Does Stock Market Liquidity Affect Real and Accrual-Based Earnings Management?

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Abstract

We study the relationship between stock market liquidity and earnings management. Using a sample of U.S. public firms over the time period from 1993 to 2012, we find that firms with more liquid stocks have lower level of both real and accrual-based earnings management. The result is robust to the use of various measures of liquidity. We address the endogeneity problem by using instrumental variable approach and two sources of exogenous shocks to stock liquidity, i.e. stock split and Decimalization. These methods provide evidence of a causal effect of liquidity on earnings management. We further find that liquidity curbs earnings management by mitigating the information asymmetry between managers and shareholder and facilitating governance by large institutional investors.

JEL Classifications: G14; G23; M41

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1. Introduction

There is growing anecdotal evidence suggesting that earnings management is a common practice in firms (e.g., Teoh, Welch, and Wong 1998; Healy and Wahlen 1999; Lo 2008). Earning management occurs when managers exercise their discretions over the choices of accounting methods or operational activities with the objective to influence the reported earnings. One type of earnings management is accrual-based earnings management in which managers alter the reported earnings by choosing different accounting methods. After the Sarbanes-Oxley Act of 2002 (SOX), managers tend to shift to real activities earnings manipulations (Graham, Harvey, and Rajgopal 2005; Cohen, Dey, and Lys 2008; Cohen and Zarowin 2010), which is accomplished by changing the timing investment or operations and less likely to be detected by auditors and regulators. The determinants of management intent to manage earnings are of interest to investors, academics, regulators and standard setters.

The effect of stock market on management decisions has attracted lots of attention and been studied in a vast literature over the past two decades (Dow and Gorton 1997; Subrahmanyam and Titman 2001). As stock market liquidity is an important indicator of stock market efficiency, most literature focus on the impact of stock liquidity on firm real activities (Fang, Noe, and Tice 2009; Fang, Tian, and Tice 2014). Stock liquidity can significantly enhance price efficiency through inducing informed traders to acquire more private information (Holden and Subrahmanyam 1992; Kyle 1984) and facilitating large institutional investors to exert governance through stock trading (Maug 1998; Edmans 2009; Edmans and Manso 2011). Can stock trading activities affect managers' incentive to manipulate earnings? In this paper, we study the effect of stock liquidity on both real and accrual-based earnings management.

On one hand, stock liquidity can curb earnings management due to two reasons. First, information asymmetry between managers and external investors is a necessary condition for the existence of earnings management (Dye 1988; Trueman and Titman 1988; Schipper 1989; Chaney and Lewis 1995). When information asymmetry is high, shareholders do not have sufficient resources, incentives or access to relevant information to monitor managers' actions, which gives rise to the practice of earnings management. As higher stock liquidity can reduce information asymmetry by inducing more informed traders to convey private information to the equity market (Kyle 1984; Holden and Subrahmanyam 1992; Holmström and Tirole 1993; Subrahmanyam and Titman 2001), it can curb earning management through mitigating information asymmetry problem. Second, stock liquidity makes it easier to form a block in a firm and facilitates large shareholder to exert governance through trading (Admati and Pfleiderer 2009; Edmans 2009; Edmans and Manso 2011). Large institutional owners have high incentive to constrain managers' opportunistic behaviors (Ashbaugh-Skaife, Collins, and LaFond 2006; Brav, Jiang, Partnoy, and Thomas 2008) due to their large size of investment. Hadani, Goranova, and Khan (2011) find evidence that large institutional ownership is negatively related to earnings management. Hence, stock market liquidity can reduce earnings management by enhancing large institutional owners' ability to discipline managers.

On the other hand, stock liquidity may increase managers' incentive to manage earnings by influencing the structure of executive compensation. Jayaraman and Milbourn (2011) provide evidence that stock liquidity can increase the proportion of equity-based compensation in total executive compensation. When managers have higher equity-based incentives, they are more likely to manipulate earnings to boost short-term stock price and sell more shares after earnings management (Cheng and Warfield 2005; Bergstresser and Philippon 2008).

In this paper, we empirically examine whether stock liquidity curbs or induces earnings management. To capture accrual-based earnings management, we use abnormal level of accruals estimated from the modified version of Jones (1991) model. To capture real earnings management, we follow Roychowdhury (2006) and Zang (2012) to calculate abnormal level of production costs and abnormal level of discretionary expenditure. Our main liquidity measure is relative effective spread. With a sample of U.S. public firms from 1993 to 2012, we show that higher stock liquidity (i.e. lower relative effective spread) is associated with lower level of both real and accrual-based earnings management. The results are robust to the use of different liquidity measures and the inclusion of observed determinants of earnings management, industry and year fixed effects.

We address the potential endogeneity issues in three separate ways. First, we use the average stock liquidity of firms in industries outside of a firm's industry as an instrumental variable for stock liquidity of the firm. The estimates from two-stage least square (2SLS) regressions also suggest that firms with more liquid stocks do less earnings management. Second, we rely on stock splits as shock to stock liquidity and find that firms announce stock splits have lower level of earnings management than non-split firms. Last but not least, we conduct difference-in-difference tests using decimalization as a quasi-natural experiment to identify the causal effect of stock liquidity on earnings management. Decimalization evet is conducted by the Securities and Exchange Commission (SEC) in 2001 to reduce trading cost. After the decimalization, the quoting and trading securities were transferred from 1/16th of a dollar to 0.01 of a dollar. This event improves stock market liquidity significantly, especially among actively traded stocks (Goldstein and A Kavajecz 2000; Furfine 2003; Bessembinder 2003). We find that, on average, firms with larger increase in stock liquidity after decimalization experience a further decline in both real and accrual-based earnings management compared to those with smaller increase in liquidity.

In addition to the above main tests, we do some further tests to study how stock liquidity affects earnings management. The evidence is mainly indirect and suggestive due to the difficulty in providing direct tests of underlying mechanism. In the first test, we try to figure out whether higher stock liquidity can curb earning management through mitigating information asymmetry problem. Using the number of financial analysts to capture the degree of information asymmetry, we find that the effects of stock liquidity on real earnings management are significantly more pronounced for the sample of firms with lower analyst coverage. Meanwhile, the effect is insignificant for firms with higher analyst coverage, suggesting that the significant effect is largely driven by the subsample with low analyst coverage. However, for the effects of liquidity on accrual-based earnings management, there is no significant difference between the two subsamples. The second mechanism is governance by large institutional owners. Employing the same method as we used to investigate the information asymmetry channel, we find that higher stock market liquidity can facilitate large institutional investors to exert governance through trading, leading to less real and accrual-based earnings management. In the third test, we explore the information role of stock liquidity. According to dividends signaling hypothesis, paying dividend is viewed as a signal of the firm's high quality of earnings. Managers are less likely to manipulate earnings for dividend-paying firms. As stock liquidity can induce the entry of informed traders, which serves as an alternative way to reveal information about the firm's intrinsic value, we show that the impact of stock liquidity on earnings management is more pronounced for non-dividend-paying firms.

To our knowledge, the existing empirical literature has never directly linked stock liquidity to earnings management. Our study fills this gap in literature by investigating the role of liquidity on managers' real and accrual-based earnings management. Our paper contributes to the growing literature by examining the relationship between stock market investors and earnings management. Both Massa, Zhang, and Zhang (2015) and Fang, Huang, and Karpoff (2014) find that short selling can force managers to do less accrual-based earnings management. We also add to the literature on the real effects of stock liquidity. Prior studies show that liquidity can improves firm value (Fang, Noe, and Tice 2009), magnifies the effect of block ownership on firm value (Bharath, Jayaraman, and Nagar 2013), and impedes firm innovation (Fang, Tian, and Tice 2014). We further show the effect of stock liquidity on management decisions is extended to earnings management.

The remainder of this paper is organized as follows. In Section 2, we describe the sample selection, data and variable construction. Section 3 presents the empirical results. In section 4, we examine the underlying mechanisms. Section 5 concludes.

2. Data and Variable Construction

2.1 Sample Selection

The sample construction starts with U.S. public firms listed on the New York Stock Exchange (NYSE), American Stock Exchange (Amex), and NASDAQ. The annual accounting data are obtained from the CRSP/Compustat merged database. Stock price, return and trading volume are from the Center for Research in Security Prices (CRSP) stock file. We obtain intraday trades and quotes from the Trade and Quote (TAQ) database to construct the high-frequency liquidity measure. The sample starts from 1993, when the intraday trades and quotes are available in TAQ. We exclude from our sample financial firms (SIC codes between 6000 and 6999) because their accounting numbers are subject to statutory capital requirements. Moreover, to assure there are enough data points to compute liquidity measures, we exclude firm-year observations with less than 200 active trading days in a fiscal year. The final sample comprises 41,062 firm-fiscal year observations between 1993 and 2012.

2.2 Earnings Management Measures

Following literature in earnings management (Roychowdhury 2006; Yu 2008; Cohen and Zarowin 2010; Zang 2011), we employ proxies for both real earnings management activities and accrual-based earnings management.

Firm can manipulate earnings through two types of real activities, the first is lowering production costs and the second is decreasing discretionary expenses including R&D expenditure, advertising, and SG&A expenses. These two types of real earnings manipulation activities are measured by the abnormal level of production costs and abnormal level of discretionary expenditure respectively.

Following Roychowdhury (2006) and Zang (2011), we first use the following equation to estimate the normal level of production costs:

$$\frac{PROD_{i,t}}{AT_{i,t-1}} = \beta_0 + \beta_1 \frac{1}{AT_{i,t-1}} + \beta_2 \frac{Sale_{i,t}}{AT_{i,t-1}} + \beta_3 \frac{\Delta Sale_{i,t}}{AT_{i,t-1}} + \beta_4 \frac{\Delta Sale_{i,t-1}}{AT_{i,t-1}} + \varepsilon_{i,t}, \qquad (1)$$

where $PROD_{i,t}$ is the sum of cost of goods sold ($COGS_{i,t}$) during fiscal year t and change in inventory from t-1 to t ($\Delta INVT_{i,t}$); $AT_{i,t-1}$ is the total asset at the end of fiscal year t; $Sale_{i,t}$ is the net sale in fiscal year t; $\Delta Sale_{i,t}$ is the change in net sale from t-1 to t; and $\Delta Sale_{i,t-1}$ is the change in net sale from t-2 to t-1. The abnormal value of production costs, RM_{PROD}, is estimated as the residual from the Eq. (1) for each fiscal year and Fama-French 48 industry with at least 15 observations. Higher residual (RM_{PROD}) means greater increase in earnings through lowering production costs.

Similarly, we estimate the abnormal level of discretionary expenses, RM_{DISX}, as the residual from the following cross-section regressions for each fiscal year and Fama-French 48 industry with at least 15 observations:

$$\frac{DISX_{i,t}}{AT_{i,t-1}} = \beta_0 + \beta_1 \frac{1}{AT_{i,t-1}} + \beta_2 \frac{Sale_{i,t-1}}{AT_{i,t-1}} + \varepsilon_{i,t}, \qquad (2)$$

where $DISX_{i,t}$ is the sum of R&D expense ($XRD_{i,t}$), advertising expense ($XAD_{i,t}$) and *SG&A* expense ($XSGA_{i,t}$). We multiply RM_{DISX} by negative one so that higher value means greater increase in reported earnings through reducing discretionary expenses. We then take the sum of the two parts, RM_{PROD} + (-1)*RM_{DISX}. Since managers have incentives to manipulate earnings not only upward but also downward (Yu, 2008), we use the absolute value of (RM_{PROD} + (-1)*RM_{DISX}), denoted by *ARM*, as the measure of real earnings manipulation.

Following Roychowdhury (2006), Yu (2008) and Zang (2011), we use discretionary accruals to proxy for accrual-based earnings management. Discretionary accruals are defined as the abnormal level of accruals, captured by the residual estimated from the following modified version of Jones (1991) model:

$$\frac{IB_{i,t} - OANCF_{i,t}}{AT_{i,t-1}} = \beta_0 + \beta_1 \frac{1}{AT_{i,t-1}} + \beta_2 \frac{\Delta Sale_{i,t}}{AT_{i,t-1}} + \beta_3 \frac{PPEGT_{i,t}}{AT_{i,t-1}} + \varepsilon_{i,t}, \qquad (3)$$

where $IB_{i,t}$ is income before extraordinary items, $OANCF_{i,t}$ indicates cash flow from operations, and $PPEGT_{i,t}$ is gross property, plant and equipment. We run the above cross-sectional regression for each fiscal year and Fama-French 48 industry with at least 15 observations. The estimated residual is the abnormal level of accruals. Likewise, we use the absolute value (*AAM*) as the measure of accrual-based earnings management.

2.3 Stock Liquidity Measures

Our main liquidity measure is relative effective spread (*RESPR*), defined as twice the difference between the execution price and the midpoint of the prevailing best bid-ask quote divided by the midpoint of the prevailing best bid-ask quote. This measure is widely used in literature to measure stock liquidity as it better captures the cost of a round-trip trading by including both price movement and market impact. It is calculated using intraday trades and quotes from the Trade and Quote database (TAQ) through Wharton Research Data Services (WRDS). Specifically, for a given stock i, the relative effective spread on the trade on time t is defined as

$$Relative\ Effective\ Spread_{i,t} = 2 \times LR_{i,t} \times \frac{(P_{i,t} - M_{i,t})}{M_{i,t}}, \tag{4}$$

where $LR_{i,t}$ is an indicator variable that equals one for buyer-initiated trade and negative one for seller-initiated trade, $P_{i,t}$ is the price of the trade, and $M_{i,t}$ is the midpoint of the matched prevailing best bid-ask quote.

To calculate relative effective spread, we follow Hasbrouck (2010) to filter the quote record for eligibility and/or errors and derive the National Best Bid and Offer (NBBO) for each security[1]. Then, we match each trade to a national best bid-ask quote and apply Lee and Ready (1991) algorithm to the matched sample to determine whether a trade is buyer-initiated or seller-initiated. Specifically, following Lee and Ready (1991), each trade from 1993 to 1998 inclusive is matched to the first quote at least five seconds prior to that trade. After 1998, the matching quote is the first quote prior to the trade. After obtaining the matched sample, we classify a trade as a buyer-initiated (seller-initiated) one if the transaction price is closer to the national best offer (bid) quote. If the trading price equals to the midpoint of the quote, a 'tick test' is used to classify the

[1] We use the SAS program posted on WRDS website to calculate NBBO. See https://wrds-web.wharton.upenn.edu/wrds/.

trade as buyer-initiated (seller-initiated) if the last price change before the trade is positive (negative). Finally, in order to get rid of erroneous records, we follow Chordia, Roll, and Subrahmanyam (2001) to apply filters to the matched sample by deleting records that satisfy the following conditions:

1. Quoted Spread>$5;
2. Effective Spread/Quoted Spread>4.0;
3. Relative Effective Spread/Relative Quoted Spread >4.0;
4. Quoted Spread/Transaction Price> 0.4;

where quoted spread is the quoted bid-ask spread, effective spread is twice the difference between the execution price and the midpoint of the prevailing best bid-ask quote, relative quoted spread is the quoted spread divided by the midpoint of the prevailing best bid-ask quote.

After getting the matched and filtered data, we calculate the annual relative effective spread (*RESPR*). We first calculate the daily relative effective spread, which is the arithmetic mean of the relative effective spreads for each matched quote and trade during a trading day for a particular stock. Then we average the daily relative effective spreads over one fiscal year to obtain the annual relative effective spread for a stock and multiply the measure by 100. Finally, we restrict that a stock must trade at least 200 days during a fiscal year. Higher relative effective spread means lower liquidity.

Another high-frequency liquidity measure, the relative quoted spread (*RQSPR*), capturing the hidden cost of stock trading, is defined as:

$$Relative\ Quoted\ Spread_{i,t} = \frac{(Offer_{i,t} - Bid_{i,t})}{(Offer_{i,t} + Bid_{i,t})/2}, \tag{5}$$

where $Offer_{i,t}$ is the quoted offer price and $Bid_{i,t}$ is the quoted bid price.

We use the National Best Bid and Offer (*NBBO*) quote sample derived from the intraday TAQ data to calculate the relative quoted spread for each quote and restrict that the quoted spread ($Offer_{it}$ - Bid_{it}) is no greater than five dollars. The filters for quote data are the same as those for the relative effective spread data. For each stock, we average the intraday relative quoted spread over a trading day to obtain the daily relative quoted spread. The annual relative quoted spread is the arithmetic mean of the daily relative quoted spread over a stock's fiscal year, multiplied by 100. We also restrict that a stock's trading days over a year must be no less than 200. Higher relative quoted spread indicates lower liquidity.

Besides high-frequency liquidity measures, we also employ a widely used low-frequency liquidity measure, Amihud illiquidity ratio, which is based on an idea that, everything else equal, illiquid stocks should experience a larger change in the stock price for the same amount of trading. We follow Amihud (2002) to construct the measure. The Amihud illiquidity measure is computed as the daily ratio of absolute value of stock return divided by dollar trading volume, multiplied by 10^6, then the daily ratios are averaged over firm i's fiscal year t:

$$Amihud_{i,t} = \frac{1}{D_{i,t}} \times \sum_{d=1}^{D} \frac{|RET_{i,d}|}{|PRC_{i,d} \times VOL_{i,d}|}, \qquad (6)$$

where $RET_{i,d}$, $PRC_{i,d}$, and $VOL_{i,d}$ are, respectively, the return, closing price, and trading volume on day d for stock i, and $D_{i,t}$ is the number of trading days for stock i in fiscal year t. Higher Amihud ratio indicates lower stock liquidity.

2.4 Measures of Control Variables

Following the earnings management literature (Yu 2008), we control for a set of variables that can affect earnings manipulation activities. Firm size, *SIZE*, is the natural logarithm of the market capitalization; Firms' growth opportunity, *MB*, is measured by market-to-book ratio; Firm profitability, *ROA*, is measured by return on assets; *GAT* denotes growth rate of assets; External financing activities, *XFIN*, is measured by the sum of net cash received from the sale (and/or purchase) of common and preferred stock less cash dividends paid and net cash received from the issuance (and/or reduction) of debt scaled by total assets; Cash flow volatility, *OCFV*, is calculated as standard deviation of cash flows scaled by lagged assets of a firm in the entire sample period. Detailed variable definitions are available in Table 1. To mitigate the influences of outliers, we winsorize all variables at the 1st and 99th percentile.

[Insert Table 1 About Here]

2.5 Summary Statistics

Table 2 reports the summary statistics for the sample firm-fiscal year observations. An average firm has an absolute level of real earnings management (*ARM*) of 0.2870 and an absolute level of abnormal discretionary accrual (*AAM*) of 0.0757. Stock liquidity measured by *RESPR* (*RQSPR*) has a mean value of 1.0182% (1.2467%) and a median value of 0.5121% (0.7111%), which is consistent with prior liquidity literature. The mean of *Amihud* ratio (multiplied by 10^6) is 0.4795. On average, a firm in our sample has \$0.44 billion in market capitalization, market-to-book ratio of 2.9121, return on assets of 11.36%, growth rate of asset of 14.58%, external financing proceeds scaled by total assets of 1.03%, and cash flow volatility of 0.0942.

[Insert Table 2 About Here]

3. Empirical Results

3.1 Baseline Specification

To study the effect of stock liquidity on earnings management, we rely on the following baseline specification model:

$$ARM_{i,t+1}(AAM_{i,t+1})$$
$$= a + b\ RESPR_{i,t}(\ RQSPR_{i,t} or\ \ Amihud_{i,t}) + c\ Controls_{i,t}$$
$$+ YR_t + IND_j + \varepsilon_{i,t}, \quad (7)$$

where i indexes firms, t indexes fiscal years, j indexes industries. $ARM_{i,t+1}(AAM_{i,t+1})$ is the absolute level of real earnings manipulation (absolute level of accrual-based earnings management) at the end of firm i's fiscal year $t+1$. $RESPR_{i,t}$ ($RQSPR_{i,t}$ or $Amihud_{,t}$) is measured for firm i over its fiscal year t. Controls is a vector of other control variables that can affect earnings management, including firm size, market-to-book ratio, return on assets, growth rate of assets, external financing activities, and cash flow volatility, measured as of fiscal year t. We include year (YR_t) and Fama-French 48-industry (IND_j) fixed effects. All the standard errors in the baseline regressions are clustered at firm level.

Table 3 reports the estimates of the baseline regressions. Panel A presents the results of the regressions with the absolute level of real earnings manipulation (*ARM*) as dependent variable. In Column (1), we run the regression without illiquidity measures. In Column (2), (3), and (4), we add *RESPR*, *RQSPR*, and *Amihud* as illiquidity measure, respectively. The coefficients of all the three illiquidity measures are significantly positive, indicating that higher stock liquidity is associated with less real earnings management. Specifically, a one-standard-deviation increase in illiquidity measured by *RESPR* (*RQSPR* or *Amihud*) can lead to 0.96% (1.04% or 0.89%) increase in *ARM,* equivalent to an increase of 4.85% (5.26% or 4.50%) over the sample median of 0.1979. Panel B shows the results of the regressions with the absolute level of accrual-based earnings management (*AAM*) as dependent variable. Similarly, the results suggest a significant negative correlation between stock liquidity and accrual-based earnings management and are robust to different measures of stock liquidity. A one-standard-deviation increase in illiquidity measured by *RESPR* (*RQSPR* or *Amihud*) can lead to 0.40% (0.57% or 0.19%) increase in *AAM*, equivalent to an increase of 8.66% (12.31% or 4.10%) over the sample median of 0.0463.

[Insert Table 3 About Here]

3.2 Endogeneity Issues

Even though the multivariate analysis includes control variables and year and industry fixed effects, some unobservable firm-specific factor correlated with both stock liquidity and earnings management may still exist and can bias our results. In this section, we address the potential endogeneity issues in the following ways: to begin with, we employ an instrumental variable approach; then, we use two sources of exogenous shocks to stock liquidity, stock splits and decimalization, to identify the causal effect of stock liquidity on earnings management.

3.2.1 Instrumental Variable Approach

In this subsection, we perform a two-stage least square (2SLS) regression to control for the endogeneity problem. A valid instrument must be correlated with stock liquidity but unrelated to any unobservable variables that may affect earnings management independently. Following Norli et al. (2015), we use the average stock liquidity of firms in industries outside of firm *i*'s industry as an instrument for stock liquidity of firm *i*. This instrumental variable is less likely to be related to firm's earnings management except through exerting an effect on stock liquidity of the firm. Fama-French 48-industry classification is used in this analysis.

In the first-stage, we regress stock liquidity measure on the instrumental variable and other control variables. In the second-stage, we regress the earnings management measure on the fitted value of stock liquidity measure obtained from the first-stage. The 2SLS regressions are as follows:

$$1st\ stage:\quad RESPR_{i,t}\left(\ RQSPR_{i,t} or\ \ Amihud_{i,t}\right)$$
$$= a + b\ Ind\_RESPR_{i,t}\left(\ Ind\_RQSPR_{i,t} or\ \ Ind\_Amihud_{i,t}\right)$$
$$+ c\ Controls_{i,t} + YR_t + \varepsilon_{i,t},$$
$$2nd\ stage:\quad ARM_{i,t+1}\left(AAM_{i,t+1}\right)$$
$$= a + b\ Fit\_RESPR_{i,t}\left(\ Fit\_RQSPR_{i,t} or\ \ Fit\_Amihud_{i,t}\right)$$
$$+ c\ Controls_{i,t} + YR_t + \varepsilon_{i,t}, \tag{8}$$

where $Ind\_RESPR_{i,t}$ ($Ind\_RQSPR_{i,t}$ or $Ind\_Amihud_{,t}$) is the average *RESPR* (*RQSPR* or *Amihud*) of firms in industries outside of firm i's industry measured fiscal year *t*. $Fit\_RESPR_{i,t}$ ($Fit\_RQSPR_{i,t}$ or $Fit\_Amihud_{,t}$) is the fitted value of *RESPR* (*RQSPR* or *Amihud*).

The results of 2SLS regressions are tabulated in Table 4. In column (1), (4) and (7), the coefficients on $Ind\_RESPR_{i,t}$, $Ind\_RQSPR_{i,t}$ and $Ind\_Amihud_{,t}$ are negative and significant at 1% level, suggesting that the instrument variable is highly correlated with stock liquidity. The other 6 columns show the results of second-stage regressions. Consistent with the results of baseline regressions, the coefficients on $Fit\_RESPR_{i,t}$ ($Fit\_RQSPR_{i,t}$ or $Fit\_Amihud_{,t}$) are all positive and significant at 1% level except for the last column. Thus, the results are robust to the controlling for endogeneity issue using instrumental variable approach.

[Insert Table 4 About Here]

3.2.2 Stock Split as Shock to Stock Liquidity

In this test, we use the stock split event as exogenous shock to stock liquidity and investigate its effects on both real and accrual-based earnings management. Maloney and Mulherin (1992) find that stock split can lead to greater number of trades and narrower bid-ask spread because the split facilitates existing shareholders to sell off a portion of their shares. Lin, Singh, and Yu (2009) provide evidence that stock split can attract uninformed traders, which reduces trading cost and improves stock liquidity. Jayaraman and Milbourn (2011) use stock split as an exogenous shock to stock liquidity and study the effect of stock liquidity on executive compensation. Stock split event serve as a good setting due to two reasons. One is that stock splits directly affect stock liquidity but are exogenous to firms' fundamentals and earnings management. The other appealing aspect is that stock split event happens in different firms at different times.

To conduct this analysis, we obtain a sample of stock splits which includes firms that announce stock split with a split factor of at least 0.25 between 1993 and 2012 from CRSP stock events database. Then we merge the split sample with CRSP/Compustat merged database and require that split firms have available data one fiscal year before and one fiscal year after the split event. After that we are left with 2,116 split events. For each split firm in a fiscal year, we match it to a non-split firm in the same fiscal year and industry[2] with the closest firm size in pre-event fiscal year. We require that the non-split firms have no stock split surrounding the matched fiscal year. The final sample contains 1,275 pairs of split and non-split observations. For pair of split and non-split observations, we examine one fiscal year before and one fiscal year after the event time.

[2] We use Fama-French 48 industry classification.

We perform the following regression:

$$ARM_{i,t}(AAM_{i,t}) = a + b\,Split * Post + c\,Split + d\,Post + d\,Controls_{i,t} + \varepsilon_{i,t}, \quad (9)$$

where *Split* is a dummy variable equals one if a firm announces stock split, and zero otherwise; *Post* is a dummy variable equals one for post-event fiscal year and zero for pre-event fiscal year; *Split*Post* is the interaction term between *Split* and *Post. Controls* capture the same set of control variables used in the baseline regressions. Table 5 presents the results.

[Insert Table 5 About Here]

The first two columns report the regressions with real earnings management measure as dependent variable. The dependent variable of the following two regressions is accrual-based earnings management. Column (2) and (4) includes industry fixed effects. Standard errors are clustered at firm level. The coefficient on *Split*Post* is negative and statistically significant at 1% level across specifications. It is -0.039 in the real earnings management specifications, which is slightly larger in magnitude than that in the accrual-based earnings management specifications (i.e. -0.021). The results show that the shock to liquidity due to stock split decreases the real (accrual-based) earnings management of split stocks by about 3.9% (2.1%).

3.2.3 Decimalization as Shock to Stock Liquidity

In this subsection, we rely on the Decimalization event to conduct a Difference-in-Difference analysis to determine the causal effect of stock liquidity on firms' earnings management.

Decimalization refers to the transition to quoting and trading securities in one penny increment from 1/16th of a dollar in 2001. Prior to decimalization, the smallest price change for stock trading was 1/16 of one dollar in a price quote. The U.S. Securities and Exchange Commission (SEC) regulated that all stock markets within the U.S. should convert all stock price quotes into decimal trading format by April 9, 2001.With the effectiveness of decimalization, the minimum price change is reduced to \$0.01, which allows for tighter spreads between the bid and the ask prices for stock trading. The decimalization is widely used in prior literature as an exogenous positive shock to stock market liquidity (Fang, Noe, and Tice 2009; Bharath, Jayaraman, and Nagar 2013; Edmans, Fang, and Zur 2013). It appears to be a good candidate for an exogenous shock to liquidity for three reasons. First, it is unlikely that event is driven by firm earnings management behavior. On the contrast, it is the result of the US Securities and Exchange Commission (SEC) and government's effort to reduce security trading cost and encourage quote competition and boost the US equity market's competitive edge relative to foreign markets[3]. Second, it is well documented in the literature that stock liquidity improved significantly after decimalization, especially among actively traded stocks (Bessembinder 2003; Furfine 2003; Chordia, Roll, and Subrahmanyam 2008). Third, the increase in liquidity shows variation in the cross-section of stocks, allowing us to perform difference-in-difference analysis to test whether larger increase in liquidity is associated with greater decline in earnings management.

We adopt a difference-in-difference (DiD) framework to compare the change in the earnings management measures for two groups of firms, which differ significantly in terms of change in relative effective spread (*RESPR*) from pre-decimalization year[4] to

[3] In the SEC Staff's 1994 report 'Market 2000: an examination of current equity market developments', the Staff expressed concern that 1/8th of a dollar tick size might "cause artificially wide spreads and hinder quote competition". The report also expressed concern that 1/8th fraction pricing might hurt "the competitive posture of the U.S. equity markets" compared to foreign equity markets. In March 1997, Congressman Michael Oxley introduced a bill in the U.S. House of Representatives that would have directed the Commission to adopt decimal pricing for all equity securities. In September 2000, the Commission further mandated that the exchanges start implementing decimal pricing and finish implementation by April 2001. The New York Stock Exchange (NYSE) and the American Stock Exchange (AMEX) replaced the system of fractional pricing by January 29, 2001. The Nasdaq Stock Market (Nasdaq) decimalized shortly and finished implementing it by April 2001.

[4] We use the fiscal year 1999 as the pre-decimalization year. The ending date of a firm's fiscal year t

post-decimalization year[5], but are otherwise comparable. The DiD method not only allows us to control for the impact of omitted variables, but also remove biases from comparisons that could be resulted from time trends. First, we construct a treatment group and a control group using propensity score matching approach. Specifically, we follow Fang, Tian, and Tice (2014) to rank and assign all sample firms into tertiles based on the change in *RESPR*, and only retain the firms in the first and last tertile. The treatment (control) group is the firms in the first (last) tertile which experience the highest (lowest) increase in stock liquidity. We next run a probit model in which the dependent variable equals one if the firm belongs to the treatment group and zero otherwise, and use the predicted probabilities, i.e. propensity scores, to match firms. The probit model includes all control variables from baseline regression measured in the pre-decimalization year. We include the variables to remove the effect of confounding factors as the DiD estimator should not capture the effect of other firm characteristics. Each treatment firm is matched to a control firm with the nearest propensity score and within a difference of 0.01. We retain all matched pairs if a control firm is matched with multiple treatment firms. We are left with 710 pairs of matched firms. The results of the probit regression are reported in column (1) of Panel A in Table 6. The probit model displayed a pseudo R-square of 0.1296 and the p-value from the chi-square test is 0.0000, suggesting that the model specification captures a significant amount of variation in the choice variable. Panel B of Table 6 reports the distribution of the propensity scores for both groups and their difference, which is rather trivial. The average distance between the propensity score of the matched samples is only 0.0001

ranges from 30 June of year t to 31 May of year t+1, fiscal year 1999 is more proper to present the pre-decimalization year as the last ending date of fiscal year 1999 is 31 May, 2000 which is prior to the date of full implementation of decimalization (April 9, 2001), while the last ending date of fiscal year 2000 is 31 May, 2001, which exceeds April 9, 2001.

[5] We use the fiscal year 2002 as the pre-decimalization year.

with a minimum of -0.0080 and a maximum of 0.0099. The validity of the DiD estimator critically depends on the assumption that the underlying ‘trends’ in the outcome variable is the same for both groups (parallel trend assumption). Besides the comparison of the propensity scores of the two groups, we also conducted another two diagnose tests to verify that the assumption holds in our data. In the first diagnose test, we run the same probit model as in the propensity score matching step but for the matched sample, and present the results in column (2) of Table 6 Panel A. Most of the control variables are insignificant and the likelihood ratio is much lower than that in the prior probit model results, implying that there is no observable difference in trends between the treatment and control groups in the pre-decimalization year. The magnitude of the coefficient estimates is smaller compared to that of the coefficient estimates in column (1), implying that the results in column (2) are not simply a result of a drop in the degrees of freedom caused by a smaller sample. In addition, the pseudo R-square drops drastically to 0.0098 from 0.1296 prior to the matching and the p-value from the chi-square test is 0.3202, suggesting that overall all coefficient estimates on independent variables are not significantly different from zero. The second diagnostic test is a t-test examining the differences between the two groups’ pre-decimalization characteristics. Panel C shows there is no significant differences between the treatment and control group of firms’ *ARM*, *AAM*, and *RESPR* in pre-decimalization year. The results indicate that the two groups of firms have similar level of earnings management and liquidity prior to decimalization. Overall, the above diagnostic tests suggest that the propensity score matching method is able to remove most of the meaningful observable difference in firm characteristics (other than stock liquidity) known to affect firm’s earnings management. As a result, the observed difference between *ARM (AAM)* around decimalization is more likely to be caused by the change in stock liquidity.

To conduct the DiD analysis, we first calculate the changes of *ARM (AAM)* around decimalization year for both groups, and run a t-test to examine whether there is significant difference in $\Delta ARM_{1999\ to\ 2002}$ ($\Delta AAM_{1999\ to\ 2002}$) between the treatment sample and control sample. The results are presented in Panel D of Table 6. On average, firms in the treatment group experiences a further decline in *ARM* (*AAM*) by 0.0505 (0.0237) compared to those in the control group. The difference is significant at 5% (1%) level. Then we run the following difference-in-difference regression based on the matched sample:

$$ARM_{i,t}\left(AAM_{i,t}\right) = a + bDDL \times YT + cDDL + dYT + eControls_{i,t} + IND_j + \varepsilon_{i,t}\ , \tag{10}$$

where *DDL* is a dummy variable equal to one if a firm is in treatment group and zero if in control group. *YT* is a dummy variable equal to one for fiscal year 2002 (post-decimalization) and zero for fiscal year 1999. *DDL**YT* is the interaction term between these two variables. The results of DiD regressions are tabulated in Panel E of Table 6. The coefficients of the interaction term are significantly negative, suggesting that the treatment firms with experience larger increase in stock liquidity tend to decrease the level of earnings management after the decimalization.

[Insert Figure 1 About Here]

[Insert Table 6 About Here]

4. Possible Mechanisms

So far, we have identified the negative causal effect of stock liquidity on firm's earnings management. In this section, we try to investigate the possible mechanisms through which stock market liquidity affects firm's earnings management activities. It is quite challenging to conduct direct and comprehensive analyses of the underlying mechanisms, thus our evidences are only indicative.

4.1 Information Asymmetry

Higher stock market liquidity can induce informed traders to acquire more private information and trade on it (Subrahmanyam and Titman 2001). As a result, more private information is revealed to the public and the information environment is improved (Holmström and Tirole 1993). Thus higher stock liquidity can reduce information asymmetry by inducing more informed traders to convey private information to the equity market. As the information asymmetry between managers and shareholders is a principal factor that induces managers to manipulate earnings (Dye 1998 and Trueman and Titman 1998), higher stock liquidity can curb earning management through mitigating information asymmetry problem. Hence, we conjecture that the effect of stock liquidity on earnings management is more pronounced for firms with higher degree of information asymmetry.

To examine this mechanism, we use the number of financial analysts to capture the degree of information asymmetry. The number of analysts is widely used in literature to proxy for the extent of information asymmetry (Chae 2005; Chang, Dasgupta, and Hilary 2006). Firms followed by a lower number of analysts have higher extent of information asymmetry. The analyst coverage data is obtained from the Institutional Brokers Estimate System (I/B/E/S) database through Wharton Research Data Services (WRDS). For each firm *i*, we calculate the number of analysts following firm *i* during fiscal year *t*. Then, we rely on the matched sample constructed in the difference-in-difference analysis and partition the matched sample into two subsamples based on the number of analysts, firms with the number of analysts above the sample median are belong to the low information asymmetry group and firms with below median analyst coverage are in the group with high information asymmetry. In each group, we run the same difference-in-difference regressions as Eq. (10). Panel A of Table 7 reports the results of the difference-in-difference regression with *ARM* as dependent variable. The last two columns present results of regressions with industry fixed effects. In column (1) and (3), the coefficients on the interaction term, *DDL*YT*, are significant and negative among the subsample with a lower number of analysts (i.e. with higher degree of information asymmetry). The coefficients on *DDL*YT* for the subsample with a higher number of analysts are statistically insignificant. The results support our information asymmetry hypothesis that when a firm is subject to a higher level of information asymmetry, higher stock market liquidity can improve the information environment through inducing more informed trading, as a result, reduce managers' incentive to engage in real activities earnings manipulation. Panel B reposts the results of regressions with *AAM* as dependent variable. However, there is no significant difference between the coefficients on *DDL*YT* of the two subsamples, indicating that we cannot attribute the managers' accrual-based earnings management to the existence of high extent of information asymmetry.

[Insert Table 7 About Here]

4.2 Blockholder Intervention

Blockholder intervention is another possible explanation for how stock liquidity curbs earnings management. Large shareholders are sophisticated investors who focus on long-term value rather than the short-term profits. They have the incentive to collect private information about the firm and are wary of the managers' opportunistic behavior.

With the ability to discipline firm managers, large shareholders can restrain managers from engaging in earnings management (Bange and De Bondt 1998; Chung et al 2002). Maug (1998) argues that higher stock market liquidity leads to more effective corporate governance by making it less costly for large shareholders to hold their shares. Admati and Pfleiderer (2009) indicate that the threat of exit can serve as an alternative mechanism of corporate governance and that stock liquidity can improve the effectiveness of governance by reducing the cost of exit. Edmans and Manso (2011) show liquidity increases blockholders' effectiveness in exerting corporate governance through disciplinary trading, which, as a result, induces a higher managerial effort. Therefore, by enhancing blockholders' ability to discipline firm managers, stock liquidity can reduce earnings management.

We employ the method used in Section 5.1 to test this mechanism. Specifically, we start with the matched sample and divide it into two subsamples based on whether the blockholder ownership is above the sample median. Institutional ownership data is obtained from the Thomson-Reuters Institutional (13F) Holdings database through WRDS. Blockholder ownership (*BLOCK*) is calculated as the total holding by investors who own no less than 5% of the shares outstanding at the end of each fiscal year. In each subsample, we run the same difference-in-difference regressions as Eq. (10). Panel A of Table 8 presents the results of the difference-in-difference regression with *ARM* as dependent variable. We add industry fixed effects in the last two regressions. In column (1) and (3), the coefficients on the interaction term, *DDL*YT*, are significant and negative for the subsample with a lower blockholder ownership. The coefficient on *DDL*YT* for the subsample with a higher blockholder ownership is statistically insignificant in column (4). The results suggest that when a firm has lower blockholder ownership, higher stock market liquidity can facilitate blockholders to exert governance through trading, therefore, discourage managers from engaging in real activities earnings manipulation. The results are similar for accrual-based earnings management. Panel B shows that there exist significant differences between the coefficients on *DDL**YT* of the two subsamples. Hence, the overall results indicate that blockholders' governance through trading is another channel through which stock liquidity reduce earnings management.

[Insert Table 8 About Here]

4.3 Dividend Signaling

The dividends signaling hypothesis states that manager's dividend decisions convey information about future earnings prospects of the firm (Miller and Modigliani 1961). Managers are reluctant to raise dividend payments unless they are confident that current and prospective earnings are large enough to meet the new committed level of dividend. Hence, paying a dividend is considered as a signal to outside investors that the firm has high quality of earnings, that is, the reported earnings accurately reflects the firm's current operating performance. As dividends allow investors to evaluate the firm's earnings quality (Skinner and Soltes 2011), managers are less likely to manipulate earnings. Fuller (2003) argues that as the amount of informed traders increases, more information is incorporated into stock price, making it effectively reflect firm's real earnings, thus there is less need for firm to signal its intrinsic value by dividends. In other words, informed trading and dividend signaling are alternative ways to reveal information about the firm's intrinsic value, leading to less earnings management. Given that non-dividend-paying firms are not able to signal using dividend payment, the entry of informed traders can impose larger constraints on managers' earnings management for these firms. Since higher stock liquidity can induce the entry of informed traders by permitting informed traders to profit more from trading (O'hara 1995), it can be implied that the impact of stock liquidity on earnings management is more pronounced for non-dividend-paying firms.

To test this conjecture, we partition the matched sample into two subsamples based on whether the firm pays dividend or not. To identify the dividend-paying firms, we obtain the stock distribution information from CRSP. A firm is defined as a dividend payer in fiscal year t if the firm has paid positive ordinary cash dividends (distribution codes between 1200 and 1299) for that fiscal year. Among the matched sample, there are 358 dividend-paying firms and 1,878 non-dividend-paying firms. We then run the regressions as Eq. (10) for each subsample. In Table 9, we present the coefficient estimates from the regressions. The results are similar for the specifications with either ARM or AAM as dependent variable. Consistent with our conjecture, the coefficient on *DDL*YT* is negative and significant for non-dividend-paying firms while it is statistically insignificant for dividend-paying firms.

[Insert Table 9 About Here]

5. Conclusion

Existing literature has not reach a conclusion concerning whether stock liquidity increase or decrease earnings management. In this paper, we contribute to literature by establishing the linkage between stock liquidity and earnings management. We show that stock liquidity is negatively related to both real and accrual-based earnings management. We employ divergent methods to identify the causal effect of stock liquidity on earnings management. The first is instrumental variable approach, in which we use the average liquidity of firms in industries outside of a firm’s industry as an instrumental variable for stock liquidity. The second is to use stock splits as shock to stock splits. The third is the difference-in-difference test using the 2001 decimalization event as an exogenous shock to stock liquidity. The results of all these methods suggest that stock liquidity has a negative causal effect on both real and accrual-based earnings management.

We then examine the underlying mechanisms that may drive this result. Information asymmetry is one possible channel. We use the number of financial analysts to measure the degree of information asymmetry and find that the negative effects of stock liquidity on real earnings management are only significant for the sample of firms with lower analyst coverage, suggesting that the stock liquidity can alleviate the information asymmetry problem for firms with low analyst coverage. In addition, we show that the impact of stock liquidity on earnings management is more pronounced for non-dividend-paying firms that are not able to signal their intrinsic value by dividends. Another possible mechanism is governance by large institutional owners. Our results suggest that higher stock market liquidity can facilitate large institutional investors to exert governance through trading, leading to less real and accrual-based earnings management.

Overall, our findings suggest that higher stock liquidity can curb real activities earnings manipulation as well as accrual-based earnings management. Our findings may be of interest to regulators and practitioners who concern about the causes of earnings management and have important implications for financial regulatory authorities when they try to promote the efficiency of secondary financial markets.

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Table 1 Variable Definition

Variable	Definition	Source
ARM	Absolute level of real activities manipulation. Calculated as the absolute value of (RM_{PROD} – RM_{DISX}), where RM_{PROD}, the abnormal level of production costs, is estimated as the residual from the following cross-section regressions for each year and Fama-French 48 industry: $\frac{PROD_{i,t}}{AT_{i,t-1}} = \beta_0 + \beta_1 \frac{1}{AT_{i,t-1}} + \beta_2 \frac{Sale_{i,t}}{AT_{i,t-1}} + \beta_3 \frac{\Delta Sale_{i,t}}{AT_{i,t-1}} + \beta_4 \frac{\Delta Sale_{i,t-1}}{AT_{i,t-1}} + \varepsilon_{i,t}$, $PROD_{i,t}$ is the sum of cost of goods sold ($COGS_{i,t}$) and change in inventory from t-1 to t ($\Delta INVT_{i,t}$); RM_{DISX}, the abnormal level of discretionary expenses, is estimated as the residual from the following cross-section regressions for each year and Fama-French 48 industry: $\frac{DISX_{i,t}}{AT_{i,t-1}} = \beta_0 + \beta_1 \frac{1}{AT_{i,t-1}} + \beta_2 \frac{Sale_{i,t-1}}{AT_{i,t-1}} + \varepsilon_{i,t}$, $DISX_{i,t}$ is the sum of R&D expense ($XRD_{i,t}$), advertising expense ($XAD_{i,t}$) and *SG&A* expense ($XSGA_{i,t}$).	Compustat
AAM	Absolute level of accrual-based earnings management. Calculated as the absolute value of the residual from the following cross-section regressions for each year and Fama-French 48 industry: $\frac{IB_{i,t} - OANCF_{i,t}}{AT_{i,t-1}} = \beta_0 + \beta_1 \frac{1}{AT_{i,t-1}} + \beta_2 \frac{\Delta Sale_{i,t}}{AT_{i,t-1}} + \beta_3 \frac{PPEGT_{i,t}}{AT_{i,t-1}} + \varepsilon_{i,t}$, where $IB_{i,t}$ is income before extraordinary items, $OANCF_{i,t}$ indicates cash flow from operations, and $PPEGT_{i,t}$ is gross property, plant and equipment.	Compustat
RESPR	Annual relative effective spread. Relative effective spread is twice the difference between the execution price and the midpoint of the prevailing best bid-ask quote divided by the midpoint of the prevailing best bid-ask quote. The daily relative effective spread is the time-weighted average of all intraday relative effective spread records; *RESPR* is then measure as the average of the daily relative effective spread over a fiscal year. *RESPR* is multiplied by 100.	TAQ
RQSPR	Annual relative quoted spread. Relative quoted spread is the prevailing best bid-ask spread divided by the midpoint of the prevailing best bid-ask quote. The daily relative quoted spread is the equal-weighted average of all intraday relative quoted spread records, *RQSPR* is then measure as the average of the daily relative quoted spread over a fiscal year. *RQSPR* is multiplied by 100.	TAQ
Amihud	Annual Amihud Measure. Average of the daily ratio of absolute value of stock return divided by dollar trading volume over a fiscal year. Amihud is multiplied by 10^6.	CRSP
SIZE	Log of the market capitalization of the firm (*PRCC_F×CSHO*).	Compustat
MB	Market-to-book ratio (market value of equity (*PRCC_F×CSHO*) divided by book value of equity (*CEQ*)).	Compustat
ROA	Operating income before depreciation (*OIBDP*) over book value of total assets (*AT*).	Compustat
GAT	Growth rate of assets (Change of assets (*AT*) scaled by lagged assets).	Compustat
XFIN	External financing activities. Measured by the sum of net cash received from the sale (and/or purchase) of common and preferred stock less cash dividends paid (*SSTK-PRSTKC-DV*) and net cash received from the issuance (and/or reduction) of debt (*DLTIS-DLTR+DLCCH*) scaled by total assets (*AT*).	Compustat
OCFV	Cash flow volatility. Calculated as standard deviation of cash flows scaled by lagged assets ($OANCF_{i,t}/AT_{i,t-1}$) of a firm in the entire sample period.	Compustat
Analyst	The number of financial analysts following the firm during a fiscal year.	I/B/E/S
Block	Blockholder ownership. Calculated as total holding by investors who own no less than 5% of the shares outstanding at the end of each fiscal year.	Thomson-Reuters
Dividend	A firm is defined as a dividend payer in fiscal year t if the firm has paid positive ordinary cash dividends (distribution codes between 1200 and 1299) for that fiscal year.	CRSP

Table 2 Summary Statistics

This table reports summary statistics for the sample firm-fiscal year observations. The sample contains 41,062 firm-fiscal year observations between 1993 and 2012 (the sample period for ARM and AAM is1994-2013).

Variable	N	Mean	Minimum	25th Pctl	Median	75th Pctl	Maximum	Std Dev
ARM	41062	0.2870	0.0033	0.0863	0.1979	0.3872	1.5446	0.2887
AAM	41062	0.0757	0.0007	0.0205	0.0463	0.0930	0.5467	0.0916
RESPR	41062	1.0182	0.0268	0.1581	0.5121	1.4722	6.0151	1.2147
RQSPR	41062	1.2467	0.0354	0.2397	0.7111	1.8768	5.3428	1.3173
Amihud	41062	0.4795	0.0000	0.0018	0.0144	0.1439	11.2308	1.5806
SIZE	41062	6.0855	2.1672	4.6834	6.0264	7.3466	11.0191	1.9189
MB	41062	2.9121	-9.3735	1.2565	2.0648	3.4787	23.2328	3.7545
ROA	41062	0.1136	-0.7096	0.0606	0.1318	0.2032	0.5432	0.1815
GAT	41062	0.1458	-0.4937	-0.0303	0.0648	0.2019	2.2445	0.3895
XFIN	41062	0.0103	-0.3162	-0.0391	0.0000	0.0247	0.5946	0.1249
OCFV	41062	0.0942	0.0129	0.0455	0.0706	0.1136	0.5246	0.0819

Table 3 Baseline Regressions

This table presents the results of the baseline regressions. There are totally 41,062 firm-fiscal year observations between 1994 and 2013. In Panel A, the dependent variable is ARM. Column (1) presents the results of the regression without liquidity measures. Column (2) to (4) report the results of regressions with Relative Effective Spread, Relative Quoted Spread, and Amihud as liquidity measure respectively. Other control variables are SIZE, MB, ROA, GAT, XFIN, and OCFV. Panel B report the baseline regressions results with AAM as dependent variable. See Table 1 for definitions of all the variables. We add year and Fama-French 48 industry dummies. Standard errors are clustered at firm level and are in parentheses. *** (**) (*) Indicates significance at 1% (5%) (10%) two-tailed level.

Panel A Real Activities Earnings Management

Dependent Variable	ARM_{t+1}			
	(1)	(2)	(3)	(4)
$RESPR_t$		0.0079***		
		(0.0024)		
$RQSPR_t$			0.0079**	
			(0.0034)	
$Amihud_t$				0.0056***
				(0.0019)
$SIZE_t$	-0.0202***	-0.0172***	-0.0162***	-0.0181***
	(0.0019)	(0.0021)	(0.0025)	(0.0019)
MB_t	0.0088***	0.0088***	0.0087***	0.0088***
	(0.0008)	(0.0008)	(0.0008)	(0.0008)
ROA_t	0.0435**	0.0465**	0.0469**	0.0445**
	(0.0208)	(0.0208)	(0.0208)	(0.0208)
GAT_t	-0.0220***	-0.0219***	-0.0220***	-0.0219***
	(0.0054)	(0.0054)	(0.0054)	(0.0054)
$XFIN_t$	0.5399***	0.5370***	0.5373***	0.5401***
	(0.0543)	(0.0544)	(0.0545)	(0.0543)
$OCFV_t$	-0.0169	-0.0143	-0.0139	-0.0137
	(0.0195)	(0.0196)	(0.0196)	(0.0196)
Intercept	0.1026***	0.0729***	0.0657***	0.0872***
	(0.0169)	(0.0194)	(0.0227)	(0.0172)
#obs	41062	41062	41062	41062
Industry&Year FE	Yes	Yes	Yes	Yes
Cluster by firm	Yes	Yes	Yes	Yes
R-square	0.1821	0.1827	0.1826	0.1828
Adj. R-square	0.1813	0.1818	0.1817	0.1820

Panel B Accrual-based Earnings Management

Dependent Variable	AAM_{t+1}			
	(1)	(2)	(3)	(4)
$RESPR_t$		0.0033***		
		(0.0005)		
$RQSPR_t$			0.0043***	
			(0.0007)	
$Amihud_t$				0.0012***
				(0.0004)
$SIZE_t$	-0.0059***	-0.0046***	-0.0037***	-0.0054***
	(0.0003)	(0.0003)	(0.0004)	(0.0003)
MB_t	0.0012***	0.0012***	0.0012***	0.0012***
	(0.0002)	(0.0002)	(0.0002)	(0.0002)
ROA_t	-0.0452***	-0.0439***	-0.0433***	-0.0449***
	(0.0052)	(0.0052)	(0.0052)	(0.0052)

GAT_t	0.0041*	0.0041*	0.0041*	0.0041*
	(0.0021)	(0.0021)	(0.0021)	(0.0021)
$XFIN_t$	0.2435***	0.2423***	0.2421***	0.2435***
	(0.0118)	(0.0118)	(0.0118)	(0.0119)
$OCFV_t$	0.0134**	0.0144**	0.0150**	0.0140**
	(0.0063)	(0.0063)	(0.0063)	(0.0063)
Intercept	0.0807***	0.0683***	0.0605***	0.0774***
	(0.0110)	(0.0111)	(0.0113)	(0.0109)
#obs	41062	41062	41062	41062
Industry&Year FE	Yes	Yes	Yes	Yes
Cluster by firm	Yes	Yes	Yes	Yes
R-square	0.1518	0.1529	0.1532	0.1522
Adj. R-square	0.1510	0.1520	0.1523	0.1513

Table 4 Instrumental Variable Approach

This table reports the two-stage least squares (2SLS) regressions results of the following models: $First\ Stage$: $RESPR_{i,t}(\ RQSPR_{i,t} or\ \ Amihud_{i,t}) = \alpha + \beta Ind\_RESPR_{i,t}(\ Ind\_RQSPR_{i,t} or\ \ Ind\_Amihud_{i,t}) + Controls_{i,t} + \varepsilon_{i,t}$, $Second\ Stage$: $ARM_{i,t+1}(AAM_{i,t+1}) = \alpha + \beta Fit\_RESPR_{i,t}(\ Fit\_RQSPR_{i,t} or\ \ Fit\_Amihud_{i,t}) + Controls_{i,t} + \varepsilon_{i,t}$.
In this approach, liquidity is instrumented using the average stock liquidity of firms in industries outside of firm i's industry (*$Ind\_RESPR_{i,t}$*, *$Ind\_RQSPR_{i,t}$* and *$Ind\_Amihud_{,t}$*). Year fixed effects are added. Standard errors are clustered at firm level and are in parentheses. *** (**) (*) Indicates significance at 1% (5%) (10%) two-tailed level.

2SLS	First-stage	Second-Stage		First-stage	Second-Stage		First-stage	Second-Stage	
Dependent Variable	$RESPR_t$ (1)	ARM_{t+1} (2)	AAM_{t+1} (3)	$RQSPR_t$ (4)	ARM_{t+1} (5)	AAM_{t+1} (6)	$Amihud_t$ (7)	ARM_{t+1} (8)	AAM_{t+1} (9)
Ind_RESPR_t	-4.8182***								
	(0.5886)								
Fit_RESPR_t		0.5240***	0.0588***						
		(0.0540)	(0.0084)						
Ind_RQSPR_t				-2.6476***					
				(0.4437)					
Fit_RQSPR_t					0.7152***	0.0663***			
					(0.0736)	(0.0108)			
Ind_Amihud_t							-7.1137***		
							(0.8976)		
Fit_Amihud_t								0.2557***	0.0050
								(0.0273)	(0.0048)
$SIZE_t$	-0.3653***	0.1728***	0.0159***	-0.5038***	0.3417***	0.0279***	-0.3593***	0.0724***	-0.0039**
	(0.0063)	(0.0199)	(0.0031)	(0.0078)	(0.0372)	(0.0055)	(0.0113)	(0.0100)	(0.0018)
MB_t	0.0101***	0.0054***	0.0007***	0.0158***	-0.0005	0.0002	0.0107***	0.0084***	0.0013***
	(0.0017)	(0.0010)	(0.0002)	(0.0017)	(0.0015)	(0.0003)	(0.0027)	(0.0009)	(0.0002)
ROA_t	-0.3915***	0.2493***	-0.0243***	-0.4652***	0.3797***	-0.0164**	-0.2077***	0.0950***	-0.0474***
	(0.0460)	(0.0295)	(0.0061)	(0.0481)	(0.0401)	(0.0074)	(0.0750)	(0.0218)	(0.0054)
GAT_t	-0.0115	-0.0141**	0.0057***	-0.0049	-0.0157***	0.0055***	-0.0279	-0.0107*	0.0055***
	(0.0157)	(0.0056)	(0.0021)	(0.0147)	(0.0056)	(0.0021)	(0.0243)	(0.0057)	(0.0021)
$XFIN_t$	-0.2749***	0.0865***	0.0307***	-0.3390***	0.1883***	0.0372***	-0.5310***	0.0792***	0.0166**
	(0.0524)	(0.0257)	(0.0066)	(0.0496)	(0.0332)	(0.0072)	(0.0882)	(0.0254)	(0.0068)
$OCFV_t$	0.3853***	0.4220***	0.2398***	0.3857***	0.3520***	0.2380***	-0.0125	0.6532***	0.2669***
	(0.1214)	(0.0625)	(0.0128)	(0.1262)	(0.0658)	(0.0132)	(0.2242)	(0.0559)	(0.0121)
Intercept	10.9326***	-1.4677***	-0.1144***	9.0401***	-3.0145***	-0.2263***	4.5853***	-0.3024***	0.0757***
	(0.9008)	(0.1857)	(0.0291)	(0.7280)	(0.3439)	(0.0506)	(0.2863)	(0.0697)	(0.0124)
#obs	41062	41062	41062	41062	41062	41062	41062	41062	41062
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cluster by firm	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R-square	0.4662	0.1000	0.1528	0.6528	0.1005	0.1523	0.2117	0.0940	0.1512
F-statistics	316.8375	32.2084	110.4808	396.3970	32.1466	109.8262	60.6667	32.1042	106.5642

Table 5 Stock Splits as Shock to Stock Liquidity

This table reports the results of regressions in which we use stock splits as exogenous shock to stock liquidity. The sample of stock splits includes firms that announce stock split with a split factor of at least 0.25 between 1993 and 2012 from CRSP stock events database. For each split firm in a fiscal year, we match it to a non-split firm in the same fiscal year and industry with the closest firm size in pre-event fiscal year. The final sample contains 1,275 pairs of split and non-split observations. For pair of split and non-split observations, we examine one fiscal year before and one fiscal year after the event time. *Split* is a dummy variable equals one if a firm announces stock split, and zero otherwise; *Post* is a dummy variable equals one for post-event fiscal year and zero for pre-event fiscal year; *Split*Post* is the interaction term between *Split* and *Post.* We add the same set of control variables used in the baseline regressions. The dependent variables are real earnings management (ARM) in the first two specifications and accrual-based earnings management in the Column (3) and (4). Column (2) and (4) include industry fixed effects. Standard errors are clustered at firm level and are in parentheses. *** (**) (*) Indicates significance at 1% (5%) (10%) two-tailed level.

Dependent Variable	(1) ARM	(2) ARM	(3) AAM	(4) AAM
Split*Post	-0.0387***	-0.0390***	-0.0209***	-0.0208***
	(0.0093)	(0.0092)	(0.0045)	(0.0045)
Split	0.0273**	0.0320***	0.0119***	0.0122***
	(0.0122)	(0.0113)	(0.0034)	(0.0033)
Post	-0.0107*	-0.0119*	0.0087***	0.0086***
	(0.0064)	(0.0063)	(0.0033)	(0.0033)
SIZE	-0.0223***	-0.0212***	-0.0040***	-0.0043***
	(0.0032)	(0.0031)	(0.0009)	(0.0008)
MB	0.0142***	0.0106***	0.0025***	0.0024***
	(0.0020)	(0.0019)	(0.0006)	(0.0006)
ROA	0.0978**	0.1046**	-0.0454***	-0.0389**
	(0.0471)	(0.0457)	(0.0154)	(0.0153)
GAT	-0.0064	-0.0127	0.0084	0.0057
	(0.0170)	(0.0161)	(0.0058)	(0.0056)
XFIN	0.5589***	0.4595***	0.3601***	0.3165***
	(0.1023)	(0.1038)	(0.0426)	(0.0418)
OCFV	-0.0343	0.0090	0.0284	0.0270
	(0.0572)	(0.0535)	(0.0177)	(0.0174)
Intercept	0.3240***	0.3349***	0.0605***	0.0657***
	(0.0245)	(0.0243)	(0.0069)	(0.0070)
#obs	5100	5100	5100	5100
Industry FE	No	Yes	No	Yes
R^2	0.0779	0.0608	0.1303	0.1043
Adjusted R^2	0.0763	0.0591	0.1287	0.1028

Table 6 Decimalization as a Shock to Stock Liquidity

This table presents the results of the difference-in-difference analysis surrounding the decimalization year (Pre-evet fiscal year=1999, post-event fiscal year=2002). The firms are ranked and assigned into tertiles based on the change in liquidity measure from 1999 to 2002, and only firms in the first and third tertiles are retained. The treatment (control) group is the firms in the first (last) tertile experiencing the highest (lowest) increase in stock liquidity. Next run a probit model in which the dependent variable is set to one if the firm belongs to the treatment group and zero for firms in the control group, and use the predicted probabilities, i.e. propensity scores, to match firms. Each treatment firm is matched to a control firm with the nearest propensity score and within a difference of 0.01.

Panel A Column (1) reports the results of the probit model based on the pre-matched firms in the treatment and the control groups. The dependent variable of the probit model equals one if the firm belongs to the treatment group and zero if the firm comes from the control group. The independent variables of the probit model are the control variables we used in the baseline regression measured in the pre-decimalization year. Panel A Column (2) report the results of the same probit model but based on the post-matched firms in the treatment and the control groups. Panel B reports the statistical distributions of the propensity scores of the treatment and control groups and their differences. Panel C reports variables means for both treatment and control group, the differences in means of each variable, and the corresponding t-statistics in the pre-decimalization fiscal year. Panel D reports the DiD estimator. Panel E reports the results of the difference-in-difference regressions based on the matched sample. *DDL* is a dummy variable equal to one if a firm's stock is in treatment group and zero if in control group. *YT* is a dummy variable equal to one for 2002 (post-decimalization fiscal year) and zero 1999. *DDL*YT* is the interaction term between these two variables. Standard errors are clustered at firm level and are in parentheses. Robust standard errors are shown in parentheses. *** (**) (*) Indicates significance at 1% (5%) (10%) two-tailed level.

Panel A Probit Regressions with Pre-matched and Post-matched samples in Pre-decimalization Year

Probit Regressions		
Dependent Variable: DDL=1 if in treatment group; 0 in control group		
Parameter	(1) Pre-match	(2) Post-match
RESPR	1.2589***	-0.0360
	(0.1272)	(0.1508)
SIZE	0.3075***	-0.0810
	(0.0765)	(0.1096)
MB	-0.0275*	-0.0060
	(0.0164)	(0.0200)
ROA	1.6788***	-0.6444
	(0.4194)	(0.5598)
GAT	0.0884	0.5385**
	(0.1478)	(0.2259)
XFIN	-0.1660	-0.5630
	(0.5881)	(0.8250)
OCFV	-0.8155	-2.0823
	(1.0091)	(1.2873)
Intercept	-3.5734***	0.7305
	(0.5480)	(0.7851)
#obs	1185	1118
P-value of χ^2	0.0000	0.3202
Pseudo R^2	0.1296	0.0098
Log Likelihood	-714.9187	-767.3492

Panel B Propensity Scores Distribution

Propensity Scores	N	Mean	Minimum	25th Pctl	Median	75th Pctl	Maximum	Std Dev
Treatment	559	0.5612	0.0918	0.4197	0.5204	0.6882	0.9678	0.1852

Control	559	0.5612	0.0912	0.4194	0.5211	0.6880	0.9580	0.1850
Difference	559	0.0001	-0.0080	-0.0005	-0.0001	0.0005	0.0099	0.0021

Panel C Differences in Variables in Pre-decimalization Year

Variable	Treatment	Control	Difference	t Value	Pr > |t|
ARM	0.0862	0.0789	0.0073	1.25	0.2114
AAM	0.3428	0.3199	0.0229	1.15	0.2514
RESPR	1.6827	1.6860	-0.0033	-0.05	0.9562
SIZE	5.2553	5.2980	-0.0427	-0.48	0.6296
MB	3.3586	3.5992	-0.2406	-0.87	0.3842
ROA	0.1362	0.1321	0.0041	0.35	0.7258
GAT	0.2391	0.1787	0.0604	2.19	0.0288
XFIN	0.0190	0.0177	0.0013	0.17	0.8671
OCFV	0.1066	0.1167	-0.0101	-2.04	0.0416

Panel D Difference-in-Difference Estimator

Variable	Treatment		Control		DID Estimator	t Value	Pr > |t|
	Before Decimalization	After Decimalization	Before Decimalization	After Decimalization			
ARM	0.3428	0.2912	0.3199	0.3187	-0.0505	-2.52	0.0120
AAM	0.0862	0.0887	0.0789	0.1050	-0.0237	-2.68	0.0075

Panel E Difference-in-Difference Regression

Dependent Variable	(1) ARM	(2) ARM	(3) AAM	(4) AAM
DDL*YT	-0.0696***	-0.0767***	-0.0205**	-0.0179***
	(0.0261)	(0.0200)	(0.0089)	(0.0060)
DDL	0.0308	0.0425	0.0080	0.0090*
	(0.0189)	(0.0259)	(0.0052)	(0.0044)
YT	0.0540***	0.0575***	0.0282***	0.0246
	(0.0197)	(0.0182)	(0.0065)	(0.0190)
SIZE	-0.0123**	-0.0060	-0.0033*	-0.0048*
	(0.0054)	(0.0105)	(0.0020)	(0.0026)
MB	0.0166***	0.0136***	-0.0003	-0.0011
	(0.0032)	(0.0044)	(0.0009)	(0.0014)
ROA	0.1218*	0.1315	-0.0493**	-0.0486
	(0.0641)	(0.0877)	(0.0250)	(0.0336)
GAT	0.0762***	0.0812***	0.0498***	0.0465***
	(0.0257)	(0.0289)	(0.0124)	(0.0167)
XFIN	0.9751***	0.8241***	0.3602***	0.3448***
	(0.1418)	(0.2347)	(0.0420)	(0.0833)
OCFV	0.2513***	0.2794**	-0.0034	-0.0026
	(0.0797)	(0.1313)	(0.0328)	(0.0598)
Intercept	0.1777***	0.1627**	0.0534***	0.0654***
	(0.0328)	(0.0648)	(0.0106)	(0.0140)
#obs	2236	2236	2236	2236
Industry FE	No	Yes	No	Yes
R^2	0.1488	0.1296	0.1301	0.1189
Adjusted R^2	0.1454	0.1261	0.1266	0.1154

Table 7 Possible Mechanisms: Information Asymmetry

This table reports the results of the difference-in-difference regressions based on the subsamples partitioned on the number of analysts following a firm. The analyst coverage data is obtained from the Institutional Brokers Estimate System (I/B/E/S) database. For each firm i, we calculate the number of analysts following firm i during fiscal year t. *Low_Analyst* indicates that the number of analysts following the firm is below sample mean and *High_Analyst* presents the group of firms with higher number of analyst. In Panel A, the dependent variable is ARM. In Panel B, the dependent valuable is AAM. *DDL* is a dummy variable equal to one if a firm's stock is in treatment group and zero if in control group. *YT* is a dummy variable equal to one for 2002 (post-decimalization fiscal year) and zero 1999. *DDL*YT* is the interaction term between these two variables. Standard errors are clustered at firm level and are in parentheses. Robust standard errors are shown in parentheses. *** (**) (*) Indicates significance at 1% (5%) (10%) two-tailed level.

Panel A Real Activities Earnings Management

Dependent Variable	ARM			
Subsample	*Low_Analyst*	*High_Analyst*	*Low_Analyst*	*High_Analyst*
	(1)	(2)	(3)	(4)
DDL*YT	-0.1311***	0.0164	-0.1549***	0.0036
	(0.0396)	(0.0347)	(0.0418)	(0.0595)
DDL	0.0145	0.0392	0.0797***	0.0203
	(0.0292)	(0.0243)	(0.0266)	(0.0334)
YT	0.0945***	-0.0259	0.1174**	-0.0139
	(0.0293)	(0.0270)	(0.0445)	(0.0527)
SIZE	0.0197*	-0.0098	0.0192	-0.0033
	(0.0112)	(0.0086)	(0.0170)	(0.0108)
MB	0.0141***	0.0150***	0.0118**	0.0130***
	(0.0048)	(0.0041)	(0.0050)	(0.0032)
ROA	0.1210	0.1863**	0.1676	0.1928**
	(0.0865)	(0.0937)	(0.1460)	(0.0918)
GAT	0.0416	0.0970***	0.0758	0.0925**
	(0.0440)	(0.0316)	(0.0610)	(0.0413)
XFIN	1.0196***	0.9441***	0.8795***	0.7457*
	(0.1784)	(0.2410)	(0.1382)	(0.4181)
OCFV	0.5135***	0.0021	0.5303**	0.0632
	(0.1215)	(0.0964)	(0.2535)	(0.1251)
Intercept	0.0594	0.1509***	0.0455	0.1449
	(0.0546)	(0.0547)	(0.0766)	(0.0888)
#obs	1120	1116	1120	1116
Industry FE	No	No	Yes	Yes
R^2	0.1761	0.1534	0.1735	0.1286
Adjusted R^2	0.1695	0.1465	0.1668	0.1215

Panel B Accrual-based Earnings Management

Dependent Variable	AAM			
Subsample	*Low_Analyst*	*High_Analyst*	*Low_Analyst*	*High_Analyst*
	(1)	(2)	(3)	(4)
DDL*YT	-0.0156	-0.0222*	-0.0170	-0.0172
	(0.0137)	(0.0125)	(0.0141)	(0.0181)
DDL	0.0115	0.0063	0.0168*	0.0025
	(0.0079)	(0.0065)	(0.0086)	(0.0056)
YT	0.0378***	0.0217**	0.0416**	0.0153
	(0.0084)	(0.0103)	(0.0195)	(0.0264)
SIZE	-0.0060*	0.0000	-0.0068	-0.0020
	(0.0033)	(0.0027)	(0.0042)	(0.0036)
MB	-0.0007	0.0008	-0.0015	0.0000
	(0.0014)	(0.0011)	(0.0019)	(0.0012)
ROA	-0.0499	-0.0750**	-0.0492	-0.0752
	(0.0373)	(0.0316)	(0.0403)	(0.0567)
GAT	0.0847***	0.0286**	0.0926***	0.0238

	(0.0222)	(0.0135)	(0.0250)	(0.0263)
XFIN	0.3728***	0.3635***	0.3693***	0.3385***
	(0.0551)	(0.0670)	(0.1036)	(0.0758)
OCFV	-0.1071**	0.0954**	-0.0954*	0.0769
	(0.0452)	(0.0417)	(0.0547)	(0.0884)
Intercept	0.0561***	0.0393***	0.0575***	0.0615***
	(0.0165)	(0.0144)	(0.0188)	(0.0163)
#obs	1120	1116	1120	1116
Industry FE	No	No	Yes	Yes
R^2	0.1461	0.1382	0.1537	0.1109
Adjusted R^2	0.1392	0.1312	0.1468	0.1036

Table 8 Possible Mechanisms: Blockholder Intervention

This table reports the results of the difference-in-difference regressions based on the subsamples partitioned on the blockholder ownership. Blockholder ownership (*BLOCK*) is calculated as the total holding by investors who own no less than 5% of the shares outstanding at the end of each fiscal year. *Low_Block* indicates that the firms' blockholder ownership is below the sample mean and *High_Block* presents the group of firms with above mean blockholder ownership. In Panel A, the dependent variable is ARM. In Panel B, the dependent valuable is AAM. *DDL* is a dummy variable equal to one if a firm's stock is in treatment group and zero if in control group. *YT* is a dummy variable equal to one for 2002 (post-decimalization fiscal year) and zero 1999. *DDL*YT* is the interaction term between these two variables. Standard errors are clustered at firm level and are in parentheses. Robust standard errors are shown in parentheses. *** (**) (*) Indicates significance at 1% (5%) (10%) two-tailed level.

Panel A Real Activities Earnings Management

Dependent Variable	ARM			
Subsample	*Low_Block*	*High_Block*	*Low_Block*	*High_Block*
	(1)	(2)	(3)	(4)
DDL*YT	-0.0828**	-0.0640*	-0.1033*	-0.0514
	(0.0391)	(0.0355)	(0.0552)	(0.0608)
DDL	0.0370	0.0328	0.0687***	0.0270
	(0.0275)	(0.0264)	(0.0239)	(0.0385)
YT	0.0555**	0.0506*	0.0720	0.0352
	(0.0274)	(0.0282)	(0.0479)	(0.0541)
SIZE	-0.0091	-0.0170*	-0.0077	-0.0107
	(0.0069)	(0.0087)	(0.0107)	(0.0122)
MB	0.0137***	0.0204***	0.0123***	0.0151***
	(0.0040)	(0.0051)	(0.0042)	(0.0046)
ROA	0.2469***	-0.0442	0.3025**	-0.0566
	(0.0821)	(0.0990)	(0.1356)	(0.1332)
GAT	0.0664**	0.1098***	0.0792**	0.1058**
	(0.0325)	(0.0425)	(0.0312)	(0.0475)
XFIN	1.1529***	0.7539***	0.9848***	0.6508***
	(0.1777)	(0.2353)	(0.2418)	(0.2025)
OCFV	0.1441	0.2874***	0.2225	0.2891**
	(0.1097)	(0.1082)	(0.1319)	(0.1410)
Intercept	0.1298***	0.2361***	0.1236*	0.2351**
	(0.0425)	(0.0519)	(0.0616)	(0.1025)
#obs	1118	1118	1118	1118
Industry FE	No	No	Yes	Yes
R^2	0.1553	0.1556	0.1579	0.1277
Adjusted R^2	0.1485	0.1488	0.1511	0.1206

Panel B Accrual-based Earnings Management

Dependent Variable	AAM			
Subsample	*Low_Block*	*High_Block*	*Low_Block*	*High_Block*
	(1)	(2)	(3)	(4)
DDL*YT	-0.0233*	-0.0147	-0.0245**	-0.0110
	(0.0141)	(0.0112)	(0.0102)	(0.0116)
DDL	0.0083	0.0043	0.0164**	0.0019
	(0.0080)	(0.0065)	(0.0063)	(0.0078)
YT	0.0325***	0.0239***	0.0328	0.0206
	(0.0096)	(0.0083)	(0.0206)	(0.0217)
SIZE	-0.0045	-0.0013	-0.0033	-0.0040
	(0.0028)	(0.0026)	(0.0033)	(0.0026)
MB	0.0007	-0.0015	-0.0002	-0.0020
	(0.0012)	(0.0011)	(0.0008)	(0.0019)
ROA	-0.0469	-0.0626	-0.0405	-0.0436

	(0.0320)	(0.0389)	(0.0309)	(0.0386)
GAT	0.0318**	0.0781***	0.0284	0.0784***
	(0.0140)	(0.0232)	(0.0256)	(0.0136)
XFIN	0.3442***	0.3644***	0.3155***	0.3479**
	(0.0531)	(0.0749)	(0.0929)	(0.1121)
OCFV	0.0656	-0.0664	0.0616	-0.0666
	(0.0509)	(0.0420)	(0.0770)	(0.0444)
Intercept	0.0605***	0.0447***	0.0572***	0.0615***
	(0.0141)	(0.0151)	(0.0139)	(0.0178)
#obs	1118	1118	1118	1118
Industry FE	No	No	Yes	Yes
R^2	0.1382	0.1191	0.1054	0.1093
Adjusted R^2	0.1312	0.1119	0.0981	0.1021

Table 9 Possible Mechanisms: Dividend Signaling

This table reports the results of the difference-in-difference regressions based on the subsamples partitioned on whether the firm pays dividend. A firm is defined as a dividend payer in fiscal year t if the firm has paid positive ordinary cash dividends (distribution codes between 1200 and 1299) for that fiscal year. Among the matched sample, there are 358 dividend-paying firms and 1,878 non-dividend-paying firms. In Panel A, the dependent variable is ARM. In Panel B, the dependent valuable is AAM. *DDL* is a dummy variable equal to one if a firm's stock is in treatment group and zero if in control group. *YT* is a dummy variable equal to one for 2002 (post-decimalization fiscal year) and zero 1999. *DDL*YT* is the interaction term between these two variables. Standard errors are clustered at firm level and are in parentheses. Robust standard errors are shown in parentheses. *** (**) (*) Indicates significance at 1% (5%) (10%) two-tailed level.

Panel A Real Activities Earnings Management

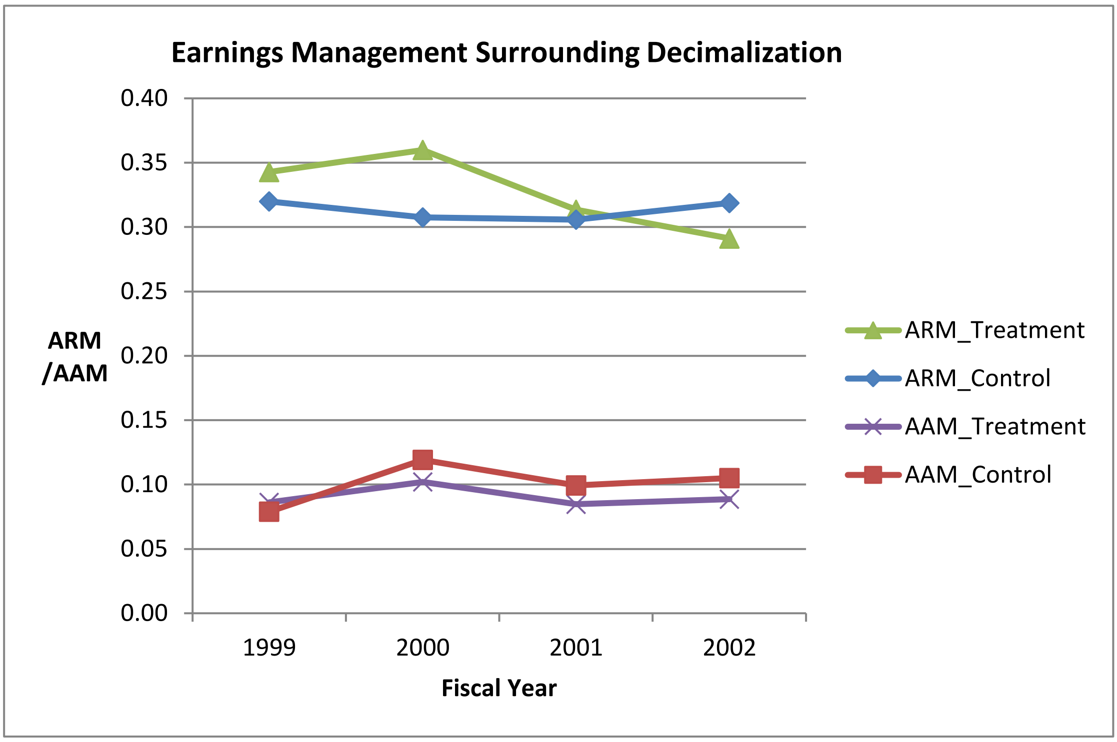
Dependent Variable	ARM			
Subsample	*No Dividend*	*Dividend*	*No Dividend*	*Dividend*
	(1)	(2)	(3)	(4)
DDL*YT	-0.0786***	-0.0038	-0.0871***	-0.0109
	(0.0292)	(0.0579)	(0.0241)	(0.0371)
DDL	0.0197	0.0744**	0.0363	0.0504
	(0.0216)	(0.0344)	(0.0287)	(0.0434)
YT	0.0565***	0.0099	0.0646***	0.0114
	(0.0215)	(0.0493)	(0.0198)	(0.0311)
SIZE	-0.0102*	-0.0189	-0.0058	-0.0121
	(0.0057)	(0.0139)	(0.0110)	(0.0134)
MB	0.0153***	0.0214	0.0130***	0.0117
	(0.0033)	(0.0137)	(0.0046)	(0.0178)
ROA	0.1203*	0.2494	0.1454	0.2330
	(0.0676)	(0.1914)	(0.1015)	(0.2308)
GAT	0.0893***	-0.0152	0.0887***	0.0057
	(0.0281)	(0.0329)	(0.0281)	(0.0475)
XFIN	0.9873***	0.3140	0.8319***	0.8075
	(0.1458)	(0.4158)	(0.2492)	(0.5293)
OCFV	0.2824***	0.0424	0.3145**	0.1415
	(0.0889)	(0.1133)	(0.1459)	(0.1138)
Intercept	0.1757***	0.1951**	0.1665**	0.1620*
	(0.0345)	(0.0817)	(0.0667)	(0.0951)
#obs	1878	358	1878	358
Industry FE	No	No	Yes	Yes
R^2	0.1551	0.0698	0.1389	0.0461
Adjusted R^2	0.1510	0.0457	0.1348	0.0214

Panel B Accrual-based Earnings Management

Dependent Variable	AAM			
Subsample	*No Dividend*	*Dividend*	*No Dividend*	*Dividend*
	(1)	(2)	(3)	(4)
DDL*YT	-0.0254**	0.0075	-0.0217***	0.0079
	(0.0103)	(0.0117)	(0.0074)	(0.0112)
DDL	0.0111*	-0.0037	0.0118**	-0.0049
	(0.0061)	(0.0072)	(0.0048)	(0.0086)
YT	0.0329***	-0.0039	0.0287	-0.0041
	(0.0073)	(0.0099)	(0.0214)	(0.0136)
SIZE	-0.0018	-0.0083**	-0.0043	-0.0094**
	(0.0023)	(0.0032)	(0.0032)	(0.0042)
MB	-0.0006	0.0050**	-0.0013	0.0038*
	(0.0010)	(0.0020)	(0.0015)	(0.0022)
ROA	-0.0438	-0.2041***	-0.0467	-0.1770**

	(0.0267)	(0.0633)	(0.0363)	(0.0715)
GAT	0.0501***	0.0447**	0.0495**	0.0421*
	(0.0137)	(0.0174)	(0.0181)	(0.0227)
XFIN	0.3518***	0.2587**	0.3407***	0.2500
	(0.0441)	(0.1040)	(0.0882)	(0.1577)
OCFV	-0.0038	-0.0019	0.0002	-0.0096
	(0.0365)	(0.0457)	(0.0691)	(0.0511)
Intercept	0.0477***	0.1011***	0.0641***	0.1071***
	(0.0114)	(0.0244)	(0.0171)	(0.0293)
#obs	1878	358	1878	358
Industry FE	No	No	Yes	Yes
R^2	0.1145	0.1651	0.1117	0.1432
Adjusted R^2	0.1103	0.1436	0.1075	0.1211

Figure 1: Earnings Management Surrounding Decimalization



This figure shows the average ARM and AAM for treatment and control firms, from fiscal year 1999 (Pre-decimalization) to 2002 (Post-decimalization). The matched sample contains 559 pairs of treatment and control firms.