Stock liquidity and the accrual anomaly

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Abstract

Purpose – This study examines the effect of stock liquidity on the magnitude of the accrual anomaly.

Design/methodology/approach – This paper examines the relation—both time-series and cross-sectional—between stock liquidity and the magnitude of the accrual anomaly and use the 2001 minimum tick size decimalization as a quasi-experiment to establish causality.

Findings – There is both cross-sectional and time-series evidence that stock liquidity is negatively related to the magnitude of the accrual anomaly. Moreover, the extent to which investors overestimate the persistence of accruals decreases with stock liquidity. Results from a difference-in-differences analysis conducted using the 2001 minimum tick size decimalization as a quasi-experiment suggest that the effect of stock liquidity on the accrual anomaly is causal. The findings of this study are consistent with the enhancing effect of stock liquidity on pricing efficiency.

Originality/value – The study's findings are well aligned with the mispricing-based explanation for the accrual anomaly, suggesting that the improvement in market-wide stock liquidity drives the contemporaneous decline in the magnitude of the accrual anomaly, at least to a great extent.

Keywords Stock liquidity, Accrual anomaly, Efficiency, Tick size, Difference in differences

Paper type Research paper

1. Introduction

In this study, we examine the effect of stock liquidity on the accrual anomaly. The accrual anomaly refers to the well-known negative relation between annual accruals and realized returns. First documented in Sloan (1996), the accrual anomaly is one of the most pervasive, robust return anomalies (Fama & French, 2008). We hypothesize a negative relation between stock liquidity and the magnitude of the accrual anomaly. Our hypothesis builds on three regularities: (1) stock liquidity increases the value of information, thereby motivating market participants to acquire information, (2) stock liquidity encourages the formation of blockholdings, thereby shifting shareholder base toward large, sophisticated institutional investors and (3) stock liquidity reduces the costs and risks of arbitrage, thereby spurring arbitrage. Because of the effect of stock liquidity on information production, shareholder base composition and arbitrage, stock price quickly and faithfully reflects value when stock liquidity is high. Therefore, greater stock liquidity ensures that stock price deviates less from value in the direction predicted by the level of annual accruals.

In the main test, we adopt the broad definition of accruals proposed in Richardson, Sloan, Soliman, and Tuna (2005) to measure annual accruals, the high-low estimate of the effective bid-ask spread from Corwin and Schultz (2012) to compute stock liquidity, and the

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characteristic-based portfolio matching procedure proposed in Daniel, Grinblatt, Titman, and Wermers (1997) to compute abnormal returns. Following Fama and French (2008), we adopt three approaches (the regression approach, the sorts approach and the Jensen alpha approach) to test the hypothesis. We use non-financial firms from years 1970–2011.

We find robust evidence consistent with the hypothesis. Specifically, using the regression approach, we find that the negative relation between annual accruals and realized returns becomes weaker as stock liquidity increases and becomes not statistically different from zero when stock liquidity is high enough; using the sorts approach, we find that the abnormal return of the hedge portfolio (long in the bottom annual accruals decile and short in the top decile) declines as stock liquidity increases; using the Jensen alpha approach, we find that the difference in the Jensen alpha between the bottom and top deciles of annual accruals declines as stock liquidity increases.

The accrual anomaly is driven by investors' tendency to overestimate the persistence of the accrual component of earnings, at least to a great extent (Sloan. 1996; Xie, 2001; Collins, Gong, & Hribar, 2003). Our hypothesis implies that the extent to which investors overestimate the persistence of the accrual component of earnings is weaker when stock liquidity is higher. Adopting the Mishkin test used in Sloan (1996), we find that the extent to which investors overestimate the persistence of annual accruals monotonically declines as stock liquidity increases.

We also find strong time-series evidence of a negative relation between stock liquidity and the magnitude of the accrual anomaly. We find that during 1970–2011 the market-wide stock liquidity and the magnitude of the accrual anomaly are highly negatively correlated: $\rho = -0.39$. Using the percentage rank of the annual magnitude of the accrual anomaly to mitigate the impact of "outliers", we document an even stronger negative relation: $\rho = -0.51$ [1]. Importantly, we find that during 2001–2011 when the accrual anomaly was widely known to investors there is a nearly perfect negative correlation between market-wide stock liquidity and the magnitude of the accrual anomaly: $\rho = -0.87$ when the equal-weight abnormal return is used to measure the magnitude of the accrual anomaly and $\rho = -0.92$ when the percentage rank of the equal-weight abnormal return is used.

To establish the direction of causality between stock liquidity and the magnitude of the accrual anomaly, we use the 2001 minimum tick size decimalization as a quasi-experiment to conduct a difference-in-differences (DiD) analysis. The decimalization results in both significant market-wide change in stock liquidity and wide cross-section variation in the change (Bessembinder, 2003; Chordia, Roll, and Subrahmanyam, 2005). We examine whether the relation between annual accruals and realized returns changes differently for firms experiencing different changes in stock liquidity surrounding the decimalization. We use the propensity score matching to obtain two matched groups: firms with changes in stock liquidity in the top one-third (treatment firms) and matched firms with changes in stock liquidity in the bottom one-third (control firms). The propensity score matching ensures that matched treatment firms and control firms are similar along a host of characteristics prior to the decimalization. We find that regarding the magnitude of the negative relation between annual accruals and realized returns treatment firms experience no material change, whereas control firms experience a significant increase. Importantly, regarding the change the difference between treatment firms and control firms is significant, suggesting a causal mitigating effect of stock liquidity on the magnitude of the accrual anomaly.

Our study contributes to the literature in several ways. First, our study helps to resolve two lingering questions about the accrual anomaly: whether the accrual anomaly is driven by mispricing and what drives the recent decline in the magnitude of the accrual anomaly. Our findings are well aligned with the mispricing explanation for the accrual anomaly. Whether the accrual anomaly is driven by mispricing has been a controversial question (Dechow, Khimich, & Sloan, 2011; Hirshleifer, Hou, & Teoh, 2012). Our study provides distinct evidence that the accrual anomaly results from market inefficiency, at least to a great extent. Moreover, our study suggests a subtle view about factors underlying the accrual anomaly. Our findings suggest that the mispricing associated with the accrual anomaly is not only due to investors' imperfection such as fixating on reported earnings but also due to rational reasons. For instance, when stock liquidity is low it may be too risky and costly to exploit potential mispricing opportunities associated with accruals. That is, private information about potential investment opportunities associated with accruals cannot be impounded into stock prices rapidly in the presence of low stock liquidity [2].

Furthermore, our study provides a market microstructure-based explanation for the temporal variation in the magnitude of the accrual anomaly, particularly the recent decline [3]. Our time-series evidence suggests that stock liquidity is a significant factor driving the temporal variation in the magnitude of the accrual anomaly. Several studies document that the magnitude of the accrual anomaly declined significantly in recent years (Richardson, Tuna, & Wysocki, 2010; Green, Hand, & Soliman, 2011; Hirshleifer, Teoh, & Yu, 2011). The dominant explanation for the recent decline is that certain large investors, especially hedge fund managers, aggressively exploit the accruals-related mispricing (Richardson *et al.*, 2010; Green *et al.*, 2011; Hirshleifer *et al.*, 2011). However, findings of studies using observations from early periods suggest that large institutional investors either ignored the accruals-related mispricing or did not exploit it aggressively enough, due to considerable institutional, microstructural and resource constraints (Richardson, 2003; Battalio, Lerman, Livnat, & Mendenhall, 2012; Lev & Nissim, 2006; Mashruwala, Rajgopal, & Shevlin, 2006). Green *et al.* (2011) attribute the aggressive exploitation of the accruals-related mispricing by hedge fund managers to the possibility that hedge funds face fewer institutional and resource constraints and provide high-powered incentives for their managers. While hedge fund managers enjoy great operational flexibility, they still cannot circumvent microstructural barriers that are found to deter informed investors from exploiting accruals-related mispricing (Lev & Nissim, 2006; Mashruwala *et al.*, 2006). Taken together, it appears puzzling why hedge funds suddenly become active in exploiting the accruals-related mispricing only recently. Our findings suggest that due to its effect on the risks and costs of arbitrage, the recent dramatic improvement in stock liquidity may account for why hedge funds are willing to and able to aggressively exploit the accruals-related mispricing recently.

Second, our study adds to research (e.g. Mashruwala *et al.*, 2006) that demonstrates the importance of attending to factors affecting the price discovery process in research design. Using stocks listed in NYSE from the period of 1993–2008, Chordia, Roll, and Subrahmanyam (2011) find that stock liquidity has been improving, especially since 2001. Chordia *et al.* (2011) attribute their finding to numerous permanent changes such as reductions in the minimum tick size, reductions in institutional commissions and emerging of new trading platforms. Our study also shows that stock liquidity constantly improved during 2001–2006 and stayed high afterward except in 2008 and 2009. Moreover, we find that during 1983–2000 market-wide stock liquidity was low. Interestingly, we find that stock liquidity was relatively high during 1970–1982 except 1974. Our study demonstrates the importance of attending to the temporal variation in market efficiency in understanding trends of accounting phenomena [4].

The rest of the paper is organized as follows. Section 2 develops the hypothesis. Section 3 describes the research design. Section 4 reports main results. Section 5 presents results from robustness tests and additional analyses. Section 6 concludes.

2. Research hypothesis [5]

The accrual anomaly refers to the predictable negative relation between the accrual component of reported earnings and realized returns. The accrual anomaly is first documented in Sloan (1996), and it is considered one of the most pervasive return anomalies (Fama & French, 2008). Considerable empirical evidence suggests that mispricing, at least to a great extent, drives the accrual anomaly (Richardson *et al.*, 2010; Dechow *et al.*, 2011;

Hirshleifer *et al.*, 2012). Specifically, investors tend to overestimate the value of firms reporting high accruals and underestimate the value of firms reporting low accruals. That is, stock prices systematically deviate from value as predicted by levels of the accrual component of reported earnings [6].

We argue that stock liquidity, one of the most important aspects of market microstructure (Harris, 2003; O'Hara, 2003), has first-order effects on the accrual anomaly. Stock liquidity is embodied in investors' capability of trading a large block of shares quickly at low costs with little price impact (Harris, 2003). We hypothesize a negative relation between stock liquidity and the magnitude of the accrual anomaly. Our hypothesis development builds on the effect of stock liquidity on the value of information, the shareholder base composition and the risks and costs of arbitrage.

Stock liquidity reduces trading costs and assists informed investors in disguising their private information (Kyle & Vila, 1991; Holmström & Tirole, 1993; Maug, 1998). Because of this, stock liquidity enhances the value of information by enabling market participants to profit from it. Therefore, stock liquidity spurs market participants to spend efforts in producing and acquiring information about firm value. Moreover, Holmström and Tirole (1993) analytically show that, to maximize profits on acquired information, market participants also need to trade more aggressively on their information in response to improvement in liquidity, leading to more efficient prices about the value of traded assets in the equilibrium (see also Grossman & Stiglitz, 1980; Edmans, 2009). Accordingly, we reason that greater stock liquidity ensures that stock prices deviate less from the value of traded stocks in the direction predicted by the levels of annual accruals.

Both analytical models and empirical findings suggest that stock liquidity encourages the formation of blockholdings (Maug, 1998; Kyle & Vila, 1991; Edmans, 2009; Brav, Jiang, & Kim, 2010; Edmans, Fang, & Zur, 2013). Blockholders arguably possess superior information for the following reasons. First, blockholders have incentives to become informed because of the large stake that they can sell upon negative information (Edmans, 2009). Second, because quality information acquisition incurs fixed costs such as hiring well-trained analysts, shareholders will only acquire information on large ownership stakes (Boehmer & Kelley, 2009). In addition, blockholders possess better capabilities of conducting high-quality fundamental analysis due to their scale and resources (Bushee & Goodman, 2007). Moreover, blockholders may have better access to management because of their large equity holdings (Bushee & Goodman, 2007).

In addition, blockholders are generally large institutional investors. Existing research has accumulated considerable evidence that confirms institutional investors' information superiority [7]. Institutional investors trade on their superior information to profit from it. Using a sophisticated method to infer daily institutional trading behavior from intraday transaction data, Campbell, Ramadorai, and Schwartz (2009) find that institutional investors anticipate earnings surprises and post-earnings announcement drifts (see also Ke & Ramalingegowda, 2005). With respect to the accrual anomaly, Lev and Nissim (2006) show that certain institutional investors do implement investment strategy in anticipation of the annual accruals information (see also Ali, Chen, Yao, & Yu, 2008; Green *et al.*, 2011). We expect that trading by informed institutional investors causes stock prices to deviate less from the fundamental values of traded stocks in the direction predicted by annual accruals. In line with our expectation, Collins *et al.* (2003) find that the accrual component of reported earnings is less mispriced in firms with greater institutional ownership. Taking all this together, we reason that because of its effect on shareholder base composition, greater stock liquidity also ensures that stock prices deviate less from their values in the direction predicted by levels of annual accruals.

Arbitrage is crucial to the price discovery process (Shleifer & Vishny, 1997; Lee, 2001; Hirshleifer *et al.*, 2011) [8]. Stock price efficiency depends not only on how informed market participants are about the value of trade stocks but also on how easily and profitably market participants can arbitrage on their information (Lee, 2001). However, arbitrage is costly and risky because arbitrage not only requires financial and intellectual investments in information acquisition and fundamental analysis, but also involves taking a long position in undervalued stocks and a short position in overvalued stocks (Shleifer & Vishny, 1997; Lee, 2001; O'Hara, 2003). Arbitrageurs are generally well-informed, possibly motivated by the great risk and cost to be overcome by arbitrageurs (Boehmer, Jones, & Zhang, 2008). For instance, Karpoff and Lou (2010) find that abnormal short interest increases steadily in 19 months before financial misrepresentation is publicly revealed.

Stock liquidity stimulates arbitrage due to its effect on arbitrage profits and risks. Stock liquidity reduces trading costs of arbitrage and allows arbitrageurs to quickly alter their holding positions at prices that do not fully reveal their private information. Therefore, stock liquidity directly increases profits of arbitrage. Moreover, arbitrage could involve taking a short position in overvalued stocks. For instance, arbitrage strategy based on anticipated levels of annual accruals involves taking a short position in firms with high anticipated levels of annual accruals (Sloan, 1996). Taking a short position is very costly in practice (Ali & Trombley, 2006; Hirshleifer *et al.*, 2011). Institutional owners provide the main loan supply of stocks (Asquith, Pathak, & Ritter, 2005). By shifting shareholder base towards large institutional investors, stock liquidity increases the availability of shares for borrowing by short arbitrageurs and thus indirectly increases profits of short arbitrage by facilitating taking a short position. Furthermore, arbitrage involves significant risks. For instance, arbitrageurs may be pressed to prematurely close out arbitrage positions or reestablish arbitrage positions owing to various reasons such as recall by stock lenders and liquidity shock. Early closeout and reestablishment of arbitrage positions not only are costly but also involve additional risks such as short and long squeeze. Stock liquidity accelerates the convergence of stock prices and fundamental values and thereby reduces risks associated with arbitrage.

Barriers to arbitrage underlie the existence and magnitude of the accrual anomaly (Lev & Nissim, 2006; Mashruwala *et al.*, 2006). Abatement of the accrual anomaly requires active arbitrage based on anticipated levels of annual accruals. We reason that, due to its the effect on arbitrage, greater stock liquidity also ensures that stock prices deviate less from their values in the direction predicted by levels of annual accruals.

In sum, stock liquidity spurs information production by increasing the value of information, tilts shareholder base toward large, sophisticated institutional investors by encouraging the formation of blockholdings and stimulates arbitrage by reducing the costs and risks of arbitrage. Taking all this together, we reason that stock prices deviate less from their values in the direction predicted by levels of annual accruals when stock liquidity is higher, which leads to the following hypothesis:

H1. The greater the stock liquidity, the smaller the magnitude of the accrual anomaly.

3. Research design

3.1 Measures

3.1.1 Accruals. We adopt the definition of operating accruals proposed in Richardson *et al.* (2005) as our primary measure of annual accruals. Following Richardson *et al.* (2005), we measure operating accruals as the sum of change in non-cash net current operating assets and change in noncurrent net operating assets, which is summarized in the following equations:

$$OA = \Delta WC + \Delta NCO \tag{1}$$

$$WC = COA - COL \tag{2}$$

$$NCO = NCOA - NCOL \tag{3}$$

where *WC* stands for working capital; *COA* stands for current operating assets and *COA = Current Assets (Compustat Item #act) – Cash and Short-term Investments (Compustat Item #che)*; *COL* stands for current operating liabilities and *COL = Current Liabilities (Compustat Item #lct) – Debt in Current Liabilities (Compustat Item #dlc)*; *NCO* stands for noncurrent net operating assets; *NCOA* stands for non-current operating assets and *NCOA = Total Assets (Compustat Item #at) – Current Assets (Compustat Item #act) – Investments and Advances (Compustat Item #ivao)*; *NCOL* stands for non-current operating liabilities and *NCOL = Total Liabilities (Compustat Item #lt) – Current Liabilities (Compustat Item #lct) – Long-Term Debt (Compustat Item #dltt)*.

We adopt the accruals measure proposed in Richardson *et al.* (2005) because the authors show that this measure provides a more complete measure of accruals than Sloan's (1996) accruals measure that only includes the change in non-cash net current operating assets. Moreover, we adopt the balance sheet approach for computing accruals. The balance sheet approach allows us to use observations from periods prior to the availability of cash flow data and thereby enables us to maximize the generalizability of our findings.

3.1.2 Stock liquidity. In most tests, we adopt the stock liquidity measure based on the high-low estimate of the effective bid-ask spread from Corwin and Schultz (2012) as our primary measure of stock liquidity. This high-low estimate has several desirable attributes. First, it has intuitive theoretical foundation. Corwin and Schultz (2012) base its development on uncontroversial empirical regularities. First, daily high prices are always buyer-initiated, whereas daily low prices are always seller-initiated. Second, the ratio of high-to-low prices reflects both the fundamental volatility and the bid-ask spread of the stock. The component of the high-to-low price ratio attributed to the fundamental volatility increases proportionately with the trading interval, whereas the component attributed to the bid-ask spread stays relatively constant over a short period.

Importantly, Corwin and Schultz (2012) show that their high-low estimate outperforms other low-frequency measures in capturing the cross-sections of both spread levels and month-to-month changes in spreads. In addition, this high-low estimate is much less computationally demanding than measures estimated from intraday transaction data. Because of the large size of samples used in this study, computational feasibility requires us to use low-frequency estimates. Furthermore, intraday transaction data are not available before 1993. By construction, this high-low estimate captures stock illiquidity. We measure stock liquidity (*LIQ_HL*) as $-1 \times$ the natural logarithm of this high-low estimate of the effective bid-ask spread [9].

3.1.3 Abnormal return. The sorts approach to examining anomalies requires calculation of abnormal stock returns. We adopt the characteristic-based portfolio matching procedure proposed in Daniel *et al.* (1997) to compute abnormal returns. This characteristic-based portfolio matching procedure controls for size, book-to-market and 12-month stock return momentum, and has been used in related studies (e.g. Hirshleifer *et al.*, 2011).

Under the characteristic-based portfolio matching procedure, to form benchmark portfolios, each month all observations are first sorted into five size quintiles, then within each size quintile into five book-to-market quintiles, and then within each of these 25 groups into quintiles based on past 12-month cumulative returns, skipping the most recent month. Stocks are weighted equally within each of these 125 portfolios. For any stock, we compute the abnormal return as the difference between its return and the equal-weight return of the benchmark portfolio to which it belongs.

3.2 Hypothesis testing techniques

To test the hypothesis, we adopt three approaches to examining anomalies: the regression approach, the sorts approach and the Jensen alpha approach. These three approaches are widely used in related studies (Fama & French, 2008). Each approach has its advantages and disadvantages (Fama & French, 2008). Therefore, it is important to apply all of them and examine whether findings are consistent across different approaches (Fama & French, 2008).

3.2.1 The regression approach. We follow Fama and French (2008) to set up the following regression equation:

$$\begin{aligned} RET_{t+1} = {} & \beta_0 + \beta_1 \times MC_t + \beta_2 \times B/M_t + \beta_3 \times MOM_t + \beta_4 \times D\_NS_t + \beta_5 \times NS_t \\ & + \beta_6 \times dA/A_t + \beta_7 \times D\_Y/B_t + \beta_8 \times Y/B(+)_t + \beta_9 \times ACC_t \\ & + \beta_{10} \times LIQ\_HL_t + \beta_{11} \times ACC_t \times LIQ\_HL_t \\ & + \text{Year \& industry fixed effects} + \varepsilon_t \end{aligned} \tag{4}$$

where RET_{t+1} is the annualized stock return that accumulates from the fourth month after the end of fiscal year t, and consistent with prior studies (e.g. Mashruwala *et al.*, 2006), we choose a three-month gap to ensure the complete dissemination of accounting information in financial statements of fiscal year t; MC_t is the natural logarithm of market value of equity at the end of fiscal year t; B/M_t is the natural logarithm of the ratio of book value of equity to market value of equity at the end of fiscal year t [10]; MOM_t is the cumulative stock return over a six-month period that ends in the third month after the end of fiscal year t; NS_t is the natural logarithm of the ratio of the split-adjusted shares outstanding at the end of fiscal year t to the split-adjusted shares outstanding at the end of fiscal year $t-1$ and the split-adjusted shares outstanding is Compustat shares outstanding (#csho) times Compustat adjustment factor (#ajex); D_NS_t is an indicator variable that equals 1 if NS_t equals 0 and 0 if otherwise; dA/A_t is the natural logarithm of the ratio of assets per split-adjusted share at the end of fiscal year t to assets per split-adjusted share at the end of fiscal year $t-1$; Y/B_t is equity income (i.e. income before extraordinary item (*Compustat Item #ib*) minus dividends on preferred (*#dvp*) if available plus income statement deferred taxes (*#txdi*) if available divided by book value of equity at the end of fiscal year t; $Y/B(+)_t$ equals Y/B_t when Y/B_t is positive and 0 if otherwise; D_Y/B_t is an indicator variable that equals 1 if Y/B_t is negative and 0 if otherwise. We also control for year and industry fixed effects. We define the industry membership of observations using the Fama-French 49 industry groups.

ACC_t is our primary measure of annual accruals: the sum of change in net non-cash current operating assets and change in net non-current operating assets from fiscal year $t-1$ to fiscal year t scaled by average total assets. LIQ_HL_t is $-1 \times$ the natural logarithm of the high-low estimate of the effective bid-ask spread from Corwin and Schultz (2012), computed over a period of 252 trading days ending in the last month of fiscal year t [11].

Control variables in Equation (4) capture the size, value, profitability, growth, net stock issues and momentum anomalies documented in prior studies (Fama & French, 2008). ACC_t captures the accrual anomaly. Studies following Sloan (1996) consistently document a robust negative relation between annual accruals and future stock returns. H1 predicts that the magnitude of the negative relation between annual accruals and future stock returns declines as stock liquidity improves. Specifically, H1 predicts that $\beta_{11} > 0$.

3.2.2 The sorts approach. To apply the sorts approach, each year we sort all observations into 10 equal groups according to annual accruals (ACC_t) and independently sort all observations into four equal groups according to stock liquidity (LIQ_HL_t). We compute the equal-weight abnormal return (*EWARET*) for each of the 10 (A) $\times$ 4 (L) portfolios each year. Greater A represents higher annual accruals and greater L represents higher stock liquidity.

We then calculate the time-series average (*MEWARET*) of *EWARET* for each of the 10 × 4 portfolios and corresponding *t*-statistics.

Consistent with existing research, we measure the magnitude of the accrual anomaly as the difference ($MEWARET_{L-H}$) between *MEWARET* of portfolio $A = 1$ and *MEWARET* of portfolio $A = 10$, given $L, L = 1$ to 4. H1 predicts that $MEWARET_{L-H}$ declines as L increases from 1 to 4. Our hypothesis builds on the regularity that stock prices more faithfully reflect their values when stock liquidity is high than when stock liquidity is low. Therefore, our hypothesis implies that both the mean and standard deviation of absolute *MEWARET* decline as L increases from 1 to 4.

3.2.3 The Jensen alpha approach. To apply the Jensen Alpha approach, each year we sort all observations into 10 equal groups according to annual accruals (ACC_t) and independently sort all observations into four equal groups according to stock liquidity (LIQ_HL_t). Within each of the 10 × 4 portfolios, we estimate the following regression:

$$R_{p,t,n} - RF_{t,n} = \alpha_p + b_p \times (RM_{t,n} - RF_{t,n}) + s_p \times SMB_{t,n} + h_p \times HML_{t,n} + d_p \times UMD_{t,n} + \varepsilon_{p,t} \tag{5}$$

where $R_{p,t,n}$ is monthly equal-weighted return on portfolio p in the *n-th* month after the end of fiscal year $t, p \in \{(A, L),\ A : 1 \text{ to } 10 \text{ and } L : 1 \text{ to } 4\}, n = 1$ to 12, $t = 1970$ to 2011; greater A represents higher annual accruals and greater L represents higher stock liquidity; $RF_{p,t,n}$ is 1-month *t*-bill rate; $RM_{p,t,n} - RF_{p,t,n}$ is monthly excess return on the value-weighted market index; $SMB_{p,t,n}$ is monthly mimicking factor portfolio return to the size factor; $HML_{p,t,n}$ is monthly mimicking factor portfolio return to the value factor; $UMD_{p,t,n}$ is monthly mimicking factor portfolio returns to the momentum factor. We obtain 1-month *t*-bill rate, the monthly excess return on the value-weight market index, and the monthly mimicking factor portfolio returns to the size, value and momentum factors from Kenneth R. French's online data library.

Consistent with prior studies (e.g. Mashruwala *et al.*, 2006) we measure the magnitude of the accrual anomaly as the difference (α_{L-H}) between α_p when $p = 1 \times L$ and α_p when $p = 10 \times L$, $L = 1$ to 4. H1 predicts that α_{L-H} declines as L increases from 1 to 4. Our hypothesis implies that both the mean and standard deviation of absolute α_p decline as L increases from 1 to 4.

3.3 Data, sample and descriptive statistics

We begin with the universe of firms that have common stocks (share code is 10 or 11) listed on NYSE, AMEX and NASDAQ with required financial and stock price information from CRSP and Compustat. Firms in the financial service industries (SIC codes 6000-6999) are excluded because accruals have different meaning for these industries. We use financial statement data for a 42-year period of 1970–2011. To maximize generalizability, we include a firm-year observation in one test only by requiring that the firm-year observation has required information for the test. Therefore, different data sets are used in different tests.

Table 1 reports descriptive statistics of variables for the sample used in the regression approach. To save space, we do not report descriptive statistics of variables for samples used in other tests, but they are available upon request. Table 1, Panel A reports summary statistics. The statistical distributions of variables used in our study are comparable to those reported in prior studies (e.g. Richardson *et al.*, 2005; Fama & French, 2008). Table 1, Panel B reports Pearson and Spearman correlations. While we are cautious about drawing inferences from correlations because of their univariate nature, we want to point out that consistent with prior studies we observe a significant negative correlation between future stock returns (RET_{t+1}) and accruals (ACC_t) in our sample.

Panel A: Summary statistics

Variable	Mean	SD	P25	P50	P75
RET_{t+1}	0.165	0.785	−0.220	0.055	0.363
MC_t	5.093	2.083	3.552	4.977	6.500
B/M_t	−0.581	0.884	−1.081	−0.504	−0.001
MOM_t	0.108	0.483	−0.140	0.049	0.262
D_NS_t	0.096	0.295	−0.000	−0.000	−0.000
NS_t	0.065	0.225	−0.000	0.006	0.036
dA/A_t	0.076	0.283	−0.024	0.066	0.168
D_Y/B_t	0.241	0.427	−0.000	−0.000	−0.000
$Y/B(+)_t$	0.066	0.070	0.003	0.053	0.093
ACC_t	0.071	0.182	−0.018	0.045	0.133
LIQ_HL_t	4.405	0.837	3.890	4.487	5.025

Panel B: Pearson (Spearman) correlations in upper (lower) triangle

Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
RET_{t+1} (1)		−0.05	0.10	−0.04	0.00	−0.03	−0.08	0.04	0.04	−0.08	−0.06
MC_t (2)	0.03		−0.33	0.00	−0.27	−0.03	0.12	−0.22	−0.06	0.04	0.64
B/M_t (3)	0.15	−0.35		−0.10	0.18	−0.16	−0.14	−0.07	0.38	−0.13	−0.03
MOM_t (4)	0.02	0.07	−0.06		0.02	−0.01	0.00	−0.03	0.02	−0.05	−0.01
D_NS_t (5)	0.01	−0.27	0.19	0.01		−0.09	−0.04	0.04	0.05	−0.08	−0.17
NS_t (6)	−0.11	0.03	−0.26	−0.04	−0.27		−0.20	0.15	−0.15	0.27	−0.13
dA/A_t (7)	−0.05	0.15	−0.22	0.02	−0.07	0.01		−0.26	0.12	0.53	0.12
D_Y/B_t (8)	−0.07	−0.22	−0.03	−0.11	0.04	0.15	−0.35		−0.53	−0.17	−0.38
$Y/B(+)_t$ (9)	0.13	0.04	0.33	0.09	0.03	−0.21	0.25	−0.75		0.05	0.21
ACC_t (10)	−0.10	0.05	−0.17	−0.07	−0.08	0.26	0.57	−0.23	0.15		0.03
LIQ_HL_t (11)	0.05	0.64	−0.04	0.10	−0.14	−0.11	0.15	−0.38	0.34	0.06	

Note(s): This table presents descriptive statistics of variables for the sample used in the regression. Panel A reports summary statistics. Panel B reports Pearson and Spearman correlations. Correlations significantly different from zero at p-values less than 5% are in boldface type. The sample consists of 79,994 observations from 1970 through 2011. RET_{t+1} is the annualized stock return that accumulates from the fourth month after the end of fiscal year t. MC_t is the natural logarithm of market value of equity at the end of fiscal year t. B/M_t is the natural logarithm of the ratio of book value of equity to market value of equity at the end of fiscal year t. MOM_t is the cumulative stock return over a six-month period that ends in the third month after the end of fiscal year t. NS_t is the natural logarithm of the ratio of split-adjusted shares outstanding at the end of fiscal year t to split-adjusted shares outstanding at the end of fiscal year $t-1$. D_NS_t is an indicator variable that equals 1 if NS_t equals 0 and 0 if otherwise. dA/A_t is the natural logarithm of the ratio of assets per split-adjusted share at the end of fiscal year t to assets per split-adjusted share at the end of fiscal year $t-1$. Y/B_t is the ratio of equity income (i.e. income before extraordinary items, minus dividends on preferred, if available, plus income statement deferred taxes, if available) in fiscal year t divided by book equity in fiscal year t. D_Y/B_t is an indicator variable that equals 1 if Y/B_t is negative and 0 if otherwise. $Y/B(+)_t$ equals Y/B_t if Y/B_t is positive and 0 if otherwise. ACC_t is the sum of change in net non-cash current operating assets and change in net non-current operating assets from fiscal year $t-1$ to fiscal year t scaled by average total assets. LIQ_HL_t is $-1 \times$ the natural logarithm of the high-low estimate of effective spread from Corwin and Schultz (2012)

Table 1. Descriptive statistics

4. Results

Table 2 reports results from the main tests of the hypothesis. Panel A reports results from the regression approach. We calculate t-statistics by using cluster-robust standard errors that are adjusted for heteroscedasticity and clustered at the firm level. Consistent with prior studies, we observe a statistically significant negative relation between annual accruals and future stock returns. Importantly, consistent with the prediction of H1, the coefficient on the interaction term between annual accruals and stock liquidity is positive and statistically significant.

To assess the economic significance of the effect of stock liquidity on the negative relation between annual accruals and future stock returns, we follow Aiken and West's (1991)

Panel A: The regression approach

Dependent variable: RET_{t+1}

Variable	Coeff.	t-stat	Coeff.	t-stat
MC_t	-0.015^{**}	−7.73	-0.011^{**}	−4.67
B/M_t	0.051^{**}	10.72	0.052^{**}	10.87
MOM_t	-0.037^{**}	−5.54	-0.038^{**}	−5.63
D_NS_t	-0.026^{**}	−2.93	-0.029^{**}	−3.19
NS_t	-0.096^{**}	−5.38	-0.096^{**}	−5.38
dA/A_t	-0.101^{**}	−5.61	-0.100^{**}	−5.54
D_Y/B_t	$0.017^{\dagger}$	1.82	0.014	1.53
$Y/B(+)_t$	0.254^{**}	4.52	0.263^{**}	4.66
ACC_t	-0.196^{**}	−7.66	-0.176^{**}	−7.28
LIQ_HL_t			-0.016^{**}	−3.17
$ACC_t \times LIQ\_HL_t$			0.066^{**}	3.01
Year fixed effects	Yes		Yes	
Industry fixed effects	Yes		Yes	
N	79,994		79,994	
R^2	0.121		0.121	

Panel B: The sorts approach

	Mean of equal-weighted $ARET_{t+1}$ ($MEWARET$)				t-stat			
	Liquidity (LIQ_HL_t)				Liquidity (LIQ_HL_t)			
Accruals (ACC_t)	L	2	3	H	L	2	3	H
Low – accruals	15.68	3.53	2.89	2.95	3.31	1.98	1.50	1.72
2	12.23	5.92	4.76	3.58	3.12	4.05	3.94	3.66
3	7.45	1.36	3.84	0.75	2.81	1.18	2.97	0.67
4	6.86	2.06	2.00	0.46	2.46	1.49	2.20	0.57
5	5.70	3.33	1.92	0.42	2.57	2.32	1.57	0.39
6	4.56	−0.22	0.15	−0.32	1.30	−0.15	0.18	−0.31
7	2.24	−1.96	−0.74	−1.34	0.73	−1.48	−0.63	−1.37
8	0.18	−3.02	−1.75	−1.53	0.07	−2.09	−1.73	−1.39
9	−0.56	−2.20	−3.24	−2.55	−0.24	−1.36	−2.90	−2.29
High – accruals	−4.05	−7.89	−5.80	−3.77	−1.77	−3.20	−3.78	−2.13
L−H	19.73	11.42	8.69	6.72	3.75	3.76	3.53	2.72
	Mean of Absolute $MEWARET$				SD of Absolute $MEWARET$			
	5.95	3.15	2.71	1.76	4.93	2.25	1.76	1.34

Panel C: The alpha approach

	α_p				t-stat			
	Liquidity (LIQ_HL_t)				Liquidity (LIQ_HL_t)			
Accruals (ACC_t)	L	2	3	H	L	2	3	H
Low – accruals	1.68	0.67	0.49	0.21	6.64	4.10	3.62	1.83
2	1.30	0.65	0.49	0.43	5.03	3.84	4.66	4.79
3	1.06	0.38	0.41	0.28	4.97	2.98	4.94	4.12
4	0.85	0.30	0.33	0.21	4.15	3.14	3.57	2.79
5	0.81	0.40	0.28	0.20	3.94	3.70	2.91	2.81
6	0.48	0.25	0.14	0.06	2.38	2.12	1.61	0.87
7	0.43	0.14	0.05	−0.04	2.28	1.18	0.55	−0.42
8	0.36	0.00	−0.05	−0.09	1.72	0.03	−0.50	−0.88
9	0.19	−0.10	−0.29	−0.18	0.86	−0.66	−2.77	−1.74
High – accruals	−0.19	−0.66	−0.54	−0.31	−0.61	−3.51	−3.98	−2.14

Table 2.
Stock liquidity and the accrual anomaly

(*continued*)

Panel C: The alpha approach

Accruals (ACC_t)	α_p Liquidity (LIQ_HL_t) L	2	3	H	t-stat Liquidity (LIQ_HL_t) L	2	3	H
$\alpha_L - \alpha_H$	1.87	1.33	1.03	0.52	4.67	5.34	5.37	2.81
	Mean of Absolute α_p				SD of Absolute α_p			
	0.73	0.36	0.31	0.20	0.50	0.24	0.18	0.12

Note(s): This table reports results from the regression, the sorts, and the alpha approaches to testing the effect of stock liquidity on the relation between accruals and future stock returns. Panel A reports results from the regression approach. The regression model extends the one used in Fama and French (2008) by including industry and year fixed effects, stock liquidity and the interaction term between stock liquidity and accruals. In Panel A, t-statistics are calculated by using cluster-robust standard errors clustered on firms. Panel B reports results from the sorts approach. $ARET_{t+1}$ is the abnormal annual stock return that cumulates over a 12-month period starting from the fourth month after the end of fiscal year t. To compute $ARET_{t+1}$ we follow the characteristic-based portfolio matching procedure proposed in Daniel *et al.* (1997) to adjust annual stock returns. *MEWARET* is the equal-weighted average of abnormal annual stock returns. Panel C reports results from the alpha approach. In Panel C, t-statistics are calculated by using standard errors adjusted for Newey–West autocorrelations of three lags

**, *, and † denote statistical significance at the 1%, 5%, and 10% levels, respectively, using a 2-tailed test

Table 2.

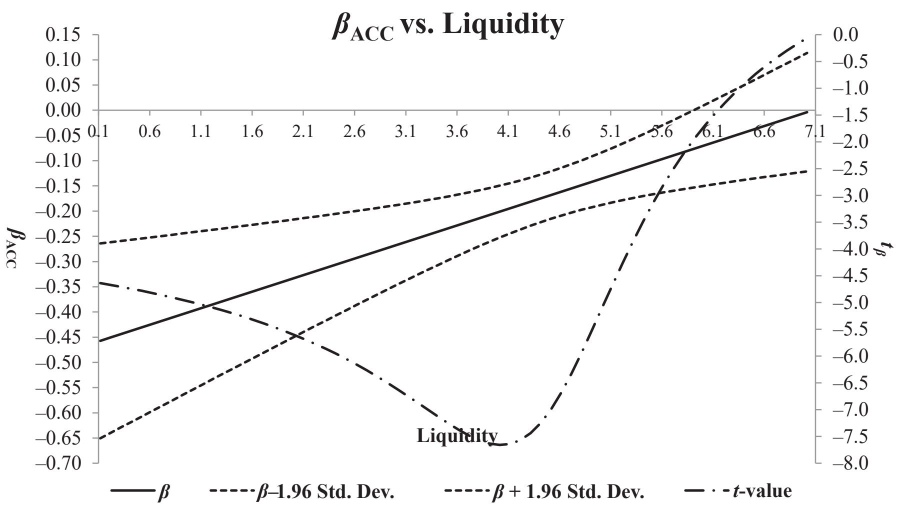
suggestion and draw Figure 1 to illustrate how the magnitude of the relation between ACC_t and RET_{t+1} varies with stock liquidity. From Equation (4), we can get

$$\frac{\partial RET_{t+1}}{\partial ACC_t} = \beta_9 + \beta_{11} \times LIQ_t \tag{6}$$

Therefore, given stock liquidity, the coefficient estimate and the corresponding test statistic for ACC_t can be calculated using following equations:

$$\frac{\partial \widehat{RET}_{t+1}}{\partial ACC_t} = \widehat{\beta}_9 + \widehat{\beta_{11}} \times LIQ_t \tag{7}$$

and



Note(s): Figure 1 depicts the effect of stock liquidity on the estimated relation between accruals and future stock returns

Figure 1.
Stock liquidity and the estimated relation between accruals and future stock returns

$$SD\left(\frac{\partial \widehat{RET}_{t+1}}{\partial ACC_t}\right) = \sqrt{Var\left(\widehat{\beta_9}\right) + LIQ_t^2 \times Var\left(\widehat{\beta_{11}}\right) + 2 \times LIQ_t \times COV\left(\widehat{\beta_9}, \widehat{\beta_{11}}\right)} \quad (8)$$

where $SD()$ denotes standard deviation, $Var()$ denotes variance and $COV()$ denotes covariance. We obtain $\widehat{\beta_9}$, $\widehat{\beta_{11}}$, $Var(\widehat{\beta_9})$, $Var(\widehat{\beta_{11}})$, and $COV(\widehat{\beta_9}, \widehat{\beta_{11}})$ from OLS estimates of Equation (4). In the sample used to estimate Equation (4), the level of stock liquidity ranges from 0.118 to 6.950. To draw Figure 1, we use the range of 0.100 to 7.020 to ensure that the value range of stock liquidity better represents the value range of the population. Figure 1 shows that, as stock liquidity increases, the magnitude of the accrual anomaly (i.e. the coefficient on ACC_t) declines. More importantly, Figure 1 shows that when stock liquidity is high enough (greater than about 5.92 in our sample), the coefficient on ACC_t is not statistically, different from zero. That is, when stock liquidity is high enough, observations in our sample does not exhibit a statistically meaningful relation between annual accruals and future stock returns.

Table 2, Panel B reports results from the sorts approach. Panel B shows that in line with prior studies, there is generally a negative relation between annual accruals and future stock returns given stock liquidity. Importantly, consistent with the prediction of H1, when measured as the equal-weight abnormal return (*EWARET*) on a hedge portfolio that longs in firms in the bottom annual accruals decile and shorts in firms in the top annual accruals decile, the magnitude of the accrual anomaly declines as stock liquidity improves. Moreover, consistent with the regularity that stock liquidity ensures that stock prices faithfully reflect their values, both the mean and standard deviation of absolute *MEWARET* decline as stock liquidity increases. Table 2, Panel C reports results from the Jensen Alpha approach. The patterns revealed in Panel C resemble those shown in Panel B with respect to the effect of stock liquidity on the magnitude of the accrual anomaly.

In sum, regardless of the test approach used, we find consistent evidence that the greater stock liquidity the smaller the magnitude of the accrual anomaly. Our finding is consistent with the view that greater stock liquidity ensures that stock prices deviate less from the values of traded stocks in the direction predicted by annual accruals levels.

5. Additional analyses

5.1 Robustness tests

We conduct a battery of robustness tests to examine whether our findings about the effect of stock liquidity on the magnitude of the accrual anomaly are sensitive to our choice of stock liquidity measures and annual accruals measures. In one robustness test, we adopt the stock liquidity measure (*LIQ_GIBBS*) based on the Gibbs sampler estimate of effective trading costs proposed in Hasbrouck (2009). Hasbrouck (2009) shows that the general distribution features of his Gibbs effective cost estimate closely match with those of effective cost measures obtained using intraday transaction data (see also Goyenko, Holden, & Trzcinka, 2009). Specifically, *LIQ_GIBBS* is $-1 \times$ the natural logarithm of Hasbrouck's Gibbs sampler estimate of effective trading costs computed over a period of 252 trading days that ends in the last month of fiscal year *t*. In untabulated results, we find that our inference about the empirical validity of H1 remains intact.

Following Sloan (1996), we use change in non-cash net current operating assets as our measure for annual accruals and find weaker but qualitatively similar results. It may be not surprising to document weaker results when using this alternative measure of accruals because the findings in Richardson *et al.* (2005) suggest that the broad definition of accruals provides a more comprehensive measure of annual accruals. Hribar and Collins (2002) recommend using the cash-flow approach to computing operating accruals. We measure operating accruals from the statement of cash flows and, in untabulated results, we find that our inference about the empirical validity of H1 remains unchanged. In sum, our findings about the relation between stock liquidity and the magnitude of the accrual anomaly are robust to our choice of stock liquidity measures and annual accruals measures.

We run the pooled OLS regression to test the hypothesis. Therefore, our results are driven by both cross-section and time-series variations in accruals and stock liquidity. Extant studies on the accrual anomaly generally focus on the cross-sectional relation between accruals and realized return. To ensure that our results are not driven mainly by time-series variations in accruals and stock liquidity, we apply the Fama–MacBeth procedure to compute coefficient estimates and corresponding t-statistics. Because the Fama–MacBeth estimate is the time-series average of OLS regression coefficient estimates that are obtained separately each year, it captures the cross-sectional relation between the dependent and independent variables. We use standard errors adjusted for Newey–West autocorrelations of three lags to compute the t-statistics. In untabulated results, we find that the coefficient estimates for ACC_t and $ACC_t \times LIQ\_HL_t$ obtained using the Fama–MacBeth regression are comparable to those obtained using the pooled OLS regression, suggesting that our results are mainly driven by cross-sectional variations in accruals and stock liquidity.

Because firm size and stock liquidity are positively related, it is thus of interest to examine the robustness of the mitigating effect of stock liquidity on the accrual anomaly to screen for firm size. In untabulated results, we find that the accrual anomaly exists even after firms in the bottom 50 percentiles of market capitalization are excluded. This finding is consistent with the finding in prior studies (e.g. Fama & French, 2008) that the accrual anomaly is not limited to small firms. Importantly, we find that excluding small firms from the estimation sample has no material impact on the estimated mitigating effect of stock liquidity on the accrual anomaly.

Asset pricing studies have generally excluded firms with low stock price, arguing that the stock price movements of those firms are susceptible to microstructure biases. It is thus of interest to examine the robustness of the mitigating effect of stock liquidity on the accrual anomaly to screen for stock price. In untabulated results, we find that the accrual anomaly exists even after the sample consists of only firms with stock price above \$5. This finding suggests that the accrual anomaly is not limited to firms with low stock price. Importantly, we find that the mitigating effect of stock liquidity on the accrual anomaly remains strong after firms with stock price below or equal to \$5 are excluded.

5.2 Stock liquidity and investors' misperception of the persistence of the accrual component of earnings

Findings of prior studies (e.g. Sloan, 1996; Xie, 2001; Collins *et al.*, 2003) suggest that the mispricing associated with the accrual anomaly is at least partially driven by investors' misperception of the persistence of the accrual component of earnings. Specifically, investors tend to overestimate the persistence of the accrual component of earnings. The direct implication of our arguments for H1 is that the extent to which investors overestimate the persistence of the accrual component of earnings is less severe when stock liquidity is higher. Finding evidence consistent with this implication will lend further support to our arguments for H1.

We adopt the Mishkin test used in Sloan (1996) to investigate whether the extent to which investors overestimate the persistence of the accrual component of earnings varies with stock liquidity. The Mishkin test requires simultaneous estimation of the following two equations:

$$E_{t+1} = \gamma_0 + \gamma_1 \times ACC_t + \gamma_2 \times CASH_t + \upsilon_{t+1} \tag{9}$$

$$ARET_{t+1} = \beta \times \left(E_{t+1} - \gamma_0^* - \gamma_1^* \times ACC_t - \gamma_2^* \times CASH_t\right) + \varepsilon_{t+1} \tag{10}$$

Equation (9) is the "rational" forecasting equation and Equation (10) is the pricing equation from which we infer the forecasting equation used by investors. E_{t+1} is the income before extraordinary items of fiscal year t+1 scaled by average total assets of fiscal years t and t+1. ACC_t is the sum of change in non-cash current net operating assets and change in non-current net operating assets scaled by average total assets of fiscal years $t-1$ and t. $CASH_t$ is the difference between E_t and ACC_t. E_t is measured in the same way as E_{t+1}. $ARET_{t+1}$ is the abnormal annualized return that cumulates over a period of 12 months that starts in the fourth month after the end of fiscal year t. We adopt the characteristic-based portfolio matching procedure used in Daniel *et al.* (1997) to compute abnormal annualized returns. The way in which we measure abnormal returns controls for more risk factors and firm characteristics found to affect stock returns than the size-adjusted abnormal returns used in Sloan (1996). Therefore, the way in which we measure abnormal returns helps to mitigate the potential omitted correlated variable problem with the Mishkin test raised in Kraft, Leone, and Wasley (2006) and Lewellen (2010).

First, we use all observations with no missing data for variables used in Equation (9) and Equation (10) to simultaneously estimate both equations. Then we sort all observations into three equal groups according to stock liquidity (low, medium and high stock liquidity), and simultaneously estimate both equations separately for each group. Table 3 presents the results. Consistent with prior studies (e.g. Sloan, 1996; Shi & Zhang, 2012), Table 3 shows that the accrual component of earnings is less persistent than the cash component and that investors overestimate the persistence of the accrual component of earnings. Consistent with Richardson *et al.* (2008), Table 3 also shows that investors also overestimate the persistence of

$$E_{t+1} = \gamma_0 + \gamma_1 \times ACC_t + \gamma_2 \times CASH_t + \upsilon_{t+1}$$
$$ARET_{t+1} = \beta \times (E_{t+1} - \gamma_0^* - \gamma_1^* \times ACC_t - \gamma_2^* \times CASH_t) + \varepsilon_{t+1}$$

Parameter	Estimate	Parameter	Estimate	Parameter	Estimate	Parameter	Estimate
All							
γ_1	0.647**	γ_1^*	1.039**	$\gamma_1^* - \gamma_1$	0.392**	$\gamma_1^*/\gamma_1 - 1$	0.606**
γ_2	0.750**	γ_2^*	0.901**	$\gamma_2^* - \gamma_2$	0.151**	$\gamma_2^*/\gamma_2 - 1$	0.201**
Liquidity: low							
γ_1	0.610**	γ_1^*	1.124**	$\gamma_1^* - \gamma_1$	0.514**	$\gamma_1^*/\gamma_1 - 1$	0.843**
γ_2	0.743**	γ_2^*	0.900**	$\gamma_2^* - \gamma_2$	0.158**	$\gamma_2^*/\gamma_2 - 1$	0.212**
Liquidity: medium							
γ_1	0.652**	γ_1^*	1.099**	$\gamma_1^* - \gamma_1$	0.447**	$\gamma_1^*/\gamma_1 - 1$	0.685**
γ_2	0.729**	γ_2^*	1.014**	$\gamma_2^* - \gamma_2$	0.285**	$\gamma_2^*/\gamma_2 - 1$	0.391**
Liquidity: high							
γ_1	0.637**	γ_1^*	0.804**	$\gamma_1^* - \gamma_1$	0.166**	$\gamma_1^*/\gamma_1 - 1$	0.261**
γ_2	0.673**	γ_2^*	0.689**	$\gamma_2^* - \gamma_2$	0.016	$\gamma_2^*/\gamma_2 - 1$	0.024

Note(s): Table 3 reports results from the Mishkin test that investigates the effect of stock liquidity on the extent to which investors overestimate the persistence of annual accruals. E_{t+1} is income before extraordinary items of fiscal year t scaled by average total assets of fiscal years t and t+1. ACC_t is the sum of change in net non-cash current operating assets and change in net non-current operating assets from fiscal year $t-1$ to fiscal year t scaled by average total assets of fiscal year $t-1$ and t. $CASH_t$ is the difference between E_t and ACC_t. $ARET_{t+1}$ is the abnormal annual stock return that cumulates over a 12-month period starting from the fourth month after the end of fiscal year t+1. We follow the characteristic-based portfolio matching procedure proposed in Daniel *et al.* (1997) to compute the abnormal annual stock return. **, * and † denote statistical significance at the 1%, 5% and 10% levels respectively, using a 2-tailed test

Table 3.
Stock liquidity and investors' misperception of the persistence of annual accruals

the cash component and that the extent to which investors overestimate the persistence of the cash component is much smaller than the extent to which investors overestimate the persistence of the accrual component.

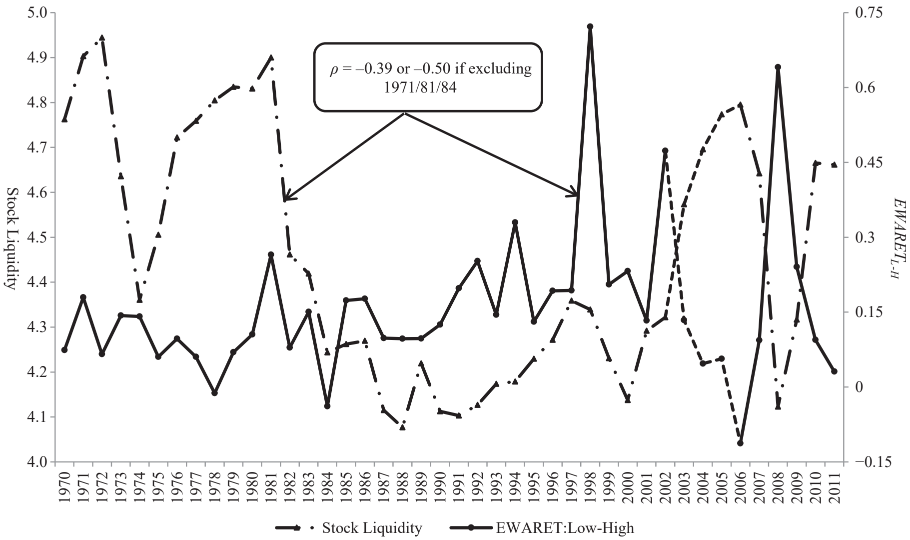
Consistent with the implication of our arguments for H1, we document a decline, in both absolute and relative scales, in the extent to which investors overestimate the persistence of the accrual component as stock liquidity increases from low to medium to high levels. Regarding the cash component, Table 3 shows that for the high stock liquidity group there is no evidence that investors overestimate the persistence of the cash component, whereas for the medium stock liquidity group, the extent to which investors overestimate the persistence of the cash component is the greatest. In sum, results from the Mishkin test further corroborate the empirical validity of our arguments for H1.

5.3 Stock liquidity and the accrual anomaly: time-series evidence

Several studies show that the magnitude of the accrual anomaly varies considerably over time (Lev & Nissim, 2006; Richardson *et al.*, 2010; Green *et al.*, 2011). Importantly, several recent studies independently find that the magnitude of the accrual anomaly declines significantly during the period of 2001–2010 (e.g. Richardson *et al.*, 2010; Green *et al.*, 2011; Hirshleifer *et al.*, 2011). Findings from the market microstructure research show that stock liquidity varies significantly over time owing to a variety of factors (Chordia, Roll, & Subrahmanyam, 2008; Chordia *et al.*, 2011). For instance, using firms listed in NYSE, Chordia *et al.* (2011) find that stock liquidity had been improving during the period of 1993–2008, especially since 2001, due to numerous changes such as reductions in the minimum tick size, reductions in institutional commissions, and emerging of new trading platforms. In prior sections, we present strong cross-section evidence for a negative relation between sock liquidity and the magnitude of the accrual anomaly. Therefore, it is of interest to examine whether the recent improvement in stock liquidity drives the recent decline in the magnitude of the accrual anomaly.

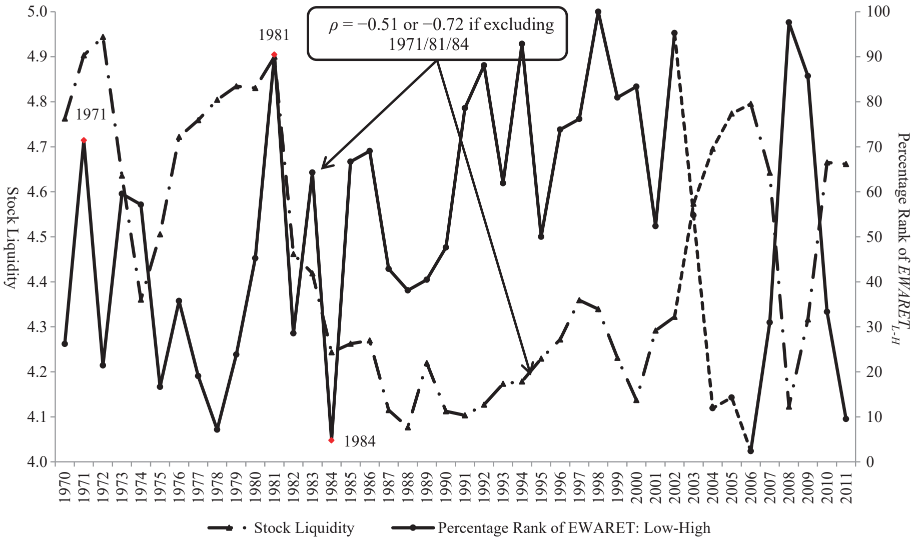
To examine the relation between stock liquidity and the magnitude of the accrual anomaly in the time series, each year we apply the sorts procedure to estimate the magnitude of the accrual anomaly [12]. Specifically, following prior studies (e.g. Green *et al.*, 2011), we measure the magnitude of the accrual anomaly as the difference ($EWARET_{L-H}$) in equal-weighted abnormal return between the bottom and top deciles of accruals each year. We also compute the market-wide stock liquidity each year. Figure 2a depicts of the trends in the magnitude of the accrual anomaly and in market-wide stock liquidity for the period of 1970–2011. As shown in Figure 2a, when market-wide stock liquidity is high, the magnitude of the accrual anomaly is generally low: $\rho = -0.39$.

Figure 2a reveals that the magnitude of the accrual anomaly is highly skewed. We use the percentage rank of $EWARET_{L-H}$ to measure the relative magnitude of the accrual anomaly. Figure 2b depicts the trends in the market-wide stock liquidity and in the relative magnitude of the accrual anomaly. Figure 2b reveals a stronger negative relation between market-wide stock liquidity and the magnitude of the accrual anomaly: $\rho = -0.51$. Figure 2b also reveals that market-wide stock liquidity and the magnitude of the accrual anomaly of 1971, 1981 and 1984 does not follow the overall negative relation well. Excluding these three years out of a total of 42 years, we observe a much stronger negative relation between market-wide stock liquidity and the magnitude of the accrual anomaly: $\rho = -0.51$ if $EWARET_{L-H}$ is used and $\rho = -0.72$ if the percentage rank of $EWARET_{L-H}$ is used. We postulate that something unique to 1971, 1981 and 1984 might account for why market-wide stock liquidity and the magnitude of the accrual anomaly of 1971, 1981 and 1984 do not follow the overall negative relation well. More importantly, we observe a nearly perfect negative relation between market-wide stock liquidity and the magnitude of the accrual anomaly for the period of 2001–2011: $\rho = -0.87$ if $EWARET_{L-H}$ is used and $\rho = -0.92$ if the percentage rank of $EWARET_{L-H}$ is used. In sum, consistent with our cross-section evidence, there is an overall negative relation between market-wide stock



Note(s): Stock liquidity and magnitude of the accrual anomaly as measured by $EWARET_{L\text{-}H}$

(a)



Note(s): Stock liquidity and magnitude of the accrual anomaly as measured by the percentage rank of $EWARET_{L\text{-}H}$

(b)

Figure 2.
Stock liquidity and the accrual anomaly: time-series evidence

liquidity and the magnitude of the accrual anomaly during 1970–2011, suggesting that the temporal variation in market-wide stock liquidity is a significant factor driving the temporal variation in the magnitude of the accrual anomaly.

5.4 Stock liquidity and the accrual anomaly: further evidence from a quasi-experiment

To establish the direction causality between stock liquidity and the magnitude of the accrual anomaly, we use the DiD method to determine the effect of exogenous changes in stock liquidity caused by the 2001 decimalization of the minimum tick size on the relation between annual accruals and future stock returns. Specifically, we compare the change in the relation between annual accruals and future stock returns for a sample of treatment firms and the change for a sample of control firms. Following Fang, Tian, and Tice (2014), we include firms with change in stock liquidity in the top one-third in the treatment sample and firms with change in stock liquidity in the bottom one-third in the control sample. We then apply nearest neighbor propensity score matching to ensure that before the exogenous event treatment firms and control firms are comparable along other determinants of returns.

The DiD methodology has several desirable features. First, the DiD methodology rules out omitted trends that are correlated with stock liquidity and the relation between annual accruals and future stock returns in both treatment firms and control firms. Second, the DiD approach helps to establish the direction of causality as the experiment is conducted surrounding an exogenous change in stock liquidity. Third, the DiD approach controls for time-invariant unobserved differences between treatment and control firms.

The 2001 decimalization is a good quasi-experiment for the following reasons. First, there is a significant market-wide improvement in stock liquidity brought about by the decimalization (Bessembinder, 2003; Chordia *et al.*, 2005). Second, the decimalization directly affects stock liquidity but unlikely affect the relation between *l* accruals and future stock returns through channels other than stock liquidity. Meanwhile, changes in stock liquidity surrounding the decimalization exhibit wide variation in the cross-section of stocks. More importantly, we would not expect the future change in the relation between accruals and future stock returns to affect the change in stock liquidity brought about by the decimalization. In sum, an examination of the change in the relation between annual accruals and future stock returns surrounding the decimalization provides a quasi-experiment for our test.

We use the nearest neighbor propensity score matching to construct a treatment group and a control group of firms. Specifically, we begin with all firms with non-missing matching variables (i.e. all variables used in the regression approach) in the pre-decimalization year ($t-1$) and the post-decimalization year ($t+1$), with t indicating the year decimalization. On the basis of change in stock liquidity surrounding the decimalization ($\Delta LIQ\_HL_{t-1\ to\ t+1}$), we sort sample firms into three equal groups and retain only the top group representing firms with the greatest improvement in stock liquidity (the treatment group) and the bottom group representing firms with the least improvement (the control group).

To apply the propensity score matching, we first estimate a *Probit* model based on the 1,231 sample firms in the top and bottom groups. The dependent variable is 1 if the firm is in the treatment group and 0 if the firm is in the control group. The *Probit* model includes all variables used in the regression approach and measured in the year immediately prior to the decimalization. We also control for industry fixed effects in the *Probit* model. These variables are included to help satisfy the parallel trends assumption, as the DiD estimator should not be driven by differences in any industry or firm characteristics. Table 4, Panel A presents parameter estimates from the *Probit* model that are used to compute the propensity scores for matching. The results show that the specification captures a significant amount of variation in the choice variable, as indicated by a pseudo R^2 of 27.9% and a p-value from the χ^2 test of the overall model fitness well below 0.001.

We then use the predicted probabilities (propensity scores) to perform nearest-neighbor propensity score matching. Specifically, each firm in the treatment group is matched to a

Panel A: Pre-match propensity score regression and post-match diagnostic regression

Variable	Pre-match Coeff.	Pre-match t-stat	Post-match Coeff.	Post-match t-stat
RET_t	0.723**	8.65	0.066	0.60
MC_{t-1}	0.094**	3.17	0.039	1.08
B/M_{t-1}	−0.015	−0.25	0.046	0.60
MOM_{t-1}	0.386**	3.67	0.118	0.87
D_NS_{t-1}	−0.008	−0.03	−0.297	−0.85
NS_{t-1}	−0.579**	−2.85	−0.032	−0.12
dA/A_{t-1}	−0.062	−0.37	−0.065	−0.28
D_Y/B_{t-1}	−0.524**	−3.87	0.075	0.43
$Y/B(+)_{t-1}$	0.543	0.66	−0.077	−0.07
ACC_{t-1}	−0.367	−1.26	0.230	0.57
LIQ_HL_{t-1}	−1.496**	−13.11	0.031	0.19
$ACC_{t-1} \times LIQ\_HL_{t-1}$	−0.570	−1.45	−0.011	−0.02
Industry fixed effects	Yes		Yes	
N	1,231		612	
p-value of χ^2	< 0.001		1.000	
Pseudo R^2	0.279		0.019	

Panel B: Statistical distributions of estimated propensity scores

	N	Mean	SD	Min	P5	P25	P50	P75	P95	Max
Treatment	306	0.487	0.200	0.022	0.154	0.354	0.477	0.609	0.860	0.967
Control	306	0.496	0.206	0.020	0.154	0.353	0.490	0.612	0.856	0.997
Difference		−0.009	−0.006	0.002	0.000	0.000	−0.013	−0.002	0.004	−0.030

Panel C: Differences in post-match characteristics

Variable	Control	Treatment	Difference	t-stat
RET_t	0.083	0.122	−0.039	−0.91
MC_{t-1}	5.927	6.137	−0.210	−1.24
B/M_{t-1}	−0.636	−0.616	−0.020	−0.26
MOM_{t-1}	−0.038	0.005	−0.042	−1.22
D_NS_{t-1}	0.029	0.020	0.010	0.78
NS_{t-1}	0.067	0.058	0.009	0.47
dA/A_{t-1}	0.125	0.114	0.010	0.44
D_Y/B_{t-1}	0.245	0.225	0.020	0.57
$Y/B(+)_{t-1}$	0.063	0.065	−0.001	−0.28
ACC_{t-1}	0.075	0.074	0.001	0.07
LIQ_HL_{t-1}	4.360	4.414	−0.054	−1.24
$ACC_{t-1} \times LIQ\_HL_{t-1}$	−0.012	−0.009	−0.003	−0.34

Panel D: Difference-in-differences test

Variable	Coeff.	t-Stat
ACC_t (β_1)	−0.671**	−3.10
$D\_T \times ACC_t$ (β_2)	−0.113	−0.46
$D\_A \times ACC_t$ (β_3)	−1.716**	−2.68
$D\_T \times D\_A \times ACC_t$ (β_4)	1.767*	2.24
Fiscal year-end month fixed effects	Yes	
Industry fixed effects	Yes	
N	1,224	
R^2	0.120	

(continued)

Table 4.
Difference-in-differences analysis using the 2001 decimalization

Panel D: Difference-in-differences test Variable	Coeff.	t-Stat
$\beta_1 + \beta_2$	−0.784**	5.17
$\beta_1 + \beta_3$	−2.388**	3.95
$\beta_1 + \beta_2 + \beta_3 + \beta_4$	−0.734†	1.71
$\beta_3 + \beta_4$	0.050	0.10

Panel E: Falsification test Variable	Coeff.		t-stat
ACC_t (β_1)	−0.495†		−1.94
$D\_T \times ACC_t$ (β_2)	−0.202		−0.50
$D\_A \times ACC_t$ (β_3)	0.269		0.67
$D\_T \times D\_A \times ACC_t$ (β_4)	0.057		0.10
Fiscal year-end month fixed effects		Yes	
Industry fixed effects		Yes	
N		728	
R^2		0.116	
$\beta_1 + \beta_2$	−0.697*		2.25
$\beta_1 + \beta_3$	−0.227		0.75
$\beta_1 + \beta_2 + \beta_3 + \beta_4$	−0.371		1.41
$\beta_3 + \beta_4$	0.326		0.82

Note(s): This table reports diagnostics and results of the DiD test on how exogenous changes in stock liquidity resulting from the minimum tick size decimalization affect the negative relation between accruals and future stock returns. Sample selection begins with all firms with non-missing matching variables in the pre-decimalization year (t−1) and the post-decimalization year (t+1), with t indicating the year of decimalization. On the basis of the change in stock liquidity surrounding the decimalization ($\Delta LIQ\_HL_{t-1\ to\ t+1}$), we sort 1,837 sample firms into three equal groups and retain only the top group with the greatest improvement in stock liquidity (the treatment group) and the bottom group with the least improvement (the control group). We match firms by using one-to-one nearest neighbor propensity score matching, without replacement. Panel A presents parameter estimates from the *Probit* model used to compute the propensity scores for matching. The dependent variable is 1 if the firm is in the treatment group and 0 if otherwise. The "Pre-match" column reports parameter estimates from the *Probit* model obtained using the sample prior to the matching. These estimates are used to generate the propensity score for matching. The "Post-match" column reports parameter estimates from the *Probit* model obtained using the matched observations. Panel B reports the statistical distribution of estimated propensity scores separately for matched treatment and control firms. Panel C reports comparisons of observable characteristics between matched treatment and control firms and the corresponding t-statistics. Panel D reports the DiD test results. Panel E reports results from the falsification test. In Panels A, E and F, the t-statistics are calculated by using cluster-robust standard errors clustered by firm. **, * and † denote statistical significance at the 1%, 5% and 10% levels, respectively, using a two-tailed test

Table 4.

firm from the control group with the closest propensity score without replacement. Meanwhile, we require that the difference in the propensity scores between the matched observations is less than 1%. We end up with 306 unique pairs of matched observations.

The validity of the DiD estimate critically relies on the parallel trends assumption. Following Fang *et al.* (2014), we conduct several diagnostic tests to demonstrate that we do not violate the parallel trends assumption. In the first test, we estimate the *Probit* model by using the matched observations. The *Probit* estimates are presented in the "Post-match" column. None of the coefficients is statistically significant. Also, for variables with significant "Pre-match" coefficient estimates the "Post-match" coefficient estimates are generally much smaller than the "Pre-match" ones, suggesting that the "Post-match" results are not simply an artifact of a decline in the degree of freedom due to the drop in sample size. In addition, pseudo R^2 drops drastically from 27.9% prior to the matching to 1.9% post the matching. And a χ^2

test for the overall model fitness shows that we cannot reject the null hypothesis that all coefficient estimates are zero (with a p-value close to one).

In the second diagnostic test, we examine the difference in the propensity scores between treatment and control firms. Table 4, Panel B shows that the difference is negligible. Finally, we report the univariate comparisons between treatment and control firms. As shown in Panel C, we observe no statistically significant differences between treatment and control firms with respect to their characteristics in the pre-decimalization regime. Importantly, control and treatment firms are comparable with respect to stock returns, stock liquidity, annual accruals and the interaction term between stock liquidity and annual accruals in the pre-decimalization regime, even though their stock liquidity is affected by the decimalization differently. Overall, our diagnostic tests suggest that the propensity score matching process has removed material observable differences (other than the difference in the change in stock liquidity surrounding the decimalization) between treatment and control firms. That is, the propensity score matching process ensures that regarding the change in the relation between annual accruals and future returns the difference between treatment and control firms is driven mainly—if not only—by the differential changes in stock liquidity resulting from the decimalization.

To obtain the DiD estimator, we run OLS regression to estimate the following equation:

$$RET_{t+1} = \beta_0 + \beta_1 \times ACC_t + \beta_2 \times D\_T \times ACC_t + \beta_3 \times D\_A \times ACC_t + \beta_4 \times D\_T \times D\_A \times ACC_t + \text{Fiscal year end month \& industry fixed effects} + \varepsilon_{t+1} \quad (11)$$

where RET_{t+1} and ACC_t are as defined earlier; D_T is an indicator variable that equals to 1 if the observation is in the treatment group and 0 if the observation is in the control group; D_A is an indicator variable that equals to 1 if the observation is from year t+1 and 0 if the observation is from year t−1 where t indicates the year of decimalization.

Table 4, Panel D presents the DiD estimator. Control firms experience a significant increase in the magnitude of the negative relation between annual accruals and future stock returns: −1.716 (t = −2.68), while treatment firms experience no material change: 0.050 (t = 0.10). Importantly, regarding the change in the magnitude of the negative relation between annual accruals and future stock returns, the difference between treatment firms and control firms is statistically significant: 1.767 (t = 2.24).

To further verify the internal validity of our DiD finding, we conduct a falsification test. Specifically, using the matched observations, we repeat the DiD analysis to examine whether significant difference already exists between treatment and control firms regarding the change in the magnitude of the negative relation between annual accruals from year t−2 to year t−1. As shown in Panel E, both treatment firms and control firms experience no significant change in the magnitude of the negative relation between annual accruals from year t−2 to year t−1. Importantly, regarding the change in the magnitude of the negative relation between annual accruals and future stock returns from year t−2 to year t−1, the difference between treatment and control firms is not statistically significant: 0.057 (t = 0.10). Findings from this falsification test suggest that our DiD finding is more likely due to the differential impact of the decimalization on the stock liquidity of treatment and control firms, as opposed to alternative forces such as continuation of pre-decimalization trends. In sum, our finding from the DiD analysis suggests a causal effect of stock liquidity on the negative relation between annual accruals and future stock returns.

6. Conclusions

Our study finds both cross-section and time-series evidence that stock liquidity is negatively related to the magnitude of the accrual anomaly. Using the 2001 minimum tick size decimalization as a quasi-experiment to conduce a DiD analysis, our study finds that the effect of stock liquidity on the accrual anomaly seems to be causal. We attribute the negative relation between stock liquidity and the magnitude of the accrual anomaly to the enhancing effect of stock liquidity on stock price efficiency. That is, higher stock liquidity ensures that stock prices deviate less from their values in the direction predicted by annual accruals.

Our study helps to resolving two lingering questions about the accrual anomaly: whether the accrual anomaly is driven by mispricing and what underlies the recent decline in the magnitude of the accrual anomaly. Our findings are aligned with the mispricing explanation for the accrual anomaly. Our study suggests a subtle view about factors underlying the accrual anomaly. Our findings suggest that the accrual anomaly may be not only due to investor imperfection but ikaalso due to rational reasons. Our study finds that the correlation between market-wide stock liquidity and the magnitude of the accrual anomaly is surprisingly high during 2001–2011: $\rho = -0.87$, suggesting that recent dramatic improvement in market-wide stock liquidity brought about by numerous permanent changes may drive, at least significantly, the recent decline in the magnitude of the accrual anomaly.

Notes

1. We document a much stronger negative relation after excluding only three "outlier" years (1971, 1981, and 1984) from the computation: $\rho = -0.51$ when the equal-weight abnormal return is used and $\rho = -0.72$ when the percentage rank of the equal-weight abnormal return is used.
2. Readers can refer to Fama (1970) for his discussion on sufficient conditions for information efficiency and on how trading costs prevents private information from being rapidly impounded into stock prices.
3. Similarly, Mashruwala *et al.* (2006) find that the accrual anomaly is concentrated in firms with high idiosyncratic stock return volatility and low-price and low-volume stocks. Idiosyncratic stock return volatility, price levels and trading volumes are related to stock liquidity because they capture risks and costs of arbitrage (Mashruwala *et al.*, 2006). Our study complements and extends Mashruwala *et al.* (2006). First, our study suggests that stock liquidity can shape the accrual anomaly through channels other than arbitrage, such as institutional ownership. Moreover, adding to Mashruwala *et al.* (2006), our study provides a market microstructure-based explanation for the recent decline in the magnitude of the accrual anomaly. However, we may not be able to refer to Mashruwala *et al.*'s (2006) findings to explain the recent decline for the following reasons. First, prior studies find that idiosyncratic return volatility has been increasing over time (Campbell, Lettau, Malkiel, and Xu. 2001; Rajgopal & Venkatachalam, 2011). Moreover, there is no evidence that stock prices have been increasing in recent years. In practice, firms tend to split stocks when stock prices become very high. Furthermore, trade volumes seem to capture something other than market frictions, such as divergence of investor opinions (Harris & Raviv, 1993; Garfinkel, 2009) and variance of stock liquidity (Johnson, 2008). In addition, trade volumes and stock liquidity seem to have no direct empirical relation (Johnson, 2008).
4. For instance, there is some evidence that accounting information has been losing its value relevance over time (Francis & Schipper, 1999; Lev & Zarowin, 1999). Fung, Su, and Zhu (2010) attribute the decreasing value relevance of accounting information to the possibility that stock prices have been becoming increasingly noisy. However, our findings suggest that stock prices have been becoming increasingly efficient in recent years (see also Chordia *et al.*, 2011). Taken together, the decreasing association between reported earnings and contemporaneous stock returns may be due to the possibility that stock prices become increasingly informative about future earnings.
5. We choose not to provide a literature review on the accrual anomaly research because readers can refer to Dechow *et al.* (2011) and Richardson *et al.* (2010) for their excellent literature reviews.
6. The value of traded stocks is the present value of expected future dividends to stockholders or expected residual incomes under the clean surplus assumption (Ohlson, 1995).
7. Readers can refer to Bushee & Goodman (2007) and Edmans (2009) for the list of references.

8. In our study, we adopt the broad definition of arbitrage to mean information-based trading aimed at profiting from imperfections in current prices (Lee, 2001; Hirshleifer *et al.*, 2011).

9. In a robustness test, we use the stock liquidity measure based on the Gibbs sampler estimate of effective trading costs from Hasbrouck (2009). In Appendix, we provide technical background for Corwin & Schultz's (2012) high-low estimate of the effective bid-ask spread and Hasbrouck's (2009) Gibbs sampler estimate of effective trading costs.

10. The book value of equity equals total assets (*Compustat Item #at*) minus liabilities (*#lt*), plus balance sheet deferred taxes and investment tax credit (*#txditc*) if available, minus preferred stock liquidating value (*#pstkl*) if available, or redemption value (*#pstkrv*) if available or carrying value (*#pstk*) if available

11. Following Aiken & West's (1991) suggestion, we center stock liquidity measure on its sample mean before we generate the interaction term between the stock liquidity measure (LIQ_HL_t) and the accruals measure (ACC_t). Centering the stock liquidity measure on its sample mean ensures that the regression coefficient on the accruals measure (β_9) is empirically meaningful because the stock liquidity measure is always positive in the sample (Aiken & West, 1991). According to our specification, β_9 measures the magnitude of the relation between ACC_t and RET_{t+1} for "representative" firms with average stock liquidity.

12. Using the Jensen alpha approach, we obtain qualitatively the same results.

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Appendix

Stock liquidity measures

In this study, we adopt two stock liquidity measures: the high-low estimate of effective bid-ask spread (*LIQ_HL*) from Corwin and Schultz (2012) and the Gibbs sampler estimate of effective trading costs (*LIQ_GIBBS*) from Hasbrouck (2009). Both measures are computed using daily stock data and have desirable properties with respect to relations with stock liquidity measures computed using intra-day transaction data, compared with other low-frequency measures (Corwin & Schultz, 2012; Hasbrouck, 2009). While we adopt *LIQ_HL* as our primary measure of stock liquidity, our findings hold when we use *LIQ_GIBBS* as the alternative stock liquidity measure.

Corwin and Schultz (2012) base their development of the high-low estimate of effective bid-ask on simple regularities. That is, daily high prices are always buyer-initiated, whereas daily low prices are always seller-initiated. Therefore, the ratio of high-to-low prices reflects both the fundamental volatility of the stock and the stock's bid-ask spread. Moreover, the component of the high-to-low price ratio attributed to fundamental volatility increases proportionately with the trading interval, whereas the component attributed to the bid-ask spread is relatively constant over a short period. As a result, the price range over a two-day period reflects two days' volatility and one bid-ask spread and the sum of the price ranges over two consecutive single days reflects two days' volatility and twice the spread. Building on these regularities, Corwin and Schultz (2012) analytically derive

$$\sigma_{HL}^2\left(k_2^2\left(2-2\sqrt{2}\right)+k_1\right)+\sigma_{HL}k_2\left(2\sqrt{2}-2\right)\sqrt{\sigma_{HL}^2\left(k_2^2-k_1\right)+\beta/2}+\frac{\beta}{2}-\gamma=0 \tag{A1}$$

$$\alpha=-k_2\sigma_{HL}+\sqrt{\sigma_{HL}^2\left(k_2^2-k_1\right)+\beta/2} \tag{A2}$$

$$S=\frac{2(e^{\alpha}-1)}{1+e^{\alpha}} \tag{A3}$$

where $k_1=4\ln(2),\ k_2=\sqrt{\frac{8}{\pi}},\ \beta=E\left\{\sum_{j=0}^{1}\left[\ln\left(\frac{H_{t+j}^O}{L_{t+j}^O}\right)\right]^2\right\},\ \gamma=\left[\ln\left(\frac{H_{t,t+1}^O}{L_{t,t+1}^O}\right)\right]^2, H_t^O(L_t^O)$ are the observed high (low) price for day t.

Empirically, we can first estimate β and γ from stock return data and then numerically solve equation (A1) to get σ_{HL}. After we get σ_{HL}, we can refer to equation (A2) to get α. Once we get α, we can refer to equation (A3) to get the empirical bid-ask spread S. Furthermore, Corwin and Schultz (2012) show that under reasonable empirical conditions, we can get a closed-form solution for α. We adopt the closed-form solution for α to compute the high-low estimate of the effective bid-ask spread. The closed-form solution for α is as follows:

$$\alpha=\frac{\sqrt{2\beta}-\sqrt{\beta}}{3-2\sqrt{2}}-\sqrt{\frac{\gamma}{3-2\sqrt{2}}} \tag{A4}$$

Hasbrouck (2009) proposes a Gibbs sampler estimate of effective trading cost. The Gibbs sampler estimate is built on Roll's (1984) model of security prices in a market with transaction costs. Roll (1984) models the price dynamics as

$$m_t=m_{t-1}+\mu_t \tag{A5}$$

$$p_t=m_t+cq_t \tag{A6}$$

where m_t is the log quote midpoint prevailing prior to the t-th trade, p_t is the log trade price, and q_t is the direction indicator that equals +1 for a buy and −1 for a sale. μ_t reflects public information uncorrelated with q_t. We can view c as the effective trading cost. Roll's model implies

$$\Delta p_t=c\Delta q_t+\mu_t \tag{A7}$$

$$c=\sqrt{-Cov(\Delta p_t,\ \Delta p_{t-1})} \tag{A8}$$

where $Cov(\Delta p_t, \Delta p_{t-1})$ is the first-order auto-covariance of price changes.

Hasbrouck's Gibbs sampler estimate takes equation (A7) as a linear regression and applies the Gibbs sampler to simulate the coefficients of the linear regression, the error covariance matrix and the trade direction indicators. Empirically, Hasbrouck (2009) extends Roll's price dynamics model by including daily market return in equation (A7). Hasbrouck (2009) argues that including daily market return in equation (A7) can sharpen the allocation of transaction price changes between “true” returns and transient trading costs.

By construction, these two measures capture stock illiquidity. We use $-1 \times$ the natural logarithm of these two stock “illiquidity” measures as our measure for stock liquidity. Table A1 reports descriptive statistics and Pearson/Spearman correlations. To generate Table A1, for the period of 1970–2011, we compute the stock illiquidity and liquidity measures over a period of 252 trading days ending in the December of each year for a sample of 156,478 observations.

Table A1.
Descriptive statistics and Pearson (upper triangle)/Spearman (lower triangle) correlations

Variable	Mean	SD	P25	P50	P75	(1)	(2)	(3)	(4)
HL (1)	0.017	0.021	0.006	0.011	0.020		0.93	−0.80	−0.73
GIBBS (2)	0.011	0.015	0.003	0.006	0.013	0.88		−0.77	−0.80
LIQ_HL (3)	4.448	0.836	3.891	4.520	5.070	−1.00	−0.88		0.90
LIQ_GIBBS (4)	5.064	1.010	4.366	5.164	5.812	−0.88	−1.00	0.88	

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