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I investigate whether information quality affects the cost of equity capital through liquidity risk. Liquidity risk is the sensitivity of stock returns to unexpected changes in market liquidity; recent asset pricing literature has emphasized the importance of this systematic risk. I find that higher information quality is associated with lower liquidity risk and that the reduction in cost of capital due to this association is economically significant. I also find that the negative association between information quality and liquidity risk is stronger in times of large shocks to market liquidity.

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1. Introduction and hypothesis

In this study, I investigate the relation between information quality and liquidity risk, with liquidity risk defined as the sensitivity of stock returns to unexpected changes in market liquidity (Pastor and Stambaugh, 2003; Acharya and Pedersen, 2005; Sadka, 2006). This study is motivated by Lambert, Leuz, and Verrecchia (2007), who suggest that higher information quality, i.e., more precise signals, lowers market risk and thus cost of capital in the traditional Capital Asset Pricing Model (CAPM) framework. The CAPM assumes perfect liquidity, which means that there are always market participants willing to take the opposite position of any trade at the current price. Consequently a firm's share price is simply a function of expectations about the firm's cash flow. With imperfect liquidity, the demand and supply of shares by some market participants could affect prices if others are not willing to trade at the current prices. While market risk exists in both perfectly and imperfectly liquid markets, liquidity risk is an additional and important systematic risk that investors face when markets are not perfectly liquid (Pastor and Stambaugh, 2003; Acharya and Pedersen, 2005; Sadka, 2006).[1]

I hypothesize that higher information quality lowers liquidity risk, which, in turn, lowers cost of capital. I define information quality as an information characteristic of a firm that affects the degree of i) uncertainty over the firm's value and/or ii) adverse selection when trades in the firm's stock occur (Healy and Palepu, 2001; Verrecchia, 2001; Easley, Hvidkjaer, and O'Hara, 2002; Easley and O'Hara, 2004).

[1] Pastor and Stambaugh (2003) find that the required return (i.e., cost of capital) for stocks with high sensitivities to unexpected changes in market liquidity exceeds that for stocks with low sensitivities by 7.5%, after adjusting for exposures to the market return, size, value, and momentum factors. They also show that this effect is distinct from the pricing of liquidity (Amihud and Mendelson, 1986; Brennan and Subrahmanyam, 1996). The difference between liquidity risk and liquidity is further discussed in Section 2.

To the best of my knowledge a theoretical model that directly links information quality (or information risk) to liquidity risk is not available, but the intuition is as follows. Systematic risk is a covariation/sensitivity effect; a stock with higher systematic risk will perform relatively worse during bad macroeconomic conditions, but relatively better during good ones (Campbell, Lo, and MacKinlay, 1997). For liquidity risk, the relevant macroeconomic condition is market liquidity. Market liquidity reflects, at the aggregated market level, the ability to trade large quantities quickly, at low cost, and without moving the price (Pastor and Stambaugh, 2003). A decline in market liquidity typically reflects a macroeconomic state in which there is investor and market maker outflow from the equity markets amidst high market volatility and risk aversion; in the extreme, this is known as a flight to quality/safety (e.g., Chordia, Roll, and Subrahmanyam, 2000; Pastor and Stambaugh, 2003; Acharya and Pedersen, 2005; Brunnermeier and Pedersen, 2009).

When market liquidity declines, different stocks will experience different degrees of investor and market maker outflow. In particular, the outflow is likely to be more significant for stocks with lower information quality because of a decline in investor demand for stocks associated with greater uncertainty and adverse selection. Market makers are also less willing to provide liquidity to such stocks due to concerns about adverse selection; this, in turn, might further dampen investor's demand for these stocks. Hence, these stocks perform worse when market liquidity declines. In contrast, when market liquidity increases, there is an inflow of investors and market makers, which increases the demand and liquidity of stocks associated with greater uncertainty and adverse selection. Note that the earlier arguments imply that the demand for stocks with higher information quality is subject to less fluctuation conditional on market liquidity changes. Thus, the returns of stocks with lower information quality (i.e., higher information risk) are expected to be more sensitive to changes in market liquidity. That is, information quality contributes to liquidity risk.

Models on disclosure typically characterize information quality as the precision of a signal of firm value, with more precise (i.e., lower variance) signals being of higher quality (Verrecchia, 2001). Thus, in order to closely match empirical proxies to the theoretical characterization of information quality, I identify measures that capture the precision of an earnings signal. Specifically, I use *Earnings precision*, *Accruals quality*, and *Analyst consensus* as proxies for information quality (see Section 3 for a detailed description of the proxies).

I investigate the relation between information quality and liquidity risk by examining how information quality contributes to the liquidity risk of ordinary shares of stocks listed on NYSE, AMEX, or NASDAQ from January 1983 to December 2008 after controlling for market characteristics (e.g. liquidity, trading volume, return volatility) and firm characteristics (e.g., sales growth, operating cycle, and capital intensity) that might be associated with either liquidity risk or information quality (e.g., Dechow and Dichev, 2002; Francis et al., 2005; LaFond, Lang, and Skaife, 2007; Dichev and Tang, 2009). I find evidence of a negative association between information quality and liquidity risk. In particular, *Earnings precision*, *Accruals quality*, and *Analyst consensus each* are individually negatively associated with liquidity risk. The association between *Aggregate quality*, which combines *Earnings precision*, *Accruals quality*, and *Analyst consensus*, and liquidity risk is also negative and statistically significant.

Next, I examine the economic significance of the effect of information quality on cost of capital through liquidity risk. As a benchmark, I also compare this effect on cost of capital through market risk (Lambert et al., 2007). I find that the economic effect of higher information quality in lowering cost of capital through liquidity risk is economically significant and larger than that obtained through market risk. For example, an analysis with *Aggregate Quality* indicates that firms in the top quintile have a cost of capital that is lower by 269 (57) basis points due to lower liquidity risk (market risk), compared to those in the bottom quintile of information quality.[2]

I then explore differences in the relation between information quality and liquidity risk in three different periods: i) periods of extreme decreases in market liquidity, ii) periods of extreme increases in market liquidity, and iii) periods of relatively stable market liquidity. I find a stronger negative association between information quality and liquidity risk in times of large, unexpected changes in market liquidity. One interpretation of this finding is that when investors decide whether to exit and enter certain stocks in times of market liquidity shocks, they pay more attention to the quality of information about the stocks.

Finally, I run a battery of robustness analyses. I find that the negative association between information quality and liquidity risk is robust to the use of alternative information quality proxies, namely earnings smoothness, analyst forecast consensus scaled by consensus mean forecast, and analyst forecast consensus scaled by consensus median forecast. I also find this negative association to be robust to the inclusion of firm fixed effects, as well as to the inclusion of the historical liquidity beta and the historical

[2] The magnitudes of the cost of capital effects documented in my paper are comparable to those documented in the prior literature (e.g., Francis et al., 2004, 2005). See Section 4.3 for a more detailed discussion.

market beta as control variables in the empirical models of liquidity risk and market risk, respectively.

My paper contributes to the broader objective of improving our understanding of the mechanisms that underlie the relation between information quality and cost of capital (e.g., Botosan, 1997; Francis et al., 2004, 2005; Core, Guay, and Verdi, 2008; Akins, Ng, and Verdi, 2011). Unlike other papers in the field, I focus on systematic liquidity risk as a mechanism linking information quality and cost of capital. In particular, I provide a rationale for and evidence of an association between information quality and liquidity risk, the latter of which has been documented in recent finance literature as an important systematic risk (e.g., Pastor and Stambaugh, 2003; Acharya and Pedersen, 2005; Sadka, 2006). I acknowledge, however, that my investigation into the effect of information quality on liquidity risk is exploratory. More rigorous studies, especially from a theoretical perspective, are needed to increase our understanding of how information quality relates to asset pricing under imperfect liquidity (e.g., Lambert and Verrecchia, 2010).

A concurrent paper by Lang and Maffett (2010) similarly examines the relation between information quality and liquidity risk. They also find that higher information quality, in terms of transparency, lowers liquidity risk. However, there are several important differences between our papers. First, I conduct my analyses within the U.S. while theirs is conducted across countries. Within-country studies have the advantage of greater homogeneity with regard to institutional features, whereas cross-country studies offer potentially greater variation in the constructs of interest. Second, I follow Pastor and Stambaugh (2003) and define liquidity risk as the covariation between stock returns with changes in market liquidity. In contrast, they investigate different dimensions of liquidity risk, namely the covariations of stock liquidity with respect to market liquidity and market returns (see the next section for a brief discussion of these dimensions).

The rest of the paper is organized as follows. Section 2 provides a brief overview of liquidity risk. Section 3 describes the research design and Section 4 discusses the results. Section 5 concludes.

2. Overview of liquidity risk

Liquidity risk is a recent innovation in the finance literature. The concept is introduced by Pastor and Stambaugh (2003) in the following way. They note that in standard asset pricing theory, expected stock returns are related cross-sectionally to returns' sensitivities to state variables that have pervasive effects on investors' overall welfare. They then argue that market liquidity is likely to be an important priced state variable; that is, investors should be compensated for holding stocks whose returns are the lowest when market liquidity declines. They then define liquidity risk as a stock's return sensitivity to unexpected changes in market liquidity. Hence, liquidity risk captures the extent of gain or loss (in terms of returns) to investors as market liquidity changes. Empirical support for the pricing of liquidity risk is found in Pastor and Stambaugh (2003), Acharya and Pedersen (2005), and Sadka (2006).

Pastor and Stambaugh (2003) operationalize their concept of liquidity by estimating the covariation of a firm's stock return to unexpected changes in aggregate liquidity (i.e., they develop a "liquidity beta"). They then construct an empirical asset pricing model that includes liquidity risk by extending the Fama and French (1993) three-factor model to include a market liquidity factor:

$$r_{i,t} = \alpha_i + \beta_{i,t}^M MKT_{t,t} + \beta_{i,t}^S SMB_t + \beta_{i,t}^H HML_t + \beta_{i,t}^L LIQ_t + \varepsilon_{i,t} \quad (1)$$

where $r_{i,t}$ is the monthly return in excess of the risk-free rate for stock i in month t, LIQ is the market liquidity factor in month t, and MKT, SMB, and HML are the Fama and French (1993) risk factors.[3] LIQ is the market liquidity factor that captures unexpected changes in market liquidity; the construction of LIQ is briefly discussed in Appendix A. A higher liquidity beta, β^L, captures, by its construction, a higher covariation between a stock's return and unexpected changes in market liquidity; that is, a higher β^L indicates higher liquidity risk.

While Pastor and Stambaugh (2003) is the seminal paper on asset pricing with liquidity risk, other definitions of liquidity risk have evolved. In particular, Acharya and Pedersen (2005) highlight the fact that with two stock characteristics, return (r) and liquidity (l), there are four possible types of systematic risk between a firm i and the market m: cov(r_i, r_m), cov(r_i, l_m), cov(l_i, l_m), and cov(l_i, r_m). The first covariation measures market risk, i.e., the exposure of a firm's returns to market returns. The next three covariations represent three different types of liquidity risk; the first, cov(r_i, l_m) is studied in Pastor and Stambaugh and is the focus of my study. The next two covariations are the types of liquidity risk that Lang and Maffett (2010) investigate.

Finally, it is important to highlight the difference between liquidity risk and liquidity (Acharya and Pedersen, 2005; Korajczyk and Sadka, 2008; Lou and Sadka,

[3] The *MKT*, *SMB*, and *HML* factors are publicly available from Kenneth French's website: http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.htmlhttp://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html . The *LIQ* factor is publicly available from Lubos Pastor's website: http://faculty.chicagobooth.edu/lubos.pastor/research. All factors are also available from Wharton Research Data Services (WRDS).

2010). In my study, the liquidity risk of a stock relates to the sensitivity of the stock's return to unexpected changes in market liquidity. In contrast, the liquidity of a stock refers to the ability to trade large quantities quickly, at low cost, and without moving the price of the stock. Unlike prior studies that have examined the effect of information quality on liquidity (e.g., Welker, 1995; Leuz and Verrecchia, 2000), my study examines the effect of information quality on liquidity risk, after controlling for liquidity. As discussed in the introduction, one motivation for studying this relation is the theoretical work by Lambert et al. (2007) on the effect of information quality on market risk. Another motivation is the substantial liquidity risk premium documented in Pastor and Stambaugh (2003); this premium suggests that, to the extent that information quality has an effect on liquidity risk, the effect of information quality on cost of capital via liquidity risk might be significant.

3. Research design

3.1 Market liquidity

The monthly time series of market liquidity from August 1962 to December 2008 is shown in Figure 1. The series reflects the liquidity cost of trading \$1 million in August 1962 "stock market" dollars, averaged across stocks in a given month. The average market liquidity is -0.032, which indicates a liquidity-related trading cost of 3.2% (\$3,200 for a trade of \$1 million). The series for August 1962 to December 1999 is the same as that documented in Figure 1 of Pastor and Stambaugh (2003); for this series, the average cost is 3%.[4] The largest downward spike in market liquidity occurred in October 1987,

[4] One reason for this seemingly high cost is that small, illiquid stocks are also included in each monthly cross-section. These stocks might be those that certain investors do not trade due to cost considerations

when the stock market suffered a significant crash that was at least partially due to a decline in market liquidity. There is also a significant downward spike in September 1998, when the collapse of Long Term Capital Management and the Russian debt crisis were widely perceived to have led to a significant decline in liquidity. Consistent with the fact that there was a market liquidity crisis in 2008, the figure also shows significant down spikes in market liquidity in 2008. Among the ten months with the lowest market liquidity from August 1962 to December 2008, three were in 2008.

Table 1 provides descriptive information of the various market factors, *LIQ*, *MKT*, *SMB*, and *HML* for the period from August 1962 to December 2008. The average of the monthly *LIQ* is zero. A zero for the average monthly *LIQ* is expected because each monthly *LIQ* is the innovation in changes in market liquidity, i.e., an unexpected change in market liquidity. The average of unexpected values should be zero. The average *MKT* is 0.402. Given that *MKT* is a traded factor, this means that the average market risk premium is 0.402% per month (or 4.824% per year). There is a significant and positive correlation of 0.344 between *LIQ* and *MKT*, indicating that, on average, times when market returns are positive are also times when market liquidity increases.

3.2 Empirical design that examines the relation between information quality and liquidity risk

In this paper, I hypothesize that higher information quality lowers liquidity risk, β^L. I also provide some analyses on the relation between information quality and market risk and use the results to compare and contrast the cost of capital effects of information quality via liquidity risk and market risk. The empirical design follows closely to that of

and/or fund management mandates. Another reason is that the time-series includes earlier periods, when tick sizes were larger, and crisis periods when stocks (and other risky assets) tend to become significantly more illiquid.

Pastor and Stambaugh (2003). In this section, I focus on the general regression specification and leave the specific variable definitions to subsequent sections.

First, I build my empirical model of liquidity risk off Pastor and Stambaugh's (2003) empirical model (see Eq. (10) in p. 664 of their paper). Pastor and Stambaugh model liquidity risk as a function of market characteristics, such as stock liquidity and return volatility:

$$\beta_{i,t}^{L} = \psi_0 + \psi_1' \; Market\ Characteristics_{i,t-1} + \varepsilon_{i,t} \tag{2}$$

where $\beta_{i,t}^{L}$ is the beta measuring liquidity risk and *Market Characteristics*$_{i,t-1}$ is a vector of market characteristics that are expected to be determinants of liquidity risk.

I extend the above model to investigate whether information quality is a determinant of liquidity risk, as follows:

$$\begin{aligned} &\beta_{i,t}^{L} = \psi_0 + \psi_1' \; Info\ Quality_{i,t-1} \\ &+\psi_2' \; Market\ Characteristics_{i,t-1} + \psi_3' \; Firm\ Characteristics_{i,t-1} + \varepsilon_{i,t} \end{aligned} \tag{3}$$

where *Info Quality*$_{i,t-1}$ is an information quality proxy that can be *Earnings precision*, *Accruals quality*, *Analyst consensus*, or *Aggregate quality*. In addition to controlling for market characteristics, I also include a vector of firm characteristics, *Firm Characteristics*$_{i,t}$, to mitigate omitted correlated variable biases.

In this paper, I also examine the relation between information quality and market risk; in particular, I use the association between information quality and market risk to determine the relative economic significance of liquidity risk and market risk as systematic risk mechanisms through which information quality influences cost of capital. The model for market risk, similar to Eq. (3), is:

$$\beta^M_{i,t-1} = \psi_{0,t} + \psi_1' \; Info\ Quality_{i,t-1}$$
$$+\psi_2' \; Market\ Characteristics_{i,t-1} + \psi_3' \; Firm\ Characteristics_{i,t-1} + \varepsilon_{i,t} \tag{4}$$

where $\beta^M_{i,t}$ is the beta measuring market risk.

Substituting the right-hand side of Eq.s (3) and (4) into Eq. (1) results in the following equation:

$$r_{i,t} = \beta_i^0 + \beta_i^S SMB_t + \beta_i^H HML_t + (\psi_{0,t} + \psi_1 \; Info\ Quality_{i,t-1}$$
$$+\psi_2' \; Market\ Characteristics_{i,t-1} + \psi_3' \; Firm\ Characteristics_{i,t-1}) LIQ_t$$
$$+(\varphi_{0,t} + \varphi_1 \; Info\ Quality_{i,t-1} + \varphi_2' \; Market\ Characteristics_{i,t-1} \tag{5}$$
$$+\varphi_3' \; Firm\ Characteristics_{i,t-1}) MKT_t + \varepsilon_{i,t}$$

Eq. (5) follows Shanken (1990) in incorporating the time variation in betas. I then restrict the coefficients on the determinants of liquidity risk and market risk to be the same across all stocks and estimate them using the whole panel of stock returns (Pastor and Stambaugh, 2003). Specifically, at the end of each year from 1983 to 2008, I construct for each stock a historical series of return residuals, $\varepsilon_{i,t}$, using all data from August 1962 (the first month with available *LIQ*) up to the current year-end, as follows:[5]

$$\varepsilon_{i,t} = r_{i,t} - \beta_i^0 - \beta_i^S SMB_t - \beta_i^H HML_t \tag{6}$$

where the $\hat{\beta}$'s are estimated from the regression of the stock's excess returns on *SMB* and *HML*. This step removes from the returns of stock *i* the effects of exposure to *SMB* and *HML* and allows the *SMB* and *HML* betas to be vary across different stocks. I retain the $\varepsilon_{i,t}$ for the current year to ensure that I am using only one return residual for each firm in each month in the analyses. Then I run a pooled time-series cross-sectional regression,

[5] Following Pastor and Stambaugh (2003), I use expanding windows to estimate the return residuals. For example, the residuals for a stock that is listed on NYSE, AMEX, or NASDAQ at the end of December 1998 (1999) are estimated using all available monthly returns for the stock until December 1998 (1999).

with standard errors clustered by firm and month, on the determinants of liquidity risk and market risk, as follows:

$$\begin{aligned}\varepsilon_{i,t} &= \psi_{0,t} + (\psi_1\, Info\ Quality_{i,t-1} + \psi_2'\, Market\ Characteristics_{i,t-1} \\ &+ \psi_3'\, Firm\ Characteristics_{i,t-1})LIQ_t + (\varphi_{0,t} + \varphi_1\, Info\ Quality_{i,t-1} \\ &+ \varphi_2'\, Market\ Characteristics_{i,t-1} + \varphi_3'\, Firm\ Characteristics_{i,t-1})MKT_t + \nu_{i,t}\end{aligned} \tag{7}$$

Unlike Pastor and Stambaugh (2003), I include the main effects for the determinants of liquidity risk and market risk in Eq. (7), so as to follow the typical regression approach of including all main effects when interaction terms are present.[6] Hence, the final regression specification used in my analyses is:

$$\begin{aligned}\varepsilon_{i,t} &= \psi_{0,t} + (\psi_1\, Info\ Quality_{i,t-1} + \psi_2'\, Market\ Characteristics_{i,t-1} \\ &+ \psi_3'\, Firm\ Characteristics_{i,t-1})LIQ_t + (\varphi_{0,t} + \varphi_1\, Info\ Quality_{i,t-1} \\ &+ \varphi_2'\, Market\ Characteristics_{i,t-1} + \varphi_3'\, Firm\ Characteristics_{i,t-1})MKT_t \\ &+ \omega_1\, Info\ Quality_{i,t-1} + \omega_2 Market\ Characteristics_{i,t-1} \\ &+ \omega_3 Firm\ Characteristics_{i,t-1} + \nu_{i,t}\end{aligned} \tag{8}$$

LIQ and *MKT* are contemporaneous with $\varepsilon_{i,t}$ because the objective is to examine the sensitivity of returns to these factors. All the other independent variables are lagged by at least one month to ensure that the information is available for investors to assess a stock before the covariation between the stock return and the changes in market liquidity takes place at time *t*. They are ranked into quintiles based on their values within each month and then scaled to range from zero to one. This is done to ease exposition when interaction terms are present, to deal with potential non-linearities in the effects on liquidity risk, and to facilitate the discussion of the economic significance of the results. The interpretation of the coefficient on each determinant is the difference in the liquidity

[6] I thank the editor for this suggestion. As an aside, untabulated analyses indicate that all inferences in this paper are robust to the exclusion of the main effects from the regression specification.

risk between firms with the highest and lowest quintiles of information quality. The coefficients of interest are those on *Info Quality*$_{t-1}$. Specifically, the coefficient, $\psi_1 (\varphi_1)$ in Eq. (8) provides evidence of the effect of information quality on liquidity (market) risk; a negative coefficient indicates that higher information quality lowers liquidity (market) risk.

3.2.1 Information quality proxies

I focus on earnings as a source of information for investors. In his survey on disclosure theories, Verrecchia (2001) notes that the theories generally predict that investors' uncertainty concerning firm value and adverse selection among investors is higher when the information is of lower precision (i.e., higher variance), ceteris paribus. In this paper, I use various measures that capture the precision of earnings signals. A common trait of these measures is that they capture the second moment associated with an earnings signal. In particular, I construct three proxies, *Earnings precision*, *Accruals quality*, and *Analyst consensus*. The data used to compute *Earnings precision* and *Accruals quality* is from the Compustat Annual database; the data for *Analyst consensus* is from the I/B/E/S Summary database.

Earnings precision measures the degree of volatility in reported earnings. Less volatile earnings are presumably more precise and are expected to be, on average, of higher quality. Consistent with this argument, Dichev and Tang (2009) show that more precise earnings are associated with higher earnings predictability after controlling for a variety of economic characteristics. Following Dichev and Tang, I measure volatility of earnings as the standard deviation of earnings over the most recent five years, with earnings defined as earnings before extraordinary items deflated by average total assets. I then multiply the standard deviation by minus one to make the higher values of *Earnings precision* reflect higher information quality.

Next, I proxy for information quality using *Accruals quality* (Dechow and Dichev, 2002; Francis et al., 2005). Earnings with an accrual component that maps with less variability into the cash flow component may be considered more precise earnings. To obtain *Accruals quality*, I follow Francis et al. (2005) and estimate the following cross-sectional regression for each of the Fama and French (1997) 48 industry groups with at least 20 firms in fiscal year *t*.

$$TCA_{i,t} = \phi_i^0 + \phi_i^1 CFO_{i,t-1} + \phi_i^2 CFO_{i,t} + \phi_i^3 CFO_{i,t+1} + \phi_i^4 \Delta REV_{i,t} + \phi_i^5 PPE_{i,t} + v_{i,t} \qquad (9)$$

where $TCA_{i,t} = \Delta CA_{i,t} - \Delta CL_{i,t} - \Delta Cash_{i,t} + \Delta STDebt_{i,t} - Depn_{i,t}$ = total current accruals, $CFO_{i,t} = NIBE_{i,t} - TCA_{i,t}$ = cash flow from operations, $NIBE_{i,t}$ = net income before extraordinary items, $\Delta CA_{i,t}$ = change in current assets, $\Delta CL_{i,t}$ = change in current liabilities, $\Delta Cash_{i,t}$ = change in cash, $\Delta STDebt_{i,t}$ = change in debt in current liabilities, $Depn_{i,t}$ = depreciation and amortization expense, $\Delta REV_{i,t}$ = change in revenues, and $PPE_{i,t}$ = gross value of plant, property, and equipment. The annual cross-sectional regression produces firm-year residuals. For each firm in each fiscal year, the standard deviation of the residuals for fiscal years *t-5* to *t-1* is computed. Seven years of data are required to obtain the residuals because of the inclusion of cash flow from operations at t-1 and t+1. Given that a higher standard deviation represents lower information quality, I then multiply the standard deviation by minus one to make the higher values of *Accruals quality* reflect higher information quality.

I measure the analyst forecast consensus, *Analyst consensus*, based on analysts' forecasts of annual earnings-per-share (EPS) for the immediate fiscal year-end. When investors rely on analysts' earnings forecasts to evaluate a firm, they are likely to regard forecasts as having greater precision if there is greater consensus/agreement among analysts (Lang and Lundholm, 1996; Barron et al., 1998; Diether, Malloy, and Scherbina, 2002; Zhang, 2006). *Analyst consensus* measures the degree of agreement among analysts in terms of their forecasts. Similar to Zhang (2006), I compute *Analyst consensus* as the negative of the inter-analyst standard deviation of EPS forecasts deflated by stock price at the time when the standard deviation is computed. To compute *Analyst consensus*, I require that at least three analysts cover the firm.

While I use the above three proxies of information quality to proxy for the precision of the earnings signals from a firm, I acknowledge that these proxies could be noisy and potentially biased. For example, *Earnings precision* and *Accruals quality* are likely to also capture innate firm characteristics that could drive cost of capital effects (e.g., Smith and Watts, 1992; Dechow and Dichev, 2002; Francis et al., 2005; LaFond et al., 2007; Dichev and Tang, 2009). Apart from also capturing innate firm characteristics, *Analyst consensus* might not fully capture investor uncertainty because forecast properties in addition to dispersion (e.g., the number of analysts forecasting earnings) also affect precision (Abarbanell, Lanen, and Verrecchia, 1995).

I address the above concerns about the proxies in two ways. First, to reduce noise and potential biases with each individual proxy, I construct an aggregate information quality proxy, *Aggregate quality*, by standardizing (i.e., dividing) each firm's proxy by the standard deviation of the proxy of all firms within each month and then summing the three standardized proxies. Second, I use an extensive array of control variables, particularly those that capture innate firm characteristics, in my regressions.

3.2.2 Market and firm characteristics

To compute the predicted liquidity beta, Pastor and Stambaugh (2003) include several market characteristics in their model of liquidity risk. They note on p. 664 that "the list of characteristics is necessarily arbitrary, though they do possess some appeal ex-ante." The arbitrariness arises because liquidity risk is a relatively new concept and the prior literature offers little guidance on its determinants. Similar to Pastor and Stambaugh, I include the following characteristics in my regression: stock liquidity (*Liquidity*), estimated as described in Appendix A; stock turnover (*Turnover*); prior returns (*Prior returns*); the standard deviation of daily returns (*Return volatility*); and market capitalization in millions (*Size*).[7] Stock liquidity and turnover are added to control for liquidity, which might vary with liquidity risk.[8] The inclusion of the level of prior returns and the standard deviation of returns allows for short-run return dynamics. Finally, market capitalization is included to control for differences in liquidity risk among stocks with different market capitalizations.[9] The standard deviation of returns also helps to control for firm value volatility, which is likely to be negatively associated with information quality. All market characteristics are computed using data from the CRSP database. I include these characteristics as control variables because they are likely to vary with information quality. For example, there is some evidence that liquidity is

[7] Pastor and Stambaugh (2003) include a prior liquidity beta as a predictor in their model. I do not include this variable because its inclusion creates a regression specification that examines the effect of the level of information quality on *changes* in liquidity risk and the objective of this paper is to examine the effect of information quality on the *level* of liquidity risk. Nevertheless, in Section 4.5, I show that inferences remain unchanged with the inclusion of the prior liquidity beta.

[8] Pastor and Stambaugh (2003) include dollar trading volume instead of stock turnover. I find that dollar trading volume and size are highly correlated within my sample (Pearson correlation is 0.80). Hence, I use stock turnover instead of trading volume in the model. Stock turnover is essentially scaled trading volume.

[9] In their model, Pastor and Stambaugh (2003) use shares outstanding and stock price, whose product is equal to the stock's market capitalization. For simplicity and ease of exposition, I include market capitalization. Inferences about the relation between information quality and liquidity risk remain the same when shares outstanding and stock price are used instead.

higher for firms with higher information quality (e.g., Welker, 1995; Leuz and Verrecchia, 2000).

I also control for firm characteristics because the prior literature has documented that a firm's information quality is likely to be associated with its innate characteristics. For example, there are arguments and evidence in the prior literature that information quality varies with investment opportunities, growth, and duration of the operating cycle (e.g., Dechow and Dichev, 2002; Francis et al., 2005; LaFond, Lang, and Skaife, 2007; Dichev and Tang, 2009). Specifically, I control for the following firm characteristics: economic distress, growth and/or investment opportunities as proxied by the ratio of the book value of equity to the market value of equity (*Book-to-market*); sales growth as proxied by the change in sales over the prior year (*Sales growth*); the duration of the operating cycle proxied by the total of the number of days in accounts receivable and inventory, divided by 365 (*Operating cycle*); capital intensity proxied by the ratio of net plant, property, and equipment to total assets (*Capital intensity*); cash liquidity proxied by the ratio of cash and cash equivalent to current liabilities (*Cash ratio*); and financial condition proxied by a dummy variable indicating whether the firm had negative earnings before extraordinary items (*Loss*). These innate firm characteristics are computed using data from the Compustat Annual database.[10]

4. Results

4.1 Sample description

[10] As return volatility is already included in the model to control for innate firm value volatility, I do not include cash flow volatility and/or sales volatility as control variables. Return volatility, measured in the month before the covariation between stock returns and the various market factors, is presumably a more timely measure.

The empirical analyses are based on Eq. (8); each observation is a firm-month. The construction of the sample begins with the monthly return residuals for all stocks from January 1983 to December 2008.[11] Each return residual is then matched with the monthly market factors, *MKT*, *SMB*, *HML*, and *LIQ*, for the same month. The determinants of liquidity risk and market risk then are matched to each firm-month with a time lag of at least one month to reduce the likelihood of reverse causality. In particular, for all variables that use financial statement data from the Compustat Annual database (e.g., *Earnings precision*, *Accruals quality*, and *Book-to-market*), their values at the most recent prior fiscal year-end are matched to the firm-month with a lag of four months; the lag is to ensure that the financial statement data is publicly available. For example, a financial statement variable measured as of 31 December 2000 is matched to each firm-month from May 2001 to April 2002. All the other variables (e.g., *Analyst consensus*, *Liquidity,* and *Volume*) are available monthly and are hence lagged by one month.

To maintain a constant sample in the empirical analyses, a firm-month is excluded if it has missing values for any of the determinants of the liquidity beta. This results in a sample of 306,624 firm-months from January 1983 to December 2008. The main constraint on the sample size is the data for computing the information quality proxies. For example, computing *Accruals quality* requires seven years of firm-specific data, while the computation of *Analyst consensus* requires that at least three analysts follow the firm. Hence, the observations used in my analyses are likely to be from firms that are typically larger and have a higher trading volume and more stable returns than those in the CRSP database. These characteristics indicate that the firms in my sample are more

[11] The sample period begins in January 1983 because the trading volume for NASDAQ firms is only available from CRSP from November 1982.

likely to survive. The survivorship bias is likely to work against finding an association between information quality and liquidity risk because these firms are likely to have less information problems.

Table 2, Panel A presents the summary statistics of the information quality proxies and the other variables that are in the empirical models of liquidity risk and market risk (see Eq.s (2) and (3)). *Earnings precision*, *Accruals quality*, and *Analyst consensus* are constructed such that higher (i.e., less negative) values reflect higher information quality; hence, the means, medians, and quartiles of these information quality proxies are negative as expected. *Aggregate quality* is the sum of standardized *Earnings precision*, *Accruals quality*, and *Analyst consensus*; the standardization is done by dividing each individual proxy by the standard deviation of the proxy for all firms within a month. As a result, values of *Aggregate quality* are also negative. The mean (median) market capitalization is \$3.95 (\$0.87) billion. This large market capitalization is expected, given that the computation of the variables, particularly the information quality proxies, imposes significant data requirements that tend to eliminate small firms from the sample. For example, computing *Accruals quality* requires seven years of firm-specific data, while the computation of *Analyst consensus* requires that at least three analysts follow the firm.

Panel B presents the correlations among the variables. The correlations between *Earnings precision* and *Accruals quality*, *Earnings precision* and *Analyst consensus*, and *Accruals quality* and *Analyst consensus* are 0.597, 0.140, and 0.061, respectively; they are also statistically significant. The correlations between *Earnings precision* and *Accruals quality* are clearly higher than the other correlations. One possible reason is that both *Earnings precision* and *Accruals quality* measure the precision of actual earnings whereas *Analyst consensus* measures the precision of forecasted earnings. Another reason may be that both *Earnings precision* and *Accruals quality* capture the within-firm time-series uncertainty in earnings, while *Analyst consensus* captures the across-analyst disagreement about the firm's future earnings at a point in time. Hence, while the three proxies attempt to capture information quality, *Analyst consensus* might be better construed as capturing a different dimension of information quality. This interpretation is consistent with Dechow, Ge, and Schrand (2010), who note in their survey paper that low correlations between different proxies for earnings quality are expected if these proxies represent different earnings attributes. Another explanation for the low correlations is the limitation of analyst consensus as a measure of investor uncertainty, as discussed in Section 3 (Abarbanell et al., 1995). Finally, the correlations between *Aggregate quality* and *Earnings precision* (*Accruals quality*, *Analyst consensus*) is 0.737 (0.776, and 0.422); these high correlations are expected as *Aggregate quality* is the sum of standardized *Earnings precision*, *Accruals quality*, and *Analyst consensus*; the standardization is done by dividing each individual proxy by the standard deviation of the proxy for all firms within a month.

4.2 The effect of information quality on liquidity risk and market risk

Table 3 presents the results of the regressions that examine how information quality is associated with liquidity risk and market risk. The regression specification used is Eq. (8). As noted earlier, the variable of interest when examining the relation between information quality and liquidity risk is the interaction term between an information quality proxy and the market liquidity factor, *LIQ*. To the extent that higher information quality is associated with lower liquidity risk (note that lower liquidity risk means smaller sensitivity of stock returns to *LIQ*), the coefficients on the information quality proxies are expected to be negative. More specifically, each coefficient represents the differences in liquidity betas between the firms in the top and bottom quintiles of information quality and a negative coefficient means that the top quintile has a lower liquidity beta. As the economic importance of differences in liquidity risk (or risk in general) typically depends on what these differences imply in terms of cost of capital, I provide a brief indication of the economic significance in this section, while leaving the details to the next section.

The first three columns present the results when *Earnings precision*, *Accruals quality*, and *Analyst consensus* are considered separately. The coefficients on the interaction terms of these information quality proxies with *LIQ* are negative and statistically significant. In particular, the coefficient on *Earnings precision* (*Accruals quality*, *Analyst consensus*) and *LIQ* indicates that firms in the top quintile have a liquidity beta that is lower than it is for those firms in the bottom quintile, by 4.787 (2.754, 5.694). The differences in liquidity betas indicate that, compared to those in the bottom quintile, firms in the top quintile of *Earnings precision* (*Accruals quality*, *Analyst consensus*) have a cost of capital that is lower by 268 (154, 319) basis points due to liquidity risk (see the next section for the computations). Finally, the significant coefficient on *Aggregate quality* in the last column indicates that firms in the top quintile of information quality have a liquidity beta that is lower by 4.794. This difference in liquidity betas translates to a cost of capital that is lower by 269 basis points due to liquidity risk (see the next section for the computation). Taken together, the results indicate that information quality is negatively associated with liquidity risk and that this association is both statistically and economically significant.

With regard to the coefficients on the other variables that are interacted with *LIQ*, there is evidence that prior returns are positively associated with liquidity risk, indicating that firms whose stocks have recently performed well have a higher exposure to liquidity risk. There is marginal evidence that firms with higher book-to-market of equity have higher liquidity risk, suggesting that firms that are more distressed and/or with less growth options have higher liquidity risk. Firms with higher capital intensity have higher liquidity risk, possibly because these firms tend to have higher financial risk due to their capital needs. If changes in market liquidity are positively associated with changes in available capital in the market, then the stock returns of these firms are expected to be more sensitive to changes in market liquidity. Finally, the stock returns of firms in a stronger liquidity position because of a higher cash ratio have lower exposure to unexpected changes in market liquidity.

As noted earlier, I use the relation between information quality and market risk to compare and contrast the cost of capital effects of information quality through different systematic risk mechanisms. To examine this relation, the coefficient of interest is the interaction term between an information quality proxy and the market return factor *MKT*. These coefficients are negative and statistically significant, as expected (Lambert et al., 2007). In particular, the coefficient on *Earnings precision* (*Accruals quality*, *Analyst consensus*) and *MKT* indicates that firms in the top quintile have a market beta that is lower than those in the bottom quintile, by 0.087 (0.065, 0.137). Finally, the significant coefficient on *Aggregate quality* in the last column indicates that firms in the top quintile of information quality have a market beta that is lower by 0.118.

4.3 Cost of capital effects through liquidity risk and market risk

To examine the economic significance of the effect of information quality on cost of capital (*CoC*) through liquidity risk, I estimate the liquidity risk premium per unit of liquidity beta using the procedures described in Appendix A; this premium is 56 basis points (bp) per year. The market risk premium per unit of market beta, as indicated in Table 1, is 482 bp (40.2 bp per month x 12).

Table 4 presents the estimates of the *CoC* effects for the difference in liquidity risk and in market risk between the top and bottom quintiles of information quality. The formula to estimate the *CoC* effects is as follows:

CoC through liquidity (market) risk = Difference in liquidity (market) risk (10)

between quintiles x risk premium per unit of liquidity (market) risk,

with the differences in the liquidity risk and market risk obtained from the coefficients in Table 3. As discussed earlier, these coefficients represent the difference in risk between the top and bottom quintiles of information quality. The above approach for estimating *CoC* effects is similar to that used in Francis et al. (2004, 2005).

The estimated *CoC* results suggest that higher information quality results in economically significant differences in *CoC* through lower liquidity risk and lower market risk. For example, compared to firms in the bottom quintile of *Aggregate quality*, firms in the top quintile have a *CoC* that is lower by 269 bp, due to the effect of information quality on liquidity risk. With market risk as the underlying mechanism, firms in the top quintile have a *CoC* that is lower by 57 bp. Hence, the effect of information quality on *CoC* through lower liquidity risk is larger than it is through lower market risk. This result is an indication of the importance of liquidity risk as a mechanism linking information quality and cost of capital.

The above estimates of cost of capital effects appear to be reasonable given the findings in the prior literature. For example, Francis et al. (2005) finds that the difference in market beta between the top and bottom quintile of accrual quality implies a 210 bp higher cost of equity for firms with the worst accrual quality relative to firms with the best accrual quality. Similarly, Francis et al. (2004) concludes that there is a 261 basis point differential cost of equity capital between the best and worst accrual quality deciles.

Consistent with this study's objective of understanding the systematic risk mechanisms through which information quality affects cost of capital, the above discussion focuses on the cost of capital effect of information quality via liquidity risk and market risk. However, Eq. (8) also allows for interpreting the effect of information quality on cost of capital via unidentified mechanisms other than liquidity risk and market risk (Brennan, Chordia, and Subrahmanyam, 1998). The effect via liquidity risk and market risk is known as indirect effects; via unidentified mechanisms, it is known as direct effects. In particular, the coefficient on information quality (as a main effect) can be interpreted as the return difference between the top and bottom quintiles of this variable. Since the coefficient on *Aggregate quality* in the last column of Table 3 is 0.005, the interpretation is that *Aggregate quality* adds 600 basis points per year to the cost of capital. Table 4 reports that *Aggregate quality* contributes -269 and -57 basis points per year to the cost of capital, via liquidity risk and market risk, respectively. Therefore, the total contribution of *Aggregate quality* to the cost of capital is a positive

274 basis points per year. Hence, one should not generalize the cost of capital effect of information quality via liquidity risk and market risk to the overall cost of capital effect of information quality.

4.4 The effect of information quality on liquidity risk in times of large, unexpected changes in market liquidity

In this section, I conduct an exploratory analysis to determine how information quality relates to liquidity risk and to market risk in different periods of unexpected changes in market liquidity. This analysis, while not guided by any clear ex-ante prediction of how the relations would differ between periods, is motivated by the fact that extreme market liquidity events, particularly extreme negative events, significantly affect investors' welfare. For example, Pastor and Stambaugh (2003) highlight that exposure to liquidity risk doomed Long-Term Capital Management during a period of widespread deterioration in market liquidity precipitated by the Russian debt crisis. Other papers have also noted that portfolio managers are concerned about freezes in liquidity (or "liquidity black holes") in the equity markets due to the disappearance of investors or market makers (Moorthy, 2003; Morris and Shin, 2003). Furthermore, the prior literature has documented that liquidity risk tends to be more pronounced during extreme negative market conditions (Brunnermeier and Pedersen, 2009; Hameed et al., 2010). Building off this literature, Lang and Maffett (2010) examine the relation between transparency and liquidity risk during crisis periods.

The regression specification used in the analysis is similar to that used earlier in Table 3 when I examined the relation between information quality and liquidity risk for the 312 months from January 1983 to December 2008. Using the time series of the monthly *LIQ* factor from January 1983 to December 2008, I identify the months with the largest decreases and increases in market liquidity. Specifically, these are months that represent approximately the top 10% and bottom 10% of changes in market liquidity from the 312 months from January 1983 to December 2008. I then run regressions separately for the following three subsamples: i) the 31 months with the largest decreases in market liquidity, ii) the 31 months with the largest increases in market liquidity, and iii) the remaining 250 months. The analyses are performed with *Aggregate quality* as the information quality proxy.

The first column of Table 5 reports the results for the 31 months with the largest decreases in market liquidity. The coefficient on *Aggregate quality x LIQ* is a statistically significant -10.203, indicating that information quality has a statistically significant effect in mitigating liquidity risk in times of large decreases in market liquidity. This coefficient is a statistically insignificant -13.274 and 1.832 for the 31 months with the largest increases in market liquidity and the remaining 250 months, respectively. These results suggest that there is an asymmetry in the relation between information quality and liquidity risk across the periods. From the perspective of statistical significance, higher information quality is significantly associated with lower liquidity risk only during months with the largest decreases in market liquidity. However, I observe that the magnitude of the coefficient in the months with largest increases in market liquidity is somewhat large (in fact, this coefficient is slightly larger than it is in the months with the largest decreases in market liquidity) and that this coefficient is marginal insignificant (t-stat = -1.53). Hence, it appears that higher information quality also has an elevated effect in lowering liquidity risk in times of large increases in market liquidity.

A possible explanation for this result relies on the notion that large negative (positive) liquidity shocks are, on average, associated with a significant "flight" of investors from (to) the equity markets (Pastor and Stambaugh, 2003). During such shocks, information quality could have a greater influence on investors' decisions if investors consider stocks with poor information quality to be risky; that is, they prefer to exit from these stocks when market liquidity declines and are only willing to invest in them when market liquidity improves. This explanation is based on the idea that information quality affects liquidity risk because, conditional on changes in market liquidity, it has different influences on the demand for individual stocks.

Table 5 also presents results for the effect of information quality on market risk during the three different periods of market liquidity changes. While these results also suggest some asymmetry across the three periods, the patterns are different from those for the relation between information quality and liquidity risk. The results indicate that higher information quality reduces market risk when market liquidity is stable or improving significantly but not when it is declining significantly.

It seems surprising to find that information quality affects liquidity risk but not market risk in times with large declines in market liquidity. One ex-post conjecture is based on Lambert et al.'s (2007) suggestion that information quality affects market risk because investors use information to assess the covariance between a firm's cash flows and those of other firms. By this logic, in times of large declines in market liquidity, investors are more concerned with exiting from stocks with information problems (as discussed earlier, this implies that information quality affects liquidity risk), as opposed to using information to assess covariances of cash flows. In contrast, when market liquidity conditions are stable or improving, investors rely on information to assess how the cash flows of individual stocks covary with those of the market.

4.5 Robustness analyses

Table 6 reports the results of several tests of the robustness of the earlier results on the effect of information quality on liquidity risk. In Panel A, I consider other information quality proxies: *Earnings smoothness*, *Analyst consensus 1*, and *Analyst consensus 2*. *Earnings smoothness* is the negative of the standard deviation of earnings scaled by the standard deviation of cash flow from operations. *Analyst consensus 1 (2)* is the negative of the inter-analyst standard deviation of earnings-per-share forecasts scaled by the mean (median) consensus earnings-per-share forecast. The coefficients on the interaction terms between these alternative proxies and *LIQ* are negative and statistically significant. This provides further support for the hypothesis that information quality is negatively associated with liquidity risk.

In Panel B, I include firm-fixed effects. The coefficients on the interaction term between the information quality proxies (*Earnings precision*, *Accruals quality*, *Analyst consensus*, and *Aggregate quality*) and *LIQ* are similar to those reported in Table 3, in terms of sign, magnitude, and statistical significance.

Finally, in Panel C, I include in the regressions controls for the historical liquidity beta and the historical market beta. The motivation for including the historical liquidity beta is to follow the liquidity risk model in Pastor and Stambaugh (2003); they find that this beta is the most reliable predictor of liquidity risk. In addition to the historical liquidity beta, I also include the historical market beta in my model of market risk; its inclusion creates symmetry in terms of both models of risk. As expected, I find that the historical liquidity and market betas are significant predictors of the current liquidity and market betas, respectively. My earlier conclusion, that there is a negative association between information quality and liquidity risk, is not affected by the inclusion of the historical betas.

5. Conclusion

In this paper, I hypothesize that higher information quality is negatively associated with liquidity risk, which is the sensitivity of stock returns to unexpected changes in market liquidity. The empirical evidence, which uses a number of information proxies motivated by disclosure theory, provides support for this association. To analyze the economic significance of this association, I estimate the effect of information quality on cost of capital through liquidity risk, and find the effect economically significant. In particular, compared to firms in the bottom quintile of information quality, firms in the top quintile have a cost of capital that is lower by 269 basis points due to lower liquidity risk. I also document that higher information quality is associated with lower market risk, but find that market risk is less economically significant than liquidity risk as a mechanism linking information quality and cost of capital. Further analyses also indicate that the negative association between information quality and liquidity risk is stronger in times of large unexpected changes in market liquidity.

The above conclusion, that higher information quality lowers liquidity risk, is subject to standard endogeneity concerns (i.e., reverse causality and omitted correlated variable biases). First, there is a concern about reverse causality—that is, that liquidity risk affects information quality and not vice versa. I use a research design that essentially examines how information quality, measured before each monthly change in market liquidity, affects the covariation between stock returns and monthly changes in market liquidity. The use of lagged information quality proxies and short windows involved in the analyses reduce the likelihood of reverse causality. An additional advantage of this design is that it allows investors and market makers to observe the information quality associated with each individual stock before they respond to changes in market liquidity. As discussed earlier, an example of such a response is the exit from certain stocks when market liquidity declines. Second, to mitigate omitted correlated variable biases, I follow the prior literature and include control variables that capture a wide range of market and firm characteristics. Nevertheless, I acknowledge the importance of caution in making strong causal conclusions, given the endogeneity concerns. Finally, the scope of this paper is limited to the effect of information quality on liquidity risk (and market risk) and what that effect means in terms of cost of capital. It does not focus on the overall effect of information quality on cost of capital or whether information quality is, by itself, a priced risk factor (Francis et al., 2005; Core et al., 2008; Lambert et al., 2008; Ogneva, 2008).[12]

An empirical implication of the evidence that higher information quality is associated with lower systematic risk is that controlling for systematic risk in regressions of cost of capital on information quality may lead to "over-controlling". While one could argue that a significant association from empirical tests that control for systematic risk provide stronger tests of the relation between information quality and cost of capital, this argument also raises questions about the underlying reasons (other than the effect of information quality through systematic risk) that are driving the results. Hence, it is

[12] This caveat is in the same spirit as Lambert et al. (2008), who state in their conclusion that while their study demonstrates that market risk could be a mechanism linking information quality and cost of capital, their study does not address the issue of whether information quality is a priced risk factor.

important not only to examine the existence of a relation between information quality and cost of capital, but also to understand the underlying mechanisms linking the two. In fact, an interesting finding in the paper is that while information quality lowers cost of capital via its effect on liquidity risk and market risk, information quality can increase the cost of capital effect via other (unidentified) mechanisms.

Appendix A. Market liquidity, market liquidity factor, and liquidity risk premium

This appendix provides a brief overview of individual stock liquidity, market liquidity, market liquidity factor (*LIQ*), and liquidity risk premium (see Pastor and Stambaugh (2003) for a more detailed description). Monthly market liquidity is obtained by aggregating the individual stock liquidity in each month. *LIQ* represents innovations (i.e., unexpected changes) in monthly market liquidity. The liquidity risk premium is an estimate of the cost of capital effects arising from exposure to *LIQ*.

A.1 The monthly liquidity (γ) for an individual stock

The monthly liquidity for stock *i* in month *t* is the ordinary least squares estimate of $\gamma_{i,t}$ in the following regression:

$$r^e_{i,d,t+1} = \theta_{i,t} + \phi_{i,t} r_{i,d,t} + \gamma_{i,t} sign(r^e_{i,d,t}) \times v_{i,d,t} + \varepsilon_{i,d+1,t}, \quad d = 1,\ldots,D, \tag{A1}$$

where $r_{i,d,t}$ is the return on stock *i* on day *d* in month *t*; $r^e_{i,d,t} = r_{i,d,t} - r_{m,d,t}$ is the daily excess return, measured as the daily stock return in excess of $r_{m,d,t}$, which is the CRSP value-weighted market return on day *d* in month *t*; and $v_{i,d,t}$ is the trading volume (measured in millions of dollars) for stock *i* on day *d* in month *t*.

γ is based on the concept of order flow, which in this case refers to the trading volume signed by the contemporaneous excess return on the stock. An order flow should be followed by a return reversal in the future if the stock is not perfectly liquid at the time of the order flow. Eq. (A1) is specified with the assumption that, on the next day, the excess return will be negatively associated with the order flow of the previous day if the lack of liquidity prevented the price from returning to its "normal" level on the previous day. The lagged stock return is included to control for return reversal effects that are not related to order flow, such as reversals due to minimum tick size. A larger return reversal, as indicated by a more negative γ, reflects lower liquidity.

A.2 Market liquidity and market liquidity innovation

The monthly market liquidity, γ_t, is measured as the equal-weighted average of the liquidity of the firms in each month:

$$\gamma_t = \frac{1}{N_t}\sum_{i=1}^{N}\gamma_{i,t} \tag{A2}$$

To construct a liquidity measure that reflects the cost of a trade where the cost is commensurate with the overall size of the stock market, each γ_t is scaled to obtain the scaled series $(m_t / m_1)\ \gamma_t$, where m_t is the total dollar value at the end of month $t\text{-}1$ of the stocks included in the average in month t, and month 1 refers to August 1962. To construct the unexpected changes in market liquidity, the following regression is run:

$$\Delta\gamma_t = a + b\Delta\gamma_{t-1} + c\left(\frac{m_t}{m_1}\right)\gamma_{t-1} + u_t \tag{A3}$$

where $\Delta\gamma_t = \left(\frac{m_t}{m_1}\right)\frac{1}{N_t}\sum_{i=1}^{N_t}(\gamma_{i,t} - \gamma_{i,t-1})$. The scaling using m_t and m_1 in Eq. (A3) is done to reflect the growth in size of the stock market. The scaled series reflects the liquidity cost (in terms of return reversal) of trading \$1 million in August 1962 "stock market" dollars, averaged across stocks at a given point in time. μ_t measures the unexpected changes in market liquidity. It is scaled by 100 to obtain the market liquidity factor, *LIQ*:

$$LIQ_t = \frac{1}{100}u_t. \tag{A4}$$

A.3 Liquidity risk premium

To obtain reliable estimates of the liquidity risk premiums, I use the longest possible time series to estimate the risk premium for liquidity risk. Specifically, I estimate this premium using the liquidity betas estimated at the end of each year from 1967 to 2008 and stock returns from 1968 to 2009. For each stock in each year, I estimate its historical liquidity beta using the regressions of the past five years of monthly returns (with a minimum requirement of 36 monthly returns) on *MKT*, *SMB*, *HML*, and *LIQ*. The liquidity beta is the slope coefficient on *LIQ*.[13]

Table A presents estimates of the liquidity risk premium using future returns. The steps closely follow those used in Tables 7 and 8 of Pastor and Stambaugh (2003). Stocks are first sorted into decile portfolios based on their historical liquidity betas at each year-end. The portfolios are then linked over time to estimate the post-ranking portfolio alphas from the standard asset pricing regressions of portfolio returns on various factors. Specifically, the value-weighted monthly returns of each portfolio are computed for the twelve months after the portfolio formation. The monthly portfolio returns are then linked over the years (e.g., the twelve months of the top decile's monthly returns in 1968 with the twelve months of the top decile's monthly returns in 1969 and so on until 2009). The hedge portfolio alpha, i.e., the alpha from the top decile minus that from the bottom decile, is an estimate of the liquidity risk premium.

The top half of the panel reports the post-ranking β^L from time-series regressions of portfolio returns on *LIQ*, *MKT*, *SMB*, and *HML*. As expected, the post-ranking liquidity betas generally increase across the deciles. The "10-1" spread, which is the spread from going long in decile 10 (stocks with high liquidity betas) and short in decile

[13] Untabulated analyses indicate that the liquidity beta has a mean of -0.473, a standard deviation of 48.352 and an interquartile range of -20.528 to 20.648. It has a negative correlation of -0.265 with the market beta, the slope on MKT.

1 (stocks with low liquidity betas), has an overall liquidity beta of 9.65, with a t-statistic of 2.80. The bottom half of the panel reports the post-ranking portfolio alphas from various factor models. In this paper, I use the Fama-French alpha, obtained from regressions of portfolio returns on *MKT*, *SMB*, and *HML*, as the estimated liquidity risk premium. The Fama-French "10-1" annualized alpha is 5.40%, with a t-statistic of 2.31. The CAPM alpha from regressions on MKT only and the Four-factor alpha from regressions on *MKT*, *SMB*, *HML*, and *UMD* (i.e., the momentum factor) indicate that stocks with higher liquidity risk have higher expected returns.

Finally, given that the "10-1" spread is 9.65 and the "10-1" alpha is 5.40, the estimated risk premium per unit of liquidity beta based on the Fama-French results is 0.56% (5.40 / 9.65) or 56 basis points per year. As a comparison, Pastor and Stambaugh (2003) document a "10-1" spread of 5.99 and a "10-1" alpha of 4.15% for their sample period from January 1968 to December 1999. This translates to a risk premium per unit of liquidity beta of 0.693% or 69.3 basis points per year.

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Figure 1 – Times series of monthly market liquidity from August 1962 to December 2008

Each month's market liquidity, $\gamma_{t,}$ is constructed by averaging the individual stock liquidity for the month, $\gamma_{i,t,}$ and then multiplying this average by (m_t / m_1), where m_t is the total dollar value at the end of month *t-1* of the stocks included in the average in month *t*, and month 1 corresponds to August 1962. An individual stock liquidity for a given month is the regression slope coefficient estimated using daily returns and volume within that month.

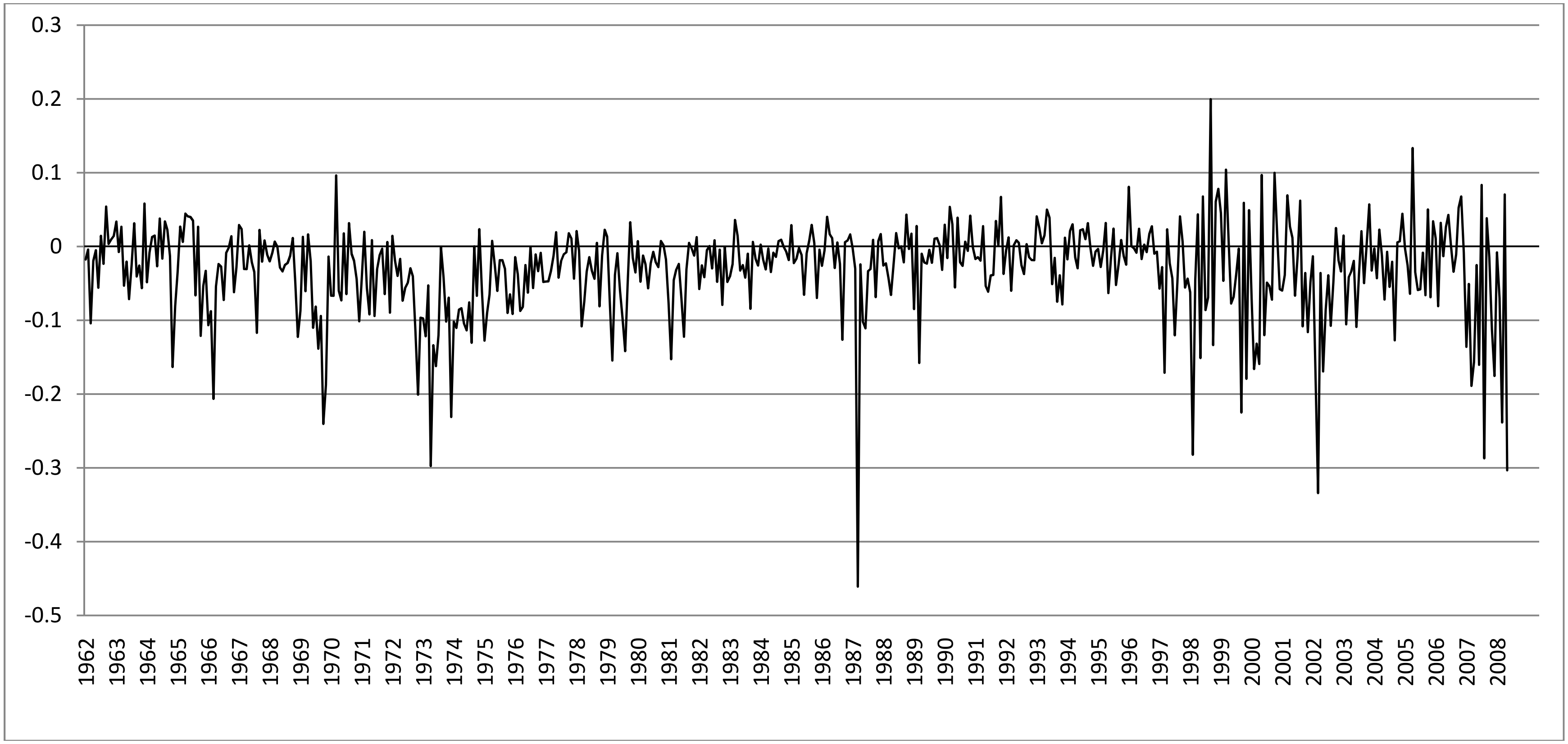

TABLE 1 – Descriptive statistics: Market factors (*LIQ*, *MKT*, *SMB*, *HML*)

This table presents descriptive statistics of Pastor and Stambaugh's monthly market liquidity factor, *LIQ*, and the Fama-and-French three monthly factors of *MKT*, *SMB*, and *HML*. *MKT*, *SMB*, and *HML* are the market return, size, and value factors, respectively. The time series used to construct the statistics are the 557 months from August 1962 to December 2008. *LIQ* is a non-traded factor and the statistics are reported after *LIQ* has been multiplied by 100. *MKT*, *SMB*, and *HML* are traded factors and their monthly returns are expressed in percentages. Panel A presents the summary statistics; Panel B reports the correlations. *, **, and *** indicate significance at the 10, 5, and 1 percent levels, respectively.

Panel A – Summary statistics

Variable	Mean	Std Dev	Q1	Median	Q3
LIQ	0.000	0.057	-0.024	0.007	0.031
MKT	0.402	4.448	-2.180	0.770	3.360
SMB	0.228	3.178	-1.520	0.060	2.060
HML	0.442	2.860	-1.150	0.420	1.780

Panel B – Correlations

	MKT	*SMB*	*HML*
LIQ	0.344***	0.169***	-0.116***
MKT		0.302***	-0.376***
SMB			-0.262***

TABLE 2 – Descriptive statistics: Information quality proxies and control variables

Panel A (B) presents the summary statistics (Pearson correlations) of the information quality proxies and various control variables. The sample consists of 306,624 firm-months. *Earnings precision* is the negative of the standard deviation of earnings scaled by the standard deviation of cash flow from operations. *Accruals quality* is the negative of the standard deviation of the residuals from regressions of total current accruals on cash flow from operations in the prior, current, and following years; change in revenues; and gross plant, property, and equipment. *Analyst consensus* is the inter-analyst standard deviation of earnings-per-share forecasts scaled by stock price at the time when the standard deviation is computed. *Aggregate quality* is the sum of standardized *Earnings precision*, *Accruals quality*, and *Analyst consensus*; the standardization is done by dividing each individual proxy by the standard deviation of the proxy for all firms within a month. *Liquidity* is the stock liquidity measured following Pastor and Stambaugh (2003); *Turnover* is the trading volume scaled by shares outstanding; *Prior return* is the prior month's stock return; *Return volatility* is the standard deviation of daily stock returns; *Size* is the market capitalization; *Book-to-market* is the book-to-market of equity; *Sales growth* is the change in sales; *Operating cycle* is the operating cycle based on inventory turnover and accounts receivable turnover; *Capital intensity* is the ratio of net plant, property, and equipment to total assets; *Cash ratio* is the ratio of cash and cash equivalent to total current liabilities; and *Loss* is a dummy variable if the firm has a negative income before extraordinary items. All continuous variables (i.e., all variables except for *Loss*) are winsorized at the 1st and 99th percentiles. In Panel B, all the correlations are significant at the 5 percent level, except for those superscripted with "ns"; "ns" indicates that the correlation is not significant.

Panel A - Summary statistics

	Variable	Mean	Std Dev	Q1	Median	Q3
(1)	*Earnings precision*	-0.0430	0.0558	-0.0495	-0.0249	-0.0125
(2)	*Accruals quality*	-0.0332	0.0267	-0.0422	-0.0257	-0.0153
(3)	*Analyst consensus*	-0.0070	0.0165	-0.0066	-0.0028	-0.0012
(4)	*Aggregate quality*	-2.2580	1.8487	-2.7895	-1.7189	-1.0652
(5)	*Liquidity* (x 10^{-3})	-0.1480	15.8193	-0.9103	-0.0154	0.6780
(6)	*Turnover*	0.1274	0.1380	0.0420	0.0787	0.1585
(7)	*Prior return*	0.0089	0.1129	-0.0509	0.0078	0.0672
(8)	*Return volatility*	0.0233	0.0141	0.0140	0.0197	0.0285
(9)	*Size*	3953	11888	295	869	2679
(10)	*Book-to-market*	0.5379	0.3440	0.3011	0.4783	0.7047
(11)	*Sales growth*	0.1284	0.2474	0.0150	0.0903	0.1895
(12)	*Operating cycle*	0.3368	0.2103	0.1900	0.2944	0.4393
(13)	*Capital intensity*	0.3748	0.2425	0.1773	0.3224	0.5599
(14)	*Cash ratio*	0.7440	1.4103	0.0816	0.2569	0.7536
(15)	*Loss*	0.1317	0.3381	0.0000	0.0000	0.0000

Panel B – Correlations

	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
(1)	0.597	0.140	0.737	0.005	-0.327	0.018	-0.335	0.054	0.163	-0.148	-0.087	0.271	-0.357	-0.378
(2)		0.061	0.776	0.004	-0.251	0.011	-0.304	0.070	0.173	-0.157	-0.153	0.397	-0.225	-0.192
(3)			0.422	-0.011	0.011	0.049	-0.233	0.090	-0.252	0.066	-0.001^{ns}	-0.092	0.008	-0.299
(4)				0.000^{ns}	-0.199	0.030	-0.373	0.127	0.032	-0.116	-0.139	0.253	-0.226	-0.378
(5)					0.002^{ns}	0.004	-0.007	0.003^{ns}	-0.001^{ns}	-0.001^{ns}	-0.003^{ns}	0.008	-0.003^{ns}	-0.003^{ns}
(6)						-0.029	0.455	0.003^{ns}	-0.190	0.188	0.034	-0.237	0.280	0.132
(7)							-0.096	0.014	0.028	-0.010	-0.002^{ns}	0.017	-0.017	-0.016
(8)								-0.080	-0.053	0.117	0.097	-0.213	0.205	0.259
(9)									-0.188	0.013	-0.005	-0.018	-0.035	-0.072
(10)										-0.205	-0.039	0.255	-0.167	0.100
(11)											0.035	-0.107	0.117	-0.066
(12)												-0.397	0.080	0.041
(13)													-0.305	-0.071
(14)														0.185

Note: The numbers in the first column and row of this panel correspond to the variable names indicated in the first column of Panel A.

TABLE 3 – The effect of information quality on liquidity risk and market risk

This table reports the results of regressions that investigate the cross-sectional effects of information quality, as proxied by *Earnings precision*, *Accruals quality*, *Analyst consensus*, and *Aggregate quality*, on liquidity risk and market risk. The sample consists of 306,624 firm-months. Liquidity risk is the sensitivity of stock returns to the market liquidity factor, *LIQ*. Market risk is the sensitivity of stock returns to the market return factor, *MKT*. The dependent variable is $\varepsilon_{i,t}$, which is the return residual after the orthogonalization of returns in excess of the risk-free rate by the *SMB* and *HML* factors. *Earnings precision* is the negative of the standard deviation of the ratio of earnings to total assets. *Accruals quality* is the negative of the standard deviation of the residuals from regressions of total current accruals on cash flow from operations in the prior, current, and following years; change in revenues; and gross plant, property, and equipment. *Analyst consensus* is the negative of the inter-analyst standard deviation of earnings-per-share forecasts scaled by stock price at the time when the standard deviation is computed. *Aggregate quality* is the sum of standardized *Earnings precision*, *Accruals quality*, and *Analyst consensus*; the standardization is done by dividing each individual proxy by the standard deviation of the proxy for all firms within a month. *Liquidity* is the stock liquidity measured following Pastor and Stambaugh (2003); *Turnover* is the trading volume scaled by shares outstanding; *Prior return* is the prior month's stock return; *Return volatility* is the standard deviation of daily stock returns; *Size* is the market capitalization; *Book-to-market* is the book-to-market of equity; *Sales growth* is the change in sales; *Operating cycle* is the operating cycle based on inventory turnover and accounts receivable turnover; *Capital intensity* is the ratio of net plant, property, and equipment to total assets; *Cash ratio* is the ratio of cash and cash equivalent to total current liabilities; and *Loss* is a dummy variable if the firm has a negative income before extraordinary items. Each of the above variables is measured before the month in which the sensitivities of monthly returns to *LIQ* and *MKT* are observed. All continuous variables that are not market factors are ranked into quintiles and scaled to range from zero to one. The Huber-White heteroscedasticity-robust t-statistics with clustered standard errors are presented in parentheses below the estimated coefficients. *, **, and *** indicate significance at the 10, 5, and 1 percent levels, respectively.

Info Quality proxies	*Earnings precision*	*Accruals quality*	*Analyst consensus*	*Aggregate quality*
Determinants of liquidity risk				
Info Quality x LIQ	**-4.784***** **(-3.44)**	**-2.754*** **(-1.87)**	**-5.694***** **(-4.01)**	**-4.794***** **(-3.22)**
Liquidity x LIQ	0.337 (0.25)	0.324 (0.24)	0.347 (0.26)	0.354 (0.27)
Turnover x LIQ	-0.512 (-0.35)	0.089 (0.06)	-0.275 (-0.19)	-0.444 (-0.30)
Prior return x LIQ	2.631** (2.02)	2.584** (1.98)	2.769** (2.12)	2.633** (2.02)
Return volatility x LIQ	-0.102 (-0.07)	0.177 (0.11)	-0.196 (-0.13)	-0.221 (-0.14)
Size x LIQ	-0.098 (-0.07)	-0.268 (-0.19)	0.335 (0.25)	0.388 (0.27)
Book-to-market x LIQ	2.725* (1.91)	2.664* (1.86)	1.000 (0.67)	2.632* (1.85)
Sales growth x LIQ	0.126 (0.09)	-0.031 (-0.02)	0.398 (0.29)	0.037 (0.03)
Operating cycle x LIQ	1.911 (1.42)	2.085 (1.55)	2.498* (1.86)	2.083 (1.54)
Capital intensity x LIQ	4.632*** (3.16)	4.950*** (3.23)	3.359** (2.30)	5.073*** (3.39)
Cash ratio x LIQ	-3.799***	-3.105**	-2.993**	-3.448**

	(-2.75)	(-2.27)	(-2.20)	(-2.51)
Loss x LIQ	-2.695	-1.583	-2.553	-2.430
	(-1.57)	(-0.95)	(-1.51)	(-1.43)
Determinants of market risk				
Info Quality x MKT	**-0.087*****	**-0.065*****	**-0.137*****	**-0.118*****
	(-3.72)	**(-2.72)**	**(-6.49)**	**(-4.93)**
Liquidity x MKT	-0.030*	-0.030*	-0.031*	-0.030*
	(-1.74)	(-1.72)	(-1.75)	(-1.71)
Turnover x MKT	0.171***	0.180***	0.174***	0.168***
	(8.04)	(8.53)	(8.24)	(7.91)
Prior return x MKT	-0.221***	-0.223***	-0.215***	-0.220***
	(-13.56)	(-13.65)	(-13.19)	(-13.47)
Return volatility x MKT	0.325***	0.329***	0.317***	0.317***
	(14.99)	(15.20)	(14.82)	(14.64)
Size x MKT	0.043*	0.043*	0.054**	0.058**
	(1.88)	(1.85)	(2.39)	(2.48)
Book-to-market x MKT	0.028	0.030	-0.016	0.028
	(1.23)	(1.29)	(-0.65)	(1.22)
Sales growth x MKT	0.049**	0.045**	0.055***	0.047**
	(2.38)	(2.20)	(2.70)	(2.29)
Operating cycle x MKT	0.017	0.022	0.030	0.021
	(0.74)	(0.92)	(1.29)	(0.88)
Capital intensity x MKT	-0.076***	-0.064**	-0.100***	-0.062**
	(-3.09)	(-2.55)	(-4.09)	(-2.45)
Cash ratio x MKT	-0.018	-0.006	-0.005	-0.014
	(-0.81)	(-0.27)	(-0.24)	(-0.63)
Loss x MKT	0.229***	0.249***	0.226***	0.227***
	(8.68)	(9.73)	(8.72)	(8.78)
Intercept and Other variables				
LIQ	3.779	1.786	4.514*	3.128
	(1.54)	(0.77)	(1.74)	(1.30)
MKT	0.631***	0.600***	0.670***	0.635***
	(15.83)	(15.88)	(16.62)	(16.43)
Info Quality	0.004***	0.004***	0.002***	0.005***
	(5.10)	(5.45)	(3.28)	(6.48)
Liquidity	-0.001**	-0.001**	-0.001**	-0.001**
	(-2.23)	(-2.22)	(-2.21)	(-2.25)
Turnover	0.001	0.000	0.000	0.001
	(0.90)	(0.61)	(0.30)	(1.12)
Prior return	-0.010***	-0.010***	-0.010***	-0.010***
	(-15.91)	(-15.85)	(-15.94)	(-15.96)
Return volatility	-0.006***	-0.006***	-0.006***	-0.006***
	(-8.70)	(-8.71)	(-8.91)	(-8.27)
Size	-0.002***	-0.002***	-0.002**	-0.002***
	(-2.65)	(-2.99)	(-2.50)	(-3.41)
Book-to-market	0.006***	0.006***	0.007***	0.006***
	(9.02)	(8.80)	(9.76)	(9.06)

Sales growth	-0.005***	-0.005***	-0.005***	-0.005***
	(-7.19)	(-6.97)	(-7.29)	(-7.10)
Operating cycle	0.000	0.000	0.000	0.000
	(0.63)	(0.50)	(0.13)	(0.50)
Capital intensity	0.004***	0.003***	0.004***	0.003***
	(5.02)	(3.84)	(5.83)	(4.20)
Cash ratio	-0.002***	-0.003***	-0.003***	-0.003***
	(-3.78)	(-4.60)	(-4.71)	(-4.11)
Loss	-0.005***	-0.006***	-0.005***	-0.005***
	(-5.53)	(-6.65)	(-6.31)	(-5.56)
Intercept	-0.002*	-0.001	-0.002	-0.003**
	(-1.93)	(-1.27)	(-1.33)	(-2.10)
R-squared (%)	10.03	10.02	10.05	10.04

TABLE 4 - Estimation of the effect of information quality on cost of capital through liquidity risk and market risk

This table presents estimates of the effect of information quality on the cost of equity capital (*CoC*) through liquidity and market risk. The information quality proxies are *Earnings precision*, *Accruals quality*, *Analyst consensus*, and *Aggregate quality*. *Earnings precision* is the negative of the standard deviation of the ratio of earnings to total assets. *Accruals quality* is the negative of the standard deviation of the residuals from regressions of total current accruals on cash flow from operations in the prior, current, and following years; change in revenues; and gross plant, property, and equipment. *Analyst consensus* is the negative of the inter-analyst standard deviation of earnings-per-share forecasts scaled by stock price at the time when the standard deviation is computed. *Aggregate quality* is the sum of standardized *Earnings precision*, *Accruals quality*, and *Analyst consensus*; the standardization is done by dividing each individual proxy by the standard deviation of the proxy for all firms within a month. The inputs for the estimation are from the prior tables. The coefficients representing the difference in risk between firms in the top and bottom quintiles of information quality are obtained from Table 3. The estimated risk premium per unit of liquidity risk (market risk) is 56 (482) basis points (see Appendix A). The computation of the *CoC* effects of information quality uses the following formula: *CoC* through systematic risk = Difference in systematic risk between top and bottom quintiles x risk premium per unit of systematic risk.

	Coefficients from model of		Risk premium (in basis points) per unit of		Effect of information quality on *CoC* (in basis points) via	
	Liquidity risk	Market risk	Liquidity risk	Market risk	Liquidity risk	Market risk
Earnings precision	-4.784	-0.087	56	482	-268	-42
Accruals quality	-2.754	-0.065	56	482	-154	-31
Analyst consensus	-5.694	-0.137	56	482	-319	-66
Aggregate quality	-4.794	-0.118	56	482	-269	-57

TABLE 5 – The effect of information quality on liquidity risk in months with extreme changes in market liquidity

This table reports the results of regressions that investigate the cross-sectional effects of information quality, as proxied by *Aggregate quality*, on liquidity risk in different periods of change in market liquidity. Months with significant decreases (increases) in market liquidity are defined as the 31 months (out of a total of 312 months from 1983 to 2008) with the lowest (highest) values of the market liquidity factor, *LIQ*. The dependent variable is $\varepsilon_{i,t}$, which is the return residual after the orthogonalization of returns in excess of the risk-free rate by the *SMB* and *HML* factors. While all variables in Table 3 are included in the regressions (see Table 3 for variable definitions), for parsimony, only the coefficients on the determinants of liquidity risk are reported. The Huber-White heteroscedasticity-robust t-statistics with clustered standard errors are presented in parentheses below the estimated coefficients. *, **, and *** indicate significance at the 10, 5, and 1 percent levels, respectively.

	31 months with extreme market liquidity decreases	31 months with extreme market liquidity increases	Remaining 250 months
Aggregate quality x LIQ	-10.203**	-13.274	1.832
	(-2.38)	(-1.53)	(0.72)
Aggregate quality x MKT	-0.006	-0.244***	-0.136***
	(-0.12)	(-3.02)	(-5.77)
Intercept and other variables in Table 3	Included	Included	Included
Observations	30,702	31,762	244,160
R-squared (%)	5.20	8.88	11.67

TABLE 6 – Robustness analyses

The table reports the results of various robustness analyses of the results in Table 3. The dependent variable is $\varepsilon_{i,t}$, which is the return residual after the orthogonalization of returns in excess of the risk-free rate by the *SMB* and *HML* factors. Panel A presents results with the alternative information quality proxies: *Earnings smoothness*, *Analyst consensus 1*, and *Analyst consensus 2*. *Earnings smoothness* is the negative of the standard deviation of earnings scaled by the standard deviation of cash flow from operations. *Analyst consensus 1 (2)* is the negative of the inter-analyst standard deviation of earnings-per-share forecasts scaled by the mean (median) consensus earnings-per-share forecast. Panel B presents the results after the inclusion of *Historical liquidity beta* and *Historical market beta* and the corresponding interaction terms as control variables. *Historical liquidity* (*market*) *beta* is estimated as the slope coefficient on *LIQ* (*MKT*), in the multi-factor asset pricing regressions of excess returns on the *LIQ*, *MKT*, *SMB*, and *HML* factors. The regressions are estimated using the past five years of monthly data (with a minimum requirement of 36 months) ending in the month before the sensitivities of monthly returns to *LIQ* and *MKT* are observed. Panel B presents the results after including firm fixed effects. Panel C presents the results after controlling for the historical liquidity beta and the market beta. The sample for each regression in Panel A is indicated in the panel. The sample for all regressions in Panels B (C) consists of 306,624 (306,230) firm-months. The Huber-White heteroscedasticity-robust t-statistics with clustered standard errors are presented in parentheses below the estimated coefficients. *, **, and *** indicate significance at the 10, 5, and 1 percent levels, respectively.

Panel A – Alternative information quality proxies

Info Quality proxies	*Earnings smoothness*	*Analyst consensus 1*	*Analyst consensus 2*
Info Quality x LIQ	-3.102**	-4.720***	-4.720***
	(-2.53)	(-3.35)	(-3.36)
Intercept and other variables in Table 3	Included	Included	Included
Observations	306,624	306,270	305,364
R-squared (%)	10.01	10.05	10.07

Panel B – Inclusion of firm fixed effects

Info Quality proxies	*Earnings precision*	*Accruals quality*	*Analyst consensus*	*Aggregate quality*
Determinants of liquidity risk				
Info Quality x LIQ	-4.817***	-2.647*	-5.680***	-4.853***
	(-3.43)	(-1.79)	(-3.98)	(-3.24)
Intercept and other variables in Table 3	Included	Included	Included	Included
R-squared (%)	10.03	10.02	10.05	10.04

Panel C – Controlling for the historical liquidity beta and the historical market beta

Info Quality proxies	*Earnings precision*	*Accruals quality*	*Analyst consensus*	*Aggregate quality*
Determinants of liquidity risk				
Info Quality x LIQ	-5.021***	-2.801*	-5.490***	-4.982***
	(-3.72)	(-1.96)	(-3.92)	(-3.46)
Historical liquidity beta x LIQ	8.032***	7.938***	7.612***	8.032***
	(6.61)	(6.53)	(6.30)	(6.61)
Determinants of market risk				
Info Quality x MKT	-0.051**	-0.044*	-0.110***	-0.083***
	(-2.22)	(-1.87)	(-5.32)	(-3.57)
Historical market beta x MKT	0.212***	0.217***	0.208***	0.209***
	(10.48)	(10.82)	(10.49)	(10.40)
Historical liquidity beta	0.001**	0.001**	0.001**	0.001**
	(2.28)	(2.37)	(2.38)	(2.35)
Historical market beta	-0.002**	-0.002***	-0.002***	-0.002**
	(-2.41)	(-2.61)	(-2.80)	(-2.24)
Intercept and other variables in Table 3	Included	Included	Included	Included
R-squared (%)	10.13	10.13	10.14	10.14

Table A – Liquidity risk premium

At each December between 1967 and 2008, the liquidity beta of each stock is computed. For each stock, its liquidity beta is estimated as the slope coefficient on *LIQ*, in multi-factor asset pricing regressions of excess returns on the *LIQ*, *MKT*, *SMB*, and *HML* factors. The regressions are estimated using the past five years of monthly data (with a minimum requirement of 36 months). The historical liquidity betas are then ranked into decile portfolios within each year. The liquidity risk premium is then calculated using post-ranking excess portfolio returns. These returns are first linked across the years to form one series of post-ranking returns for each decile from 1968 to 2009. The post-ranking liquidity beta is the factor loading on *LIQ* from regressions of these returns on the *LIQ*, *MKT*, *SMB*, and *HML* factors. The post-ranking Fama-French (1993) alpha is the intercept from the regressions of the excess portfolio returns on the *MKT*, *SMB*, and *HML* factors. The annualized liquidity risk premium is the difference in the Fama-French alphas between the top and bottom portfolios. As sensitivity analyses, the CAPM alpha (from regressions on the *MKT* factor only) and the Four-factor alpha (from regressions on the *MKT*, *SMB*, and momentum factor) are provided. The t-statistics of tests of differences between the top and bottom portfolios are in parentheses. *, **, and *** indicate significance at the 10, 5, and 1 percent levels, respectively.

	1	2	3	4	5	6	7	8	9	10	10 - 1
Post-ranking liquidity beta	-7.68	-2.88	0.03	-1.00	-0.44	-0.39	1.51	3.28	5.21	1.97	9.65***
											(2.80)
Liquidity risk premium											
Fama-French alpha	-2.23	-1.22	0.03	0.04	-0.36	1.23	0.41	0.99	1.34	3.17	5.40**
											(2.31)
CAPM alpha	-3.40	-1.07	-0.01	0.44	0.62	1.86	0.93	1.13	1.64	2.65	6.05***
											(2.64)
Four-factor alpha	-3.47	-1.65	-0.32	0.36	0.03	0.91	0.72	1.95	2.66	4.56	8.03***
											(3.41)