stock i (not including announcements in month t), $E_{i,q-4}$ is earnings for the prior four quarters, and $\sigma_{i,t}$ and $c_{i,t}$ are the standard deviation and average, respectively, of $(E_{i,q} - E_{i,q-4})$ over the preceding eight quarters. This measure has been used by Chan, Jegadeesh, and Lakonishok (1996), and by Chordia and Shivakumar (2002), except that they do not include a drift term; i.e. they assume $c_{i,t} = 0$. The drift term is added here to comply with Bernard and Thomas (1989, 1990) and Ball and Bartov (1996), who use a seasonal random walk with a trend.[20] The SUE portfolios are rebalanced every month while holding each stock up to four months after the announcement date. The stocks in each portfolio are equally weighted.

The returns (excess of the risk-free rate) of the test portfolios as well as their risk-adjusted returns are reported in Table 3. The first set of 25 momentum portfolios exhibit the usual observed momentum-return spread. Past winners (stocks in Portfolio 25) earn 1.44% per month on average, while past losers (stocks in Portfolio 1) earn -0.50% per month. The monthly return spread is 1.93% with a t-statistic of 3.28. The CAPM and Fama-French (1993) risk-adjusted returns are 1.98% and 2.22% with t-statistics of 3.32 and 3.68, respectively. The second set of SUE portfolios also exhibit significant return spreads. The return spread of highest minus lowest SUE groups (i.e. good-news firms minus bad-news firms) is 0.69% per month with a t-statistic of 3.23. The risk-adjusted return spreads are similar: 0.71% per month for the CAPM and 0.76% using the Fama-French three factors. Notice that the test portfolios ensure sufficient cross-sectional variation

[19] As explained above, the sample is restricted to NYSE firms with available data on ISSM and TAQ. Note that the test results presented below using 25 momentum portfolios and 25 SUE portfolios are robust to forming the portfolios using all NYSE-listed firms available on CRSP and COMPUSTAT.

[20] The results are robust to eliminating the drift term while computing SUE.

in expected returns, which increases the challenge for the asset-pricing tests below.

2.3 Cross-Sectional Regressions

The asset-pricing models tested here are of the form

$$E[R_i] = \gamma_0 + \gamma' \beta_i \tag{10}$$

where $E[R_i]$ denotes the expected return of portfolio i (excess of risk-free rate), β_i are factor loadings and γ is a vector of premiums. Since loadings are unobservable, they are pre-estimated through a multiple time-series regression

$$R_{i,t} = \beta_{0,i} + \beta_i' f_t + \varepsilon_{i,t} \tag{11}$$

where f_t is a vector of factors (either traded or non-traded).

The unconditional[21] model (10) may be consistently estimated using the cross-sectional regression method proposed by Black, Jensen, and Scholes (1972) and Fama and MacBeth (1973). First, regression (11) is estimated using the full sample. Then, (10) is estimated every month resulting in a time series $\widehat{\gamma}_t$. Finally, the time-series mean and standard error are calculated. In addition, since (10) is estimated using sample estimates of β_i' rather than the true values, (10) is subject to the "errors-in-variables" problem. Thus, I follow Shanken (1992) to correct standard errors for this bias. Last, for each model specification, the adjusted R^2 is calculated using one cross-sectional regression of the time-series average excess return of each portfolio on its factor loadings. This provides an intuitive measure that expresses the fraction of the cross-sectional variation of average excess returns captured by the model (see Jagannathan and Wang (1996)). Nevertheless, the adjusted R^2 should be interpreted with caution as they are based on a relatively small cross-section of 25 portfolios.

The model in Equation (10) is tested for several factor model specifications. First, the CAPM is re-examined using MKT as a single factor. The non-traded factors $LIQ^{\overline{\Psi}}$ and LIQ^{λ} are then added to the market factor in the second specification. Another model includes the Fama and French (1993) three factors, MKT, SMB and HML, and finally $LIQ^{\overline{\Psi}}$ and LIQ^{λ} are added to this setting as well.

[21] Note that the portfolios are rebalanced monthly. Therefore as suggested by the analysis in Pástor and Stambaugh (2003), while the loadings are fixed at the portfolio level, they are "conditional" at the firm level.

The results of the first step of the estimation (i.e. regression (11)) are presented in Table 4 and Figure 3. The liquidity loadings of the portfolios with respect to a particular liquidity factor are calculated by estimating (11) using the Fama-French factors and the liquidity factor. Focusing on momentum portfolios, the results for $LIQ^{\overline{\Psi}}$ indicate no particular pattern and most of the loadings on $LIQ^{\overline{\Psi}}$ are not significant. In contrast, when considering the loadings on LIQ^{λ}, momentum losers have negative liquidity loadings, while winner portfolios have positive liquidity loadings. Moreover, most of the loadings of winners and losers are statistically significant. The momentum return spread (portfolio 25 minus portfolio 1) has a loading of 3.59 with a t-statistic of 3.61. Notice that the negative liquidity loadings of loser portfolios suggest that losers are a hedge against liquidity fluctuations. Perhaps a possible explanation is that volume gets pulled away from them when aggregate liquidity increases. The SUE portfolios reveal similar yet weaker patterns of liquidity loadings. The loadings on LIQ^{λ} are negative for bad-news firms and positive for good-news firms, while the loadings on $LIQ^{\overline{\Psi}}$ do not exhibit a particular pattern.

A graphical illustration of these results for LIQ^{λ} are presented in Figure 3. This figure plots the Fama-French risk-adjusted returns of each portfolio as well as its liquidity loading. The graphs illustrate that risk-adjusted returns increase with liquidity loadings. The statistical significance of this relation is tested in the second step of the estimation as follows.

The results of the estimation of (10) are reported in Table 5 and plotted in Figure 4. The panels in Table 5 show that CAPM clearly fails to explain the returns of the two sets of test portfolios. The adjusted R^2 are practically zero and the market premium is insignificant. Adding the liquidity factor LIQ^{λ} has a significant effect. The adjusted R^2 increases to 83% and 60% respectively for MOM and SUE. The liquidity premium is statistically significant for the two portfolio sets, with (corrected) t-statistics of 2.21 and 2.35, respectively.

The Fama-French three factors improve on the CAPM. In the case of the 25 momentum portfolios, the adjusted R^2 increases to 86%, while in the case of 25 SUE portfolios, the adjusted R^2 increases to 41%. Interestingly, the estimated premium on HML is negative. This can be explained by the nature of the portfolios chosen here. As shown in Asness (1997), momentum is stronger among growth (i.e. low book-to-market ratio) firms. Therefore when testing the model using momentum portfolios, HML receives a negative premium. When the non-traded liquidity factor LIQ^{λ} is added as a fourth factor to the existing Fama-French factors, the adjusted R^2s of MOM and SUE remain almost unchanged at 87% and 62%, respectively. The liquidity premium is statistically significant in the case of the SUE portfolio sets.

As for the non-information liquidity factor $LIQ^{\overline{\Psi}}$, none of its coefficients are significant and its addition to the CAPM and Fama-French factors does not seem to have a significant impact on the adjusted R^2. These results suggest that it is LIQ^{λ}, rather than $LIQ^{\overline{\Psi}}$, which is important for understanding momentum returns.

The premiums on liquidity risk estimated here are not returns of traded portfolios and they are also subject to scaling effects (see Equation (11)) because the liquidity factors are not traded portfolios. Yet the scaling does not affect the t-statistics nor the product of liquidity loading and the liquidity premium. To get an idea of the contribution of liquidity risk to the expected return of the MOM and SUE return spreads, one could simply multiply the spread in loadings of Portfolios 1 and 25 (reported in Table 4) by the corresponding liquidity premiums. This results with premiums of 54 and 57 basis points per month for the MOM and SUE portfolio spreads respectively. Comparing these returns to the total monthly return spread of MOM and SUE, 1.93% and 0.69% respectively (and Fama-French risk-adjusted returns of 2.22% and 0.76%), shows that the premium on the variable component of liquidity risk, LIQ^{λ}, can explain part of the momentum return spread and especially a large fraction of PEAD return spread. The annualized premiums translate to 6.5% and 6.8%, which are slightly lower than the Pástor and Stambaugh (2003) estimated annual premium of 7.5%.[22]

2.4 The Stochastic Discount Factor Approach

The stochastic discount factor approach is another method used to test different asset-pricing models. This method utilizes the General Method of Moments (GMM), and is added to the analysis for robustness purposes.

It is well known that as long as the law of one price holds in the economy, there exists some random variable, a stochastic discount factor d_t, which prices all assets: i.e., for any (excess) return $R_{i,t}$, the following is satisfied

$$E\left[R_{i,t}d_t\right] = 0 \tag{12}$$

If the factor-based asset-pricing model explains returns, the stochastic discount factor can be ex-

[22] The correlations of $LIQ_t^{\overline{\Psi}}$ and LIQ_t^{λ} with the Pástor and Stambaugh (2003) non-traded liquidity risk factor are 0.14 and 0.28, respectively. I thank Ľuboš Pástor for providing the time series of their non-traded liquidity factor.

pressed as[23]

$$d_t(\delta) = 1 - \delta' f_t \tag{13}$$

The universe contains 25 portfolios, which translates to 25 moment conditions over 222 months. The asset-pricing models tested here have four factors at most. Therefore we are left with an over-identified system. The moment conditions are constructed as follows. Define R_t as the 25×1 vector of portfolio returns at time t. Define the sample analogs

$$R_T = \frac{1}{T}\sum_{t=1}^{T} R_t \tag{14}$$

$$D_T = \frac{1}{T}\sum_{t=1}^{T} R_t f_t'$$

The sample analog of the moment conditions is given by

$$w_T = R_T - D_T\delta \tag{15}$$

For a given weighting matrix Ω the estimates of δ are those that minimize $J(\delta)$ such that

$$J(\delta) = w_T'\Omega^{-1}w_T \tag{16}$$

Since the system is linear the solution is analytically solved as

$$\delta_T = \left(D_T'\Omega^{-1}D_T\right)^{-1} D_T'\Omega^{-1}R_T \tag{17}$$

and the risk premiums can be calculated through $E[ff']\delta$ (where here f are demeaned factors).

Two weighting matrices are used for the empirical tests. First, following Hansen (1982), the optimal weighting matrix is used.This is achieved by first using the identity matrix for Ω and then conducting several iterations until only a marginal improvement in the objective function is observed. In this case, δ_T is a consistent estimator of δ, and it has an asymptotically normal distribution. Hansen (1982) shows that when Ω^{-1} is optimal, then $T \times J(\delta_T)$ is asymptotically distributed χ^2 with N-K degrees of freedom (N is the number of moment conditions, i.e., the number of portfolios, and K is the dimension of δ). This is the basis for the over-identifying restriction tests, which are used to test the different asset-pricing models here. Second, notice that the optimal weighting matrix depends on the asset-pricing model tested. Hansen and Jagannathan

[23] Since excess returns of the portfolios are used, the constant term is normalized to a value of 1.

(1997) develop a method that helps to evaluate the different asset-pricing models on a common scale. They propose a common weighting matrix for all models

$$\Omega = E\left[R_t R_t'\right] \tag{18}$$

They show that the resulting $J(\delta)$ can be interpreted as the least-square distance between the given estimated stochastic discount factor and the nearest point to it in the set of all discount factors that price assets correctly. However, since Ω^{-1} may not be optimal, $T \times J(\delta_T)$ will not generally converge to a χ^2 distribution. Therefore, to calculate the p-values, I follow the correction presented in Jagannathan and Wang (1996). To adjust for serial correlation of the moment conditions, both when using the Hansen (1982) optimal matrix and the Hansen and Jagannathan (1997) sample moment matrix, a Bartlett kernel with four lags is applied.

For brevity, I focus here only on the pricing of LIQ^{λ}, since the cross-sectional regressions suggest that only LIQ^{λ} seems priced. (The results for $LIQ^{\overline{\Psi}}$ are available from the author upon request.) The empirical results are presented in Table 6. These results support the conclusions from the analysis of the cross-sectional regressions above. The coefficients of LIQ^{λ} are statistically significant for seven out of eight factor model specifications. These estimated premiums vary between 32 and 76 basis points per month depending on the portfolios used for the pricing tests. As for the p-values of the different models, it is difficult to draw a clear conclusion. Some models that include LIQ^{λ} are not rejected at the 5 percent confidence level, while others are rejected. This result further emphasizes the above-mentioned note regarding the caution that should be exercised while interpreting the adjusted R^2 of the cross-sectional regressions above.

2.5 Portfolios Sorted on Momentum, SUE, and Liquidity

Two additional sets of portfolios are considered: 5-by-5 portfolios sorted on momentum and the variable component of liquidity (MOM/λ), and 5-by-5 portfolios sorted on SUE and the variable component of liquidity (SUE/λ). To form the first set of portfolios firms are sorted every month into five groups according to momentum, and then the firms within each group are sorted again into five λ groups. Similarly, the second set of portfolios is formed using dependent sorts of SUE and λ. For brevity, the analysis in this section focuses on the variable component of liquidity risk LIQ^{λ}.

The portfolio returns and their loadings on LIQ^{λ} are reported in Table 7. The momentum and SUE return spreads are economically and statistically significant across high and low liquidity groups. For example, the Fama-French risk-adjusted returns of winners minus losers are 0.89% and 1.25% per month with t-statistics of 2.68 and 3.08 for groups of low and high λ, respectively. Similarly, these returns for SUE groups are 0.80% and 1.07% with t-statistics of 4.39 and 4.37. Moreover, the return spreads of momentum and SUE also exhibit significant loadings on LIQ^{λ}.

The results of the cross-sectional regressions and GMM tests using the two sets of portfolios are reported in Table 8 and Figure 5. The results of the cross-sectional regressions are consistent with those for MOM and SUE portfolios in Table 5. The coefficients of liquidity risk are all statistically significant (at the 10 percent level), and the addition of LIQ^{λ} to CAPM and Fama-French three factors seems to significantly increase the adjusted R^2. The GMM tests are also consistent with those performed in Table 6 using momentum and SUE portfolios. Five out of eight estimated liquidity premiums are statistically significant at the 5 percent level, and one more at the 10 percent level. The estimated liquidity risk premiums vary between 40 and 66 basis points per month, which is consistent the magnitude of the premiums reported in Tables 5 and 6. The results of the cross-sectional regressions and the GMM tests provide further evidence for the pricing of the variable component of liquidity risk.

3 Discussion and Additional Tests

3.1 Economic Interpretation

The evidence in this paper shows that the variable component of liquidity risk is the component that is priced. How can one interpret this liquidity risk factor, and why does it change over time? One can seek guidance from theoretical models such as Kyle (1985) and Admati and Pfleiderer (1988). For example, Admati and Pfleiderer (1988) show that concentrated-trading patterns can arise as a results of the interaction between informed traders, discretionary liquidity traders, and nondiscretionary liquidity traders (noise traders). They study λ, the inverse of market depth or price change per unit of order flow, which corresponds to the variable component estimated here. They express λ as a function of the precision of the information of informed investors, the number of informed investors, and the total variance of liquidity and noise trades.[24] In addition, the number of informed traders is determined in equilibrium depending on the cost of obtaining information in

[24] See their Equations (5) and (18).

a given period. A change in any of the above-mentioned determinants would cause a change in λ, and it is difficult to conclude which determinant has the most prominent effect in practice.

The multi-period model of Admati and Pfleiderer implies periods of concentrated trading, which suggests time variation in λ at the firm level. Yet to relate their results to the pricing of a systematic component of liquidity, one needs to make the leap to the aggregate level. This would require some additional assumptions, such as that stocks are substitutes, or that at least one of the determinants of liquidity at the firm level is governed by a systematic, or market-wide process.

For example, a severe case of accounting fraud in a particular firm might have an aggregate effect as it could lead to a state of the world in which investors become more skeptical about the information contained in financial reports as a whole. In the model of Admati and Pfleiderer this would have several effects: informed traders may receive less precise signals; the costs of obtaining reliable information may increase, which would decrease the number of informed investors trading in the market; and the total volatility of liquidity and noise trades may decrease, as discretionary liquidity traders pull out of the market so as to not being mistakenly thought of as informed investors.

Some studies, such as De Long, Shleifer, Summers, and Waldmann (1990), consider the fluctuations of noise trading activity as a source of systematic risk (see also Black (1986) and Campbell and Kyle (1993)). They advance that aggregate unexpected fluctuations in the amount of noise traders could affect asset prices. This hypothesis is also consistent with the findings in this paper about the pricing of the variable component of liquidity risk, because the fluctuations in noise-traders' activity could lead to fluctuations in λ, as suggested by Kyle (1985) and Admati and Pfleiderer (1988).

3.2 Liquidity-Loading Sorted Portfolios

Although the pricing of liquidity risk focuses on momentum and PEAD strategies in this paper, it can also address a broad asset-pricing perspective. An additional robustness test of the pricing of liquidity risk is therefore offered here by conducting simple sorts of portfolios according to liquidity loadings as follows: using the monthly returns of all NYSE-listed firms on CRSP (with stock price between 1 and 1000 dollars at the end of previous month), I estimate each stock's liquidity loading every month using the past 60 months (5-year rolling window). The liquidity loading is calculated through a time-series regression of monthly returns (excess of risk-free rate) on the Fama-French three factors and a liquidity factor. Ten portfolios are then formed each month according to the estimated liquidity loadings. Portfolios are rebalanced monthly. This procedure is repeated for each of the four liquidity factors, using monthly returns for the 162-month period March 1988 through August 2001.

The results indicate that only the portfolios sorted by loadings on LIQ_t^{λ} exhibit a significant pattern: the average monthly returns (excess of risk-free rate) of these portfolios increase from 0.62% for the lowest liquidity-loading portfolio to 1.06% for the highest liquidity-loading portfolio. The average return spread (high minus low) is 0.44% per month, or 5.3% annually, with a t-statistic of 2.43. Its corresponding risk-adjusted returns are 0.44% per month (a t-statistic of 2.38) using CAPM, and 0.51% per month (a t-statistic of 2.79) using the Fama-French three factors. These results support the conclusion that the variable component of liquidity risk is priced with a premium of about 5-6% annually.

3.3 Additional Components of Liquidity

The pricing of liquidity risk thus far has focused on $LIQ^{\overline{\Psi}}$ and LIQ^{λ} corresponding to the non-information and information components of price impact. However, as noted above, Ψ and $\overline{\lambda}$ may also contain information about asset prices. To complete our discussion of the pricing of the different components of liquidity risk, we construct LIQ^{Ψ} and $LIQ^{\overline{\lambda}}$ based on Ψ and $\overline{\lambda}$, respectively, similar to the construction of $LIQ^{\overline{\Psi}}$ and LIQ^{λ}. The time series analysis of aggregate Ψ and $\overline{\lambda}$ suggest using ARIMA(0,1,3) to extract LIQ^{Ψ} and ARIMA(0,1,1) to extract $LIQ^{\overline{\lambda}}$. To eliminate possible correlation, each of LIQ^{Ψ} and $LIQ^{\overline{\lambda}}$ are orthogonalized to both $LIQ^{\overline{\Psi}}$ and LIQ^{λ}.

To test whether LIQ^{Ψ} and $LIQ^{\overline{\lambda}}$ are important for pricing momentum and SUE portfolio returns I conduct additional cross-sectional regressions using these two liquidity factors. The results (omitted for brevity) indicate that LIQ^{Ψ} does not earn a significant premium and its addition to the CAPM and Fama-French factors does not seem to have a significant impact on the adjusted R^2. Coupled with similar findings above with respect to $LIQ^{\overline{\Psi}}$, the results lead to the conclusion that neither fixed components of price impact, permanent (LIQ^{Ψ}) or transitory ($LIQ^{\overline{\Psi}}$), are pricing momentum and SUE portfolios. Moreover, $LIQ^{\overline{\lambda}}$ seems also not to be priced. Finally, adding all four liquidity factors to the pricing model shows that except for LIQ^{λ}, all factors have a premium which is statistically insignificant. The factor LIQ^{λ} has the highest (corrected) t-statistic, and in most cases it is statistically significant at the 5% level. All of these results suggest that among the four systematic components of price impact only LIQ^{λ} seems to be priced.

3.4 Conditional Models

The asset-pricing model in (10) and is an unconditional model. However, Grundy and Martin (2001) show a significant time variation in the loadings of momentum returns on Fama-French three factors. Therefore, I re-estimate (10) and (11) using conditional Fama-French factor loadings (the liquidity risk loadings remain unconditional).

Grundy and Martin (2001) derive a model in which momentum-based portfolios have conditional factor risk exposures that are linear functions of the ranking-period factor portfolio returns. As do Korajczyk and Sadka (2004), I rely on the results of Grundy and Martin (2001) and model a portfolio's conditional factor risk as a linear function of the ranking-period returns of Fama-French three factors (see Equations (6) and (7) in Korajczyk and Sadka (2004)). The Fama-MacBeth regressions are then estimated with the conditional Fama-French factor loadings and the unconditional liquidity loadings, using the 25 MOM and 25 SUE portfolio sets.

In general, the results (which for the purposes of brevity are not reported here) indicate that the estimated premiums as well as their statistical significance are similar to those estimated using the unconditional model for both sets of momentum portfolios and all factor model specifications considered in this paper. Specifically, the premiums on $LIQ^{\overline{\Psi}}$ and LIQ^{λ} do not change significantly, yet the statistical significance of the premium of LIQ^{λ} increase. For example, in the case of using 25 momentum portfolios for the model that includes the Fama-French three factors and LIQ^{λ}, the t-statistic of the coefficient of LIQ^{λ} increases from 0.74 to 2.50 when moving from the unconditional model to the conditional model. This result does not change when including both $LIQ^{\overline{\Psi}}$ and LIQ^{λ} factors. Therefore, I conclude that the results with respect to the pricing of liquidity risk presented above seem to be robust to using conditional Fama-French factor loadings.

4 Conclusions

This paper demonstrates that it is the variable permanent component of price impact which can explain part of momentum and PEAD portfolio returns. The result enhances our understanding of the sources of the cross-sectional variations of stock returns. Although many interpret financial anomalies as a ground for rejecting the efficient-market hypothesis, still the significance of these anomalies is reduced if they are associated with some type of risk and/or are too costly to exploit. The liquidity factor introduced here can be used to test whether asset-pricing anomalies carry a premium for liquidity risk, which may explain their persistence. Furthermore, the portfolios that are formed to test market anomalies in the literature often require frequent rebalancing and are therefore likely to be subject to liquidity concerns. The momentum anomaly and the post-earnings-announcement drift anomaly are investigated here as examples of such market anomalies. The paper emphasizes the liquidity risk that one must bear while engaging in trading these anomalies.

The ability to decompose the level of liquidity into variable and fixed components has a broad range of potential applications. For example, investors' reactions to corporate news and events such as equity issues and corporate mergers have been the focus of many studies. Volume-based measures (usually measured on a daily level) are often used in these type of studies to assess how investors process new information. Only a few such studies use intraday data such as bid-ask spreads (see, e.g., Lee, Mucklow, and Ready (1993) and Affleck-Graves, Callahan, Chipalkatti (2002)). Price impacts can contribute to understanding the nature of informational versus non-informational trades around these financial events. Using the decomposition described in this paper, one could investigate whether there is evidence of trading based on private information before the announcement. This might point to information leakage.

The evidence in this paper emphasizes the need for an equilibrium asset-pricing model that incorporates price-impact costs. Preliminary studies in this direction are the equilibrium model in the working paper version of Brennan and Subrahmanyam (1996), the portfolio choice models in Sadka (2002) and Liu (2004), the work of Acharya and Pedersen (2004), and the general equilibrium models in Eisfeldt (2004), and in Vayanos (2004). Future work should focus on developing general equilibrium models with liquidity premia for price impacts. Such models should provide theoretical guidelines as to the exact formulation in which transaction costs affect expected returns. With a rigorous benchmark model at hand, one may be able to further sharpen the empirical tests of the pricing of liquidity. This is also related to the question of what economic forces are captured by the liquidity risk factor. The effects underpinning the changes to liquidity in financial markets should be the focus of future research.

Last, one can make the following observation. The evidence about price momentum and post-earnings-announcement drift point to a relation of these anomalies to the variable (informational) component of liquidity risk. Notice that these anomalies are related to investors' reactions to new information about firms: momentum can be viewed as investors' reaction to news about the stock (see Chan (2003)), while the post-earnings-announcement drift can be viewed as reaction to news about earnings. Since these anomalies are news-related, it should come as no surprise that their associated returns are sensitive to shocks to the market-wide information asymmetry environment. The portfolios constructed to illustrate these anomalies generally outperform during months of positive liquidity shocks and underperform during months of negative liquidity shocks. This supports the hypothesis that the empirically observed premia for bearing liquidity risk or information-asymmetry risk is associated with investors' preferences with respect to risk in different states of the world. We seem to observe a systematic positive drift to firms following good news and a negative drift following bad news. These results suggest that when testing for market efficiency following news releases, the benchmark asset-pricing model should include an information-based liquidity risk factor.

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Table 1
Diagnostics of Price-Impact Components

Price impacts are estimates of the Glosten and Harris (1988) model $\Delta p_t = \alpha + \Psi D_t + \lambda DV_t + \overline{\Psi}\Delta D_t + \overline{\lambda}\Delta DV_t + y_t$ where Δp_t is the price improvement (in dollars) as a result of trading V_t shares at time t, where t represents event time, D_t is an indicator for buyer-initiated (+1) or seller-initiated (-1) trade, and y_t represents price movements related to public available information. The model is estimated using dummy variables for trades above 10,000 shares. In addition, the model is corrected for unanticipated trade sign and signed volume (see Section 1). The model identifies both permanent and transitory components of the total price impact, as well as fixed and variable costs. Price impacts are separately estimated on a monthly basis for every stock. Time-series means of monthly cross-sectional statistics are calculated below. Panel A uses raw estimates of price impact, while Panel B scales the measures by the stock price at the beginning of the month. The estimation analysis includes NYSE-listed stocks (with available intraday data) for the period January 1983 to August 2001.

		Mean	Std	1%	25%	Median	75%	99%
Panel A: Price-impact components								
Permanent Variable × 10^6	λ	7.90	12.00	-20.00	2.15	5.57	10.00	71.00
Permanent Fixed	Ψ	0.02	0.03	-0.08	0.00	0.01	0.02	0.14
Transitory Variable × 10^6	$\overline{\lambda}$	-3.08	7.15	-30.00	-5.32	-2.94	-0.64	26.00
Transitory Fixed	$\overline{\Psi}$	0.05	0.01	0.01	0.05	0.05	0.06	0.10
Panel B: Scaled price-impact components								
Permanent Variable × 10^7		4.45	7.97	-14.50	0.90	2.37	5.49	45.79
Permanent Fixed (%)		0.08	0.18	-0.59	0.01	0.05	0.12	1.00
Transitory Variable × 10^7		-2.02	5.32	-28.73	-2.86	-1.19	-0.28	16.02
Transitory Fixed (%)		0.37	0.43	0.03	0.15	0.25	0.42	2.95

Table 2
Price Impacts and Other Characteristics

Price impacts are estimated through the model described in Section 1. The model identifies both variable (information) and fixed (non-information) components of price impact ($\bar{\Psi}$ and λ respectively). Price impacts are estimated separately for every stock on a monthly basis. Price impacts are scaled by beginning-of-the-month price. Other characteristics and liquidity measures existing in the literature are independently computed: size is measured as the natural logarithm of market capitalization (in millions of dollars); the natural logarithm book-to-market equity (BE/ME) is computed according to the description in Cohen, Polk, and Vuolteenaho (2002); volume is the total number of shares traded of each stocks every month; turnover is volume divided by the number of shares outstanding; and the illiquidity measure is that used in Amihud (2002) which is defined as the monthly average of absolute value of daily return divided by daily dollar volume. The table reports the time-series average of monthly cross-sectional correlations. The analysis includes NYSE-listed stocks (with available intraday data) for the period January 1983 to August 2001.

	Variable component	Fixed component	Size	BE/ME	Volume	Turnover
Fixed component	0.28					
Size	-0.37	-0.53				
BE/ME	0.07	0.12	-0.24			
Volume	-0.18	-0.14	0.58	-0.10		
Turnover	-0.11	-0.05	0.06	0.07	0.32	
Amihud (2002)	0.15	0.36	-0.23	0.10	-0.06	-0.05

Table 3

Risk-Adjusted Returns of Portfolios Based on Momentum and SUE

This table reports average returns (excess of risk-free rate) and risk-adjusted returns (relative to CAPM and Fama-French (1993) three factors) for two sets of portfolios: 25 momentum (MOM) portfolios and 25 portfolios sorted by standardized unexpected earnings (SUE). Momentum is calculated as the past 12-month cumulative returns excluding the last month. The variable SUE for stock *i* in month *t* is defined as $[(E_{i,q} - E_{i,q\text{-}4}) - c_{i,t}]/\sigma_{i,t}$ where $E_{i,q}$ is the quarterly earnings most recently announced as of month *t* for firm *i* (not including announcements in month *t*); $E_{i,q\text{-}4}$ is earnings four quarters ago; and $\sigma_{i,t}$ and $c_{i,t}$ are the standard deviation and average, respectively, of $(E_{i,q} - E_{i,q\text{-}4})$ over the preceding eight quarters. The stocks are equally weighted in each portfolio and the portfolios are rebalanced monthly. Returns are reported in percent. The analysis includes NYSE-listed stocks with available intraday data for the period March 1983 to August 2001.

Panel A: MOM Portfolios

MOM Ranking	Excess Return	T of Return	CAPM Alpha	T of Alpha	FF Alpha	T of Alpha
1	-0.50	-0.76	-1.37	-2.49	-1.64	-3.19
	0.34	0.80	-0.36	-1.19	-0.65	-2.29
	0.60	1.64	-0.04	-0.19	-0.30	-1.32
	0.58	1.71	-0.03	-0.13	-0.36	-1.84
5	0.57	1.78	0.00	-0.02	-0.37	-1.98
	0.59	1.94	0.03	0.18	-0.33	-2.05
	0.79	2.75	0.26	1.46	-0.06	-0.41
	0.60	2.13	0.07	0.42	-0.27	-1.90
	0.85	3.23	0.36	2.23	0.06	0.44
10	0.73	2.70	0.22	1.36	-0.07	-0.54
	0.64	2.47	0.15	0.98	-0.16	-1.25
	0.78	3.27	0.33	2.34	0.06	0.50
	0.65	2.64	0.18	1.26	-0.11	-0.90
	0.63	2.55	0.17	1.12	-0.13	-1.07
15	0.71	2.82	0.22	1.57	-0.07	-0.56
	0.81	3.10	0.29	2.11	-0.01	-0.06
	0.73	2.60	0.17	1.15	-0.12	-0.93
	0.79	3.05	0.28	2.00	0.00	-0.04
	0.91	3.29	0.36	2.46	0.10	0.74
20	0.78	2.71	0.22	1.37	-0.07	-0.50
	0.90	3.03	0.31	1.97	0.01	0.09
	0.99	3.31	0.38	2.56	0.13	0.99
	1.10	3.43	0.45	2.84	0.24	1.67
	1.02	2.89	0.31	1.71	0.09	0.58
25	1.44	3.39	0.62	2.59	0.58	2.67
25 - 1	1.93	3.28	1.98	3.32	2.22	3.68

Panel B: SUE Portfolios

SUE Ranking	Excess Return	T of Return	CAPM Alpha	T of Alpha	FF Alpha	T of Alpha
1	0.59	1.67	-0.05	-0.23	-0.35	-1.72
	0.32	0.95	-0.31	-1.54	-0.63	-3.53
	0.32	1.02	-0.28	-1.45	-0.60	-3.61
	0.51	1.67	-0.07	-0.38	-0.31	-1.96
5	0.53	1.73	-0.06	-0.38	-0.35	-2.37
	0.72	2.44	0.14	0.87	-0.14	-1.03
	0.66	2.24	0.09	0.52	-0.18	-1.22
	0.70	2.32	0.13	0.71	-0.21	-1.45
	0.62	2.11	0.05	0.32	-0.20	-1.32
10	0.70	2.29	0.12	0.66	-0.25	-1.66
	0.75	2.42	0.17	0.89	-0.25	-1.72
	0.76	2.41	0.15	0.83	-0.14	-0.86
	0.68	2.28	0.12	0.66	-0.20	-1.29
	0.83	2.68	0.23	1.32	-0.12	-0.86
15	1.02	3.43	0.45	2.65	0.14	0.95
	1.00	3.25	0.39	2.38	0.14	0.93
	0.85	2.70	0.26	1.37	-0.04	-0.25
	0.99	3.20	0.39	2.27	0.10	0.72
	0.87	2.74	0.24	1.42	-0.07	-0.53
20	1.16	3.57	0.52	2.92	0.20	1.28
	1.15	3.56	0.52	2.92	0.19	1.27
	0.98	2.99	0.33	1.89	0.05	0.30
	1.09	3.39	0.44	2.72	0.17	1.15
	1.30	3.90	0.64	3.53	0.34	2.06
25	1.27	4.10	0.65	4.04	0.41	2.76
25 - 1	0.69	3.23	0.71	3.27	0.76	3.46

Table 4
Liquidity Loadings of Momentum and PEAD Portfolios

This table reports the loadings of different portfolios on two non-traded liquidity factors. The loadings are calculated through a time-series regression of portfolio returns (excess of risk-free rate) on the Fama and French three factors and each liquidity factor separately. Two different sets of portfolios are analyzed: 25 momentum (MOM) portfolios and 25 portfolios sorted by standardized unexpected earnings (SUE). Momentum is calculated as the past 12-month cumulative returns (excluding the last month). The variable SUE for stock *i* in month *t* is defined as $[(E_{i,q} - E_{i,q-4}) - c_{i,t}]/\sigma_{i,t}$ where $E_{i,q}$ is the quarterly earnings most recently announced as of month *t* for firm *i* (not including announcements in month *t*); $E_{i,q-4}$ is earnings four quarters ago; and $\sigma_{i,t}$ and $c_{i,t}$ are the standard deviation and average, respectively, of $(E_{i,q} - E_{i,q-4})$ over the preceding eight quarters. The stocks are equally weighted in each portfolio and the portfolios are rebalanced monthly. Liquidity measures are estimated per firm, per month using the Glosten and Harris (1988) model $\Delta p_t = \alpha + \Psi D_t + \lambda DV_t + \bar{\Psi}\Delta D_t + \bar{\lambda}\Delta DV_t + y_t$ where Δp_t is the price improvement (in dollars) as a result of trading V_t shares at time *t* (here *t* represents event time), D_t is an indicator for buyer-initiated (+1) or seller-initiated (-1) trade, and y_t represents price movements related to public available information. The model is estimated using dummy variables for trades above 10,000 shares (four dummy variables). In addition, the model is corrected for unanticipated trade sign and signed volume (see Section 1). The transitory fixed component is $\bar{\Psi}$ and the permanent variable component is λ. Price impacts are estimated on a monthly basis separately for every stock, and they are scaled by beginning-of-month price. To construct liquidity factors, every month aggregate price impacts are calculated as cross-sectional averages. Liquidity factors LIQ($\bar{\Psi}$) and LIQ(λ) are computed as shocks to the (fitted) time series of aggregate $\bar{\Psi}$ and λ, respectively. Shocks are proxied by the residuals of ARIMA models (random walk model for LIQ(λ), and a model of two autoregression lags and one lag of moving average for LIQ($\bar{\Psi}$)). The liquidity loadings of each portfolio are calculated using a time-series regression of portfolio returns on the Fama-French three factors and a liquidity factor. The analysis includes NYSE-listed stocks with available intraday data for the period March 1983 to August 2001.

Panel A: MOM Portfolios

Momentum Ranking	LIQ ($\bar{\Psi}$) Loading	T Statistic	LIQ (λ) Loading	T Statistic
1	0.62	0.32	-2.47	-2.89
	0.56	0.52	-0.52	-1.10
	-0.03	-0.03	-0.45	-1.18
	0.62	0.82	-0.39	-1.18
5	-0.30	-0.42	-0.56	-1.76
	-0.57	-0.93	-0.63	-2.35
	0.03	0.06	-0.30	-1.12
	0.12	0.22	-0.06	-0.26
	-0.72	-1.35	-0.24	-1.01
10	-0.29	-0.54	-0.12	-0.49
	0.55	1.14	0.16	0.73
	-0.42	-0.91	0.17	0.84
	-0.49	-1.06	0.07	0.34
	0.69	1.45	0.14	0.66
15	-0.04	-0.08	0.34	1.72
	0.44	1.01	0.38	1.97
	-0.14	-0.29	0.23	1.09
	-0.61	-1.37	0.46	2.31
	0.38	0.76	0.44	2.00
20	-0.31	-0.59	0.65	2.84
	-0.26	-0.49	0.58	2.56
	-0.10	-0.21	0.63	2.95
	0.38	0.70	0.76	3.23
	-0.25	-0.40	0.81	3.02
25	1.37	1.66	1.11	3.11
25 - 1	0.74	0.32	3.59	3.61

Panel B: SUE Portfolios

SUE Ranking	LIQ ($\bar{\Psi}$) Loading	T Statistic	LIQ (λ) Loading	T Statistic
1	-1.00	-1.30	-0.21	-0.60
	-0.45	-0.66	-0.26	-0.88
	0.37	0.58	-0.14	-0.51
	-0.40	-0.65	-0.08	-0.29
5	0.52	0.92	0.20	0.80
	-0.28	-0.53	0.15	0.64
	-0.26	-0.45	0.01	0.03
	-0.15	-0.27	0.19	0.75
	-0.17	-0.29	0.22	0.86
10	-0.03	-0.05	0.18	0.71
	0.36	0.66	0.14	0.55
	0.35	0.58	-0.13	-0.48
	1.38	2.32	0.33	1.25
	-0.23	-0.42	0.34	1.40
15	0.45	0.82	0.24	0.99
	0.61	1.06	0.36	1.42
	1.39	2.23	0.26	0.93
	0.30	0.55	0.28	1.15
	0.80	1.49	-0.03	-0.12
20	-0.75	-1.28	0.02	0.07
	-0.36	-0.61	0.19	0.73
	-0.24	-0.41	0.14	0.54
	-0.21	-0.38	0.37	1.52
	0.02	0.04	0.03	0.12
25	0.87	1.55	0.48	1.93
25 - 1	1.88	2.27	0.69	1.87

Table 5

Pricing Liquidity Risk with Cross-sectional Regressions

Two different sets of portfolios are analyzed: 25 momentum (MOM) portfolios and 25 portfolios sorted by standardized unexpected earnings (SUE). Momentum is calculated as the past 12-month cumulative returns (excluding the last month). The variable SUE for stock i in month t is defined as $[(E_{i,q} - E_{i,q\text{-}4}) - c_{i,t}]/\sigma_{i,t}$ where $E_{i,q}$ is the quarterly earnings most recently announced as of month t for firm i (not including announcements in month t); $E_{i,q\text{-}4}$ is earnings four quarters ago; and $\sigma_{i,t}$ and $c_{i,t}$ are the standard deviation and average, respectively, of $(E_{i,q} - E_{i,q\text{-}4})$ over the preceding eight quarters. The stocks are equally weighted in each portfolio and the portfolios are rebalanced monthly. Liquidity measures are estimated per firm, per month using the Glosten and Harris (1988) model $\Delta p_t = \alpha + \Psi D_t + \lambda DV_t + \bar{\Psi}\Delta D_t + \bar{\lambda}\Delta DV_t + y_t$ where Δp_t is the price improvement (in dollars) as a result of trading V_t shares at time t (here t represents event time), D_t is an indicator for buyer-initiated (+1) or seller-initiated (-1) trade, and y_t represents price movements related to public available information. The model is estimated using dummy variables for trades above 10,000 shares (four dummy variables). In addition, the model is corrected for unanticipated trade sign and signed volume (see Section 1). The transitory fixed component is $\bar{\Psi}$ and the permanent variable component is λ. Price impacts are estimated on a monthly basis, separately for every stock, and they are scaled by beginning-of-month price. To construct liquidity factors, every month aggregate price impacts are calculated as cross-sectional averages. Liquidity factors LIQ($\bar{\Psi}$) and LIQ(λ) are computed as shocks to the (fitted) time series of aggregate $\bar{\Psi}$ and λ, respectively. Shocks are proxied by the residuals of ARIMA models (random walk model for LIQ($\bar{\Psi}$), and a model of two autoregression lags and one lag of moving average for LIQ(λ)). The returns (excess of risk-free rate) of the two sets of 25 portfolios are used separately to estimate the cross-sectional regression models of the form $E(R_{i,t}) = \gamma_0 + \gamma`\beta_i$, where $R_{i,t}$ are the returns of portfolio i, β_i is a vector of factor loadings. The loadings are computed through a time-series multiple regression of portfolio excess returns on the factors tested over the entire sample period. The factors considered here are the Fama-French three factors, MKT, SMB, HML, and the non-traded liquidity factors. The regression models are estimated using the Fama-MacBeth procedure. Premium estimates are reported in percents. Standard errors are corrected for the sampling errors in the estimated β_i (Shanken (1992)). Each adjusted R^2 is computed from a single cross-sectional regression of average excess returns of the portfolios on their factor loadings. The analysis includes NYSE-listed stocks with available intraday data for the period March 1983 to August 2001.

Panel A: MOM Portfolios

	Intercept	MKT	SMB	HML	LIQ ($\bar{\Psi}$)	LIQ (λ)	Adjusted R^2
Premium	1.08	-0.43					0.00
T-Statistic	2.83	-0.76					
Premium	0.62	0.60			-0.32		0.16
T-Statistic	1.14	0.82			-1.66		
Premium	0.62	-0.02				0.47	0.83
T-Statistic	1.42	-0.04				2.21	
Premium	0.54	0.19			-0.03	0.42	0.83
T-Statistic	1.29	0.33			-0.49	2.23	
Premium	1.08	1.29	-1.41	-2.37			0.86
T-Statistic	1.74	1.47	-1.58	-2.38			
Premium	1.09	1.31	-1.36	-2.45	-0.11		0.86
T-Statistic	1.60	1.36	-1.41	-2.14	-1.24		
Premium	0.92	0.87	-0.89	-1.56		0.15	0.87
T-Statistic	1.65	1.15	-1.23	-2.37		0.74	
Premium	0.93	0.88	-0.83	-1.64	-0.07	0.13	0.87
T-Statistic	1.60	1.12	-1.08	-2.44	-1.20	0.66	

Panel B: SUE Portfolios

	Intercept	MKT	SMB	HML	LIQ ($\bar{\Psi}$)	LIQ (λ)	Adjusted R^2
Premium	-2.06	3.27					0.21
T-Statistic	-2.72	3.69					
Premium	-2.55	3.69			0.08		0.20
T-Statistic	-2.86	3.70			1.29		
Premium	-3.18	4.19				1.03	0.60
T-Statistic	-1.96	2.41				2.35	
Premium	-3.10	4.12			0.06	1.04	0.58
T-Statistic	-1.81	2.27			0.55	2.34	
Premium	-1.00	2.94	-2.32	-1.04			0.41
T-Statistic	-1.02	2.96	-2.32	-1.74			
Premium	-1.29	3.20	-2.09	-1.14	0.01		0.39
T-Statistic	-1.26	3.06	-2.14	-1.90	0.09		
Premium	-2.44	3.85	-0.66	-1.35		0.82	0.62
T-Statistic	-1.41	2.33	-0.44	-1.48		2.24	
Premium	-2.37	3.79	-0.69	-1.32	0.02	0.83	0.60
T-Statistic	-1.36	2.27	-0.47	-1.46	0.25	2.24	

Table 6
Pricing Liquidity Risk with the Stochastic Discount Factor Approach

Two different sets of portfolios are analyzed: 25 momentum (MOM) portfolios and 25 portfolios sorted by standardized unexpected earnings (SUE). Momentum is calculated as the past 12-month cumulative returns (excluding the last month). The variable SUE for stock i in month t is defined as $[(E_{i,q} - E_{i,q\text{-}4}) - c_{i,t}]/\sigma_{i,t}$ where $E_{i,q}$ is the quarterly earnings most recently announced as of month t for firm i (not including announcements in month t); $E_{i,q\text{-}4}$ is earnings four quarters ago; and $\sigma_{i,t}$ and $c_{i,t}$ are the standard deviation and average, respectively, of $(E_{i,q} - E_{i,q\text{-}4})$ over the preceding eight quarters. The stocks are equally weighted in each portfolio and the portfolios are rebalanced monthly. Liquidity measures are estimated per firm per month using the Glosten and Harris (1988) model $\Delta p_t = \alpha + \Psi D_t + \lambda DV_t + \overline{\Psi}\Delta D_t + \overline{\lambda}\Delta DV_t + y_t$ where Δp_t is the price improvement (in dollars) as a result of trading V_t shares at time t where t represents event time, D_t is an indicator for buyer-initiated (+1) or seller-initiated (-1) trade, and y_t represents price movements related to public available information. The model is estimated using dummy variables for trades above 10,000 shares. In addition, the model is corrected for unanticipated trade sign and signed volume (see Section 1). The model identifies both variable (permanent) and fixed (transitory) components of price impact. Price impacts are estimated on a monthly basis, separately for every stock and they are scaled by beginning-of-month price. Every month, aggregate price impact is calculated as the cross-sectional average of the variable component. The liquidity factor, LIQ(λ), is computed as shocks to this time series, proxied by the residuals of an ARMA model of two autoregression lags and one lag of moving average. The returns (excess of risk-free rate) of the 25 portfolios in each set are used to estimate the following model for the moments $E[R_{i,t}(1-\delta' f_t)]=0$ where $R_{i,t}$ are the returns of portfolio i, and f_i is a vector of factors. The factors considered here are the Fama-French three factors, MKT, SMB, HML, and the non-traded liquidity factor. The models are estimated with the Generalized Method of Moments. Both the Hansen (1982) optimal weighted matrix and the weighting matrix proposed by Hansen and Jagannathan (1997) are used. Premiums are calculated as $E[ff']\delta$ (using demeaned factors) and reported in percent return. The t-statistic of δ (below each premium) tests whether the factor has additional pricing power given the other factors. P-values of Chi-Squared tests of the different models are also reported. The analysis includes NYSE-listed stocks with available intraday data for the period March 1983 to August 2001.

Panel A: MOM Portfolios

Hansen (1982)	MKT	SMB	HML	LIQ (λ)	P-value
Premium	1.94				0.00
T-Statistic	5.89				
Premium	1.34			0.34	0.03
T-Statistic	2.59			3.04	
Premium	2.38	-1.73	-1.37		0.06
T-Statistic	3.30	-3.18	-2.30		
Premium	1.39	-1.56	-0.26	0.34	0.69
T-Statistic	1.87	-2.87	-0.99	2.54	

Hansen-Jagannathan (1997)	MKT	SMB	HML	LIQ (λ)	P-value
Premium	0.80				0.01
T-Statistic	1.42				
Premium	0.63			0.49	0.40
T-Statistic	0.06			2.26	
Premium	2.42	-2.21	-1.87		0.50
T-Statistic	1.31	-1.93	-1.57		
Premium	1.11	-0.84	-0.35	0.32	0.62
T-Statistic	0.60	-0.83	-0.40	1.04	

Panel B: SUE Portfolios

Hansen (1982)	MKT	SMB	HML	LIQ (λ)	P-value
Premium	1.78				0.00
T-Statistic	5.17				
Premium	2.27			0.62	0.08
T-Statistic	2.85			4.03	
Premium	1.54	-1.14	0.00		0.00
T-Statistic	4.99	-1.85	0.39		
Premium	1.63	-0.66	0.06	0.44	0.14
T-Statistic	3.13	-1.08	0.77	3.44	

Hansen-Jagannathan (1997)	MKT	SMB	HML	LIQ (λ)	P-value
Premium	0.91				0.00
T-Statistic	1.69				
Premium	0.55			0.76	0.09
T-Statistic	-0.37			3.29	
Premium	1.60	-2.86	0.01		0.00
T-Statistic	2.95	-3.83	-1.17		
Premium	1.32	-1.76	-0.28	0.55	0.07
T-Statistic	0.47	-2.51	-1.31	3.22	

Table 7

Risk-Adjusted Returns and Liquidity Loadings of Momentum/Liquidity and PEAD/Liquidity Portfolios

This table reports average returns (excess of risk-free rate), risk-adjusted returns (relative to Fama-French (1993) three factors), and the liquidity loadings of two sets of portfolios: 5x5 portfolios sorted on momentum and the variable component of liquidity (MOM/λ) and 5x5 portfolios sorted by standardized unexpected earnings and the variable component of liquidity (SUE/λ). Momentum is calculated as the past 12-month cumulative returns (excluding the last month). The variable SUE for stock i in month t is defined as $[(E_{i,q} - E_{i,q-4}) - c_{i,t}]/\sigma_{i,t}$ where $E_{i,q}$ is the quarterly earnings most recently announced as of month t for firm i (not including announcements in month t); $E_{i,q-4}$ is earnings four quarters ago; and $\sigma_{i,t}$ and $c_{i,t}$ are the standard deviation and average, respectively, of $(E_{i,q} - E_{i,q-4})$ over the preceding eight quarters. Liquidity measures are estimated per firm per month using the Glosten and Harris (1988) model $\Delta p_t = \alpha + \Psi D_t + \lambda DV_t + \overline{\Psi}\Delta D_t + \overline{\lambda}\Delta DV_t + y_t$ where Δp_t is the price improvement (in dollars) as a result of trading V_t shares at time t where t represents event time, D_t is an indicator for buyer-initiated (+1) or seller-initiated (-1) trade, and y_t represents price movements related to public available information. The model is estimated using dummy variables for trades above 10,000 shares. In addition, the model is corrected for unanticipated trade sign and signed volume (see Section 1). The model identifies both variable (permanent) and fixed (transitory) components of price impact. Price impacts are estimated on a monthly basis, separately for every stock and they are scaled by beginning-of-month price. To form the first set of portfolios firms are sorted every month into five groups according to momentum, and then the firms within each group are sorted again into five λ groups. Similarly, the second set of portfolios is formed using dependent sorts of SUE and λ. The stocks are equally weighted in each portfolio and the portfolios are rebalanced monthly. Every month, aggregate price impact is calculated as the cross-sectional average of the variable component. The liquidity factor, LIQ(λ), is computed as shocks to this time series, proxied by the residuals of an ARMA model of two autoregression lags and one lag of moving average. The liquidity loadings of each portfolio are calculated using a time-series regression of portfolio returns on the Fama-French three factors and a liquidity factor. The analysis includes NYSE-listed stocks with available intraday data for the period March 1983 to August 2001.

Panel A: MOM/λ Portfolios

Momentum Ranking	λ Ranking	Excess Return	T of Return	FF Alpha	T of Alpha	LIQ (λ) Loading	T Statistic
1	1 (low)	0.43	1.03	-0.63	-2.30	-0.80	-1.74
(losers)		0.58	1.56	-0.36	-1.49	-0.81	-2.00
		0.38	0.91	-0.69	-2.74	-0.62	-1.44
		0.25	0.58	-0.72	-2.54	-1.03	-2.16
	5 (high)	-0.04	-0.09	-0.89	-2.47	-1.19	-1.96
2	1	0.66	2.48	-0.12	-0.82	0.14	0.55
		0.76	2.68	-0.10	-0.67	-0.51	-2.03
		0.82	2.99	0.00	-0.03	-0.18	-0.78
		0.60	2.06	-0.28	-1.88	-0.18	-0.74
	5	0.66	2.15	-0.21	-1.19	-0.60	-2.05
3	1	0.79	3.52	0.11	0.95	0.13	0.66
		0.65	2.54	-0.17	-1.49	0.09	0.44
		0.77	2.95	-0.04	-0.34	0.41	1.94
		0.52	1.97	-0.26	-1.91	0.23	1.00
	5	0.66	2.64	-0.05	-0.33	0.04	0.15
4	1	0.72	2.76	-0.07	-0.61	0.42	2.19
		0.93	3.36	0.08	0.65	0.47	2.37
		0.93	3.32	0.07	0.57	0.48	2.27
		0.65	2.34	-0.17	-1.37	0.33	1.60
	5	0.77	2.83	-0.01	-0.08	0.45	1.98
5	1	1.11	3.56	0.26	1.79	0.89	3.73
(winners)		1.03	3.20	0.22	1.50	0.95	3.95
		1.02	3.02	0.12	0.73	0.76	2.72
		0.98	2.74	0.04	0.27	0.64	2.42
	5	1.27	3.45	0.36	2.03	0.63	2.12
1	5-1	-0.47	-1.73	-0.26	-1.02	-0.39	-0.88
5	5-1	0.16	0.90	0.10	0.60	-0.26	-0.89
5-1	1	0.68	2.13	0.89	2.68	1.69	3.08
5-1	5	1.31	3.30	1.25	3.08	1.82	2.69

Panel B: SUE/λ Portfolios

SUE Ranking	λ Ranking	Excess Return	T of Return	FF Alpha	T of Alpha	LIQ (λ) Loading	T Statistic
1	1 (low)	0.48	1.64	-0.35	-2.48	-0.20	-0.84
(bad news)		0.67	2.21	-0.24	-1.57	0.18	0.70
		0.67	2.09	-0.26	-1.67	-0.07	-0.25
		0.32	0.96	-0.60	-3.63	0.08	0.27
	5 (high)	0.12	0.30	-0.78	-2.93	-0.49	-1.09
2	1	0.66	2.37	-0.17	-1.31	0.29	1.31
		0.82	2.79	-0.10	-0.71	0.20	0.85
		0.87	2.84	-0.05	-0.36	0.08	0.32
		0.51	1.59	-0.43	-2.74	0.15	0.57
	5	0.55	1.67	-0.24	-1.21	0.02	0.06
3	1	0.95	3.37	0.12	0.86	0.34	1.45
		1.01	3.37	0.08	0.60	0.40	1.88
		0.87	2.83	-0.09	-0.60	0.09	0.37
		0.68	2.03	-0.32	-1.88	-0.10	-0.34
	5	0.54	1.61	-0.35	-1.90	0.18	0.57
4	1	0.91	2.92	0.00	-0.02	0.49	2.05
		0.99	3.37	0.11	0.84	0.24	1.14
		0.93	3.01	0.01	0.10	0.04	0.15
		0.83	2.64	-0.08	-0.53	0.41	1.71
	5	1.21	3.17	0.28	1.20	-0.28	-0.73
5	1	1.32	4.24	0.45	2.96	0.47	1.86
(good news)		1.07	3.44	0.19	1.56	0.27	1.27
		1.06	3.32	0.13	0.82	0.46	1.81
		1.08	3.23	0.10	0.66	-0.01	-0.05
	5	1.26	3.47	0.29	1.43	0.03	0.09
1	5-1	-0.36	-1.34	-0.42	-1.74	-0.28	-0.69
5	5-1	-0.06	-0.27	-0.16	-0.71	-0.44	-1.19
5-1	1	0.84	4.77	0.80	4.39	0.68	2.21
5-1	5	1.14	4.74	1.07	4.37	0.52	1.25

Table 8

Pricing Liquidity Risk with Momentum/Liquidity and PEAD/Liquidity Portfolios

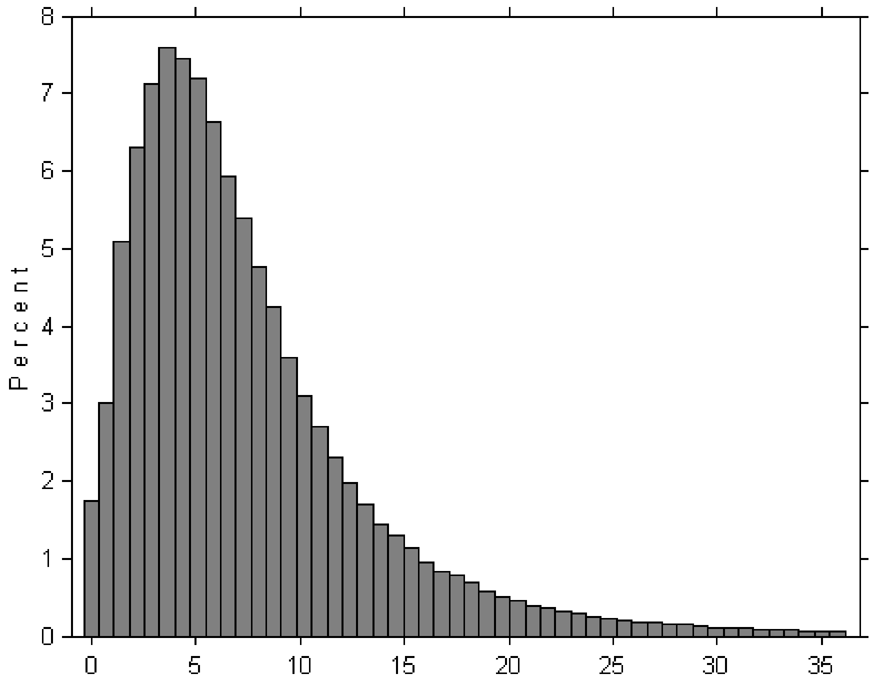
Two different sets of portfolios are analyzed: 5x5 portfolios sorted on momentum and the variable component of liquidity (MOM/λ) and 5x5 portfolios sorted by standardized unexpected earnings and the variable component of liquidity (SUE/λ). Momentum is calculated as the past 12-month cumulative returns (excluding the last month). The variable SUE for stock *i* in month *t* is defined as $[(E_{i,q} - E_{i,q-4}) - c_{i,t}]/\sigma_{i,t}$ where $E_{i,q}$ is the quarterly earnings most recently announced as of month *t* for firm *i* (not including announcements in month *t*); $E_{i,q-4}$ is earnings four quarters ago; and $\sigma_{i,t}$ and $c_{i,t}$ are the standard deviation and average, respectively, of $(E_{i,q} - E_{i,q-4})$ over the preceding eight quarters. Liquidity measures are estimated per firm per month using the Glosten and Harris (1988) model $\Delta p_t = \alpha + \Psi D_t + \lambda DV_t + \bar{\Psi}\Delta D_t + \bar{\lambda}\Delta DV_t + y_t$ where Δp_t is the price improvement (in dollars) as a result of trading V_t shares at time *t* where *t* represents event time, D_t is an indicator for buyer-initiated (+1) or seller-initiated (-1) trade, and y_t represents price movements related to public available information. The model is estimated using dummy variables for trades above 10,000 shares. In addition, the model is corrected for unanticipated trade sign and signed volume (see Section 1). The model identifies both variable (permanent) and fixed (transitory) components of price impact. Price impacts are estimated on a monthly basis, separately for every stock and they are scaled by beginning-of-month price. To form the first set of portfolios firms are sorted every month into five groups according to momentum, and then the firms within each group are sorted again into five λ groups. Similarly, the second set of portfolios is formed using dependent sorts of SUE and λ. The stocks are equally weighted in each portfolio and the portfolios are rebalanced monthly. Every month, aggregate price impact is calculated as the cross-sectional average of the variable component. The liquidity factor, LIQ(λ), is computed as shocks to this time series, proxied by the residuals of an ARMA model of two autoregression lags and one lag of moving average. The different analyses are performed: cross-sectional regressions, Hansen (1982) GMM tests, and Hansen and Jagannathan (1997) GMM tests. For cross-sectional regressions tests, the returns (excess of risk-free rate) of the two sets of 25 portfolios are used separately to estimate the cross-sectional regression models of the form $E(R_{i,t}) = \gamma_0 + \gamma'\beta_i$, where $R_{i,t}$ are the returns of portfolio *i*, β_i is a vector of factor loadings. The loadings are computed through a time-series multiple regression of portfolio excess returns on the factors tested over the entire sample period. The factors considered here are the Fama-French three factors, MKT, SMB, HML, and the non-traded liquidity factor. The regression models are estimated using the Fama-MacBeth procedure. Premium estimates are reported in percents. Standard errors are corrected for the sampling errors in the estimated β_i (Shanken (1992)). Each adjusted R^2 is computed from a single cross-sectional regression of average excess returns of the portfolios on their factor loadings. For the GMM tests, the portfolio returns (excess of risk-free rate) are used to estimate the following model for the moments $E[R_{i,t}(1-\delta' f_t)]=0$ where f_t is a vector of factors. The factors considered here are the Fama-French three factors, MKT, SMB, HML, and LIQ(λ). Both the Hansen (1982) optimal weighted matrix and the weighting matrix proposed by Hansen and Jagannathan (1997) are used. Premiums are calculated as $E[ff']\delta$ (using demeaned factors) and reported in percent return. The *t*-statistic of δ (below each premium) tests whether the factor has additional pricing power given the other factors. *P*-values of Chi-Squared tests of the different models are also reported. The analysis includes NYSE-listed stocks with available intraday data for the period March 1983 to August 2001.

Panel A: MOM/λ Portfolios

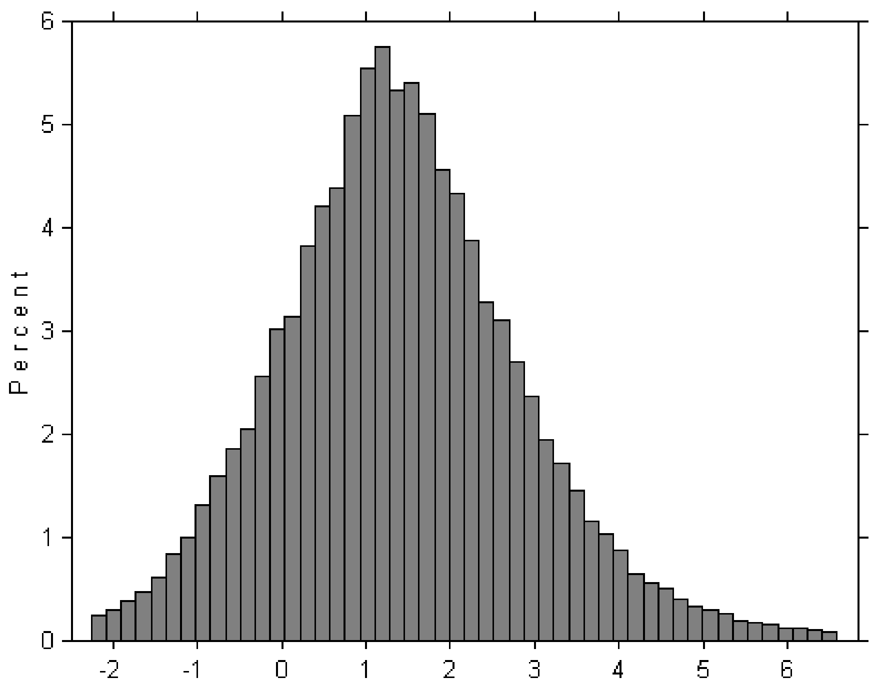
	MKT	SMB	HML	LIQ (λ)	Adjusted R^2
Cross-Sectional Regressions					
Premium	0.04				-0.04
T-Statistic	0.09				
Premium	0.15			0.42	0.67
T-Statistic	0.29			1.95	
Premium	0.18	-0.14	-1.64		0.32
T-Statistic	0.37	-0.38	-1.79		
Premium	0.39	-0.23	0.21	0.40	0.70
T-Statistic	0.80	-0.58	0.31	1.95	
Hansen (1982)	MKT	SMB	HML	LIQ (λ)	P-value
Premium	2.10				0.00
T-Statistic	7.99				
Premium	2.97			0.49	0.00
T-Statistic	7.24			4.27	
Premium	1.26	-0.95	1.35		0.00
T-Statistic	7.49	-0.23	5.03		
Premium	1.71	-0.41	1.22	0.40	0.12
T-Statistic	8.12	0.89	5.41	3.61	
Hansen-Jagannathan (1997)	MKT	SMB	HML	LIQ (λ)	P-value
Premium	0.82				0.06
T-Statistic	1.38				
Premium	0.66			0.42	0.65
T-Statistic	0.19			1.19	
Premium	0.91	-0.68	-0.01		0.17
T-Statistic	1.30	-1.25	0.08		
Premium	0.41	-0.29	0.60	0.40	0.53
T-Statistic	0.53	-0.12	0.55	0.99	

Panel B: SUE/λ Portfolios

	MKT	SMB	HML	LIQ (λ)	Adjusted R^2
Cross-Sectional Regressions					
Premium	2.33				0.08
T-Statistic	3.10				
Premium	2.55			0.66	0.23
T-Statistic	2.32			1.90	
Premium	2.38	-0.17	-0.86		0.13
T-Statistic	2.98	-0.40	-1.32		
Premium	2.54	0.11	-0.73	0.56	0.23
T-Statistic	2.40	0.21	-0.86	2.08	
Hansen (1982)	MKT	SMB	HML	LIQ (λ)	P-value
Premium	2.66				0.00
T-Statistic	8.03				
Premium	3.00			0.66	0.00
T-Statistic	5.81			3.53	
Premium	2.00	0.17	0.64		0.00
T-Statistic	9.25	3.09	5.17		
Premium	1.97	0.37	0.47	0.56	0.01
T-Statistic	6.03	2.50	4.40	3.24	
Hansen-Jagannathan (1997)	MKT	SMB	HML	LIQ (λ)	P-value
Premium	0.91				0.00
T-Statistic	1.33				
Premium	0.60			0.65	0.17
T-Statistic	-0.14			2.46	
Premium	0.41	-0.69	0.98		0.00
T-Statistic	2.09	-0.29	1.82		
Premium	0.26	-0.34	0.90	0.53	0.02
T-Statistic	0.56	-0.06	1.28	1.93	

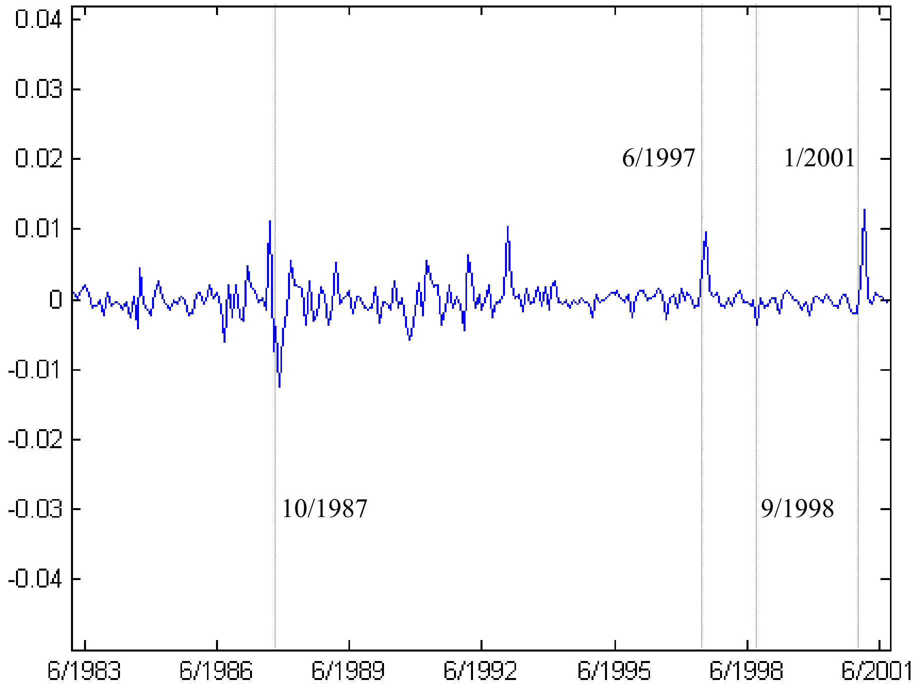


Panel A: Fixed component of price impact ($\overline{\Psi}$)

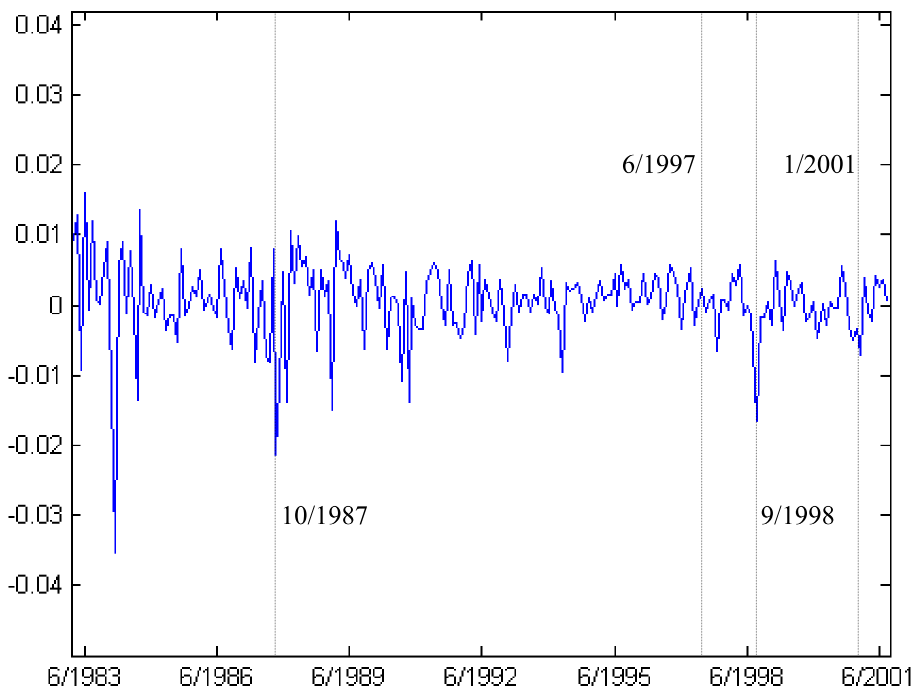


Panel B: Variable component of price impact (λ)

Figure 1, T-statistics of estimated measures of price impact. Price impacts are estimates of the Glosten and Harris (1988) model $\Delta p_t = \alpha + \Psi D_t + \lambda D V_t + \overline{\Psi}\Delta D_t + \overline{\lambda}\Delta D V_t + y_t$ where Δp_t is the price improvement (in dollars) as a result of trading V_t shares at time t (here t represents event time), D_t is an indicator for buyer-initiated (+1) or seller-initiated (-1) trade, and y_t represents price movements related to public available information. The model is estimated using dummy variables for trades above 10,000 shares (four dummy variables). In addition, the model is corrected for unanticipated trade sign and signed volume (see Section 1). The model identifies both variable (informational) and fixed (non-informational) components of price impact. All functions are estimated on a monthly basis, separately for every each NYSE-listed stock (with available intraday data). The panels plot the distribution of the t-statistics of the pooled cross-section and time series sample (truncated at 1 and 99 percent cutoffs) for NYSE-listed stocks for the period January 1983 through August 2001.

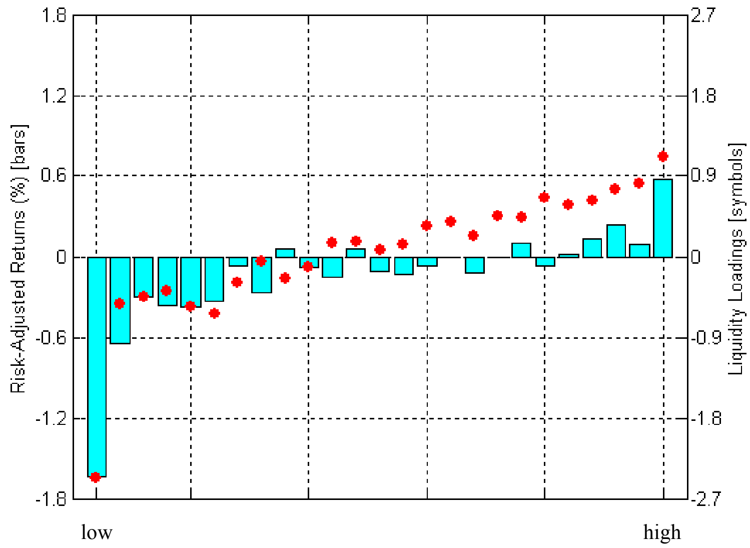


Panel A: Fixed component of liquidity risk – LIQ($\bar{\Psi}$)
[units: relative price change per trade]

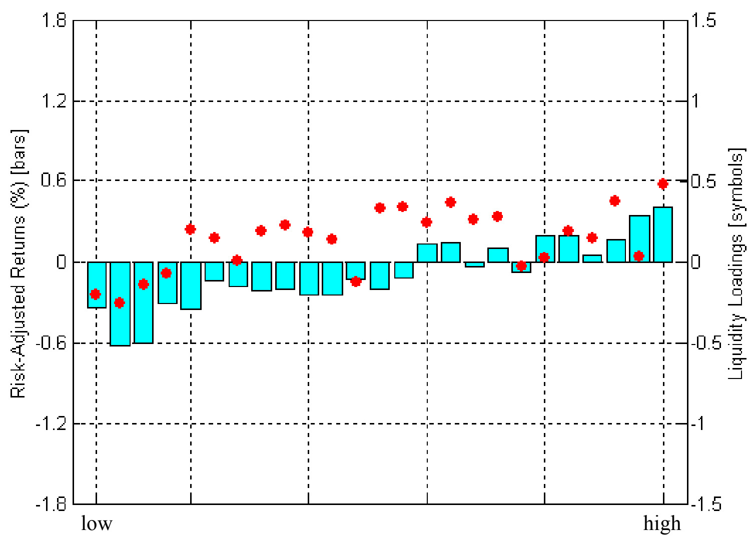


Panel B: Variable component of liquidity risk – LIQ(λ)
[units: relative price change per unit share traded × 10^5]

Figure 2. The time series of shocks to aggregate components of price impact. The time series of cross-sectional averages of estimated price-impact functions are plotted above. The function coefficients are estimates of the Glosten and Harris (1988) model $\Delta p_t = \alpha + \Psi D_t + \lambda DV_t + \bar{\Psi}\Delta D_t + \bar{\lambda}\Delta DV_t + y_t$ where Δp_t is the price improvement (in dollars) as a result of trading V_t shares at time t (here t represents event time), D_t is an indicator for buyer-initiated (+1) or seller-initiated (-1) trade, and y_t represents price movements related to public available information. The model is estimated using dummy variables for trades above 10,000 shares (four dummy variables). In addition, the model is corrected for unanticipated trade sign and signed volume (see Section 1). The model identifies both variable (informational) and fixed (non-informational) components of price impact. Price impacts are estimated on a monthly basis, separately for every stock, and they are scaled by beginning-of-month price. Every month aggregate price impacts are calculated as cross-sectional averages. Liquidity factors LIQ($\bar{\Psi}$) and LIQ(λ) are computed as shocks to the (fitted) time series of aggregate $\bar{\Psi}$ and λ, respectively. Shocks are proxied by the residuals of ARIMA models (random walk model for LIQ($\bar{\Psi}$), and a model of two autoregression lags and one lag of moving average for LIQ(λ)). The ticks on the horizontal axis correspond to the month of June of a given year. The analysis includes NYSE-listed firms (with available intraday information) for the period March 1983 to August 2001.

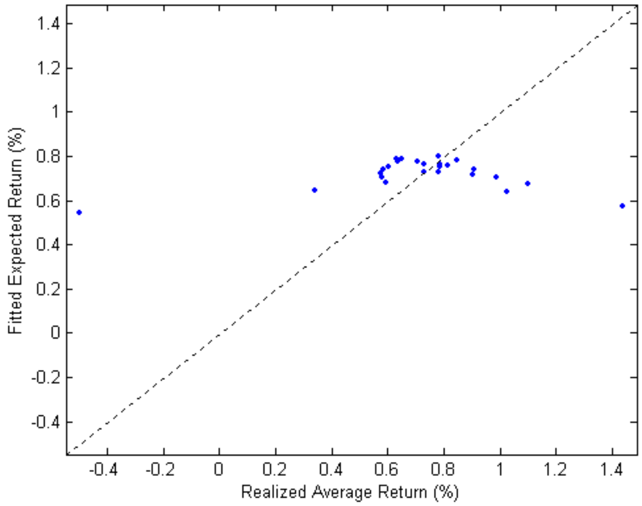


Panel A: MOM Portfolios

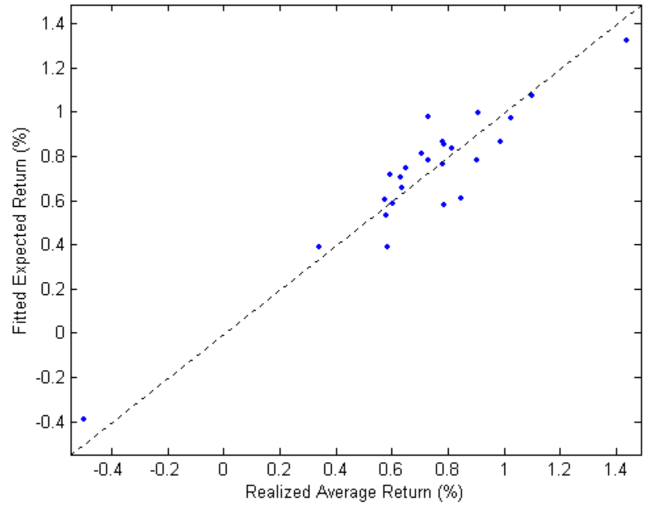


Panel B: SUE Portfolios

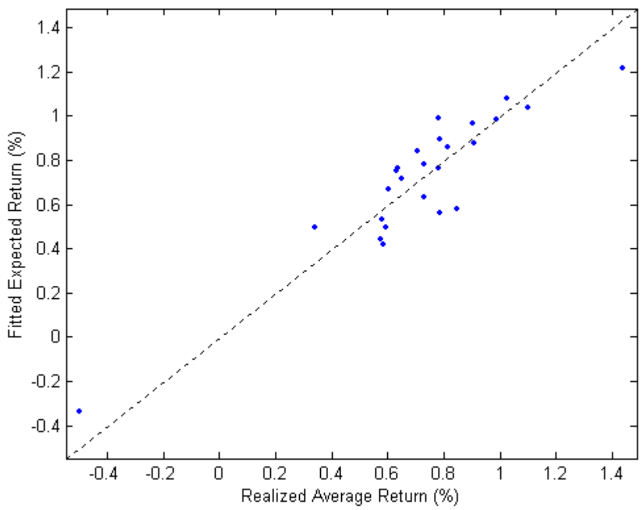
Figure 3. Risk-adjusted returns and liquidity loadings of price- and earnings-momentum portfolios. Two different sets of portfolios are analyzed: 25 momentum (MOM) portfolios and 25 portfolios sorted by standardized unexpected earnings (SUE). Momentum is calculated as the past 12-month cumulative returns (excluding the last month). The variable SUE for stock *i* in month *t* is defined as $[(E_{i,q} - E_{i,q\text{-}4}) - c_{i,t}]/\sigma_{i,t}$ where $E_{i,q}$ is the quarterly earnings most recently announced as of month *t* for firm *i* (not including announcements in month *t*); $E_{i,q\text{-}4}$ is earnings four quarters ago; and $\sigma_{i,t}$ and $c_{i,t}$ are the standard deviation and average, respectively, of $(E_{i,q} - E_{i,q\text{-}4})$ over the preceding eight quarters. The stocks are equally weighted in each portfolio, and the portfolios are rebalanced monthly. Liquidity measures are estimated per firm, per month using the Glosten and Harris (1988) model $\Delta p_t = \alpha + \Psi D_t + \lambda DV_t + \bar{\Psi}\Delta D_t + \bar{\lambda}\Delta DV_t + y_t$ where Δp_t is the price improvement (in dollars) as a result of trading V_t shares at time *t* (here *t* represents event time), D_t is an indicator for buyer-initiated (+1) or seller-initiated (-1) trade, and y_t represents price movements related to public available information. The model is estimated using dummy variables for trades above 10,000 shares (four dummy variables). In addition, the model is corrected for unanticipated trade sign and signed volume (see Section 1). The fixed (transitory) component is $\bar{\Psi}$ and the variable (permanent) component is λ. Price impacts are estimated on a monthly basis, separately for every stock, and they are scaled by beginning-of-month price. Every month, aggregate price impact is calculated as the cross-sectional average of the permanent variable price-impact component. The liquidity factor, LIQ(λ), is computed as shocks to this time series, proxied by the residuals of an ARMA model of two autoregression lags and one lag of moving average. The liquidity loadings (points on the graphs) are calculated using time-series regressions of portfolio returns on the Fama-French three factors MKT, SMB, and HML, and the non-traded liquidity factor LIQ(λ). Risk-adjusted returns (bars on the graph) are calculated using similar time-series regressions, but without including the non-traded factor. The analysis includes NYSE-listed firms with available intraday data for the period March 1983 to August 2001.



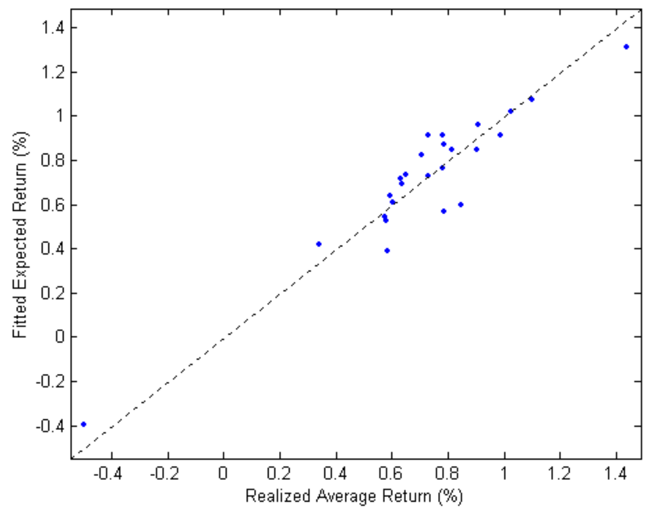
(a1) CAPM



(b1) FF



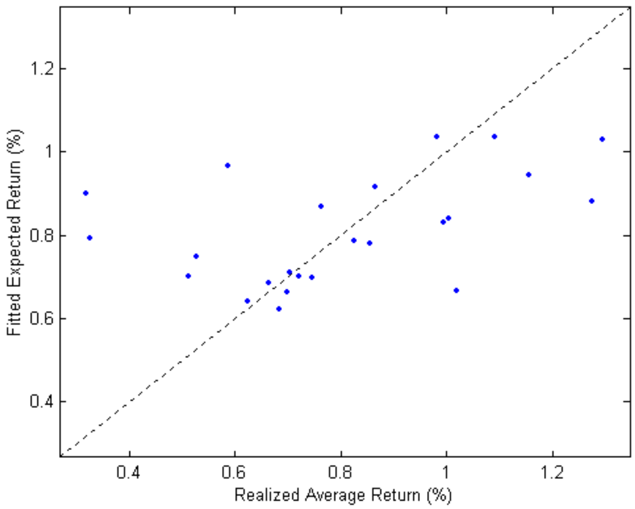
(c1) CAPM + LIQ(λ)



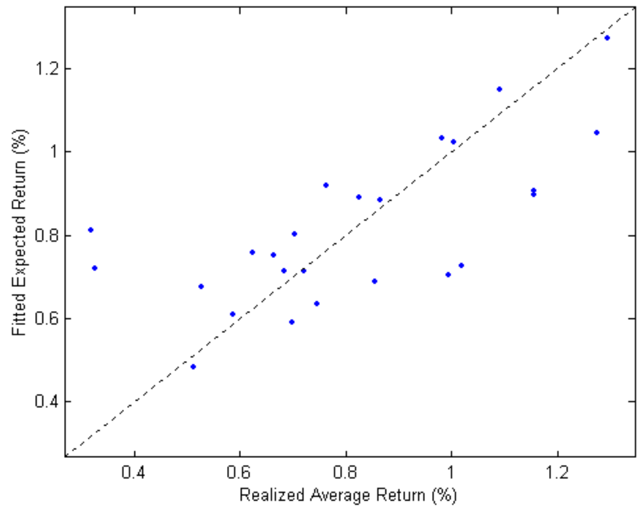
(d1) FF + LIQ(λ)

MOM Portfolios

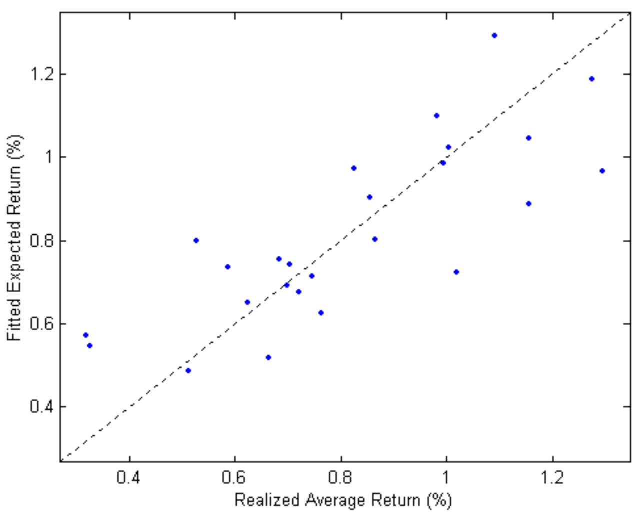
Figure 4. The cross-section of momentum and PEAD portfolio returns and liquidity risk. Two different sets of portfolios are analyzed: 25 momentum (MOM) portfolios and 25 portfolios sorted by standardized unexpected earnings (SUE). Momentum is calculated as the past 12-month cumulative returns (excluding the last month). The variable SUE for stock *i* in month *t* is defined as $[(E_{i,q} - E_{i,q-4}) - c_{i,t}]/\sigma_{i,t}$ where $E_{i,q}$ is the quarterly earnings most recently announced as of month *t* for firm *i* (not including announcements in month *t*); $E_{i,q-4}$ is earnings four quarters ago; and $\sigma_{i,t}$ and $c_{i,t}$ are the standard deviation and average, respectively, of $(E_{i,q} - E_{i,q-4})$ over the preceding eight quarters. The stocks are equally weighted in each portfolio, and the portfolios are rebalanced monthly. Liquidity measures are estimated per firm, per month using the Glosten and Harris (1988) model $\Delta p_t = \alpha + \Psi D_t + \lambda DV_t + \bar{\Psi}\Delta D_t + \bar{\lambda}\Delta DV_t + y_t$ where Δp_t is the price improvement (in dollars) as a result of trading V_t shares at time *t* (here *t* represents event time), D_t is an indicator for buyer-initiated (+1) or seller-initiated (-1) trade, and y_t represents price movements related to public available information. The model is estimated using dummy variables for trades above 10,000 shares (four dummy variables). In addition, the model is corrected for unanticipated trade sign and signed volume (see Section 1). The fixed (transitory) component is $\bar{\Psi}$ and the variable (permanent) component is λ. Price impacts are estimated on a monthly basis, separately for every stock, and they are scaled by beginning-of-month price. Every month, aggregate price impact is calculated as the cross-sectional average of the variable component. The liquidity factor, LIQ(λ), is computed as shocks to this time series, proxied by the residuals of an ARMA model of two autoregression lags and one lag of moving average. Each scatter point in each of the graphs represents one of the 20 portfolios, with the realized average return (excess of risk-free rate) on the horizontal axis, and the fitted expected return on the vertical axis. The realized average return is the time-series average return, and the fitted expected return is calculated as the fitted value from $E(R_{i,t}) = \gamma_0 + \gamma`\beta_{i,}$, where $R_{i,t}$ are the returns of portfolio *i*, β_i is a vector of factor loadings, and γ is a vector of the estimated risk premiums. The loadings are computed through a time-series multiple regression of portfolio excess returns on the factors tested over the entire sample period. The factors considered here are the Fama-French three factors, MKT, SMB, and HML, and the non-traded liquidity factor LIQ(λ). The straight line in each graph is the 45° line from the origin. The analysis includes NYSE-listed stocks with available intraday data for the period March 1983 to August 2001.



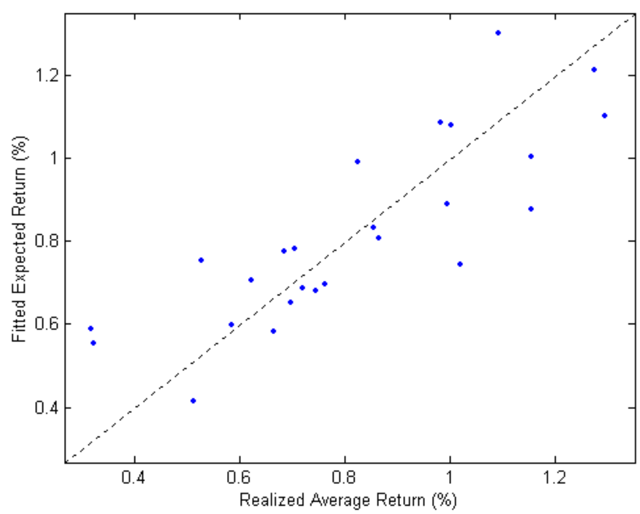
(a2) CAPM



(b2) FF

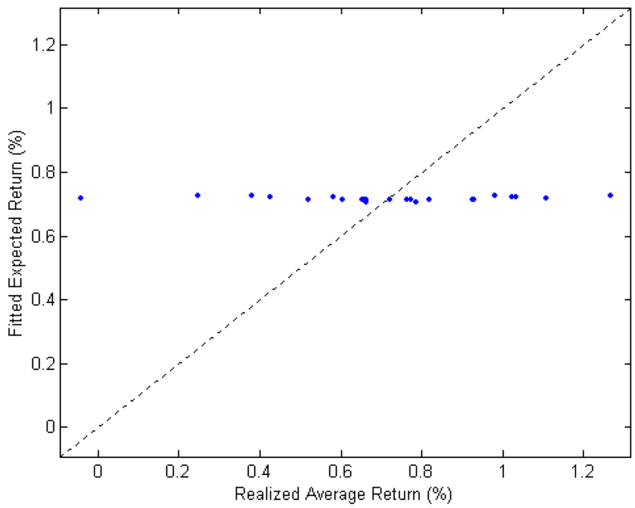


(c2) CAPM + LIQ(λ)

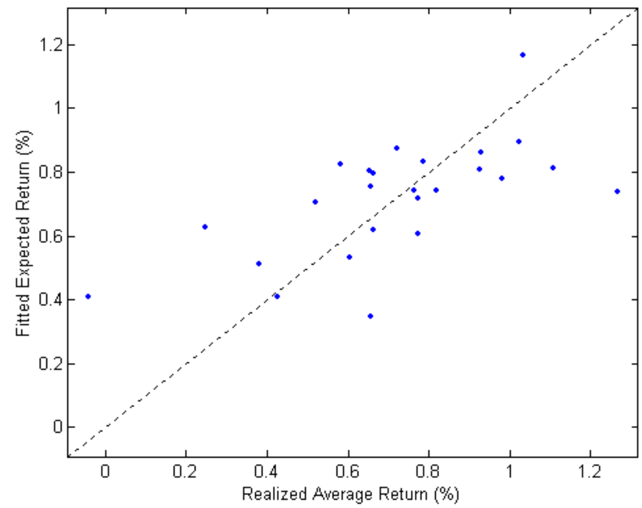


(d2) FF + LIQ(λ)

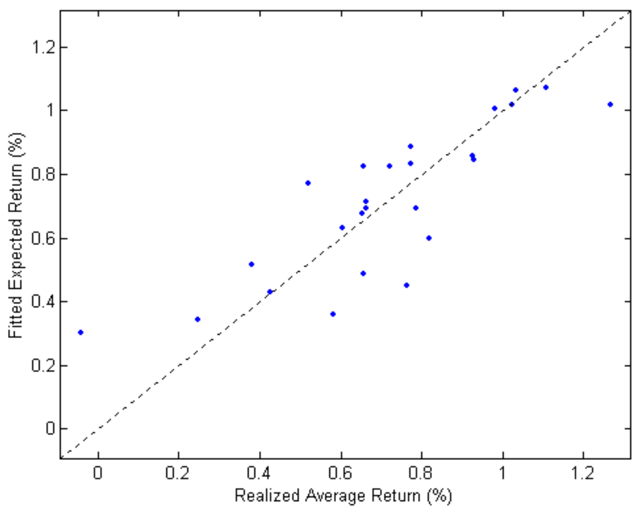
SUE Portfolios



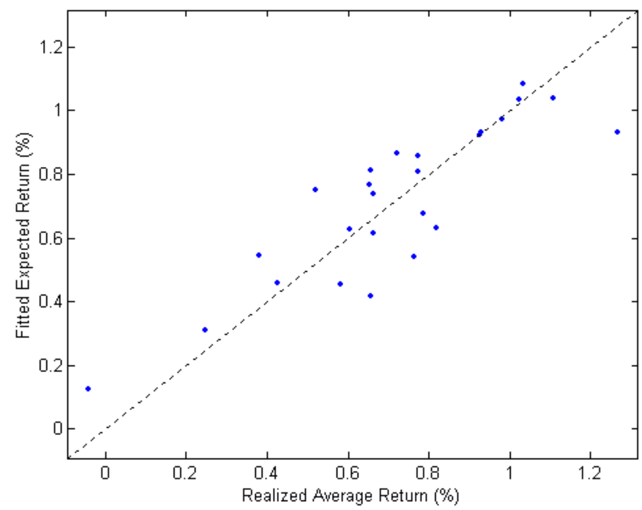
(a1) CAPM



(b1) FF



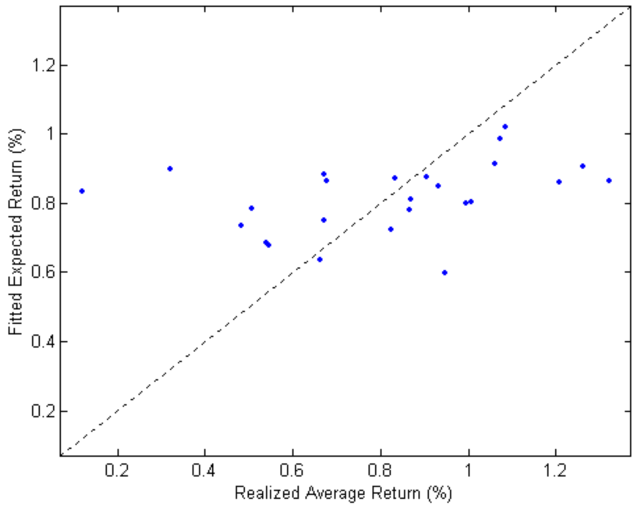
(c1) CAPM + LIQ(λ)



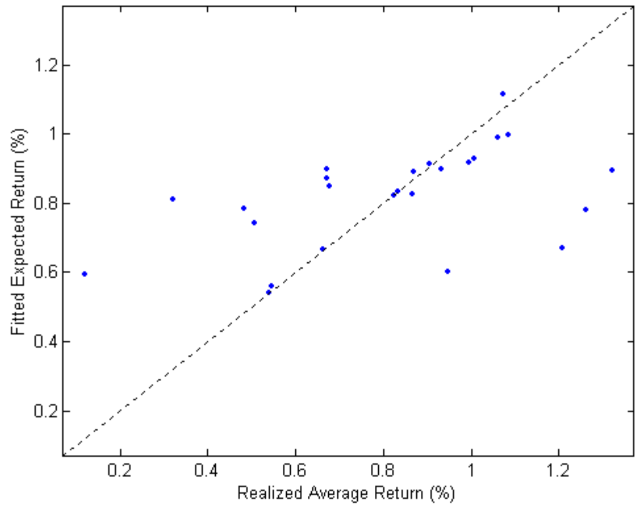
(d1) FF + LIQ(λ)

MOM / λ Portfolios

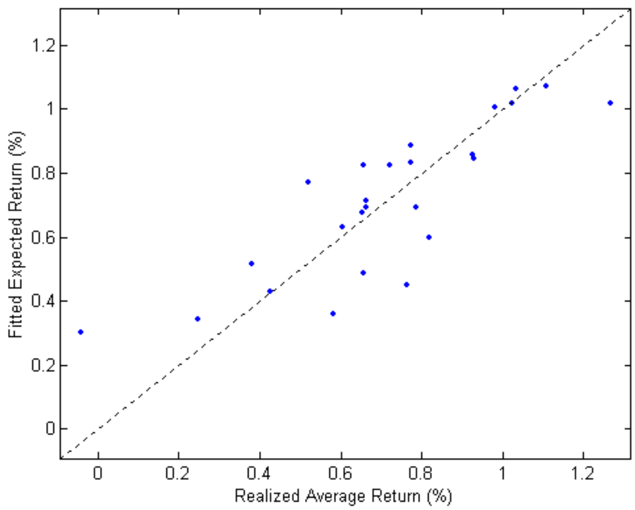
Figure 5. The cross-section of momentum/liquidity and PEAD/liquidity portfolio returns and liquidity risk. Two different sets of portfolios are analyzed: 5x5 portfolios sorted on momentum and the variable component of liquidity (MOM/λ) and 5x5 portfolios sorted by standardized unexpected earnings and the variable component of liquidity (SUE/λ). Momentum is calculated as the past 12-month cumulative returns (excluding the last month). The variable SUE for stock *i* in month *t* is defined as $[(E_{i,q} - E_{i,q-4}) - c_{i,t}]/\sigma_{i,t}$ where $E_{i,q}$ is the quarterly earnings most recently announced as of month *t* for firm *i* (not including announcements in month *t*); $E_{i,q-4}$ is earnings four quarters ago; and $\sigma_{i,t}$ and $c_{i,t}$ are the standard deviation and average, respectively, of $(E_{i,q} - E_{i,q-4})$ over the preceding eight quarters. The stocks are equally weighted in each portfolio, and the portfolios are rebalanced monthly. Liquidity measures are estimated per firm, per month using the Glosten and Harris (1988) model $\Delta p_t = \alpha + \Psi D_t + \lambda DV_t + \bar{\Psi}\Delta D_t + \bar{\lambda}\Delta DV_t + y_t$ where Δp_t is the price improvement (in dollars) as a result of trading V_t shares at time *t* (here *t* represents event time), D_t is an indicator for buyer-initiated (+1) or seller-initiated (-1) trade, and y_t represents price movements related to public available information. The model is estimated using dummy variables for trades above 10,000 shares (four dummy variables). In addition, the model is corrected for unanticipated trade sign and signed volume (see Section 1). The fixed (transitory) component is $\bar{\Psi}$ and the variable (permanent) component is λ. Price impacts are estimated on a monthly basis, separately for every stock, and they are scaled by beginning-of-month price. To form the first set of portfolios firms are sorted every month into five groups according to momentum, and then the firms within each group are sorted again into five λ groups. Similarly, the second set of portfolios is formed using dependent sorts of SUE and λ. The stocks are equally weighted in each portfolio and the portfolios are rebalanced monthly. Every month, aggregate price impact is calculated as the cross-sectional average of the variable component. The liquidity factor, LIQ(λ), is computed as shocks to this time series, proxied by the residuals of an ARMA model of two autoregression lags and one lag of moving average. Each scatter point in each of the graphs represents one of the 20 portfolios, with the realized average return (excess of risk-free rate) on the horizontal axis, and the fitted expected return on the vertical axis. The realized average return is the time-series average return, and the fitted expected return is calculated as the fitted value from $E(R_{i,t}) = \gamma_0 + \gamma`\beta_{i,}$, where $R_{i,t}$ are the returns of portfolio *i*, β_i is a vector of factor loadings, and γ is a vector of the estimated risk premiums. The loadings are computed through a time-series multiple regression of portfolio excess returns on the factors tested over the entire sample period. The factors considered here are the Fama-French three factors, MKT, SMB, and HML, and the non-traded liquidity factor LIQ(λ). The straight line in each graph is the 45° line from the origin. The analysis includes NYSE-listed stocks with available intraday data for the period March 1983 to August 2001.



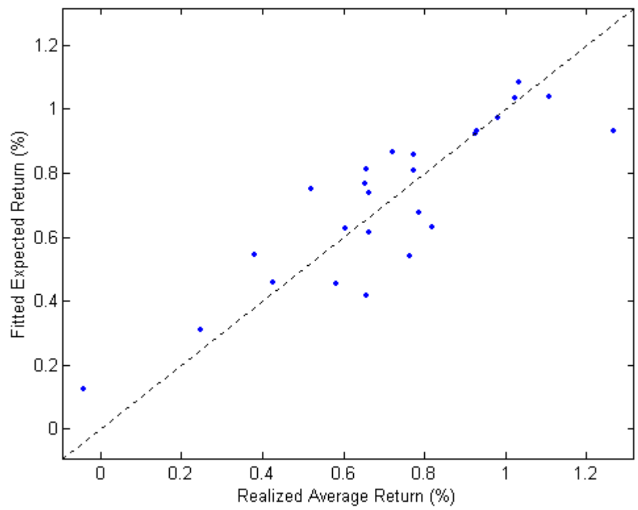
(a2) CAPM



(b2) FF



(c2) CAPM + LIQ(λ)



(d2) FF + LIQ(λ)

SUE / λ Portfolios