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# Do markets anticipate capital structure decisions? — Feedback effects in equity liquidity☆,☆☆

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ABSTRACT

We analyze the impact of expected (targeted) capital structure decisions on information asymmetries. We measure information asymmetry from equity liquidity through the use of an information asymmetry index that is based on six measures that capture trading activity, trading costs, and the price impact of order flow. Modeling the joint determination of leverage and liquidity, the data indicate that expected increases in leverage (target leverage changes) decrease the information asymmetry index. This is consistent with the signaling hypothesis of Ross (1977), and is equivalent to increases in equity liquidity.



## 1. Introduction

What are the determinants of capital structure? This has been one of the most enduring and challenging questions in the corporate finance literature since the pioneering works of Modigliani and Miller (1958) and Myers (1984). Most studies on this topic have investigated certain firm characteristics (e.g., profitability, tangibility, size) or country and industry effects as determinants of leverage or the speed of adjustment toward a target capital structure. Our analysis focuses on the information revealed by the process that firms take toward these targets.

In this sense, we posit that managers (or "insiders") have reasonably well-defined policies by which they adjust their firm's capital structure towards a long run target. Capital structure is normally stable over time (see Lemmon et al., 2008), until some type of change in, e.g., the financial environment makes an adjustment necessary (see Korajczyk and Levy, 2003). By comparing current capital structure with target leverage, we can predict future financial securities issuances (e.g., seasoned equity or bond offerings). If the issuance realized deviates from expectations, this information can be a valuable sign for market participants

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("outsiders") because it affects information asymmetries. However, the inherent information content of future issuances can also be estimated today using current equity liquidity, which we assume can proxy for asymmetric information.

The cash flow information hypothesis of Ross (1977) states that more profitable firms can afford higher debt. Previous work has tested this hypothesis, but only for observed changes in capital structure. Masulis (1980) and Erwin and Miller (1998) use event studies to measure the effect of leverage signaling on short-term returns. Dann et al. (1991) and Shah (1994) analyze firm performance after capital structure transactions by measuring, e.g., operating cash flow. Other authors, such as Ofer and Siegel (1987) or Israel et al. (1989), have examined adjustments of financial analysts' forecasts in response to leverage signaling.[3]

In contrast, we use expected changes in leverage, denoted as "target leverage changes", proxied for by estimated changes in capital structure from leverage regressions. We believe that this is a sound method, because investors use available information to form expectations about firms' future performance and risk. From the pioneering works of Merton (1973) and Modigliani and Miller (1958), we know that firm leverage is related to both. Therefore, market participants should also develop expectations about future capital structure.

Our work deviates from the previous literature in a second key aspect, because we measure information revelations by using liquidity. We thus avoid using analyst coverage, which can be affected by conflicts of interest (see, e.g., Lin and McNichols, 1998; Michaely, 1999) or the reliability of analyst data in general, as pointed out by Ljungqvist et al. (2009). Furthermore, we do not need to rely on static balance sheet items such as size or growth opportunities, which are potentially driven by accounting policy and cannot react as quickly as equity liquidity.

We thus propose equity liquidity, although imperfect, as a viable proxy for measuring information asymmetries between managers (insiders) and the remaining market participants (outsiders). In the market microstructure literature, asymmetric information between traders as an illiquidity source has been modeled and discussed extensively (see, e.g., Brennan and Subrahmanyam, 1996; Easley and O'Hara, 1987; Foster and Viswanathan, 1993; Glosten, 1989; Kyle, 1985).[4]

In our case managers are well-informed. They have improved capabilities in the assessment of good (bad) news on their own firm and are more likely to buy (sell) larger volumes of stocks to use their information advantage. Therefore, market makers who step in if orders fail to arrive will lose money (Bagehot, 1971). In awareness of these expected losses, trading volume will either be reduced, or higher discounts in the form of spreads or price impacts will be expected (Amihud et al., 2006). The classic adverse selection problem described by Akerlof (1970) is a direct consequence. So we propose that liquidity should proxy for managers' information advantages about a firm's future prospects.

As per Bharath et al. (2009), our argument is based on the assumption that managers constitute a subgroup of informed traders for three reasons: 1) They naturally have access to insider information, 2) they own a considerable amount of shares in the company, and 3) they trade in their own firms' stocks. The first argument is common sense. Regarding (2), studies have shown that management compensation usually includes granted common stock and stock option awards (Agrawal and Mandelker, 1987; Jensen and Meckling, 1976; Yermack, 1995). As Morck et al. (1988) show, these instruments can amount to a considerable share of the firm. (3) comes from the results of several studies on company executives' and directors' trades that find that they use their information for trading and tend to earn abnormal returns (Finnerty, 1976; Jaffe, 1974; Jeng et al., 2003; Lakonishok, 2001).

We therefore propose using liquidity, despite its imperfections, as a proxy for the market's view on information asymmetries between insiders and outsiders. Higher informational asymmetries involve less liquidity, and liquidity measures are sensitive to information-revealing firm characteristics such as ownership structure (Gompers and Metrick, 2001), asset liquidity and ratings (Odders-White, 2006), events such as takeover announcements (Jennings, 1994) and agency costs (Hirth and Uhrig-Homburg, 2010). Moreover, firms with less liquid equity (and therefore most likely higher information asymmetries) exhibit higher levels of debt (Baker and Stein, 2004; Butler et al., 2005).

In summary, linking liquidity to corporate capital structure can yield valuable insights into three related strands of literature. First, we analyze the signaling effect of anticipated (targeted) leverage changes. We therefore contribute to the discussion on whether (unexpected) changes in leverage convey information to the public from an innovative perspective. Second, we expand the work of Bharath et al. (2009) by analyzing the entire chain from information asymmetries to (target) leverage, as well as its feedback effects to information asymmetries. Third, we improve the understanding of the drivers of liquidity. For owners and managers, this is extremely relevant, because liquidity has a direct effect on equity returns (see, e.g., Acharya and Pedersen, 2005; Amihud, 2002; Pastor and Stambaugh, 2003), the cost of capital, and thus shareholder value. Amihud and Mendelson (1986, 1988, 2008), for example, have regularly called for an analysis of the link between capital structure and liquidity. For academia, it is also valuable to better understand the variations in liquidity that have been observed in the cross-section of firms and over time by Chordia et al. (2000, 2001), Hasbrouck (2001) and Huberman and Halka (2001). In this context, our paper also contributes to the empirical literature on the relationship between equity liquidity and capital structure. As documented by Lipson and Mortal (2009) firms with more liquid equity use less debt and prefer equity when raising outside capital. Frieder and Martell (2006) go further and analyze the bi-directional relationship between leverage and liquidity using an instrumental variable approach. Their findings indicate that bid–ask spreads decrease as a reaction to increases in leverage. This is in line with lower agency costs induced by debt (Jensen (1986)) and Amihud and Mendelson's (1989) notion that managers also consider a potentially detrimental effect of illiquidity on firm value when making capital structure decisions. Our results extend this literature along two dimensions. First, when interpreting our information asymmetry index more broadly, our findings indicate that (unexpected)

[3] For a detailed survey of the early literature, see Masulis (1988); for a more recent overview, see Klein et al. (2002).

[4] Liquidity is also considered a result of order processing, transaction costs (Amihud et al., 2006) and inventory costs (Ho and Stoll, 1981; O'Hara and Oldfield, 1986; Stoll, 1978). For a detailed overview of the theoretical concepts of liquidity, see O'Hara (1995).

changes in capital structure affect firm-level liquidity. In other words, we extend the literature beyond observed changes by considering target leverage changes. Second, we complement the findings by Lipson and Mortal (2009) and Frieder and Martell (2006) by providing empirical evidence that decreases in leverage (through SEOs) lead to decreases in liquidity, which we interpret as increases in information asymmetry.[5]

To test the link between capital structure and information asymmetry, we use daily stock and annual balance sheet data for U.S. firms from 1989 through 2008. Our procedure encompasses four steps:

1. Using a principal component analysis, as per Bharath et al. (2009), we derive the common informational component of six different liquidity measures.
2. We then use the resulting year-by-year information asymmetry index to estimate (book and market) leverage targets, as is commonly done in the literature (see Rajan and Zingales, 1995; Titman and Wessels, 1988). Here, we find that leverage is a linear function of our information asymmetry index, and that an increase (of information asymmetry) by one standard deviation results in an increase in leverage of about 2%.
3. Next, we calculate the distance between a firm's current leverage and its target capital structure as a proxy for expected development. We also demonstrate its reliability for predicting true changes.
4. Finally, we determine the effect of these target leverage changes on our information asymmetry index (measures of liquidity), in order to model feedback effects.

Note that steps (2)–(4) yield a two-stage system estimation. If we use observed (i.e. realized) changes in leverage to explain changes in information asymmetry, we find diverging signs for the coefficients for book and market leverage in similar estimations. This is a consequence of endogeneity between market prices (and thus market leverage) and liquidity (used for our index). To address the endogeneity problem inherent in an estimation of the relation between information asymmetry and leverage, we therefore use the instrument obtained in step 3. We find that target leverage changes reduce our information asymmetry index by a significant amount, a factor ranging from −0.25 to −0.29. We take both results to mean that market participants anticipate capital structure decisions of managers, which is reflected in our information asymmetry index. Targeted increases in leverage tend to also increase liquidity, which supports Ross's (1977) signaling hypothesis.

For robustness, we estimate results for several indexes constructed on liquidity risk measures and for single measures of liquidity. Further we find that our results are even stronger if we ignore small changes in leverage. We control for the latter, because small changes in capital structure due to, e.g., maturing bonds that require refinancing, should not reveal any significant information to market participants.

As an alternative approach – and to further mitigate endogeneity concerns – we conduct a series of event studies of capital structure changes. Specifically, we examine the effect of announcements of seasoned equity offerings (SEOs) for all components of our information asymmetry index. By using SEOs, we are looking at negative changes in leverage (i.e. decreases in the relative amount of debt in a firm's capital structure). All event study results (except round trip transaction costs) are in line with the findings above, showing increases in information asymmetry as a result of expected decreases in leverage. Again, these results are in line with Ross (1977) in that lower expected leverage signals lower predictability of cash flows. Alternatively, the decrease in liquidity we observe could be due to an increase in agency costs. In line with Jensen (1986) market participants may be concerned that the (relative) decrease in disciplining debt may lower managerial discipline.

The remainder of the article proceeds as follows. Section 2 describes our data sources, sample construction, and definitions. In Section 3, we present our information asymmetry index. Section 4 contains our empirical analysis. Section 4.2 describes the determination of leverage targets, while Section 4.3 discusses their effect on information asymmetries. Section 4.4 presents our event study results. In Section 5, we conduct robustness checks. Section 6 gives our conclusions.

## 2. Data, definitions, and descriptions

### *2.1. Database and sample construction*

All of the daily stock data we use come from the Center for Research in Security Prices (CRSP) North America database.[6] Included are U.S. stocks listed on the New York Stock Exchange (NYSE), the American Stock Exchange (AMEX), and the National Association of Securities Dealers Automated Quotations (NASDAQ). We limit our analysis to all non-ADR and regular shares.

Balance sheet items come from Standard & Poor's (S&P) Compustat database,[7] where we account for varying fiscal year-ends. Our observation period is from 1989 through 2008. Appendix A describes the construction our liquidity measures in detail. We

[5] It should be noted that both Lipson and Mortal (2009) and Frieder and Martell (2006) make (and test) the prediction that the degree of (il)liquidity causes firms to chose one form of outside capital (i.e. equity or debt) over the other. We do not make such predictions, but rather focus on the consequences that (expected) changes in capital structure have on liquidity and information asymmetries.

[6] Source: CRSP®, Center for Research in Security Prices. Graduate School of Business, The University of Chicago. Used with permission. All rights reserved. http://crsp.uchicago.edu.

[7] Source: Standard & Poor's Compustat®. Used with permission. All rights reserved. http://www.compustat.com/Research_Insight/.

**Table 1**
Data construction.

| Steps | Obs | Share | Selection rules |
|---|---|---|---|
| *General* | | | |
| 1 | 137,080 | 100.0% | Matched data |
| 2 | 109,970 | 80.2% | SIC |
| 3 | 108,656 | 79.3% | Eliminate duplicate entries |
| 4 | 88,347 | 64.4% | Trimming outliers per item |
| 5 | 88,143 | 64.3% | Leverage unit interval |
| 6 | 76,758 | 56.0% | Minimum daily obs |
| 7 | 73,369 | 53.5% | Stock price |
| 8 | 30,474 | 22.2% | No missing data |
| *Full samples* | | | |
| 9 | 29,687 | 21.7% | Measures of liquidity and liquidity risk ex. spreads ("FullexS") |
| 10 | 27,183 | 19.8% | Measures of liquidity and liquidity risk ("Full") |
| *Subsamples* | | | |
| 11 | 10,821 | 7.9% | "exNASDAQ" |
| 12 | 5557 | 4.1% | "Survivors" (15 years) |

The data consists of all U.S. listed firms in the CRSP®, Center for Research in Security Prices North America database, and the Standard & Poor's Compustat® database from 1989 through 2008. The general selection rules are described in detail in Section 2.1.

also use the three factors provided on Kenneth French's webpage.[8] All absolute U.S. dollar values are deflated by GDP growth, also from S&P's Compustat database.

Table 1 gives an overview of our general selection rules. After the matching procedure, we exclude all financial firms (SIC: 6000–6999),[9] all firms that are publicly administrated (SIC: 9200–9999), and all firms with a zero standard industrial classification (SIC) code. We also eliminate duplicate entries for unique firms (PERMCO) in the CRSP database by restricting our data to the largest market cap issues.

Furthermore, by trimming the 1% per item outliers on both sides of the variable distribution, as per Lemmon et al. (2008), we can mitigate the effects of outliers or misrecorded data.[10] We then restrict leverage to the unit interval, so as to exclude any technically bankrupt firm.

We also exclude stocks with less than 200 return observations per year, in order to limit problems from unreliable liquidity measure calculations. We subsequently restrict our analysis to stocks with prices between U.S. $1.00 and $1000.00 per share, as in Acharya and Pedersen (2005). This guarantees that we capture only regularly traded stocks.[11] Next, we limit our sample to firms that have all balance sheet and P/L items available. We also exclude firm observations with no measures of liquidity or liquidity risk except for spreads. Day-end bid and ask prices are only available from 1992 in the CRSP database. We decided to use both, but we denote the latter as the "Full" sample.

Lastly, we construct two subsamples for robustness checks. In the first subsample, we exclude all NASDAQ firms ("exNASDAQ"). This accounts for the NASDAQ effect found by Brennan et al. (1998) or Lesmond et al. (2008), where some liquidity measures such as trading volume and the Amihud (2002) liquidity measure are exaggerated, as follows. On NASDAQ interdealer trades, as well as on after-hours trades, volumes are included in the current day. Trades on all exchanges connected to NASDAQ's composite pricing network are also included in the volume. On the CRSP tapes, bid, ask, and missing price quotes are paired with non-zero volumes in some cases. Finally, prior to June 15, 1992, volumes were reported differently for the NASDAQ National Market and the NASDAQ Small-Cap Market. In the former, traded volumes were reported for one party, while for the latter they were reported for both parties.

In the second subsample, we included firms in our panel only if they had existed for at least fifteen years ("survivors"), to avoid any potential survivorship bias, as in Lemmon et al. (2008). We refrain from presenting results here because they are structurally similar.

## 2.2. Measures of capital structure

We define our capital structure measures in a traditional manner (see, e.g., Baker and Wurgler, 2002; de Miguel and Pindado, 2001; Fama and French, 2002; Kayhan and Titman, 2007; Titman and Wessels, 1988), where book leverage ($Lev^B_{i,t}$) is the ratio of total book debt-to-total assets of firm ($i$) in period ($t$). Note, however, that market leverage ($Lev^M_{i,t}$) is the ratio of total book debt-to-market value of assets.[12] We use both measures in order to account for this discrepancy.

[8] See http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/.

[9] We exclude banks because the high level of deposits can generate extremely high levels of leverage. Publicly administrated firms have access to higher levels of debt due to government guarantees. Results remain structurally unchanged if the finance, insurance, and real estate divisions are included, however, as the subsequent trimming alleviates the high leverage problem. Tables are available from the authors upon request.

[10] Chang and Dasgupta (2009) exclude 0.5% of the outliers. Winsorizing leads to qualitatively similar results. Tables are available from the authors upon request.

[11] By doing this, we also reduce price discreteness problems that can impact liquidity. At the NYSE, the minimum price variation for all stocks above U.S. $1 is now U.S. $0.01, but it was U.S. $0.125 prior to May 1997 (see NYSE Rule 62, http://nyserules.nyse.com/NYSE/Rules/). This has an automatic effect on spreads.

[12] Titman and Wessels (1988) state that firms refer mostly to book leverage when adjusting their leverage ratios. Most of our control variables are scaled to book value of total assets, but equity liquidity is linked to market capitalization and market equity.

**Table 2**
Cross sectional data on leverage.

| | Full | | exNASDAQ | | Survivors | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| | $Lev^B_{i,t}$ | $Lev^M_{i,t}$ | $Lev^B_{i,t}$ | $Lev^M_{i,t}$ | $Lev^B_{i,t}$ | $Lev^M_{i,t}$ |
| Mean | 0.21 | 0.21 | 0.25 | 0.26 | 0.22 | 0.23 |
| Std | 0.18 | 0.22 | 0.17 | 0.22 | 0.15 | 0.20 |
| Skew | 0.97 | 1.25 | 0.75 | 0.99 | 0.92 | 1.16 |
| Kurt | 3.76 | 3.90 | 3.60 | 3.36 | 4.21 | 3.89 |
| 95% quant | 0.56 | 0.68 | 0.57 | 0.72 | 0.51 | 0.64 |
| Median | 0.18 | 0.13 | 0.24 | 0.21 | 0.20 | 0.17 |
| 5% quant | 0.00 | 0.00 | 0.02 | 0.01 | 0.01 | 0.01 |
| Firm years | 29,687 | 29,687 | 10,821 | 10,821 | 5557 | 5557 |

The sample consists of the "Full" sample from 1992 through 2008. The table shows cross-sectional data on book and market leverage $Lev^B_{i,t}$, $Lev^M_{i,t}$ by samples, as indicated in the columns. For the former, it is total debt to value of total assets ($\frac{DT}{at}$); for the latter ($\frac{DT}{ME+DT}$), it is total debt to total debt plus market equity (shares outstanding times year-end market price).

Table 2 shows that both measures fall within the "typical" leverage range. Rajan and Zingales (1995) report an average (median) of 0.31 (0.27) for book leverage, and 0.24 (0.20) for market leverage (see also Lemmon et al. (2008) and Shyam-Sunder and Myers (1999)). In our sample, the average book and market leverage ratio is 0.21 (see columns 1 and 2); excluding NASDAQ firms in columns 3 and 4 leads to slightly higher debt ratios. Note that market leverage shows a higher variation.

### 2.3. Control variables for leverage

The number of leverage determinants analyzed in the literature is large (see, e.g., Chang and Dasgupta, 2009; Fama and French, 2002; Flannery and Rangan, 2006; Frank and Goyal, 2003; Shyam-Sunder and Myers, 1999; Titman and Wessels, 1988). We limit our research to a concise set of control variables that have been shown to be correlated with capital structure: size ($Size_{i,t-1}$), profitability ($Profit_{i,t-1}$), market-to-book ($M2B_{i,t-1}$), collaterals ($Coll_{i,t-1}$), uniqueness ($Uni_{i,t-1}$), tax rate ($Tax_{i,t-1}$) and industry effects ($Ind_{i,t}$). Each variable is discussed in more detail below.

- Size is a commonly used explanatory variable that reflects higher diversification and less risk of financial distress. Less bankruptcy probability should lead to a higher debt capacity for larger firms (Rajan and Zingales, 1995). We use sales ($Size_{i,t-1}$), scaled using a natural logarithm, as an indicator of firm size instead of total assets. Leverage ratios directly incorporate total asset value, which may lead to endogeneity problems.
- The key prediction of Myers (1984) and Myers and Majluf (1984) is that profitability is negatively related to leverage, while growth opportunities are positively related. If investments are fixed, higher profitability allows management to avoid external financing due to higher information costs. If profitability is fixed, higher growth opportunities should lead to an increase in debt, which leads to a positive relationship.
  In contrast, the trade off-theory argues that increasing cash flows lead to higher agency costs. Firms thus commit a larger percentage of pre-interest earnings to debt and interest payments in order to gain improved control over investment opportunities (Fama and French, 2002). We use the market-to-book asset ratio ($M2B$), as defined in Fama and French (1993), and profitability ($Profit_{i,t-1}$) as operating income before depreciation to total assets.
- Firms with more tangible assets should exhibit higher leverage for two reasons: Collaterals retain more of their value to debtors in case of liquidation, and agency costs of debt, such as risk-shifting, can be reduced (see Rajan and Zingales, 1995). We use inventory plus property, plant, and equipment net to total assets as our collateral measure ($Coll_{i,t-1}$), which proxies for a lender's willingness to lend to a firm.
- Titman and Wessels (1988) argue that more specialized firms impose higher costs on their customers, suppliers, and employees in case of bankruptcy, which leads to a lower debt capacity. The ratio of research and development expenses to sales (uniqueness, $Uni_{i,t-1}$) should reflect specialization.
- The value of the leveraged firm is the sum of the unlevered firm and the tax shield effect (Modigliani and Miller, 1963). Low tax ratios ($Tax_{i,t-1}$) reflect a low tax shield, which drives managers to increase debt (higher leverage), ultimately increasing firm value.
- All explanatory variables are lagged variables from the previous period to explain current leverage. Other forces, such as market or industry conditions, may drive financial decision making as well. Low levels of goodness-of-fit in standard leverage regressions support this argument. To mitigate the omitted variables problem, we include an industry control variable ($Ind_{i,t}$), following Lemmon et al. (2008). We calculate industry effects as the time series median for one-digit SIC industry classifications.

Panel A in Table 3 gives brief descriptions of all the control variables in our three samples except the industry factor. A quick inspection reveals that the means, medians, and standard deviations are comparable to those in Lemmon et al. (2008), who analyze a similar period. Size, as expected, is larger for survivors and exNASDAQ firms, but exhibits a little less variation.

**Table 3**
Descriptive statistics.

| Variable | Full Mean | Full Std | exNASDAQ Mean | exNASDAQ Std | Survivors Mean | Survivors Std |
|---|---|---|---|---|---|---|
| *Panel A: Control variables for leverage* | | | | | | |
| $Size_{i,t}$ | 18.59 (18.60) | 2.09 | 19.98 (20.20) | 1.85 | 19.50 (19.65) | 1.67 |
| $Profit_{i,t}$ | 0.05 (0.11) | 0.21 | 0.12 (0.13) | 0.13 | 0.13 (0.13) | 0.10 |
| $M2B_{i,t}$ | 1.80 (1.22) | 1.95 | 1.43 (1.07) | 1.31 | 1.42 (1.10) | 1.11 |
| $Coll_{i,t}$ | 0.42 (0.41) | 0.23 | 0.47 (0.47) | 0.20 | 0.48 (0.48) | 0.18 |
| $Tax_{i,t}$ | 0.23 (0.31) | 0.20 | 0.29 (0.34) | 0.18 | 0.29 (0.35) | 0.17 |
| $Uni_{i,t}$ | 1.46 (0.03) | 44.28 | 0.22 (0.02) | 12.80 | 0.24 (0.02) | 5.51 |
| *Panel B: Control variables for liquidity* | | | | | | |
| $V_{i,t}$ | 0.65 (0.58) | 0.35 | 0.45 (0.39) | 0.23 | 0.49 (0.44) | 0.25 |
| $R_{i,t}$ | 0.10 (0.00) | 0.64 | 0.11 (0.05) | 0.51 | 0.16 (0.08) | 0.55 |
| $AV = \frac{V*ME}{at}$ | 0.51 (0.45) | 0.31 | 0.32 (0.27) | 0.18 | 0.37 (0.33) | 0.21 |
| $Z''$ | 162.34 (8.98) | 2465.90 | 42.49 (8.05) | 729.41 | 34.50 (9.44) | 316.14 |
| *Panel C: Sample size* | | | | | | |
| Daily observations | 251.9 (252) | 3.0 | 251.9 (252) | 3.2 | 252.0 (252) | 2.3 |
| Firms | 5362 | | 1637 | | 330 | |
| Firm years | 29,687 | | 10,821 | | 5557 | |

The table shows descriptive statistics for control variables for the "full", "exNASDAQ", and "survivors" samples, indicated by columns for leverage (panel A) and liquidity (panel B) from 1989 through 2008. The variables for the whole paper are calculated using data items from the databases CRSP and Compustat. Profitability is operating income before depreciation to total assets ($\frac{OIBDP}{at}$, Market-to-Book is market equity plus preferred stock minus investment, tax credit, and deferred taxes to total assets ($\frac{ME+PFS-ITCB-TXDB+DT}{at}$), where market equity is $ME_{i,t} = P * Shrout$ stock price times shares outstanding. Preferred stocks are defined as $PFS_{i,t}$ redemption value or liquidating value or parvalue if the previous does not exist (1. PSTKRV; 2. PSTKL; 3. PSTK). Collaterals are calculated as inventory and property, plant and equipment to total assets ($\frac{INVT+PPENT}{at}$). The tax rate is income taxes to pretax income $100 * \frac{TXT}{PI}$, while uniqueness is defined as ($\frac{XRD}{at}$) research and development expenses to total assets. Volatility p.a. is standard deviation of daily returns ($std(R) * \sqrt{250}$), where Returns are arithmetic $\frac{P_y}{P_{y-1}} - 1$. Asset volatility $AV_{i,t}$ is equity volatility times market equity to total assets. The (Altman and Saunders, 1998) Z″-score is calculated as in previous studies $Z''_{i,t} = 3.25 + 6.56 * \frac{ACT-LCT}{at} + 3.26 * \frac{RE}{at} + 6.72 * \frac{EBIT}{at} + 1.05 * \frac{BE}{DT}$ using total assets ($at$), current assets and liabilities ($ACT$, $LCT$), retained earnings ($RE$), earnings before tax ($EBIT$) and book equity ($BE$). Panel C gives further information on the composition of our sample, where "daily observations" indicates the number of daily observations per year and firm, "firms" is the total number of firms in the sample, and "firm years" is the total number of observations in the sample period. Medians are given in parentheses.

By economic intuition, we hypothesize that profits will be negatively correlated with the probability of bankruptcy. Profitability, a proxy for the availability of internal sources of funding, is largest in our survivor subsample (with a value of 0.13). Collateral, reflecting the assets of a firm that are available to support debt and lower the cost of financial distress, also slightly increases from 0.42 to 0.48 from the full to the survivor sample. In addition, the market-to-book ratio decreases from our largest sample to our smallest subsample. Many firms on NASDAQ are small, innovative tech companies, and are characterized by higher growth opportunities, less collateral, less profitability, and larger R&D investments (i.e. $Uni_{i,t-1}$).

## 2.4. Control variables for liquidity

To extract the impact of leverage on liquidity, we control for firm-specific variables that also impact liquidity (described below). We use equity volatility ($V_{i,t}$), annual returns ($R_{i,t}$), asset volatility ($AV_{i,t}$), Z″ score ($Z''_{i,t}$) and profits ($Profit_{i,t}$).

- Increased leverage leads to increased equity volatility (Merton, 1974). This is equivalent to a higher sensitivity of equity prices to private information and can attract insider trading (Harris and Raviv, 1993) and uninformed investors, who may gamble on investment decisions (Kumar, 2009). But the increased probability of information-based trading increases the inventory risk of market makers and subsequently decreases liquidity (Amihud and Mendelson, 2008; Lesmond et al., 2008). Stoll (2000) also proposes that stock volatility measures the risk of adverse price changes, which reflects inventory arguments in Stoll (1978), Ho and Stoll (1981) and O'Hara and Oldfield (1986).
- We assume that changes in fair prices must exceed transaction costs and minimum price variations to obtain any observable price variation. Thus, prices could have an effect. Authors such as Brennan and Subrahmanyam (1996), Stoll (2000) and Chordia

et al. (2000) find a significant and negative relationship between prices and relative spreads. Prices can also be considered as proxies for other variables: Annual returns (price differences) could reflect a firm's economic prosperity, because we assume that firms with positive future earnings have positive returns. However, as per Subrahmanyam (1991), insiders with firm-specific information might be able to anticipate returns and use strategic trading to exploit the information.
- Higher firm risk increases the attractiveness of equity, a contingent claim (Black and Scholes, 1973; Merton, 1973). We use annual asset volatility to proxy for general business risk and the volatility of a firm's total value (Merton, 1974).
- Any theory on capital structure considers information asymmetries as a driving force, where managers use superior information to their own advantage. In the case of higher profits, information asymmetries could become more severe. On the other hand, increased profits could ease the predictability of future returns, and reduce information asymmetries on firm value. Consequently we add profits to our liquidity regressions.
- According to Odders-White (2006) we control for proximity to bankruptcy as a final firm characteristic, using a newer version of Altman's (1968) original Z-score model ($Z''_{i,t}$).[13]

While the Z″-scores are high on average (see Altman and Saunders, 1998), the medians are about 8.98 (see Table 3). Firms thus have a AAA-rating in more than 50% of all firm-year observations.[14] Asset and equity volatility are higher for our largest sample, and equity returns are highest for our survivor subsample. Both findings follow economic intuition. Our restricted subsamples include older, larger, and more profitable firms. Panel C provides information on sample composition and number of observations. The number of daily observations per year and firm is roughly 252. The total number of firms is 5362, but it decreases to 330 if we require firms be in our subsample for at least fifteen years.

## 3. Liquidity and information asymmetry index

Our analysis concentrates solely on equity liquidity for several reasons. First, bond payments are fixed, thus uncertainty about the future predictability of returns is limited to defaults, which is marginal compared to equity. Second, our aim is to investigate information asymmetries between management and the remaining owners. Third, we assume that the capital structure is defined in favor of the equityholders, due to incentives for managers to act on their behalf.

The research on market microstructure, mainly asset pricing, is vast. Assets that can be traded in very large volume and – within a marginal time frame – without any price impact are considered perfectly liquid (Bernstein, 1987). However, although the quality of the concept is widely accepted, neither a generally recognized definition of liquidity, nor a unique measure capturing all its aspects, exists (Chordia et al., 2009). We can categorize the large variety of liquidity measures into three groups: trading activity, trading costs, and the price impact of order flow.[15]

Chordia et al. (2000, 2001), Hasbrouck (2001) and Huberman and Halka (2001) show that absolute liquidity varies over time, which implies the existence of liquidity risk. The asset pricing literature claims that investors also need to be compensated for this type of risk (Acharya and Pedersen, 2005; Amihud, 2002; Pastor and Stambaugh, 2003). Considerations about liquidity risk were introduced by Ellul and Pagano (2006) in corporate finance by modeling the impact on IPO underpricing. They study newly listed firms on the London Stock Exchange using observed liquidity in the subsequent four weeks of the IPO. Post-IPO proxies for liquidity risk show significant explanatory power for underpricing.

In our context, we could interpret this to mean that high volatility in liquidity measures is evidence of strong variation in informational asymmetries over time. Holding everything else equal, higher volatility should increase adverse selection problems. Thus, for the sake of robustness, we must also consider liquidity risk in our analysis. Various concepts and measures of liquidity and liquidity risk have contributed to the understanding of the underlying problem (Hasbrouck, 2007). However, the amount of diversity means that no single measure can fully capture all aspects of this elusive concept, although they all will contain information asymmetries.

We thus follow Bharath et al. (2009) and construct a composite, time-varying index by using principal component analysis (PCA) on six measures: 1) trading volume ($TV_{i,t}$), 2) the proportion of zero returns, ($LOT_{i,t}$), as proposed by Lesmond et al. (1999), 3) the relative bid–ask-spread ($S_{i,t}$), 4) the effective spread, ($ROLL_{i,t}$), as proposed by Roll (1984), 5) round-trip transaction costs ($RTC_{i,t}$) from Lesmond et al. (1999), and 6) the Amihud (2002) price impact measure ($ALM_{i,t}$). As pointed out in Bharath et al. (2009), it is highly unlikely that any single of the selected liquidity measures is driven exclusively by adverse selection. However, combining the most direct measures of adverse selection with additional measures to form an index based on their first principal component minimizes the likelihood that the index is related to “non-informational” liquidity. In addition, we calculate an index based on the *variation* in these measures to capture liquidity risk. We do not limit our analysis to a single measure, because we wish to retain the largest possible amount of available information on market perceptions.[16] As a robustness check, we provide relevant results for liquidity measures separately in Section 5.2.

[13] The insolvency ratio ($Z''$) is a linear combination of the ratio of working capital to total assets ($Z_1$), retained earnings to total assets ($Z_2$), EBIT to total assets ($Z_3$), and book value of equity to total liabilities ($Z_4$). This results in: $Z'' = 3.25 + 6.56 * Z_1 + 3.26 * Z_2 + 6.72 * Z_3 + 1.05 * Z_4$.

[14] Altman and Saunders (1998) provide a U.S. bond rating equivalent.

[15] In fact, most measures represent illiquidity. We use both terms – illiquidity and liquidity – equivalently, but we must be careful about the contrary properties.

[16] In Appendix A (Table 12), we report summary statistics for the liquidity measures and our index that are comparable to those in Table 1 in Bharath et al. (2009). Each of the proxy means is of the expected sign, just as in Bharath et al. (2009), who interpret this as a sign of information asymmetry in the U.S. stock market during the observation period. For a more detailed description of the measures of liquidity and methods of calculation, see Appendix A.

We assume that our set of empirical liquidity measures ($x_{i,t}$, $x_{j,t}$), with ($n$) realizations in period ($t$), can be fully described by a linear combination ($\theta_{k,t}$) of ($k$) hypothetical and orthogonal factors ($f_{i,t,k}$) including noise. The first factor identified by PCA is our information asymmetry component (see Eq. (1)).[17]

$$x_{i,t} = \bar{x}_i + \sum_{k=1}^{K} \left( \theta_{k,t} * f_{i,t,k} \right) + \epsilon_{i,t}. \tag{1}$$

We use all liquidity and liquidity risk measures mentioned earlier to calculate two year-by-year indexes for any firm ($i$). Due to the availability of CRSP spreads, our index only covers the period 1992 to 2008.[18] We denote the isolated first common factor in liquidity measures as $ASY_{i,t}$, and as $\sigma_{ASY_{i,t}}$ for liquidity risk measures.

The different factor loadings exhibit the expected signs and do not change over time for absolute liquidity measures (see Table 4). Furthermore, our index does not exclude any single measure by close to zero factor loadings. In 1992, the weights of the spread, the trading volume, and the round-trip transaction costs were the highest in relative terms.

The decrease of factor loadings over time, especially for $S_{i,t}$, $LOT_{i,t}$, $ROLL_{i,t}$ may be a hint of their reduced relevance. In other words, spreads tightened considerably over time because of improvements in exchange technology. On the other hand, however, $ALM_{i,t}$ and $TV_{i,t}$ gained strongly, and the former is the single most important measure in 2008. For measures of liquidity risk, we expect all factor loadings to take effect in the same direction, so that a high variation in trading volume would characterize increased uncertainty, which also holds for a higher variation in spreads. All factor loadings exhibit positive signs except for the Roll (1984) factor loading, which alters around zero, indicating low relevance.

The full cross-sectional distribution of our firm-level illiquidity index exhibits a mean of zero, which comes from the z-transformation of original liquidity measures and a standard deviation of 1.89 ($std\left(\sigma_{ASY_{i,t}}\right) = 1.79$).[19] The distribution is slightly positively skewed, similarly to standard measures of illiquidity. Note further that, in accordance with Bharath et al. (2009), we estimate the first principal component of the correlation matrix of the available standardized proxies for the full extent of firm-level adverse selection in each fiscal year. Similarly, we also find that the first principal component explains, on average, more than 50% of the corresponding cross-sectional sample variance (see Table 14 in Appendix A), and that each component always enters the index with the correct sign.[20] It thus seems reasonable to conclude that one factor alone captures most of the common variation among the six proxies, i.e., the variation due to adverse selection. To summarize, we are convinced that the results and arguments presented above constitute strong evidence that our index has characteristics comparable to those of Bharath et al. (2009).

Notwithstanding our discussion above, a potential caveat is in order at this point. As documented in the market microstructure literature, equity liquidity is driven by a number of underlying economic factors (e.g. inventory risk, order-processing costs, funding liquidity, and fundamental volatility). Hence, adverse selection is only one possible interpretation. Several papers have attempted to decompose the bid–ask spread (e.g. Stoll (1989), George et al. (1991)) and found the adverse selection component to account for roughly 13–40% of the spread. More recently, Bharath et al. (2009) pursue a different approach based on principal component analysis, a methodology that we generally follow. As pointed out, there is no single best approach that can identify the adverse selection component with certainty. As a result, we cannot rule out the possibility that the first factor of our PCA is also influenced by non-informational components. For the reasons mentioned above, we are confident that the factor captures the variation that is due to adverse selection. However, it should be noted that even if this were not the case (i.e. our metric merely captures "general" liquidity), our analysis would still present new and important findings that help explain the relationship between (expected) changes in capital structure and equity liquidity.

## 4. Empirical results

### 4.1. Determinants of leverage

To investigate the effect of expected changes in capital structure (target leverage changes) on information asymmetries, we implement a two-stage equation model that simultaneously includes the determinants of leverage and liquidity.

Our first step is to use standard leverage regressions, as proposed by Titman and Wessels (1988), Rajan and Zingales (1995), and Shyam-Sunder and Myers (1999) (see also Eq. (2)). The fitted value of this regression is then used as the leverage target. In order to show that the distance from this leverage target has predictive power for observed changes in leverage, we conduct adjustment regressions. Third, we use these target leverage changes in Section 4.3 to estimate their effect on our information asymmetry index.

[17] Comparing the year-level Spearman rank correlations in Appendix A (panel A in Table 13), we find that the standardized proxies for firm-level information asymmetry are mostly positively correlated with each other. The trading volume variable is the only exception, which is not surprising because liquidity is measured in the "opposite direction". This result is highly comparable to the Spearman rank correlations shown in Bharath et al.'s (2009) Table 2.

[18] We also calculate two information asymmetry indexes that exclude spreads and spread risk. However, an inclusion seems adequate as spreads are widely used in the market microstructure literature. The results are not shown here, but factor loadings ($\theta_{t,k}$) are slightly higher using these definitions. Our latter results remain qualitatively unchanged. Tables are available upon request.

[19] Cross-sectional information not tabulated, but available upon request.

[20] Further note that only the first eigenvalue is significantly larger than 1, which indicates consistency with the Kaiser criterion (eigenvalue >1) (see Table 14 in Appendix A).

**Table 4**
Constructing a liquidity index.

| Year | Factor loadings of liquidity measures $S_{i,t}$ | $TV_{i,t}$ | $ALM_{i,t}$ | $ROLL_{i,t}$ | $LOT_{i,t}$ | $RTC_{i,t}$ | VarEx (%) | Obs |
|---|---|---|---|---|---|---|---|---|
| *Panel A: Index $ASY_{i,t}$ based on absolute measures of liquidity* | | | | | | | | |
| 1992 | 0.53 | −0.42 | 0.37 | 0.32 | 0.35 | 0.42 | 76.39 | 1191 |
| 1993 | 0.50 | −0.41 | 0.40 | 0.38 | 0.29 | 0.44 | 79.75 | 1572 |
| 1994 | 0.50 | −0.40 | 0.41 | 0.38 | 0.28 | 0.45 | 78.31 | 1729 |
| 1995 | 0.50 | −0.41 | 0.41 | 0.37 | 0.28 | 0.44 | 77.93 | 1792 |
| 1996 | 0.49 | −0.42 | 0.43 | 0.39 | 0.29 | 0.41 | 77.06 | 1939 |
| 1997 | 0.47 | −0.43 | 0.45 | 0.36 | 0.32 | 0.40 | 77.02 | 2115 |
| 1998 | 0.40 | −0.45 | 0.48 | 0.37 | 0.34 | 0.39 | 75.30 | 2020 |
| 1999 | 0.38 | −0.48 | 0.50 | 0.35 | 0.35 | 0.35 | 72.54 | 1784 |
| 2000 | 0.39 | −0.51 | 0.52 | 0.33 | 0.35 | 0.29 | 68.50 | 1717 |
| 2001 | 0.34 | −0.53 | 0.55 | 0.32 | 0.34 | 0.27 | 72.17 | 1650 |
| 2002 | 0.32 | −0.56 | 0.58 | 0.28 | 0.33 | 0.25 | 70.21 | 1515 |
| 2003 | 0.25 | −0.59 | 0.62 | 0.28 | 0.29 | 0.20 | 70.15 | 1292 |
| 2004 | 0.22 | −0.59 | 0.62 | 0.34 | 0.26 | 0.19 | 68.53 | 1303 |
| 2005 | 0.19 | −0.57 | 0.64 | 0.35 | 0.24 | 0.21 | 68.03 | 1264 |
| 2006 | 0.17 | −0.57 | 0.67 | 0.33 | 0.24 | 0.17 | 69.33 | 1176 |
| 2007 | 0.19 | −0.57 | 0.67 | 0.29 | 0.21 | 0.22 | 64.42 | 1253 |
| 2008 | 0.32 | −0.52 | 0.66 | 0.25 | 0.18 | 0.32 | 67.90 | 1084 |
| Mean | 0.36 | −0.50 | 0.53 | 0.34 | 0.29 | 0.32 | 72.56 | 1552.71 |
| *Panel B: Index $\sigma_{ASY_{i,t}}$ Based on Measures of Liquidity Risk* | | | | | | | | |
| 1992 | 0.22 | 0.53 | 0.52 | 0.11 | 0.35 | 0.52 | 53.45 | 1191 |
| 1993 | 0.48 | 0.50 | 0.52 | −0.15 | 0.24 | 0.42 | 55.52 | 1572 |
| 1994 | 0.48 | 0.48 | 0.51 | −0.18 | 0.24 | 0.43 | 53.65 | 1729 |
| 1995 | 0.48 | 0.48 | 0.52 | −0.10 | 0.26 | 0.45 | 55.07 | 1792 |
| 1996 | 0.48 | 0.50 | 0.54 | −0.04 | 0.29 | 0.39 | 53.75 | 1939 |
| 1997 | 0.55 | 0.45 | 0.50 | −0.02 | 0.30 | 0.38 | 55.23 | 2115 |
| 1998 | 0.56 | 0.41 | 0.47 | 0.03 | 0.35 | 0.42 | 57.65 | 2020 |
| 1999 | 0.56 | 0.42 | 0.47 | 0.01 | 0.35 | 0.41 | 54.50 | 1784 |
| 2000 | 0.49 | 0.41 | 0.49 | 0.07 | 0.43 | 0.39 | 56.36 | 1717 |
| 2001 | 0.60 | 0.40 | 0.47 | 0.12 | 0.41 | 0.29 | 55.99 | 1650 |
| 2002 | 0.40 | 0.48 | 0.55 | 0.04 | 0.48 | 0.28 | 61.52 | 1515 |
| 2003 | 0.27 | 0.52 | 0.55 | 0.10 | 0.54 | 0.23 | 62.69 | 1292 |
| 2004 | 0.25 | 0.53 | 0.56 | 0.15 | 0.54 | 0.20 | 58.52 | 1303 |
| 2005 | 0.23 | 0.50 | 0.60 | 0.14 | 0.51 | 0.25 | 55.58 | 1264 |
| 2006 | 0.19 | 0.49 | 0.62 | 0.28 | 0.48 | 0.17 | 56.19 | 1176 |
| 2007 | 0.28 | 0.43 | 0.61 | 0.24 | 0.49 | 0.26 | 55.13 | 1253 |
| 2008 | 0.69 | 0.29 | 0.49 | 0.07 | 0.32 | 0.30 | 60.73 | 1084 |
| Mean | 0.42 | 0.46 | 0.53 | 0.05 | 0.39 | 0.34 | 56.56 | 1552.71 |

The table gives results for the "full" sample from 1992 through 2008. Panel A shows the time series of factor loadings for the first component derived using year-by-year principal component analysis (PCA) on absolute liquidity measures. These include spread ($S_{i,t}$), trading volume ($lnTV_{i,t}$), the adjusted (Amihud, 2002) liquidity measure ($lnALM_{i,t} * 10^6$), the (Roll, 1984) liquidity measure ($ROLL_{i,t}$), the ratio of zero trades ($LOT_{i,t}$), and round trip transaction costs based on market returns ($RTC_{i,t}$).
Panel B shows results for measures of liquidity risk. The last two columns indicate the explained variance (VarEx) of the first principal component in percentage, and firm observations per year (obs).

We estimate target leverage as:

$$Lev_{i,t} = \beta_0 + \beta_{ASY} * ASY_{i,t-1} + \sum \beta_C * C_{i,t-1} + \epsilon_{i,t} \tag{2}$$

where $Lev_{i,t}$ is (book or market) leverage in year $t$ of firm $i$ and $\sum \beta_C * C_{i,t-1}$ describes the effect of control variables and the industry leverage factor, presented in Section 2.3. We thus assume that the impact of lagged information asymmetries on leverage drives managerial decision making.[21]

This specification of the model makes the following question testable: Do information costs drive capital structure decisions? To cope with the notation problem that arises from having two indexes of information asymmetry, as well as measures of liquidity and liquidity risk for robustness purposes, we use $ASY_{i,t}$ as a replacement character in our analysis.

The error term ($\epsilon_{i,t}$) is a well behaved, classically uncorrelated disturbance term with constant variance. Although it can be considered the "work horse" when analyzing capital structure, pooled ordinary least squares (POLS) methods lead to an

[21] This specification of the empirical model seems appropriate, but stands in contrast to Frieder and Martell (2006), who assume capital structure to be driven by fitted values of lagged liquidity. From an economic point of view, using fitted liquidity measures implies that managers know what drives liquidity, and have a rich data source from which to derive a subsequent estimate of lagged spread that they can consider in their decision making process. In a model that uses simple lagged liquidity values to proxy for informational asymmetries, this assumption is redundant.

estimation bias. We find that omitted variables, such as the disregard of time-invariant components (Lemmon et al., 2008), explain the higher importance of cross-sectional variation versus time series variation in capital structure, as noted by Flannery and Rangan (2006).

The sources for individual effects, such as strategic focus and market, technology, and resource leads, constantly shape a business model. This implies that the independent sampling assumption is violated (Petersen, 2008). Panel methods such as fixed effects are the most appropriate method to account for firm-specific effects in capital structure. If changing slowly (see Lemmon et al., 2008), they can even absorb unidentified transitory components.

However, we are not interested in the size of the firm fixed effect, which allows for the use of within-transformation. By subtracting the firm-specific time series mean ($\overline{x}_i = \frac{1}{T}\sum_{t=1}^{T} x_{i,t}$) from every variable observed over time $t$, ($x_{i,t} - \overline{x}_i = x_{i,t}$), we get its time-demeaned observation. Firm-specific effects are solved out (see Eq. (3)), and coefficients remain unchanged. We also add year fixed effects ($Y_{i,t}$) for variable intercepts ($\beta_Y * Y_{i,t}$) as least squares dummy variables (LSDV).[22]

$$\ddot{Lev}_{i,t} = \beta_Y * Y_{i,t} + \beta_{ASY} * \ddot{ASY}_{i,t-1} + \sum \beta_C \ddot{C}_{i,t} + \ddot{\epsilon}_{i,t} \tag{3}$$

We apply White's correction to account for heteroscedasticity from firmwise differencing.[23] Table 5 gives estimation results for Eq. (3), using our information asymmetry indexes and a restricted model without these variables (specifications (1) and (4)). If information asymmetries are a driver of corporate debt policy, we expect a positive and significant coefficient. Note that we explicitly do not include both indexes of information asymmetry ($ASY_{i,t}$, $\sigma_{ASY_{i,t}}$) in one model, because of high collinearity. Both indexes should measure the same informational content, and thus have a correlation coefficient of $\rho = 0.95$.

We add our liquidity index to model specifications (2), (3), (5), and (6) of Table 5. The coefficients are positive and highly significant ($p < 0.01$) in all specifications.[24] In contrast to Bharath et al. (2009), who report a coefficient of 0.004 for market leverage, our coefficient for ($ASY_{i,t}$) is twice as high, with $\beta_{ASY,Lev^M} = 0.009$ (see model (5)).

For book leverage, our values are very similar, with $\beta_{ASY,Lev^B} = 0.009$.[25] In terms of economic significance, a reduction of our information asymmetry index by one standard deviation leads to a reduction in market and book leverage of ($1.89 * 0.009$) 1.7%. Effects for the index based on liquidity risk are similar (see models (3) and (6)).

We briefly summarize our main results for conventional leverage control variables in models (2) and (5). The industry factor is the single most powerful predictor of leverage in terms of economic relevance, and is highly significant, as shown by Lemmon et al. (2008). Collateral and size are also positively related, in line with our previous arguments. Uniqueness shows positive coefficients, but economic significance is unlikely. Investment opportunities (*M2B*) have a large positive effect on market leverage, but much less of an effect on book leverage.

Note that size and growth opportunities were considered as proxies for information asymmetries in the literature. In fact, $M2B_{i,t}$ is only weakly significant for book leverage, which supports the idea that our index captures a relevant fraction of informational asymmetries.[26] We conclude that liquidity seems to partially capture effects for $M2B_{i,t}$, but the size effect may only be partially justified by information asymmetries, as captured by our indexes. High profitability has a negative, large, and significant coefficient. This confirms the results of, e.g., Fama and French (2002).

Except for $M2B_{i,t}$, all coefficients are significant at the 1% level. Due to the firm fixed effects estimation, the standard errors of the regression (SER) are low at 0.01, as well as the adjusted goodness-of-fit ($\widetilde{R}^2$), which is 0.06 for $Lev^B_{i,t}$ and 0.19 for $Lev^M_{i,t}$.[27] Overall, our regression results are structurally very similar to those found in previous studies.[28]

### 4.2. Target leverage and leverage adjustment

Having shown that information asymmetries are an important determinant of leverage, we next address the question of possible feedback effects that capital structure changes might have on information asymmetries. In a first step, we examine whether managers follow a target capital structure over time. Of course, firms' leverage targets are not directly observable. As in other recent papers, we therefore use the estimated debt ratios from Eq. (3) as a proxy for time-variant targets.[29] Following Hovakimian et al. (2001), we then use a standard partial adjustment model, where the speed of adjustment ($\delta_{Lev^*}$) toward leverage targets ($Lev^*_{i,t}$) is estimated. Low rates are interpreted as support for the freedom of managers to deviate from targets. Leary and Roberts (2005) pinpoint costs that slow down the speed of adjustment.

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[22] Excluding year effects yields estimation results with only minimal changes.

[23] The sample size is large, which justifies White heteroscedasticity robust $t$-values.

[24] Our results are structurally similar to other estimation methods such as POLS, the Fama and MacBeth (1973) method, and firm fixed effects without controlling for year effects.

[25] The lower number of 17.651 observations in Table 9, as compared to the "Full" sample in Table 1, results from the requirement that firms have either three firm-year observations in a row, or a total of four observations. The leverage equation requires control variables and consecutive observations for leverage, while fixed effects estimation requires a minimum of two observations per explanatory and dependent variable.

[26] This is also the case for estimating the leverage equation with standard liquidity measures (see Section 5.2). The correlations between liquidity measures and *M2B* range from −0.2 to 0.2, which removes the problem of multicollinearity.

[27] The small size of goodness-of-fit does not violate any model assumptions of ordinary least squares estimation. The partial interpretation of the effect of liquidity on leverage remains precise because of the large sample size. It only implies that we have not accounted for a large fraction of factors that explain leverage.

[28] Adding liquidity measures instead of our information asymmetry index does not change our results. Tables are available from the authors upon request.

[29] The question of whether leverage targets are time-varying is of no interest to us here, but more details can be found in Frank and Goyal (2007).

**Table 5**
Effect of information asymmetries on leverage.

| | Panel A: $Lev^{B}_{i,t}$ | | | Panel B: $Lev^{M}_{i,t}$ | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| $ASY_{i,t-1}$ | | 0.009** | | | 0.009** | |
| | | (7.90) | | | (6.19) | |
| $\sigma_{ASY_{i,t-1}}$ | | | 0.008** | | | 0.009** |
| | | | (6.58) | | | (6.01) |
| $Size_{i,t-1}$ | 0.03** | 0.03** | 0.03** | 0.04** | 0.05** | 0.05** |
| | (14.61) | (15.39) | (15.36) | (22.06) | (21.28) | (21.32) |
| $M2B_{i,t-1}$ | 0.01** | 0.003* | 0.00** | 0.07** | 0.06** | 0.06** |
| | (4.40) | (1.74) | (2.62) | (19.93) | (16.02) | (16.55) |
| $Profit_{i,t-1}$ | −0.14** | −0.11** | −0.11** | −0.17** | −0.14** | −0.14** |
| | (−12.40) | (−9.59) | (−9.95) | (−16.34) | (−13.31) | (−13.58) |
| $Coll_{i,t-1}$ | 0.07** | 0.06** | 0.06** | 0.09** | 0.07** | 0.07** |
| | (6.34) | (5.11) | (5.13) | (7.18) | (5.85) | (5.81) |
| $Tax_{i,t-1}$ | −0.03** | −0.02** | −0.02** | −0.03** | −0.02** | −0.02** |
| | (−4.64) | (−3.20) | (−3.40) | (−3.98) | (−2.73) | (−2.82) |
| $Uni_{i,t-1}$ | 0.00** | 0.00** | 0.00** | 0.00** | 0.00** | 0.00** |
| | (8.17) | (8.69) | (8.55) | (4.78) | (4.92) | (4.84) |
| $Ind_{i,t-1}$ | 0.57** | 0.53** | 0.54** | 0.65** | 0.56** | 0.56** |
| | (14.35) | (12.30) | (12.43) | (20.02) | (14.30) | (14.35) |
| Obs | 20,095 | 17,651 | 17,651 | 20,095 | 17,651 | 17,651 |
| SER | 0.009 | 0.008 | 0.008 | 0.012 | 0.011 | 0.011 |
| $\widetilde{R}^2$ | 0.06 | 0.06 | 0.06 | 0.195 | 0.187 | 0.186 |
| $FE_Y$ | Yes | Yes | Yes | Yes | Yes | Yes |
| $FE_F$ | Yes | Yes | Yes | Yes | Yes | Yes |

The table gives results for the "full" sample from 1992 through 2008. Estimation results with year and firm fixed effects (FEY, FEF ) are shown, where we regress book leverage (panel A: $Lev^B$) and market leverage (panel B: $Lev^M_{i,t}$) on our year-by-year information asymmetry indexes ($ASY_{i,t}, \sigma_{ASY_{i,t}}$), as described in Section 3. Control variables are e sales ($Size_{i,t-1}$), market-to-book ($M2B_{i,t-1}$), profitability ($Profit_{i,t-1}$), collaterals ($Coll_{i,t-1}$), uniqueness ($Uni_{i,t-1}$), tax ratio ($Tax_{i,t-1}$) and the time series leverage median for one-digit SIC industry classifications ($Ind_{i,t}$) as variable ($t$).
Below the control variables are the number of observations (obs), the standard errors of regression (SER), and the adjusted goodness-of-fit ($\widetilde{R}^2$). The standard errors and $t$-statistics, respectively, of the coefficients are White heteroscedasticity corrected and given in parentheses below coefficients. * and ** denote statistical significance at the 5% and 1% levels.

In Eq. (4), the observed change in leverage ($\Delta Lev_{i,t} = Lev_{i,t} - Lev_{i,t-1}$) partially absorbs the target leverage change, which is the difference in (estimated) target leverage and lagged leverage ($\Delta Lev^*_{i,t} = Lev^*_{i,t} - Lev_{i,t-1}$).[30] A positive value for $\Delta Lev^*_{i,t}$ denotes that the lagged leverage is below the target. If targets exist, management will increase leverage, while a negative $\delta_{Lev^*}$ denotes the opposite. $\delta_{Lev^*} = 1$ implies a full adjustment; $\delta_{Lev^*} = 0$ implies no adjustment.

$$\Delta Lev_{i,t} = \delta_0 + \delta_{Lev^*} * \Delta Lev^*_{i,t} + z_{i,t} \tag{4}$$

We estimate Eq. (4) to give a simple but clear indication of the speed of adjustment of analyzed firms (see Table 6). However, more importantly, we can test the relevance of our instrument, distance from target leverage, for realized changes in leverage, which we apply in the subsequent subsection.

For our purposes, $Cov(\Delta Lev^*_{i,t}; \Delta Lev_{i,t}) \neq 0$ is a necessary condition to identify a relevant instrument. For POLS, we observe mean reversion rates of about 11% − 15% per year, depending on the sample, the inclusion or exclusion of year effects, and book or market leverage. If we use fixed effects estimation, estimated adjustment speed increases to 36%–53%. Furthermore, significance is well below 1%, independent of the sample or method used. Our results are structurally very similar to previous findings by Huang and Ritter (2005), who find 8%–15% for POLS and 25%–75% for fixed effects, as well as Fama and French (2002), Flannery and Rangan (2006), Lemmon et al. (2008) or Xu (2007).

Our conclusion is threefold. First, in support of Myers (1984), we find that market leverage is a linear function of information asymmetries. Other factors driving leverage are industry effects, profitability, size, and collateral. Second, firms adjust toward capital structure targets, although the speed and thus the interpretation are in dispute (see, e.g., Fama and French, 2002; Frank and Goyal, 2007; Lemmon et al., 2008; Shyam-Sunder and Myers, 1999). Third, $\Delta Lev^*_{i,t}$ is a useful instrument for explaining variation in leverage ($\Delta Lev_{i,t}$), and thus for analyzing feedback effects on information asymmetries to avoid endogeneity problems.

[30] By transformation, the adjustment model can also be written as an equation, where actual leverage is a weighted average of lagged and target leverage:

$$Lev_{i,t} = (1-\delta_{Lev^*}) * Lev_{i,t-1} + \delta_{Lev^*} * (\beta_0 + \beta_{ASY} * ASY_{i,t-1} + \sum \beta_C * C_{i,t} + \epsilon_{i,t}) + z_{i,t}$$

**Table 6**
Leverage adjustment of firms.

| | Panel A: $Lev^B_{i,t}$ | | | | Panel B: $Lev^M_{i,t}$ | | | |
|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| Method | POLS | POLS$_Y$ | FE$_F$ | FE$_Y$ | OLS | OLS$_Y$ | FE$_F$ | FE$_Y$ |
| *Full* | | | | | | | | |
| $\delta_0$ | 0.00** | −0.01** | | | 0.01** | −0.02** | | |
| | (5.36) | (−4.42) | | | (14.15) | (−6.68) | | |
| $\Delta Lev^*_{i,t}$ | 0.15** | 0.15** | 0.47** | 0.47** | 0.12** | 0.11** | 0.51** | 0.46** |
| | (26.26) | (26.33) | (71.97) | (43.80) | (19.25) | (18.08) | (68.26) | (41.54) |
| Obs | 17,651 | 17,651 | 17,651 | 17,651 | 17,651 | 17,651 | 17,651 | 17,651 |
| SER | 0.009 | 0.009 | 0.006 | 0.006 | 0.013 | 0.012 | 0.009 | 0.008 |
| FE$_Y$ | No | Yes | No | Yes | No | Yes | No | Yes |
| $R^2$ | 0.06 | 0.07 | 0.23 | 0.23 | 0.03 | 0.11 | 0.21 | 0.23 |
| *exNASDAQ* | | | | | | | | |
| $\delta_0$ | 0.00 | −0.01** | | | 0.01** | −0.03** | | |
| | (1.45) | (−3.87) | | | (6.76) | (−5.81) | | |
| $\Delta Lev^*_{i,t}$ | 0.13** | 0.13** | 0.47** | 0.46** | 0.11** | 0.09** | 0.53** | 0.46** |
| | (17.39) | (17.38) | (46.08) | (30.05) | (12.62) | (11.26) | (45.86) | (28.25) |
| Obs | 6890 | 6890 | 6890 | 6890 | 6890 | 6890 | 6890 | 6890 |
| SER | 0.006 | 0.006 | 0.004 | 0.004 | 0.012 | 0.011 | 0.008 | 0.008 |
| FE$_Y$ | No | Yes | No | Yes | No | Yes | No | Yes |
| $R^2$ | 0.06 | 0.08 | 0.24 | 0.24 | 0.03 | 0.14 | 0.23 | 0.26 |
| *Survivors* | | | | | | | | |
| $\delta_0$ | 0.00 | −0.01** | | | 0.00 | −0.02** | | |
| | (−0.65) | (−2.51) | | | (2.16) | (−3.38) | | |
| $\Delta Lev^*_{i,t}$ | 0.15** | 0.15** | 0.35** | 0.35** | 0.17** | 0.15** | 0.45** | 0.38** |
| | (15.84) | (15.77) | (29.96) | (21.73) | (13.64) | (12.78) | (32.46) | (19.87) |
| Obs | 4096 | 4096 | 4096 | 4096 | 4096 | 4096 | 4096 | 4096 |
| SER | 0.006 | 0.006 | 0.005 | 0.005 | 0.011 | 0.009 | 0.009 | 0.008 |
| FE$_Y$ | No | Yes | No | Yes | No | Yes | No | Yes |
| $R^2$ | 0.07 | 0.09 | 0.18 | 0.19 | 0.06 | 0.17 | 0.20 | 0.24 |

The table gives estimation results for the "full," "exNASDAQ," and "survivors" samples by rows from 1989 through 2008. Results are shown for partial adjustment regressions of book leverage (panel A: $Lev^B_{i,t}$) and market leverage (panel B: $Lev^M_{i,t}$), where we estimate Eq. (4). $\Delta Lev^*_{i,t}$ is the difference between the fitted value of Eq. (3) (see also Table 5), and the leverage observed in the previous period ($t-1$). Estimation methods are pooled OLS (POLS) and firm fixed effects (FE$_F$), excluding and including year effects (POLS$_Y$, FE$_Y$), as indicated by columns.
The number of observations (obs), standard errors of regression (SER), and an indication for year effects (year) and adjusted goodness-of-fit ($R^2$) are given for every estimation. Standard errors and $t$-statistics of coefficients are White heteroscedasticity corrected and presented in parentheses below coefficients. Statistical significance at the 1% (5%) level is indicated by two (one) asterisks.

### 4.3. Feedback effects of capital structure decisions

We now turn to the main question: Are capital structure decisions anticipated by capital markets? In contrast to authors who have studied the effects on returns of exchange offer announcements (Shah, 1994), debt-to-equity swaps (Campbell et al., 1991), share repurchases (Erwin and Miller, 1998; Vermaelen, 1981), and seasoned equity offers (Korajczyk et al., 1991),[31] we analyze feedback effects on our index based on liquidity.

In comparison to leverage adjustment regressions (see Eq. (4)) we determine the effect of target leverage changes ($\Delta Lev^*_{i,t}$) on changes in our information asymmetry index ($\Delta ASY_{i,t} = ASY_{i,t} - ASY_{i,t-1}$) (see Eq. (5)), which results in a two-stage least squares estimation. In the previous subsection, we already demonstrated the relevance of our instrument. We now add changes in control variables ($\Delta C_{i,t}$) to our empirical model. Because returns already represent changes in stock prices, we do not use first differences for stock prices.[32]

$$\Delta ASY_{i,t} = \gamma_0 + \gamma_{Lev^*} * \Delta Lev^*_{i,t} + \sum \gamma_C \Delta C_{i,t} + \epsilon_{i,t} \tag{5}$$

We believe that this approach is appealing on both economic and econometric levels. Economically, we are able to map the impact of "targeted actions" of management on the market, which represent signaling effects. As we noted in the previous subsection, asymmetric information between managers and outside owners (which is represented in liquidity) drives corporate financial decision making. We now consider a possible feedback effect: Ross (1977) argues that more profitable firms can afford high levels of debt. Hence, corporate debt policy reveals information about firm prospects to the market. If this reasoning holds, a

31 For a detailed review of relevant papers see Klein et al. (2002).
32 The error term ($\epsilon_{i,t}$) is required to satisfy instrument exogeneity, $Cov(\Delta C_{i,t}; \epsilon_{i,t}) = 0$.

firm's tendency toward leverage targets should impact any measure that reliably proxies for informational asymmetries such as our index. Moreover, we assume that market participants anticipate management efforts, and use data on the informational and incentive environment of the firm. From an economic standpoint, this would justify the use of leverage targets as instruments, because they are known in advance of real capital structure changes.

Econometrically, it seems reasonable to expect that, if all else remains equal, two stocks priced at U.S. $1000 and U.S. $1 should have similar relative spreads. We then do not expect to find any relationship between absolute prices and measures of liquidity. However, Brennan and Subrahmanyam (1996), Stoll (2000) and Chordia et al. (2000) have all found significant negative relationships between prices and relative spreads. Using an instrument circumvents such endogeneity problems, which are rooted in hidden factors that probably drive liquidity and equity prices and thus market leverage.

First differencing in Eq. (5) offers another advantage. If we examine liquidity measures over time, we find non-stationarity, or a decrease over time, which is very obvious for observed spreads, the Amihud (2002) liquidity measure, and the proportion of zero returns.[33] A main rationale is technological advances as they reduce information and transaction costs while increasing the number of market participants. This drives our index as well. Gallant et al. (1992) propose alleviating this problem by using a linear transformation of liquidity measures based on market capitalization time series for each firm.

However, we also find a high level of autocorrelation for balance sheet items (despite GDP deflation), profits, and Altman and Saunders's (1998) Z″-scores. Here, a market capitalization-based transformation seems inadequate. It would likely result in biased coefficients in POLS and Fama and MacBeth (1973) regressions, which do not converge to true population estimates (Chordia et al., 2009). By first-differencing the high values of autocorrelation (about 0.5 on average), we can reduce them immediately to between −0.1 and 0.1.

Finally, our approach also reduces complexity and makes our calculations traceable, obviating the need to use several transformations for different control variables. Our approach is a regular instrumental variable and two-stage least squares estimation. We assume $E(\epsilon_{i,t}|Lev^*_{i,t}) = 0$, which implies no correlation between the error term in information asymmetry Eq. (5) and the target leverage change. We use an industry variable to control for potentially omitted variables that might impact liquidity (and our index).[34]

$$\Delta \ddot{ASY}_{i,t} = \gamma_Y Y_{i,t} + \gamma_{Lev^*} * \Delta \ddot{Lev}^*_{i,t} + \sum \gamma_C \Delta \ddot{C}_{i,t} + \ddot{\epsilon}_{i,t} \quad (6)$$

Table 7 gives results for a within-fixed effects estimation of Eq. (6). Our index, based either on liquidity measures (panel A) or liquidity risk measures (panel B), is the dependent variable. The restricted models (1) and (6) exclude measures of (target) leverage. Target changes in book, models (3) and (8), and market leverage, models (5) and (10), are explanatory. We also give results for realized changes in leverage, models (2), (4), (7), and (9). All models control for year fixed effects.

Adding realized changes of market leverage ($\Delta Lev^M_{i,t}$) to explain changes in our liquidity and liquidity risk index, models (4) and (9), leads to positive coefficients that are highly significant, similar to Frieder and Martell (2006). For book leverage, however, coefficients are negative and significant (see model (2) for $ASY_{i,t}$) and model (7) for $\sigma_{ASY_{i,t}}$).

These contradictory results for observed changes in book and market leverage are most likely a result of endogeneity. A decrease in market leverage might be driven by an increase in market prices (positive returns), instead of by actual management decisions. As already discussed in this subsection, higher prices are related to higher spreads and illiquidity. This could explain the positive coefficient for realized changes in market leverage on our information asymmetry index.

If we instead use target leverage changes ($\Delta Lev^*_{i,t}$), results are very different (see models (3), (5), (8), and (10)). The expected changes in leverage all exhibit a negative coefficient. This not only supports Ross's (1977) conclusions, where changes in capital structure indicate future firm profitability, but also extends the signaling hypothesis. Our analysis reveals that capital markets anticipate financial policies based on available fundamental firm data that is reflected in our index of information asymmetry and liquidity. Independent of the leverage ratio and of index composition, we observe results that are significant at the 1% level. We believe the small standard errors signal that $\Delta Lev^*_{i,t}$ is a reliable instrument for our purposes.

The size of the feedback effect is also economically significant. For example, a large positive distance from target leverage leads to the expectation of an increase in debt. This would be taken as a signal of the predictability of future cash flows. A positive target leverage change of, say, 10%, would indicate that the firm's debt ratio is 10% below the target. Because we would thus expect an adjustment toward target leverage, we can observe a clear reduction of the index by −2.5 to −2.9% (book leverage), and by −4.9 to −5.9% (market leverage).[35] Note that, for original measures of liquidity, trading volume would then increase by 3.5% for book leverage and 6% for market leverage, and the price impact would be reduced by roughly 3% and 5% from the previous year (see columns 4 and 8 in Table 11 in Section 5.2).

Concerning the set of control variables, our results confirm the importance of transaction costs and inventory risk for liquidity. The positive coefficient of equity volatility ($\Delta V_t$) confirms the findings of Stoll (1978), Ho and Stoll (1981), Amihud and Mendelson (2008) and Lesmond et al. (2008), where an increase in inventory risk and information-based trading increases information asymmetries.

[33] The firm variable mean of autocorrelation in $S_{i,t}$ is 0.61, for the $ALM_{i,t}$ it is 0.57 and the $LOT_{i,t}$ it is 0.60. Augmented Dickey–Fuller unit root tests are on average highly significant in rejecting stationarity for our survivor sample. Tables can be provided by the authors upon request.

[34] We estimate a simultaneous model, where changes in actual control variables and leverage instruments can impact the changes in our index. However, endogeneity between the strictly exogenous control variables and our index may exist and can affect our estimation results. We believe future research should consider using a three-stage least squares approach (Zellner and Theil, 1962), or a model incorporating seemingly unrelated regressions (Zellner, 2010).

[35] Results for subsamples and indexes excluding spreads are structurally similar, and are available from the authors upon request.

**Table 7**
Feedback effect of leverage changes and target leverage changes.

| Dep. variable | Panel A: Liquidity index ($ASY_{i,t}$) | | | | | Panel B: Liquidity risk index ($\sigma_{ASY_{i,t}}$) | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| Leverage | $\Delta Lev^B_{i,t}$ | | | $\Delta Lev^M_{i,t}$ | | $\Delta Lev^B_{i,t}$ | | | $\Delta Lev^M_{i,t}$ | |
| Model | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) |
| $\Delta Lev_{i,t}$ | | −0.20** | | 0.70** | | | −0.17** | | 0.49** | |
| | | (−2.82) | | (6.36) | | | (−2.39) | | (4.84) | |
| $\Delta Lev^*_{i,t}$ | | | −0.25** | | −0.49** | | | −0.29** | | −0.59** |
| | | | (−4.26) | | (−7.45) | | | (−5.10) | | (−9.58) |
| $R_{i,t}$ | 0.02** | 0.02** | 0.02** | 0.03** | 0.01* | 0.14** | 0.15** | 0.14** | 0.15** | 0.13** |
| | (2.79) | (3.11) | (2.89) | (4.39) | (1.66) | (18.96) | (19.20) | (19.07) | (19.46) | (17.47) |
| $\Delta V_{i,t}$ | 2.17** | 2.23** | 2.19** | 1.77** | 2.23** | 2.67** | 2.72** | 2.70** | 2.39** | 2.74** |
| | (32.10) | (30.50) | (32.24) | (17.23) | (32.43) | (41.87) | (39.21) | (42.05) | (25.21) | (42.41) |
| $\Delta AV_{i,t}$ | −1.40** | −1.49** | −1.44** | −0.89** | −1.49** | −1.16** | −1.23** | −1.21** | −0.81** | −1.27** |
| | (−17.84) | (−17.01) | (−18.14) | (−6.99) | (−18.63) | (−15.21) | (−14.42) | (−15.62) | (−6.81) | (−16.29) |
| $\Delta Z''_{i,t}$ | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| | (1.02) | (0.69) | (1.05) | (1.56) | (1.13) | (0.99) | (0.79) | (1.02) | (1.21) | (1.14) |
| $\Delta Profit_{i,t}$ | −0.88** | −0.91** | −0.89** | −0.83** | −0.88** | −0.56** | −0.58** | −0.58** | −0.53** | −0.56** |
| | (−13.17) | (−13.41) | (−13.35) | (−12.47) | (−13.21) | (−8.81) | (−9.12) | (−9.07) | (−8.27) | (−8.87) |
| Obs | 17,651 | 17,651 | 17,651 | 17,651 | 17,651 | 17,651 | 17,651 | 17,651 | 17,651 | 17,651 |
| SER | 0.43 | 0.43 | 0.43 | 0.43 | 0.43 | 0.39 | 0.39 | 0.39 | 0.39 | 0.39 |
| $\widetilde{R}^2$ | 0.18 | 0.18 | 0.18 | 0.19 | 0.19 | 0.29 | 0.29 | 0.30 | 0.30 | 0.30 |
| LM-p | | 0 | 0 | 0 | 0 | | 0 | 0 | 0 | 0 |
| $FE_Y$ | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| $FE_F$ | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |

The data consist of the "full" sample from 1992 through 2008. Panel A shows estimation results with year and firm fixed effects ($FE_Y$, $FE_F$), where we regress changes in the liquidity indexes ($ASY_{i,t}$) in panel A on changes in book ($\Delta Lev^B_{i,t}$) and market leverage ($\Delta Lev^M_{i,t}$), or on changes in target book and target market leverage ($\Delta Lev^{*B}_{i,t}$, $\Delta Lev^{*B}_{i,t}$).
In panel B, the dependent variable is $\sigma_{ASY_{i,t}}$ (see Section 3 for the calculation). The estimated (target) leverage change $\Delta Lev^*_{i,t} = Lev^*_{i,t} - Lev_{i,t-1}$ is the difference between the fitted value of Eq. (3) and the leverage observed in the previous period ($t-1$), either for book or market leverage. Control variables include equity returns, changes in equity volatility, asset volatility, Z″-score, and profit ($R_{i,t}$, $\Delta V_{i,t}$, $\Delta AV_{i,t}$, $\Delta Z''_{i,t}$, $\Delta Profit_{i,t}$).
Below the control variables we indicate the number of observations (obs), standard errors of regression (SER), Durbin–Watson statistics (DW), adjusted goodness-of-fit ($\widetilde{R}^2$), and indicators for the inclusion of fixed effects and heteroscedasticity robust Lagrange-Multiplier statistic probabilities (LM-p). Standard errors and $t$-statistics of coefficients are White heteroscedasticity corrected and presented in parentheses below coefficients. * and ** denote statistical significance at the 5% and 1% levels.

In contrast, note that an increase in firm risk ($\Delta AV_{i,t}$) increases liquidity (and leads to a decrease in our index). Equity is a contingent claim on firm value. Thus, higher riskiness increases the value of the option, which in turn attracts investors. The results for the original measures of liquidity are not reported here, but all had the same direction. We interpret this as strong support of our view.[36]

Stock prices have also been shown to impact liquidity. Controlling for returns ($R_{i,t}$), or price changes, we observe positive coefficients that are mostly significant at a 1% level. This again highlights the problem of endogeneity, which we encounter by our system estimation. The economic significance is minor, though. A 10% increase in returns would result in only a 0.2% increase in our index.[37] And the changes in distance to bankruptcy, measured by the Z″-score, have no impact on our analysis.

Increases in profitability lead to a highly significant and economically relevant reduction in the index. This finding underlines the link between liquidity and information asymmetries regarding firm profitability. An increase in profits would ease investors' problems in evaluating true firm value. We also argue that higher profits attract traders, thereby providing more liquidity.

Our conclusion thus far is that information asymmetries, measured in equity liquidity, determine the level of debt. However, any change in capital structure also has a feedback effect on informational asymmetries between managers and outside owners. Any measure that characterizes this principal-agent relationship – such as our information asymmetry indexes – should reflect this. However, endogeneity between liquidity and market prices (and thus market leverage) makes the use of system estimation inevitable. The "target leverage changes" we introduce here can solve this problem.

We take the latter as a signal of the anticipation of an adjustment process of firms' capital structures. Market participants can use information about a firm's fundamentals to build expectations about managers' financial policy decision making. The identified negative and economically significant relationship between target leverage changes and changes in our information asymmetry index supports the signaling hypothesis of Ross (1977). Thus, higher expected levels of debt reveal information about the predictability of future cash flows.

### 4.4. Event study results

In this section, we follow an alternative approach and measure the extent of the relationship between firm-level equity liquidity and changes in capital structure over a relatively short time horizon using event-study methodology. The advantages

[36] Tables are available from the authors upon request.
[37] We assume that the positive coefficient stems primarily from the ALM measure, which by calculation is positively related to returns and is a main driver of our index (see Table 4).

over the previously shown two-stage regression model are that we can directly relate market expectations towards leverage changes, and do not have to specify a regression model. Furthermore, the “event window” in an event-study naturally covers a much shorter time horizon. Therefore, it is less likely to include disturbances from any confounding events, and it is not as prone to endogeneity as a two-stage regression model.

We analyze the relationship between firm-level equity liquidity and the issuance of equity in the context of seasoned equity offerings (SEOs). Given that event study evidence on the issue already exists for dividends (Graham et al. (2006)), we focus on SEOs. In our opinion, the former approach is inferior for our purposes, because dividend announcements imply only relatively small changes in capital structure. In contrast, SEOs represent substantial changes in leverage.

We believe that SEOs are exceptionally well-suited for studying the adverse selection portion of firm-level equity liquidity for several reasons. First, SEOs have been studied widely in the literature, but with little or no emerging consensus on their determinants or economic consequences. Proposed determinants of SEOs include capital investments, refinancing, liquidity squeezes, corporate control, stock market microstructure, timing by managers in possession of private information about stock overvaluations, and the use of equity as an inflated acquisition currency for takeovers during times of high valuations (Autore et al., 2009; Baker and Wurgler, 2002; Graham and Harvey, 2001; Khan et al., 2012; Loughran and Ritter, 1995, 1997; Shleifer and Vishny, 2003). Eckbo and Norli (2005) and Eckbo et al. (2000) provide empirical evidence that explains poor post-IPO and post-SEO performance by differences in liquidity and leverage.

Second, it has been suggested that skillful managers will conduct dynamic equity timing strategies that exploit both the under- and overpricing of stocks. Accordingly, the issuance of (seemingly overpriced) equity is regarded as a bad signal (Eckbo and Masulis (1995)). While disclosure (whether good or bad) generally lowers information asymmetries, the resulting decrease in leverage might then lead to higher information asymmetries and lower liquidity for two reasons[38]: First, in the sense of Ross (1977) lower leverage may signal lower predictability of future cash flows. Second, less debt and more cash at managers' disposal gives rise to potential agency conflicts (Jensen (1986)).

To summarize, we expect for SEOs that the level of asymmetric information in the market will be comparatively high. This is due to uncertainty about the riskiness of future investments and to the high degree of inside information, which both result in uncertain valuation levels. Under this premise, we expect an “immediate” decrease in equity liquidity following an SEO.

The SEO data for our analysis come from Thomson Financial's SDC database, and the sample includes offerings by publicly listed U.S. issuers of common stock for the January 1, 1980 through December 31, 2005 period. We define $t_0$ as the announcement date, identified as the earlier of (1) the SDC-reported filing date; or (2) the earliest news report or news wire mentioning the issue (see Carlson et al. (2010)), and we measure the impact of the announcement on equity liquidity by changes in stock liquidity (measured by our six liquidity measures) from $t_0$ to the end of event window.

Next, we compare stock liquidity after the announcement date with our benchmark period from 200 until 30 trading days prior to the event. The results are in Table 8. As expected, we find that all (except RTC) liquidity measures show statistically significantly lower equity liquidity compared to the benchmark period prior to the event. In light of these event study results – combined with those of the two-stage regression model – we are confident that expected decreases in leverage (target leverage changes) will increase our information asymmetry index.

In addition to providing complementary evidence that supports our main findings, the results of the SEO event study contribute to the empirical literature at a more general level. As pointed out earlier, the literature on the relationship between (broader) equity liquidity and capital structure has found that liquidity increases as a reaction to increases in leverage (Frieder and Martell (2006)). Against this background, our result presents complementary evidence from the opposite direction: a decrease in leverage (through an increase in equity) leads to lower equity liquidity, as evidenced by the significant reaction over all event windows.

## 5. Robustness

### 5.1. Structural changes in capital structure

One might argue that our main results are driven by small but irrelevant changes in capital structure, and that small changes in leverage could occur unintentionally rather than by management mandate. For example, consider maturing bonds, for which follow-up financing is not arranged or is just not available due to market conditions. In this case, market leverage could be driven by small changes in equity prices rather than by clear management decisions. We therefore analyze solely firms that undergo substantial changes in capital structure, as in Lesmond et al. (2008) or Xu (2007).

Our results could also be driven by firms that are close to bankruptcy. In both cases, changes in liquidity indexes or unclear effects in traditional measures of liquidity may be influenced by other factors. We control for these effects by interacting a dummy variable with changes in (target) leverage ($D * \Delta Lev_{i,t}$; $D * \Delta Lev^*_{i,t}$) in estimating Eq. (7). The dummy variable is equal to 1 if true leverage changes exhibit real shocks of more than $\pm 5\%$ and $\pm 10\%$. In a third specification, we further require that firms

[38] Diamond and Verrecchia (1991) provide an alternative explanation for lower liquidity following the release of information. Their model predicts that at very low levels of information asymmetry some market makers might be forced to exit (due to the reduction in the volatility of order imbalances). Thus, large traders are better off with some degree of information asymmetry.

**Table 8**
Impact of seasoned equity offerings on liquidity.

| | | Liquidity measure | | | | | |
|---|---|---|---|---|---|---|---|
| | | $S_{i,t}$ | $TV_{i,t}$ | $ALM_{i,t}$ | $Roll_{i,t}$ | $LOT_{i,t}$ | $RTC_{i,t}$ |
| [0; +20] | Mean | 0.18*** | −1.63*** | 1.74*** | 0.006 | 0.01*** | −0.001*** |
| | t-Value | 16.25 | −107.31 | 23.54 | 1.38 | 3.83 | −24.82 |
| | DF | 5394 | 6523 | 6485 | 6499 | 6701 | 6489 |
| [0; +15] | Mean | 0.16*** | −1.61*** | 1.52*** | 0.013*** | 0.011*** | −0.001*** |
| | t-Value | 15.57 | −107.27 | 22.19 | 2.81 | 5.65 | −25.45 |
| | DF | 5402 | 6528 | 6482 | 6508 | 6697 | 6495 |
| [0; +10] | Mean | 0.15*** | −1.51*** | 1.15*** | 0.013*** | 0.015*** | −0.001*** |
| | t-Value | 14.22 | −106.47 | 22.15 | 2.77 | 7.69 | −25.20 |
| | DF | 5412 | 6535 | 6489 | 6514 | 6727 | 6506 |
| [0; +5] | Mean | 0.12*** | −1.31*** | 0.84*** | 0.013*** | 0.023*** | −0.0003*** |
| | t-Value | 12.23 | −100.48 | 18.10 | 2.83 | 13.32 | −19.71 |
| | DF | 5424 | 6543 | 6508 | 6525 | 6643 | 6513 |

This table shows results of an event study that measures the impact of Seasoned Equity Offerings (SEOs) on equity liquidity. The event window is designed relative to the issuing date $t_0$. Number of trading days after the issuing date in an event window is marked with +. The included measures are percentage spread ($S_{i,t}$), trading volume ($TV_{i,t}$), the (Amihud, 2002) liquidity measure ($ALM_{i,t}$), proportion of zero returns ($LOT_{i,t}$), the (Roll, 1984) measure ($ROLL_{i,t}$), and the "round trip" transaction costs ($RTC_{i,t}$).
We test for differences in means for the liquidity measures between the final day of the event window and the issuing day, the event respectively. Asterisks (***, **, and *) indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

have a Z″-score larger than 2. This explicitly excludes marginal changes in capital structure and firms that are close to bankruptcy, but facilitates an investigation of panel data.

$$\Delta \ddot{ASY}_{i,t} = \gamma_Y * \ddot{Y}_{i,t} + \gamma_{Lev^*} * D * \Delta \ddot{Lev}^*_{i,t} + \sum \gamma_C \Delta \ddot{C}_{i,t} + \ddot{\epsilon}_{i,t} \tag{7}$$

Table 9 shows estimated values for our general sample and for the exNASDAQ and survivor subsamples. For the sake of conciseness, we do not display full results for the control variables, which are structurally very similar to those in Table 7.

The coefficients of realized changes in book leverage are strictly negative. They increase in absolute terms and in significance by imposing additional restrictions. However, we cannot draw the same conclusions for market leverage (see panel B). Here, we observe some positive coefficients, as in Lesmond et al. (2008). Note that the effect of small realized changes in market leverage on liquidity could stem from the positive link between liquidity and market price dynamics, rather than from active management

**Table 9**
Feedback effect of structural leverage changes on the liquidity index ($ASY_{i,t}$).

| | Panel A: $\Delta Lev^B_{i,t}$ | | | | Panel B: $\Delta Lev^M_{i,t}$ | | | |
|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| Dummy | No | $\|\Delta Lev\| > 0.05$ | $\|\Delta Lev\| > 0.05$ & $Z'' > 2$ | $\|\Delta Lev\| > 0.1$ & $Z'' > 2$ | No | $\|\Delta Lev\| > 0.05$ | $\|\Delta Lev\| > 0.05$ & $Z'' > 2$ | $\|\Delta Lev\| > 0.1$ & $Z'' > 2$ |
| *Realized: $D * \Delta Lev_{i,t}$* | | | | | | | | |
| All | −0.20** | −0.22** | −0.23** | −0.31** | 0.70** | 0.55** | 0.35** | 0.15* |
| $n = 17651$ | (−2.82) | (−3.00) | (−3.00) | (−3.62) | (6.36) | (5.04) | (3.87) | (1.65) |
| exNASDAQ | −0.39** | −0.40** | −0.44** | −0.47** | 0.27* | 0.19 | 0.02 | −0.19* |
| $n = 6{,}890$ | (−3.87) | (−3.87) | (−4.34) | (−4.19) | (2.07) | (1.51) | (0.20) | (−1.65) |
| Survivors | −0.80** | −0.81** | −0.83** | −0.93** | 0.05 | 0.00 | −0.03 | −0.37* |
| $n = 4{,}096$ | (−5.38) | (−5.44) | (−5.34) | (−5.33) | (0.21) | (−0.01) | (−0.16) | (−1.94) |
| *Targeted: $D * \Delta Lev_{i,t}^*$* | | | | | | | | |
| All | −0.25** | −0.29** | −0.25** | −0.17 | −0.49** | −0.52** | −0.47** | −0.46** |
| $n = 17{,}651$ | (−4.26) | (−3.62) | (−2.79) | (−1.44) | (−7.45) | (−6.11) | (−5.48) | (−4.47) |
| exNASDAQ | −0.23** | −0.31** | −0.29** | −0.33* | −0.41** | −0.45** | −0.46** | −0.50** |
| $n = 6{,}890$ | (−2.79) | (−2.70) | (−2.51) | (−2.03) | (−4.67) | (−3.96) | (−4.19) | (−3.75) |
| Survivors | −0.41** | −0.64** | −0.60** | −0.80** | −0.50** | −0.74** | −0.68** | −0.81** |
| $n = 4{,}096$ | (−3.86) | (−3.95) | (−3.49) | (−3.14) | (−4.35) | (−4.67) | (−4.26) | (−4.03) |

The data consist of the "full", "exNASDAQ", and "survivors" samples for 1992 through 2008. The table shows the estimation results of Eq. (7) with firm and year fixed effects ($FE_Y$, $FE_F$). We regress the information asymmetry index ($ASY_{i,t}$) on changes in leverage or target leverage interacted with a dummy ($D$), which is equal to 1 if specified conditions are met as described in row "dummy" implying structural changes in capital structure. Calculation of the year-by-year information asymmetry index is described in Section 3.
Panel A depicts values for book leverage ($\Delta Lev^B_{i,t}$), while panel B shows values for market leverage ($\Delta Lev^M_{i,t}$). Coefficients for the control variables return, equity volatility, asset volatility (Altman and Saunders's, 1998), Z″-score, and profitability (($R_{i,t}$, $\Delta V_{i,t}$, $\Delta AV_{i,t}$, $\Delta Z''_{i,t}$, $\Delta Profit_{i,t}$) are suppressed. The target leverage change is the fitted value of Eq. (3) and the leverage observed during the previous period ($t - 1$). Standard errors and $t$-statistics of coefficients are White heteroscedasticity corrected and presented in parentheses below coefficients. * and ** denote statistical significance at the 5% and 1% levels.

**Table 10**
Feedback effect of structural leverage changes on the liquidity risk index ($\sigma_{ASY_{i,t}}$).

| | Panel A: $\Delta Lev^B_{i,t}$ | | | | Panel B: $\Delta Lev^M_{i,t}$ | | | |
|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| Dummy | No | $\|\Delta Lev\| > 0.05$ | $\|\Delta Lev\| > 0.05$ & $Z'' > 2$ | $\|\Delta Lev\| > 0.1$ & $Z'' > 2$ | No | $\|\Delta Lev\| > 0.05$ | $\|\Delta Lev\| > 0.05$ & $Z'' > 2$ | $\|\Delta Lev\| > 0.1$ & $Z'' > 2$ |
| $D * \Delta Lev_{i,t}$ | | | | | | | | |
| All | −0.17** | −0.16* | −0.18** | −0.23** | 0.49** | 0.36** | 0.20* | 0.09 |
| $n = 17{,}651$ | (−2.39) | (−2.19) | (−2.40) | (−2.72) | (4.84) | (3.66) | (2.30) | (1.08) |
| exNASDAQ | −0.30** | −0.30** | −0.40** | −0.40** | −0.09 | −0.17 | −0.18 | −0.22* |
| $n = 6{,}890$ | (−2.43) | (−2.43) | (−3.30) | (−2.98) | (−0.59) | (−1.08) | (−1.37) | (−1.69) |
| Survivors | −0.52** | −0.57** | −0.58** | −0.64** | 0.26 | 0.19 | 0.12 | −0.07 |
| $n = 4{,}096$ | (−3.38) | (−3.67) | (−3.70) | (−3.69) | (1.28) | (0.94) | (0.65) | (−0.37) |
| $D * \Delta Lev^*_{i,t}$ | | | | | | | | |
| All | −0.29** | −0.37** | −0.40** | −0.28** | −0.59** | −0.57** | −0.56** | −0.51** |
| $n = 17{,}651$ | (−5.10) | (−4.88) | (−4.76) | (−2.63) | (−9.58) | (−7.20) | (−6.99) | (−5.40) |
| exNASDAQ | −0.34** | −0.45** | −0.50** | −0.47** | −0.62** | −0.67** | −0.65** | −0.58** |
| $n = 6{,}890$ | (−3.86) | (−3.77) | (−4.06) | (−2.84) | (−6.53) | (−5.20) | (−5.20) | (−3.85) |
| Survivors | −0.46** | −0.64** | −0.66** | −0.86** | −0.59** | −0.64** | −0.65** | −0.61** |
| $n = 4{,}096$ | (−4.51) | (−4.35) | (−4.19) | (−3.76) | (−5.52) | (−4.30) | (−4.48) | (−3.24) |

The data consist of the "full", "exNASDAQ", and "survivors" samples for 1992 through 2008. The table shows the estimation results of Eq. (7) with firm and year fixed effects ($FE_Y$, $FE_F$). We regress the information asymmetry index ($\sigma_{ASY_{i,t}}$) on changes in leverage or target leverage interacted with a dummy ($D$), which is equal to 1 if specified conditions are met as described in row "dummy" implying structural changes in capital structure. Calculation of the year-by-year information asymmetry index is described in Section 3.
Panel A depicts values for book leverage ($\Delta Lev^B_{i,t}$), while panel B shows values for market leverage ($\Delta Lev^M_{i,t}$). Coefficients for the control variables return, equity volatility, asset volatility (Altman and Saunders's, 1998), Z″-score, and profitability (($R_{i,t}$, $\Delta V_{i,t}$, $\Delta AV_{i,t}$, $\Delta Z''_{i,t}$, $\Delta Profit_{i,t}$) are suppressed. The target leverage change is the fitted value of Eq. (3) and the leverage observed during the previous period ($t - 1$). Standard errors and $t$-statistics of coefficients are White heteroscedasticity corrected and presented in parentheses below coef ($\sigma_{ASY_{i,t}}$) on changes in leverage or target leverage interacted with a dummy ($D$), which is 1 if specified conditions are met as described in row 'dummy' implying structural changes in capital structure. Calculation of the year-by-year information asymmetry index $ASY_{i,t}$ is described in Section 3.
Panel A depicts values for book leverage ($\Delta Lev^B_{i,t}$) while panel B shows values for market leverage ($\Delta Lev^M_{i,t}$). Coefficients for control variables return, equity volatility, asset volatility (Altman and Saunders, 1998), Z″-Score, and profitability ($R_{i,t}$, $\Delta V_{i,t}$, $\Delta AV_{i,t}$, $\Delta Z''_{i,t}$, $\Delta Profit_{i,t}$) are suppressed. The target leverage change is the fitted value of Eq. (3) and the leverage observed in the previous period ($t$-1). Standard errors, $t$-statistics respectively, of coefficients are White heteroscedasticity corrected and presented in parentheses below coefficients. * and ** denote statistical significance at the 5% and 1% levels.

decisions conveying information to the public. This could explain why imposing restrictions leads to a reduction in coefficients and significance (see columns 6 to 8).

By excluding NASDAQ firms, we observe even lower coefficients and a reduction in significance. Both suggest a NASDAQ bias, where exaggerated measures of liquidity for NASDAQ firms seem to drive results for market leverage in our general sample. Overall, the positive relationship between market leverage and our index disappears if we require structural capital changes and exclude firms that are close to bankruptcy. We also obtain a negative relationship when concentrating solely on survivors and exNASDAQ firms.

For target leverage changes, the picture is very distinct. We find strong support for our view that the distance from leverage targets has an effect on liquidity. All coefficients, independent of the sample, dummy restrictions, or the leverage ratio, are strictly negative and significant, most at the 1% level. The NASDAQ effect, if observable at all, only slightly amplifies coefficients. We also find that "Survivors" firms show considerably larger (negative) coefficients, particularly for book leverage. Market participants' perceptions of information asymmetries are impacted more strongly by anticipated changes in capital structure for more profitable, higher collateralized firms with fewer business opportunities, although their speed of leverage adjustment is not clearly lower.

Table 10 gives results for estimating Eq. (7) for our index based on measures of liquidity risk ($\sigma_{ASY_{i,t}}$), which are structurally very similar to the previous table.[39] It is interesting to note that coefficients are generally lower for realized changes in capital structure (upper half of Table 10) for both leverage ratios, where market leverage is again mostly insignificant. For target leverage changes (lower half of Table 10), the results are highly significant and the coefficients are almost unanimously higher.

In summary, we observe a strong impact of changes in book leverage on liquidity. Capital structure decisions apparently reveal information to the public. On the contrary, however, the empirical link between liquidity and stock prices, and thus market leverage, leads to endogeneity and distorts results. By requiring structural changes in capital structure, we find that this formerly positive link partially disappears. Furthermore, a system estimation using target leverage changes greatly improves our results, and leads to a consistently negative relationship between leverage and changes in our indices. This is independent of the sample, any size requirements for the capital structure change, the leverage ratio, and the information asymmetry index.

The NASDAQ effect also seems to affect our results somewhat, as does the survivorship bias. Overall, the robustness checks in this subsection confirm our results from Section 4.3 that capital markets anticipate financial policy by using target leverage changes ($\Delta Lev^*_{i,t}$).

[39] Estimation results for indexes constructed without spreads or spread volatility show structurally similar patterns. Tables are available from the authors upon request.

**Table 11**
Comparison of results for measures of liquidity by estimation methodology.

| | Panel A: $\Delta Lev^{B}_{i,t}$ | | | | Panel B: $\Delta Lev^{M}_{i,t}$ | | | |
|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| Method | POLS | FM | $FE_F$ | $FE_Y$ | POLS | FM | $FE_F$ | $FE_Y$ |
| $\Delta S_{i,t}$ | −0.003** | −0.004** | 0.001 | 0.000 | −0.005** | −0.006** | 0.001 | 0.001 |
| | (−4.67) | (−3.04) | (0.58) | (0.33) | (−3.84) | (−3.51) | (0.27) | (0.58) |
| Obs | 19.181 | 1.199 | 18.307 | 18.307 | 19.181 | 1.199 | 18.307 | 18.307 |
| $\Delta TV_{i,t}$ | 0.057* | 0.099* | 0.296** | 0.351** | 0.438** | 0.357** | 0.350** | 0.595** |
| | (1.87) | (2.20) | (4.83) | (5.80) | (5.89) | (5.20) | (4.07) | (6.60) |
| Obs | 21.030 | 1.168 | 20.146 | 20.146 | 21.030 | 1.168 | 20.146 | 20.146 |
| $\Delta ALM_{i,t}$ | −0.131** | −0.130** | −0.245** | −0.297** | −0.486** | −0.343** | −0.160* | −0.471** |
| | (−4.29) | (−3.22) | (−3.93) | (−4.87) | (−7.10) | (−5.74) | (−1.93) | (−5.40) |
| Obs | 21.030 | 1.168 | 20.146 | 20.146 | 21.030 | 1.168 | 20.146 | 20.146 |
| $\Delta ROLL_{i,t}$ | −0.025** | −0.020* | 0.026* | 0.016 | −0.032* | −0.023 | 0.031* | 0.012 |
| | (−3.69) | (−2.14) | (1.92) | (1.21) | (−1.92) | (−1.54) | (1.68) | (0.65) |
| Obs | 20.464 | 1.137 | 19.613 | 19.613 | 20.464 | 1.137 | 19.613 | 19.613 |
| $\Delta LOT_{i,t}$ | −0.010** | −0.017** | −0.007 | −0.012** | −0.025** | −0.032** | −0.036** | −0.040** |
| | (−4.19) | (−5.14) | (−1.41) | (−2.52) | (−3.87) | (−5.90) | (−5.46) | (−5.79) |
| Obs | 21.030 | 1.168 | 20.146 | 20.146 | 21.030 | 1.168 | 20.146 | 20.146 |
| $\Delta RTC_{i,t}$ | −0.001* | −0.001** | 0.004** | 0.004** | −0.002* | −0.002** | 0.007** | 0.008** |
| | (−2.28) | (−3.31) | (5.21) | (5.15) | (−1.99) | (−4.90) | (5.18) | (5.87) |
| Obs | 20,989 | 1166 | 20,105 | 20,105 | 20,989 | 1166 | 20,105 | 20,105 |
| $FE_Y$ | No | – | No | Yes | No | – | No | Yes |
| $FE_Y$ | No | – | Yes | Yes | No | – | Yes | Yes |

The data consist of the "FullexS" sample from 1990 through 2008. For spreads, it is the "full" sample. The table shows estimation results where changes in liquidity were regressed on changes in target book (panel A: $\Delta Lev^{B}_{i,t}$ and market leverage (panel A: $\Delta Lev^{M}_{i,t}$ and other controls. The methods used are pooled ordinary least squares (POLS) (Fama and MacBeth, 1973), regressions (FM), and firm and year fixed effects ($FE_F$, $FE_Y$), sorted by columns.
Liquidity measures are indicated by rows, and include spread ($\Delta S_{i,t}$), trading volume ($\Delta TV_{i,t}$), the (Amihud, 2002) liquidity measure ($\Delta ALM_{i,t}$), the (Roll, 1984) liquidity measure ($\Delta ROLL_{i,t}$), the ratio of zero trades ($\Delta LOT_{i,t}$), and round trip transaction costs based on market returns ($\Delta RTC_{i,t}$). Control variables are return p.a., changes in equity volatility, asset volatility Altman and Saunders's (1998), Z″-score, and profits ($R_{i,t}$, $\Delta V_{i,t}$, $\Delta AV_{i,t}$, $\Delta Z''_{i,t}$, $\Delta Profit_{i,t}$).
Results of the first stage estimation and coefficients of controls are suppressed for the sake of brevity, but are structurally very similar to the results found in Tables 5 and 7. The estimated (target) leverage change $\Delta Lev^{*}_{i,t} = Lev^{*}_{i,t} - Lev_{i,t-1}$ represents the difference between the fitted value of Eq. (3) and the leverage observed during the previous period ($t-1$). For FM estimation, obs does not reflect the total number but rather the time series mean of yearly observations. Standard errors and $t$-statistics of coefficients are White heteroscedasticity corrected and presented in parentheses below coefficients. We also provide an indicator for year and firm fixed effects ($FE_F$, $FE_Y$). * and ** denote statistical significance at the 5% and 1% levels.

### 5.2. Results for original measures of liquidity

This subsection discusses estimation results for traditional measures of liquidity to determine whether our results could be driven by the construction methodology of our index. We thus begin by estimating Eq. (3) to derive our leverage targets (results not tabulated, but available upon request). All coefficients for the liquidity measures and the control variables are significant at the 1% level, and show similar directions as those previously found except for $M2B_{i,t}$, which loses significance. The regression results are structurally similar to those in Section 4.2. The adjusted R-squared of 0.071 is the highest for $ALM_{i,t}$, which also holds for market leverage ($\widetilde{R}^2 = 0.192$).

For the sake of brevity, we do not show full second-stage results here, where we estimate the effect of target leverage changes on liquidity measures. The control variables show structurally the same coefficients as for our liquidity index estimations. For trading volume, which is a measure of liquidity, not illiquidity, we expect to find the opposite signs in the coefficients. Our calculation method shows that the returns exhibit a positive and significant sign in estimating changes in $ALM_{i,t}$ (see model (3)).[40] However, in terms of economic significance, we doubt any impact of returns on liquidity. Equity volatility, asset volatility, and profits are highly economically and statistically significant.

For $TV_{i,t}$, $ALM_{i,t}$, and $LOT_{i,t}$, target changes in leverage show the expected direction, and are highly significant at the 1% level. In terms of economic significance, an expected increase in leverage of, say, 10% would result in a 3.5% growth in trading volume ($TV_{i,t} = exp0.345 * 0.1 * TV_{i,t-1}$). The price impact is reduced by roughly 3% ($ALM_{i,t} = exp - 0.297 * 0.1 * ALM_{i,t-1}$), and the number of days with zero returns is reduced by 0.1%.

All models show improved economic power by adding target leverage changes, again except for the Roll (1984) measure. The coefficient is not significantly different from zero, nor is the model jointly significant. Effects of target leverage changes on spreads are indistinguishable from zero, and round-trip transaction costs have the opposite sign.

The results are the same for market leverage, and thus are not provided here. We believe that survivorship bias is the probable explanation. If we inspect the results for survivors that are not reported here, we find mostly insignificant results, with larger coefficients ($\beta_{Lev^*,All} < \beta_{Lev^*,survivior}$). This implies that the liquidity of younger firms, where information asymmetries are even higher, is impacted more strongly by management behavior toward capital structure. The coefficients for liquidity risk measures are mostly negative and are not shown here. We found that increases in leverage lead to a reduction in liquidity risk measures.

[40] As a ratio of returns to trading volume, higher returns must lead to an increase.

Although proven biased, we estimate pooled ordinary least squares (POLS) and Fama and MacBeth (1973) (FM) results for comparison with other studies. For the sake of conciseness, we again do not show the tables here.[41] Instead, we provide an overview of the estimated coefficients and the White heteroscedasticity robust $t$-statistics in Table 11 for the signaling effect (see Eq. (5)).

We find that pooled POLS and FM coefficients show the expected negative (positive for $TV_{i,t}$) signs, independent of the capital structure or liquidity measure used. The Amihud (2002)measure, trading volume, and the ratio of zero returns all exhibit stable coefficients, also for fixed effects estimation and are strongly significant at the 1% level. The difference in $t$-values is driven solely by the coefficients, which indicates the bias of using regular OLS.

In contrast, FM results show varying coefficients and standard errors. One reason may be our relatively short sample period of twenty years. The results for the measures of transaction costs remain unclear. Coefficients for $S_{i,t}$ and $ROLL_{i,t}$ become indistinguishable from zero, while a change in signs is obvious for $RTC_{i,t}$. It may follow from this that transaction cost-based liquidity measures are driven less by information asymmetries than others. As alternative explanations, the NASDAQ effect and survivorship bias could play a role.

## 6. Conclusion

In summary, this paper analyzes the impact of expected (targeted) capital structure decisions on information asymmetries, measured in equity liquidity. The link between capital structure and liquidity is based on the assumption that managers are a subset of informed traders. As liquidity is driven by information asymmetries it is a viable, although imperfect, proxy for moral hazard problems between managers and owners. Few researchers have shed light on this endogenous interdependence.

Our results are twofold: 1) Market participants can form expectations on target capital structure of listed firms based on available fundamental data and the firm's informational environment (including liquidity). 2) Deviations from these leverage targets – denoted as "target leverage changes" – have a significant impact on information asymmetries (and liquidity). This feedback effect supports Ross's (1977) signaling hypothesis. An expected increase in debt is a reliable market signal about the true profitability of a firm, and it thus reduces informational asymmetries (increases liquidity).

To test our hypotheses, we construct a year-by-year information asymmetry index as per Bharath et al. (2009) for U.S.-listed firms from 1990 through 2008. We use six measures of liquidity (trading activity, trading costs, and price impact of order flow) as well as two measures of capital structure. Accounting for the endogeneity of liquidity and equity prices, and thus market leverage, we find that an expected 10% increase in leverage is accompanied by a 3.5% increase in trading volume and a 3% decrease in price impact compared to the previous year.

As an alternative approach, we conduct a series of event studies that relate (negative) changes in leverage to our measures of liquidity. Investigating the effect of SEO announcements (i.e. increases in equity, and hence decreases in leverage) in an event study context we find that all of our index components (except round trip transaction costs) indicate, as expected, a decrease in liquidity. This result, combined with the findings of the two-stage regression model, provides strong support for a signaling effect in the sense of Ross (1977). As an alternative explanation, investors might be concerned about agency costs that result from lower levels of debt (Jensen (1986)).

Our findings are robust to differently constructed information asymmetry indexes, e.g., excluding spreads, and for replacing the index with most of the original liquidity measures. In contrast, liquidity risk measures and firm-level adverse selection indexes based on liquidity risk measures reveal mixed results. Different subsamples analyze survivorship bias and the NASDAQ liquidity effect, however results remain stable.

As another robustness check, we analyze structural capital changes, which even amplifies the signaling effect. We also control for commonly used leverage determinants, including size, market-to-book, profitability, collaterals, taxes, and actual industry effects. For liquidity, we control for equity returns, volatility, asset volatility, bankruptcy Z″-scores, and profitability. For further robustness we employ pooled OLS, the Fama and MacBeth (1973) method and fixed effects estimation.

Even though we strongly believe that our metric is a valid proxy for adverse selection, we cannot rule out the possibility that it is also influenced by "non-informational" liquidity. When interpreting our results at a more general level (implying that our metric captures broader equity liquidity), our paper contributes to the existing literature by empirically documenting that changes in capital structure affect firm-level liquidity.

Overall, we conclude that liquidity is an excellent source from which to derive insights into corporate finance. It also confirms the views of contract theories, where informational imbalances significantly drive the decision making of market participants and managers. An avenue for further research may shed light on how issuance policy, such as bond issues or mezzanine capital, might affect informational asymmetries (and liquidity) in more detail. Another important question is how specific market liquidity shocks, such as those occurring during the latest crises in 2008 and 2009, might impact corporate finance.

## Appendix A. Measures of liquidity

Trading activity is often measured as simple trading volume ($TV_{i,t} = lnVol_{i,t} * P_{i,t}$), where we assume that stocks with a high trading volume (defined as the volume of traded stocks ($V_{i,t}$) times the actual price ($P_{i,t}$)) can be sold within very short periods and at literally no price impact. As Foster and Viswanathan (1993) propose, trading volume is a function of information asymmetries on an asset value.

[41] Measures of liquidity all show highly significant coefficients, with the expected sign on the first stage and both ratios of leverage. Results are available from the authors upon request.

The proportion of zero returns is another variable that tries to capture this aspect of liquidity. Lesmond et al. (1999) argue that informed traders only trade if new information yields higher profits than transaction costs Kyle (1985). Similar as they do, we calculate ($LOT_{i,t} = \frac{n_{R_{i,t}=0} + n_{\nexists P}}{T_{i,t}}$) as the ratio of zero returns ($n_{R_{i,t}=0}$) and CRSP estimated mid-prices (which indicate that no real transactions occurred ($n_{\nexists P_{i,t}}$) to trading days per year ($T_{i,t}$).

Both measures ignore trading book orders because of a deviation from bid and ask prices. But transactions could be enforced if price discounts (premiums) were accepted (paid). The relative bid–ask spread is the most commonly used measure (e.g. Amihud and Mendelson, 1986). We can calculate $S_{i,t} = 2 * \frac{(Ask_{i,t} - Bid_{i,t})}{P_{i,t}}$ as the ratio of the difference between ask ($P^{Ask}_{i,t}$) and bid price ($P^{Bid}_{i,t}$) to mid price ($P^{Mid}_{i,t}$).

Roll (1984) proposes the "effective spread" (Hasbrouck, 2009) be calculated as the first-order autocorrelation of stock returns (see Eq. (8c)). In efficient markets, stock prices ($P^*_{i,t}$) fluctuate randomly (see Eq. (8a)), where trading costs (Eq. (8cc) lead to negative serial autocorrelation in observed stock returns.

$$P^*_{i,t} = P^*_{i,t-1} + u_{i,t} \tag{8a}$$

$$P_{i,t} = P^*_{i,t} + cd_{i,t} \tag{8b}$$

$$\Leftrightarrow c_{i,t} = \sqrt{-Cov\left(\Delta P_{i,t}, \Delta P_{i,t-1}\right)} \tag{8c}$$

The final trading price $P_{i,t}$ is the efficient price plus some $c$ as the half bid–ask spread, where $d_{i,t}$ is a dummy variable equal to $+1$ for a buy and $-1$ for a sell with equal probability (see Eq. (8b)). However, empirically and depending on the observation period, we randomly observe positive return autocovariance for some stocks. We follow Harris's (1990) proposition and set those values to zero.[42] We face further problems for the previous transaction cost measures if no trades are observed over one day. In this case, mid-prices would be disclosed in CRSP. We are either unable to infer any transaction costs, or we potentially underestimate true transaction costs.

The "round-trip transaction costs" (RTC) proposed by Lesmond et al. (1999) account for this fact, and can be calculated by using only return series in a limited dependent variable model (see Tobin, 1958; Rosett, 1959 and Eq. (9a)). This methodology also offers an asymmetric consideration of buy and sell orders. True returns $R^*_{i,t}$ are driven by market returns ($R_{BM,i,t}$), where informed investors trade only if transaction costs are exceeded. This results in measured returns $R_{i,t}$. The RTC are calculated as $RTC_{i,t} = |\alpha^u_{i,t}| + |\alpha^d_{i,t}|$, calculated by yearly regressions of positive and separately negative observed stock returns on market returns.[43]

$$R^*_{i,t} = \beta * R_{BM,i,t} + \epsilon_{i,t} \tag{9a}$$

$$R_{i,t} = R^*_{i,t} - \alpha^d_{i,t} \qquad if\ R^*_{i,t} < \alpha^d_{i,t} \tag{9b}$$

$$R_{i,t} = 0 \qquad if\ \alpha^d_{i,t} < R^*_{i,t} < \alpha^u_{i,t} \tag{9c}$$

$$R_{i,t} = R^*_{i,t} - \alpha^u_{i,t} \qquad if\ R^*_{i,t} > \alpha^u_{i,t} \tag{9d}$$

Previous measures have ignored the potential price impact. Amihud (2002) proposes calculating the daily ratio of the absolute value of observed returns to trading volume to account for price changes implied by order size; we use the daily average of $ALM_{i,t} = ln\left(10^6 * \frac{|R_{i,t}|}{TV_{i,t}}\right)$. Holding everything else equal, higher daily returns would proxy for a strong price impact. Hasbrouck (2009) finds a 0.67 correlation between ALM and Kyle's (1985) λ, and a correlation of 0.61 between ALM and effective costs as the difference between transaction price and previous mid-price. Both are derived from intraday data. We use a transformed version to reduce extreme skew.

In our estimation, we need only one yearly observation. For spreads ($S_{i,t}$), trading volume ($TV_{i,t}$), and the Amihud (2002) liquidity measure, we use averages of daily observations ($S_{i,t} = \frac{1}{D_i}\sum_{d=1}^{D_i} S_{i,d}$). $LOT_{i,t}$, $ROLL_{i,t}$, and $RTC_{i,t}$ are yearly values by calculation method. Liquidity risk measures are standard deviations of monthly averages of $S_{i,t}$, $TV_{i,t}$, $ALM_{i,t}$, $ROLL_{i,t}$, and $LOT_{i,t}$, and the risk measures of round-trip transaction costs stem from bootstrap simulations. Thus, we draw a 100 times 25% of all observed positive and negative stock returns, and we calculate regressions as in Eq. (9). The standard deviation of the resulting distribution of round-trip transaction costs is $\sigma_{RTC_{RM,i,t}}$.

[42] We prefer this over dropping observed prices, which in turn is likely to lead to heteroscedasticity because of multiperiod observations. Hasbrouck (2009) assumes a Bayesian approach to this problem, resulting in the Gibbs measure.

[43] We also use the Fama and French (1993) three-factor models; we find that the descriptions and the coefficients in the regressions are the same. The correlation is about 0.99.

**Table 12**
Cross sectional data on liquidity measures.

| Measure | Mean | Std | Skew | Kurt | 95% quant | Median | 5% quant | Obs |
|---|---|---|---|---|---|---|---|---|
| $S_{i,t}$ | 3.01 | 3.61 | 3.15 | 20.27 | 9.66 | 1.85 | 0.13 | 26,396 |
| $TV_{i,t}$ | 10.00 | 2.50 | −0.56 | 3.28 | 13.76 | 10.25 | 5.34 | 29,687 |
| $ALM_{i,t}$ | 3.02 | 2.49 | 0.56 | 2.23 | 7.61 | 2.57 | 0.08 | 29,687 |
| $ROLL_{i,t}$ | 0.23 | 0.21 | 0.38 | 1.89 | 0.60 | 0.22 | 0.00 | 29,687 |
| $LOT_{i,t}$ | 0.17 | 0.18 | 1.85 | 7.73 | 0.50 | 0.13 | 0.01 | 29,687 |
| $RTC_{i,t}$ | 6.63 | 4.06 | 1.77 | 8.08 | 14.42 | 5.67 | 2.25 | 29,687 |
| $ASY_{i,t}$ | 0.00 | 1.90 | 1.15 | 4.96 | 3.63 | −0.42 | −2.40 | 26,396 |
| $\sigma_{S_{i,t}}$ | 1.58 | 1.99 | 5.20 | 70.83 | 5.05 | 0.97 | 0.12 | 26,396 |
| $\sigma_{TV_{i,t}}$ | 1.51 | 1.11 | 1.35 | 3.70 | 4.07 | 1.04 | 0.50 | 29,687 |
| $\sigma_{ALM_{i,t}}$ | 3.39 | 2.87 | 0.49 | 2.02 | 8.47 | 2.85 | 0.05 | 29,687 |
| $\sigma_{ROLL_{i,t}}$ | 0.23 | 0.04 | −0.40 | 3.18 | 0.29 | 0.23 | 0.15 | 29,687 |
| $\sigma_{LOT_{i,t}}$ | 0.08 | 0.04 | 0.43 | 2.89 | 0.15 | 0.07 | 0.01 | 29,687 |
| $\sigma_{RTC_{i,t}}$ | 0.85 | 0.56 | 2.67 | 18.29 | 1.87 | 0.71 | 0.28 | 29,687 |
| $\sigma_{ASY_{i,t}}$ | 0.00 | 1.70 | 1.34 | 5.84 | 3.33 | −0.46 | −2.01 | 26,396 |

The table shows cross-sectional data on liquidity for the 'FullexS' sample from 1989 (1992 for spreads) through 2008. The measures, all daily averages, include percentage spread ($S_{i,t}$), natural logarithmic trading volume ($TV_{i,t}$), and the Amihud (2002) liquidity measure ($ALM_{i,t}$). The proportion of zero returns ($LOT_{i,t}$) per year, the Roll (1984) measure ($ROLL_{i,t}$), and the "round trip" transaction costs ($RTC_{i,t}$).
Liquidity risk measures are standard deviations of monthly averages of $S_{i,t}$, $TV_{i,t}$, $ALM_{i,t}$, $ROLL_{i,t}$, and $LOT_{i,t}$. The risk measures of round-trip transaction costs stem from bootstrap simulations. We draw a 100 times 25% of all observed positive and negative stock returns, and we calculate regressions as in Eq. (9). The standard deviation of the resulting distribution of round-trip transaction costs is $\sigma_{RTCRM,i,t}$. $ASY_{i,t}$ and $\sigma_{ASY_{i,t}}$ indicate the first principal component in liquidity measures and liquidity risk measures, respectively.

**Table 13**
Correlation of liquidity measures.

| | $ASY$ | $\sigma_{ASY}$ | $ASYxS$ | $\sigma_{ASYxS}$ | $S$ | $TV$ | $ALM$ | $tROLL$ | $LOT$ | $RTC$ | $\sigma_S$ | $\sigma_{TV}$ | $\sigma_{ALM}$ | $\sigma_{ROLL}$ | $\sigma_{LOT}$ |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| *Panel A: Pearson correlation, pairwise, n = 29,687 or 26,396* | | | | | | | | | | | | | | | |
| $ASY$ | 1 | | | | | | | | | | | | | | |
| $\sigma_{ASY}$ | 0.94 | 1 | | | | | | | | | | | | | |
| $ASYxS$ | 0.99 | 0.93 | 1 | | | | | | | | | | | | |
| $\sigma_{ASYxS}$ | 0.93 | 0.98 | 0.93 | 1 | | | | | | | | | | | |
| $S$ | 0.80 | 0.74 | 0.75 | 0.69 | 1 | | | | | | | | | | |
| $TV$ | −0.91 | −0.87 | −0.93 | −0.89 | −0.60 | 1 | | | | | | | | | |
| $ALM$ | 0.92 | 0.91 | 0.92 | 0.91 | 0.77 | −0.87 | 1 | | | | | | | | |
| $ROLL$ | 0.68 | 0.53 | 0.68 | 0.53 | 0.57 | −0.50 | 0.59 | 1 | | | | | | | |
| $LOT$ | 0.70 | 0.67 | 0.66 | 0.61 | 0.78 | −0.60 | 0.72 | 0.43 | 1 | | | | | | |
| $RTC$ | 0.71 | 0.69 | 0.69 | 0.66 | 0.80 | −0.47 | 0.69 | 0.45 | 0.49 | 1 | | | | | |
| $\sigma_S$ | 0.72 | 0.79 | 0.68 | 0.66 | 0.77 | −0.56 | 0.70 | 0.43 | 0.57 | 0.71 | 1 | | | | |
| $\sigma_{TV}$ | 0.77 | 0.80 | 0.77 | 0.83 | 0.67 | −0.79 | 0.84 | 0.50 | 0.75 | 0.46 | 0.55 | 1 | | | |
| $\sigma_{ALM}$ | 0.89 | 0.89 | 0.89 | 0.89 | 0.76 | −0.82 | 0.99 | 0.59 | 0.72 | 0.69 | 0.69 | 0.83 | 1 | | |
| $\sigma_{ROLL}$ | 0.00 | 0.04 | 0.00 | 0.02 | −0.08 | −0.01 | 0.01 | 0.00 | −0.07 | −0.06 | −0.01 | −0.06 | 0.02 | 1 | |
| $\sigma_{LOT}$ | 0.56 | 0.63 | 0.50 | 0.58 | 0.62 | −0.45 | 0.65 | 0.41 | 0.59 | 0.42 | 0.50 | 0.62 | 0.66 | 0.05 | 1 |
| $\sigma_{RTC}$ | 0.58 | 0.64 | 0.58 | 0.63 | 0.59 | −0.41 | 0.54 | 0.26 | 0.37 | 0.86 | 0.60 | 0.35 | 0.53 | −0.01 | 0.27 |
| *Panel B: Spearman rank correlation, pairwise, n = 29,687 or 26,396* | | | | | | | | | | | | | | | |
| $ASY$ | 1 | | | | | | | | | | | | | | |
| $\sigma_{ASY}$ | 0.95 | 1 | | | | | | | | | | | | | |
| $ASYxS$ | 1.00 | 0.95 | 1 | | | | | | | | | | | | |
| $\sigma_{ASYxS}$ | 0.94 | 0.99 | 0.94 | 1 | | | | | | | | | | | |
| $S$ | 0.64 | 0.65 | 0.64 | 0.63 | 1 | | | | | | | | | | |
| $TV$ | −0.94 | −0.91 | −0.94 | −0.91 | −0.55 | 1 | | | | | | | | | |
| $ALM$ | 0.89 | 0.89 | 0.89 | 0.89 | 0.83 | −0.87 | 1 | | | | | | | | |
| $ROLL$ | 0.64 | 0.49 | 0.65 | 0.50 | 0.50 | −0.48 | 0.53 | 1 | | | | | | | |
| $LOT$ | 0.56 | 0.59 | 0.57 | 0.59 | 0.88 | −0.50 | 0.77 | 0.45 | 1 | | | | | | |
| $RTC$ | 0.60 | 0.61 | 0.62 | 0.62 | 0.70 | −0.45 | 0.68 | 0.39 | 0.50 | 1 | | | | | |
| $\sigma_S$ | 0.70 | 0.71 | 0.70 | 0.68 | 0.89 | −0.61 | 0.83 | 0.46 | 0.71 | 0.74 | 1 | | | | |
| $\sigma_{TV}$ | 0.73 | 0.80 | 0.74 | 0.82 | 0.78 | −0.73 | 0.90 | 0.42 | 0.78 | 0.57 | 0.73 | 1 | | | |
| $\sigma_{ALM}$ | 0.87 | 0.88 | 0.87 | 0.88 | 0.84 | −0.83 | 0.99 | 0.53 | 0.79 | 0.68 | 0.83 | 0.91 | 1 | | |
| $\sigma_{ROLL}$ | 0.12 | 0.12 | 0.09 | 0.09 | 0.06 | −0.08 | 0.08 | 0.08 | 0.02 | 0.01 | 0.09 | 0.03 | 0.08 | 1 | |
| $\sigma_{LOT}$ | 0.52 | 0.59 | 0.47 | 0.55 | 0.82 | −0.43 | 0.68 | 0.40 | 0.85 | 0.43 | 0.68 | 0.69 | 0.70 | 0.07 | 1 |
| $\sigma_{RTC}$ | 0.55 | 0.59 | 0.56 | 0.60 | 0.53 | −0.43 | 0.56 | 0.27 | 0.33 | 0.92 | 0.63 | 0.47 | 0.56 | 0.02 | 0.28 |

The table indicates pairwise Pearson (panel A) and Spearman rank (panel B) correlations for the "full" sample from 1992 through 2008. Variables are the information asymmetry indexes ($ASY$, $\sigma_{ASY}$, $ASYxS$, $\sigma_{ASYxS}$) (see Section 3), liquidity measures ($S$, $TV$, $ALM$, $ROLL$, $LOT$, $RTC$), and liquidity risk measures ($\sigma_S$, $\sigma_{TV}$, $\sigma_{ALM}$, $\sigma_{ROLL}$, $\sigma_{LOT}$, $\sigma_{RTC}$)).

**Table 14**
Variance explained by factors in principal component analysis.

| Abs. liquidity measures in (%) | | | | | | |
|---|---|---|---|---|---|---|
| Year | $ASY_{i,t}$ | 2 | 3 | 4 | 5 | 6 |
| 1992 | 76.39* | 10.79 | 6.85 | 4.18 | 1.49 | 0.30 |
| 1993 | 79.75* | 10.16 | 7.16 | 1.73 | 0.93 | 0.26 |
| 1994 | 78.31* | 11.27 | 7.33 | 1.85 | 0.96 | 0.27 |
| 1995 | 77.93* | 10.40 | 8.09 | 2.23 | 1.04 | 0.32 |
| 1996 | 77.06* | 10.80 | 8.22 | 2.40 | 1.16 | 0.36 |
| 1997 | 77.02* | 10.14 | 8.58 | 2.66 | 1.19 | 0.42 |
| 1998 | 75.30* | 10.64 | 9.45 | 3.01 | 1.20 | 0.40 |
| 1999 | 72.54* | 12.07 | 9.79 | 3.85 | 1.30 | 0.45 |
| 2000 | 68.50* | 16.28 | 10.79 | 2.51 | 1.45 | 0.47 |
| 2001 | 72.17* | 13.12 | 10.25 | 2.73 | 1.26 | 0.48 |
| 2002 | 70.21* | 14.60 | 10.18 | 3.29 | 1.26 | 0.46 |
| 2003 | 70.15* | 19.34 | 6.23 | 2.75 | 1.04 | 0.49 |
| 2004 | 68.53* | 20.38 | 7.14 | 2.52 | 1.07 | 0.35 |
| 2005 | 68.03* | 21.76 | 6.15 | 2.53 | 1.23 | 0.30 |
| 2006 | 69.33* | 21.59 | 5.43 | 2.15 | 1.24 | 0.26 |
| 2007 | 64.42* | 27.06 | 5.05 | 1.94 | 1.23 | 0.29 |
| 2008 | 67.90* | 22.24 | 5.64 | 2.61 | 1.02 | 0.58 |
| Liquidity risk factors in (%) | | | | | | |
| Year | $\sigma_{ASY_{i,t}}$ | 2 | 3 | 4 | 5 | 6 |
| 1992 | 53.45* | 19.10* | 14.10 | 6.40 | 4.64 | 2.31 |
| 1993 | 55.52* | 21.81* | 12.40 | 6.15 | 2.40 | 1.72 |
| 1994 | 53.65* | 21.82* | 14.74 | 5.40 | 2.40 | 1.99 |
| 1995 | 55.07* | 20.75* | 13.14 | 5.75 | 2.99 | 2.30 |
| 1996 | 53.75* | 21.71* | 12.54 | 5.85 | 3.66 | 2.49 |
| 1997 | 55.23* | 18.30* | 12.33 | 6.28 | 5.61 | 2.26 |
| 1998 | 57.65* | 15.41 | 13.61 | 7.51 | 3.74 | 2.09 |
| 1999 | 54.50* | 15.28* | 14.68 | 9.76 | 3.82 | 1.97 |
| 2000 | 56.36* | 18.18* | 14.40 | 5.10 | 4.19 | 1.78 |
| 2001 | 55.99* | 15.99* | 13.51 | 10.37 | 2.23 | 1.89 |
| 2002 | 61.52* | 16.78 | 12.96 | 3.89 | 2.72 | 2.12 |
| 2003 | 62.69* | 20.46 | 9.44 | 3.45 | 2.49 | 1.48 |
| 2004 | 58.52* | 22.68 | 10.53 | 4.47 | 2.87 | 0.94 |
| 2005 | 55.58* | 23.75 | 12.59 | 4.25 | 3.16 | 0.67 |
| 2006 | 56.19* | 26.70 | 9.36 | 4.42 | 2.74 | 0.59 |
| 2007 | 55.13* | 25.33 | 11.12 | 4.60 | 2.38 | 1.44 |
| 2008 | 60.73* | 15.03 | 10.73 | 9.63 | 2.49 | 1.40 |

The table shows explained variance and eigenvalues of principal components in six liquidity measures by years from 1992 through 2008. The included measures are percentage spread ($S_{i,t}$), trading volume ($TV_{i,t}$), the Amihud (2002) liquidity measure ($ALM_{i,t}$), proportion of zero returns ($LOT_{i,t}$), the Roll (1984) measure ($ROLL_{i,t}$), and the "round trip" transaction costs ($RTC_{i,t}$).
Liquidity risk measures are standard deviations of monthly averages of $S_{i,t}$, $TV_{i,t}$, $ALM_{i,t}$, $ROLL_{i,t}$, and $LOT_{i,t}$, and standard deviation of bootstrapped round-trip transaction costs $\sigma_{RTCRM,i,t}$. $ASY_{i,t}$ and $\sigma_{ASY_{i,t}}$ indicate the first principal component of the PCA. An asterisk (*) indicates consistency with the Kaiser criterion (eigenvalue > 1) and thus the factor to be at least equivalent to one original variable.

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