Transparency and Liquidity Uncertainty in Crisis Periods

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Abstract

We document, for a diverse global sample, that firms with greater transparency (based on accounting standards, auditor choice, earnings management, analyst following and analyst forecast accuracy) experience less liquidity volatility, fewer extreme illiquidity events and lower correlations between firm-level liquidity and both market liquidity and market returns. Results are robust to a wide range of sensitivity analyses, including controls for endogeneity and propensity matching. Results are particularly pronounced during crises, when liquidity variances, covariances and extreme illiquidity events generally increase substantially, but less so for transparent firms. Finally, liquidity variance, covariance and frequency of extreme illiquidity events are all negatively correlated with Tobin's Q.

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Abstract

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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 liquidity matter, but its timing matters as well. Liquidity is of special concern if it tends to dry up 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 (2009)'), 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

[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." Similarly, Lou and Sadka (2010) provide evidence that liquidity risk is more appropriate for predicting stock return performance during crisis periods than is the level of liquidity.
[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."

a 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 less affected 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 third 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 liquidity providers 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, speculators' 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, 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 a global sample for several reasons. First, the U.S. setting tends to be relatively homogenous in terms of firm-level transparency, liquidity and other institutions. Internationally, firms are more likely to differ based on factors such as accounting standards, auditor quality, earnings management, analyst following, investor protection, institutional holdings and country-level transparency. Second, we are interested in crises 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.

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 (2010)), 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, and also report results using firm fixed effects to control for other firm-level differences.

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.[4]

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 one variable based on the percentile ranks of the five transparency characteristics.[5] As expected, this measure is strongly negatively correlated with liquidity volatility. Next, we examine the incidence of extreme illiquidity, measured by the skewness of the liquidity distribution as well as by our measure of

[4] 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.
[5] 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.

"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.

Although market microstructure and design features differ significantly across exchanges, and potentially confound cross-country comparisons, we expect that the implications of our transparency measures for liquidity variability and covariability likely vary based on country-level institutions. Prior literature (e.g. Ball (2001) and Lang et al. (2004)) suggests there are likely to be two countervailing effects depending on whether our transparency measures are complements or substitutes for the more general institutional environment. Consistent with this prediction, we find that international accounting standards and 'Big-5' auditors reduce liquidity uncertainty most in environments with stronger overall investor protection and enforcement, while analyst following, forecast accuracy and earnings management are more important in countries in which weak institutions reduce the overall level of transparency.

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.[6] While this definition is

[6] On average, by our definition, 6.7% 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.

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 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 6 – 22.5% monthly downturn depending on the country, averaging 10.5% over our entire sample) and those of more than 2.0 standard deviations (a 8 - 30% monthly downturn depending on country, averaging nearly 15% 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.[7] In addition, 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. Again, results suggest that the increase in beta during downturns tends to be less pronounced for transparent firms.[8]

[7] 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).

[8] 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.

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.[9] 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 covariability are important in practice and that none of our variability measures subsumes any of the others. Moreover, we find that the effect of transparency on valuation through liquidity uncertainty appears to be at least as important as the effect of transparency on valuation through the level of liquidity.

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. In addition, our results appear to be both statistically and economically significant. In fact, our valuation analysis suggests that the magnitude of the transparency effect on valuation through liquidity variability and covariability is larger than the transparency effect through the level of liquidity. 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, our results are robust to the inclusion of firm fixed effects, an alternative measure of liquidity based on bid-ask spreads, a specification based on changes and a two-stage analysis which instruments transparency to control for potential endogeneity. In addition, our results are consistent for the vast majority of our sample countries. Also, 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

[9] 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.

with transparency, particularly in crisis periods. Finally, the results are consistent with the implications of theoretical research. That being said, conclusions on causality should be drawn with caution.[10]

In the next section, we discuss the related literature. In Section 3, we present our primary hypotheses. We discuss our data and empirical approach in Section 4. In Section 5, we provide empirical results. Section 6 concludes.

2. Related Literature

As noted earlier, our primary interest is in the relation between firm-level transparency and the variability and covariability of firm-level liquidity. While firm-level liquidity uncertainty and covariability are clearly of interest to investors, corporations and regulators, there is, to our knowledge, no direct research on their relation to firm-level transparency. However, there are several related literatures.

First is the literature on transparency and the level of liquidity, surveyed in Amihud, Mendelson and Pedersen (2005). The basic premise in this stream of research is built on the theoretical work of Glosten and Milgrom (1985) and Amihud and Mendelson (1986) which shows that the level of liquidity is related to transparency through its effect on information asymmetry. Recent examples of empirical tests of this idea in the international setting include Daske et al. (2008, 2009), which examine the relation between IFRS adoption and the level of liquidity, and Lang et al. (2010), which examines the relation between firm-level characteristics of the information environment and liquidity levels.

While understanding determinants of average liquidity is clearly important, relatively little is known about factors that cause liquidity to fluctuate or covary with macroeconomic events,

[10] 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. (2010) provides evidence that transparency is lower for firms which are likely to benefit more from opacity.

which are clearly important to understanding liquidity effects during crises. Theoretical research such as BP (2009) and Vayanos (2004) helps to fill that void by suggesting mechanisms which may cause liquidity to fluctuate, evaporate suddenly and covary with market-wide returns and market-wide liquidity. In particular, BP (2009), discussed in more detail in the next section, suggests that funding constraints can cause important variation and covariation in liquidity, including situations in which liquidity evaporates entirely.[11] In those types of models, transparency has the potential to mitigate liquidity variability and covariability by reducing uncertainty about intrinsic values. Further, research such as Acharya and Pedersen (2005) provides theoretical and empirical evidence that the covariability of firm-level liquidity with market liquidity and with market returns are systematic risk factors that are components of cost of capital, above and beyond the overall average liquidity of the stock.[12] In all of our analyses, we control for the average level of liquidity, so our results for liquidity variability and covariability are incremental to the direct effects of the relation between transparency and average liquidity.

Second is the 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) provides evidence that the correlation between firm-level returns and market-wide liquidity is a priced risk factor, and Ng (2008), using a U.S. sample, investigates the potential role of information in that relation.[13] However, those papers consider a fundamentally different question than the one posed here in the sense that they do not investigate variation and covariation in firm-level liquidity, which is the focus of our analysis. It is not possible to draw direct conclusions about determinants or

[11] Comerton-Forde, Hendershott, Jones, Moulton and Seasholes (2010) (CHJMS) provide empirical evidence that funding constraints on liquidity providers matter in practice and are pervasive. Using detailed data on NYSE specialist investor positions, they find that spreads widen when specialists have large positions or lose money and that the effects are most prominent when positions and losses are large, and for high volatility stocks.

[12] Kamara, Lou and Sadka (2008) document that cross-sectional variation of liquidity commonality has increased over the period 1963-2005, which they relate to patterns in institutional ownership. Their results suggest that it has become more difficult to diversify systematic risk and aggregate liquidity shocks, potentially increasing the fragility of the U.S. equity market.

[13] In addition, Lou and Sadka (2010) provide evidence that the stocks with high liquidity betas (covariation between firm return and unexpected changes in aggregate liquidity) underperformed the market irrespective of their historic liquidity levels. Hutton, Marcus and Tehranian (2009) find that opacity, as measured by earnings management, is associated with higher synchronicity in returns for U.S. firms and that opaque firms are more prone to stock price crashes, although the relation dissipated after passage of Sarbanes-Oxley. Korajczyk and Sadka (2008) estimate a latent factor model of liquidity, aggregated across various liquidity measures, and show that the common component across measures is a primary priced factor.

consequences of firm-level liquidity variability or covariability from these analyses because they focus on firm-level returns, not liquidity.[14]

Empirically, the underlying phenomena we investigate are also fundamentally different from those explored in Pastor and Stambaugh (2003) and Ng (2008). The correlations between the co-movement in firm-level returns and market liquidity from Pastor and Stambaugh (2003) and Ng (2008) and the liquidity co-movements we examine are 0.02 for market returns and 0.08 for market liquidity, confirming that we are studying fundamentally different constructs. More importantly, controlling for the covariation between firm-level returns and market liquidity does not change any of our conclusions.[15] Further, our Tobin's Q results confirm that the liquidity variability and covariability measures we consider have separable and incremental effects on firm value relative to the measures in Pastor and Stambaugh (2003) and Ng (2008).

Third, there are country-level studies comparing 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 shows 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

[14] Further, the fundamental underlying economic drivers of the correlation between firm-level returns and market liquidity are likely to differ from those that drive the correlations between firm-level liquidity and market liquidity and returns. For example, as Ng (2008) notes, the correlation between firm-level returns and market liquidity is likely driven by changes in investor risk aversion and portfolio allocations during periods of market illiquidity, while BP (2009) suggests that firm-level liquidity variability and covariability is driven by the capital and funding available to liquidity providers.

[15] At some level, that is not surprising because Acharya and Pedersen (2005) document theoretically and empirically that the three correlations (firm-level returns with market liquidity, firm-level liquidity with market returns and firm-level liquidity with market liquidity) have separable effects on cost of capital (in fact, the largest effect is for the covariability of firm-level liquidity with market liquidity).

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.

Overall, while there are related empirical literatures, none addresses the central question of our paper which is the potential role of firm-level transparency in mitigating the uncertainty and covariability of firm-level liquidity. Given the potential significance of this issue conceptually as well as practically for a wide range of constituents, we believe this is an important contribution to the literature.

3. 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.[16] 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 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.[17] Margins in turn are set based on an asset's "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

[16] 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.

[17] BP (2009) discuss a variety of parties that serve the role of liquidity providers and are subject to funding constraints including market makers, trading desks at banks and other institutions such as hedge funds.

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.[18] This implies commonality in liquidity will increase when markets decline.[19]

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.[20] As a result, there will be less of a "flight to quality" among liquidity providers for more transparent stocks in response to funding and capital shocks and, therefore, less volatility in their liquidity.[21] That leads to our first hypothesis:

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

[18] Although speculator capital tends to be lowest when markets are down, prior research (e.g. CHJMS (2010)) suggests that liquidity provider funding is generally binding to some extent.
[19] 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.
[20] 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.
[21] 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. Liquidity variability then creates uncertainty for investors because they are unsure how large a discount to expect when they need to sell.

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.[22] 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 liquidity providers, 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 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.*

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

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 following sharp market downturns, leading to the following hypothesis:[23]

> ***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, leading to our final hypothesis:

> ***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.*

4. Research Design and Data

4.1. 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 indicators, following Lang et al. (2010).[24]

[23] Based on BP (2009), we expect transparency to be negatively associated with liquidity variability and covariability during both crisis and non-crisis periods, but anticipate that the association will be more pronounced during crises when the funding constraints are likely to become particularly binding across a wide range of liquidity providers.

[24] We use a variety of transparency indicators because each likely measures transparency with error. To provide greater confidence that our measures reflect aspects of transparency, in untabulated analysis we find that each of our measures, individually and incrementally, is significantly associated with the information asymmetry component of the bid-ask spread.

Our first transparency variable assesses the degree to which a firm engages in discretionary earnings management.[25] Following the procedure discussed in Lang et al. (2010), 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 idea is that earnings management is manifested in the use of accruals to smooth out fluctuations in 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: log of total assets, leverage, book value relative to market value, volatility of sales, frequency of accounting losses, 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_SMTH*, is predicted to be indicative of greater earnings management and associated with greater opacity.[26]

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)).[27] Because our primary data source (Datastream) maintains firm-specific auditor data for only the most current fiscal year, we collect time-series data on firm auditor from a variety of additional sources, including historical point-in-time data from Datastream and Compustat Global. Auditor descriptions from these data sources are classified as 'Big-5' manually.

[25] Further details on the construction of each of the transparency indicators can be found in the Appendix.
[26] 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. (2010)). 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. (2010)).
[27] Our auditor variable is admittedly crude because the extent of oversight by the "parent" audit firm may vary across environments. While we do not have a direct measure of the link between the local and parent audit firms, in later analysis we split our sample at the country level based on institutional structure and find that auditor choice is more strongly associated with transparency in environments with stronger enforcement oversight.

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. (2008, 2009) and Lang et al. (2010) suggests that the benefits of adoption of IFRS obtain only for firms that seriously adopt IFRS rather than simply 'adopting a label' of international accounting standards. Accordingly, following Lang et al. (2010), we define serious adopters (*INTGAAP* = 1) to be adopting firms which have an above-median aggregate transparency score (calculated excluding the *INTGAAP* variable) and either a) are mandated by country regulations to adopt international accounting standards, or b) voluntarily adopted international standards.[28]

Additional transparency variables, other than those related to accounting choices, are likely to be important determinants 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 accurately forecast earnings.

[28] The notion is that firms with large auditors, a large and accurate analyst following, and less evidence of earnings smoothing are more likely to have adopted international accounting standards in substance rather than in form only.

In models testing our first hypothesis, we measure the volatility of a firm's liquidity, *LIQVOL*, as the log of the monthly standard deviation of the daily Amihud (2002) price impact of trade measure (*DPI*).[29] 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 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 daily price impact (*DPI*) 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 *DPI* 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.[30] The Amihud 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."[31] To measure liquidity skewness we take the monthly skewness of our price impact of trade measure (*DPI*). The notion is that, for firms with more frequent illiquidity events, the illiquidity distribution will be more positively

[29] Looking ahead to the descriptive statistics in Table 2, we see that *LIQVOL* is positively skewed. Taking the natural log of *LIQVOL* eliminates much of this skewness. Descriptive statistics for logged *LIQVOL* indicate that the mean and median are virtually identical, -3.97 and -3.99 respectively.

[30] Results are very similar if we include zero return days with reported volume either as zero returns (i.e., the measure is invariant to volume) or as returns of 0.01% (to capture variation in volume), discussed in further detail in Section 5.4.

[31] As discussed in more detail in Section 5.4, 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.

skewed. Our second proxy for the frequency of extreme illiquidity events, *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." *LBH* is defined as the percentage of trading days in the month during which a firm's Amihud (2002) price impact of trade measure (*DPI*) is more than 50 times the country-level median.[32] Since *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 *LBH* in tests of our primary hypotheses.

Our third and fourth hypotheses are that firms with lower levels of transparency will experience greater commonality of liquidity with both market liquidity and market returns. To capture a stock's level of these two types of commonality we use two measures, *COM(FL,ML)* and *COM(FL,MR)*. These measures are based on a long line of literature (e.g. Roll (1988) and Morck et al. (2000)) which uses 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 (*COM(FL,ML)*) as well as firm liquidity and market returns (*COM(FL,MR)*).

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

$$\%\Delta DPI_{i,d} = \alpha_i + \beta_{i,1}\%\Delta DPI_{m,d-1} + \beta_{i,2}\%\Delta DPI_{m,d} + \beta_{i,3}\%\Delta DPI_{m,d+1} + \varepsilon_{i,d} \tag{2}$$

where $\%\Delta DPI_{i,d}$ is equal to the daily percentage change in *DPI* for firm *i* on day *d* and $\%\Delta DPI_{m,d}$ is equal to the daily percentage change in *DPI* for the market on day *d*. We define market illiquidity at the country-level as the daily equal-weighted average *DPI* of the individual stocks on a given day.[33] 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

[32] Since we are unaware of other papers that attempt to define extreme illiquidity events, our choice of cutoff is admittedly arbitrary. Results based on firm-level illiquidity greater than ten times the firm-level average are similar, as are results using cutoffs based on firm-level standard deviations of liquidity and absolute return cutoffs.
[33] Results are very similar if we estimate the relation using value-weighted market liquidity.

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 *DPI*. Because *COM(FL,ML)* is based on an R^2, it is bounded by zero and one and we use a log transformation in the regression analyses.

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

$$\%\Delta DPI_{i,d} = \alpha_i + \beta_{i,1} MKTRET_{m,d-1} + \beta_{i,2} MKTRET_{m,d} + \beta_{i,3} MKTRET_{m,d+1} + \varepsilon_{i,d} \tag{3}$$

where $\%\Delta DPI_{i,d}$ is calculated as defined above and $MKTRET_{m,d}$ is equal to the daily country-level market return.

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.[34] 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*).[35]

Following prior literature (e.g. Stoll (2000)), models used in testing H1 through H5 include controls for monthly: market value of equity (*SIZE*), book to market (*BM*), return variability (*STDRET*) and firm-specific returns (*FRET*). To ensure our results are attributable to the

[34] We use the prior month's downturn because, following BP (2009), we are interested in the dynamics of liquidity when speculator capital is low (i.e., stock prices have recently dropped). Further, using lagged returns reduces the likelihood of a mechanical relation between liquidity and crises (i.e., that we are simply documenting that liquidity decreases as stock prices drop). However, results are very similar if we use crises defined contemporaneously to our liquidity measures.

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

variability of liquidity, as opposed to its level, we include in all models a control for the firm's monthly average level of liquidity (*ILLIQ*). All market-based control variables are measured as of the beginning of the prior month. 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.[36] Similarly, we include a control for the proportion of the firm's shares that are closely-held (*CLHLD*) because closely-held shares are typically not available to be traded and may affect a firm's overall liquidity. Finally, to control for differences in business risk across firms, we include controls for the standard deviation of sales (*STD_SALES*) and the frequency of accounting losses (*LOSS_FREQ*). All accounting-based control variables are measured as of the prior fiscal year-end date. The calculation of the control variables is described in more detail in the Appendix.

For our main specifications, we include country and year fixed effects. While transparency likely differs across countries, market microstructure and general institutions do as well, so country fixed effects are potentially important.[37] Year fixed effects should mitigate the influence of changes in overall macroeconomic conditions. In addition, we report in the text untabulated regression results including firm fixed effects to focus on variation within a firm over time. While firm fixed effects have the advantage of abstracting from firm-level characteristics that may differ between transparent and opaque firms, they also limit our ability to detect effects associated with our primary accounting variables since changes in auditor and accounting standards are relatively uncommon and earnings smoothing is computed over multi-year windows and, therefore, changes slowly.

Our final hypothesis is that each of our liquidity variability and covariability measures 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

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[36] Results are not sensitive to exclusion of the cross-listed firms.
[37] We limit our sample to the primary exchange in each country, so variation across exchanges within a country should not be an issue.

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 variable we include the following controls suggested by prior literature (e.g. Claessens et al. (2002)) and further described in the Appendix: *LNTOTASS*, *LEV*, *CASH*, *NIEX*, *IND_Q*, *AGROWTH, ADR_EX*, *ADR_NEX,* and *ILLIQ*.

4.2. 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 that observations 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 (*DPI*). We exclude any country with less than 1,000 firm-month observations. In total, our sample contains 507,822 firm-month observations from 37 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 and the U.S., reflecting both the relative size of the economies as well as data availability.[38]

Table 2 provides descriptive statistics for our sample firms. As would be expected, the sample firms are medium-sized on average, and range from very large to much smaller firms. The median firm is covered by three analysts, with a mean of nearly six analysts. Of the sample firms, 47.4% have Big-5 auditors, 26.8% follow an international form of GAAP and 7.5% trade ADRs, of which 3.3% are exchange-traded. The average firm has about 30% concentrated ownership with a mean book-to-market ratio of 0.95, indicating that, on average, market capitalization exceeds book value of equity.

[38] As discussed later, results are not sensitive to excluding Japan, the U.S. or any other country.

Table 3, Panel A provides a correlation matrix for our primary dependent 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 *LIQSKEW* (0.45 Spearman, 0.47 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. Table 3, Panel B shows correlations between our transparency proxies and control variables. Correlations amongst these variables are generally consistent with expectations.

5. Empirical Results

5.1. 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-market, return variability, firm return, ownership structure, ADR listing, sales volatility, loss frequency and country fixed effects) 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 across different levels of firm-level transparency. However, during crisis periods, when uncertainty increases, volatility of liquidity increases as well, but particularly for the more 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 and 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, unprofitable and closely held.[39] 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 include country and year fixed effects (coefficients not reported), and standard errors that are clustered at the firm level.

In terms of our primary relations of interest, our transparency variables are correlated with liquidity volatility, consistent with expectations. In particular, liquidity is more volatile when transparency is lower as reflected in more evidence of earnings management, use of a small auditor and reliance on local accounting standards.[40] Similarly, liquidity volatility is lower for firms that are followed by more analysts and for whom analyst forecasts are more accurate. 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 as well as analyst forecast accuracy and, potentially, analysts willingness to cover the firm). For parsimony going forward, we combine the transparency measures by ranking each variable and summing the ranks to compute an overall transparency measure, *TRANS.*[41] Table 4 also reports a

[39] While we use lagged stock returns as a measure of performance in our primary analysis, results are robust to using return on assets, return on sales or return on equity, either at the firm or country-level measured either concurrently or lagged, as a control.
[40] As in Daske et al. (2008, 2009), results for *INTGAAP* are only significantly negative if we limit our analysis to serious adopters. However, all other results in the paper are robust to including all IFRS and U.S. GAAP adopters in the *INTGAAP* variable.
[41] Including the five transparency variables together, each retains its sign and significance, except for *INTGAAP*, which is no longer significantly negative.

regression including the overall transparency variable.[42] As expected, *TRANS* is strongly negatively correlated with liquidity volatility.[43]

Next, we replicate the analysis with firm fixed effects replacing country fixed effects. Results are consistent in the sense that all of the transparency variables retain their signs and four of the five transparency components remain statistically significant (the exception is *BIG5* which has a p-value of 0.15, likely reflecting limited within-firm variation), as does aggregate *TRANS*. The results are reassuring in the sense that they help mitigate the concern that our primary results simply capture variation in inter-firm characteristics.

5.2. 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 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 extreme illiquidity events, the distribution of liquidity will exhibit more positive skewness. 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. To provide an illustration, our median illiquidity measure is 0.022, implying that a

[42] Admittedly, the aggregation of the transparency variables is somewhat arbitrary. Weightings based on a factor analysis yield similar results. In addition, any of the individual transparency components can be excluded from the construction of the *TRANS* variable with consistent results.

[43] It is difficult to assess economic significance since liquidity volatility does not have a natural intuitive interpretation. However, based on the coefficient estimates in Table 4, an interquartile shift from the 25th to the 75th percentile of *TRANS* is associated with a 38.9% decrease in liquidity volatility for the median firm.

five million dollar block sale would decrease share price by 0.11%.[44] An extreme illiquidity event would then be defined as one in which the stock price decrease associated with the sale of five million dollars would be 5.5%. 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 lower liquidity and less variable sales. Results for the other control variables differ based on the specification. In terms of our primary variable of interest, transparency is strongly associated with the frequency of extreme illiquidity events. Specifically, *TRANS* is negatively correlated with *LIQSKEW*, suggesting that extreme illiquidity events are less common for more transparent firms. Conclusions are similar for the "liquidity black hole" variable, with *TRANS* significantly negatively related to *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, on average, opaque firms (below-median *TRANS*) are nearly three times as likely to experience an extreme illiquidity event as transparent firms (above-median *TRANS*).[45]

As with the analysis of liquidity volatility, results (untabulated) for liquidity black holes and skewness are consistent when applying firm fixed effects. In particular, the coefficient on *TRANS* remains strongly negatively associated with both liquidity skewness and the probability of a liquidity black hole, helping to mitigate concerns about omitted correlated variables. Overall, the results strongly suggest that more transparent firms are less sensitive to the incidence of extreme illiquidity events.

5.3. Transparency and Liquidity Commonality

[44] Note that *DPI* has been multiplied by 1,000 for readability and dollar volume is measured in thousands.

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

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 covariances of firm-level liquidity with market liquidity and with market returns are components 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 and smaller stocks with less variable returns that do not trade on U.S. exchanges and that experience more frequent losses, consistent with the intuition in BP (2009). 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. 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.[46]

Similar conclusions obtain for the covariance between firm-level liquidity and market returns in Table 6 Column (2). Again, the coefficient on *TRANS* is significantly negative, suggesting 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)).[47] Overall, our results suggest that liquidity is less cyclical for more transparent firms, both relative to market liquidity and market returns.

5.4. Robustness

The preceding sections mention 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 robustness tests designed to increase confidence in the interpretation of our results.

First, we investigate measures of illiquidity other than the standard Amihud measure. We focus on measures of price impact because the theoretical framework of BP (2009) is developed using the magnitude of the discount associated with transacting blocks of stock as a proxy for liquidity, which incorporates both the bid-ask spread as well as depth. For our purposes, we need a

[46] The modest R^2 here reflects, at least in part, the fact that our dependent variables are measured monthly while some of our independent variables are measured annually. Prior research (e.g., Hameed et al. (2010)) does not report R^2's, so it is difficult to benchmark this result.

[47] Coefficients remain negative in both specifications using firm fixed effects, but the coefficient estimates are no longer statistically significant, potentially reflecting the limited variation the transparency variable. However, in our crisis analysis, the *TRANS* coefficient is significantly negative for both of the liquidity covariance measures during both large and small crisis periods when firm fixed effects are included in the analysis, suggesting that transparency is particularly important during crisis periods.

variable that can be measured on a daily basis (unlike measures such as zero return days) and captures market depth. Goyenko et al. (2009) suggest several measures of price impact in addition to the standard Amihud measure. One that can be computed on a daily basis is the spread impact measure (based on the ratio of the bid-ask spread to dollar trading volume).

In Table 7, Panel A, we replicate our primary analyses using the bid-ask spread impact measure, *BAVOL*, as the underlying liquidity variable (in place of *DPI*) in the construction of our liquidity variability and covariability measures.[48] *BAVOL* is calculated as the firm's daily bid-spread, in percentage terms, scaled by daily U.S. dollar trading volume. The notion is that liquid stocks are those for which a substantial volume can be transacted without affecting bid-ask spreads. The derivative liquidity risk measures are then calculated as described in Section 4.1. Results are consistent with those reported earlier for the standard Amihud measure. In particular, transparency is significantly negatively associated with liquidity volatility measured based on bid-ask spread. Similar results obtain for both measures of extreme illiquidity events (liquidity skewness and liquidity black holes) and for liquidity commonality both with respect to market liquidity and market returns. Overall, these results provide some assurance that our conclusions are not sensitive to unique features of the Amihud price impact measures.

Second, we consider an alternate construction of the Amihud price impact measure including zero return days.[49] Conceptually, the problem with using zero return days in the Amihud measure is that the measure is invariant to trading volume and, therefore, a day with a thousand dollars traded and zero returns is treated the same way as a day with a million dollars traded and zero returns, even though those are potentially quite different from a liquidity perspective. To circumvent this issue, we replicate the analysis substituting a small return (0.01%) in place of a zero return on days with positive volume so that trading volume enters into the calculation. All results (untabulated) are robust to this modification. Similarly, results are robust to assigning an illiquidity of 0% to all zero return days.

[48] Another alternative measure in Goyenko et al. (2009) is the Amivest measure based on the ratio of trading volume to the absolute value of returns. Results are also robust to this measure of price impact.
[49] Our primary specification is consistent with prior literature (e.g., Karolyi et al. (2009) and Daske et al. (2008)) in excluding zero return days.

Third, because they represent such a significant portion of our sample, and thus threaten the generalizability of our results, we repeat our analyses limiting Japanese and U.S. firms to 10% of our sample and eliminating Japanese and U.S. firms from our sample entirely. Our results (untabulated) are robust to limiting or excluding Japanese and U.S. firms. Moreover, our inferences are robust to limiting or excluding any other country in our sample. As a result, it does not appear that Japan, the U.S. or any other country, has undue influence on our conclusions. In fact, repeating our analysis within each of the 37 countries in our sample, the coefficient estimate on transparency is negative in 34 countries (32 significantly) for liquidity volatility, 26 countries (22 significantly) for liquidity skewness, 28 countries (20 significantly) for liquidity black holes, 23 countries (16 significantly) for the correlation between firm-level liquidity and market liquidity and 25 countries (14 significantly) for the correlation between firm-level liquidity and market returns. Overall, these results confirm the consistency of our primary findings across a wide range of countries.

Fourth, we repeat our analyses using a changes specification. While the firm fixed effects analysis controls for static firm-wide effects, an analysis based on first differences more explicitly focuses on time series covariation between the dependent and independent variables. Because our accounting transparency variables are measured primarily using annual data, we conduct our changes analysis by annualizing the dependent and independent variables and then computing first differences. Note that, as is the case in our primary analysis, transparency is lagged with respect to the liquidity variables such that the change in transparency is measured between the fiscal years prior to the annual change in the liquidity uncertainty proxies. Results of these regressions are reported in Table 7, Panel B. Results for the control variables are consistent with those obtained for firm fixed effects. More importantly, the coefficient estimate on the *TRANS* variable is negative in all of our specifications and significant, at least at the 10% level, in four of the five specifications (with the other significant at the 10.1% level).[50] To provide further evidence on the time-series variation between transparency and liquidity uncertainty, we focus on cases where the change in transparency is relatively large (greater than the median).

[50] Since it is possible that some of the time series variation in transparency that we capture in the changes analysis arises from changes in a firm's transparency ranking when other firms adjust their transparency, as an additional robustness check, we estimate transparency rankings for the entire pooled sample period, rather than annually, with similar results.

Consistent with expectations, untabulated results suggest that the relation between changes in transparency and changes in our liquidity measures is strongest for firms experiencing pronounced changes in transparency. While our changes analysis does not imply a causal relation, it provides further comfort that our results are not driven by omitted firm-level variables.

Fifth, we repeat our analyses using only firms located in the United States for comparability with prior U.S.-based research. While our primary analysis includes U.S. firms, they tend to be relatively homogenous in terms of transparency and liquidity, and exhibit very limited variability on several of our transparency variables (e.g., accounting standards, large auditor and earnings smoothing). Overall, conclusions are similar to those reported earlier, with *TRANS* significantly negatively related to each of our primary independent variables of interest.

Sixth, a potential concern is that each of the variability and covariability measures may be capturing the same underlying economic construct. We do not believe this is a significant issue because the correlations among the constructs are generally fairly low. However, to ensure that our results are incremental across variables, 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. 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 (2008).

Seventh, we consider several other fixed effects. Our primary analyses include country and year fixed effects and standard errors clustered at the firm level, 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 of, for example, the effects of differences in business models. Results are robust to inclusion of industry fixed effects. Results are also consistent when including combinations of the various fixed effects, including, country-year and industry-year.

Eighth, we consider an alternate sample selection technique based on propensity score matching to ensure that our results are not being driven by dissimilarities between high and low transparency firms not captured by the control variables. Our concern is that our results might capture differences in business risk, as opposed to transparency, that affect liquidity. Ideally, we would like to include in the control sample low transparency firms which face identical business risks as the high transparency firms and see whether the groups differ in terms of our measures of liquidity uncertainty. However, matching in this environment is difficult because our analysis essentially includes the population of firms. The approach we take is to divide the sample into two groups based on country-level median transparency and then estimate the propensity to be in the high- versus low-transparency group based on a variety of proxies for general economic and business risk, including size, leverage, book to market, sales volatility, loss frequency, operating cycle, sales growth, operating leverage, average cash flows and industry membership. Given the propensity scores, we then exclude the 25% of high transparency firms with the highest propensity scores and the 25% of low transparency firms with the lowest propensity scores. The notion is that we are left with the 50% of the sample that is most similar in terms of the business risk characteristics associated with the likelihood of being highly transparent. Results from this alternate sample are very similar to those reported in our primary analyses. At some level, that is not particularly surprising because our earlier analyses indicate that our results are consistent with firm fixed effects, suggesting that differences in firm characteristics do not drive the empirical results.

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.[51] We follow Roulstone (2003) and Yu (2008), in modeling

[51] 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, thus, 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 could bias in favor of our results. It is more difficult to make an analogous argument for our other measures of

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 (*ILLIQ, 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*, *COM(FL,ML)* and *COM(FL,MR)*) with similar results.[52]

5.5. Institutional Analysis

To this point we have controlled for country effects, and not compared results across countries, because market microstructure and design features vary substantially across exchanges, potentially confounding these comparisons. Market microstructure differences are particularly a concern for price impact measures because they incorporate volume, which is often calculated differently across exchanges (Lesmond, 2005). Nonetheless, implications for our measures of transparency and, therefore, for liquidity uncertainty, likely vary based on country-level institutions. Prior literature suggests there are potentially two countervailing effects depending on whether our transparency measures are more likely complements or substitutes for the more general institutional environment.

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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.

[52] Results are consistent if we instrument only the analyst following variable (since prior research has focused on the potential endogeneity of analyst following) or exclude analyst following entirely from our analyses.

First, research such as Daske et al. (2009) and Hope et al. (2009) suggests stronger overall investor protection and enforcement likely increase the impact of the adoption of high quality accounting standards and the benefits of hiring high quality auditors. In particular, Daske et al. (2009) argue that high quality accounting standards are likely to be most important in environments in which strong regulatory oversight ensures that the standards are applied substantively rather than simply asserted. Similarly, research such as Ball (2001), Francis et al. (2003), Francis et al. (2006) and Hope et al. (2009) argues that reliance on high quality auditors is likely to be more important in environments in which the underlying oversight and litigation environments increase the bonding role of auditor choice. In other words, the use of international accounting standards and high quality auditors is likely to be most beneficial in environments in which there is substantial local oversight and litigation exposure. As a result, we expect the presence of 'Big-5' auditors and international accounting standards to be a complement to stronger local institutions in terms of their effect on overall firm transparency.

On the other hand, research such as Lang et al. (2004) suggests that firm-level transparency is likely to be especially important in environments in which weak investor protection and disclosure standards limit the overall level of transparency. Lang et al. (2004) provide evidence that analyst following is more strongly associated with firm value when local institutions are weak because the incremental information they provide is more important when other sources of information are lacking. As a consequence, we expect the association between the analyst following and forecast accuracy components of our transparency measure to be more strongly associated with liquidity uncertainty when local institutions are weak since the information analysts provide is likely to be more important in those environments. Similarly, to the extent that earnings management reduces the information content of reported earnings, we expect discretionary smoothing to be more of an issue in environments with a low overall level of transparency.

We follow the classification in Leuz (2010), which splits countries into clusters using regulatory, enforcement and reporting practice variables. Countries classified as having a strong institutional infrastructure are in Cluster 1, while countries with progressively weaker institutions are placed into Clusters 2 and 3. Accordingly, our weak institutional infrastructure indicator (*WEAK*) takes a value of one if a country is in Regulatory Cluster 2 or 3, and zero otherwise.[53] In addition, we split our transparency variables into those that are likely to be complements to local institutions (*INTGAAP* and *BIG5*, aggregated into *COMP_TRANS*) and those that are likely to be substitutes (*ANALYST*, *ACCURACY* and *DIS_SMTHC*, aggregated into *SUB_TRANS*).[54]

Results for liquidity volatility, presented in Table 8, are consistent with expectations. Specifically, *COMP_TRANS*WEAK* is significantly positive while *SUB_TRANS*WEAK* is significantly negative, suggesting that weak country-level institutions mitigate the effectiveness of international accounting standards and 'Big-5' auditors but reinforce the importance of analyst following, forecast accuracy and discretionary smoothing.[55] Table 8 also reports results for incidence of extreme liquidity events, liquidity skewness and liquidity black holes, with an interaction for country-level institutions. Results are consistent with those for liquidity volatility. As predicted, the interaction between *COMP_TRANS* and *WEAK* is positive and the interaction between *SUB_TRANS* and *WEAK* is negative.[56] Similar results hold for the two measures of liquidity commonality, with a positive interaction between *COMP_TRANS* and *WEAK* and a negative interaction between *SUB_TRANS* and *WEAK*.[57]

Subject to the caveat that our liquidity measures may not be entirely comparable due to differences in market microstructure across countries, the results of the institutional analysis suggest that the effects of our transparency indicators vary predictably across local institutional environments, with international accountings standards and 'Big-5' auditors serving as

[53] We combine Clusters 2 and 3 because we have very few observations in Cluster 3, and both clusters represent "insider" economies. Results are consistent if we exclude Cluster 3 countries. Further, because it comprises a substantial portion of our sample, following prior literature (e.g. Allen, Qian and Qian (2005)) we include China in the weak institutional group although cluster data are not available for China in Leuz (2010). Results are consistent if we exclude China from the analysis.

[54] An alternate approach, which yields very similar results, is to include only the analyst variables in the *SUB_TRANS* category under the assumption that the local regulatory and enforcement environment substantially affects the application of accounting standards and auditing, but has less of an effect on the activity of analysts.

[55] Comparing the *WEAK* interaction coefficients for the transparency subcomponents (not tabulated for parsimony), each is of the predicted sign, and *ANALYST*, *BIG5* and *INTGAAP* are statistically significant.

[56] For parsimony, in our primary analysis only the transparency indicators are interacted with the *WEAK* indicator. However, results are very similar if we also allow the control variables to vary based on the institutional environment.

[57] Interestingly, the coefficient on the interaction between *COMP_TRANS* and *WEAK* is often nearly as large as the coefficient on *COMP_TRANS*, suggesting that weak local institutions may almost totally undo the transparency effects of international accounting standards and large auditors, consistent with Daske et al. (2009).

complements to local institutions and analyst following, forecast accuracy and earnings management serving as substitutes.

5.6. Transparency, Liquidity Uncertainty 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, BP (2009) shows that 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 capital intensive stocks. In addition, overall uncertainty tends to increase during sharp downturns. Together, both effects will tend to increase the sensitivity of liquidity to funding constraints and, hence, the potential importance of transparency during crises. As discussed earlier, the descriptive evidence in Figure 1 supports the notion that liquidity volatility increases substantially during crisis periods, especially for less transparent firms.

Table 9, Column (1), presents results for the liquidity volatility analysis 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 a 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 statistically significant, suggesting that transparency is substantially more important in mitigating liquidity volatility following down markets.[58] This finding is generally consistent with the implications of

[58] Additional, untabulated, analyses indicate that the coefficient on our transparency variable spikes during a crisis before returning to near average levels six months afterward, indicating that transparency maintains a heightened importance for several months following a large market decline.

BP (2009), which suggests that assets with less uncertainty about underlying firm value will be less affected by general liquidity shocks.[59]

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 omitted variable would need to be both correlated with transparency and the strength of that relation would need to change substantially during market downturns. While it is possible that might occur, it is more difficult to envision a variable with those features. Similarly, the increased importance of transparency during crisis periods 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 measure is computed annually. 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. Also, the fact that the transparency measure is computed prior to the beginning of the crisis period makes it more difficult to imagine a role for reverse causality.

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 9, Column (2), we divide our crisis variable into two pieces, smaller downturns (monthly downturns between 1.5 and 2.0 standard deviations) and larger downturns (monthly downturns of more than 2.0 standard deviations). Based on the descriptive evidence from Tables 1 and 2, our smaller downturns involve a monthly negative stock return of 10.5% on average, ranging from 6% for the United Kingdom (and others) to over 20% for Turkey, while our larger downturns average 14%, ranging from 8% for the United Kingdom to 30% for Turkey.[60]

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[59] For parsimony, only the transparency indicators are interacted with the crisis indicators. However, results are very similar if we allow all coefficients to vary by the crisis indicator.

[60] 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.

Results, reported in Table 9, 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 stronger the greater is the downturn, with the coefficient on the large downturn indicator being significantly larger than the smaller downturn indicator variable. 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.[61]

Very similar conclusions hold for the analyses with firm fixed effects (untabulated). In particular, the coefficient on the *MKTDOWN_BIG* indicator is over 30% larger for big downturns relative to small downturns. These results suggest that similar patterns obtain for within-firm variation, reducing the likelihood that the results are driven by omitted general firm characteristics.

Similar conclusions obtain for extreme illiquidity events, as measured by liquidity skewness, reported in Table 9, Column (3). In particular, large down markets increase the skewness of liquidity, consistent with the notion that extreme illiquidity events are more common during market downturns. Further, transparency remains significantly negative suggesting that skewness in liquidity is less pronounced for more transparent firms. Most importantly, the interaction between market downturns and skewness is significantly negative, suggesting that transparency is particularly important to skewness in crisis periods.[62] Further, splitting by the size of the down market in Table 9, Column (4), transparency is more than twice 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 9, Columns (5) and (6). Liquidity black holes increase in frequency during market downturns and, as before, transparency is negatively correlated with the frequency of extreme illiquidity events.

[61] In terms of economic significance, an interquartile shift in transparency is associated with a 47.8% decrease in liquidity volatility for small crises and a 57.5% decrease in liquidity volatility for large crises.

[62] In interpreting the coefficient estimates on the interactions between crises and transparency, it is important to recognize that *MKTDOWN_BIG* is an indicator variable while *TRANS* is a continuous variable with a mean of 0.50. As a result, the magnitude of the coefficient on *MKTDOWN_BIG*TRANS* is directly comparable to the coefficient on *TRANS* but not to the coefficient on *MKTDOWN_BIG*.

Again, 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 significantly stronger for larger downturns relative to smaller downturns. The coefficient magnitudes indicate that, for the average firm, a market downturn of between 1.5 and 2.0 standard deviations makes experiencing a liquidity black hole almost 65% more likely than in a normal period. A larger downturn, greater than 2.0 standard deviations, increases the probability of an extreme illiquidity event almost 400%. 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 2.0 standard deviations being only about 40% as much for a transparent firm (90^{th} percentile of transparency) relative to an opaque firm (10^{th} percentile of transparency) and only about 30% as much for a transparent firm relative to an opaque firm during a larger market downturn.

Results are again consistent for firm fixed effects (untabulated) for both measures of extreme illiquidity events. In particular, liquidity skewness is more pronounced and liquidity black holes are more frequent during crisis periods, and transparency is more important to mitigating those increases during crisis periods. Further, the greater is the crisis, the greater is the increase in extreme illiquidity events and the greater is the mitigation effect of transparency.

In Table 9, Columns (7) and (8), we present results for the covariability of firm-level liquidity with market liquidity. Recall that we predict 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. Conclusions are consistent with expectations and with results for liquidity volatility and extreme illiquidity events. Several points are worth noting in the table. First, when the market drops, liquidity covariability increases significantly, 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. Specifically, the interaction coefficient between *MKTDOWN_BIG* and *TRANS* is nearly seven times as large during larger downturns relative to non-crisis periods. 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.

Next, we report results for the effect of crises on the covariability of firm-level liquidity with market returns in Table 9, Columns (9) and (10). Again, results 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 noted before, transparency is associated with lower comovement overall. Further, and most importantly, the effect of transparency in mitigating comovement is substantially more pronounced during down markets, with the effect of transparency being more than two times as large during market downturns. Splitting between large and small downturns, the coefficient estimate on the interaction between transparency and the downturn indicator variable is significantly more negative for larger downturns as predicted.

Results are consistent with firm fixed effects (untabulated). In particular, both measures of covariance increase during crises, but significantly less so for firms that are more transparent. Further, the effects of a crisis on the covariation of firm-level liquidity with market liquidity, and the mitigating effect of transparency, are significantly more pronounced for larger crises.

5.7. Other Analyses

To provide further support for the previously documented relation between transparency and liquidity uncertainty during crises, we supplement our primary crisis analysis in several ways.

First, a potential concern is that we may not be capturing transparency during a crisis month since our transparency indicators are measured with a lag. This approach implicitly assumes that firms with higher levels of our transparency indicators prior to the crisis will also be more transparent during the crisis. Given that we use data from annual financial reports, we have limited flexibility in measuring our auditor, accounting standard and earnings management variables at alternative points in time. However, since the I/B/E/S summary file includes monthly updates for many firms, we do have some flexibility with the measurement of the transparency indicators based on analyst data. Accordingly, to capture firm-level transparency as close to the time of the crisis as possible, we re-estimate our analyses using a measure of transparency based solely on analyst following and forecast accuracy during the crisis month.

Results (untabulated) indicate our inferences are robust to this alternative approach. Specifically, we find that greater levels of transparency, based on monthly analyst following and forecast accuracy, are associated with lower values of each of our liquidity variability and covariability measures, and that the effect of this monthly transparency variable is significantly more pronounced during crisis periods for each measure of liquidity uncertainty. Further, including the monthly analyst transparency indicator along with our annual transparency measure, the monthly analyst variable is incrementally significant, consistent with the notion that transparency during the crisis period is particularly important to liquidity variability and covariability.

Second, and closely related, is the question of whether the firms we identify as having high levels of transparency actually disclose more during crisis periods. Our primary hypotheses imply transparency can mediate the effect of a crisis on liquidity uncertainty as long as the firm has a high level of transparency during a crisis period, regardless of whether that occurs by virtue of high transparency levels in general or changes in transparency during the crisis (i.e. market participants will be more comfortable providing liquidity in crises for firms with better quality auditors, better accounting standards and greater analyst following regardless of whether those variables increased during the crisis). However, one might expect that more transparent firms would also be more likely to increase transparency during crises in response to increased investor demand for information. While it is difficult to directly examine changes in disclosure that occur during crisis periods, prior research (e.g. Lang and Lundholm (1993)) suggests one way to infer such changes is by examining changes in the frequency of analyst forecast updates. In other words, if more information is reaching the market, either through firm-provided disclosure or private information acquisition, analyst forecast updates should be more frequent. To directly address this question, we examine the number of forecast revisions per analyst during crisis months across high and low transparency firms (based on the sample median), controlling for the other variables used in our primary analyses. Results (untabulated) indicate that firms we identify as more transparent have more analyst forecast revisions per analyst during crisis months, suggesting more new information is available for these firms during crises.

Third, we examine the effect of downturns on the overall relation between transparency and the CAPM beta.[63] Our analysis to this point, and the CAPM disaggregation in Acharya and Pedersen (2005), suggest that, because downturns decrease speculator capital, they can increase the price pressure associated with trading and increase a firm's CAPM beta. To test this hypothesis directly, we replicate our crisis period analysis substituting a measure of firm-specific monthly CAPM beta for our measures of liquidity covariability. Untabulated results are consistent with those for the covariation of liquidity with market liquidity and market returns.[64] Specifically, we document a marked increased in CAPM betas on the whole during downturns, suggesting that firm returns co-move with market returns more during a crisis. More interestingly, the increase in betas following downturns is substantially smaller for more transparent firms. In conjunction with the results from the preceding analyses, and BP (2009), these results are consistent with the notion that as speculator capital dries up, firms' returns respond more strongly to macroeconomic conditions because of increased price pressure associated with trading. The results also suggest that transparency, by reducing the liquidity "flight to quality," mitigates this effect.

Fourth, we attempt to provide more direct evidence on the mechanism which drives variability and covariability in firm liquidity. As noted earlier, while we do not view our analyses as tests of any specific model, we use the BP (2009) framework to motivate our tests. This framework assumes that funding constraints faced by speculators are the impetus for variation and

[63] We emphasize that our results are only intended to be descriptive since we do not address issues such as the role of market integration in computing beta factors, the role of information in a CAPM world or alternate approaches to computing beta.
[64] For consistency with prior covariance results in the paper, we estimate a firm's beta relative to its own-country return (although results are consistent if we estimate beta based on world-wide returns).

covariability in liquidity. While we believe our results are relevant regardless of what is the fundamental driver of liquidity uncertainty, it is also interesting to directly explore the implications of the BP (2009) framework and to consider whether speculator funding constraints appear to be a primary driver of liquidity variability and covariability in our sample. Unfortunately, we do not directly observe funding constraints, so our evidence is naturally circumstantial. However, the evidence we have provided to this point is consistent with the BP (2009) framework and is at least suggestive of the effects of funding constraints. In particular, the fact that there is a strong negative association between transparency and each of our five liquidity measures is consistent with the effects of transparency reducing uncertainty and, hence, funding constraints. More importantly, our crisis analysis results are consistent with the notion that sharp decreases in share price reduce speculator capital and make funding constraints more binding, increasing sensitivity to uncertainty about firm value and, hence, the benefits of disclosure.

An alternate approach to assessing the effects of limited speculator funding is to directly test the BP (2009) model prediction that low volatility securities will be less sensitive to specialists funding constraints because they are less risky and thus less capital intensive. CHJMS (2010) confirm this empirically, in a U.S. setting, showing evidence of a 'flight-to-quality' by market makers (i.e. funding (and shocks thereto) is less associated with liquidity for low volatility stocks.) To the extent that speculator funding constraints are at work in our setting, increases in liquidity volatility, and the effect of transparency in mitigating these increases during crisis periods, should be most pronounced for high volatility stocks. We test this prediction by splitting our sample into high and low volatility subgroups, based on the country-level median stock return volatility. Results (untabulated) are consistent with these predictions. First, consistent with CHJMS (2010), the effect of a crisis on liquidity volatility is significantly larger for stocks from countries with high levels of return volatility. Second, the role of transparency in mitigating the increase in liquidity volatility associated with crises is significantly more pronounced for high volatility stocks.

Finally, to provide additional evidence based on the predictions of the BP (2009) framework in our setting, we compare results across subgroups based on country-specific levels of institutional ownership. BP (2009) specifically suggest that institutional investors (e.g., hedge funds, commercial banks and investment banks) can play the role of speculators in their model. If institutional investors are a primary source of speculator activity, the effects of crises on liquidity volatility, and the mitigating effect of transparency, should be most pronounced in environments with higher levels of institutional ownership. Dividing our sample by country-level institutional ownership, based on the data provided in Ferreira and Matos (2008), we find results consistent with our prediction. Specifically, we find that the effect of crises on liquidity volatility is most pronounced for firms with higher levels of institutional ownership, and that the mitigating effect of transparency is more pronounced in these settings as well. These results provide further evidence of the consistency between our findings and the implications of the BP (2009) framework.

5.8. Liquidity Variation, Covariation and Valuation

In our final set of analyses, we examine the relation between our measures of liquidity variability and covariability 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 little evidence that these factors matter for valuation. If investors prefer firms with less liquidity uncertainty, they should be willing to pay more for shares of those firms.

Table 10 provides evidence on the relation between *Q* and the variability of liquidity as well as extreme illiquidity events and liquidity commonality. In this analysis we control for a variety of variables suggested by the prior literature (e.g. Claessens et al. (2002)). The regressions also include controls for country, industry and year fixed effects.[65] Results for these controls are consistent with expectations. Specifically, valuations are higher for firms that are smaller, have

[65] A potential concern with our liquidity variability and covariability measures is that they are correlated with market value of equity, which is a component of Tobin's Q. To ensure that relation is not driving our results, we repeat the analysis with market value of equity as a control, with very similar results.

more cash, are more profitable, trade ADR's, are from industries with high Q's and are more liquid on average.[66]

Most importantly, each of our liquidity variability 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.[67] In terms of firm fixed effects (untabulated), results are very consistent with those in our primary analysis across all measures. In particular, each measure is negatively and significantly associated with Tobin's Q, both individually and incrementally, again suggesting that each captures a different aspect of liquidity uncertainty. The fact that the results obtain with firm fixed effects suggests that the relation between liquidity uncertainty and Tobin's Q is not driven by fundamental differences in the types of firms across the sample.

Next, in order to relate these findings back to our earlier analyses, we additionally examine whether liquidity uncertainty is an important channel through which transparency effects valuation. Prior research (e.g. Lang et al. (2010)) suggests that the average level of liquidity is one channel through which transparency affects firm value. However, it is not known whether liquidity uncertainty also serves as such a channel and, if so, how it compares to average liquidity in terms of importance. One crude way to examine this question is through mediation analysis. For our purposes, a mediation analysis is conducted by examining the effect on the transparency coefficient, in a Tobin's Q regression, of including the level of liquidity and our measures of liquidity uncertainty in the regression. To the extent that transparency affects firm valuation through its effect on liquidity level and liquidity uncertainty, including those variables should reduce the coefficient on transparency.

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[66] Somewhat contrary to prior research (e.g. Doidge et al. (2004)) the coefficients on exchange-traded and non-exchange-traded ADRs are not significantly different in our Tobin's Q analysis, although the coefficient on *ADR_EX* is larger (as expected). This difference could be caused by the fact that we have a different sample period and composition or be related to recent evidence that suggests the valuation benefit of exchange-traded ADRs may be only temporary or declining in recent years (e.g. Sarkissian and Schill (2009) and Hostak, Karaoglu, Lys and Yang (2009)).

[67] 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.

Performing this mediation analysis, we find that, as in prior research, transparency is significantly positively associated with firm value. Moreover, we find that the inclusion of both the level of liquidity as well as each of our measures of liquidity uncertainty in the *Q* regressions significantly mediates the relation between transparency and firm value. Interestingly, the effect of transparency on valuation through our liquidity uncertainty measures is more than twice as large as the effect through the average level of liquidity. While this approach is admittedly crude, it suggests that the effect of transparency through liquidity uncertainty may be at least as important as the effect through the level of liquidity.

6. Conclusion

Prior research has typically focused 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 a stock's liquidity at the time they choose to transact. The recent financial crisis illustrates this point and the importance of liquidity variability during large market downturns. Transparency is important because it 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). Our results suggest a striking and consistent relation between our measures of transparency and liquidity variance and covariance, consistent with both intuition and predictions of theoretical research. Moreover, our results suggest a 'flight to quality' in liquidity during which more transparent stocks are less sensitive to liquidity shocks in general and particularly to the liquidity uncertainty that accompanies crisis periods.

In this paper, we find transparency is negatively correlated with liquidity volatility, liquidity skewness, the likelihood of extreme illiquidity events, and the co-movement between firm-level liquidity and market returns and market liquidity. Further, we document that the effect of transparency on each of these liquidity variables is more pronounced during market downturns. In addition, our institutional analysis suggests that the effects of our transparency indicators vary predictably across local institutional environments in terms of their effects on liquidity variability and covariability, with international accountings standards and ‘Big-5’ auditors serving as complements to local institutions and analyst following, forecast accuracy and earnings management servings as substitutes. Also, we find that each of our liquidity uncertainty measures is negatively correlated with valuation as measured by Tobin’s Q. Finally, we note that our results are robust to inclusion of firm fixed effects, suggesting that they reflect intra-firm variation, and not simply cross-firm differences. While it is dangerous to draw strong causal implications, taken at face value our results suggest that liquidity variability and covariability are important channels through which transparency could affect firm value.

Of course, our conclusions are subject to caveats. Most importantly, they do not imply causality. However, we have conducted numerous additional analyses to increase confidence that the primary relations we document are not simply endogenous. Foremost, it seems unlikely that our findings suffer from reverse causality because we measure transparency prior to the calculation of our liquidity uncertainty variables. Further, the fact that the association between transparency and liquidity uncertainty increases during crises reduces the set of alternative explanations for our results. Also, the fact that results are robust to a wide range of sensitivity tests reduces the likelihood of spurious inference. Finally, our empirical results are consistent with the theoretical predictions of prior analytical research such as Vayanos (2004) and BP (2009), which reduces the likelihood that they are spurious or reflect omitted variables. That being said, causal conclusions should still be drawn with caution.

Overall, we believe our results represent an important first step in understanding the relation between transparency and liquidity variability and covariability. We think these results are particularly timely given the concerns about liquidity generated by the recent economic crisis. Given that money managers and investors view liquidity variability and covariability as major concerns, our results are potentially useful as they offer a deeper understanding of their potential determinants.

In terms of extensions, it would be interesting to delve deeper into specific causal links. In particular, as an initial analysis of the relation between transparency variability and covariability, our approach has been fairly broad brush. It would be worthwhile to try and identify the specific mechanisms through with changes in disclosure could potentially affect liquidity variation. For example, one of the potential benefits of IFRS adoption could be a reduction in liquidity variability. 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 of a particular crisis in more detail. For example, a study focusing on the recent financial crisis might permit a more nuanced examination of the causes and consequences of the links between transparency and liquidity uncertainty.

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Appendix: Variable Definitions

Variable	Definition
ACCURACY	= the residual value from a regression of *RAW_ACCURACY* on *SUE* and *BIAS*, where *RAW_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 fiscal year, and zero otherwise (hand collected from a variety of sources, including the Bank of New York, Citibank, JP Morgan and Datastream)
ADR_NEX	= an indicator variable equal to one if the firm has an U.S. ADR but is not traded on a U.S. exchange during the fiscal year, and zero otherwise (hand collected from a variety of sources, including the Bank of New York, Citibank, JP Morgan and Datastream)
AGROWTH	= the annual percentage change in total assets (WorldScope item 02999)
ANALYST	= the number of analysts making a forecast of the firm's annual earnings, obtained from the I/B/E/S Summary File
BAVOL	= the daily bid-ask spread impact measure, calculated as described in Section 5.4
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 'Big-5' auditing firm during the fiscal year, and zero otherwise (collected from a variety of sources, including historical point-in-time Datastream data and Compustat Global)
BM	= annual book value of common equity (WorldScope item 03501) divided by monthly market value of common equity (Datastream item MV)
CASH	= cash and cash equivalents (WorldScope item 02001) scaled by total assets (WorldScope item 02999)
CLHLD	= the proportion of the firm's shares that are closely held at the end of the fiscal year (WorldScope item 08021)
COM(FL,ML)	= the monthly R-squared from an OLS regression of firm liquidity on

market liquidity, calculated as described in Section 4.1

COM(FL,MR)	= the monthly R-squared from an OLS regression of firm liquidity on market returns, calculated as described in Section 4.1
COM(FR,ML)	= the monthly R-squared from an OLS regression of firm returns on market liquidity, calculated as described in Section 4.1
DIS_SMTH	= a measure of the firm's discretionary earnings smoothing, calculated following Lang et al. (2010) 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 4.1
DPI	= the daily Amihud (2002) price impact of trade illiquidity measure, calculated as described in Section 4.1
FRET	= the monthly buy and hold return (Datastream item RI)
IND_Q	= the annual equally-weighted average *Q* for the firm's industry, based on the firm's two-digit ICB code
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 has an above-median aggregate transparency score (calculated excluding the *INTGAAP* variable) and either a) are mandated by country regulations to adopt international accounting standards, or b) voluntarily adopted international standards
ILLIQ	= the average monthly *DPI*
LBH	= the monthly probability that a firm experiences an extreme illiquidity event, or a 'liquidity black hole', calculated as described in Section 4.1
LEV	= the firm's ratio of total debt (WorldScope item 03351) divided by total assets (WorldScope item 02999)
LIQSKEW	= the monthly skewness of *DPI*, calculated as described in Section 4.1
LIQVOL	= the monthly volatility of *DPI*, calculated as described in Section 4.1
LNTOTASS	= the natural log of total assets measured in U.S. dollars (millions) (WorldScope item 02999)
LOSS_FREQ	= the proportion of years that the firm experienced a loss in the last three to five fiscal years (WorldScope item 01551)

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 4.1
NIEX	= net income before extraordinary items (WorldScope item 01551) scaled by total assets (Worldscope item 02999)
Q	= the sum of total assets (WorldScope item 02999) plus market value of equity (Datastream item MV) minus book value of equity (Worldscope item 03501) scaled by total assets (WorldScope item 02999)
SIZE	= the natural log of monthly market value of equity measured in U.S. dollars (millions) (Datastream item MV)
STD_SALES	= the standard deviation of total sales (WorldScope item 01001), calculated over the last three to five fiscal years
STDRET	= the monthly standard deviation of daily stock returns (Datastream item RI)
SUE	= unexpected earnings scaled by stock price at the end of the prior fiscal year (Datastream item P), where unexpected earnings is defined as earnings per share (Worldscope item 05201) less earnings per share from the prior fiscal year
TRANS	= the average scaled percentile rank of the variables: *ANALYST*, *ACCURACY*, *INTGAAP*, *BIG5*, and *(*1-*DIS_SMTH)*

TABLE 1
Breakdown of Sample by Country

Country	N	Percent		STD Index	Institutional Cluster
ARGENTINA	1,408	0.28		0.09	3
AUSTRALIA	13,155	2.59		0.04	1
AUSTRIA	2,072	0.41		0.05	2
BELGIUM	3,399	0.67		0.05	2
BRAZIL	4,131	0.81		0.08	3
CANADA	23,376	4.60		0.04	1
CHILE	1,897	0.37		0.05	2
CHINA	19,936	3.93		0.11	3*
DENMARK	3,415	0.67		0.05	2
FINLAND	4,417	0.87		0.09	2
FRANCE	20,963	4.13		0.05	2
GERMANY	18,556	3.65		0.05	2
GREECE	5,635	1.11		0.08	2
HONG KONG	10,968	2.16		0.07	1
INDIA	9,415	1.85		0.09	1
INDONESIA	1,248	0.25		0.09	3
IRELAND	1,398	0.28		0.06	1
ISRAEL	1,852	0.36		0.06	1
ITALY	10,320	2.03		0.06	2
JAPAN	96,682	19.04		0.05	2
KOREA (SOUTH)	31,528	6.21		0.10	2
MALAYSIA	11,338	2.23		0.08	1
MEXICO	3,244	0.64		0.07	3
NETHERLANDS	6,257	1.23		0.05	2
NEW ZEALAND	1,429	0.28		0.04	1
NORWAY	3,649	0.72		0.06	2
PORTUGAL	1,526	0.30		0.06	2
SINGAPORE	5,743	1.13		0.06	1
SOUTH AFRICA	4,138	0.81		0.06	1
SPAIN	6,999	1.38		0.06	2
SWEDEN	9,710	1.91		0.06	2
SWITZERLAND	6,636	1.31		0.05	2
TAIWAN	25,515	5.02		0.08	1
THAILAND	5,877	1.16		0.10	1
TURKEY	3,781	0.74		0.15	3
UNITED KINGDOM	23,456	4.62		0.04	1
UNITED STATES	102,753	20.23		0.04	1
TOTAL	**507,822**	**100**	**AVERAGE**	**0.07**	

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 4). 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. 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. Institutional Cluster is equal to the three-level regulatory cluster classification from Leuz (2010).
* Following prior literature, we include China in the weak institutional group although cluster data are not available in Leuz (2010).

TABLE 2
Descriptive Statistics

Variable	N	Mean	Std	P25	Median	P75
LIQVOL	507,822	0.488	2.268	0.002	0.018	0.141
LIQSKEW	496,954	1.444	0.872	0.799	1.275	1.931
LBH	507,822	0.006	0.043	0.000	0.000	0.000
COV(FL,ML)	498,314	0.194	0.143	0.083	0.159	0.271
COV(FL,MR)	498,193	0.177	0.125	0.079	0.149	0.248
COV(FR,ML)	498,726	0.170	0.119	0.076	0.143	0.238
Q	54,022	1.534	0.921	0.999	1.255	1.718
DIS_SMTH	507,822	0.479	0.253	0.260	0.490	0.680
BIG5	507,822	0.474	0.499	0.000	0.000	1.000
ANALYST	507,822	5.722	6.682	1.000	3.000	9.000
ACCURACY	348,442	0.000	0.025	0.001	0.008	0.010
INTGAAP	507,822	0.268	0.443	0.000	0.000	1.000
TRANS	507,822	0.501	0.159	0.379	0.496	0.624
SIZE	507,822	13.131	2.161	11.676	12.857	14.327
BM	507,822	0.949	1.200	0.332	0.625	1.119
STDRET	507,822	0.026	0.014	0.016	0.023	0.032
FRET	507,822	0.002	0.026	-0.012	0.002	0.015
ILLIQ	507,822	0.348	1.416	0.003	0.022	0.144
CLHLD	507,822	28.871	25.036	1.550	26.380	48.940
ADR_EX	507,822	0.033	0.178	0.000	0.000	0.000
ADR_NEX	507,822	0.042	0.200	0.000	0.000	0.000
STD_SALES	507,822	0.235	0.545	0.073	0.136	0.258
LOSS_FREQ	507,822	0.164	0.251	0.000	0.000	0.200
LNTOTASS	54,022	13.478	1.658	12.334	13.363	14.552
LEV	54,022	0.524	0.193	0.390	0.536	0.661
CASH	54,022	0.127	0.128	0.036	0.088	0.175
NIEX	54,022	0.034	0.156	0.012	0.039	0.072
AGROWTH	54,022	0.015	0.237	0.000	0.000	0.000
MKTDOWN_BIG	507,822	0.067	0.251	0.000	0.000	0.000
MKTDOWN_BIG1	507,822	0.038	0.191	0.000	0.000	0.000
MKTDOWN_BIG2	507,822	0.029	0.169	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 Matrices

Panel A - Dependent Variable Correlation Matrix

VARIABLE	*LIQVOL*	*LIQSKEW*	*LBH*	*COM(FL,ML)*	*COM(FL,MR)*	*COM(FR,ML)*
LIQVOL	.	0.47	0.36	0.08	0.08	0.03
LIQSKEW	0.45	.	0.22	0.03	0.04	-0.01
LBH	0.32	0.20	.	0.03	0.03	0.01
COM(FL,ML)	0.08	0.03	0.03	.	0.08	0.05
COM(FL,MR)	0.09	0.05	0.03	0.08	.	0.02
COM(FR,ML)	0.03	-0.01	0.01	0.05	0.02	.

Panel B - Independent Variable Correlation Matrix

VARIABLE	*DIS_SMTH*	*INTGAAP*	*BIG5*	*ANALYST*	*ACCURACY*	*SIZE*	*BM*	*STDRET*	*FRET*	*ILLIQ*	*CLHLD*	*ADR_EX*	*ADR_NEX*	*STD_SALES*	*LOSS_FREQ*
DIS_SMTH	.	-0.20	-0.13	-0.11	0.00	-0.17	0.06	0.05	-0.01	0.04	0.03	-0.05	-0.03	0.04	0.10
INTGAAP	-0.20	.	0.39	0.29	0.10	0.24	-0.13	-0.09	0.01	-0.10	-0.14	-0.02	-0.06	0.01	-0.05
BIG5	-0.13	0.39	.	0.27	0.04	0.22	-0.07	-0.09	0.00	-0.06	-0.17	0.08	0.01	0.03	-0.04
ANALYST	-0.13	0.37	0.30	.	0.14	0.53	-0.10	-0.10	0.00	-0.15	-0.06	0.21	0.20	-0.02	-0.19
ACCURACY	-0.02	0.16	0.08	0.18	.	0.16	-0.13	-0.08	0.02	-0.10	-0.06	0.00	0.01	-0.02	-0.15
SIZE	-0.18	0.29	0.24	0.60	0.21	.	-0.38	-0.17	0.00	-0.25	-0.09	0.22	0.15	-0.03	-0.21
BM	0.09	-0.16	-0.11	-0.22	-0.17	-0.46	.	0.07	0.00	0.12	0.07	0.00	0.00	-0.04	0.02
STDRET	0.05	-0.11	-0.10	-0.13	-0.08	-0.20	0.03	.	0.03	0.17	-0.02	-0.02	-0.03	0.07	0.25
FRET	0.00	0.01	0.00	0.01	0.00	0.01	0.00	0.01	.	-0.01	0.00	0.00	0.00	0.00	-0.01
ILLIQ	0.15	-0.36	-0.28	-0.53	-0.23	-0.74	0.36	0.21	-0.02	.	0.05	-0.04	-0.03	0.03	0.15
CLHLD	0.02	-0.10	-0.13	0.00	-0.06	-0.02	0.08	-0.04	0.00	0.15	.	-0.02	0.04	0.00	-0.04
ADR_EX	-0.05	-0.02	0.08	0.17	0.00	0.18	-0.03	-0.02	0.00	-0.15	-0.02	.	-0.04	-0.02	0.00
ADR_NEX	-0.03	-0.06	0.01	0.18	0.00	0.15	-0.02	-0.03	0.00	-0.12	0.05	-0.04	.	-0.02	-0.03
STD_SALES	0.02	0.04	0.07	-0.03	-0.06	-0.11	-0.16	0.14	0.01	0.08	-0.02	-0.05	-0.07	.	0.07
LOSS_FREQ	0.03	-0.04	-0.04	-0.21	-0.13	-0.23	0.02	0.23	-0.02	0.21	-0.04	0.01	-0.02	0.11	.

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

VARIABLES	(1) *LIQVOL*	(2) *LIQVOL*	(3) *LIQVOL*	(4) *LIQVOL*	(5) *LIQVOL*	(6) *LIQVOL*
SIZE	-1.025	-1.025	-1.025	-0.852	-1.049	-0.970
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
BM	-0.101	-0.099	-0.099	-0.055	-0.158	-0.093
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
STDRET	-1.575	-1.591	-1.708	-1.095	2.598	-1.517
	(0.002)	(0.000)	(0.001)	(0.026)	(0.000)	(0.003)
FRET	-1.353	-1.350	-1.342	-1.321	-1.210	-1.318
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
ILLIQ	0.300	0.300	0.299	0.287	0.369	0.293
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
CLHLD	0.012	0.012	0.013	0.011	0.015	0.012
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
ADR_EX	-0.709	-0.705	-0.680	-0.483	-0.611	-0.644
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
ADR_NEX	-0.690	-0.691	-0.677	-0.461	-0.598	-0.633
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
STD_SALES	-0.013	-0.011	-0.010	-0.016	-0.017	-0.015
	(0.367)	(0.005)	(0.473)	(0.266)	(0.183)	(0.285)
LOSS_FREQ	0.229	0.238	0.230	0.131	0.190	0.133
	(0.000)	(0.000)	(0.000)	(0.003)	(0.001)	(0.003)
DIS_SMTH	**0.121**					
	(0.001)					
INTGAAP		**-0.120**				
		(0.000)				
BIG5			**-0.193**			
			(0.000)			
ANALYST				**-0.080**		
				(0.000)		
ACCURACY					**-1.239**	
					(0.000)	
TRANS						**-2.009**
						(0.000)
Fixed Effects	C,Y	C,Y	C,Y	C,Y	C,Y	C,Y
Observations	507,822	507,822	507,822	507,822	348,442	507,822
Adjusted R-squared	0.709	0.709	0.709	0.725	0.722	0.714

Table 4 presents results of OLS estimation of our Transparency and Liquidity Volatility analysis using firm-level monthly observations. In all specifications, we take the natural log of the dependent variable, *LIQVOL*. All variables are otherwise calculated as described in the Appendix. P-values (two-sided) are based on robust standard errors clustered at the firm level. We include country (C) and year (Y) fixed effects in the models as indicated, 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

	(1)	(2)
VARIABLES	***LIQSKEW***	***LBH***
SIZE	-0.120	-0.211
	(0.000)	(0.000)
BM	-0.014	0.030
	(0.000)	(0.003)
STDRET	-2.429	-1.301
	(0.000)	(0.011)
FRET	0.097	-0.463
	(0.027)	(0.000)
ILLIQ	0.038	0.385
	(0.000)	(0.000)
CLHLD	0.002	-0.001
	(0.000)	(0.021)
ADR_EX	-0.123	0.283
	(0.000)	(0.000)
ADR_NEX	-0.118	0.227
	(0.000)	(0.000)
STD_SALES	-0.009	-0.016
	(0.014)	(0.250)
LOSS_FREQ	-0.112	0.278
	(0.000)	(0.000)
TRANS	**-0.189**	**-0.873**
	(0.000)	**(0.000)**
Fixed Effects	C,Y	C,Y
Observations	496,954	507,822
Adjusted R-squared	0.155	0.136

Table 5 presents results of OLS estimation of our Transparency and Extreme Illiquidity Events analysis using firm-level monthly observations. In all specifications, we take the natural log of the dependent variable, *LBH*. All variables are otherwise calculated as described in the Appendix. P-values (two-sided) are based on robust standard errors clustered at the firm level. We include country (C) and year (Y) fixed effects in the models as indicated, 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

	(1)	(2)
VARIABLES	***COM(FL,ML)***	***COM(FL,MR)***
SIZE	-0.021	-0.025
	(0.000)	(0.000)
BM	-0.002	-0.004
	(0.297)	(0.006)
STDRET	-0.247	-0.187
	(0.048)	(0.116)
FRET	-0.123	-0.072
	(0.030)	(0.180)
ILLIQ	0.014	0.015
	(0.000)	(0.000)
CLHLD	0.000	0.000
	(0.703)	(0.002)
ADR_EX	-0.024	-0.025
	(0.017)	(0.008)
ADR_NEX	-0.008	-0.018
	(0.402)	(0.041)
STD_SALES	-0.004	0.002
	(0.175)	(0.436)
LOSS_FREQ	0.053	0.030
	(0.000)	(0.000)
TRANS	**-0.118**	**-0.080**
	(0.000)	**(0.000)**
Fixed Effects	C,Y	C,Y
Observations	498,314	498,193
Adjusted R-squared	0.020	0.011

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. P-values (two-sided) are based on robust standard errors clustered at the firm level. We include country (C) and year (Y) fixed effects in the models as indicated, but do not report the coefficients. All continuous non-logarithmic variables are truncated at the 1st and 99th percentiles.

TABLE 7
Robustness Analyses

Panel A: *BAVOL* Analysis

VARIABLES	(1) *LIQVOL*	(2) *LIQSKEW*	(3) *LBH*	(4) *COM(FL,ML)*	(5) *COM(FL,MR)*
SIZE	-1.257	-0.093	-0.491	-0.004	-0.011
	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)
BM	-0.097	-0.008	0.069	0.007	0.003
	(0.000)	(0.001)	(0.000)	(0.000)	(0.031)
STDRET	-5.257	-0.962	0.832	0.386	0.328
	(0.000)	(0.000)	(0.324)	(0.002)	(0.006)
FRET	-1.879	0.231	-1.194	-0.040	-0.038
	(0.000)	(0.000)	(0.000)	(0.510)	(0.503)
ILLIQ	0.069	0.003	0.125	0.004	0.003
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
CLHLD	0.014	0.001	-0.005	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
ADR_EX	-1.165	-0.093	0.656	0.016	-0.001
	(0.000)	(0.000)	(0.000)	(0.150)	(0.953)
ADR_NEX	-0.825	-0.101	0.298	0.005	0.003
	(0.000)	(0.000)	(0.000)	(0.585)	(0.761)
STD_SALES	-0.029	-0.000	-0.056	-0.000	0.000
	(0.203)	(0.937)	(0.087)	(0.916)	(0.848)
LOSS_FREQ	-0.002	-0.151	0.175	-0.006	-0.018
	(0.979)	(0.000)	(0.040)	(0.375)	(0.010)
TRANS	**-3.104**	**-0.083**	**-1.801**	**-0.113**	**-0.066**
	(0.000)	**(0.003)**	**(0.000)**	**(0.000)**	**(0.000)**
Fixed Effects	C,Y	C,Y	C,Y	C,Y	C,Y
Observations	399,923	393,143	399,709	392,876	392,745
Adjusted R-squared	0.694	0.109	0.197	0.007	0.004

Table 7 Panel A presents results of OLS estimation of our *BAVOL* analysis using firm-level monthly observations. In all specifications, we take the natural log of the dependent variables, *LIQVOL* and *LBH*. *LIQVOL*, *LIQSKEW*, *LBH*, *COM(FL,ML)* and *COM(FL,MR)* are calculated as described in Section 4.1 except that *BAVOL*, instead of *DPI* is used as the underlying liquidity construct. All variables are otherwise calculated as described in the Appendix. P-values (two-sided) are based on robust standard errors clustered at the firm level. We include country (C), and year (Y) fixed effects in the models as indicated, but do not report the coefficients. All continuous non-logarithmic variables are truncated at the 1st and 99th percentiles.

TABLE 7- Continued
Robustness Analyses

Panel B: Changes Analysis

VARIABLES	(1) **ΔLIQVOL**	(2) **ΔLIQSKEW**	(3) **ΔLBH**	(4) **ΔCOM(FL,ML)**	(5) **ΔCOM(FL,MR)**
ΔSIZE	0.006	-0.011	-0.034	0.029	0.005
	(0.482)	(0.008)	(0.015)	(0.000)	(0.300)
ΔBM	0.227	0.022	0.105	0.015	0.013
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
ΔSTDRET	-0.633	-0.664	0.631	-0.628	-0.567
	(0.067)	(0.000)	(0.304)	(0.003)	(0.006)
ΔFRET	-0.518	0.003	-0.089	-0.136	-0.078
	(0.000)	(0.970)	(0.724)	(0.135)	(0.373)
ΔILLIQ	-0.019	-0.008	-0.014	0.002	0.003
	(0.001)	(0.010)	(0.308)	(0.615)	(0.437)
ΔCLHLD	0.002	0.000	0.001	0.000	-0.000
	(0.000)	(0.146)	(0.025)	(0.045)	(0.747)
ΔADR_EX	0.050	-0.019	0.075	0.074	0.012
	(0.300)	(0.412)	(0.052)	(0.019)	(0.671)
ΔADR_NEX	0.023	-0.004	0.084	0.053	0.023
	(0.570)	(0.864)	(0.070)	(0.075)	(0.437)
ΔSTD_SALES	0.003	-0.002	-0.001	-0.008	-0.003
	(0.772)	(0.463)	(0.900)	(0.020)	(0.561)
ΔLOSS_FREQ	0.243	0.050	0.357	-0.016	0.006
	(0.000)	(0.026)	(0.000)	(0.567)	(0.814)
ΔTRANS	**-0.554**	**-0.055**	**-0.373**	**-0.083**	**-0.077**
	(0.000)	**(0.101)**	**(0.000)**	**(0.049)**	**(0.055)**
Fixed Effects	C,Y	C,Y	C,Y	C,Y	C,Y
Observations	40,733	40,698	40,733	40,679	40,672
Adjusted R-squared	0.297	0.011	0.011	0.005	0.002

Table 7 Panel B presents results of OLS estimation of our Changes analysis using firm-level annual observations. In all specifications, we take the natural log of the dependent variables, *LIQVOL* and *LBH*. A Δ prefix indicates that the first-differences annual change in the variable is included in the regression. All variables are otherwise calculated as described in the Appendix. P-values (two-sided) are based on robust standard errors clustered at the firm level. We include country (C) and year (Y) fixed effects in the models as indicated, but do not report the coefficients. All continuous non-logarithmic variables are truncated at the 1st and 99th percentiles.

TABLE 8
Transparency, Liquidity Uncertainty and Country-Level Institutions

VARIABLES	(1) *LIQVOL*	(2) *LIQSKEW*	(3) *LBH*	(4) *COM(FL,ML)*	(5) *COM(FL,MR)*
SIZE	-0.969	-0.120	-0.213	-0.021	-0.025
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
BM	-0.096	-0.014	0.029	-0.002	-0.005
	(0.000)	(0.000)	(0.003)	(0.296)	(0.005)
STDRET	-1.430	-2.416	-1.322	-0.227	-0.190
	(0.005)	(0.000)	(0.011)	(0.069)	(0.110)
FRET	-1.320	0.098	-0.460	-0.127	-0.073
	(0.000)	(0.025)	(0.000)	(0.026)	(0.178)
ILLIQ	0.293	0.038	0.387	0.014	0.015
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
CLHLD	0.012	0.002	-0.001	0.000	0.000
	(0.000)	(0.000)	(0.016)	(0.608)	(0.002)
ADR_EX	-0.674	-0.121	0.280	-0.025	-0.027
	(0.000)	(0.000)	(0.000)	(0.014)	(0.006)
ADR_NEX	-0.627	-0.115	0.237	-0.007	-0.018
	(0.000)	(0.000)	(0.000)	(0.498)	(0.047)
STD_SALES	-0.017	-0.009	-0.015	-0.004	0.002
	(0.251)	(0.015)	(0.268)	(0.190)	(0.433)
LOSS_FREQ	0.124	-0.112	0.282	0.053	0.030
	(0.006)	(0.000)	(0.000)	(0.000)	(0.000)
SUB_TRANS	**-1.131**	**-0.051**	**-0.320**	**-0.033**	**-0.037**
	(0.000)	**(0.008)**	**(0.000)**	**(0.031)**	**(0.011)**
SUB_TRANS*WEAK	**-0.383**	**-0.098**	**-0.250**	**-0.068**	**-0.030**
	(0.001)	**(0.000)**	**(0.051)**	**(0.001)**	**(0.118)**
COMP_TRANS	**-0.380**	**-0.064**	**-0.488**	**-0.032**	**-0.022**
	(0.000)	**(0.000)**	**(0.000)**	**(0.006)**	**(0.057)**
COMP_TRANS*WEAK	**0.414**	**0.045**	**0.432**	**0.025**	**0.033**
	(0.000)	**(0.029)**	**(0.000)**	**(0.107)**	**(0.028)**
Fixed Effects	C,Y	C,Y	C,Y	C,Y	C,Y
Observations	496,954	496,954	507,822	498,314	498,193
Adjusted R-squared	0.155	0.155	0.137	0.020	0.011

Table 8 presents results of OLS estimation of our Transparency, Liquidity Uncertainty and Country-level Institutional analysis using firm-level monthly observations. In all specifications, we take the natural log of the dependent variables, *LIQVOL* and *LBH*. *WEAK* is an indicator variable equal to one if a firm is in Institutional Cluster 2 or 3, and zero otherwise. All variables are otherwise calculated as described in the Appendix. P-values (two-sided) are based on robust standard errors clustered at the firm level. We include country (C) and year (Y) fixed effects in the models as indicated, but do not report the coefficients. All continuous non-logarithmic variables are truncated at the 1st and 99th percentiles.

TABLE 9
Transparency, Liquidity Uncertainty and Crises

VARIABLES	(1) *LIQVOL*	(2) *LIQVOL*	(3) *LIQSKEW*	(4) *LIQSKEW*	(5) *LBH*	(6) *LBH*	(7) *COM(FL,ML)*	(8) *COM(FL,ML)*	(9) *COM(FL,MR)*	(10) *COM(FL,MR)*
SIZE	-0.971	-0.971	-0.120	-0.120	-0.212	-0.212	-0.021	-0.021	-0.025	-0.025
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
BM	-0.094	-0.094	-0.014	-0.014	0.029	0.029	-0.002	-0.002	-0.004	-0.004
	(0.000)	(0.000)	(0.000)	(0.000)	(0.003)	(0.004)	(0.288)	(0.284)	(0.007)	(0.007)
STDRET	-1.538	-1.590	-2.417	-2.416	-1.250	-1.302	-0.199	-0.202	-0.160	-0.162
	(0.002)	(0.002)	(0.000)	(0.000)	(0.015)	(0.011)	(0.110)	(0.105)	(0.179)	(0.172)
FRET	-1.307	-1.293	0.099	0.098	-0.448	-0.437	-0.118	-0.117	-0.070	-0.070
	(0.000)	(0.000)	(0.024)	(0.026)	(0.000)	(0.000)	(0.038)	(0.039)	(0.196)	(0.197)
ILLIQ	0.293	0.293	0.038	0.038	0.385	0.385	0.014	0.014	0.015	0.015
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
CLHLD	0.012	0.012	0.002	0.002	-0.001	-0.001	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.020)	(0.019)	(0.730)	(0.733)	(0.002)	(0.002)
ADR_EX	-0.646	-0.647	-0.123	-0.123	0.281	0.281	-0.024	-0.024	-0.025	-0.025
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.016)	(0.016)	(0.008)	(0.008)
ADR_NEX	-0.632	-0.632	-0.118	-0.118	0.228	0.228	-0.008	-0.009	-0.018	-0.018
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.378)	(0.375)	(0.037)	(0.036)
STD_SALES	-0.016	-0.016	-0.009	-0.009	-0.016	-0.016	-0.004	-0.004	0.002	0.002
	(0.272)	(0.272)	(0.014)	(0.014)	(0.240)	(0.240)	(0.156)	(0.157)	(0.446)	(0.445)
LOSS_FREQ	0.136	0.137	-0.113	-0.113	0.279	0.280	0.052	0.052	0.030	0.030
	(0.003)	(0.002)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
TRANS	**-1.961**	**-1.957**	**-0.181**	**-0.181**	**-0.812**	**-0.810**	**-0.094**	**-0.094**	**-0.070**	**-0.070**
	(0.000)	**(0.000)**	**(0.000)**	**(0.000)**	**(0.000)**	**(0.000)**	**(0.000)**	**(0.000)**	**(0.000)**	**(0.000)**
MKTDOWN_BIG	**0.838**		**0.072**		**0.722**		**0.159**		**0.038**	
	(0.000)		**(0.000)**		**(0.000)**		**(0.000)**		**(0.047)**	
MKTDOWN_BIG1		**0.745**		**0.053**		**0.500**		**0.134**		**0.006**
		(0.000)		**(0.008)**		**(0.000)**		**(0.000)**		**(0.818)**
MKTDOWN_BIG2		**1.046**		**0.091**		**1.070**		**0.193**		**0.079**
		(0.000)		**(0.000)**		**(0.000)**		**(0.000)**		**(0.006)**
MKTDOWN_BIG*TRANS	**-0.692**		**-0.119**		**-0.901**		**-0.361**		**-0.159**	
	(0.000)		**(0.000)**		**(0.000)**		**(0.000)**		**(0.000)**	
MKTDOWN_BIG1*TRANS		**-0.699**		**-0.070**		**-0.605**		**-0.316**		**-0.096**
		(0.000)		**(0.054)**		**(0.000)**		**(0.000)**		**(0.043)**
MKTDOWN_BIG2*TRANS		**-0.840****		**-0.168****		**-1.370*****		**-0.418***		**-0.234****
		(0.000)		**(0.000)**		**(0.000)**		**(0.000)**		**(0.000)**
Fixed Effects	C,Y	C,Y	C,Y	C,Y	C,Y	C,Y	C,Y	C,Y	C,Y	C,Y
Observations	507,822	507,822	496,954	496,954	507,814	507,814	498,314	498,314	498,193	498,193
Adjusted R-squared	0.715	0.716	0.155	0.155	0.137	0.137	0.020	0.020	0.011	0.011

Table 9 presents results of OLS estimation of our Transparency, Liquidity Uncertainty and Crises analysis using firm-level monthly observations. In all specifications, we take the natural log of the dependent variables, *LIQVOL* and *LBH*. All variables are otherwise calculated as described in the Appendix. P-values (two-sided) are based on robust standard errors clustered at the firm level. We include country (C) and year (Y) fixed effects in the models as indicated, but do not report the coefficients. All continuous non-logarithmic variables are truncated at the 1st and 99th percentiles. ***, ** and * denote that the *MKTDOWN_BIG2*TRANS* coefficient is significantly different from the *MKTDOWN_BIG1*TRANS* coefficient at the 1%, 5% and 10% level, respectively.

TABLE 10
Liquidity Variation, Covariation and Valuation

VARIABLES	(1) *Q*	(2) *Q*	(3) *Q*	(4) *Q*	(5) *Q*	(6) *Q*
LNTOTASS	-0.077	-0.109	-0.091	-0.076	-0.076	-0.122
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
LEV	0.040	0.052	0.050	0.043	0.043	0.067
	(0.366)	(0.236)	(0.261)	(0.343)	(0.336)	(0.127)
CASH	1.497	1.456	1.481	1.504	1.505	1.442
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
NIEX	0.558	0.614	0.548	0.570	0.576	0.580
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
IND_Q	0.136	0.126	0.138	0.140	0.138	0.124
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
AGROWTH	0.056	0.057	0.060	0.061	0.060	0.056
	(0.041)	(0.048)	(0.031)	(0.028)	(0.031)	(0.043)
ADR_EX	0.225	0.176	0.250	0.220	0.217	0.197
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
ADR_NEX	0.203	0.161	0.224	0.201	0.202	0.176
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
A_ILLIQ	-0.041	-0.050	-0.042	-0.058	-0.057	-0.038
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
A_LIQVOL	**-0.025**					**-0.005**
	(0.000)					**(0.038)**
A_LIQSKEW		**-0.303**				**-0.263**
		(0.000)				**(0.000)**
A_LBH			**-0.042**			**-0.023**
			(0.000)			**(0.000)**
A_COM(FL,ML)				**-0.094**		**-0.070**
				(0.000)		**(0.000)**
A_COM(FR,ML)					**-0.103**	**-0.067**
					(0.000)	**(0.000)**
Fixed Effects	C,Y	C,Y	C,Y	C,Y	C,Y	C,Y
Observations	54,022	53,984	54,014	53,956	53,959	53,854
Adjusted R-squared	0.222	0.239	0.228	0.221	0.221	0.246

Table 10 presents results of OLS estimation of our Liquidity Variation, Covariation and Valuation analysis using firm-level annual observations. The prefix *A_* indicates that the included variable is an annual average of the underlying monthly variable. All other variables are otherwise calculated as described in the Appendix. P-values (two-sided) are based on robust standard errors clustered at the firm-level. We include country (C) and year (Y) fixed effects in the models as indicated, 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

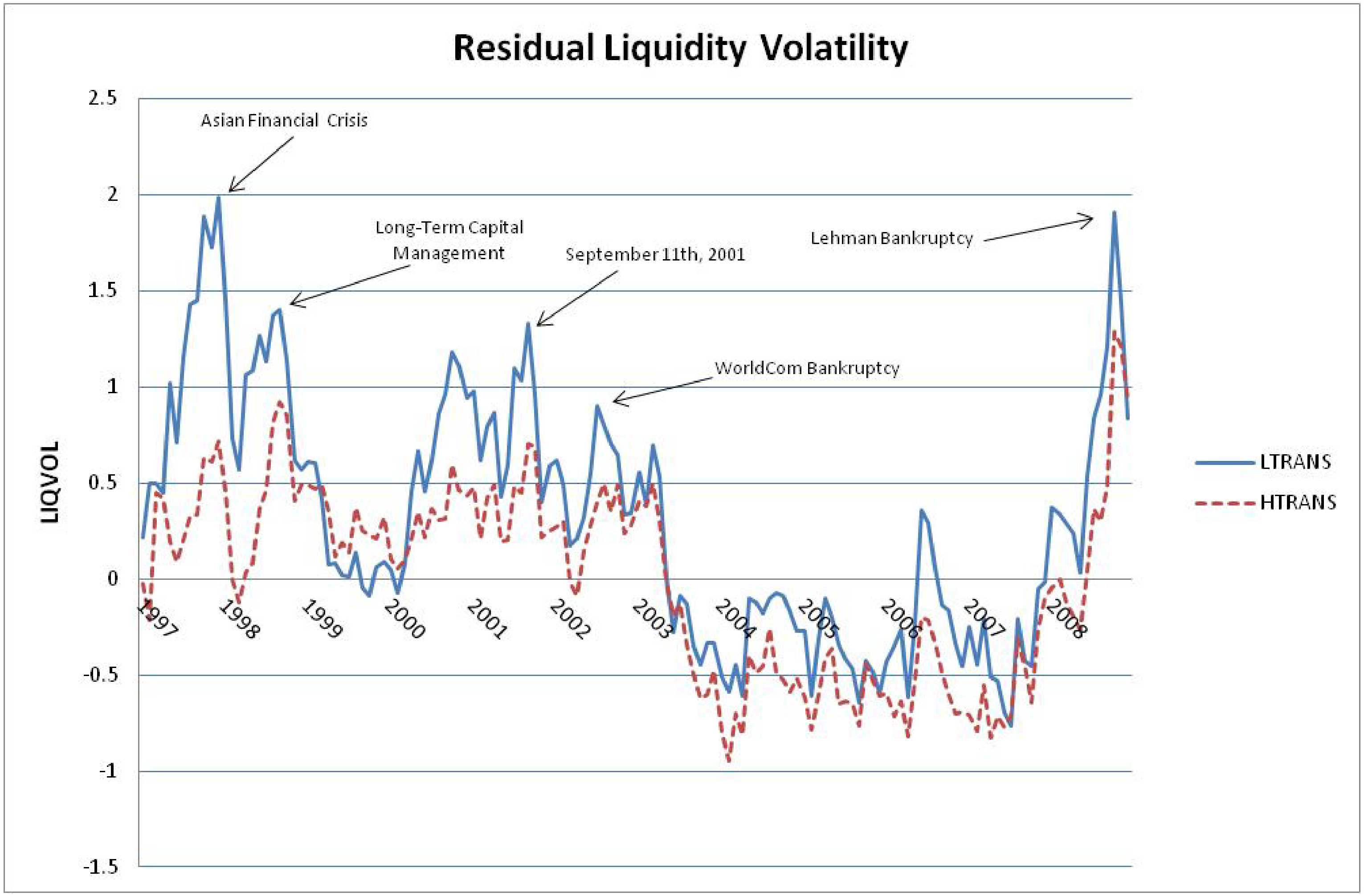

Figure 1 depicts a time-series graph of residual liquidity volatility for high and low transparency groups. A firm is classified as high transparency (*HTRANS*) if it has a *TRANS* value higher than the sample median during a particular year, and low transparency (*LTRANS*) otherwise. Residual liquidity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