Transparency and Liquidity Uncertainty in Crisis Periods

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Abstract

We examine the effects of firm-level transparency on the variability and covariability of liquidity across a wide range of countries, with a particular focus on crisis periods. We find that firms with greater transparency, as measured by quality of accounting standards, quality of auditor, level of earnings management, analyst following and analyst forecast accuracy, are characterized by less volatility in liquidity, as well as lower correlations between firm level liquidity and market liquidity and between firm level liquidity and stock returns. Further, more transparent firms are less likely to experience "extreme liquidity events," where liquidity essentially vanishes and trading becomes prohibitively costly. Results are particularly pronounced during crisis periods, when liquidity variances and covariances and extreme illiquidity events generally tend to increase substantially, but significantly less so for transparent firms. Similarly, firms generally experience substantial increases in CAPM betas during crisis periods, but the increases are significantly mitigated for more transparent firms. Finally, we show that liquidity variance, covariance and frequency of extreme illiquidity events are all negatively correlated with Tobin's Q, suggesting that these features of liquidity are important to valuation.

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1. Introduction

A substantial body of research demonstrates that, all else equal, investors prefer stocks that are liquid and that transparency has the potential to improve liquidity (for a summary see, Amihud, Mendelson and Pedersen (2005)). However, the concern for an investor is broader than simply the average level of liquidity because what matters is the liquidity at the time they choose to transact. Investors prefer firms with relatively predictable liquidity because they are able to better anticipate the likely trading costs associated with closing a position at the time they make the initial purchase decision.[1] To the extent a stock's liquidity is highly variable, it increases the uncertainty attached to a position and limits a potential investor's flexibility. For example, investors who need to reduce overall exposure may face the alternative of either selling shares at substantially below intrinsic value due to price pressure or switching to liquidating other positions. In extreme cases, stocks may be subject to periods where liquidity suddenly dries up, effectively eliminating the opportunity for a trader to enter or exit a position at all. For example, Moorthy (2003) discusses, from the perspective of a portfolio manager, the possibility of "liquidity black holes" in equity markets in which liquidity freezes in the absence of investors willing to take the other side of positions and fund managers faced with redemptions are forced to either offload positions at fire-sale prices or unbalance their portfolios by selling their most liquid securities.[2]

Not only does the variability of illiquidity matter, but its timing matters as well. Illiquidity is of special concern if it tends to occur at inopportune times. If liquidity in a given stock is highly correlated with liquidity in other stocks or with market returns, it is likely to be expensive to sell at exactly the time the investor wants to liquidate the position. Research such as Brunnermeier and Pedersen (2009) (hereafter referred to as 'BP'), discussed in more detail in the next section, suggests that firm-level liquidity will naturally be positively correlated with overall market liquidity and with market returns because traders' ability to provide liquidity is typically a

[1] For example, Persaud (2003) notes, "there is a broad belief among users of financial liquidity—traders, investors and central bankers—that the principal challenge is not the average level of financial liquidity, but its variability and uncertainty."

[2] McCoy (2003) notes that, "As important as the level of liquidity is its *uncertainty*. In an age where there is intolerance for risks that cannot be quantified, investors may avoid markets altogether where liquidity is uncertain."

function of the availability of funds (their capital and the margins charged by their financiers), which can induce co-movement in liquidity across stocks as well as co-movement between firm-specific liquidity and market returns. Acharya and Petersen (2005) decompose the CAPM beta to show that cost of capital is a function of the covariance between firm liquidity and both market returns and market liquidity. They provide empirical evidence that U.S. stocks that maintain a relatively constant level of liquidity when overall markets become illiquid, or when stock returns are negative, enjoy a lower cost of capital because investors are willing to pay more for shares if they expect to be able to exit their positions at a relatively low cost during these periods.

While liquidity variance and covariance are important in general, the recent financial market turmoil illustrates that they can be particularly important during crisis periods. For example, BP (2009) argues that liquidity constraints, and hence firm-specific liquidity co-movement with market liquidity and market returns, will be particularly pronounced when market returns are negative and, consequently, liquidity constraints are likely to be binding. Empirically, the results in Hameed et al. (2010) suggest that liquidity decreases and comovement increases during market downturns, consistent with a reduction in liquidity supply when the market drops. In addition, downturns can increase firms' betas. In the theoretical framework of Vayanos (2004), CAPM betas are relatively unaffected by liquidity during normal periods but, during crisis periods, illiquid assets become riskier in the sense that their market betas increase due to the effect of uncertainty on their liquidity.

As discussed in more detail in the next section, transparency has the potential to affect liquidity variability and co-movement. Models in papers such as BP (2009) and Vayanos (2004) show liquidity can dry up because of a "flight to quality," where investors flee from assets with high levels of uncertainty about fundamental value. To the extent that transparency provides information about, for example, future cash flows, it reduces uncertainty about intrinsic value. Because transparency has the ability to reduce uncertainty about firm value, it has the potential to reduce the variability of liquidity and the incidence of extreme illiquidity, as well as the covariability of liquidity with respect to market-wide liquidity and market returns. In other words, information can reduce not only the transactions costs associated with liquidity, but also the risk induced by liquidity uncertainty. For example, to the extent transparency reduces uncertainty about firm fundamentals, liquidity is less likely to fluctuate, is less likely to be "fragile" in the sense that it dries up suddenly (Morris and Shin (2004)), and is less likely to covary with market liquidity and market returns (BP (2009)).

Further, transparency effects are likely to be particularly pronounced during crisis periods. During large market downturns, investors' willingness to provide liquidity will be a function of their level of uncertainty about the intrinsic value of the underlying assets – particularly if liquidity providers are risk averse, funding levels are constrained and margins are more likely to be binding. In the recent financial crisis, for example, the liquidity effects were more pronounced for asset classes with greater uncertainty. To the extent a stock is more transparent, it is likely to be more liquid in general, but a high transparency stock is also likely to be less subject to market-wide liquidity shocks because more firm-specific information permits investors to differentiate between stocks (Persaud (2003)). In the face of flight to quality, more transparent firms are also less likely to be affected by overall shifts in liquidity. Similarly, Vayanos (2004) suggests that liquidity providers become more risk averse in the face of uncertainty about fundamental asset values. To the extent that transparency reduces uncertainty it will reduce the tendency to withdraw liquidity during market downturns.

While there are theoretical reasons to believe liquidity variance and covariance could be affected by transparency, and theoretical and empirical evidence showing that liquidity covariance is an important component of cost of capital, we are unaware of any empirical research that explicitly examines the link between firm-level transparency and liquidity variance and covariance. That is the focus of our study.[3]

[3] While the same underlying rationale should apply to U.S. firms (and has not, to our knowledge, been addressed for a U.S. sample), we focus on an international sample for several reasons. First, the U.S. setting tends to be relatively homogenous in terms of firm-level transparency and liquidity. Internationally, firms are more likely to differ in terms of factors such as accounting standards, auditor, earnings quality and analyst following. Second, we are interested in crisis periods and an international setting provides a much wider set of economic environments with significant country-level variation. Third, the international setting seems inherently interesting because the effects of the recent economic crisis on liquidity varied markedly across economic settings, and the precipitating factors are not well understood. As discussed later, results are robust to inclusion of U.S. firms.

Perhaps closest to our research are country-level studies that compare cross-country return and liquidity co-movement. For example, Brockman and Chung (2002) documents cross-country commonality in liquidity and finds that exchange-level sources represent about 39 percent of total commonality in liquidity, with global sources representing an additional 19 percent. Qin (2008) documents significantly higher commonality in liquidity in emerging markets, and that liquidity commonality is more affected by market prices than individual stock prices, consistent with the effects of inventory risk. Morck, Yeung and Yu (2000) document greater "synchronicity" in returns for low-income relative to high-income economies, which appears to be associated with property rights. Jin and Myers (2006) develop a model to explain return synchronicity and link return comovement to control rights and information. Finally, Karolyi et al. (2009) evaluate country-level determinants of commonality in returns, liquidity, and turnover across countries and over time, and argue that results are more consistent with demand-side explanations (related to investor protection, the trading behavior of international and institutional investors, and investor sentiment) than supply-side explanations (related to the funding liquidity of financial intermediaries), especially for stocks in emerging market countries. While the country-level analyses are informative, country-level factors are largely outside of an individual firm's control and the inherent mix of factors at work at the country level makes it more difficult to tease out the underlying relations. All of our analyses are at the firm-level after controlling for country-level effects and, therefore, focus on firm-level variation.

In addition, there is research evidence in the U.S. on the relation between firm-level returns and market liquidity as a potential priced risk factor. Pastor and Stambaugh (2003) provide evidence that the correlation between firm-level returns and market-wide liquidity is a priced risk factor, and Ng (2009), using a U.S. sample, investigates the potential role of information in that relation. However, those papers consider a fundamentally different question in the sense that they do not investigate variation and covariation in firm-level liquidity, which is the focus of our analysis.[4]

[4] Further, the underlying phenomena are fundamentally different in the sense that the correlations between their measures and the liquidity co-movements we document are .03 for market returns and .06 for market liquidity, confirming that we are examining fundamentally different constructs. Controlling for the covariation between firm-level returns and market liquidity does not change any of our conclusions.

We focus on five firm-level measures of transparency—auditor choice, accounting standard choice, earnings management, analyst following and analyst forecast accuracy—and relate them to characteristics of liquidity as reflected in the Amihud (2002) price impact measure. We choose these measures because they have been used in previous research to capture characteristics of firms' information environments (e.g., Lang, Lins and Maffett (2009)), and tend to vary substantially across firms. Because our interest is in firm-level variation in liquidity variability and covariability, we control for fixed country-level effects (as well as year-level effects) in our primary analyses. In addition, we control for a wide range of factors from the prior literature, including the level of liquidity, to ensure that our results do not simply reflect omitted correlated variables.

We use the Amihud (2002) measure to capture the liquidity of a firm's shares based on the price impact of trades; liquid stocks are those for which a relatively large volume of shares can be transacted without substantially affecting price. Price impact is a major consideration to investors contemplating an investment in a stock because it reduces the potential return by driving up the price paid when the investor attempts to buy and reducing the price received when the investor attempts to sell.[5]

We begin by examining the relation between our five measures of transparency and the volatility of liquidity. As predicted, we find that the volatility of liquidity is significantly negatively correlated with transparency as measured by each of our five underlying transparency variables. For parsimony going forward, we collapse the five measures into two (earnings characteristics as measured by auditor, accounting standards and earnings management, and analyst characteristics as measured by analyst following and accuracy).[6] Both are negatively correlated with liquidity volatility. Next, we examine the incidence of extreme illiquidity, measured by the skewness of

[5] In addition, this seems like a natural approach because theoretical research such as BP (2009) defines liquidity based on the extent to which prices move away from fundamental values as a result of buying and selling pressure.

[6] The approach of aggregating across measures is consistent with the notion that we cannot be sure that we have separated the effect of, say, auditor choice from accounting standard choice or from other changes that may have occurred in the firm to increase transparency such as improved investor relations. Rather, we are simply arguing that firms with better auditors, international accounting standards, less evidence of earnings smoothing, greater analyst following and more accurate analyst forecasts are more likely to be transparent and, therefore, likely to be characterized by less uncertainty about intrinsic value.

the liquidity distribution as well as by our measure of "liquidity black holes," defined as cases in which transactions costs are at least 50 times their normal levels for a given country. We find that stocks with greater transparency experience fewer cases of extreme illiquidity as reflected both in terms of the skewness of illiquidity as well as the number of extreme illiquidity events.

In addition, we examine the relation between transparency and liquidity covariance with market liquidity and market returns. We find that more transparent firms experience lower covariance between their liquidity and both market liquidity and market returns. In other words, firms that are more transparent are particularly less likely to have liquidity dry up at inopportune times when market liquidity is low and returns are negative. This result is important because Acharya and Pedersen (2005) suggest that liquidity covariances with both market liquidity and market returns are positively correlated with cost of capital.

Next, we examine the effect of crisis periods on the relation between transparency and liquidity variability and covariability. We define a crisis period at the country-month level, following prior literature (e.g. Hameed et al. (2010)), as a month in which the country's stock market index falls by more than one and a half times its historical standard deviation.[7] While this definition is somewhat arbitrary, it captures the notion that liquidity providers are more likely to be constrained when their own capital has decreased due to a market downturn and it is more difficult to borrow from funding sources due to increased uncertainty.

Our results suggest that the effects of transparency on all of our liquidity measures are more pronounced during downturns. In particular, while liquidity volatility is generally lower for more transparent firms, the effect is particularly pronounced during downturns. Similarly, opaque firms have a particularly high frequency of extreme illiquidity events during downturns. Moreover, transparency matters significantly more to the correlation between firm-level liquidity and both market liquidity and market returns during downturns. Because our measure of downturns is fairly modest to be termed a "crisis" and because theory suggests that the liquidity

[7] On average, by our definition, 7.6% of months are "crisis periods." and the average stock price drop during these months is 9.5%. All inferences regarding our primary hypotheses are robust to alternative specifications of a crisis period, such as when a market drops by more than 10% in a month, or when a market falls by more than 20% over the course of three months. Similarly, results are consistent when a crisis is defined as an increase in return volatility of greater than 1.5 standard deviations or greater than 2.5 standard deviations.

sensitivity will be greater the larger is the downturn, we divide our crisis variable into those downturns of more than 1.5 standard deviations (a 5 - 14% monthly downturn depending on the country, averaging 9.5% over our entire sample) and those of more than 2.5 standard deviations (a 10 - 32.5% monthly downturn depending on country, averaging nearly 16% over our entire sample). Consistent with predictions, the results across all measures are substantially stronger for larger downturns. Overall, the results are consistent with the theoretical and intuitive notion that transparency matters most to liquidity variability and covariability during crisis periods as manifested in sharp market downturns.[8]

Next, we examine whether transparency mitigates the increase in market beta which tends to occur during down markets as documented in Ang and Chen (2002). Intuitively, the increase in market beta in down markets is consistent with the notion that the price pressure associated with trades in illiquid securities will increase the stock price change associated with trading during down markets and increase beta. Similarly, an implication of Vayanos (2004) is that increases in beta during down markets will be more pronounced for firms with greater uncertainty about intrinsic value. Again, results suggest that the increase in beta during downturns tends to be less pronounced for transparent firms.[9]

Finally, we examine whether Tobin's Q is associated with the liquidity variability and co-variability measures we consider. In particular, while the analysis to this point implicitly assumes that liquidity variability and covariability are important to firm value, there is relatively little empirical evidence on that point.[10] Our results suggest that all of our variables—liquidity volatility, liquidity skewness, frequency of extreme illiquidity events, covariance of firm-level liquidity and market liquidity and covariance of firm-level liquidity and market return—are strongly and incrementally correlated with firm value, suggesting that liquidity variability and

[8] The idea of looking at a market downturn over a relatively short window is consistent with the BP (2009) notion that, over longer windows, speculators may be able to refinance their positions, but that capital is generally "slow moving," consistent with the empirical evidence in Mitchell, Pedersen and Pulvino (2007).

[9] This result is also consistent with Leuz and Schrand (2009), which provides evidence that firms' disclosure responses reduce cost of capital (measured through the impact on a firm's beta coefficient) and mitigate the impact of crises.

[10] An exception is Acharya and Pedersen (2005), which documents that, for a sample of U.S. firms, covariability of firm-level liquidity with market liquidity and with market return are positively correlated with cost of capital. We use Tobin's Q in our analysis because we lack sufficient analyst forecast data to infer cost of capital for most of our sample firms and those with sufficient data are generally only the largest and most liquid firms.

covariability are important in practice and that none of our variability measures subsumes any of the others.

Overall, our results suggest that transparency has a strong and consistent association with liquidity variability and covariability, and that liquidity variability and covariability appear to be consistently correlated with firm value. While it is dangerous to draw causal links, the fact that we control for a wide range of variables, including country and year fixed effects, lessens the probability of omitted correlated variables, and the fact that our liquidity variables are measured over short windows reduces the likelihood that causality is reversed. Further, the fact that our results are predictably stronger during crisis periods suggests that the effects do not simply reflect systematic differences in the variability and covariability of underlying economics for the sample firms, since it is difficult to imagine alternative reasons why liquidity variance and covariance shifts would be associated with transparency, particularly in crisis periods. Finally, the results are consistent with the implications of theoretical research. That said, conclusions on causality should be drawn with caution.[11]

In the next section, we present our primary hypotheses. Then, we discuss our data and empirical approach, followed by our results and conclusions.

2. Hypothesis Development

While we do not view our analysis as a test of a particular theory, our hypotheses generally follow from the intuition underlying the BP (2009) model.[12] BP (2009) link an asset's "market liquidity" (e.g., the ease with which a stock is traded) to traders' "funding liquidity" (e.g., the

[11] A reasonable question is why, if transparency provides benefits to shareholders, all firms wouldn't choose to be transparent. However, there are direct and indirect costs associated with transparency. Direct costs include the incremental expenditures for higher quality auditors, application of international accounting standards and improved investor relations. Indirect costs, which are likely to be larger, include the effect on private control rights for management, large blockholders and other stakeholders. Research such as Leuz et al. (2003) and Lang et al. (2009) provides evidence that transparency is lower for firms which are likely to benefit more from opacity.

[12] While it is expositionally helpful to set up the hypotheses using the framework of BP (2009), the intuition underlying our hypotheses does not require that particular set of assumptions. For example, if speculators are risk averse, as in Grossman and Miller (1988), they will be less willing to provide liquidity in stocks with greater uncertainty about fundamental value and will reduce liquidity for high-uncertainty stocks as a group in response to increased overall uncertainty. As a result, liquidity variability and covariability will tend to be a function of transparency and the effects will potentially increase during crisis periods consistent with our hypotheses.

ease with which speculative traders can obtain outside capital). Speculative traders provide market liquidity but face funding constraints because they have limited amounts of their own capital and rely on funding liquidity to purchase stock, which is subject to margin requirements on long and short sales. Margins in turn are set based on an assets "value-at-risk," which reflects the "largest possible price drop within a certain confidence interval." Market declines and decreases in funding liquidity decrease traders' capital and increase margins, leading traders to withdraw liquidity, particularly from "capital intensive" (high margin) securities. As traders shift out of high margin stocks, market liquidity in those stocks dries up. As a result, stocks with greater uncertainty about fundamental value experience greater volatility in liquidity. Further, because traders own shares in a range of stocks and funding liquidity tends to be correlated across traders, stocks experience commonalities in liquidity. Also, because trader capital fluctuates with market conditions, liquidity covaries with market returns. Finally because traders in general are net long the market, capital tends to be lowest when markets are down and the effect of capital on liquidity tends to be nonlinear. This implies commonality in liquidity will increase when markets decline.[13]

The link to information obtains because margin requirements in the model are a function of the ability to determine the fundamental value of the asset. To the extent that information allows market participants to better understand underlying firm value, there will be less uncertainty about a firm's underlying fundamentals and correspondingly narrower bounds on a trader's value-at-risk.[14] As a result, there will be less of a "flight to quality" among speculators for more transparent stocks in response to funding and capital shocks and, therefore, less volatility in their liquidity.[15] That leads to our first hypothesis:

[13] Hameed et al. (2010) provides empirical support consistent with the notion that liquidity comovement with market liquidity and with market returns tends to be higher during market downturns when uncertainty is higher.

[14] An example of a liquidity provider is a large block desk that stands ready to take the other side of large trades. One of the authors interviewed traders on three large block desks to get a sense for the factors considered in pricing blocks for an unrelated project under conditions of anonymity. The traders indicated that discounts were based on the financing cost and risk of the position in terms of the subjective probability of an imminent large stock price drop. Pricing, which was "more art than science," varied across securities and over time based on the trader's overall uncertainty about intrinsic value, including factors such as past volatility, analyst research and perceived general firm-level transparency.

[15] It is important to remember that, under this definition, liquidity is measured as the price impact of trade. In other words, there may still be substantial trading volume in "illiquid" markets and speculators may still be active but, because there is greater uncertainty about fundamental value, speculators require relatively larger discounts.

H1: *The lower is firm-level transparency, the greater is the variability of liquidity.*

Further, BP (2009) argues that assets will be subject to extreme illiquidity events due to "liquidity spirals." For example, in a "margin spiral" a shock to speculator capital will cause speculators to provide less liquidity, which increases the variability of share price, which leads financiers to increase margins, worsening the speculator's capital problem. Similarly, in a "loss spiral" stock price drops will lead to losses in speculators positions, reducing their capital and causing them to reduce liquidity, resulting in further price declines. In fact, the total effect of a loss spiral coupled with a margin spiral can be larger than the sum of their separate effects. These spirals can be started by shocks to liquidity demand, fundamentals or volatility and, because the effects are compounded by the spirals, they will be incremental to the general level of liquidity volatility.[16] These effects will be particularly pronounced for assets with greater uncertainty about fundamental value, leading to our second hypothesis:

H2: *The lower is firm-level transparency, the more frequent are extreme illiquidity events.*

Variability of liquidity would be less of an issue if liquidity changes were uncorrelated across securities. However, as BP (2009) points out, funding shocks will generally be correlated across investors, causing comovement in liquidity across assets. Assets with greater uncertainty will be more sensitive to shocks, leading to our third hypothesis:

H3: *The lower is firm-level transparency, the greater is the covariability of firm-level liquidity with market liquidity.*

BP (2009) further notes that speculators are, on average, net long in the market and thus their funding capital tends to drop during market downturns. Therefore, the liquidity they provide

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Liquidity variability then creates uncertainty for investors because they are unsure how large a discount to expect when they need to sell.

[16] Similar results obtain in Morris and Shin (2004) where market selling can feed on itself, forming "liquidity black holes."

tends to covary with market returns, particularly for assets with greater uncertainty, leading to our fourth hypothesis:

> ***H4:*** *The lower is firm-level transparency, the greater is the covariability of firm-level liquidity with market returns.*

BP (2009) also highlights the fact that, because liquidity is particularly sensitive to uncertainty when speculator capital is low and uncertainty is high, liquidity variability, extreme illiquidity and liquidity covariances are expected to be particularly pronounced during sharp market downturns, leading to the following hypothesis:

> ***H5:*** *Firm-level liquidity is most important to liquidity variability, extreme illiquidity and the covariation of firm-level liquidity with both market liquidity and market returns following sharp market downturns.*

Finally, to the extent that investors are less willing to invest in stocks with high liquidity volatility, more frequent periods of extreme illiquidity and higher correlation between firm-level liquidity and both market liquidity and market returns, the share prices for those companies should be correspondingly lower.

> ***H6:*** *Tobin's Q is negatively related to the variability of liquidity, the frequency of extreme illiquidity events, the covariation between firm-level liquidity and market liquidity and the covariation between firm-level liquidity and market returns.*

3. Research Design and Data

3.1 Research Design

Our hypotheses center on the relation between transparency and liquidity variability and co-variability. Because transparency is inherently difficult to measure, we consider several measures, following Lang et al. (2009).

Our first transparency variable assesses the degree to which a firm engages in discretionary earnings management. Following the procedure discussed in Lang et al. (2009), we combine two commonly used measures of earnings management: variability of net income relative to cash flows and correlation between accruals and cash flows (e.g., Leuz et al. (2003) and Barth et al. (2008)). The underlying argument is that earnings management is manifested in the use of accruals to smooth out fluctuations in underlying cash flows. However, there are clearly nondiscretionary components to earnings smoothness. Therefore, following the discretionary accruals literature (e.g., Jones (1991)), we first regress out a set of fundamental determinants of earnings smoothness, including controls for: the log of total assets, leverage, book value relative to market value, the volatility of sales, the frequency of accounting losses, the length of the firm's operating cycle, sales growth, operating leverage, average cash flows from operations, year fixed effects and industry fixed effects. We use the resulting residuals to form our measure of discretionary earnings smoothness. This measure, *DIS_SMTHC*, is predicted to be indicative of greater earnings management and associated with greater opacity.[17]

Second, we consider the quality of the auditor. The informativeness of accounting data is likely to be higher if such data are audited by an affiliate of a global accounting firm, so we include an indicator variable, *BIG5*, if a firm's auditor is affiliated with a Big-5 audit firm (Francis (2004) and Fan and Wong (2005)).[18]

Third, we consider accounting standards. Prior research such as Barth et al. (2008) and Bradshaw and Miller (2008) suggests that accounting quality is generally higher for firms reporting under IFRS or U.S. GAAP, so we expect greater transparency for firms that use non-local accounting standards. However, research such as Daske et al. (2009) and Lang et al. (2009)

[17] While earnings management is, by its very nature, difficult to measure, prior research demonstrates that earnings smoothing behaves empirically as though it reflects earnings management in the sense that it is lower for firms in countries with better investor protection and a weaker link between tax and financial reporting, and in firms with higher analyst following and a Big-5 auditor that report under IFRS or U.S. GAAP in their local accounts and trade in the U.S., particularly if they trade on a U.S. exchange (Lang et al. (2009)). Similar conclusions follow from Leuz et al. (2003), Barth et al. (2008) and Bradshaw and Miller (2008). Further, firms with less evidence of earnings management tend to have greater liquidity and lower cost of capital (Lang et al. (2009)).

[18] Our auditor variable is admittedly crude because the extent of oversight by the "parent" audit firm may vary across environments. However, we are unaware of feasible empirical approaches to measure the strength of those relations for our sample firms.

suggests that the benefits of voluntary adoption of IFRS only obtain for firms that seriously adopt IFRS rather than simply 'adopting a label' of international accounting standards. Accordingly, following Lang et al. (2009), we define serious adopters (*INTGAAP* = 1) to be adopting firms which were either mandated to adopt an international GAAP or are voluntary adopters with values in the remaining transparency variables above the sample level median.[19]

Additional transparency variables, other than those related to accounting choices, are likely to be important determinates of a market participant's ability to understand underlying firm value as well. As argued in papers such as Roulstone (2003), analysts are important information intermediaries who gather and aggregate information, increasing firm-level transparency. Moreover, Lang et al. (2004) argue that, in an international setting, analysts are likely to play a particularly important oversight and information processing role. We therefore include *ANALYST*, the number of analysts forecasting the firm's earnings, as an additional measure of transparency.

In addition to the number of analysts following a firm, the accuracy of their forecasts is likely a function of the transparency of the firm's information environment, including both the effects of analyst private information acquisition as well as firms' disclosure policies. To the extent that there is more transparency in a firm's information environment, analyst forecasts should be more accurate. Following Lang and Lundholm (1996), we measure forecast accuracy after controlling for the size of the earnings surprise and bias during the period. Thus, our *ACCURACY* measure captures, for a given magnitude of earnings surprise and bias, the extent to which analysts were able to forecast earnings.

In models testing our first hypothesis, we measure the volatility of a firm's liquidity, *LIQVOL,* as the monthly standard deviation of the Amihud (2002) price impact of trade measure (*ILLIQ*). The Amihud (2002) price impact of trade measure is based on a notion of liquidity similar to that espoused in Kyle (1985) and is intended to capture the ability (or inability) of an investor to trade in a stock without affecting its price. This is consistent with the notion in BP (2009) that a

[19] The notion is that firms with large auditors, a large and accurate analyst following, and less evidence of earnings smoothing are more likely to adopt international accounting standards in substance rather than in form only. Results are similar if we include all IFRS and U.S. GAAP adoptions.

stock's liquidity is based on "the ease with which it can be traded" as reflected in the extent of price pressure associated with buying and selling. A liquid market is one in which investors can trade while having a minimal effect on price.

We calculate *ILLIQ* as the average price impact over the month, where price impact is defined as:

$$\frac{\left|R_{i,d}\right|}{P_{i,d}VO_{i,d}} \tag{1}$$

where $R_{i,d}$ is the daily percentage price change, $P_{i,d}$ is price in \$U.S., and $VO_{i,d}$ is the trading volume for stock *i* on day *d* (measured in thousands). Higher values of *ILLIQ* indicate a stock that is more illiquid. Following prior research (e.g. Daske et al. (2008)) we exclude zero-return days from the calculation of the monthly averages to avoid the misclassification of days with no trading activity. We collect all daily price and volume data from Datastream. The resulting measure has the intuitive interpretation of being an estimate of the price impact which would be associated with buying or selling a thousand dollars worth of stock in a given day.

Our second hypothesis is that lower firm-level transparency leads to more frequent extreme illiquidity events. We use two measures of extreme illiquidity events: liquidity skewness and the probability that a firm experiences a "liquidity black hole."[20] To measure liquidity skewness we take the monthly skewness of our price impact of trade measure (*ILLIQ*). The notion is that, for firms with more frequent illiquidity events, the illiquidity distribution will be more positively skewed. Our second proxy for the frequency of extreme illiquidity events, *PROB_LBH*, is intended to capture the frequency with which a firm experiences an extreme increase in the cost of trading its shares, or a "liquidity black hole." We define a liquidity black hole as a trading day (or series of trading days) when a firm's Amihud (2002) price impact of trade measure (*ILLIQ*) is more than 50 times the country-level median. *PROB_LBH* is then defined as the percentage of

[20] As discussed in more detail later, while these two liquidity variables are clearly related, results for each are robust to controls for the other, suggesting that they capture related, but incremental, effects.

trading days in the month during which a firm experiences an extreme illiquidity event.[21] Since *PROB_LBH* is bounded by zero and one, it is not suitable for use as a dependent variable in our OLS regressions; therefore we use the log transformation of *PROB_LBH* in tests of our primary hypotheses.

Our third and fourth hypotheses are that firms with lower levels of transparency will experience greater covariability of liquidity with both market liquidity and market returns. To capture a stock's level of these two types of covariability we use two measures, *LIQCOV1* and *LIQCOV2*. These measures are based on a long line of literature (e.g. Roll (1988) and Morck et al. (2000)) which use the R^2 from a regression of individual stock returns on the market return as a measure of the extent to which firms' stock prices co-move within a country. We follow this approach to measure the commonality of firm liquidity and market liquidity (*LIQCOV1*) as well as firm liquidity and market returns (*LIQCOV2*).

More specifically, to construct a monthly time-series of *LIQCOV1* for tests of our third hypothesis, we use the R^2 from the following regression (run by firm and month):

$$\%\Delta ILLIQ_{i,d} = \alpha_i + \beta_{i,1}\%\Delta ILLIQ_{m,d-1} + \beta_{i,2}\%\Delta ILLIQ_{m,d} + \beta_{i,3}\%\Delta ILLIQ_{m,d+1} + \varepsilon_{i,d} \qquad (2)$$

where $\%\Delta ILLIQ_{i,d}$ is equal to the daily percentage change in *ILLIQ* for firm *i* on day *d* and $\%\Delta ILLIQ_{m,d}$ is equal to the daily percentage change in *ILLIQ* for the market on day *d*. We define market illiquidity at the country-level as the daily equal-weighted average *ILLIQ* of the individual stocks on a given day. Following prior literature, we take the percentage change to capture innovations in illiquidity (e.g. Hameed et al. (2010)) and include one-day leading and lagging changes in market illiquidity to account for nonsynchronous trading (e.g. Jin and Myers (2006)). We require a minimum of 10 daily observations to estimate a firm-month R^2 and a minimum of 10 firms to estimate the daily country-level average *ILLIQ*. Again, because *LIQCOV1* is bounded by zero and one, we use the log transformation in all regression analyses.

[21] Since we are unaware of other papers that attempt to define extreme illiquidity events, our choice of cutoff is admittedly arbitrary. For robustness, we also use cutoffs based on firm-level standard deviations of liquidity and absolute return cutoffs with very similar results, as discussed later.

To construct the monthly time-series of *LIQCOV2* for tests of our fourth hypothesis we follow procedures similar to those used in constructing *LIQCOV1* and take the R^2 from the following regression (run by firm and month):

$$\%\Delta ILLIQ_{i,d} = \alpha_i + \beta_{i,1}MKTRET_{m,d-1} + \beta_{i,2}MKTRET_{m,d} + \beta_{i,3}MKTRET_{m,d+1} + \varepsilon_{i,d} \quad (3)$$

where $\%\Delta ILLIQ_{i,d}$ is calculated as defined above and $MKTRET_{m,d}$ is equal to the daily country-level market return. All country-level market returns are obtained from Datastream.

Our fifth hypothesis is that firm-level transparency is most important to liquidity variability, extreme illiquidity and liquidity covariances following sudden large market downturns. To capture large market downturns, we use a country-month level indicator variable (*MKTDOWN_BIG*) which is equal to one if, in the prior month, the country's stock market fell by more than one and a half times its average historical standard deviation. To capture the incremental importance of transparency to our liquidity uncertainty proxies during a 'crisis period' we interact our aggregate transparency variable (*TRANS*) with the market downturn indicator (*MKTDOWN_BIG*).[22]

Models used in testing H1 through H6 include controls for market value of equity (*SIZE*), book to market (*BM*) and return variability (*STDRET*) following prior literature (e.g. Stoll (2000)). To ensure our results are attributable to the variability of liquidity, as opposed to its level, we include in all models a control for the firm's average level of liquidity (*AILLIQ*). We further include indicator variables for whether the stock trades in the U.S., either on an exchange (*ADR_EX*) or on the OTC or PORTAL markets (*ADR_NEX*). We include controls for U.S. listing because the turnover measures we use in computing illiquidity reflect only the local market and may be affected by whether or not a firm also has a foreign listing. Similarly, we include a control for the proportion of the firm's shares that are closely-held (*CLHLD*) because

[22] As discussed later, we consider various other "crisis" cutoffs as well with very similar results.

closely-held shares are typically not available to be traded and may affect a firm's overall liquidity.

Our final hypothesis is that each of our liquidity measures of interest (liquidity variability, liquidity skewness, the frequency of extreme illiquidity events, the covariation between firm-level liquidity and market liquidity, and the covariation between firm-level liquidity and market returns) is negatively related to Tobin's Q. Following the prior literature, such as Tobin (1969) and Claessens et al. (2002), Tobin's Q (*Q*) is defined as: (book value of assets + (market value of equity – book value of equity))/book value of assets. It is designed to reflect the valuation placed on the assets by the market relative to their book value and inherently incorporates the cost of capital used by the market in discounting future cash flows. In regressions where *Q* is the dependent variables we include the following controls suggested by prior literature (e.g. Claessens et al. (2002)) and further described, either previously, or in the Appendix: *AILLIQ*, *SIZE*, *LEV*, *CASH_TA*, *NIEX_TA*, *ADR_EX*, and *ADR_NEX*.

Finally, for our main specifications, we include country and year fixed effects. While transparency likely differs across countries, market microstructure does as well, so country fixed effects are potentially important. Year fixed effects should mitigate the influence of changes in overall macroeconomic conditions.

3.2 Data

Accounting and market data are collected from Datastream Advance (a collaboration of market statistics from Datastream and accounting data from WorldScope) over the 1996-2008 time period. We require firm-year observations to have the necessary income statement and balance sheet data to calculate our transparency and primary control variables and to have sufficient market data to calculate the Amihud (2002) price impact of trade measure (*ILLIQ*). We exclude any country with less than 1,000 firm-month observations. In total, our sample contains 424,808 firm-month observations from 35 countries.

Table 1 reports the country representation for our sample firms. The firms in our sample represent a wide range of transparency, liquidity and general economic circumstances. To the extent that there is clustering, it is in Japan, reflecting the availability of volume data.[23]

Table 2 provides descriptive statistics for our sample firms. As would be expected, the sample firms are medium-sized on average, with a market value of equity around $260 million, and range from extremely large to much smaller firms. The median firm is covered by two analysts, with a mean of four analysts. Of the sample firms, 28.2% have Big-5 auditors, 14.3% follow a non-local GAAP and 5.2% trade ADRs, of which 1.4% are exchange-traded. The average firm has about 30% concentrated ownership and a book-to-market ratio of 0.84, indicating that, on average, market capitalization exceeds book value of equity.

Table 3 provides a correlation matrix between our primary independent variables of interest. The correlations between the liquidity covariance measures and our other liquidity variables are generally very low, suggesting that liquidity covariances are largely independent of our other variables. Among the other variables, the highest correlation is between *LIQVOL* and *PROB_LBH* (0.51 Spearman, 0.35 Pearson). As discussed later, results are robust to including the other variables as controls in the analysis of each of our primary variables, suggesting that each variable captures a different underlying economic construct.

4. Empirical Results

4.1 Transparency and Liquidity Volatility

In our initial analysis, we investigate the relation between liquidity volatility and transparency. Before turning to the formal empirical analysis, Figure 1 provides an illustration of the time-series behavior of liquidity volatility. Here, we divide the sample based on firms with above the sample median transparency (*HTRANS*) and those with transparency below the median (*LTRANS*). We have also included controls from our primary analysis (liquidity, size, book-to-

[23] As discussed later, results are not sensitive to excluding Japan (or any other country) or limiting its representation in the sample. Similarly, results are consistent if the U.S. is included in the sample, either in total or on a limited basis.

market, return variability, ownership structure and ADR listing) to enhance comparability across the transparency partitions.

Several points are worth noting, each of which is consistent with our hypotheses. First, liquidity volatility is variable, consistent with the notion in BP (2009) that exogenous shocks create variability in liquidity, and those shocks vary over time. Second, the volatility of liquidity is, on average, lower for more transparent stocks. Third, during periods of relative calm, the volatility of liquidity is low and more similar irrespective of firm-level transparency. However, during crisis periods, when uncertainty increases, volatility of liquidity increases as well, but particularly for the most opaque firms. In particular, there are five clear spikes on the graph—the Asian Financial Crisis in 1997, the Long-term Capital Management crisis in 1998, September 11, 2001, the bankruptcy of WorldCom, the end of the dot-com boom in 2002 and the beginning of the current financial crisis in 2008. This pattern is consistent with the notion in BP (2009) and Vayanos (2004) that uncertainty about intrinsic value and, therefore, transparency is less of an issue during periods in which markets are calm and trader capital and funding liquidity are high, but becomes much more of an issue during crisis periods when trader capital and funding liquidity are more limited and economic uncertainty is elevated.

Table 4 reports the results for liquidity volatility and transparency more formally. In terms of control variables, liquidity variability tends to be higher for firms that are small, illiquid and closely held. These results for the control variables are generally as expected because, for example, BP (2009) suggests that it will be assets with relatively greater uncertainty about intrinsic value and greater illiquidity for which the effects of exogenous shocks will be most pronounced in terms of liquidity variability and covariability. All analyses are with country and year fixed effects (coefficients not reported), and standard errors that are clustered at the firm level.[24]

[24] R^2 s are lower than they otherwise would be because we measure our liquidity variables monthly, but measure transparency and our other independent variables annually (i.e., the dependent variables fluctuate while the independent variables are constant). We measure liquidity monthly for comparability with our later tests in which crises are measured monthly. As discussed later, results are consistent if we measure our liquidity variables based on annual averages, but R^2 s are two to five times larger, depending on the specification.

In terms of our primary relations of interest, each of our transparency variables is correlated with liquidity volatility, consistent with expectations. In particular, liquidity is more volatile when transparency is likely to be lower as reflected in more evidence of earnings management, use of a small auditor and reliance on local accounting standards. Of course, the transparency variables are unlikely to be independent of each other (e.g., high quality auditors and non-local accounting standards likely affect the ability to manage earnings). For parsimony going forward, we combine these three variables into one variable we refer to as "accounting transparency" (*ACC_TRANS*).[25]

Similarly, liquidity volatility is lower for firms that are followed by more analysts and for whom analyst forecasts are more accurate. Again, for parsimony we combine the analyst forecast variables together going forward into a variable we refer to as "analyst transparency" (*ANALYST_TRANS*).[26] Table 4 also reports a regression including both the accounting transparency and analyst transparency variables. As expected, both are strongly negatively correlated with liquidity volatility.[27]

4.2 Transparency and Extreme Illiquidity Events

In Hypothesis 2, we predict that greater opacity will be associated with more frequent extreme illiquidity events. In particular, BP (2009) notes that, in the face of uncertainty about underlying asset value, liquidity can become extremely sensitive to shocks through two amplification mechanisms: "liquidity spirals" and "margin spirals." In the extreme, liquidity can become "fragile" in the sense that "a small change in fundamentals can lead to a large jump in illiquidity."

As noted earlier, we take two approaches to assess extreme illiquidity events. The first is simply based on the skewness in liquidity. In other words, if a stock tends to have a large number of

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[25] Including the three earnings transparency variables together in the regression, the three earnings transparency variables maintain their sign, but the discretionary smoothing variable becomes insignificant (p-value of 0.13).

[26] Including both analyst variables together with the other transparency variables, both analyst variables remain statistically significant and negative.

[27] Admittedly, the split and aggregation of the transparency variables are somewhat arbitrary. A factor analysis also suggests a similar breakdown, with similar results.

extreme illiquidity events, the distribution of liquidity will exhibit more skewness toward extreme illiquidity. A second approach is to look specifically for extreme illiquidity events. Although the magnitude of "extreme" is not well defined, we choose a cutoff of 50 times normal trading costs for the firm's country during a particular year. In other words, if a stock is more than 50 times as expensive to transact as the median cost for that country-year, then we view that as a day of extreme illiquidity.[28] To provide an illustration, our mean illiquidity measure is 0.389, implying that a one million dollar block of stock sale would decrease share price by 0.39%.[29] An extreme illiquidity event would then be defined as one in which the stock price decrease associated with the sale of one million dollars would be 19.35%. Clearly, the potential to have to liquidate a position under such circumstances would be a troubling risk for most investors.

Table 5 reports results relating transparency to liquidity skewness and extreme illiquidity events. In terms of control variables, for both specifications, extreme illiquidity tends to be more pronounced for smaller firms with higher book-to-market ratios and lower liquidity that are more closely held. Results for the other control variables differ based on the specification.

In terms of our primary variables of interest, transparency is strongly associated with liquidity skewness controlling for other factors. Both *ACC_TRANS* and *ANALYST_TRANS* are negatively correlated with *LIQSKEW*, suggesting that extreme liquidity events are less common for more transparent firms. Conclusions are similar for the "liquidity black hole" variable, with both accounting transparency and analyst transparency significantly negatively related to *PROB_LBH*, suggesting again that extreme illiquidity events are less common for high transparency firms after controlling for a range of other factors. In separate calculations, we find that an opaque firm is approximately twice as likely to experience an extreme illiquidity event as a transparent firm, all else equal.[30]

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[28] This cutoff is somewhat arbitrary, but is designed to capture cases in which trading becomes substantially more expensive than is normal for a given country. Results are very similar when extreme events are defined relative to the median for the firm or are defined using cutoffs based on the distribution of liquidity (e.g., two or three standard deviations from the mean).

[29] Note that *AILLIQ* has been multiplied by 1,000 for readability.

[30] As discussed in more detail later, the results for *LIQSKEW* are robust to controlling for *PROB_LBH* and vice versa, suggesting that, while both variables are related to the probability of extreme illiquidity events, neither subsumes the other.

4.3 Transparency and Liquidity Commonality

The preceding results are informative about the general variability of liquidity and incidence of extreme illiquidity as a function of transparency. However, the earlier discussion suggests that transparency also has the potential to affect the covariability of firm-level liquidity with market liquidity and market returns. This is particularly important because Acharya and Pedersen (2005) suggest that the covariance of firm-level liquidity with market liquidity and with market returns are a component of the CAPM beta and are, therefore, positively correlated with cost of capital. The model in BP (2009) suggests that liquidity covariances should be stronger for stocks about which there is more uncertainty about intrinsic value because it is for these stocks that the shocks that cause liquidity comovement are most pronounced. In other words, if overall funding liquidity dries up, that will cause firm liquidity to co-move with market liquidity because liquidity will dry up simultaneously across many shares. However, the effect will be most pronounced for the shares with the most uncertainty about intrinsic value since those shares tie up more of speculators' now-scarce capital. Similarly, as stock prices drop, speculator capital will drop, causing speculators to withdraw liquidity particularly from the shares with the greatest uncertainty, causing higher covariability of liquidity in those shares with the overall market return.

Table 6 presents results on the covariability of firm-level liquidity with market liquidity and with market returns. In terms of control variables, across both specifications liquidity covariability tends to be higher for less liquid stocks, consistent with BP (2009). Liquidity covariability tends to be higher for closely-held stocks, perhaps reflecting the fact that the smaller free float exacerbates liquidity sensitivity. Other control variables tend to be insignificant or differ based on the specification.

In terms of our primary variables of interest, as predicted, the covariance of firm-level liquidity with market liquidity tends to be significantly lower when firms are more transparent, both with respect to accounting transparency and analyst transparency. In other words, more transparent firms are less likely to have substantial reductions in liquidity at the same time that liquidity is low for other firms in the market. This is likely to be particularly important to investors because they value liquidity in a given stock more highly when other stocks in their portfolio have become illiquid.[31]

For the relation between firm-level liquidity and market returns, *ANALYST_TRANS* is negatively correlated with the *LIQCOV2* (although *ACC_TRANS* is insignificant).[32] Again, this suggests that more transparent firms are less likely to experience illiquidity at times when investors are more likely to want to sell shares (during market downturns when speculator capital tends to be low). The fact that liquidity holds up well throughout the business cycle is likely to be of value to, for example, money managers because it means they can cheaply open and close positions as their investors add to and withdraw assets from equity funds. Further, to the extent liquidity is less cyclical, it can reduce the firm's CAPM beta because the effect of liquidity on price movements during bull and bear markets is mitigated (Acharya and Pedersen (2005)).

4.4 Robustness

The preceding sections discuss a variety of robustness tests applying alternative variable definitions and specifications to our primary analyses. Overall, our results are robust to a wide range of alternative specifications. In this section, we discuss in more detail the results of several untabulated robustness tests designed to increase confidence in the interpretation of our results.

First, because it represents such a significant portion of our sample, and thus threatens the generalizability of our results, we repeat our analyses limiting Japanese firms to 10% of our sample, and eliminating Japanese firms from our sample entirely. Our inferences are robust to limiting or excluding Japanese firms. Moreover, our inferences are robust to limiting or

[31] As noted earlier, the modest R^2 here reflects the fact that our dependent variables are measured monthly while our independent variables are measured annually for consistency with later analysis. Annualizing the liquidity variables increases the R^2 to 8.4%. Prior research (e.g., Hameed et al. (2010)) does not report R^2's, so it is difficult to benchmark this result. However, combining the coefficient estimates with the descriptive statistics, the results suggest that an interquartile shift in transparency from the 1st to the 3rd quartile is associated with a .057 shift in the covariance, which represents a 37% increase. Further, later results in crisis periods are substantially stronger, suggesting that the economic implications are potentially substantial.

[32] Although accounting transparency is insignificant for the sample as a whole, an untabulated analysis suggests that, focusing on large market downturns (when the effect of transparency should be strongest), accounting transparency is significantly negatively correlated with comovement as predicted.

excluding any other country in our sample. As a result, it does not appear that Japan, or any other country, has undue influence on our conclusions.

Second, we repeat our analyses including firms from the United States. As noted earlier, we excluded these firms from our primary analyses because they tend to be relatively homogenous in terms of transparency and liquidity, and exhibit limited variability on several of our explanatory variables (e.g., accounting standards, large auditor and earnings smoothing). In addition, if included, the number of firm-months from the U.S. would comprise nearly 40% of the total sample and, thus, potentially limit the generalizability of our results. However, a replication of our analyses including the entire population of U.S. firms confirms that all of our primary inferences are robust to the inclusion of these firms.[33]

Third, a potential concern is that each of the variability and covariability measures may be capturing the same underlying economic construct. We do not believe that is a significant issue because the correlations among the constructs are generally fairly low. However, to ensure that our results are incremental across constructs, we repeat each of the analyses including the other four liquidity uncertainty variables as controls. Results are robust to inclusion of the other variables, either individually or as a group, indicating that each of our dependent variables of interest is separable from the other variables. Interestingly, as mentioned earlier, the liquidity skewness results are significant controlling for our liquidity black holes variable and vice versa, indicating that the two variables capture different aspects of illiquidity. As noted earlier, results are also robust to controlling for the correlation between firm-level returns and market liquidity discussed in Pastor and Stambaugh (2003) and Ng (2009).

Fourth, we consider lagged transparency variables. In our primary analysis transparency is measured contemporaneously with our liquidity variables creating the possibility of reverse causality (although that is unlikely given that our liquidity variables are measured over a month but transparency is measured over a year). Results are robust to replicating the analysis using

[33] The only change to our primary results is that the earnings smoothing variable in Table 4 retains its sign but becomes marginally insignificant. We also repeated the analyses including only a random sampling of U.S. firms not permitting any country to exceed 10% of the entire sample. Inferences for all of our primary analyses remained consistent with those reported for all variables.

lagged transparency variables. Similarly, results are robust to re-estimating the relation after annualizing the liquidity variables by taking the average over the year.

Fifth, we consider several other fixed effects. Our primary analyses include country and year fixed effects and firm clustering, but it is possible that other factors could be important. For example, because liquidity might be correlated with calendar month, we include indicator variables for each month with very similar conclusions. Alternatively, liquidity might be correlated with a firm's industry because, for example, of the effects of differences in business models. Results are robust to inclusion of industry fixed effects.

We also consider firm fixed effects. Firm effects are potentially problematic in this setting, particularly for the accounting variables, because auditor and accounting standards do not change during the sample period for the majority of our firms, and, because the earnings smoothing variable must be calculated over multiple years, it only changes very slowly. Nonetheless, to provide some additional assurance that our results do not reflect reverse causality or omitted correlated variables, we replicate our analyses including firm fixed effects. Using the aggregate transparency variable and annualized liquidity variables, we find that results are consistent with our primary analysis for each of our five liquidity variables when firm fixed effects are included. Splitting the transparency variable into its two components, results are consistent with those in our primary specifications across all liquidity variables for analyst transparency and, for accounting transparency, are consistent for all liquidity variables except for liquidity black holes, where the relation is negative but insignificant.

Finally, to provide further assurance that our results do not reflect the effects of endogeneity, we explicitly model transparency and liquidity variability in a two-stage least squares framework. Following prior research such as Roulstone (2003) and Yu (2008), our primary concern is that the analyst following component of transparency may be endogenously determined based on investor demand for information.[34] We follow Roulstone (2003) and Yu (2008), in modeling

[34] The argument with respect to analyst following could be in either direction. First, analysts may be attracted to firms with liquidity volatility because the liquidity changes tend to move prices away from fundamentals and provide opportunities for profitable trade, which would bias against our findings. Alternatively, analysts may avoid firms where future liquidity is expected to be volatile because investors prefer not to invest in those stocks, which

determinants of transparency. In our two-stage least squares analysis (not tabulated for brevity), we estimate a first-stage model which features transparency (*TRANS*) as a function of two sets of variables: potentially endogenous variables (*AILLIQ, SIZE, BM, STDRET, CLHLD, ADR_EX,* and *ADR_NEX*), and those suggested by research such as Lang and Lundholm (1996), Roulstone (2003), and Yu (2008) which can be used as instruments for transparency (return-earnings correlation and asset growth, computed over the prior three to five year window, and one-year lagged return on assets). Our second-stage (structural) model uses the same independent variables as the liquidity volatility equations of Table 4, with our liquidity volatility measure, *LIQVOL*, as the dependent variable. Analysis of the first stage suggests that our instruments are significantly related to transparency and the Cragg-Donald statistic indicates that we do not suffer from weak instruments (see Stock and Yogo (2005)). Results from the structural model are consistent with those reported earlier in that transparency remains significantly negatively correlated with liquidity volatility. We repeat this analysis for our other measures of liquidity variability (*Extreme Illiquidity*, *LIQCOV1* and *LIQCOV2*) with similar results. Results are also consistent if we instrument separately for *ANALYST_TRANS* instead of the aggregate *TRANS* variable, and if we exclude analyst following from our transparency measure entirely.

4.5 Transparency, Liquidity and Crises

To this point, we have implicitly assumed that the relation between transparency and liquidity variability and covariability is invariant to the stage in the economic cycle. However, in BP (2009) the effect of transparency should be substantially more pronounced during sharp market downturns. Intuitively, when the market drops suddenly, speculators' capital tends to drop, limiting their ability to take positions, especially in high-capital stocks. In addition, overall uncertainty tends to increase during sharp downturns. Together, both effects will tend to increase the sensitivity of liquidity to funding shocks and, hence, the potential importance of transparency during crises. As discussed earlier, the descriptive evidence in Figure 1 strongly

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could bias in favor of our results. It is more difficult to make an analogous argument for our other measures of transparency because that would imply that firms, faced with the possibility of volatile liquidity would reduce transparency by choosing lower quality auditors and accounting standards, and increasing earnings management.

supports the notion that liquidity volatility increases substantially during crisis periods, especially for less transparent firms.

Table 7, Panel A, Column (1), presents results from the analysis of liquidity volatility with an interaction term for large market downturns. Several points are worth noting. First, the indicator variable for large market downturns is positive and strongly significant suggesting that, consistent with the predictions in BP (2009) and with Figure 1, large downturns are associated with greater liquidity volatility reflecting the reduction in speculator capital and increased uncertainty. Second, the coefficient on transparency remains strongly negative, confirming that transparency is associated with reduced liquidity volatility on average. Third, and most importantly, the coefficient on the interaction between transparency and the market downturn indicator is negative and very strong, suggesting that transparency is much more important in mitigating liquidity volatility during down markets. In particular, the coefficient on the interaction is larger than the coefficient on the un-interacted transparency variable, suggesting that transparency is more than twice as important in reducing liquidity volatility during crisis periods. This finding is generally consistent with the implications of BP (2009), which suggests that liquid assets with less uncertainty about underlying firm value will be much less affected by general liquidity shocks.

Finally, the fact that the effects are strongest for crisis periods provides some comfort that our overall results do not reflect omitted correlated variables. For example, one might conjecture that liquidity volatility is somehow capturing a variable that is not included in the regression and is correlated with transparency. However, for that to be the case the effect of the omitted variable would need to both be correlated with transparency and the strength of that relation would need to change substantially during market downturns. While it is possible that that might occur, it is more difficult to envision a variable with those features. Similarly, it reduces the likelihood that our results reflect reverse causality because the market downturn shock is exogenous to the firm and the liquidity volatility is measured over a month-long window, while the transparency measures are over the year. As a result, it is unlikely that the stronger relation between liquidity volatility and transparency during crisis months is driven by decreases in transparency for firms that suddenly experience increased liquidity volatility.

Another implication of BP (2009) is that the effect of the level of uncertainty about intrinsic firm value and, hence, transparency, should be substantially larger the greater is the market downturn because the effect of speculator capital on liquidity provision is nonlinear. In Table 7, Panel A, Column 2, we divide our crisis variable into two pieces, smaller downturns (monthly downturns of more than 1.5 standard deviations from the mean for the country) and larger downturns (monthly downturns of more than 2.5 standard deviations). Based on the descriptive evidence from Tables 1 and 2, our smaller downturns involve a monthly negative stock return of 9.5% on average, ranging from 6% for the United Kingdom to 20% for Turkey, while our larger downturns average 15%, ranging from 10% for the United Kingdom to 33% for Turkey.[35] Put another way, smaller downturns comprise 6.4% of sample months, while large downturns comprise only 1.2%.

Results, reported in Table 7, panel A, Column (2), indicate that, as predicted, liquidity volatility increases substantially the more extreme is the downturn. More importantly, the interaction between the downturn and transparency variables is clearly stronger the greater is the downturn, with the coefficient on the large downturn indicator more than three times the size of the coefficient on the smaller downturn indicator variable.[36] In other words, the greater is the crisis, the greater is the increase in liquidity volatility, and the greater is the mitigating effect of transparency on liquidity volatility. This result is very consistent with the graph of liquidity volatility in Figure 1, where both high and low transparency stocks experience large increases in liquidity volatility during market downturns, but the effect is substantially mitigated for more transparent firms.

Very similar results hold for extreme illiquidity events, as measured by liquidity skewness, reported in Table 7, Panel B, Column (1). In particular, large down markets increase the skewness of liquidity, consistent with the notion that liquidity becomes more skewed toward extreme illiquidity during market downturns. Further, transparency remains significantly

[35] We chose to define our crisis events relative to country averages because a given size downturn is less likely to be viewed as representing a crisis for a country in which returns are typically more volatile. However, results are very similar if we impose the same criterion (in terms of a return magnitude) for downturns across countries.

[36] An F-test of the difference between the *MKTDOWN_BIG1*TRANS* and *MKTDOWN_BIG2*TRANS* coefficients indicates that the coefficients are significantly different from one another (p-value of .00).

negative suggesting that, consistent with the prior results, skewness in liquidity is less pronounced for more transparent firms. Most importantly, the interaction between the market downturn and skewness is significantly positive suggesting that transparency is particularly important to skewness in crisis periods, with the coefficient estimate suggesting that transparency is more than twice as important during crisis periods relative to non-crisis periods. Further, splitting by size of the down market in Table 7, Panel B, Column (2), transparency is nearly four times as important to skewness in large down markets relative to smaller down markets, suggesting that transparency is particularly important during more extreme crises.

Similar conclusions hold for the incidence of extreme illiquidity events reported in Table 7, Panel B, Columns (3) and (4). Extreme illiquidity events increase in frequency during strong market downturns and, as before, transparency is negatively correlated with the frequency of extreme illiquidity events. More importantly, the interaction between transparency and market downturns is significantly negative, suggesting that transparency is more important to the frequency of extreme illiquidity events during crisis periods. Further, the relation is much stronger for larger downturns relative to smaller downturns. More specifically, for the average firm, a market downturn of between 1.5 and 2.5 standard deviations makes the probability of experiencing a liquidity black hole almost two and a half times as likely as in a normal period. A larger downturn, greater than 2.5 standard deviations, increases the probability of an extreme illiquidity event more than tenfold. However, these increases in extreme illiquidity events are significantly less pronounced for high transparency firms, with the probability of experiencing an extreme illiquidity event during a market downturn of between 1.5 and 2.5 standard deviations increasing by only about 30% as much for a transparent firm relative to an opaque firm and by only 25% as much for a transparent firm relative to an opaque firm during a larger market downturn.

In Table 7 Panel C, Columns (1) and (2), we present results for the covariability of firm-level liquidity with market liquidity. Conclusions are consistent with expectations and with results for liquidity volatility, skewness and extreme illiquidity events. We predict that comovement in liquidity will increase during sharp downturns, especially for high uncertainty stocks, because speculators will be forced to withdraw liquidity from capital-intensive positions, causing waves of illiquidity concentrated in opaque stocks. Several points are worth noting from the table. First, when the market drops, liquidity covariability increases dramatically, consistent with predictions from BP (2009) and with empirical evidence for U.S. firms in Hameed et al. (2010). Second, as before, transparency is associated with lower liquidity covariability in general. Third, and most important, the effect of large market downturns on liquidity covariance is substantially mitigated in the presence of greater transparency. The coefficient on transparency interacted with the market downturn indicator suggests that transparency is more than three times as important during downturns relative to other periods.

Again, the effect becomes even more dramatic when we focus on particularly large downturns. In particular, the interaction coefficient between *MKTDOWN_BIG* and *TRANS* is more than two times as large during larger downturns relative to smaller downturns. Overall, the results are strongly consistent with expectations and indicate that firm-level liquidity holds up much better relative to market-wide liquidity for stocks that are more transparent, especially during major crises.

In addition, we report results for the effect of crises on the covariability of firm-level liquidity with market returns in Table 7, Panel C, Columns (3) and (4). Again, results overall are consistent with expectations. Recall that the intuition here is that the covariability of firm-level liquidity with market returns increases during downturns because speculators are capital constrained and therefore are more sensitive to market movements. Results indicate that the comovement between firm-level liquidity and market returns tends to increase during market downturns, consistent with predictions from BP (2009) and with empirical evidence for U.S. firms in Hameed et al. (2010). As before, transparency is associated with lower comovement overall. Further, the effect of transparency in mitigating comovement is substantially more pronounced during down markets, with the effect of transparency being more than four times as large during market downturns. However, splitting between large and small downturns, the effects of transparency are not statistically different, inconsistent with the results for the other liquidity variables.[37]

[37] At some level, the limited mitigating effect of transparency for large downturns is not particularly surprising because the covariation between liquidity and market returns does not appear to increase during large downturns

Finally, we examine the effect of downturns on the overall relation between transparency and the CAPM beta. Following the logic to this point and the CAPM disaggregation in Acharya and Pedersen (2005), because downturns decrease speculator capital, they can increase the price pressure associated with trading and, therefore, the CAPM beta. Untabulated results are consistent with those for the covariation of liquidity with market liquidity and market returns. In particular, we find that, as predicted, there is a marked increased in CAPM betas on the whole during downturns, suggesting that firm returns have more of a tendency to move with market returns during a crisis. Second, and of primary interest, the increase in betas around downturns is substantially smaller for more transparent firms. In conjunction with the results from the preceding analyses and BP (2009), an interpretation is that, as speculator capital dries up, firms' returns respond more strongly to macroeconomic conditions because of increased price pressure associated with trading. Transparency, by reducing the liquidity "flight to quality," mitigates that effect. Overall, results are consistent with the notion that transparency effects are substantial enough to be detectable in betas during downturns.

4.6 Liquidity Variation, Covariation and Valuation

Finally, we examine the relation between our measures and Tobin's Q. While the notion that investors prefer stocks that have less liquidity volatility, fewer instances of extreme illiquidity and lower covariability of liquidity with market returns and market liquidity follows theoretically and intuitively, there is less evidence that it matters for valuation in practice. If investors prefer firms with less liquidity variability and co-variability, they should be willing to pay more for shares of those firms.

Table 8 provides evidence on the relation between Q and our liquidity variability and co-variability measures, controlling for variables from the prior literature such as Claessens et al. (2002). In terms of the control for liquidity, across all specifications, illiquidity is negatively

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for our sample, so there is no increased effect for transparency to mitigate. Further, it is difficult to benchmark our results relative to prior research such as Hameed et al. (2010) since they do not examine the effects of extreme market downturns.

correlated with firm value as predicted. However, conditional on liquidity, each of our volatility and covariability measures are separately and incrementally negatively correlated with firm value. In particular, investors appear to be willing to pay more for firms that have lower liquidity variability, lower liquidity skewness, fewer instances of extreme illiquidity, lower covariability with market liquidity and lower covariability with market returns. Again, the fact that each liquidity characteristic is incrementally significant suggests that each one captures a different underlying construct. While the results do not necessarily imply that transparency matters to valuation through its effect on liquidity variation and co-variation, it does, in conjunction with the preceding results, suggest that transparency is associated with lower liquidity volatility, lower liquidity skewness, fewer extreme illiquidity events and lower correlations between firm-level liquidity and market returns, and that each of those variables, in turn, is negatively correlated with valuation.[38]

5. Conclusion

Previous research typically focuses on transparency as a determinant of the average level of liquidity. While average liquidity is clearly important, the variability and covariability of liquidity are also important because what ultimately matters to a potential investor is liquidity when they trade. Transparency has the potential to reduce liquidity variability and covariability to the extent that uncertainty about intrinsic firm value increases the sensitivity of liquidity to economic shocks as in BP (2009). Overall, our results suggest a striking and consistent relation between our measures of transparency and liquidity variance and covariance, consistent with the intuition and with the predictions of theoretical research. In particular, transparency is negatively correlated with liquidity volatility, skewness, likelihood of extreme illiquidity events, and the covariance between firm-level liquidity and market returns and liquidity. Further, the effect of transparency on each of our liquidity variables is more pronounced during market downturns, consistent with transparency mitigating flight to quality during crises. Finally, each of our liquidity measures is negatively correlated with valuation as measured by Tobin's Q.

[38] Results are robust to including our transparency measures in the regression, suggesting that transparency matters to valuation incrementally to its effect on our liquidity variables, consistent with the notion that transparency could, for example, also limit expropriation of assets. However, including transparency significantly reduces the magnitude of our liquidity variables, suggesting that our liquidity variables are a significant path through which transparency affects valuation.

While it is dangerous to draw strong causal implications, taken at face value our results suggest an important channel through which transparency could matter to firm value, based on the variability and covariability of liquidity. The recent financial crisis illustrates the importance of liquidity variability in practice and the ramifications when liquidity dries up. Our results are consistent with the "flight to quality" notion that more transparent stocks are less sensitive to liquidity shocks in general and particularly to the liquidity volatility that accompanies crisis periods.

Of course, our conclusions are subject to caveats. Most importantly, it is always dangerous to draw causal links. It seems unlikely that there is reverse causality here because the liquidity variables are measured over windows which are too short for substantial transparency changes and results are similar based on lagged measures of transparency. Further, the fact that results differ based on the size of the market drop reduces the set of alternative explanations for the results. In particular, our variation, covariation and downturn variables are measured over a month. If, for example, the covariation of liquidity was driven by the covariation of expected cash flows (which happened to be correlated with liquidity), it is hard to see how the expected covariation of cash flows would change radically depending on whether that month's stock return was negative. Further, the facts that we consider a wide range of variables and all of the primary empirical results match our predictions based on the intuition from theoretical research such as Vayanos (2004) and BP (2009) reduce the likelihood that our results are spurious or reflect omitted variables. That said, causal conclusions should be drawn with caution.

In terms of extensions, it would be interesting to delve deeper into the specific causal links. In particular, as an initial analysis of the relation between transparency variability and co-variability, our approach has been fairly broad brush. It would be useful to try to infer specific mechanisms through with changes in disclosure could potentially affect liquidity variation. For example, one of the potential benefits of IFRS may be through reducing liquidity variability and it might be worth specifically examining that relation in more detail. Similarly, we do not attempt to specifically include proxies for funding liquidity in the analysis. An approach which explores in more detail the mechanisms underpinning the relation between funding liquidity and market liquidity would be useful. Finally, it would be interesting to investigate the effects more specifically in terms of a particular crisis. For example, focusing on the recent financial crisis might permit a more focused examination of the causes and consequences of links between transparency and liquidity volatility.

Overall, though, we believe that the results represent a potentially important first step in understanding the potential relation between transparency and liquidity variability and covariability. Also, the results are particularly timely given liquidity concerns generated by the recent economic crisis. Given that money managers clearly view liquidity variation and covariation as major concerns, our results would appear to be particularly relevant to beginning to understand the potential importance of transparency to crises. Our results provide an intuitive link between transparency, flight to quality and liquidity variation.

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Appendix: Variable Definitions

Variable	Definition
ACC_TRANS	= the average scaled percentile rank of the variables: *INTGAAP*, *BIG5*, and (1-*DIS_SMTHC*)
ACCURACY_R	= the residual value from a regression of *ACCURACY* on *SUE* and *BIAS*, where *ACCURACY* is the absolute value of the forecast error multiplied by -1, scaled by the stock price at the end of the prior fiscal year, where the forecast error is the I/B/E/S analysts' mean annual earnings forecast less the actual earnings as reported by I/B/E/S
ADR_EX	= an indicator variable equal to one if the firm trades on a U.S. exchange during the year, and zero otherwise
ADR_NEX	= an indicator variable equal to one if the firm has an ADR but is not traded on a U.S. exchange during the year, and zero otherwise
AILLIQ	= the annual average *ILLIQ*, calculated over the firm's fiscal year
ANALYST	= the number of analysts making a forecast for the firm's year *t* earnings, obtained from the I/B/E/S Summary File
ANALYST_TRANS	= the average scaled percentile rank of the variables: *ANALYST* and *ACCURACY*
BIAS	= the signed value of the forecast error, scaled by stock price at the end of the prior fiscal year, where the forecast error is the I/B/E/S analysts' mean annual earnings forecast less the actual earnings as reported by I/B/E/S
BIG5	= an indicator variable equal to one if the firm is audited by a 'BIG5' auditing firm, and zero otherwise
BM	= the firm's book value of common equity divided by firm's market value of common equity
CASH_TA	= the firm's cash and cash equivalents as of the end of the fiscal year, scaled by the firm's total assets
CLHLD	= the average proportion of the firm's shares that are closely held as of the end of year *t* as reported in Datastream
DIS_SMTHC	= a measure of the firm's discretionary earnings smoothing, calculated following Lang et al. (2009) using the average of the scaled percentile rank of *DIS_SMTH1* and *DIS_SMTH2*, where *DIS_SMTH1* & *2* are the residual values from an earnings smoothness model described in Section 3.1

INTGAAP	= an indicator variable, based on Daske et al. (2009), that is equal to one if the firm is classified as a 'serious' adopter of an international GAAP, where a serious adopter is a firm that reports under IFRS or U.S. GAAP during the fiscal year and is either mandated to report under this standard or is audited by a 'BIG5' accounting firm and has an *ANALYST*, (1-*DIS_SMTHC*), and *ACCURACY* (where applicable) value above the sample median.
ILLIQ	= the daily Amihud (2002) price impact of trade illiquidity measure, calculated as described in Section 3.1
LEV	= the firm's total debt divided by total assets
LIQCOV1	= the monthly covariance between firm liquidity and market liquidity, calculated as described in Section 3.1
LIQCOV2	= the monthly covariance between firm liquidity and market returns, calculated as described in Section 3.1
LIQSKEW	= the monthly skewness of *ILLIQ*, calculated as described in Section 3.1
LIQVOL	= the monthly volatility of *ILLIQ*, calculated as described in Section 3.1
LNTOTASS	= the natural log of total assets measured in U.S. dollars (millions)
MKTDOWN_BIG	= an indicator variable equal to one if the market experienced a large downturn in the prior month, and zero otherwise, calculated as described in Section 3.1
NIEX_TA	= net income before extraordinary items scaled by total assets
PROB_LBH	= the monthly probability that a firm experiences an extreme illiquidity event, or a 'liquidity black hole', calculated as described in Section 3.1
Q	= total assets less book value plus market value scaled by total assets
TRANS	= the average scaled percentile rank of the variables: *ANALYST*, *ACCURACY*, *INTGAAP*, *BIG5*, and *(*1-*DIS_SMTHC)*
SIZE	= the natural log of the firm's market value of equity measured in U.S. dollars (millions)
STDRET	= is the standard deviation of monthly stock returns
SUE	= unexpected earnings, scaled by the market value of equity at the end of the prior fiscal year, where unexpected earnings is defined as net income before extraordinary items less a forecast of net income based on a random walk time-series model

TABLE 1
Breakdown of Sample by Country

Country	N	Percent		STD Index
AUSTRALIA	12,407	2.92		0.04
AUSTRIA	1,718	0.40		0.05
BELGIUM	3,612	0.85		0.05
BRAZIL	4,956	1.17		0.08
CANADA	23,821	5.61		0.04
CHILE	1,165	0.27		0.04
CHINA	37,478	8.82		0.10
DENMARK	2,632	0.62		0.05
FINLAND	4,314	1.02		0.09
FRANCE	21,831	5.14		0.05
GERMANY	17,651	4.16		0.05
GREECE	5,857	1.38		0.08
HONG KONG	9,614	2.26		0.07
INDIA	8,512	2.00		0.08
IRELAND	1,112	0.26		0.06
ISRAEL	1,553	0.37		0.05
ITALY	10,731	2.53		0.06
JAPAN	104,811	24.67		0.05
KOREA (SOUTH)	40,199	9.46		0.08
MALAYSIA	9,488	2.23		0.07
MEXICO	3,094	0.73		0.06
NETHERLANDS	6,611	1.56		0.06
NEW ZEALAND	1,102	0.26		0.04
NORWAY	3,636	0.86		0.06
POLAND	1,644	0.39		0.07
PORTUGAL	1,322	0.31		0.06
SINGAPORE	5,684	1.34		0.06
SOUTH AFRICA	3,574	0.84		0.06
SPAIN	7,423	1.75		0.06
SWEDEN	9,632	2.27		0.06
SWITZERLAND	6,936	1.63		0.05
TAIWAN	26,394	6.21		0.07
THAILAND	5,422	1.28		0.10
TURKEY	3,808	0.90		0.13
UNITED KINGDOM	15,064	3.55		0.04
TOTAL	**424,808**	**100**	**AVERAGE**	**0.06**

Table 1 presents the country distribution of sample firm-months during the period from 1997-2008 with sufficient data from the Worldscope and Datastream databases to estimate our least restrictive specification (Model 1 for *LIQVOL* in Table 3). STD Index is the average standard deviation of the country's stock market index over the sample period, where stock index data are obtained from Datastream. Following the Datastream convention, we refer to Hong Kong as a country for simplicity. Any country with less than 1,000 firm-month observations is excluded from the sample.

TABLE 2
Descriptive Statistics

Variable	N	Mean	Std	P25	Median	P75
AILLIQ	424,808	0.389	1.013	0.012	0.059	0.279
LIQVOL	424,808	0.555	2.196	0.007	0.038	0.214
LIQSKEW	416,339	1.548	0.900	0.875	1.380	2.068
PROB_LBH	424,802	0.008	0.045	0.000	0.000	0.000
LIQCOV1	416,945	0.193	0.146	0.080	0.155	0.269
LIQCOV2	417,201	0.172	0.121	0.077	0.145	0.241
Q	419,304	1.438	0.803	0.956	1.190	1.624
DIS_SMTHC	424,808	0.498	0.256	0.275	0.520	0.705
BIG5	424,808	0.282	0.450	0.000	0.000	1.000
ANALYST	424,808	4.228	5.816	0.000	2.000	6.000
ACCURACY	256,738	-0.002	0.031	-0.001	0.008	0.011
INTGAAP	424,808	0.143	0.350	0.000	0.000	0.000
ACC_TRANS	424,808	0.465	0.128	0.357	0.463	0.547
ANALYST_TRANS	424,808	0.435	0.247	0.160	0.420	0.640
TRANS	424,808	0.468	0.135	0.364	0.464	0.569
SIZE	424,808	12.531	1.942	11.325	12.307	13.490
BM	424,808	0.848	0.734	0.370	0.637	1.077
STDRET	424,808	0.025	0.013	0.016	0.022	0.031
ADR_EX	424,808	0.014	0.119	0.000	0.000	0.000
ADR_NEX	424,808	0.038	0.190	0.000	0.000	0.000
CLHLD	424,808	29.400	26.087	0.000	28.610	50.780
LNTOTASS	419,304	13.018	1.520	11.985	12.915	13.970
LEV	419,304	0.510	0.195	0.370	0.519	0.650
CASH_TA	419,304	0.141	0.130	0.050	0.104	0.192
NIEX_TA	419,304	-0.022	8.487	0.006	0.032	0.065
MKTDOWN_BIG	424,808	0.076	0.265	0.000	0.000	0.000
MKTDOWN_BIG1	424,808	0.064	0.245	0.000	0.000	0.000
MKTDOWN_BIG2	424,808	0.012	0.109	0.000	0.000	0.000

Table 2 presents descriptive statistics based on all firm-months between 1997 and 2008 with sufficient data to estimate the basic regression model in which the data item is included. All variables are calculated as defined in the Appendix.

TABLE 3
Correlation Matrix

	LIQVOL	*LIQSKEW*	*PROB_LBH*	*LIQCOV1*	*LIQCOV2*
LIQVOL	.	**0.38**	**0.35**	**0.02**	**0.03**
LIQSKEW	**0.25**	.	**0.24**	**-0.01**	**0.02**
PROB_LBH	**0.51**	**0.14**	.	**0.01**	**0.02**
LIQCOV1	**0.02**	0.00	**0.02**	.	**0.07**
LIQCOV2	**0.03**	**0.02**	**0.02**	**0.09**	.

Table 3 reports Pearson correlation coefficients (above the diagonal) and Spearman coefficients (below the diagonal for variables used in our primary analyses. Correlations that are significant at the 5% level or better are presented in bold.

TABLE 4
Transparency and Liquidity Volatility

$$LIQVOL_{i,m} = \alpha_i + \beta_1 AILLIQ_{i,t} + \beta_2 SIZE_{i,t} + \beta_3 BM_{i,t} + \beta_4 STDRET_{i,t} + \beta_5 CLHLD_{i,t} + \beta_6 ADR\_EX_{i,t} + \beta_7 ADR\_NEX_{i,t} + Transparency VAR + Fixed Effects + \varepsilon_{i,t}$$

Dependent Variable: ***LIQVOL***

	(1)		(2)		(3)		(4)		(5)		(6)	
	Estimate	**p-value**	**Estimate**	**p-value**	**Estimate**	**p-value**	**Estimate**	**p-value**	**Estimate**	**p-value**	**Estimate**	**p-value**
INTERCEPT	2.722	0.00	2.688	0.00	2.756	0.00	2.108	0.00	1.765	0.00	2.589	0.00
AILLIQ	0.765	0.00	0.765	0.00	0.765	0.00	0.756	0.00	0.838	0.00	0.755	0.00
SIZE	-0.130	0.00	-0.129	0.00	-0.130	0.00	-0.088	0.00	-0.084	0.00	-0.101	0.00
BM	0.090	0.00	0.099	0.00	0.090	0.00	0.084	0.00	0.059	0.00	0.077	0.00
STDRET	0.990	0.03	0.631	0.17	0.988	0.03	0.772	0.09	0.584	0.27	0.832	0.07
CLHLD	0.001	0.00	0.001	0.00	0.001	0.00	0.001	0.00	0.002	0.00	0.001	0.00
ADR_EX	0.049	0.26	0.039	0.36	0.055	0.20	0.107	0.01	0.036	0.38	0.077	0.08
ADR_NEX	0.001	0.98	0.006	0.83	0.001	0.96	0.083	0.00	0.010	0.61	0.033	0.22
DIS_SMTHC	**0.037**	**0.08**										
INTGAAP			**-0.046**	**0.03**								
BIG5					**-0.066**	**0.00**						
ANALYST							**-0.027**	**0.00**				
ACCURACY									**-1.607**	**0.00**		
ACC_TRANS											**-0.177**	**0.00**
ANALYST_TRANS											**-0.540**	**0.00**
Fixed Effects	C,Y		C,Y		C,Y		C,Y		C,Y		C,Y	
Clustered SE	Firm		Firm		Firm		Firm		Firm		Firm	
Adj. R^2	0.21		0.21		0.21		0.22		0.20		0.22	
N	424,808		424,808		424,808		424,808		424,808		424,808	

Table 4 presents results of OLS estimation of our Liquidity Volatility and Transparency analysis using firm-level monthly observations. All variables are calculated as described in the Appendix. OLS coefficient estimates and P-values (one-sided if we have a directional prediction, two-sided otherwise) are based on robust standard errors clustered at the firm level. We include country and year fixed effects in all models, but do not report the coefficients. All continuous non-logarithmic variables are truncated at the 1st and 99th percentiles.

TABLE 5
Transparency and Extreme Illiquidity Events

$$Extreme\,Illiquidity_{i,m} = \alpha_i + \beta_1 AILLIQ_{i,t} + \beta_2 SIZE_{i,t} + \beta_3 BM_{i,t} + \beta_4 STDRET_{i,t} + \beta_5 CLHLD_{i,t} + \beta_6 ADR\_EX_{i,t} + \beta_7 ADR\_NEX_{i,t} + \beta_8 ACC\_TRANS_{i,t} + \beta_9 ANALYST\_TRANS_{i,t} + Fixed\,Effects + \varepsilon_{i,t}$$

	LIQSKEW		***PROB_LBH***	
	Estimate	**p-value**	**Estimate**	**p-value**
INTERCEPT	3.860	0.00	-7.911	0.00
AILLIQ	0.052	0.00	0.615	0.00
SIZE	-0.104	0.00	-0.192	0.00
BM	0.024	0.00	0.158	0.00
STDRET	-3.429	0.00	-0.837	0.14
CLHLD	0.002	0.00	0.002	0.00
ADR_EX	-0.134	0.00	-0.092	0.26
ADR_NEX	-0.101	0.00	0.113	0.01
ACC_TRAN	**-0.042**	**0.04**	**-0.244**	**0.00**
ANALYST_TRANS	**-0.081**	**0.00**	**-0.503**	**0.00**
Fixed Effects	C,Y		C,Y	
Clustered SE	Firm		Firm	
Adj. R^2	0.11		0.13	
N	416,339		424,802	

Table 5 presents results of OLS estimation of our Transparency and Extreme Illiquidity Events analysis using firm-level monthly observations. All variables are calculated as described in the Appendix. OLS coefficient estimates and P-values (one-sided if we have a directional prediction, two-sided otherwise) are based on robust standard errors clustered at the firm level. We include country and year fixed effects in all models, but do not report the coefficients. All continuous non-logarithmic variables are truncated at the 1st and 99th percentiles.

TABLE 6
Transparency and Liquidity Commonality

$$\begin{aligned} LIQCOV_{i,m} &= \alpha_i + \beta_1 AILLIQ_{i,t} + \beta_2 SIZE_{i,t} + \beta_3 BM_{i,t} + \beta_4 STDRET_{i,t} + \beta_5 CLHLD_{i,t} \\ &+ \beta_6 ADR\_EX_{i,t} + \beta_7 ADR\_NEX_{i,t} + \beta_8 ACC\_TRANS_{i,t} + \beta_9 ANALYST\_TRANS_{i,t} \\ &+ Fixed\ Effects + \varepsilon_{i,t} \end{aligned}$$

	LIQCOV1		***LIQCOV2***	
	Estimate	**p-value**	**Estimate**	**p-value**
INTERCEPT	-1.736	0.00	-1.787	0.00
AILLIQ	0.010	0.00	0.015	0.00
SIZE	0.001	0.57	-0.005	0.00
BM	0.003	0.27	0.010	0.00
STDRET	0.140	0.32	-0.006	0.96
CLHLD	0.000	0.00	0.000	0.90
ADR_EX	0.007	0.66	-0.015	0.35
ADR_NEX	0.012	0.25	0.016	0.11
ACC_TRAN	**-0.058**	**0.00**	**0.013**	**0.22**
ANALYST_TRANS	**-0.096**	**0.00**	**-0.039**	**0.00**
Fixed Effects	C,Y		C,Y	
Clustered SE	Firm		Firm	
Adj. R^2	0.02		0.01	
N	416,945		417,201	

Table 6 presents results of OLS estimation of our Transparency and Liquidity Commonality analysis using firm-level monthly observations. All variables are calculated as described in the Appendix. OLS coefficient estimates and P-values (one-sided if we have a directional prediction, two-sided otherwise) are based on robust standard errors clustered at the firm level. We include country and year fixed effects in all models, but do not report the coefficients. All continuous non-logarithmic variables are truncated at the 1st and 99th percentiles.

TABLE 7- PANEL A
Transparency, Liquidity Uncertainty and Crises

$$LIQVOL_{i,m} = \alpha_i + \beta_1 AILLIQ_{i,t} + \beta_2 SIZE_{i,t} + \beta_3 BM_{i,t} + \beta_4 STDRET_{i,t} + \beta_5 CLHLD_{i,t} + \beta_6 ADR\_EX_{i,t} + \beta_7 ADR\_NEX_{i,t} + \beta_8 TRANS_{i,t} + \beta_9 MKTDOWN\_BIG_{i,t} + \beta_{10} MKTDOWN\_BIG * TRANS_{i,t} + FixedEffects + \varepsilon_{i,t}$$

Dependent Variable: ***LIQVOL***

	(1)		(2)		
	Estimate	**p-value**	**Estimate**	**p-value**	
INTERCEPT	2.761	0.00	2.753	0.00	
AILLIQ	0.761	0.00	0.761	0.00	
SIZE	-0.110	0.00	-0.111	0.00	
BM	0.076	0.00	0.076	0.00	
STDRET	0.705	0.12	0.598	0.19	
CLHLD	0.001	0.00	0.002	0.00	
ADR_EX	0.080	0.07	0.081	0.07	
ADR_NEX	0.029	0.29	0.028	0.29	
TRANS	**-0.830**	**0.00**	**-0.827**	**0.00**	
MKTDOWN_BIG	**0.816**	**0.00**			
MKTDOWN_BIG1			**0.656**	**0.00**	
MKTDOWN_BIG2			**2.049**	**0.00**	
MKTDOWN_BIG*TRANS	**-1.055**	**0.00**			
MKTDOWN_BIG1*TRANS			**-0.859**	**0.00**	
MKTDOWN_BIG2*TRANS			**-2.770**	**0.00**	***
Fixed Effects	C,Y		C,Y		
Clustered SE	Firm		Firm		
Adj. R^2	0.21		0.21		
N	424,808		424,808		

Table 7 Panel A presents results of OLS estimation of our Transparency, Liquidity Volatility and Crises analysis using firm-level monthly observations. All variables are calculated as described in the Appendix. OLS coefficient estimates and P-values (one-sided if we have a directional prediction, two-sided otherwise) are based on robust standard errors clustered at the firm level. We include country and year fixed effects in all models, but do not report the coefficients. All continuous non-logarithmic variables are truncated at the 1st and 99th percentiles. *** denotes that the *MKTDOWN_BIG2* coefficient is significantly different from the *MKTDOWN_BIG1* coefficient at the 1% level.

TABLE 7- PANEL B
Transparency, Liquidity Uncertainty and Crises

$$ExtremeIlliquidiy_{i,m} = \alpha_i + \beta_1 AILLIQ_{i,t} + \beta_2 SIZE_{i,t} + \beta_3 BM_{i,t} + \beta_4 STDRET_{i,t} + \beta_5 CLHLD_{i,t} + \beta_6 ADR\_EX_{i,t} + \beta_7 ADR\_NEX_{i,t}$$
$$+\beta_8 TRANS_{i,t} + \beta_9 MKTDOWN\_BIG_{i,t} + \beta_{10} MKTDOWN\_BIG * TRANS_{i,t} + FixedEffects + \varepsilon_{i,t}$$

	LIQSKEW			***LIQSKEW***			***PROB_LBH***			***PROB_LBH***		
	Estimate	**p-value**		**Estimate**	**p-value**		**Estimate**	**p-value**		**Estimate**	**p-value**	
INTERCEPT	3.881	0.00		3.880	0.00		-7.776	0.00		-7.789	0.00	
AILLIQ	0.053	0.00		0.053	0.00		0.621	0.00		0.621	0.00	
SIZE	-0.106	0.00		-0.106	0.00		-0.199	0.00		-0.200	0.00	
BM	0.024	0.00		0.024	0.00		0.155	0.00		0.156	0.00	
STDRET	-3.445	0.00		-3.458	0.00		-0.985	0.08		-1.138	0.04	
CLHLD	0.002	0.00		0.002	0.00		0.002	0.00		0.002	0.00	
ADR_EX	-0.134	0.00		-0.134	0.00		-0.087	0.29		-0.086	0.29	
ADR_NEX	-0.102	0.00		-0.102	0.00		0.111	0.01		0.111	0.01	
TRANS	**-0.120**	**0.00**		**-0.120**	**0.00**		**-0.879**	**0.00**		**-0.874**	**0.00**	
MKTDOWN_BIG	**0.107**	**0.00**					**0.722**	**0.00**				
MKTDOWN_BIG1				**0.079**	**0.00**					**0.528**	**0.00**	
MKTDOWN_BIG2				**0.301**	**0.00**					**2.306**	**0.00**	
MKTDOWN_BIG*TRANS	**-0.147**	**0.00**					**-0.785**	**0.00**				
MKTDOWN_BIG1*TRANS				**-0.104**	**0.01**					**-0.583**	**0.00**	
MKTDOWN_BIG2*TRANS				**-0.448**	**0.00**	***				**-2.859**	**0.00**	***
Fixed Effects	C,Y			C,Y			C,Y			C,Y		
Clustered SE	Firm			Firm			Firm			Firm		
Adj. R^2	0.11			0.11			0.13			0.13		
N	416,339			416,339			424,802			424,802		

Table 7 Panel B presents results of OLS estimation of our Transparency, Extreme Illiquidity Events and Crises analysis using firm-level monthly observations. All variables are calculated as described in the Appendix. OLS coefficient estimates and P-values (one-sided if we have a directional prediction, two-sided otherwise) are based on robust standard errors clustered at the firm level. We include country and year fixed effects in all models, but do not report the coefficients. All continuous non-logarithmic variables are truncated at the 1st and 99th percentiles. *** denotes that the *MKTDOWN_BIG2* coefficient is significantly different from the *MKTDOWN_BIG1* coefficient at the 1% level.

TABLE 7- PANEL C
Transparency, Liquidity Uncertainty and Crises

$$LIQCOV_{i,m} = \alpha_i + \beta_1 AILLIQ_{i,t} + \beta_2 SIZE_{i,t} + \beta_3 BM_{i,t} + \beta_4 STDRET_{i,t} + \beta_5 CLHLD_{i,t} + \beta_6 ADR\_EX_{i,t} + \beta_7 ADR\_NEX_{i,t}$$
$$+\beta_8 TRANS_{i,t} + \beta_9 MKTDOWN\_BIG_{i,t} + \beta_{10} MKTDOWN\_BIG * TRANS_{i,t} + FixedEffects + \varepsilon_{i,t}$$

	LIQCOV1		***LIQCOV1***		***LIQCOV2***		***LIQCOV2***	
	Estimate	**p-value**	**Estimate**	**p-value**	**Estimate**	**p-value**	**Estimate**	**p-value**
INTERCEPT	-1.704	0.00	-1.703	0.00	-1.756	0.00	-1.755	0.00
AILLIQ	0.011	0.00	0.011	0.00	0.015	0.00	0.015	0.00
SIZE	0.000	0.99	0.000	0.99	-0.005	0.00	-0.005	0.00
BM	0.003	0.34	0.003	0.32	0.011	0.00	0.011	0.00
STDRET	0.119	0.40	0.120	0.39	-0.007	0.96	0.002	0.99
CLHLD	0.000	0.00	0.000	0.00	0.000	0.88	0.000	0.90
ADR_EX	0.008	0.62	0.008	0.62	-0.014	0.37	-0.014	0.37
ADR_NEX	0.012	0.28	0.012	0.28	0.015	0.12	0.015	0.12
TRANS	**-0.171**	**0.00**	**-0.171**	**0.00**	**-0.048**	**0.00**	**-0.048**	**0.00**
MKTDOWN_BIG	**0.166**	**0.00**			**0.071**	**0.00**		
MKTDOWN_BIG1			**0.139**	**0.00**			**0.078**	**0.00**
MKTDOWN_BIG2			**0.304**	**0.00**			**-0.005**	**0.46**
MKTDOWN_BIG*TRANS	**-0.361**	**0.00**			**-0.212**	**0.00**		
MKTDOWN_BIG1*TRANS			**-0.296**	**0.00**			**-0.215**	**0.00**
MKTDOWN_BIG2*TRANS			**-0.670**	**0.00** ***			**-0.127**	**0.12**
Fixed Effects	C,Y		C,Y		C,Y		C,Y	
Clustered SE	Firm		Firm		Firm		Firm	
Adj. R^2	0.02		0.02		0.01		0.01	
N	416,945		416,945		417,201		417,201	

Table 7 Panel C presents results of OLS estimation of our Transparency, Liquidity Commonality and Crises analysis using firm-level monthly observations. All variables are calculated as described in the Appendix. OLS coefficient estimates and P-values (one-sided if we have a directional prediction, two-sided otherwise) are based on robust standard errors clustered at the firm level. We include country and year fixed effects in all models, but do not report the coefficients. All continuous non-logarithmic variables are truncated at the 1st and 99th percentiles. *** denotes that the *MKTDOWN_BIG2* coefficient is significantly different from the *MKTDOWN_BIG1* coefficient at the 1% level.

TABLE 8
Liquidity Variation, Covariation and Valuation

$$Q_{i,t} = \alpha_i + \beta_1 AILLIQ_{i,t} + \beta_2 LNTOTASS_{i,t} + \beta_3 LEV_{i,t} + \beta_4 CASH + TA_{i,t} + \beta_5 NIEX\_TA_{i,t} + \beta_6 ADR\_EX_{i,t} + \beta_7 ADR\_NEX_{i,t} + \beta_8 TRANS_{i,t} + LiquidityVAR + FixedEffects + \varepsilon_{i,t}$$

Dependent Variable: *Q*

	(1)		(2)		(3)		(4)		(5)		(6)	
	Estimate	**p-value**	**Estimate**	**p-value**	**Estimate**	**p-value**	**Estimate**	**p-value**	**Estimate**	**p-value**	**Estimate**	**p-value**
INTERCEPT	2.794	0.00	3.239	0.00	2.742	0.00	2.782	0.00	2.748	0.00	3.428	0.00
AILLIQ	-0.040	0.00	-0.061	0.00	-0.056	0.00	-0.070	0.00	-0.071	0.00	-0.037	0.00
LNTOTASS	-0.091	0.00	-0.102	0.00	-0.086	0.00	-0.083	0.00	-0.082	0.00	-0.107	0.00
LEV	0.073	0.06	0.072	0.06	0.065	0.09	0.062	0.11	0.062	0.11	0.085	0.03
CASH_TA	1.267	0.00	1.250	0.00	1.271	0.00	1.275	0.00	1.281	0.00	1.241	0.00
NIEX_TA	0.384	0.00	0.455	0.00	0.390	0.00	0.406	0.00	0.410	0.00	0.417	0.00
ADR_EX	0.067	0.20	0.038	0.47	0.055	0.30	0.063	0.24	0.060	0.26	0.044	0.40
ADR_NEX	0.217	0.00	0.191	0.00	0.214	0.00	0.211	0.00	0.211	0.00	0.198	0.00
LIQVOL	**-0.038**	**0.00**									**-0.023**	**0.00**
LIQSKEW			**-0.180**	**0.00**							**-0.156**	**0.00**
PROB_LBH					**-1.172**	**0.00**					**-0.435**	**0.00**
LIQCOV1							**-0.550**	**0.00**			**-0.485**	**0.00**
LIQCOV2									**-0.446**	**0.00**	**-0.294**	**0.00**
Fixed Effects	C, I, Y		C, I, Y		C, I, Y		C, I, Y		C, I, Y		C, I, Y	
Clustered SE	Firm		Firm		Firm		Firm		Firm		Firm	
Adj. R^2	0.23		0.22		0.27		0.27		0.27		0.28	
N	45,266		45,266		45,266		45,266		45,266		45,266	

Table 8 presents results of OLS estimation of our Liquidity Variation, Covariation and Valuation analysis using firm-level annual observations. All variables are calculated as described in the Appendix. OLS coefficient estimates and P-values (one-sided if we have a directional predication, two-sided otherwise) are based on robust standard errors clustered at the firm-level. We include country and year fixed effects in all models, but do not report the coefficients. All continuous non-logarithmic variables are truncated at the 1st and 99th percentiles.

FIGURE 1
Residual Liquidity Volatility by Transparency Group

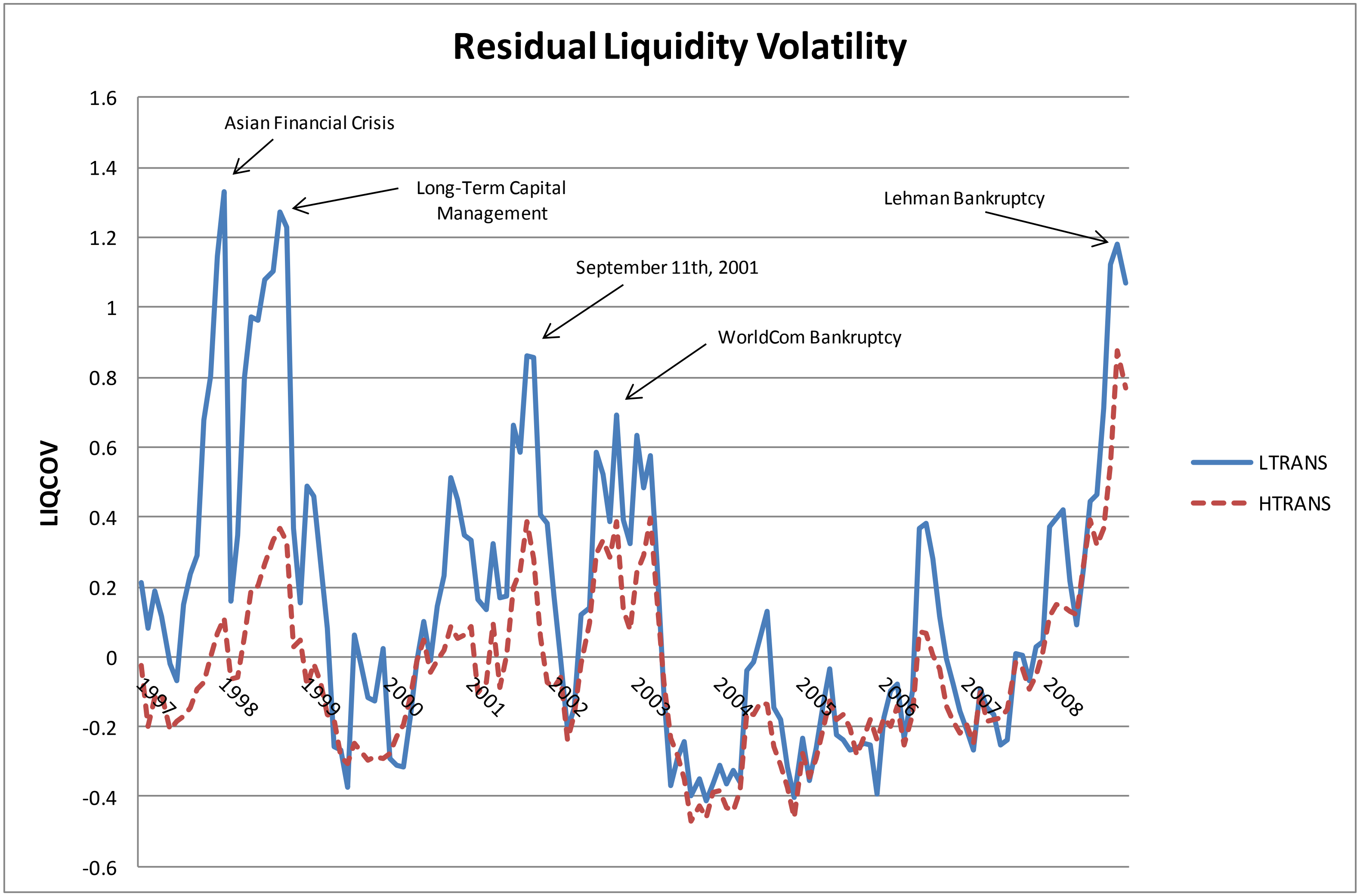

Figure 1 depicts a time-series graph of residual liquidity volatility for high and low transparency groups. A firm is classified as high transparency (*HTRANS*) if it has a *TRANS* value higher than the sample median during a particular year, and low transparency (*LTRANS*) otherwise. Residual liquidity is the residual value from a regression of *LIQVOL* on *ALLIQ*, *SIZE*, *BM*, *STDRET*, *CLHLD*, *ADR_EX*, *ADR_NEX* and country fixed effects.