Stock liquidity risk and the cross-sectional earnings-returns relation

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Abstract

We argue that a higher sensitivity to aggregate market-wide liquidity shocks (i.e. a higher liquidity risk) implies a tendency for a stock's price to converge to fundamentals. We test this intuition within the framework of the earnings-returns relation. We find a positive liquidity risk effect on the relation between return and expected change in earnings. This effect on the earnings-returns relation is distinct from the negative effect observed for stock illiquidity level. Notably, the liquidity risk effect is evident (absent) during periods of neutral/low (high) aggregate market liquidity. We also show that the liquidity risk effect is dominant in firms that: (a) are of intermediate size; (b) are of intermediate book-to-market; and (c) are profit making.

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1. Introduction

In this paper we seek evidence on whether, and under what circumstances, individual stock liquidity risk enhances the tendency for share price to move towards fundamentals? Part of our motivation comes from Sadka (2006), who studies the implications of liquidity risk for the momentum and post-earnings announcement drift (PEAD), returns. He finds that PEAD and momentum profits are highly sensitive to market-wide liquidity shocks. A more general motivation for our paper comes from consumption asset pricing theory which holds that cross-sectional stock return differences should be explained by return sensitivities to state variables that affect investor utility derived from

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consumption (Pástor and Stambaugh, 2003). Stock liquidity which is both time-varying and uncertain, can impact investors' welfare at inopportune times. Empirical results also show that liquidity is correlated across assets (Galariotis and Giouvris, 2007, Hasbrouck and Seppi, 2001, Huberman and Halka, 2001, Chordia et al., 2000). Thus, liquidity is a likely candidate as a state variable that should be priced (Pástor and Stambaugh, 2003). A number of studies document the existence of a liquidity risk premium (Watanabe and Watanabe, 2008, Liu, 2006, Acharya and Pedersen, 2005). What is less understood is the economic forces that liquidity risk embodies (Sadka, 2006).

The intuition underlying our argument that liquidity risk is linked to convergence to fundamentals derives from some key empirical findings. Specifically, Sadka and Scherbina (2007) and Sadka and Scherbina (2010) show that positive market-wide liquidity shocks lead to lower transaction costs (i.e. lower arbitrage costs) across assets, which in turn leads to price convergence to fundamentals in the time-series. We argue that if positive shocks to market-wide liquidity lower arbitrage costs across stocks, then a higher sensitivity to market-wide liquidity shocks would see relevant stock returns more strongly related to fundamentals.

Given that the earnings-returns relation reflects how well stock returns associate with fundamentals, we choose to explore our hypothesis in terms of this linkage. Specifically, we predict that liquidity risk has a positive impact on the correlation between returns and changes in expected earnings (as a proxy for cash flows i.e. fundamentals). To test this hypothesis, we estimate regressions of returns at time t on the change in earnings from t to t+1, conditioning on liquidity risk in a cross-sectional framework. Our analysis adopts the definition of stock liquidity risk from Acharya and Pedersen (2005).[1]

Our main empirical analysis is careful to distinguish from Kerr et al. (2013) who study the *illiquidity* impact on the earnings-returns relation – we achieve this distinction by interacting our liquidity risk variable with individual stock liquidity (thereby allowing us to control the effect of the latter). Our core hypothesis is further expanded to consider whether the liquidity risk impact is influenced: (a) by aggregate market liquidity or (b) by firm size; (c) whether the relation is stronger for value stocks versus growth stocks; or (d) whether the relation is stronger for positive-earnings firms versus negative-earnings firms. Each of these analyses are executed by creating triple interactions, derived from appropriately enhancing the base two-way liquidity risk-earnings interaction term.

Our results are summarized in a few key points. First, as predicted, stock liquidity risk has a positive moderating effect on the return relation with expected change in earnings. Moreover, this liquidity risk effect is distinct from (and after controlling for) the negative effect observed for stock illiquidity level (Kerr et al., 2013). Second, we find that the liquidity risk effect is evident (absent) during

[1] Acharya and Pedersen's (2005) measure of liquidity risk encompasses three components: (a) a stock's individual liquidity sensitivity to market liquidity shocks (b) a stock's return sensitivity to shocks to market-wide liquidity (Watanabe and Watanabe, 2008, Pástor and Stambaugh, 2003); and (c) a stock's liquidity sensitivity to shocks to market return innovations. The net liquidity beta (our liquidity risk proxy) is a linear combination of these three components: that is, (a) – [(b) + (c)].

periods of neutral/low (high) aggregate market liquidity. Third, the liquidity risk effect on the earnings-returns relation is dominant for firms that: (a) are of intermediate size; (b) are of intermediate book-to-market; and (c) are profitable. In other words, the liquidity risk effect is negligible or non-existent in companies that: (a) are either small or big in size; (b) are either strongly growth or value stocks; or (c) are loss-making.

Our paper makes a number of contributions. We argue that the liquidity risk premium could be a compensation for risk related to arbitrageurs' attempts to exploit arbitrage opportunities.[2] Our work also has implications for studies that investigate arbitrage risk but use proxies that do not include liquidity risk (Edelen et al., 2016, Chou et al., 2013, Doukas et al., 2010, Ali et al., 2003). For example, Chou, Huang and Yang (2013) document a persistent turnover premium that is associated with higher transaction costs, which they attribute to arbitrage risk. But transactions costs are considered arbitrage costs by others (Sadka and Scherbina, 2010, 2007; Korajczyk and Sadka, 2004). Thus, there is a need to further our understanding of what captures arbitrage risk. Our study also complements the evidence in Sadka and Scherbina (2007) which shows that positive shocks to market liquidity lead to price convergence to fundamentals; and Jacobs (2015) and Conrad et al. (2016) who suggest that arbitrage costs are important to understanding anomalies persistence. Our evidence suggests that sensitivity to market liquidity shocks leads to a similar effect in the cross-section of firms.

Our work also complements the study of Kerr et al. (2013). Those authors test the hypothesis that the level of stock liquidity is indicative of price informativeness about future earnings. That is, stock liquidity is indicative of the predictability of future earnings growth from stock prices. Our intuition is that a stock's liquidity sensitivity to shocks to market-wide liquidity (i.e. liquidity risk, as opposed to the liquidity level) influences a stock's price tendency to converge to (diverge from) fundamentals. Our study, thus, has implications for understanding the economic forces embodied in liquidity risk (i.e. the second moment of liquidity), while Kerr et al. (2013) demonstrates the effects of liquidity level (i.e. the first moment of liquidity) for price efficiency.

The remainder of our paper is organized as follows. Section 2 provides a brief development of the liquidity risk hypothesis and we detail our sample selection in Section 3. Section 4 outlines the empirical framework. Section 5 presents and discusses the results and analysis. We offer concluding remarks in the final section of the paper.

2. Hypothesis Development

Arbitrageurs trade to exploit arbitrage opportunities (stock mispricing) and, among other things, their ability to execute this strategy assumes that transaction costs are not prohibitive. But Sadka and Scherbina (2007) provide evidence that when transactions costs are (and illiquidity is) prohibitive, stock mispricing persists. Further, Sadka and Scherbina (2010) observe that positive

[2] Our contention that liquidity risk is an element of arbitrage risk, is supported by evidence documented by Chordia et al. (2014) that anomalies will not vanish due to limits of arbitrage.

shocks to market-wide liquidity lead to improved liquidity (lower transaction costs) across stocks. Since transactions costs (illiquidity) is a good proxy for arbitrage costs (Korajczyk and Sadka, 2004), the implication is that positive shocks to market-wide liquidity would lower arbitrage costs, thereby facilitating arbitrage trades and, by extension, ensure that stock prices are more closely aligned with expectations about fundamentals (cash flows). Indeed, Sadka and Scherbina (2007) report time series evidence of stock price convergence to fundamentals given positive shocks to market-wide liquidity.

The foregoing line of argument implies that an individual stock's sensitivity to market-wide liquidity shocks is a useful indicator of the tendency for its stock price to reflect expectations about fundamentals (i.e. price convergence to fundamentals). The rationale is as follows. Sensitivity to market-wide liquidity shocks implies a sensitivity to factors that might increase or decrease arbitrage costs. So, a higher positive sensitivity to market-wide liquidity shocks indicates an association with lower arbitrage costs events – or, in general, a tendency for a stock's price to converge to fundamentals.

The study of the earnings-returns relation reveals how well stock prices reflect fundamentals (Hecht and Vuolteenaho, 2006). Accordingly, we choose to express our main hypothesis in terms of the earnings-returns relation. Taking price convergence to fundamentals to imply that returns better reflect cash flow (earnings) expectations, the testable hypothesis is stated as follows:

H1: *In the cross-section, stock liquidity risk has a positive effect on the returns association with expected change in earnings.*

The "unconditional" nature of our core hypothesis implies that all stocks with higher liquidity risk would tend have a stronger earnings-returns relation in the cross-section, irrespective of prevailing market conditions or of well-known ("anomalous") firm characteristics. We design our tests such that the potential for these conditional influences are captured. To this end, our main empirical setup is careful to distinguish from Kerr et al. (2013) who study the illiquidity (level) impact on the earnings-returns relation. Specifically, using an interactive variables design, in our main analysis we test the positive liquidity risk effect, while controlling for individual stock illiquidity.

So, how might market conditions be meaningfully factored into our research design?[3] Adopting the view that there are real limits to arbitrage and/or convergence risk, one can argue that high liquidity beta firms converge to fundamentals (more strongly) when the market is liquid, while there is no (or less) such convergence when the market is illiquid (less liquid). For example, if there is an asset pricing anomaly such as momentum and this anomaly very likely associates with high liquidity beta stocks, one would expect faster convergence to fundamental value during liquid times and greater

[3] We thank an anonymous referee for pushing us to explore the market conditions angle on our core hypothesis.

deviation from fundamental value during illiquid times (Sadka and Scherbina, 2007). Thus, high risk can be either "good" or "bad" depending on aggregate illiquidity.

It is also expected that the effect of liquidity risk on the earnings-returns relation will strongly manifest in stock characteristics associated with mispricing or anomalous returns such as the size and the book-to-market effects (see Chen et al., 2008, Petkova and Zhang, 2005, Zhang, 2005). In particular, other things equal, small stocks tend to have severe information asymmetry environments making them less liquid. Accordingly, we are more likely to find their liquidity improve with positive shocks to market liquidity.[4] If the value anomaly is related to transaction costs (Ali et al., 2003), we predict that the hypothesized positive liquidity risk effect on the earnings-returns relation manifests mainly within value stocks.[5]

A final extension of our analysis is to consider the potential differential effects of negative versus positive earnings on the earnings-returns relation, under the influence of the liquidity risk effect. Prior studies suggest that the positive contemporaneous cross-sectional earnings-returns relation is stronger for profitable firms than it is for firms reporting losses (Collins et al., 1999, Burgstahler and Dichev, 1997, Hayn, 1995).The rationale is that losses should not persist and, therefore, unexpected earnings contain little information about expected future cash flows (Hayn, 1995). Hence, we predict that the positive liquidity risk effect on the earnings-returns relation should only be evident within positive-earnings firms.

3. Data and Sampling

3.1 General

Our sample selection and empirical measures draw on both Acharya and Pedersen (2005) for the liquidity risk computation and Sadka and Sadka (2009) for the earnings and return variables. Our sample includes US firms listed on NYSE/AMEX for the period 1962 to 2009.[6] Returns and volume data are from CRSP. Only common stocks with prices between \$5 and \$1000 are included to mitigate the effects of outliers in the illiquidity measure.

Returns are annual, cumulated from 12-monthly returns over the fiscal year to three months after the fiscal year-end (Sadka and Sadka, 2009, Beaver et al., 2007). For example, for a firm with December fiscal year-end, annual return is computed from April of the fiscal year t to March in the year $t + 1$. Delisting returns are included if available and when missing a substitute value is

[4] Indeed, prior accounting studies such as Collins et al.(1987) and Freeman (1987) find that stock returns predict earnings growth better for large firms than for small firms because large firms have less opaque information environments.

[5] Akbas et al. (2010) suggest that value stocks have high liquidity risk on average across both good and bad states. Further, Asness et al.(2013) also find that liquidity risk is positively associated with the value premium.

[6] We exclude NASDAQ stocks because of problems with volume double counting that may bias illiquidity estimates (Acharya and Pedersen, 2005).

calculated as the average delisting return within the firm's delisting code (Beaver et al., 2007).[7] For earnings, we require valid earnings observations and price at the end of the fiscal year from COMPUSTAT. Our earnings variable is income before extraordinary items, and book equity is common equity and if not available we use common equity liquidation value (Sadka and Sadka, 2009). The final dataset is truncated at the top and bottom one per cent to mitigate problems of outliers.

3.2 Liquidity Risk

The primary illiquidity proxy for the study is the Amihud (2002) illiquidity measure. The Amihud (2002) illiquidity measure, defined as follows, relies on the theoretical model of Kyle (1985):

$$ILLIQ_{id} = \frac{|r_{id}|}{DVOL_{i,d}} \tag{1}$$

Equation (1) defines the illiquidity ratio of stock $i$on day d, r is percentage return and$DVOL$ is dollar volume in millions. The measure in equation (1) gives the percentage price response to a dollar volume of trade. Monthly values of $ILLIQ$ are obtained by averaging equation (1) over the month. Annual values are obtained as averages of monthly values over a firm's fiscal year, which does not coincide with the period of firm return computation. A stock must have at least 15 days of returns and volume data during the month for the illiquidity computation. The illiquidity ratio is calculated as the ratio of percentage return to dollar volume in millions, which is then normalized to: reduce inflation effects, ensure stationarity and approximate transaction costs (Acharya and Pedersen, 2005).

Our choice of the Amihud (2002) illiquidity measure is motivated by the literature that assesses various liquidity measures for commonality and validity such as Hasbrouck (2009), Goyenko, Holden and Trzcinka (2009), and Korajczyk and Sadka(2008).[8] Hasbrouck (2009) obtains Bayesian Gibbs sampler estimates of Roll's (1984) liquidity measure, compares it to spread-based liquidity measures (liquidity measures based on high frequency data) including depth, and the Amihud (2002) measure. Hasbrouck (2009) provides evidence of a strong correlation between the Amihud (2002) measure, the Gibbs sampler estimates of Roll (1984) liquidity measure and the other liquidity measures. In a latent factor analysis, Korajczyk and Sadka (2008) find commonality between proxies of liquidity.[9] The evidence in Goyenko et al (2009) suggest that the Amihud (2002) illiquidity

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[7] Beaver et al (2007) shows that unlike in Shumway (1997), delisting returns vary across alternative delisting reasons. The authors also report results that suggest that excluding delisting returns may have implications for earnings-returns regressions in terms of coefficient magnitudes.

[8] Goyenko et al (2009) study a wide range of different measures of liquidity including the Gibbs sampler estimates of Roll (1984) and raw Roll (1984), Lesmond et al (1999) liquidity and the LOT measure, the Amihud (2002) illiquidity measure, effective spread, Amivest, Pastor and Stambaugh (2003) gamma measure.

[9] The liquidity proxies are effective and quoted spread, Amihud (2002), Sadka's (2006) permanent and fixed price impact, and turnover.

measure is a parsimonious substitute for high frequency data proxies for price impact measures of liquidity.

Our measure of liquidity risk follows Acharya and Pedersen (2005) in which liquidity risk is defined as a linear combination of stock liquidity sensitivity to market liquidity shocks, stock return sensitivity to market liquidity shocks and stock liquidity sensitivity to market return shocks. Thus, Acharya and Pedersen (2005) define a net liquidity beta as follows:

$$\lambda_4 = \lambda_1 - \lambda_2 - \lambda_3 \tag{2}$$

where the liquidity risk components in equation (2) are defined as:

$$\lambda_1 = \frac{Cov(L_{i,t}, L_{m,t})}{Var(R_{m,t} - L_{m,t})}, \quad \lambda_2 = \frac{Cov(R_{i,t}, L_{m,t})}{Var(R_{m,t} - L_{m,t})}, \text{ and } \lambda_3 = \frac{Cov(L_{i,t}, R_{m,t})}{Var(R_{m,t} - L_{m,t})} \tag{3}$$

In equation (3), L is the illiquidity innovation, described in equation (4) below, and R is return. The subscripts i and m indicate individual stock and the market. The three lambda values measure different components of liquidity risk. λ_1 measures a stock's commonality in liquidity (Chordia et al., 2000, among others). λ_2, is the individual stock return sensitivity to market liquidity innovations (similar to the Pástor and Stambaugh (2003) liquidity risk variable and Sadka's (2010) computation of hedge fund liquidity risk). Finally, λ_3 is stock liquidity sensitivity to market return.

The liquidity risk components in Acharya and Pedersen (2005) are defined in terms of innovations (shocks) in liquidity. Thus, to estimate the coefficients in equation (3) we start by estimating the necessary shocks. A second order autoregressive model is used to extract illiquidity innovations because illiquidity is highly persistent, which has implications for stationarity of the innovations (Lee, 2011, Korajczyk and Sadka, 2008, Watanabe and Watanabe, 2008, Daley and Green, 2016, and Acharya and Pedersen, 2005). Innovations are extracted using the following regression:

$$ILLIQ_{i,t}P_{t-1}^{M} = \alpha_0 + \alpha_1 ILLIQ_{i,t-1}P_{t-1}^{M} + ILLIQ_{i,t-2}P_{t-1}^{M} + u_{i,t} \tag{4}$$

The variables in equation (4) are illiquidity of the market or individual stock, $ILLIQ_{i,t}$, and P_{t-1}^{M} is the ratio of market capitalization at time t to market capitalization in the initial month (July, 1962) included as an adjustment for the time trend in the aggregate illiquidity (Watanabe and Watanabe, 2008, Acharya and Pedersen, 2005). The residuals, $u_{i,t}$, is the measure of illiquidity innovations for the market and for the individual stocks. Illiquidity innovations are generated from un-normalized illiquidity ratios. Aggregate liquidity and market returns are computed as equally-weighted averages of sample firm values.

Market return innovations are residuals from regressing an equal-weight market return on two lags of monthly market return, log one-month lag market capitalization, log of six-month average turnover and six-month average dollar volume, and six-month average market illiquidity.

Liquidity betas are then estimated using rolling regressions requiring at least 36 months and a maximum of 60 months for all three components of the our liquidity risk measure. These procedures are in line with Acharya and Pedersen's (2005) liquidity risk estimates.

3.3 Descriptive Statistics

Table 1 reports the summary statistics of analysis variables. The mean return in the sample is about 15.13%, with a median of 10.48%. The mean expected change in earnings to price (FEP) is about 0.91%, while the mean expected change in earnings to book equity (FEB) is about 1.09%. The mean liquidity risk is about 0.71, with a median of 0.61. Returns, liquidity risk and the earnings proxies show moderate skewness.[10]

4. Empirical Framework

4.1 General Framework

Hecht and Vuolteenaho (2006) show that the covariance between earnings and returns can be decomposed as follows:

$$cov(R_t, \Delta X_t) = cov(E_{t-1}[R_t], E_{t-1}[X]) + cov(N_{cf}, \Delta X_t) - cov(N_R, \Delta X_t) \quad (5)$$

where ΔX_t is unexpected earnings, N_R is change in expected returns (return news), and N_{cf} is expected change in earnings (cash flow-news). Equation (5) shows that the earnings-returns relation is positive in the cross-section because cash flow news is positively correlated with unexpected earnings; that is, $cov(R_t, \Delta X_t) > 0$ because $cov(N_{cf}, \Delta X_t) > 0$. This is based on the assumption that earnings follow a random walk, which implies that $cov(E_{t-1}[R_t], E_{t-1}[X]) = 0$. In the context of our hypothesis that sensitivity to market liquidity shocks implies that stock returns more strongly reflect expectations about fundamentals, we expect that high liquidity risk would lead to higher values of $cov(N_{cf}, \Delta X_t)$. Thus, liquidity risk would have a positive impact on the earnings-returns relation.

Broadly speaking, our econometric testing approach follows Sadka and Sadka(2009) and Collins et al.(1987). Specifically, we use the specification in Sadka and Sadka(2009) as follows:

$$R_{it} = \alpha + \beta . \Delta X_{it+1} + \varepsilon_{it} \quad (6)$$

[10] A few comments on (untabulated) pairwise correlations are worthy of mention. Returns are positively correlated with the earnings proxies and size, and negatively correlated with liquidity risk, beta, BM, and average annual illiquid ratio (ILLIQ). Liquidity risk is positively correlated with the illiquidity ratio but negatively correlated with the earnings proxies, size and book-to-market. The illiquidity ratio is also highly correlated with size (negative) and BM (positive). In sum, there are no seriously high correlations that suggest any concern about the main analysis.

where R_t is gross stock return, ΔX_{t+1} is change in earnings from t to $t+1$. The above equation relies on arguments of market efficiency. The market efficiency property implies that $E_{t-1}(\Delta X) = \Delta X + \eta$ or equivalently, realized change in earnings equates to expected earnings change, with error. In effect the value of β in equation (6) improves as the error, η, declines (Sadka and Sadka, 2009). Since arbitrage activities are expected to eliminate mispricing (or pricing biases) to align returns with expectations about fundamentals, equation (6) should be adjusted by conditioning on systematic liquidity risk, as a test of our hypothesis. Accordingly, we specify the following empirical model:

$$R_{it} = \alpha + \beta.\Delta X_{it+1} + \gamma.(\Delta X_{it+1} \times LIQRISK_{it}) + \delta.LIQRISK_{it} + \varepsilon_{it} \tag{7}$$

As argued above, we predict that the coefficient on the interaction term will be positive (i.e. $\gamma > 0$). We also include liquidity risk as a main effect in our model to control for the relation between liquidity risk and returns. For robustness, our analysis uses two alternative variants of the earnings variable: one-period expected change in earnings scaled by (a) market value and (b) book equity.

4.2 Differential Effects of Liquidity Risk and the Level of Illiquidity on the Earnings-Returns Relation

To distinguish from Kerr et al. (2013) who study the illiquidity impact on the earnings-returns relation, using an interactive variables design we test the positive liquidity risk effect, while controlling for individual stock illiquidity. Moreover, to facilitate the interpretation of results we use dummy variable regressions. That is, instead of continuous variable interactions we create interactions with dummy variables similar to Collins and Kothari (1989). Using dummy variables has the advantage that we can easily obtain and test the differential effect of various levels of liquidity risk. We construct the dummy variables based on the independent ranking of liquidity risk and illiquidity level by year. Using tercile splits, we exhaustively generate nine dummy variables from the pairings of all permutations and all dummy variables are separately interacted with our earnings proxy. The full model becomes:

$$\begin{aligned} R_{it} = \alpha + \ (&\beta_1 DLRLI_{it} + \beta_2 DLRMI_{it} + \beta_3 DLRHI_{it} + \beta_4 DMRLI_{it} \\ &+ \beta_5 DMRMI_{it} \beta_6 DMRHI_{it} + \beta_7 DHRLI_{it} \\ &+ \beta_8 DHRMI_{it} + \beta_9 DHRHI_{it}) \times \Delta X_{it+1} + \varepsilon_{it} \end{aligned} \tag{8}$$

where $DLRLI_{it}$ ($DLRMI_{it}$) [$DLRHI_{it}$] is a dummy variable denoting low liquidity risk and low (mid) [high] illiquidity level: the variable takes a value of unity if the stock in question has an estimated liquidity risk in the bottom tercile and an illiquidity level in the bottom (mid) [top] tercile, and zero otherwise; $DMRLI_{it}$ ($DMRMI_{it}$) [$DMRHI_{it}$] is a dummy variable denoting mid liquidity risk and low (mid) [high] illiquidity level: the variable takes a value of unity if the stock in question has an estimated liquidity risk in the middle tercile and an illiquidity level in the bottom (mid) [top] tercile, and zero otherwise; $DHRLI_{it}$ ($DHRMI_{it}$) [$DHRHI_{it}$] is a dummy variable denoting high liquidity risk and low (mid) [high] illiquidity level: the variable takes a value of unity if the stock in question has an estimated liquidity risk in the top tercile and an illiquidity level in the bottom (mid) [top] tercile, and zero otherwise. Hypothesis H1 predicts that, matched on liquidity level, the coefficient on high liquidity risk exceeds the counterpart coefficient on low liquidity risk (both greater than zero): $\beta_7 > \beta_1 > 0$; $\beta_8 > \beta_2 > 0$; $\beta_9 > \beta_3 > 0$.

4.3 Extended Analysis

4.3.1 Differential effects of liquidity risk conditioned on aggregate market liquidity

To test the potential for an aggregate liquidity level effect on the cross-sectional liquidity risk implications for the earnings-returns relation, we first assign the time-series observations across our sample period into empirical quintiles of aggregate market liquidity (AML). AML is proxied by the equally-weighted average of sample firms annual Amihud illiquidity measures. The lowest (highest) quintile observations of AML are denoted illiquid (liquid). The middle quintiles are tagged as periods of neutral aggregate liquidity. Analogous to the approach described in the previous sub-section, we create dummy variables for each of the three aggregate liquidity designations and then form triple interaction terms with the liquidity risk terciles and earnings. Similar sets of tests (as previously described) are performed on the high minus low liquidity risk combinations, this time controlling for AML.

4.3.2 Differential effects of liquidity risk conditioned on size

As noted in our hypothesis development, small firms are more illiquid and therefore would more likely find their liquidity improve with positive shocks to market liquidity. Accordingly, we rank stocks by size (market capitalization) every year and assign dummy variables for the lowest size quintile (Small), middle three quintiles (midcap) and the highest size quintile (Big). Consistent with the core analysis we form triple interactions between the size-systematic liquidity risk dummy variables and earnings. Again we test the high minus low liquidity risk combinations, this time controlling for size.

4.3.3 Differential effects of liquidity risk conditioned on value versus growth

Similar to the size analysis, we rank stocks every year on book-to-market, with the measurement of book-to-market following Sadka and Sadka (2009). Market values are taken at the end of the return computation period – three months after the end of the fiscal year – and book equity from the beginning of the fiscal year. We then assign dummy variables for the highest book-to-market quintile (value stocks), middle three quintiles (mid BM) and the lowest book-to-market quintile (growth stocks). The analysis then proceeds in a fashion similar to the earlier sections.

4.3.4 Differential effects of liquidity risk conditioned on positive versus negative earnings

As outlined in the hypothesis development section, we predict that the positive liquidity risk effect on the earnings-returns relation only manifests within profitable firms. To test our prediction, we construct two dummy variables one for the case of firms reporting positive contemporaneous earnings and one for firms reporting contemporaneous losses (income before extraordinary activities). Like the analysis for size and BM, liquidity risk dummy variables are formed from tercile splits by year and interactions created and tested similarly.

5. Empirical Tests of the Positive Liquidity Risk Impact on the Earnings-Returns Relation

5.1 Controlling for Stock Liquidity Level

Our baseline results are presented in Table 2. The table presents the results of Wald tests of the statistical significance of the differential effects of the various levels of liquidity risk and illiquidity level. Wald tests are based on estimates using two-way clustered standard errors. The cells at the intersection of the first three columns and rows report the point estimate of earnings coefficient for the dummy variable representing the joint values of liquidity risk and illiquidity in that cell. For example in Panel A, the value 1.1488 (0.6729) that is, β_1 (β_3) in the cell at low (high) illiquidity and low liquidity risk indicates the earnings relation with returns for stocks that have low (high) illiquidity and low liquidity risk. Notably, all point estimates indicate a positive relation between contemporaneous returns and one-period expected change in earnings.

The last two columns of Panels A and B of Table 2, show the differential illiquidity effect and the average illiquidity effect (controlling for liquidity risk), while the last two rows of the two panels report the corresponding values for liquidity risk (controlling for illiquidity). The differences, $(\beta_7 - \beta_1)$ and $(\beta_9 - \beta_2)$, show that at either level of illiquidity (i.e. controlling for either low or high stock illiquidity), higher liquidity risk is associated with a stronger contemporaneous returns relation with expected change in earnings, supporting our hypothesis. For example in Panel A, conditioning on low (high) illiquidity, the liquidity risk differential effect on the coefficients is 0.3600 (0.3243), significant at the 5% level. The last cell in the last column of Table 2 in both Panels A and B, is a test of whether the average earnings-returns relation is stronger at higher liquidity risk than at lower liquidity risk i.e. it shows the average of the two component liquidity risk differential effects discussed above. For example, in Panel A this average effect is 0.3546, significant at the 1% level. As such, based on the collective thrust of all of these findings (both panels), we see that the prediction coming from our hypothesis is supported, namely that the earnings-returns linkage is stronger for stocks with high liquidity risk.

On the other hand, the corresponding differences for illiquidity reflect a negative illiquidity effect between the levels of liquidity risk. For example in Panel A, conditioning on low (high) liquidity risk, the illiquidity differential effect on the estimated coefficient is 0.4759 (0.5116), both significant at the 1% level. The last cell in the last row of Table 2 in both Panels A and B, is a test of whether the earnings-returns relation is stronger at lower illiquidity levels than at higher illiquidity levels. For example, in Panel A the positive difference (0.4648) shows that this is the case; with the p-value from the Wald test indicating that the difference is statistically significant at the 1% level. This confirms the findings of Kerr et al.(2013). The findings documented in Table 2 collectively show that both stock illiquidity and liquidity risk have separate and important effects on the relation between returns and future earnings.

5.2 Controlling for Aggregate Market Liquidity

In this section we address the concern that our hypothesis needs to be conditioned on the aggregate illiquidity level. The results are reported in Table 3. The lower panel of the table reports the Wald tests results. The results confirm that the differential effect of aggregate liquidity is evident in both the neutral and illiquid periods. Interestingly, while the monotonic liquidity risk effect is observed for neutral and illiquid periods, it is absent during the liquid market periods in our sample. In the latter case, the results suggest a U-shaped effect.

5.3 Controlling for Size

Table 4 presents the results on size differences of the liquidity risk effect on the earnings-returns relation. Interestingly, the positive earnings-returns association is not broadly evident. In one group of cases the estimated coefficient is negative and statistically significant – indeed, a distinct pattern emerges: these cases are the terms involving small firms. Moreover, we see that the insignificant cases are those involving big firms. Thus, it is notable that the cases showing positive significant estimates on the triple interaction terms all involve midcap firms. But even here there is a distinct pattern – holding midcap size constant, consistent with our hypothesis the estimated coefficients grow monotonically with liquidity risk: 0.9846, 1.1965 and 1.4166 (0.7543, 0.9110 and 0.9570) for the price (book equity) scaled analysis, all significant at the 1% level, based on clustered standard errors.

At the bottom of Table 4 the Wald tests show that for the midcap firms the liquidity risk differential is statistically significant – irrespective of scaling (1% level for price scaled and 5% level for book equity scaled cases). Thus, the liquidity risk differential seems to be driven by midcap firms – for small firms and large firms the core finding of our paper is absent.

5.4 Controlling for Value vs. Growth

Table 5 presents our results testing the moderating effect of liquidity risk on the earnings-returns relation, conditioning on the three groups of book-to-market. As was the case in the size conditioned results of Table 4, the positive earnings-returns association is not broadly evident across the three book-to-market categories. Once more, there are three groups of results. For one group the estimated coefficient is negative and statistically significant. These cases are those involving value (i.e. high book to market) firms. The second group is growth (i.e. low book to market) stocks, for which we see insignificant estimates on the triple interaction terms. This pair of findings is consistent with the parallel findings for small (negative) and big (insignificant) firms, respectively, in Table 4 – and this makes sense since value (growth) and small (big) capitalization, empirically, are natural "allies".[11] The third group of results, exclusively captured by the mid book-to-market firms, exhibit positive and significant estimates on the triple interaction terms.

As it was for midcap size, the finding here is monotonic – holding mid book to market constant, consistent with our hypothesis the estimated coefficients grow monotonically with liquidity risk: 1.0847, 1.2450 and 1.4895 (0.6544, 0.7946 and 0.9486) for the price (book equity) scaled analysis, all significant at the 1% level, based on clustered standard errors. Further in parallel with the size-based Wald tests (Table 4), in Table 5 we see that for the mid-BM firms the liquidity risk differential is statistically significant and positive (a differential of 0.4048 based on price scaling and 0.2942 based on book equity scaling, both at the 1% level).

5.5 Controlling for Positive vs. Negative earnings

Table 6 reports results for differences in the liquidity risk effect between profitable and unprofitable firms. The positive relation between returns and expected profitability is only evident in the case of positive earnings – thus, our prediction is supported. Moreover, the Wald test supports the positive liquidity risk effect on the relation between contemporaneous returns and one-period expected change in earnings for the group of profitable firms but not for the loss-making firms.

5.6 Discussion: Puzzling Non-monotonic/Nonlinear Patterns

It is evident from the results discussed in the previous sub-sections that some puzzling non-monotonicity and/nonlinearity occurs across segments of our analysis. While we cannot provide definitive answers that invoke unambiguous theoretic justification(s) for such occurrences, we offer some discussion here aimed at calming undue reader anxiety.

In Section 5.2, liquid market periods in our sample present an anomalous finding, suggesting a U-shaped effect. One interpretation is that during liquid periods, the overall regime of liquidity reduces the relevance of any close sensitivity to market-wide liquidity shocks in stock pricing. In contrast,

[11]Indeed, in unreported results restricting the sample to only positive earnings firms does not change the results on the size and book-to-market differences.

during an illiquid regime, it seems that higher sensitivity to market-wide liquidity shocks (i.e. higher liquidity risk) is important in stock price convergence to fundamentals.

In Section 5.3 (Section 5.4), size (BM) conditioning reveals anomalies in small and big sized ("value" and "growth") firm cohorts. Why do we see a non-linear effect around size/ book-to-market, in the liquidity risk moderation of the earnings-returns relation? Again, while these findings also present a puzzle, we should remind ourselves that such empirical anomalies are far from unique in the accounting literature. Indeed, the challenges of non-monotonic and nonlinear relations are already well known – see, for example, Freeman and Tse (1992), Ali and Zarowin (1992) and Ali and Pope (1995).

One angle on this is to re-interpret our size/BM results in light of the very intuitive findings shown in Section 5.5 regarding profitable/loss-making firms. For example, we can gain relevant insights from Freeman and Tse (1992) who persuasively argue that earnings persistence is vital in such relationships – a greater valuation impact attaches to permanent earnings than to transitory earnings. Firms that belong to the small size group or to the value category, both have similar findings – and these are the firms that are less (more) likely to exhibit earnings persistence (be loss making). Moreover, firms that belong to the big size group or to the growth category, also both have similar findings – and these are the firms that are more likely to be "informationally rich". Firms that belong to informationally rich environments, have many competing and timely sources of data being released about them that could generally help weaken the earnings-returns nexus.

A final observation on the puzzling findings relates specifically to the MB conditioning analysis. In the earnings-returns association literature, our results extend the evidence of Collins and Kothari (1989) of a positive effect of market-to-book on the contemporaneous earnings-response coefficient. In our setting, an intriguing non-linearity arises. Notably, our results contrast the Akbaset al. (2010) evidence. Finding that the liquidity risk effect on the earnings-returns relation is not stronger for value stocks questions the view that value stocks have high liquidity risk relative to growth stocks. In general, the results also raise the question within our setting, of the relation between arbitrage risks and the value anomaly as reported by Ali et al. (2003). Perhaps the value anomaly has more to do with investment frictions than limits-to-arbitrage as argued in studies such as Li et al.(2009) and consistent with recent evidence documented by Edelen et al. (2016). But yet another angle on why we observe nonlinear patterns in our results could be informed by the work of Stambaugh et al. (2015) who examine the implications of asymmetry in arbitrage risk (in the context of the idiosyncratic volatility puzzle).

6. Conclusion

We find evidence in favour of the hypothesis that stock liquidity risk has a positive impact on the earnings-return relation. Further, our results indicate that the liquidity risk effect is not subsumed by the negative effect of stock illiquidity (Kerr et al.(2013)). In fact, we document that liquidity risk and illiquidity have distinguishable effects on the predictability of returns with one-period expected change in earnings. We also find that the effect of illiquidity could be non-monotonic in contrast to the results reported by Kerr et al.(2013).

Our core hypothesis is expanded to consider whether the liquidity risk impact is stronger during liquid periods or illiquid periods of the (aggregate) market; is influenced by firm size; whether the relation is stronger for value stocks or growth stocks; or whether the relation is stronger for positive-earnings firms or negative-earnings firms. Notably, we document that the liquidity risk effect is evident (absent) during periods of neutral/low (high) aggregate market liquidity. With regard to the positive vs. negative earnings analysis the findings are the most intuitively appealing. Specifically, we document that the positive liquidity risk effect on the earnings-returns relation is dominant for profitable firms but is totally absent for the group of loss-making firms. This fully accords with the prior accounting literature on the informational import of positive vs. negative earnings.

The size and book to market results present new and unexpected insights. Put simply, the positive effect of liquidity risk on the return predictability of future earnings is stronger / dominant for "intermediate" stocks – both in the value/growth and size dimensions. Such a finding poses an interesting puzzle: why do we see a non-linear effect around size/BM, in the liquidity risk moderation of the earnings-returns relation? In contrast to the evidence in Ali et al.(2003) our BM results suggest that the value effect does not persist because of arbitrage risk as the authors assume; and we conjecture that it is related to investment frictions as argued in Li et al.(2009). We commend the resolution of this puzzle as a worthy future research direction.

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Table 1 Summary Statistics

This table presents descriptive statistics of the sample data. is 12-month annual cumulative returns measured from year t to three months after the end of the fiscal year 1, FEP is calculated as $\Delta X_{it+1}/P_{it-1}$, change in earnings from year t to year scaled by market value at the end of the fiscal year and is FEB is earnings scaled by lagged book equity. SIZE is log of market capitalization, BM is book-to-market ratio, LIQRISK is the proxy for liquidity risk, and BETA is CAPM beta and ILLIQ is annual average Amihud (2002) illiquidity ratio average over the fiscal year. Data is the merge of CRSP-COMPUSTAT for the period 1965 to 2009 and excludes Nasdaq stocks.

Variable	Mean	Std	Min	Median	Max	Skewness	Kurtosis	Count
RET	0.1513	0.3726	-0.6317	0.1048	1.8641	0.9593	4.7563	49069
FEP	0.0091	0.0747	-0.4272	0.0090	0.3967	-0.3829	10.0750	49069
FEB	0.0109	0.1029	-0.6184	0.0164	0.5206	-0.7845	9.8376	49069
LIQRISK	0.7098	0.9985	-3.4360	0.6068	4.8532	0.2912	5.7143	49069
BETA	0.8272	0.4376	-0.1021	0.8016	2.1213	0.3312	2.6949	49069
BM	0.7758	0.5263	0.0012	0.6537	7.9860	2.2213	13.4869	49068
SIZE	6.0664	1.8029	1.0679	6.0806	12.1614	0.0947	2.5570	49068
ILLIQ	0.0285	0.0653	0.0000	0.0034	0.5190	3.8826	20.6287	49069

Table 2 Testing the moderating role of systematic liquidity risk in the earnings-returns relation – exploring a stock illiquidity differential

This table presents results from regressions with contemporaneous returns as the dependent variable, based on the specification of equation (8) in the main text. The independent variables are interactions involving the change in earnings next period (ΔX), scaled by either market price (Panel A) or book equity (Panel B). Interaction terms are formed using double-sorted dummy variables defined over stock-based liquidity risk and illiquidity level. Liquidity risk is defined here as systematic liquidity risk based on the Amihud (2002) metric and derived from the Acharya and Pedersen (2005) model, as described in the main text around equation (2). DLRLI (DLRMI) [DLRHI] is a dummy variable denoting low liquidity risk and low (mid) [high] illiquidity level: the variable takes a value of unity if the stock in question has an estimated liquidity risk in the bottom tercile and an illiquidity level in the bottom (mid) [top] tercile, and zero otherwise; DMRLI (DMRMI) [DMRHI] is a dummy variable denoting mid liquidity risk and low (mid) [high] illiquidity level: the variable takes a value of unity if the stock in question has an estimated liquidity risk in the middle tercile and an illiquidity level in the bottom (mid) [top] tercile, and zero otherwise; DHRLI (DHRMI) [DHRHI] is a dummy variable denoting high liquidity risk and low (mid) [high] illiquidity level: the variable takes a value of unity if the stock in question has an estimated liquidity risk in the top tercile and an illiquidity level in the bottom (mid) [top] tercile, and zero otherwise. The sample includes US listed common stocks at the intersection of COMPUSTAT and CRSP for period 1965 to 2009. P-values are in parentheses (*** = p<0.01, ** = p<0.05, *= p<0.1).

Panel A: Earnings scaled by Price

	Low illiquidity (LI)	Med illiquidity (MI)	High illiquidity(HI)	Illiquidity Differential LI-HI	Illiquidity Average (LI+MI+HI)/3
Low Liq risk (LR)	1.1488***(β_1) (p<.01)	1.0599***(β_2) (p<.01)	0.6729***(β_3) (p<.01)	$\beta_1 - \beta_3$ 0.4759*** (p<.01)	$(\beta_1 + \beta_2 + \beta_3)/3$ 0.9605*** (p<.01)
Mid Liq Risk (MR)	1.1374***(β_4) (p<.01)	1.3133***(β_5) (p<.01)	0.7304***(β_6) (p<.01)	$\beta_4 - \beta_6$ 0.4070** (p=0.0071)	$(\beta_4 + \beta_5 + \beta_6)/3$ 1.0604*** (p<.01)
High Liq Risk (HR)	1.5088***(β_7) (p<.01)	1.4393*** (β_8) (p<.01)	0.9972***(β_9) (p<.01)	$\beta_7 - \beta_9$ 0.5116*** (p<.01)	$(\beta_7 + \beta_8 + \beta_9)/3$ 1.3151*** (p<.01)
Liq risk Differential HR-LR	$\beta_7 - \beta_1$ 0.3600** (p=0.0214)	$\beta_8 - \beta_2$ 0.3794 (p=0.0119)	$\beta_9 - \beta_3$ 0.3243** (p=0.014)		$[(\beta_7 + \beta_8 + \beta_9) - (\beta_1 + \beta_2 + \beta_3)]/3$ 0.3546*** (p<.01)
Average Liq Risk (LR+MR+HR)/3	$(\beta_1 + \beta_4 + \beta_7)/3$ 1.2650*** (p<.01)	$(\beta_2 + \beta_5 + \beta_8)/3$ 1.2708*** (p<.01)	$(\beta_3 + \beta_6 + \beta_9)/3$ 0.8002*** (p<.01)	$[(\beta_1 + \beta_4 + \beta_7) - (\beta_3 + \beta_6 + \beta_9)]/3$ 0.4648*** (p<.01)	

Table 2 continued

Panel B: Earnings scaled by book equity					
	Low illiquidity (LI)	Med illiquidity (MI)	High illiquidity(HI)	Illiquidity Differential LI-HI	Illiquidity Average (LI+MI+HI)/3
				$\beta_1 - \beta_3$	$(\beta_1 + \beta_2 + \beta_3)/3$
Low Liq risk (LR)	0.7242***(β_1)	0.7638***(β_2)	0.5595***(β_3)	0.1647	0.6825***
	(p<.01)	(p<.01)	(p<.01)	(p > 0.1)	(P< 0.01)
				$\beta_4 - \beta_6$	$(\beta_4 + \beta_5 + \beta_6)/3$
Mid Liq Risk (MR)	0.8255***(β_4)	1.0047***(β_5)	0.6316***(β_6)	0.1939	0.8206***
	(p<.01)	(p<.01)	(p<.01)	(p=0.0554)	(P< 0.01)
				$\beta_7 - \beta_9$	$(\beta_7 + \beta_8 + \beta_9)/3$
High Liq Risk (HR)	0.8836***(β_7)	1.0018*** (β_8)	0.7734***(β_9)	0.1102	0.8863***
	(p<.01)	(p<.01)	(p<.01)	(P >0.1)	(P< 0.01)
Liq risk Differential HR-LR	$\beta_7 - \beta_1$	$\beta_8 - \beta_2$	$\beta_9 - \beta_3$		$[(\beta_7 + \beta_8 + \beta_9) - (\beta_1 + \beta_2 + \beta_3)]/3$
	0.1594*	0.2380**	0.2139*		0.2038***
	(p=0.0806)	(p=0.0209)	(p=0.0621)		(P< 0.01)
Average Liq Risk (LR+MR+HR)/3	$(\beta_1 + \beta_4 + \beta_7)/3$	$(\beta_2 + \beta_5 + \beta_8)/3$	$(\beta_3 + \beta_6 + \beta_9)/3$	$[(\beta_1 + \beta_4 + \beta_7) - (\beta_3 + \beta_6 + \beta_9)]/3$	
	0.8111***	0.9234***	0.6548***	0.1563**	
	(p<.01)	(p<.01)	(p<.01)	(p=0.0384)	

Table 3 Testing the moderating role of systematic liquidity risk in the earnings-returns relation – exploring an aggregate market liquidity differential

This table presents results from regressions with contemporaneous returns as the dependent variable. The independent variables are interactions involving the change in earnings next period (*ΔX)*, scaled by either market price (Panel A) or book equity (Panel B). Interaction terms are formed using dummy variables defined over stock-based liquidity risk and further conditions the liquidity risk effect on aggregate market liquidity, AML (defined as an equally-weighted average of sample firms' annual illiquidity values). Liquidity risk is defined here as systematic liquidity risk based on the Amihud (2002) metric and derived from the Acharya and Pedersen (2005) model, as described in the main text. Across all sample years, stocks are sorted into quintiles based on AML and dummy variables constructed for the smallest quintile (Illiquid), middle three quintiles (Neutral) and largest (Liquid) quintile. Liquidity risk dummy variables are based on tercile splits by year, denoted as low, mid and high liquidity risk. "Clustered" is two-way clustered standard errors and "FMB" is Fama-MacBeth regressions. The Wald tests are based on the clustered standard errors. The sample includes US listed common stocks at the intersection of COMPUSTAT and CRSP for period 1965 to 2009. T-statistics are in parentheses (*** = p<0.01, ** = p<0.05, *= p<0.1).

	Panel A: Earnings scaled by price		Panel B: Earnings scaled by book equity	
	Clustered	FMB	Clustered	FMB
ΔX x Liquid period x Low liquidity risk	1.9750***	0.5019***	1.0071***	0.2532***
	(6.96)	(3.62)	(9.16)	(3.78)
ΔX x Neutral period x Low liquidity risk	1.1538***	0.8447***	0.8265***	0.6448***
	(9.93)	(4.45)	(9.89)	(4.63)
ΔX x Illiquid period x Low liquidity risk	0.8592***	0.1225*	0.7223**	0.1155**
	(2.83)	(1.70)	(2.33)	(2.51)
ΔX x Liquid period x Mid liquidity risk	1.6717***	0.3774***	0.9438***	0.2059***
	(10.93)	(3.75)	(12.25)	(3.78)
ΔX x Neutral period x Mid liquidity risk	1.3575***	0.9334***	1.0595***	0.6715***
	(8.87)	(4.22)	(8.42)	(5.07)
ΔX x Illiquid period x Mid liquidity risk	1.2777***	0.2127***	1.4376***	0.2346***
	(5.10)	(2.81)	(4.64)	(2.71)
ΔX x Liquid period x High liquidity risk	1.9818***	0.4455***	1.0708***	0.2361***
	(11.22)	(3.81)	(10.97)	(3.85)
ΔX x Neutral period x High liquidity risk	1.5236***	1.0597***	1.0637***	0.6816***
	(11.85)	(4.64)	(11.52)	(5.40)
ΔX x Illiquid period x High liquidity risk	1.5061***	0.2644***	1.3930***	0.2384***
	(12.37)	(2.89)	(6.81)	(2.95)
Constant	0.1560***	0.1505***	0.1553***	0.1496***

	(6.66)	(6.28)	(6.56)	(6.19)
Observations	45825	45825	45825	45825
Adjusted R^2	0.070		0.072	
Wald tests	Diff	p-value		
Neutral Period High LR-Neutral Period Low LR	0.3698***	0.0004	0.2372***	0.0017
Illiquid Period High LR-Illiquid Period Low LR	0.6469***	0.0041	0.6707***	0.0003

Table 4 Testing the moderating role of systematic liquidity risk in the earnings-returns relation – exploring a size differential

This table presents results from regressions with contemporaneous returns as the dependent variable. The independent variables are interactions involving the change in earnings next period (*ΔX)*, scaled by either market price (Panel A) or book equity (Panel B). Interaction terms are formed using dummy variables defined over stock-based liquidity risk and further conditions the liquidity risk effect on size. Liquidity risk is defined here as systematic liquidity risk based on the Amihud (2002) metric and derived from the Acharya and Pedersen (2005) model, as described in the main text. Each year stocks are sorted into quintiles based on size and dummy variables constructed for the smallest quintile (Small), middle three quintiles (Midcap) and largest (Big) quintile. Liquidity risk dummy variables are based on tercile splits by year, denoted as low, mid and high liquidity risk. "Clustered" is two-way clustered standard errors and "FMB" is Fama-MacBeth regressions. The Wald tests are based on the clustered standard errors. The sample includes US listed common stocks at the intersection of COMPUSTAT and CRSP for period 1965 to 2009. t-statistics are in parentheses (*** = p<0.01, ** = p<0.05, *= p<0.1).

	Panel A: Earnings scaled by price		Panel B: Earnings scaled by book equity	
Variable	Clustered	FMB	Clustered	FMB
ΔX. Small and Low Liquidity Risk	-0.3540***	-0.5026***	-0.2692***	-0.1979
	(-2.59)	(-3.17)	(-2.69)	(-1.27)
ΔX x Midcap and Low Liquidity Risk	0.9846***	1.2080***	0.7543***	0.9069***
	(7.59)	(7.63)	(8.97)	(7.89)
*ΔX x*Big and Low Liquidity Risk	0.2389	0.1669	-0.0566	-0.1422
	(1.13)	(0.73)	(-0.43)	(-0.84)

ΔX x Small and Mid-Liquidity Risk	-0.6060***	-0.7963***	-0.3645***	-0.4410***
	(-4.71)	(-5.80)	(-3.38)	(-3.17)
ΔX x Midcap and Mid Liquidity Risk	1.1965***	1.4071***	0.9110***	1.0325***
	(10.83)	(6.77)	(10.97)	(9.97)
*ΔX x*Big and Mid Liquidity Risk	0.0792	-0.0882	-0.0495	-0.0826
	(0.41)	(-0.15)	(-0.44)	(-0.39)
ΔX x Small and High Liquidity Risk	-0.4709***	-0.6637***	-0.2075**	-0.2018***
	(-4.02)	(-3.57)	(-2.54)	(-2.72)
ΔX x Midcap and High Liquidity Risk	1.4166***	1.5995***	0.9570***	1.0214***
	(13.63)	(7.85)	(13.30)	(10.63)
*ΔX x*Big and High Liquidity Risk	-0.0827	0.4036	-0.1446	-0.1711
	(-0.43)	(0.97)	(-1.11)	(-1.23)
Constant	0.1412***	0.1365***	0.1424***	0.1362***
	(6.12)	(5.73)	(6.10)	(5.64)
Observations	49,068	49,068	49,068	49,068
R-squared	0.048	0.063	0.051	0.071
Number of groups		45		45
Wald tests	Diff	p-value	Diff	p-value
Midcap High LR – Midcap Low LR	0.4320***	0.0017	0.2027**	0.0333

Table 5 Testing the moderating role of systematic liquidity risk in the earnings-returns relation – exploring a book-to-market differential

This table presents results from regressions with contemporaneous returns as the dependent variable. The independent variables are interactions involving the change in earnings next period (*ΔX)*, scaled by either market price (Panel A) or book equity (Panel B). Interaction terms are formed using dummy variables defined over stock-based liquidity risk and further conditions the liquidity risk effect on book to market. Liquidity risk is defined here as systematic liquidity risk based on the Amihud (2002) metric and derived from the Acharya and Pedersen (2005) model, as described in the main text around equation. Each year stocks are sorted into quintiles based on book to market and dummy variables constructed for the smallest quintile (Low), middle three quintiles (Mid) and largest (High) quintile. Liquidity risk dummy variables are based on tercile splits by year, denoted as low, mid and high liquidity risk. “Clustered” is two-way clustered standard errors and “FMB” is Fama-MacBeth regressions. The Wald tests are based on the clustered standard errors. The sample includes US listed common stocks at the intersection of COMPUSTAT and CRSP for period 1965 to 2009. T-statistics are in parentheses (*** = p<0.01, ** = p<0.05, *= p<0.1).

	Panel A: Earnings scaled by price		Panel B: Earnings scaled by book equity	
Variable	Clustered	FMB	Clustered	FMB
ΔX x Low BM and Low Liquidity Risk	1.5499***	3.2875***	0.1830	0.3796**
	(3.34)	(5.20)	(1.45)	(2.02)
ΔX x Mid BM and Low Liquidity Risk	1.0847***	1.2079***	0.6544***	0.6932***
	(7.33)	(6.46)	(7.77)	(7.19)
ΔX x High BM and Low Liquidity Risk	-0.6238***	-0.6269***	-0.1434	-0.0716
	(-4.09)	(-4.07)	(-1.26)	(-0.42)
ΔX x Low BM and Mid Liquidity Risk	2.0889***	2.7549***	0.2555**	0.4411***
	(6.71)	(5.63)	(2.21)	(3.55)
ΔX x Mid BM and Mid Liquidity Risk	1.2450***	1.3945***	0.7946***	0.8447***
	(9.69)	(7.97)	(8.58)	(9.08)
ΔX x High BM and Mid Liquidity Risk	-0.7228***	-0.8745***	-0.2353*	-0.2971**
	(-5.15)	(-6.49)	(-1.74)	(-2.17)
ΔX x Low BM and High Liquidity Risk	0.9370***	1.4089**	-0.1041	-0.0101
	(2.93)	(2.51)	(-1.13)	(-0.05)
ΔX x Mid BM and High Liquidity Risk	1.4895***	1.6167***	0.9486***	0.9580***
	(14.42)	(12.04)	(14.21)	(13.76)
ΔX x High BM and High Liquidity Risk	-0.8412***	-1.0397***	-0.2204***	-0.2057
	(-7.89)	(-7.698)	(-2.95)	(-1.36)
Constant	0.1369***	0.1306***	0.1420***	0.1359***

	(5.93)	(5.47)	(6.07)	(5.62)
Observations	49,068	49,068	49,068	49,068
R-squared	0.060	0.086	0.051	0.076
Number of groups		45		45
Wald tests	Diff	p-value	Diff	p-value
Mid BM High LR – Mid BM Low LR	0.4048***	0.0066	0.2942***	0.0004

Table 6 Testing the moderating role of systematic liquidity risk in the earnings-returns relation – exploring a positive/negative earnings differential

This table presents results from regressions with contemporaneous returns as the dependent variable. The independent variables are interactions involving the change in earnings next period (ΔX), scaled by either market price (Panel A) or book equity (Panel B). Interaction terms are formed using dummy variables defined over stock-based liquidity risk and further conditions the liquidity risk effect on positive/negative earnings. Liquidity risk is defined here as systematic liquidity risk based on the Amihud (2002) metric and derived from the Acharya and Pedersen (2005) model, as described in the main text around equation. Dummy variables are constructed for negative (E^-) and positive (E^+) earnings stocks based on annual accounting data. Liquidity risk dummy variables are based on tercile splits by year, denoted as low, mid and high liquidity risk. "Clustered" is two-way clustered standard errors and "FMB" is Fama-MacBeth regressions. The Wald tests are based on the clustered standard errors. The sample includes US listed common stocks at the intersection of COMPUSTAT and CRSP for period 1965 to 2009. T-statistics are in parentheses (*** = p<0.01, ** = p<0.05, *= p<0.1).

	Panel A: Earnings scaled by price		Panel B: Earnings scaled by book equity	
Variable	Clustered	FMB	Clustered	FMB
ΔX x E^+ x Low Liquidity Risk	1.2665***	1.4779***	0.8907***	1.0245***
	(11.031)	(8.099)	(13.216)	(8.720)
ΔX x E^+ x Mid Liquidity Risk	1.4088***	1.5247***	1.0639***	1.1175***
	(13.044)	(8.023)	(13.426)	(9.983)
ΔX x E^+ x High Liquidity Risk	1.5951***	1.7661***	1.1078***	1.1553***
	(18.208)	(9.488)	(16.376)	(12.156)
ΔX x E^- x Low Liquidity Risk	-0.0560	0.0492	-0.0901	-0.1915

	(-0.520)	(0.238)	(-0.937)	(-0.757)
ΔX x E^- x Mid Liquidity Risk	-0.1039	-0.2195	-0.1897	-0.3899**
	(-0.847)	(-1.436)	(-1.544)	(-2.312)
ΔX x E^- x High Liquidity Risk	0.0494	-0.1617	-0.0031	-0.1104
	(0.308)	(-1.373)	(-0.026)	(-1.072)
Constant	0.1449***	0.1403***	0.1461***	0.1398***
	(6.284)	(5.874)	(6.262)	(5.785)
Observations	49,069	49,069	49,069	49,069
R-squared	0.063	0.078	0.066	0.085
Number of groups		45		45
Wald test	Diff	p-value	Diff	p-value
E^+ High LR – E^+ Low LR	0.3286***	0.0008	0.2171***	0.0014
E^- High LR – E^- Low LR	0.1054	0.4952	0.0870	0.5300