The Effect of Information Quality on Liquidity Risk

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The relation between information quality and cost of capital is of significant academic interest and many explanations (e.g., estimation risk, market risk, liquidity) have been posited for the relation. In this paper, I investigate whether information quality could affect cost of capital through liquidity risk. Liquidity risk is measured as the covariation between the returns of a stock and unexpected changes in market liquidity. The empirical evidence indicates that: i) higher information quality is associated with lower liquidity risk; and ii) a firm's cost of capital is lower due to the effect of higher information quality in lowering liquidity risk. In additional analyses, I find some evidence that the effect of higher public information quality in lowering liquidity risk is greater for firms with less private information. Assuming that private information substitutes for public information, this evidence supports the argument that information effects drive the negative association between information quality and liquidity risk. I also present some evidence of an asymmetry in the effect of information quality on liquidity risk. Higher information quality is associated with lower liquidity risk when there are significant declines in market conditions, but not when there are significant improvements.

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1. Introduction

Lambert, Leuz, and Verrecchia (2007) highlight that in the traditional Capital Asset Pricing Model (CAPM) higher information quality could lower a firm's cost of capital through non-diversifiable market risk (i.e., covariation between a firm's cash flow and the market cash flow). The CAPM is based on a model of perfect competition in which the firm's share price is a function of investors' expectations about the firm's cash flow, but is independent of the order flow for the shares. In contrast, in a model of imperfect competition, a firm's share price is also a function of order flow (Verrecchia, 2001). In a model of imperfect competition, order flow captures the element of adverse selection in the trades of a firm's shares and there could be non-diversifiable risk incremental to market risk that captures the effect of order flow on share prices. Following Pastor and Stambaugh (2003), I refer to this incremental risk as "liquidity risk." Being an incremental component of a firm's cost of capital, higher liquidity risk increases the discount in the pricing of a firm's expected cash flow in much the same fashion as higher market risk increases the discount. In this paper, I investigate whether liquidity risk could provide an additional explanation for the relation between information quality and cost of capital.

Pastor and Stambaugh (2003) define liquidity risk as the covariation ("liquidity beta") between the returns of a stock (due to the effects of order flow) and the market liquidity factor.[1] The market liquidity factor captures the unexpected changes in market liquidity, with market liquidity measured as the aggregate (i.e., market-level) price

[1] Liquidity and liquidity risk are distinct properties of a stock. In this paper, liquidity generally refers to the ease and cost of trading the stock without moving its price and this property is idiosyncratic to the stock. In contrast, liquidity risk, being a type of systematic risk, is the covariation between the returns of a stock and market liquidity changes. Similarly, market risk is the covariation between the returns of a stock and the market returns.

fluctuations induced by order flows in the equity market. Lower market liquidity reflects greater aggregate price fluctuations induced by order flows. Stocks with higher liquidity risk have returns that covary more positively with changes in market liquidity because of the greater impact of their order flows on their prices. Ex-ante, investors expect higher returns from stocks with higher liquidity risk because the returns of these stocks when market liquidity declines are expected to be relatively more negative than other stocks.[2] Consistent with this argument, Pastor and Stambaugh provide evidence that stocks with higher liquidity risk have higher expected returns, i.e. higher cost of capital.

I hypothesize that higher information quality could lower liquidity risk. In this paper, I define information quality as an attribute of publicly available information that could lower i) investors' information uncertainty over the value of a stock and/or ii) adverse selection among investors when stock trades occur.[3] Higher information quality reduces uncertainty and adverse selection, and thereby could reduce liquidity risk by attenuating the sensitivity of a firm's share price to the non-diversifiable component of risk due to order flows. For example, the more market makers know about firm value from public information of higher quality, the less they need to depend on order flows to make inferences about firm value and price-protect against the possibility of adverse selection. This means that in times of a decline (improvement) in market liquidity when there is significant selling (buying) pressure on equities in general, the negative (positive) price impact of sell (buy) order flows could be less for a stock with higher information

[2] Given that liquidity risk is a covariation property, stocks with high liquidity risk are also expected to have higher returns when there are increases in market liquidity. In standard asset pricing theory, risk-averse investors expect higher returns ex-ante for the downside risk of lower returns in bad market conditions, even when there is the upside potential of higher returns in good market conditions.

[3] Higher information quality can be interpreted as more information or higher quality information (Leuz and Verrecchia, 2000). In this paper, I use both types of information quality attributes to investigate the relation between information quality and liquidity risk.

quality. Consequently, in a model of imperfect competition higher information quality could reduce a firm's cost of capital through liquidity risk, along with the reduction in cost of capital through market risk. More details on the above hypothesis, including some arguments against the hypothesis, are provided in section 2.

The empirical results indicate that information quality is negatively associated with liquidity risk. I measure information quality as the relevance and reliability of reported earnings, frequency and precision of management earnings forecasts, and coverage and consensus of analyst earnings forecasts. I find significant evidence that more precise management forecasts, more frequent management forecasts, greater analyst coverage, and more consensus among analysts are associated with lower liquidity risk. Consistent with Lambert et al.'s (2007) theoretical prediction that higher information quality lowers market risk, I also find that information quality is negatively associated with market risk.

The economic significance of the effect of higher information quality in lowering cost of capital through lower liquidity risk appears to be reasonable and larger than that through lower market risk. For example, a firm with management forecast frequency that is one standard deviation above the mean has an annual cost of capital that is lower by about 0.85% due to lower liquidity risk and 0.24% due to lower market risk. This result suggests the importance of information quality in affecting trade-related outcomes such as liquidity risk. As for market risk, investors' assessment of the covariation between the cash flow of a firm and the market might be driven more by the economic fundamentals of the firm than by the quality of the information used in the assessment. I also find evidence that suggests that the attributes of management forecasts and analyst forecasts are more economically significant than those of reported earnings in lowering cost of capital through liquidity risk and market risk. This may be due to the fact that management forecasts and analyst forecasts are timelier, forward-looking, and less constrained by general accounting standards.

Using cross-sectional analyses, I find the effect of higher public information quality in lowering liquidity risk is stronger for firms with less private information. Assuming that private information substitutes for public information, this evidence supports the argument that information effects drive the relation between information quality and liquidity risk. Finally, I present some evidence of an asymmetry in the effect of information quality on liquidity risk. Higher information quality is associated with lower liquidity risk when there are significant declines in market conditions in terms of market liquidity changes and market returns, but not when there are significant improvements. This suggests that information quality may be more important in lowering liquidity risk when market conditions deteriorate, perhaps because of the importance of information in influencing trade-related outcomes in these market conditions.

My paper contributes towards the broader objective of improving our understanding of the mechanisms underlying the relation between information quality and cost of capital, a relation that has been of significant academic interest (e.g., Botosan, 1997; Francis et al., 2004, 2005; Core, Guay, and Verdi, 2007). More specifically, I investigate and provide empirical evidence on the relation between information quality and liquidity risk, a risk that has been identified recently in the asset pricing literature to be significantly associated with cost of capital. By providing evidence that higher information quality could lower cost of capital through lower liquidity risk (and lower market risk), my paper extends Lambert et al. (2007) who demonstrate theoretically that higher information quality could lower cost of capital through lower market risk. I acknowledge, however, that my hypothesis on the effect of information quality on liquidity risk is exploratory, and thus requires more rigorous study before it could be interpreted as offering a comprehensive theory of how information quality relates to asset pricing under imperfect competition. Finally, I also investigate related issues such as the differences in the effect of different information quality attributes, as well as compare and contrast the effect of information quality on cost of capital through liquidity risk and market risk.

The rest of this paper is organized as follows. Section 2 provides a review of the related literature and develops the hypothesis on the effect of information quality on liquidity risk. In Section 3, I describe the main variables used in my empirical tests. Sections 4 and 5 present my empirical designs and the results of my empirical analyses. Section 6 concludes.

2. The effect of information quality on liquidity risk

2.1 Brief overview of liquidity risk

The recent asset pricing literature highlights that liquidity risk is a significant systematic risk that is priced by investors (Pastor and Stambaugh, 2003; Acharya and Pedersen, 2005). Pastor and Stambaugh define liquidity risk as the covariation between a stock's return and the market liquidity factor (*LIQ*) that represents unexpected changes in market liquidity. A higher covariation indicates higher liquidity risk. Note also that lower market liquidity reflects greater aggregate price fluctuations induced by order flows in the equity market. Pastor and Stambaugh provide evidence that liquidity risk has a significant incremental risk premium using the following four-factor asset pricing model

$$r_t - r_{rf,t} = \alpha + \beta^L LIQ_t + \beta^M MKT_t + \beta^S SMB_t + \beta^H HML_t + \varepsilon_t \tag{1}$$

where $r_t - r_{rf,t}$ is the monthly return in excess of the risk-free rate for a stock at time t, *LIQ* is the market liquidity factor at time t, and *MKT*, *SMB*, and *HML* are the Fama and French (1993) factors at time t.

The focus of this paper is on the effect of information quality on liquidity risk, β^L. In this paper, I also provide some analyses of the effect of information quality on market risk, β^M, to compare and contrast the effect of information quality on cost of capital through the two types of systematic risk. In this paper, I do not examine the potential effects of information quality through the risk related to the *SMB* and *HML* factors (i.e., β^S and β^H). While the literature suggests that size and book-to-market capture covariations in returns beyond the covariation explained by market returns, the exact nature of the covariations remains unclear (Davis, Fama, and French, 2000). This makes it difficult to develop hypotheses on the relation between i) information quality and β^S and ii) information quality and β^H.[4] In addition, I do not examine the potential effect of information quality on cost of capital that arises through *liquidity,* as opposed to *liquidity risk* (Leuz and Verrecchia, 2000; Verrecchia and Weber, 2006). Nor do I examine the cost of capital effect that may occur if information quality itself is a priced risk factor (Francis et al., 2005).[5]

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[4] For example, assume that information quality is negatively associated with β^S. The direct interpretation of the result is that stocks with higher information quality are smaller and consequently have returns that are similar to smaller firms. However, it is difficult to make further inferences about how information quality is associated with any specific type of covariation (i.e., systematic risk) captured by size.

[5] I do not include an information risk factor into Eq. (1) for three reasons. First, from a theoretical perspective, it is not clear that information quality per se is a risk factor (Lambert et al., 2007). Second,

2.2 *The effect of information quality*

Lambert et al. (2007) demonstrate theoretically that firms with higher information quality have lower market risk. The intuition for this result is fairly straightforward. Market risk is defined by the covariation between the expected cash flow of a firm and the market. When information quality is better, expectations about a firm's cash flow are more precise, and therefore the covariation is smaller. This means that market risk, β^M, is expected to be negatively related to information quality. As discussed earlier in the introduction, in a model of imperfect competition, the exposure of the returns of a stock to changes in market liquidity could give rise to liquidity risk, β^L. Early studies on liquidity risk document the existence of liquidity risk as a systematic risk (Chordia, Roll, and Subrahmanyam, 2000; Hasbrouck and Seppi, 2001; Huberman and Halka, 2001) and examine the asset pricing consequences of liquidity risk (Pastor and Stambaugh, 2003; Acharya and Pedersen, 2005; Sadka, 2005). To my knowledge, there is no prior literature on whether information quality could be a determinant of liquidity risk.

I hypothesize that higher information quality could lower liquidity risk. That is, I argue the returns of a stock with higher information quality will be less sensitive to changes in market liquidity. Higher information quality reduces uncertainty and adverse selection, and thereby could reduce liquidity risk by attenuating the sensitivity of a firm's share price to the non-diversifiable component of risk due to order flows. For example, in times of a decline in market liquidity, there is generally selling pressure on equities.[6]

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there is no clear consensus based on empirical evidence that information quality per se has the properties of a risk factor (e.g., Francis et al., 2005; Core et al., 2007). Finally, for comparability, I want to obtain the betas using an empirical asset pricing model that follows Pastor and Stambaugh (2003).

[6] Pastor and Stambaugh (2003) provide some evidence of phenomenon, which they term as "flight to quality". For parsimony, I illustrate the hypothesis using an economic state in which there is a decline in market liquidity. The illustration can be easily adapted to an economic state in which there is an increase in market liquidity.

Stocks with lower information quality could experience more negative returns if buyers offer lower prices to sellers of these stocks because of the higher information uncertainty and/or greater probability of adverse selection associated with poor information quality. For example, market makers, in response to the sell orders, may offer lower bid prices or reduce depth (i.e., quantities that they are willing to buy at each bid price) due to concerns of buying stocks with more uncertain outcomes or of buying "lemons" due to the greater adverse selection.[7] Note that a reduction in depth increases the downward price impact of large sell trades. These concerns may be exacerbated by the fact that there is usually significant market volatility/uncertainty when market liquidity is low. For example, Pastor and Stambaugh (2003) provide evidence of a significant negative correlation (correlation = -0.57) between market liquidity and market volatility.

Furthermore, the relative returns of stocks with lower information quality could be even more negative if: i) investors tend to be more risk averse in times of low market liquidity and commonality in trading decisions creates pressure on stock prices (Pastor and Stambaugh, 2003); and ii) investors selling some stocks in their portfolios generally prefer to mitigate risk by selling stocks with more information uncertainty. The second assumption relies on the notion that investors perceive stocks with lower information quality (and consequently higher information uncertainty) as being riskier (e.g., Klein and Bawa, 1976; Barry and Brown, 1985; Zhang, 2006).

Hence, my hypothesis, stated in the alternative form, is:

Liquidity risk is negatively associated with information quality.

[7] Note that other investors may also not be willing to step in to act as trade counterparties for similar reasons.

It is important to note, however, that there are also some arguments for liquidity risk to be positively associated with information quality. For example, in times of declines in market liquidity, if investors prefer to sell liquid stocks to save on transaction costs and higher information quality is associated with more liquid stocks, then the selling pressure will be on stocks with higher information quality (Pastor and Stambaugh, 2003). This, in turn, may lead to stocks with higher information quality having higher liquidity risk. Other reasons for preferring to sell stocks with higher information quality include less uncertainty about getting a fair price and greater availability of buyers who are willing to act as trade counterparties due to the higher information quality. Hence, there appears to be some "tension" in the above hypothesis. In fact, given the positive risk premium for liquidity risk, a positive association between information quality and liquidity risk would be intriguing in that it suggests that higher information quality could result in higher cost of capital (note that cost of capital equals risk multiplied by risk premium).

3. Measurement of systematic risk and information quality

3.1 Measurement of systematic risk (liquidity beta and market beta)

I measure the systematic risk of each stock at the end of each year, using data from 1967 to 2005 that is obtained from the CRSP database. The computation of a stock's liquidity beta, β^L, and market beta, β^M, as expressed in Eq. (1), requires the following steps (details provided in Appendix A): i) estimate for a stock its monthly liquidity, γ, using the daily stock data within each month, ii) create a monthly time-series of monthly market liquidity by averaging the γ of all stocks in each month, iii) estimate the monthly market liquidity factor, *LIQ*, by estimating the innovations in the changes in market liquidity from the time series, and iv) for each stock in each year, estimate its β^L and β^M, using the past five years of monthly returns (with a minimum requirement of 36 monthly returns) and an asset pricing regression with *LIQ* and Fama and French (1993) three factors of *MKT*, *SMB*, and *HML*. More specifically, β^L (β^M) is the slope coefficient on *LIQ* (*MKT*).

3.1.1 Estimation of risk premiums

To estimate the cost of capital effect of information quality through systematic risk later in the paper, I also need the expected risk premiums (note that cost of capital equals risk multiplied by risk premium). To obtain more reliable estimates of the risk premiums, I use the longest possible time series of realized returns, i.e., from 1968 to 2006, to estimate the risk premiums for liquidity risk and market risk (Pastor and Stambaugh, 2003; Acharya and Pedersen, 2005). Note that the estimation procedure differs for liquidity risk and market risk because *LIQ* is a non-traded factor while *MKT* is a traded factor.

Table 1 shows how I estimate the liquidity risk premium following Pastor and Stambaugh (2003). To obtain a large spread in the post-ranking portfolio liquidity betas, I first sort stocks into decile portfolios based on individual stocks' historical liquidity betas at each year end.[8] I then link the portfolios over time and estimate the post-ranking portfolio betas and alphas. Specifically, I compute the value-weighted monthly returns of

[8] Given that there is persistence in the liquidity risk, this sort will result in a large spread in the post-ranking liquidity risk. To obtain decile portfolios, Pastor and Stambaugh (2003) sort by two types of liquidity beta: liquidity beta that is predicted by a set of market characteristics and liquidity beta per se. Their results are robust to either method. For simplicity, the results that I present in Table 1 are from sorting by liquidity beta per se. Untabulated results confirm that sorting by predicted liquidity betas produce qualitatively similar asset pricing results.

each portfolio for the next twelve months after the portfolio formation. The monthly portfolio returns are then linked over the years (e.g., twelve months of the top decile's monthly returns in 1968 with twelve months of the top decile's monthly returns in 1969 and so on). The top half of Table 1 reports the post-ranking portfolio betas from time-series regressions of portfolio returns on the market liquidity factor, *LIQ*, and the Fama and French (1993) three factors of *MKT*, *SMB*, and *HML*. The bottom half of Table 1 reports the portfolio alphas from regressions of portfolio returns on *MKT*, *SMB*, and *HML* only. The risk premium of 5.54% between the top and bottom portfolios is the difference in the annualized alphas (monthly alphas multiplied by 12), and confirms Pastor and Stambaugh's result that stocks with higher liquidity risk have higher expected returns.[9] As the difference in the liquidity beta between the top and bottom portfolios is 7.73, the estimated risk premium per unit of liquidity beta is 0.72% (5.54% / 7.73).[10] This estimated risk premium is similar to those in Pastor and Stambaugh (note that Pastor and Stambugh use a variety of ways to estimate the liquidity risk premium to demonstrate the robustness of their results).

Given that *MKT* is a traded factor, the risk premium for market risk can be estimated simply as the average of the estimates of *MKT* over time. To estimate the market risk premium, I average the monthly estimates of *MKT* from 1968 to 2006. This average is 0.44% per month (t-statistic of 2.08) or 5.28% per year. For comparison, Fama

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[9] In Table 1, I do not follow Pastor and Stambaugh's (2003) criterion of including only stocks with prices between $5 and $1000 when forming portfolios to estimate the risk premiums. This is because I use all stocks in my analyses of the effect of information quality on systematic risk later. Untabulated results indicate that the asset pricing results are qualitatively similar with the price restriction.

[10] The use of the extreme portfolios in estimating the liquidity risk premium follows the main analyses in Pastor and Stambaugh (2003) and is common in the asset pricing literature. In supplementary analyses that estimates the risk premium using all the portfolios using generalized method of moments (GMM), Pastor and Stambaugh (2003) show the estimated risk premium is similar.

and French (1993) report an average market risk premium for their sample period from 1963 to 1991 of 0.43% (t-statistic of 1.76) per month.

3.2 *Measurement of information quality attributes*

In this paper, I study the relevance and reliability of reported earnings, frequency and precision of management earnings forecasts, and coverage and consensus of analyst earnings forecasts. I use various information quality attributes to more comprehensively investigate the effect of information quality on liquidity risk and to explore the differences in the effect of different attributes. I measure the information quality of each firm whose stock's systematic risk I am able to measure. For consistency with the five-year estimation period used to measure systematic risk, I generally measure these attributes (and control variables) over the same five-year period. In other words, given that the systematic risk of the stock of a firm in year *t* is measured using stock returns from *t-4* to *t*, I measure information quality in year *t* using data from *t-4* to *t*. The only exception is the relevance of reported earnings that is estimated over a ten-year period (i.e., *t-9* to *t*) due to data requirements. I construct each attribute such that higher values are expected, at least on the average, to reflect higher information quality. Though I briefly justify why a higher value reflects higher information quality as I describe each attribute, I acknowledge that there could be some counter-arguments that a higher value could also reflect lower information quality, at least for some of the attributes.

3.2.1 *Quality of reported earnings*

The accounting framework emphasizes that relevance, *Relevance*, and reliability, *Reliability*, are two important properties for accounting information to be useful. The data used to compute *Relevance* and *Reliability* is from the CRSP and Compustat databases.

One may consider *Relevance* to be the extent to which earnings explain changes in the value of the firm (e.g., Collins, Maydew and Weiss, 1997; Francis and Schipper, 1999). Hence, I obtain the explained variability, R^2, of earnings from a time-series regression of stock returns (i.e., changes in firm value) on levels of and changes in earnings of the firm

$$RET_{i,t} = \phi_{0,i} + \phi_{1,i} NIBE_{i,t} + \phi_{2,i} \Delta NIBE_{i,t} + \upsilon_{i,t} \qquad (2)$$

where for firm i, $RET_{i,t}$ is the 15-month return ending three months after fiscal year t, $NIBE_{i,t}$ is the income before extraordinary items in fiscal year t, scaled by market value at the end of fiscal year t-1, and $\Delta NIBE_{i,t}$ is the change in *NIBE* in fiscal year t, scaled by market value at the end of fiscal year t-1. *Relevance* in fiscal year t is the R^2 from estimating Eq. (2) for the firm over rolling ten-year windows for fiscal years t-9 to t. To match *Relevance* that is measured as at fiscal year end with systematic risk that is measured as at calendar year end, I assign *Relevance* as at fiscal year t to systematic risk as at calendar year t.

Earnings with accruals that map with less variability into the operating cash flows may be considered more reliable earnings. I measure *Reliability* using accruals quality (*AQ*) (Dechow and Dichev, 2002). To obtain *AQ*, I follow Francis et al. (2005) and estimate the following cross-sectional regression for each of Fama and French (1997) 48 industry groups with at least 20 firms in fiscal year t

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

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 a firm, the *AQ* in fiscal year *t* is the standard deviation of the residuals for fiscal years *t-5* to *t-1*. Note that *AQ* is lagged by a year because of the *t+1* term in Eq. (3). Given that higher *AQ* represents lower information quality, the *Reliability* in fiscal year *t* is the negative of *AQ* as at fiscal year *t*. To match *Reliability* that is measured as at fiscal year end with systematic risk that is measured as at calendar year end, I assign *Reliability* as at fiscal year *t* with systematic risk as at calendar year *t*.

3.2.2 Quality of management earnings forecasts

For voluntary earnings disclosures, I measure the precision, *Precision*, and frequency, *Frequency*, of management forecasts of annual and quarterly earnings per share (EPS) using management forecasts from the First Call database. More precise forecasts are likely to be more informative than less precise forecasts because they convey more certainty of the prospects of the firm (Baginski, Conrad, and Hassell, 1993). For each forecast, I assign zero to *Precision* for a point forecast or a range forecast for which the firm has indicated that the number is likely to be at the higher end or lower end of the range. For other types of range forecasts, I compute the precision of each forecast as the range of the forecast as

$$Precision = -\frac{Upper\ Bound - Lower\ Bound}{|(Upper\ Bound + Lower\ Bound)/2|} \tag{4}$$

where *Upper Bound* (*Lower Bound*) is the upper (lower) bound of the range forecast. The *Precision* for year *t* is the average of the precision of all EPS forecasts provided by the firm from *t-4* to *t*. More frequent management forecasts means that investors receive more voluntary updates on the prospects of the firm. The number of forecasts from *t-4* to *t* is the measure of *Frequency* for year *t*.

3.2.3 Quality of analyst earnings forecasts

I measure the extent of the analyst forecast coverage, *Coverage*, and analyst forecast consensus, *Consensus*, based on analysts' forecasts of annual EPS for the current fiscal year end from the I/B/E/S database.[11] Higher *Coverage* means that more analysts are providing publicly available forecasts of EPS and may also be indicative of more publicly available information available about a firm. The average monthly number of analysts following the firm from *t-4* to *t* is the measure of *Coverage* in year *t*. When investors rely on analyst earnings forecasts to evaluate a firm, they are likely to find the forecasts to be of higher quality if there is more agreement among the analysts. *Consensus* measures the degree of agreement among the analysts in terms of their forecasts. I first compute the analyst forecast consensus for firm *i* in month *m* as:

$$Consensus_m^i = -\frac{\sigma_m(Analyst\ Forecasts)}{\mu_m(Analyst\ Forecasts)} \tag{5}$$

where $\sigma_m(Analyst\ Forecasts)$ and $\mu_m(Analyst\ Forecasts)$ are the inter-analyst standard deviation and mean, respectively, of annual EPS forecasts among the analysts covering the firm in month *m*. I require at least three analysts covering the firm in month *m* before computing $Consensus_m^i$. I then average the $Consensus_m^i$ from *t-4* to *t* to measure the *Consensus* in year *t*

3.2.4 Sample characteristics

[11] Unlike management forecasts for which I use all forecasts, I restrict analyst forecasts to forecasts of annual EPS for the current fiscal year end because the computation of the information quality attributes related to analyst forecasts require the same type of forecasts from various analysts and annual EPS for the current fiscal year end are the most common forecasts.

Table 2 provides the annual number of firms for which I can measure systematic risk and the various information quality attributes. The sample period is from 1987 due to data requirements. As noted earlier, the variables that I use in my empirical analyses are generally estimated using data over a five-year period, e.g., data from 1983 to 1987 is used to compute the value of a variable for 1987. Given that trading volume, a control variable in all my regressions, is provided by CRSP for NASDAQ firms only from late 1982, I use the period from 1987 to 2005 as the longest possible period for my analyses.[12] Note that *Precision* and *Frequency* are available only from 1999 due to lack of First Call coverage prior to 1995.

Table 3 presents the summary statistics and correlations among the information quality attributes. As noted earlier, each attribute is constructed such that higher values of each measure are expected to reflect higher information quality. The correlations between the information quality variables are generally positive, suggesting that higher information quality on certain dimensions is generally associated with higher information quality on other dimensions. A notable exception is the negative and significant correlation between *Relevance* and *Coverage*. A possible explanation for the negative correlation is that *Relevance*, by construction, measures the relevance of reported earnings relative to other information in explaining contemporaneous returns. More information provided by analysts may result in reported earnings being less relevant.

4. Empirical analyses of the effect of information quality on systematic risk

[12] The sample period is not increased significantly even without trading volume as a constraint. I/B/E/S coverage of EPS forecasts begins in 1980. Institutional holding, which is another control variable, is available from CDA/Spectrum Institutional Holdings from 1980.

My regressions include year fixed effects when examining how the cross-sectional variation in information quality is contemporaneously associated with the cross-sectional variation in systematic risk. To take into account cross-sectional dependence that may lead to biases in the standard errors, I cluster the standard errors by industry.[13]

4.1 Liquidity risk regressions

The general specification for my regressions to examine the effect of information quality on liquidity risk is

$$\begin{aligned}\beta^L_{i,t} = \psi_{0,t} + \psi'_{1,t} Quality_{i,t} + \psi'_{2,t} Market\ Characteristics_{i,t} + \\ \psi_{3,t} Institution_t + \psi'_{4,t} Year + \varepsilon_{i,t}\end{aligned} \tag{6}$$

where for the stock of firm i in year t, $\beta^L_{i,t}$ is the liquidity beta estimated using monthly stock returns in the past five years and $Quality_{i,t}$ is a vector that contains any combination of the information quality attributes of *Relevance*, *Reliability*, *Precision*, *Frequency*, *Coverage*, and *Consensus*. $Market\ Characteristics_{i,t}$ is a vector that contains six market characteristics, computed using data from CRSP: average monthly stock liquidity (measured by γ) in the past five years, *Average liquidity*; log of the average monthly dollar trading volume in the past five years, *Average volume*; cumulative returns in the past five years, *Cumulative return*; standard deviation of monthly returns in the past five years, *Return volatility*; log of the average monthly price in the past five years, *Price*; and log of the average monthly shares outstanding in the past five years, *Shares outstanding*. *Institution* is the average percentage of outstanding shares held by institutions for the past five years computed using data obtained from CDA/Spectrum Institutional Holdings database. All variables are winsorized to the 1st and 99th percentile to reduce the effects of

[13] Results remain qualitatively the same when I cluster the standard errors by firm.

outliers. *Year* refers to the vector of year dummy variables to implement year fixed effects for the regressions.

The above market characteristics have been used to predict liquidity beta by Pastor and Stambaugh (2003) who note that the characteristics are necessarily arbitrary (presumably because liquidity risk is a relatively new concept with little prior literature guidance on its determinants) although they do possess some appeal ex ante.[14] *Average liquidity* and *Average volume* can matter if liquidity risk is related to liquidity per se. However, it is not clear whether more or less liquid stocks have higher liquidity risk. For example, Pastor and Stambaugh note that if investors sell more liquid stocks in times of decreases in market liquidity to save on transaction costs, then more liquid stocks may have higher liquidity risk. The inclusion of *Price* and *Shares outstanding* takes into account the possibility that stocks with different market capitalizations have different liquidity risk. *Cumulative return* and *Return volatility* are included to control for the return dynamics that may affect liquidity risk. By including *Cumulative return* and *Return volatility*, I also control for the performance and volatility of the business, respectively. Finally, I include *Institution* because the trading characteristics of institutional investors may explain the cross-sectional variation in liquidity risk (Kamara, Lou, and Sadka, 2007).

Table 4 presents the results of the liquidity risk regressions. Based on my hypothesis that information quality is negatively associated with liquidity risk, I expect

[14] Unlike Pastor and Stambaugh (2003) who use shorter windows, I use five-year windows to estimate the market characteristics. Pastor and Stambaugh also include the prior liquidity beta as a predictor to produce a model that to best predicts the current liquidity beta. I do not include the prior liquidity beta because its inclusion creates a regression specification that examines the effect of the level of information quality on changes in systematic risk over time (note that the inclusion of the lag of the dependent variable creates a pseudo-change specification), which is inconsistent with nature of the hypothesis in this paper.

the coefficient on an information quality attribute to be negative. I observe from the regression results that the significant coefficients on the information quality attributes are generally negative. Hence, I conclude that the overall results indicate that higher information quality is associated with lower liquidity risk. For example, in the sixth column, the significantly negative coefficients on *Precision* and *Frequency* of -6.919 and -0.105, respectively, indicate that stocks of firms that provide more precise and more frequent management forecasts are associated with lower liquidity risk. Similarly, the significantly negative coefficients on *Coverage* and *Consensus* of -0.280 and -3.775, respectively, in the ninth column, indicate that the stocks of firms with greater analyst coverage and more consensus among analyst earnings forecasts have lower liquidity risk. There is no significant evidence, however, that the information quality attributes of reported earnings, *Relevance* and *Reliability*, are associated with liquidity risk.

4.2 Market risk regressions

The general specification for my regressions to examine the effect of information quality on market risk is

$$\begin{aligned}\beta^{M}_{i,t} = {} & \psi_{0,t} + \psi'_{1,t} Quality_{i,t} + \psi'_{2,t} Business\ Characteristics_{i,t} + \\ & \psi'_{3,t} Liquidity_{i,t} + \psi'_{4,t} Year + \varepsilon_{i,t}\end{aligned} \tag{7}$$

where for the stock of firm *i* in year t, $\beta^{M}_{i,t}$ is the market beta estimated using monthly stock returns in the past five years and $Quality_{i,t}$ is a vector that contains any combination of the information quality attributes of *Relevance*, *Reliability*, *Precision*, *Frequency*, *Coverage*, and *Consensus*. The vector $Business\ Characteristics_{i,t}$ contains seven characteristics computed using data from Compustat: average of the annual sales growth in the past five years, *Sales growth*; average of the financing leverage (i.e., financial liabilities minus financial assets divided by market equity) in the past five years, *Financing leverage*; average of the operating leverage (i.e., book value of assets divided by estimated market value of assets) in the past five years, *Operating leverage*; log of the average of total assets in the past five years, *Total assets*; volatility of cash flow from operations in the past five years, *CFO volatility*; volatility of sales in the past five years, *Sales volatility*; and proportion of years with negative earnings in the past five years, *Loss proportion*.[15] To match the business characteristics with systematic risk, I assign the business characteristics as at fiscal year t with systematic risk as at calendar year t. The vector $Liquidity_{i,t}$ contains two characteristics, computed using data from CRSP: average of the monthly stock liquidity, measured by γ, in the past five years, *Average liquidity*; and average of the monthly dollar trading volume in the past five years, *Average volume*. All variables are winsorized to the 1st and 99th percentile to reduce the effects of outliers. *Year* refers to the vector of year dummy variables to implement year fixed effects for the regressions.

I include *Total assets* and *Sales growth* to control for the effects of size and growth on market risk (Beaver et al., 1970). Larger firms are expected to have lower market risk than smaller firms. The relation between growth and market risk is less clear. Growing firms may be more risky if the future cash flows related to the growth are more susceptible to how the economy performs. On the other hand, growing firms may have lower market risk if these firms are less likely to be in a distressed state. *Operating leverage* and *Financing leverage* are included because of prior evidence that market risk is positively associated with operating leverage and financing leverage (Beaver et al.,

[15] *Financing leverage* and *Operating leverage* are computed based on the formulas for operating and financing leverage in Penman, Richardson, and Tuna (2007).

1970; Hamada, 1972; Lev, 1974; Mandelker and Rhee, 1984). I include *CFO volatility* and *Sales volatility* because the returns of firms with more economic volatility are expected to be more sensitive to market performance. I include *Loss Proportion* to control for the effects of the probability of default on market risk. Finally, I include *Average Liquidity* and *Average Volume* to control for the effects of liquidity on non-synchronous trading (i.e., the lack of trading activity), which leads to downward biased market beta estimates (Scholes and Williams, 1977; Dimson, 1979).

Table 5 presents the results of the market risk regressions. Given that the significant coefficients on the information quality attributes are generally negative, I conclude that the overall results support the theoretical prediction of Lambert et al. (2007) that higher information quality is associated with lower market risk. For example, the significantly negative coefficient on *Reliability* of -1.122 in the third column indicates that the stocks of firms that report more reliable earnings have lower market risk This result is consistent with Francis et al. (2005), Core et al. (2007), and Bhattacharya et al. (2007), who find a negative association between accrual quality (my measure of *Reliability*) and market risk. The significantly negative coefficients on *Precision* and *Frequency* in the sixth column and on *Coverage* in the ninth column also indicate a negative association between information quality and market risk.

4.3 Sensitivity analyses

4.3.1 Inclusion of additional control variables for liquidity risk regressions

The control variables, which have been selected based on the prior literature, are generally different for the liquidity risk and market risk regressions. Despite the lack of support in the literature, including more control variables may be especially important for the liquidity risk regressions because the determinants of liquidity risk are relatively unexplored and there may be significant omitted correlated variable bias in the coefficients of the information quality attributes. As a sensitivity check, I include the control variables used for the market risk regressions into the liquidity risk regressions. Untabulated results indicate that the additional control variables, while reducing the sample size due to data requirements, leads to some increase in the explanatory power of the liquidity risk regressions. More importantly, the coefficients on *Precision* and *Coverage* are significantly negative while the coefficients on the remaining information quality attributes are statistically insignificant. As a comparison, the coefficients on *Precision*, *Frequency*, *Coverage*, and *Following* in Table 4 are significantly negative.

4.3.2 Joint analyses of all information quality variables

The regression analyses in Tables 4 and 5 examine the information quality attributes of reported earnings, management forecasts, and analyst forecasts separately. A key reason is because the sample sizes and sample periods differ significantly across the information sources (see Table 2). However, one may still be interested in the results of a "horse race" among the information quality attributes to have some idea of the relative importance of the attributes.

Table 6 presents the results when all the information quality attributes are jointly included in the regressions. Note that the sample is restricted from 1999 to 2005 due to the data limitation for the management forecast attributes. The first column reports the results of the liquidity risk regression and the second column reports the results of the market risk regression. The result in the first column indicates that *Precision*, *Frequency*, *Coverage*, and *Consensus* are significantly negatively associated with liquidity risk. This suggests that the attributes of management forecasts and analyst forecasts are more important than those of reported earnings in reducing liquidity risk. The result in the second column indicates that *Reliability*, *Precision*, and *Frequency* have significant negative associations with market risk. This suggests that the attributes of reported earnings and management forecasts are more important than those of analyst forecasts in lowering market risk.

4.3.3 Combining information quality attributes

As another sensitivity analysis, I attempt to combine the information quality attributes first along each information source and then across all the information sources. An advantage of combining the different information quality attributes is that the combined measure may provide a more holistic measure of the overall quality of information available about a firm. To combine the information quality attributes, I construct simple and admittedly crude aggregate measures of information quality.[16] As the measurement units of the attributes are different, it is not possible to simply sum the values of the attributes. Instead, for each attribute of each firm in each year, I first assign a quintile rank from 1 to 5 based on the distribution of the attribute within each year. Higher ranks represent higher quality. For each firm in each year, I then construct *Reported earning quality* by summing the ranks of *Relevance* and *Reliability*, *Management forecast quality* by summing the ranks of *Precision* and *Frequency*, *Analyst forecast quality* by summing the ranks of *Coverage* and *Consensus*, and *Total quality* by

[16] I note that there is no prior theoretical or empirical guidance on how to construct aggregate information quality measures. The closest to an aggregate information quality measure that has been used in the prior literature appears to be the Association of Investment and Management Research (AIMR) score (e.g., Healy, Hutton, and Palepu, 1999; Bushee and Noe, 2000). This score captures analysts' assessments of the informativeness of various aspects of firms' disclosure practices along three dimensions: (1) annual report/l0-K disclosures, (2) interim report/l0-Q disclosures, and (3) investor relations activities.

summing the ranks of all six attributes.[17] Hence, the minimum (maximum) possible value is 2 (10) for the *Reported earning quality*, *Management forecast quality,* and *Analyst forecast quality*. The minimum (maximum) possible value is 6 (30) for *Total quality*.

The first (last) four columns of Table 7 report the liquidity (market) risk regression results when each of the above aggregate quality variables are included. The results indicate that *Management forecast quality* and *Analyst forecast quality* have significant negative associations with both liquidity risk and market risk. *Reported earning quality* is significantly negatively associated with market risk only. Finally, *Total quality* has significant negative associations with both liquidity risk and market risk.

4.4 Cost of capital effects through systematic risk

Taken together, the above regression results provide statistically significant evidence that information quality is negatively associated with systematic risk in terms of liquidity risk and market risk. A follow-up question then is the economic significance of the results in terms of effect of information quality on cost of capital (*CoC*) through liquidity risk and market risk. Table 8 presents the estimates of the *CoC* effects for a one standard deviation from the mean of each information quality attribute. The use of standard deviations is to obtain some comparability across the attributes that have different measurement units and distributional properties. To estimate the *CoC* effects, I use the following formula

$$CoC = Std\ Dev \text{ x } \frac{\partial \beta}{\partial Quality} \text{ x risk premium per unit of systematic risk} \qquad (8)$$

[17] As an aside, I note that averaging as opposed to summing the attributes will lead to the same statistical inferences because averaging merely involves scaling the sum by a fixed number.

where *Std Dev* is a one standard deviation from the mean for an information quality attribute and $\frac{\partial \beta}{\partial Quality}$ is the coefficient on the information quality attribute. The standard deviations are obtained from Table 3 and the coefficients are obtained from Table 4 (Table 5) for liquidity risk (market risk). As discussed in section 3.1.1, the estimated risk premium per unit of risk is 0.72% for liquidity risk and 5.28% for market risk. I then multiply *CoC* by 100 to report the results in basis points (bps).

The estimated *CoC* results suggest that higher information quality results in a modest reduction in *CoC* through lower liquidity risk and lower market risk. For example, a one standard deviation above the mean for *Precision* is associated with a *CoC* that is lower by 146 bps, with 105 bps through a lower liquidity risk and 41 bps through lower market risk. Similarly, a one standard deviation above the mean for *Frequency* is associated with a decrease in *CoC* of 109 bps, with 85 bps through a reduction in liquidity risk and 24 bps through a reduction in market risk. The *CoC* effects appear to be economically reasonable. The quality of public information about a firm is likely to be only one of many determinants of the systematic risk of a firm's stock. Measurement error in the information quality attributes might also lead to an attenuation of the regression coefficients that are used to estimate the *CoC* effects.

Finally, I observe from Table 8 that the effect of information quality on *CoC* through lower liquidity risk seems to be larger than that through lower market risk. This result might be an indication of the importance of information quality in affecting trade-related outcomes, more specifically, liquidity risk.[18] As discussed earlier, liquidity risk is

[18] An econometric explanation is different biases in the regression coefficients due to different ability to control for omitted correlated variables in different regressions. While not the perfect solution, I check the sensitivity of the result to the use of regression coefficients from liquidity risk and market risk regressions

a trade-related outcome arising from the price impact of order flow on returns in times of changing market liquidity. As for market risk, investors' assessment of the covariation between the cash flow of a firm and the market might be driven more by the economic fundamentals of the firm than by the quality of the information used in the assessment. In addition, the overall *CoC* effects through systematic risk (i.e., liquidity risk and market risk) appear to be larger for the information quality attributes of management forecasts and analyst forecasts than for those of reported earnings. I conjecture that this difference may be due to the fact that management forecasts and analyst forecasts are timelier, forward-looking, and less constrained by general accounting standards.

4.5 Cross-sectional analyses of how private information affects the relation between information quality and liquidity risk

Under the assumption that private information substitutes for public information, I expect the negative association between information quality and liquidity risk to be larger when there is less private information about a stock. As it is not possible to directly measure the amount of private information that investors have about a stock, I use two indirect measures based on the outcomes of private information.

The first measure is the average of the past five years' annual probability of information-based trading, *PIN*. The estimation of probability of information-based trading is described in Appendix B. *PIN* is available only from 1997 onwards due to data requirements. The second measure is the average of the past five years' annual number of shares traded by top executives scaled by the annual trading volume, *Insider*. The trades by top executives (identified as insiders whose roles are classified as chief executive

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that have the same full set of control variables (this also results in the same sample size). I still find that information quality has a larger effect on cost of capital through liquidity risk than through market risk.

officer, chief financial officer, chief operating officer, president, or chairman of board) are from the Thomson Financial Insider Filing database. Trading volume is computed using data from CRSP. *Insider* is available for the full sample period from 1987 to 2005.

To analyze the effect of private information on the relation between information quality and liquidity risk, I retain the general regression framework as specified in Eq (6). However, the vector $Quality_{i,t}$ now contains the main effects and interaction terms to study the interaction between private information and public information quality. To ease exposition, mitigate the effects of outliers, and reduce measurement error, I rank *PIN*, *Insider*, and the various information quality attributes into quintiles based on their distribution within each year and scale the quintile ranks from 0 to 1. For example, *PIN quintile* and *Relevance quintile* are used in the regressions instead of *PIN* and *Relevance*.

Table 9 presents the results of the analyses of the effect of private information on the relation between information quality and liquidity risk. If private information substitutes for public information and reduces the effect of public information quality in lowering liquidity risk, I expect the coefficients on the interaction terms to be positive. I observe from Table 9 that the coefficients on the interaction terms are generally positive and the statistically significant coefficients are positive. For example, the coefficient on the interaction term between *PIN quintile* and *Precision quintile* indicates that a stock in the highest quintile of public information quality and lowest quintile of private information has a liquidity risk that is 12.441 units (of liquidity beta) less than a stock in the highest quintile of public information quality and highest quintile of private information. Hence, there is some evidence that less private information increases the effect of public information quality in lowering liquidity risk. This evidence supports the argument that information effects are driving the association between public information quality and liquidity risk.[19]

5. Effect of information quality on liquidity risk in times of significant changes in market conditions

In this section, I analyze whether there is any asymmetry in the relation between information quality and liquidity risk when market conditions decline or improve in terms of market liquidity changes and market returns. Using the time series of the *LIQ* factor from 1987 to 2005, I identify 20 months with the largest decreases and 20 months with largest increases in market liquidity.[20] Similarly, using the time series of the *MKT* factor from 1987 to 2005, I identify 20 months with most negative and 20 months with the most positive market returns. I then analyze the effect of information quality on liquidity risk for each of the four sets of 20 months.

The earlier regression analyses on the effect of information quality on liquidity risk in section 4 involve regressions of stock-specific liquidity betas on stock-specific information quality variables. An advantage of such a regression specification is that it is a natural specification to investigate the cross-sectional relation between information quality and liquidity risk. A disadvantage of this approach is that it cannot be used to investigate the differential effects of information quality on liquidity risk in times of significant changes in market conditions. This is because the measurement of each liquidity beta uses monthly data measured over the prior five years. In this section, I use

[19] In untabulated analyses, I also find some evidence that less private information results in a larger negative association between information quality and market risk, suggesting that private information also substitutes for public information in lowering market risk.

[20] The choice of 20 months on the downside and 20 months on the upside is to select approximately the top 10% and bottom 10% of the months from 1987 to 2005 (note that there are 228 months in total).

an alternative regression specification to investigate the differences in the effect of information quality on liquidity risk in times of significant changes in market conditions.

To do this, I model the event returns of each stock using the four-factor asset pricing model

$$r_{i,t} - r_{rf,t} = \alpha_i + \beta_i^M MKT_t + \beta_i^S SMB_t + \beta_i^H HML_t + \beta_i^L LIQ_t + \varepsilon_{i,t} \qquad (9)$$

where $r_{i,t}$ is the monthly return in excess of the risk-free rate for stock i at time t, LIQ is the market liquidity factor in month t, and MKT, SMB, and HML are the Fama and French (1993) risk factors.

Substituting the right-hand side of Eq. (6) (i.e., equation on how liquidity beta could be determined by information quality, market characteristics, and institutional holdings) into Eq. (9), I obtain the following equation for how I expect event returns to vary with the interaction of information quality and LIQ

$$\begin{aligned} r_{i,t} - r_{rf,t} = \beta_i^0 + \beta_i^M MKT_t + \beta_i^S SMB_t + \beta_i^H HML_t + (\psi_{0,t} + \\ \psi_{1,t}' Quality_{i,t} + \psi_{2,t}' Market\ Characteristics_{i,t} + \psi_{3,t} Institution_t) LIQ_t + \varepsilon_{i,t} \end{aligned} \qquad (10)$$

To run the above regression while allowing for stock-specific MKT, SMB, and HML betas, I use a two-stage process (Pastor and Stambaugh, 2003). First, I measure the return residual for each stock i for each month t with a significant change in market condition

$$e_{i,t} = r_{i,t} - r_{rf,t} - \hat{\beta}_i^M MKT_t - \hat{\beta}_i^S SMB_t - \hat{\beta}_i^H HML_t \qquad (11)$$

where the $\hat{\beta}$'s are from the regression of stock i's excess returns on MKT, SMB, HML, and LIQ. To obtain the $\hat{\beta}$'s, five years of monthly excess returns (with a minimum requirement of 36 months) prior to the significant change in market condition are used.

The return residual, $e_{i,t}$, is the unexpected returns after controlling the influence of the *MKT*, *SMB*, and *HML* factors. I then run a pooled time-series, cross-sectional regression

$$\begin{aligned} e_{i,t} &= \alpha + \psi_0 LIQ_t + (\psi_1' \, Quality_{i,t} + \\ &\quad \psi_2' \, Market\ Characteristics_{i,t} + \psi_3 Institution_t) LIQ_t + \upsilon_{i,t} \end{aligned} \qquad (12)$$

with the determinants of liquidity risk measured prior to the significant changes in the market conditions. As this regression specification examines the relation between information quality and liquidity risk for specific months with significant changes in market conditions, I generally measure the determinants over shorter periods, compared to Eq. (6), so as to obtain more recent and potentially more accurate estimates of the determinants. To take into account cross-sectional dependence that may lead to biases in the standard errors, I cluster the standard errors by industry.[21]

The vector $Quality_{i,t}$ contains any combination of the six information quality attributes for stock *i*. *Relevance* and *Reliability* are measured as at each fiscal year end as described in section 3, and assumed to be publicly available four months after the fiscal year end. The more recently available *Relevance* and *Reliability* are assigned to month *t*. *Precision* and *Frequency* are measured using the formulas in section 3 but using the management forecasts in the year before month *t*. *Coverage* and *Consensus* are measured using the formulas in section 3 but using the consensus analyst forecasts in the month before month *t*. $Market\ Characteristics_{i,t}$ is a vector that contains six market characteristics: average monthly stock liquidity from months *t-6* to month *t-1*, *Average liquidity*; log of the average monthly dollar trading volume from months *t-6* to month *t-1*, *Average volume*; cumulative returns from months *t-6* to month *t-1*, *Cumulative return*; standard deviation of monthly returns from months *t-6* to month *t-1*, *Return volatility*; log

[21] Results remain qualitatively the same when I cluster the standard errors by firm.

of the price in month *t-1*, *Price*; and log of the monthly shares outstanding in month *t-1*, *Shares outstanding*. The period for measuring each market characteristic follows Pastor and Stambaugh (2003). *Institution* is the average percentage of outstanding shares held by institutions as reported in the previous calendar quarter end before month *t*.

Table 10 Panel A reports the regression results for the 20 months with the largest decreases and 20 months with the largest increases in market liquidity. A negative (positive) sign for the coefficient on an information quality attribute indicates that higher (lower) information quality is associated with lower liquidity risk. The first three columns document the regression results of the association between information quality and liquidity risk for the months with significant decreases in market liquidity. The results provide some significant evidence that higher information quality is associated with lower liquidity risk. In particular, the coefficients on *Precision* and *Consensus* are significantly negative. The last three columns document the regression results of the association between information quality and liquidity risk for the months with significant increases in market liquidity. None of the coefficients on the information quality attributes are statistically significant. Panel B repeats the analyses for the 20 months with the largest negative and the 20 months with the largest positive market returns. The results provide some evidence that higher information quality is associated with lower liquidity risk when there are very large negative market returns. In particular, the coefficients on *Relevance* and *Coverage* are significantly negative. As for the results when there are very large positive market returns, only the coefficient on *Coverage* is statistically significant and unexpectedly positive.

Taken together, the results in Table 10 provide some evidence that higher information quality is associated with lower liquidity risk when there are significant declines, but not when there are significant improvements in market conditions. This suggests that information quality is more important in lowering liquidity risk when market conditions deteriorate, perhaps because of the importance of information in influencing trade-related outcomes in these market conditions.

6. Conclusion

In this study, I provide evidence that higher information quality is associated with lower liquidity risk. To analyze the economic significance of this association, I estimate the magnitude of the effect on the firm's cost of capital resulting from this link between higher information quality and lower liquidity risk. The estimated effects seem economically plausible. For example, a firm with management forecast frequency that is one standard deviation above the mean has an annual cost of capital that is lower by about 0.85% due to lower liquidity risk. I also document that higher information quality is associated with lower market risk. However, I find that the economic significance of the effect of information quality on cost of capital through market risk is smaller than that through liquidity risk. In additional analyses, I provide some evidence that the effect of higher public information quality in lowering liquidity risk is stronger for firms with less private information. This evidence strengthens the argument that information effects are driving the relation between information quality and liquidity risk. I also provide some evidence of an asymmetry in the effect of information quality in lowering liquidity risk.

Information quality is associated with lower liquidity risk when there are significant declines in market conditions, but not when there are significant improvements.

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". That is, the effects of information on cost of capital through systematic risk may be reduced or eliminated with the inclusion of the controls. 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, it also raises questions of what are the underlying reasons (other than the effect of information quality through systematic risk) that are driving the results. Hence, not only is it important to examine the existence of a relation between information quality and cost of capital, it is also important to understand the underlying mechanisms linking information quality and cost of capital. This study takes a step in this direction by investigating whether information quality affects cost of capital through liquidity risk.

Future research could examine whether there are other channels through which information quality affects cost of capital. It may also be useful to extend the analyses of whether different information quality attributes have different effects on cost of capital through the different channels. In addition, the identification of significant events in this paper uses events identified through ranking of the time-series of market liquidity changes and market returns. It may be useful to run similar analyses for specific event dates for which the nature of the events is well-documented. To the extent that the underlying nature of each event is known, more powerful tests of the effect of information quality, perhaps for a subset of stocks, can be designed. Finally, future research could also examine how information quality affects changes in stock liquidity in response to changes in market liquidity, as opposed to stock returns in response to changes in market liquidity as studied in this paper.

Appendix A Estimation of liquidity betas and market betas

This appendix summarizes the steps to estimate the betas. I refer interested readers to Pastor and Stambaugh (2003) for more details.

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

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

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

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*.[22]

γ is based on 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 the excess return on the next day will be negatively associated with the order flow of the previous day if the lack of liquidity prevents the price from returning to the "normal" level in the previous day. Hence, a larger return reversal, as indicated by a more negative *γ*, reflects a lower liquidity. 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.

[22] Following Pastor and Stambaugh (2003), a stock's monthly liquidity is computed in a given month only there are more than 14 observations with which to estimate Eq. (A1). This requirement is modified to more than 13 observations for September 2001 only because the stocks market was closed from September 11-16, 2001.

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: [23]

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

To construct a liquidity measure that reflects the cost of a trade whose cost is commensurate with the overall size of the stock market, each γ_t is then 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-1* of the stocks included in the average in month *t*, and month 1 refers to August 1962. I plot the scaled series from 1962 to 2006 in Figure 1. The market liquidity series from August 1962 to December 1999 is similar to that in Figure 1 of Pastor and Stambaugh (2003). For example, the largest downward spike in market liquidity occurs in October 1987 during which the stock market suffered a significant crash that could be at least partially due to a decline in market liquidity. The scaled series reflect liquidity cost (in terms of return reversal), average across stocks at a given point in time, of trading \$1 million in August 1962 "stock market" dollars. The average market liquidity from August 1962 to December 2006 is -0.031, which indicates a cost of 3.1% for such a trade.

To construct the unexpected changes in market liquidity, I then follow Pastor and Stambaugh (2003) and run the following regression

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

[23] Pastor and Stambaugh (2003) exclude NASDAQ stocks in constructing the market liquidity measure mainly because NASDAQ returns and volume data are available from CRSP only from 1982 and the estimation of unexpected market liquidity uses a consistent sample over a long time series. In addition, stocks with share prices less than \$5 and greater than \$1,000 at the end of the previous month are excluded, presumably to reduce market microstructure noise and outlier effects in estimating market liquidity.

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. μ_t measures the unexpected changes in market liquidity. To provide more convenient magnitudes of the liquidity betas, I scale μ_t by 100 to obtain the market liquidity factor, i.e.,

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

A.3 Computation of liquidity and market betas

For each NYSE, AMEX, and NASDAQ stock *i* at the end of each calendar year, I compute its liquidity beta, β_i^L, and market beta, β_i^M, using the following time-series asset pricing regression:

$$r_{i,t} = \alpha_i + \beta_i^L LIQ_t + \beta_i^M MKT_t + \beta_i^S SMB_t + \beta_i^H HML_t + \varepsilon_{i,t} \tag{A5}$$

where $r_{i,t}$ is the monthly return in excess of the risk-free rate for stock *i* at time *t*, *LIQ* is market liquidity factor in month *t*, and the Fama and French (1993) three factors of *MKT*, *SMB*, and *HML*. To compute the betas for a stock at each calendar year-end, I use the monthly returns for the past five years, with a minimum requirement of at least 36 monthly returns. Though only the liquidity beta and market beta are used in this paper, I follow Pastor and Stambaugh (2003) and include the *SMB* and *HML* factors to control for the effects on expected returns that are due to the factors related to size and book-to-market.

Appendix B Computation of probability of information-based trading (PIN)

B.1 Description of PIN

The *PIN* measure is a measure of the information asymmetry between informed and uninformed traders in individual stocks. Its value is estimated by the numerical maximization of the likelihood function of the underlying market microstructure model specified in Easley et al. (1997), henceforth known as the EKO model.

The EKO model is a learning model in which market makers draws inferences about the probability of information asymmetry based on the observed order flow. Specifically, the model uses the number of daily buys and daily sells for a certain period, usually a quarter or a year, to estimate the PIN measure. Within each day, trades are assumed to arrive sequentially to the market according to Poisson processes. Mathematically, the model specifies that, on any day i, the likelihood of observing the number of buys B_i and the number of sells S_i is given by:

$$\begin{aligned} L(\theta|B_i,S_i) = {} & \alpha(1-\delta)e^{-(\mu+\varepsilon_B)}\frac{(\mu+\varepsilon_B)^{B_i}}{B_i!}e^{-\varepsilon_S}\frac{\varepsilon_S^{S_i}}{S_i!} \\ & +\alpha\delta e^{-\varepsilon_B}\frac{\varepsilon_B^{B_i}}{B_i!}e^{-(\mu+\varepsilon_S)}\frac{(\mu+\varepsilon_S)^{S_i}}{S_i!}+(1-\alpha)e^{-\varepsilon_B}\frac{\varepsilon_B^{B_i}}{B_i!}e^{-\varepsilon_S}\frac{\varepsilon_S^{S_i}}{S_i!} \end{aligned} \tag{B1}$$

where $\theta = (\alpha,\delta,\mu,\varepsilon_B,\varepsilon_S)$ are the five structural parameters in the model to be estimated. α is the probability of an information event occurring, δ is the probability of good news when an information event occurs, μ is the daily arrival rate on a day when an information event occurs, ε_B is the daily arrival rate of buy orders from uninformed traders who are not aware of the new information, ε_S is the daily arrival rate of sell orders from uninformed traders who are not aware of the new information.

In the EKO model, trading is a game between a market maker and trader that repeats over the trading days within the period. Assuming that the days are independent, the joint likelihood of observing a series of daily buys and daily sells over trading days I = 1,..., I is the product of daily likelihoods:

$$L(\theta|M) = \prod_{i=1}^{I} L(\theta|B_i, S_i) \quad \text{(B2)}$$

where $M = ((B_1, S_1),...,(B_I, S_I))$ represents the dataset.

Maximizing the joint likelihood in equation (B2) over the parameters in θ provides the estimates of the parameters. Since there is no closed form solution to the maximization problem, numerical maximization is used to estimate the parameters. Using the estimated parameters, the PIN can be estimated using the following equation:

$$PIN = \frac{\alpha\mu}{\alpha\mu + \varepsilon_B + \varepsilon_S} \quad \text{(B3)}$$

In equation (B3), the numerator is the expected number of orders from privately informed investors and the denominator is the number of orders each day. Hence, the PIN measure is the expected fraction of trades that are information-based.

As in any structural model, the PIN measure suffers from limitations related to the assumptions underlying the model. The major limitations are: (1) All orders are assumed to be the same size and this ignores the information that traders potentially reveal by choice of trade order size, (2) each trading day is assumed to be independent, and (3) privately-informed buy and sell orders are not allowed to occur on the same day.

B.2 Estimation of PIN

The market microstructure data to compute *PIN* is obtained from the NYSE Trade and Quotes (TAQ) database. This database, which provides data from 1993 onwards, consists of a trades file and a quotes file. To ensure data integrity, I remove the errors and outliers from the files:

For the trades file, I retain the following:

1. Trades inside regular trading hours (9:30-16:00)
2. Good trades (corr = 0, 1)
3. Regular sale conditions (cond = blank or *)
4. Trades with positive trade price (price > 0) and positive trade size (siz > 0)
5. Trades with absolute change in trade price from the previous trade price of less than or equal to 10%

For the quotes file, I retain the following:

1. Quotes inside regular trading hours (9:30-16:00)
2. Regular quotes (mode = 12)
3. Quotes with positive bid price (bid > 0), positive ask price (ofr > 0), bid price greater than ask price (ofr > bid), positive bid size (bidsiz > 0) or positive ask size (ofrsiz > 0)
4. Quotes with relative quoted spreads less than or equal to 20%
5. Quotes with absolute change in bid price from the previous bid price in each day of less than or equal to 10% and with absolute change in ask price from the previous ask price in each day of less than or equal to 10%.

The matching of trades and quotes is required for the determination of the direction of the trade. In combining the trades and quotes, I following Lee and Ready (1991) and match each trade with the latest available quote at least 5 seconds earlier. I then collapse all trades that took place at the same price and quotes into a single trade (Huang and Stoll, 1997). According to Huang and Stoll, “a large order may be executed at a single price but be reported in a series of smaller trades” and “a single large limit order may be executed at a single price against various incoming market orders”.

The determination of trade direction is required for the computation of the probability of informed trade (*PIN*). I classify the order flow of each trade as a buyer-initiated or seller-initiated using the standard Lee-Ready algorithm (Lee and Ready, 1991), which involves a “quote test” and a “tick test”. For the “quote test”, any trade that takes place above (below) the midpoint of the current quoted spread is classified as a buyer-initiated (seller-initiated) order because trades originating from buyers (sellers) are most likely to be executed at or near the bid (ask). For trades taking place at the midpoint, a "tick test" is used to classify the trade. This test classifies a trade as a buy (sell) order if the trade price is above (below) the previous price. In the event there is no change in the trade price, the order flow is regarded as indeterminable and this trade is not used in computations. I then determine the daily number of buyer-initiated orders and sell-initiated orders by summing the number of orders in each category for each day for each firm.

For each firm in each year, I then use the daily buyer-initiated and seller-initated orders to estimate the parameters in Eq. (B2). There are various numerical methods to solve the maximization problem. I use the SAS NLMIXED procedure with the Quasi-Newton method to maximize the likelihood function. To increase the stability of the parameter estimates, I require the firm to have at least 40 days of non-zero orders before estimating the parameters. I also check for convergence of the maximization solution before using the parameter estimates. *PIN* is then computed by using the parameter estimates with Eq. (B3).

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Figure 1 - Market liquidity

Each month's observation is constructed by averaging the individual stock liquidity for the month and then multiplying 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. Tick marks on the x-axis correspond to July of the given year.

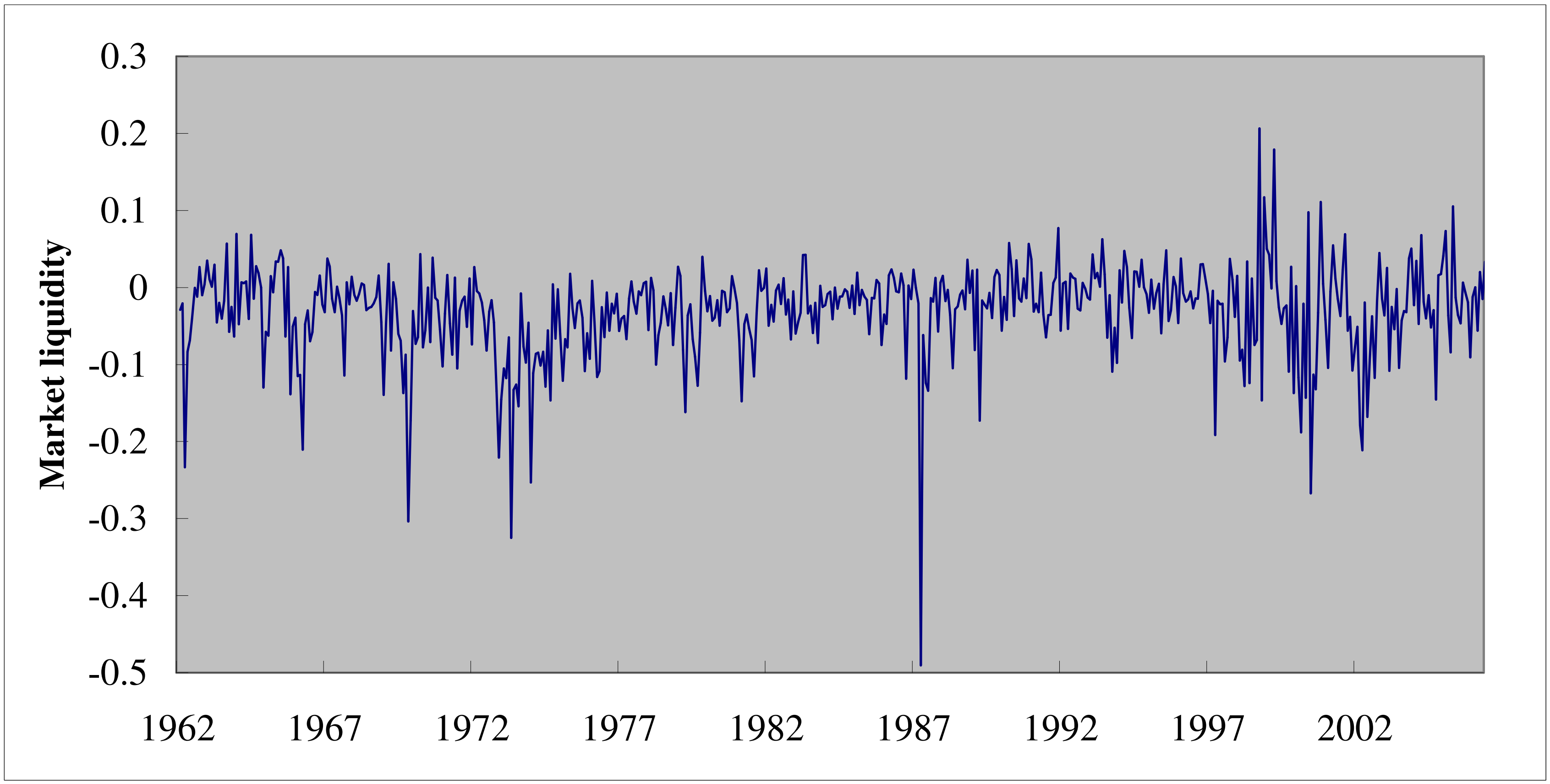

TABLE 1 - Estimation of the liquidity risk premium

At each year-end between 1967 and 2005, stocks are sorted into decile portfolios based on their historical liquidity betas. The historical liquidity betas are estimated as the slope coefficients on *LIQ*, in multi-factor asset pricing regressions of excess returns on *LIQ*, *MKT*, *SMB*, and *HML* factors. The regressions are estimated using the past five years of data, with a minimum requirement of 36 months. After forming the decile portfolios, post-ranking betas and alphas are obtained for each portfolio. The post-ranking excess portfolio returns are first linked across the years to form one series of post-ranking returns for each decile from 1968 to 2006. The post-ranking betas are the factor loadings from regressions of the excess portfolio returns on the *LIQ*, *MKT*, *SMB*, and *HML* factors. The post-ranking Fama and French (1993) alpha is the intercept from regressions of the excess portfolio returns on the *MKT*, *SMB*, and *HML* factors. The liquidity risk premium is the difference in the Fama and French alphas between the top and bottom portfolios. As sensitivity analyses, the raw returns and the CAPM alpha (from regressions on the MKT factor only) are provided. The t-statistics are in parentheses.

	1	2	3	4	5	6	7	8	9	10	10 - 1
					Portfolio betas						
LIQ beta	-7.38	-4.60	0.92	0.78	2.04	0.45	-0.16	2.67	-0.22	0.35	7.73
	(-3.00)	(-2.81)	(0.68)	(0.75)	(1.68)	(0.48)	(-0.15)	(2.20)	(-0.13)	(0.17)	(2.53)
MKT beta	1.29	1.13	1.06	0.97	0.97	0.94	1.00	1.01	1.03	1.16	-0.14
	(35.66)	(46.91)	(52.63)	(63.36)	(54.41)	(68.10)	(63.81)	(56.38)	(42.27)	(37.36)	(-3.03)
SMB beta	0.38	0.03	-0.02	-0.14	-0.17	-0.18	-0.09	-0.08	0.17	0.51	0.13
	(8.55)	(0.92)	(-0.69)	(-7.21)	(-7.87)	(-10.58)	(-4.60)	(-3.63)	(5.68)	(13.28)	(2.25)
HML beta	-0.33	-0.04	0.03	0.04	0.14	0.09	0.17	0.08	-0.05	-0.10	0.23
	(-6.47)	(-1.12)	(1.17)	(1.64)	(5.42)	(4.78)	(7.60)	(2.96)	(-1.48)	(-2.37)	(3.58)
					Portfolio returns						
Fama-French alpha	-2.59	-0.34	-1.41	-0.41	-0.73	0.64	-0.23	1.63	2.40	2.95	5.54
	(-1.51)	(-0.30)	(-1.49)	(-0.57)	(-0.86)	(0.98)	(-0.31)	(1.93)	(2.10)	(2.03)	(2.60)
Raw returns	2.79	5.36	4.40	4.77	5.02	5.90	5.89	7.36	7.84	9.31	6.52
	(0.68)	(1.74)	(1.56)	(1.91)	(2.02)	(2.50)	(2.35)	(2.79)	(2.63)	(2.51)	(3.06)
CAPM alpha	-4.85	-0.64	-1.17	-0.21	0.20	1.23	0.94	2.15	2.11	2.42	7.27
	(-2.53)	(-0.57)	(-1.27)	(-0.28)	(0.21)	(1.67)	(1.19)	(2.54)	(1.82)	(1.42)	(3.45)

TABLE 2 - Number of observations for each key variable by year

This table presents the distribution across the calendar years of the key variables used in my empirical analyses of the effect of information quality on systematic risk. *Risk* refers to the measures of liquidity beta, β^L, and market beta, β^M. β^L (β^M) is estimated as the slope coefficient on *LIQ* (*MKT*) in regressions of excess stock returns on the *LIQ*, *MKT*, *SMB*, and *HML* factors. *Relevance* and *Reliability* measure the relevance and reliability of reported earnings, respectively. *Precision* and *Frequency* measure the precision and frequency of management forecasts, respectively. *Coverage* and *Consensus* measure the coverage and consensus of analyst forecasts, respectively.

		Reported Earnings		Management Forecasts		Analyst Forecasts	
Year	*Risk*	*Relevance*	*Reliability*	*Frequency*	*Precision*	*Coverage*	*Consensus*
1987	4,204	1,634	1,723			2,906	2090
1988	4,165	1,615	1,739			2,929	2082
1989	4,473	1,646	1,734			3,228	2271
1990	4,642	1,653	1,819			3,370	2348
1991	4,576	1,726	1,922			3,356	2369
1992	4,423	1,755	1,938			3,307	2358
1993	4,430	1,845	2,080			3,341	2444
1994	4,541	1,946	2,188			3,490	2573
1995	4,715	1,946	2,187			3,712	2747
1996	5,014	2,049	2,131			4,012	2971
1997	5,104	2,110	2,020			4,181	3077
1998	4,997	2,049	1,952			4,193	3117
1999	4,998	1,913	1,910	1,638	1,638	4,243	3190
2000	4,811	1,799	1,960	1,814	1,814	4,066	3068
2001	4,537	1,788	1,988	2,052	2,052	3,834	2944
2002	4,471	1,807	1,983	2,241	2,241	3,817	2991
2003	4,383	2,043	2,095	2,287	2,287	3,754	3005
2004	4,189	2,110	2,095	2,251	2,251	3,594	2882
2005	3,973	2,153	2,018	2,157	2,157	3,410	2758
Total	86,646	35,587	37,482	14,440	14,440	68,743	51,285

TABLE 3 - Descriptives of information quality measures

Panel A (B) presents the summary statistics (correlations) of various information quality attributes. *Relevance* and *Reliability* measure the relevance and reliability of reported earnings, respectively. *Precision* and *Frequency* measure the precision and frequency of management forecasts, respectively. *Coverage* and *Consensus* measure the coverage and consensus of analyst forecasts, respectively. Each reported correlation in Panel B is the time-series average of the annual correlations between the variables. The t-statistics for the correlations, in parentheses, are obtained by dividing the average of the annual correlations by the standard deviation of the annual correlations.

Panel A - Summary statistics

Variable	N	Mean	Std Dev	Min	Q1	Median	Q3	Max
Relevance	35,587	0.416	0.244	0.006	0.213	0.405	0.605	0.945
Reliability	37,482	-0.047	0.037	-0.202	-0.061	-0.036	-0.021	-0.004
Precision	14,440	-0.141	0.21	-1.330	-0.161	-0.068	-0.023	0.000
Frequency	14,440	9.63	11.22	1.00	2.00	5.00	13.00	72.00
Coverage	68,743	6.03	6.60	1.00	1.57	3.29	7.68	33.13
Consensus	51,285	-0.184	0.317	-2.873	-0.177	-0.068	-0.033	-0.007

Panel B - Correlations

	Relevance	*Reliability*	*Frequency*	*Precision*	*Coverage*	*Consensus*
Relevance		0.028**	0.052**	-0.006	-0.090***	0.080***
		(2.20)	(2.29)	(-0.50)	(-8.54)	(8.64)
Reliability			0.169***	0.153***	0.288***	0.239***
			(13.11)	(7.47)	(32.07)	(13.95)
Frequency				0.094***	0.168***	0.271***
				(32.47)	(19.07)	(8.20)
Precision					0.322***	0.190***
					(33.05)	(18.42)
Coverage						0.121***
						(32.02)
Consensus						

TABLE 4 - Effect of information quality on liquidity risk

This table reports the results of the year fixed effects regressions to investigate the cross-sectional effects of the information quality of reported earnings, management forecasts, and analyst forecasts on liquidity risk. The liquidity risk of a stock is measured by its liquidity beta, β^L. β^L is estimated as the slope coefficients on *LIQ* in regressions of excess stock returns on the *LIQ*, *MKT*, *SMB*, and *HML* factors. The regressions are estimated using the past five years of monthly returns, with a minimum requirement of 36 months. *Relevance* and *Reliability* measure the relevance and reliability of reported earnings, respectively. *Precision* and *Frequency* measure the precision and frequency of management forecasts, respectively. *Coverage* and *Consensus* measure the coverage and consensus of analyst forecasts, respectively. With the exception of *Relevance* that is measured using data from the past 10 years, all the other information quality attributes are measured using data from the past five years. *Average liquidity* is the average monthly stock liquidity in the past five years, *Average volume* is the log of the average monthly dollar trading volume in the past five years, *Cumulative return* is the cumulative returns in the past five year, *Return volatility* is the standard deviation of monthly returns in the past five years, *Price* is the log of the average monthly price in the past five years, *Shares outstanding* is the log of the average monthly shares outstanding in the past five years, and *Institution* is the average percentage of outstanding shares held by institutions for the past five years. The Huber-White heteroscedasticity-robust t-statistics with standard errors clustered by industry are presented in parentheses below the estimated coefficients. *, **, and *** indicate significance at the 10, 5, and 1 percent levels, respectively.

	Reported earnings			Management forecasts			Analyst forecasts		
Intercept	-3.724	-5.128	5.591	-34.989***	-34.321***	-37.624***	-26.011***	-20.750***	-33.832***
	(-0.62)	(-1.01)	(0.93)	(-3.18)	(-3.35)	(-3.69)	(-4.67)	(-3.35)	(-5.15)
Relevance	-1.197		-1.446						
	(-1.14)		(-1.25)						
Reliability		2.964	7.625						
		(0.36)	(0.67)						
Precision				-6.956***		-6.919***			
				(-2.99)		(-3.02)			
Frequency					-0.106*	-0.105*			
					(-1.87)	(-1.89)			
Coverage							-0.226***		-0.280***
							(-4.29)		(-5.06)
Consensus								-3.737**	-3.775**
								(-2.14)	(-2.19)

TABLE 4 (continued)

	Reported earnings			Management forecasts			Analyst forecasts		
Average liquidity	4.690	4.693	5.968	12.301	11.605	12.600	5.647*	0.051	1.071
	(1.25)	(1.50)	(1.54)	(0.94)	(0.88)	(0.97)	(1.75)	(0.01)	(0.11)
Average volume	-0.039	0.292	-0.907	1.539	1.700	1.719	1.950***	1.605**	2.050***
	(-0.05)	(0.48)	(-1.01)	(1.00)	(1.16)	(1.17)	(3.38)	(2.56)	(3.38)
Cumulative return	0.228	0.236	0.311	-0.547***	-0.588***	-0.551***	-0.108	-0.180	-0.201*
	(1.18)	(1.35)	(1.61)	(-3.37)	(-3.58)	(-3.38)	(-0.91)	(-1.59)	(-1.72)
Return volatility	-3.155	-3.119	-0.880	-8.659**	-8.202**	-8.996***	-2.999*	-2.657	-3.357*
	(-1.51)	(-1.56)	(-0.43)	(-2.51)	(-2.46)	(-2.67)	(-1.78)	(-1.36)	(-1.75)
Price	0.432	0.285	1.777	5.032**	4.672**	4.935**	0.288	1.882**	1.971**
	(0.43)	(0.27)	(1.61)	(2.38)	(2.25)	(2.36)	(0.35)	(2.15)	(2.26)
Shares outstanding	-0.587	-1.230	0.023	-2.128	-2.201	-2.215	-1.710*	-2.171**	-1.502
	(-0.64)	(-1.59)	(0.02)	(-1.12)	(-1.20)	(-1.19)	(-1.90)	(-2.36)	(-1.57)
Institutional holdings	1.248	1.898	4.067	-4.752	-3.826	-4.036	-3.891	-7.192***	-7.027***
	(0.44)	(0.58)	(1.23)	(-1.53)	(-1.23)	(-1.28)	(-1.60)	(-2.72)	(-2.67)
Year dummies	Included	Included	Included	Included	Included	Included	Included	Included	Included
R-square	0.87%	1.49%	1.13%	4.11%	4.04%	4.19%	1.68%	1.36%	1.44%
Observations	35,346	37,196	27,026	14,393	14,393	14,393	67,183	50,463	50,463

TABLE 5 - Effect of information quality on market risk

This table reports the results of the year fixed effects regressions to investigate the cross-sectional effects of the information quality of reported earnings, management forecasts, and analyst forecasts on market risk. The market risk of a stock is measured by its liquidity beta, β^M. β^M is estimated as the slope coefficients on *MKT* in regressions of excess stock returns on the *LIQ*, *MKT*, *SMB*, and *HML* factors. The regressions are estimated using the past five years of monthly returns, with a minimum requirement of 36 months. *Relevance* and *Reliability* measure the relevance and reliability of reported earnings, respectively. *Precision* and *Frequency* measure the precision and frequency of management forecasts, respectively. *Coverage* and *Consensus* measure the coverage and consensus of analyst forecasts, respectively. With the exception of *Relevance* that is measured using data from the past 10 years, all the other information quality attributes are measured using data from the past five years. *Total assets* is the log of the average of total assets in the past five years, *Sales growth* is the average of the annual sales growth in the past five years, *Financial leverage* is the average of the financing leverage (i.e., financial liabilities minus financial assets divided by market equity) in the past five years, *Operating leverage* is the average of the operating leverage (i.e., book value of assets divided by market value of assets) in the past five years, *CFO volatility* is the cash flow from operations volatility in the past five years, *Sales volatility* is the sales volatility in the past five years, *Loss proportion* is the proportion of losses in the past five years, *Average liquidity* is the average monthly stock liquidity in the past five years, and *Average volume* is the log of the average monthly dollar trading volume in the past five years. The Huber-White heteroscedasticity-robust t-statistics with standard errors clustered by industry are presented in parentheses below the estimated coefficients. *, **, and *** indicate significance at the 10, 5, and 1 percent levels, respectively.

	Reported earnings			Management forecasts			Analyst forecasts		
Intercept	-1.436***	-1.359***	-1.435***	-1.791***	-1.845***	-1.884***	-1.662***	-1.387***	-1.662***
	(-9.21)	(-8.41)	(-9.02)	(-4.91)	(-5.00)	(-5.27)	(-7.99)	(-5.95)	(-6.71)
Relevance	-0.020		-0.024						
	(-0.71)		(-0.87)						
Reliability		-0.966***	-1.122***						
		(-3.15)	(-3.15)						
Precision				-0.375***		-0.374***			
				(-7.07)		(-6.95)			
Frequency					-0.004**	-0.004**			
					(-2.52)	(-2.46)			
Coverage							-0.010***		-0.008***
							(-6.63)		(-4.12)
Consensus								-0.010	-0.010
								(-0.26)	(-0.26)

TABLE 5 (continued)

	Reported earnings			Management forecasts			Analyst forecasts		
Total assets	-0.040	0.050	-0.034	0.329	0.294	0.343	0.012	-0.351	-0.302
	(-0.79)	(1.20)	(-0.67)	(0.85)	(0.77)	(0.89)	(0.12)	(-1.19)	(-1.01)
Sales growth	0.179***	0.173***	0.176***	0.188***	0.195***	0.194***	0.193***	0.176***	0.192***
	(12.88)	(12.27)	(12.70)	(7.18)	(7.45)	(7.65)	(10.87)	(8.91)	(9.60)
Financing leverage	-0.030	-0.005	-0.023	-0.198***	-0.216***	-0.201***	-0.020	-0.047*	-0.050*
	(-1.08)	(-0.27)	(-0.82)	(-3.24)	(-3.34)	(-3.26)	(-0.93)	(-1.75)	(-1.88)
Operating leverage	0.085***	0.078***	0.081***	0.069***	0.067***	0.069***	0.070***	0.071***	0.067***
	(5.50)	(6.45)	(5.23)	(3.60)	(3.44)	(3.63)	(5.33)	(5.07)	(4.74)
CFO volatility	0.166***	0.144***	0.167***	0.264***	0.278***	0.266***	0.186***	0.236***	0.233***
	(7.92)	(8.56)	(7.69)	(3.42)	(3.57)	(3.45)	(6.62)	(5.81)	(5.79)
Sales volatility	-0.127***	-0.115***	-0.120***	-0.131***	-0.136***	-0.130***	-0.109***	-0.137***	-0.122***
	(-6.53)	(-6.33)	(-6.32)	(-4.38)	(-4.40)	(-4.25)	(-5.05)	(-5.91)	(-5.10)
Loss proportion	-0.067	-0.283***	-0.205*	-0.036	-0.047	-0.048	-0.089	0.027	0.029
	(-0.56)	(-4.20)	(-1.74)	(-0.20)	(-0.25)	(-0.27)	(-0.81)	(0.13)	(0.14)
Average liquidity	0.264***	0.239***	0.250***	0.285***	0.294***	0.284***	0.232***	0.267***	0.256***
	(5.81)	(5.26)	(5.48)	(3.34)	(3.21)	(3.34)	(4.64)	(4.06)	(3.89)
Average volume	0.252***	0.216***	0.225***	0.559***	0.600***	0.527***	0.313***	0.351***	0.355***
	(4.71)	(5.63)	(4.29)	(5.78)	(6.02)	(5.50)	(6.19)	(6.33)	(6.16)
Year dummies	Included	Included	Included	Included	Included	Included	Included	Included	Included
R-square	15.12%	14.10%	15.45%	17.95%	17.41%	18.30%	14.50%	15.03%	15.28%
Observations	27,022	35,655	25,940	8,823	8,823	8,823	33,766	26,549	26,549

TABLE 6 - Joint analyses of information quality attributes

This table reports the results of the year fixed effects regressions to investigate the cross-sectional effects of the information quality of reported earnings, management forecasts, and analyst forecasts on liquidity risk and market risk. For each regression, all the information quality attributes are included. The regression specification and the description of all the variables used for the liquidity risk and market risk regressions are provided in Tables 5 and 6, respectively. For parsimony, only the coefficients on the information quality attributes are reported. The Huber-White heteroscedasticity-robust t-statistics with standard errors clustered by industry are presented in parentheses below the estimated coefficients. *, **, and *** indicate significance at the 10, 5, and 1 percent levels, respectively.

	Liquidity risk regression	Market risk regression
Relevance	-2.676	0.026
	(-1.05)	(0.53)
Reliability	15.049	-1.205*
	(0.48)	(-1.71)
Precision	-10.383**	-0.246***
	(-2.50)	(-2.83)
Frequency	-0.109*	-0.004*
	(-1.88)	(-1.96)
Coverage	-0.296	-0.006
	(-1.50)	(-1.37)
Consensus	-12.755**	-0.043
	(-2.44)	(-0.47)
Intercept, control variables, year dummies	Included	Included
Adjusted R-square	5.12%	24.62%
Observations	5,127	5,089

TABLE 7 - Aggregation of information quality attributes

This table reports the results of the year fixed effects regressions to investigate the cross-sectional effects of the information quality of reported earnings, management forecasts, and analyst forecasts on liquidity risk and market risk. *Reported earnings quality* is the sum of the quintile ranks of *Relevance* and *Reliability*, *Management forecast quality* is the sum of the quintile ranks of *Precision* and *Frequency*, and *Analyst forecast quality* is the sum of the quintile ranks of *Coverage* and *Consensus*, and *Total quality* is the sum of the quintile ranks of all six individual information quality attributes. The description of all other (control) variables used for the liquidity risk and market risk regressions are provided in Tables 5 and 6, respectively. For parsimony, only the coefficients on the aggregate information quality attributes are reported. The Huber-White heteroscedasticity-robust t-statistics with standard errors clustered by industry are presented in parentheses below the estimated coefficients. *, **, and *** indicate significance at the 10, 5, and 1 percent levels, respectively.

	Liquidity risk regressions				Market risk regressions			
Reported earnings quality	-0.048				-0.017***			
	(-0.30)				(-3.34)			
Management forecast quality		-0.754***				-0.054***		
		(-2.81)				(-7.91)		
Analyst forecast quality			-1.691***				-0.029***	
			(-5.08)				(-3.60)	
Aggregate quality				-0.697**				-0.025***
				(-2.60)				(-5.25)
Intercept, control variables, year dummies	Included	Included	Included	Included	Included	Included	Included	Included
Adjusted R-square	1.12%	4.09%	2.04%	4.00%	15.49%	18.71%	15.35%	24.99%
Observations	27,026	14,393	26,831	5,127	25,940	8,823	26,549	5,089

TABLE 8 - Estimation of the effect of information quality on cost of capital through liquidity risk and market risk

This table presents estimates of the effect, through liquidity risk and market risk, of a one standard deviation of the information quality attribute, on cost of equity capital (*CoC*). *Relevance* and *Reliability* measure the relevance and reliability of reported earnings, respectively. *Precision* and *Frequency* measure the precision and frequency of management forecasts, respectively. *Coverage* and *Consensus* measure the coverage and consensus of analyst forecasts, respectively. The inputs for the estimations are from the prior tables. *Std Dev*, obtained from Table 3, refers to a one standard deviation from the mean for the information quality attribute. The coefficients on the information quality attributes in Table 4 (Table 5) measure the change in the liquidity (market) beta in response to a one unit change in the information quality attribute. *, **, and *** indicate the significance of these coefficients at the 10, 5, and 1 percent levels, respectively, as documented in these tables. As discussed in section 3.1.1, the estimated risk premium per unit of liquidity beta (market beta) is 0.72% (5.28%). The computation of the *CoC* effects uses the following formulas

$$CoC \text{ through systematic risk} = Std\ Dev\ x \frac{\partial \beta}{\partial Quality} \text{ x risk premium per unit of systematic risk}$$

where *Std Dev* is one standard deviation from the mean for an information quality attribute and $\frac{\partial \beta}{\partial Quality}$ is the coefficient on the information quality attribute.

The CoC effects are then multiplied by 100 to report the results in basis points (bps).

	Inputs					Effect of information quality on *CoC* (bps) through		
		Coefficients		Risk premium (%) per unit of				
	Std Dev	Liquidity risk	Market risk	Liquidity risk	Market risk	Liquidity risk	Market risk	Overall
Reported earnings								
Relevance	0.244	-1.446	-0.024	0.72	5.28	-25	-3	-28
Reliability	0.037	7.625	-1.122***	0.72	5.28	20	-22	-2
Management earnings forecasts								
Precision	0.210	-6.919***	-0.374***	0.72	5.28	-105	-41	-146
Frequency	11.22	-0.105*	-0.004**	0.72	5.28	-85	-24	-109
Analyst earnings forecasts								
Coverage	6.599	-0.280***	-0.008***	0.72	5.28	-133	-28	-161
Consensus	0.317	-3.775**	-0.010	0.72	5.28	-86	-2	-88

Table 9 - Effect of private information on the relation between information quality and liquidity risk

This table reports the results of year fixed effects regressions to investigate how private information affects the relation between public information quality and liquidity risk. The dependent variable is liquidity beta, β^L. The regression specification is based on Eq. (6). *Private information* is measured using either *PIN* or *Insider*. *PIN* is the average of the past five years' annual probability of information-based trading. *Insider* is the average of the past five years' annual number of shares traded by top executives scaled by the annual trading volume. *PIN, Insider,* and the various information quality attributes (*Relevance*, *Reliability*, *Precision*, *Frequency*, *Coverage*, and *Consensus*) are ranked into quintiles based on their distribution within each calendar year and scaled to range from 0 to 1. Further description of β^L, *Relevance*, *Reliability*, *Precision*, *Frequency*, *Coverage*, *Consensus,* as well as the control variables can be found in Table 4. The Huber-White heteroscedasticity-robust t-statistics with standard errors clustered by industry are presented in parentheses below the estimated coefficients. *, **, and *** indicate significance at the 10, 5, and 1 percent levels, respectively.

	Private info dummy measured using					
	PIN			*Insider*		
Relevance	-3.410**			-2.460**		
	(-2.15)			(-2.17)		
Reliability	1.550			1.682		
	(0.76)			(0.72)		
Precision		-6.677***			-1.763	
		(-3.14)			(-0.90)	
Frequency		-6.671***			-6.786***	
		(-3.06)			(-3.16)	
Coverage			-4.609**			-5.227***
			(-2.17)			(-3.29)
Consensus			-9.160***			-2.815*
			(-4.84)			(-1.69)
Private info dummy	-5.498	-11.769***	-6.137	0.125	-1.277	-2.506
	(-1.43)	(-3.22)	(-1.48)	(0.04)	(-0.44)	(-0.91)
Private info dummy x Relevance	8.246**			2.745		
	(2.42)			(1.28)		
Private info dummy x Reliability	1.841			-0.834		
	(0.49)			(-0.19)		
Private info dummy x Precision		12.441***			-0.380	
		(2.95)			(-0.11)	
Private info dummy x Frequency		9.209**			7.693**	
		(2.18)			(2.36)	
Private info dummy x Coverage			9.772**			9.533***
			(2.25)			(3.09)
Private info dummy x Consensus			1.244			-4.062*
			(0.34)			(-1.68)
Intercept, control variables, year dummies	Included	Included	Included	Included	Included	Included
R-square	2.38%	4.33%	2.18%	1.14%	4.19%	1.47%
Observations	13,093	14,392	26,815	27,026	14,393	50,463

Table 10 – Effect of information quality on liquidity risk in times of significant changes in market conditions

This table reports the results of pooled regressions to examine the effect of information quality on liquidity risk when there are significant changes in market conditions. Panel A (Panel B) reports the results for months with significant market liquidity changes (market returns) during the period from 1987 to 2005. *Precision* and *Frequency* measure the precision and frequency of management forecasts, respectively. *Coverage* and *Consensus* measure the coverage and consensus of analyst forecasts, respectively. *Average liquidity* is the average monthly stock liquidity, *Average volume* is the log of the average monthly dollar trading volume, *Cumulative return* is the cumulative returns, *Return volatility* is the standard deviation of monthly returns, *Price* is the log of the monthly price, *Shares outstanding* is the log of the monthly shares outstanding, and *Institution* is the percentage of outstanding shares held by institutions. The Huber-White heteroscedasticity-robust t-statistics with standard errors clustered by industry are presented in parentheses below the estimated coefficients. *, **, and *** indicate significance at the 10, 5, and 1 percent levels, respectively.

Panel A – Months with largest decreases and increases in market liquidity

	20 largest decreases in market liquidity			20 largest increases in market liquidity		
Intercept	7.369	-8.681	-8.199	42.287***	42.679**	35.602**
	(1.07)	(-0.49)	(-0.51)	(3.49)	(2.54)	(2.43)
Relevance	-3.004			3.404		
	(-1.01)			(0.78)		
Reliability	1.102			1.970		
	(0.67)			(0.84)		
Precision		-0.234***			-0.030	
		(-4.23)			(-0.40)	
Frequency		-0.073			-0.421	
		(-0.13)			(-1.33)	
Coverage			-0.093			0.342
			(-0.57)			(1.66)
Consensus			-11.132***			-4.028
			(-5.45)			(-0.99)
Average liquidity	2.205	33.169	40.960	5.749	8.824	-54.327
	(0.39)	(1.07)	(0.91)	(0.85)	(0.25)	(-1.13)
Average volume	-6.368***	-12.652***	-6.997***	-2.291	1.523	0.167
	(-3.99)	(-4.21)	(-3.15)	(-1.38)	(0.48)	(0.09)
Cumulative return	22.378***	16.310**	16.308***	35.461***	21.979***	22.758***
	(6.81)	(2.52)	(4.15)	(7.97)	(5.34)	(6.34)
Return volatility	0.425	4.404	-1.432	4.798*	6.484**	1.944
	(0.20)	(1.37)	(-0.54)	(1.93)	(2.41)	(0.69)
Price	17.068***	35.061***	17.452***	-0.459	0.394	1.459
	(6.87)	(6.76)	(7.51)	(-0.24)	(0.12)	(0.66)
Shares outstanding	3.112*	8.357***	4.413**	1.863	-3.461	-2.839
	(1.69)	(2.72)	(2.25)	(0.91)	(-1.03)	(-1.34)
Institution	21.153***	18.396**	13.058**	9.178	-10.929	-3.964
	(3.93)	(2.26)	(2.31)	(1.24)	(-1.03)	(-0.67)
R-square	2.02%	3.11%	1.86%	1.68%	0.92%	0.94%
Observations	27,086	16,063	38,616	28,644	16,173	41,707

Panel B – Months with largest negative and positive market returns

	20 largest negative market returns			20 largest positive market returns		
Intercept	23.928**	1.510	-18.786	94.194**	-102.37*	84.629*
	(2.33)	(0.05)	(-1.12)	(2.50)	(-1.77)	(1.88)
Relevance	-9.877**			-16.166		
	(-2.17)			(-1.13)		
Reliability	-2.536			-7.026		
	(-1.20)			(-0.77)		
Precision		-0.106			-0.078	
		(-0.87)			(-0.37)	
Frequency		-0.869			-1.784	
		(-0.80)			(-1.24)	
Coverage			-0.343*			1.437**
			(-1.69)			(2.47)
Consensus			-1.538			-16.915
			(-0.53)			(-0.93)
Average liquidity	-0.655	48.981	5.831	15.490	33.779	104.764
	(-0.15)	(1.31)	(0.17)	(1.13)	(0.40)	(1.39)
Average volume	0.294	1.600	-3.810**	-8.726	25.489**	10.975**
	(0.16)	(0.31)	(-2.05)	(-1.65)	(2.35)	(2.52)
Cumulative return	4.596	0.165	-6.634	18.539	-5.292	-0.587
	(0.93)	(0.01)	(-1.01)	(1.23)	(-0.19)	(-0.03)
Return volatility	1.267	-3.721	-3.081	17.002*	-14.488	10.518
	(0.44)	(-0.46)	(-0.66)	(1.78)	(-0.76)	(1.38)
Price	-1.179	-9.605	1.774	-4.808	-68.732***	-32.641***
	(-0.66)	(-1.15)	(0.53)	(-0.44)	(-3.70)	(-3.25)
Shares outstanding	-2.413	-0.277	6.207***	10.048*	-17.501	-15.770***
	(-1.06)	(-0.05)	(3.20)	(1.79)	(-1.40)	(-2.89)
Institution	9.445	-21.249*	11.675	49.316***	27.502	21.154
	(1.19)	(-1.88)	(1.35)	(2.85)	(0.58)	(0.87)
R-square	0.04%	0.18%	0.33%	0.27%	0.92%	0.56%
Observations	26,665	17,053	38,303	26,952	13,396	38,648