Does Earnings Quality Affect Information Asymmetry? Evidence from Trading Costs*

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1. Introduction

A fundamental role of accounting information in financial markets is to serve as a basis for capital allocation. An important attribute of the quality of accounting information is the extent to which earnings (accruals) map into cash flows. A poor mapping of accruals into cash flows reduces the information content of reported earnings and results in lower-quality earnings. If investors differ in their ability to process earnings related information, then poor earnings quality can result in differentially informed investors and thereby exacerbate the information asymmetry in financial markets (Diamond and Verrecchia 1991; Kim and Verrecchia 1994). Analytical models (e.g., Kyle 1985; Glosten and Milgrom 1985) predict that differential information among market participants increases the adverse selection risk for liquidity providers. In response, liquidity providers demand a larger compensation and widen the spread between the bid and the ask prices, thereby lowering liquidity and increasing the cost of capital.[1]

Consequently, the determinants and consequences of earnings quality are of interest to investors, managers, regulators, and standard-setters. The linkages discussed above are best summarized by the words of Arthur Levitt, former Chairman of the Securities and Exchange Commission (SEC), "an important benefit of high quality accounting standards is improved liquidity and lower cost of capital."[2] A notion implicit in this remark is that regulators and standard-setters view the reduction in information asymmetry to be an important benefit of improved earnings quality. In this study, we examine whether poor earnings quality is associated with higher information asymmetry in capital markets.

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1. The linkage between liquidity and the cost of capital is well established. Amihud and Mendelson (1986) and Brennan and Subrahmanyam (1996), among others, document the cross-sectional association between liquidity costs and expected returns. Using an event study methodology, Amihud et al. (1997) and Venkataraman and Waisburd (2007) show that the improvements in market structure (i.e., improvements in liquidity) are associated with positive abnormal returns around the event.
2. The remarks are excerpted from the speech given by Arthur Levitt to the Inter-American Development Bank on September 29, 1997.

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Using an accruals-based measure of earnings quality (Francis, LaFond, Olsson, and Schipper 2005) (FLOS) and a market microstructure based measure of information asymmetry (the price impact of trade), we test for the association between earnings quality and information asymmetry for a large sample of NYSE and NASDAQ firms over the period 1998–2007. We find that poor earnings quality is significantly and incrementally (i.e., over and above a well-established benchmark model of trading costs) associated with higher information asymmetry. We further investigate whether the negative effects on information asymmetry are more pronounced for certain types of firms than others. We find that poor earnings quality has a more pronounced impact on firms operating in a poor information environment, such as small firms and those with low institutional ownership and low analyst following. Specifically, the magnitude of the association between earnings quality and information asymmetry is estimated to be more than twice as large for small firms as compared to large firms.

The extent to which a firm's earnings (accruals) map into cash flows is affected by its operating environment and the business model (innate factors) as well as by discretionary reporting choices made by the managers (discretionary factors). To assess the relative contribution of each of the above factors to information asymmetry, we decompose the earnings (accruals) quality measure into an innate component and a discretionary component following the approach in FLOS. We find that the innate component has a significant incremental impact on information asymmetry, suggesting that informed investors have a greater advantage in firms that are operating in uncertain and volatile environments. Furthermore, both extreme positive and extreme negative discretionary accruals increase information asymmetry. The latter result suggests that discretionary choices made by managers that cause accruals to map "too well" into cash flows relative to other firms in the same industry can befuddle investors and contribute to information asymmetry.

In order to account for omitted firm characteristics that may simultaneously affect information asymmetry and earnings quality, we employ a two-stage instrumental variable (IV) approach. We continue to find a significant association between the earnings quality instrument and information asymmetry in the IV regressions. We also implement an event study approach to examine whether poor earnings quality exacerbates information asymmetry around earnings releases (see Lee, Mucklow, and Ready 1993). The event study design helps address possible endogeneity concerns because each firm serves as its own control and hence mitigates the concern that the association between earnings quality and information asymmetry is due to omitted firm characteristics. Our results suggest that poor earnings quality is associated not only with information asymmetry during non-event periods but also with the increase in information asymmetry around earnings releases.

Our study contributes to the literature along several dimensions. Prior studies examining the association between disclosure quality and information asymmetry are based on small samples because the disclosure measure is either self-constructed (Botosan 1997) or based on AIMR disclosure scores (e.g., Welker 1995; Healy, Hutton, and Palepu 1999; Heflin, Shaw, and Wild 2005). Because AIMR scores are available only for large firms with significant analyst following, it is unclear how a firm's information environment affects the relation between earnings quality and information asymmetry. Moreover, AIMR scores are not available after 1996. The last two decades have witnessed the enactment of several major regulations including Regulation Fair Disclosure, SEC Staff Accounting Bulletin 101 and the Sarbanes-Oxley Act. These regulations have been enacted with the intended effect of improving earnings quality and leveling the informational playing field for market participants.

However, recent research (Campbell, Lettau, Malkiel, and Xu 2001) finds that idiosyncratic volatility has increased in recent years. Rajgopal and Venkatachalam (2011) show that reduced earnings quality is associated with increased firm-level volatility. Furthermore, Fama and French (2004) and Klein and Mohanram (2006) document an increased incidence of younger and less profitable firms going public in recent years. These developments are likely to adversely affect the earnings quality of public firms and increase the information advantage of sophisticated investors, thereby exacerbating information asymmetry. Consequently, it is important to understand the extent to which earnings quality influences information asymmetry in recent time periods. Our study, based on a larger and more representative sample over a recent period, is timely and relevant for regulators and market participants.

Moreover, there is significant controversy in the literature regarding the underlying mechanism through which earnings quality affects cost of capital. FLOS argue that accruals quality is an important source of nondiversifiable ''information risk'' (Easley and O'Hara 2004). However, Core, Guay, and Verdi (2008) show that the pricing effect of accruals/earnings quality documented in FLOS is not robust. Our study contributes to this debate by examining whether earnings quality affects the cost of capital via its impact on trading costs. As discussed earlier, this linkage relies on the well documented relation from the market microstructure literature that (a) information asymmetry increases liquidity cost (Glosten and Milgrom 1985) and (b) liquidity is priced as investors maximize expected returns, net of liquidity costs (Amihud and Mendelson 1986, among others). Thus, notwithstanding the debate on whether information risk is diversifiable, our evidence suggests that poor earnings quality increases the cost of capital via its impact on market liquidity.

Our study also provides empirical support for predictions from recent theoretical work. Lambert and Verrecchia (2011) argue that the adverse consequences of information asymmetry are inversely related to the degree of investor competition in a stock. We find that the association between earnings quality and information asymmetry is more pronounced for small firms and firms with low institutional ownership. Such firms are likely to be characterized by imperfect competition among investors in that sophisticated investors are likely to have a greater informational advantage over liquidity-motivated traders. Our results provide indirect empirical support for these theoretical predictions and identify certain types of firms (e.g, small firms) and information events (e.g., earnings announcements) where earnings quality has a disproportionate adverse effect on information asymmetry. These findings are important because the value of liquidity provision is much greater for smaller firms and during periods surrounding the release of fundamental information due to the elevated level of uncertainty (see Kaniel, Liu, Saar, and Titman forthcoming for recent evidence).

We note that the information asymmetry proxy used by the study, the price impact of trade, is a direct measure of the adverse selection risk faced by liquidity providers as reflected in trading costs. Kyle (1985) and Glosten and Milgrom (1985) provide theoretical support for this measure based on the adverse information conveyed by a trade, while Brennan and Subrahmanyam (1996) document that adverse information, as measured by the price impact of trade, affects asset prices. The price impact measure is also widely used in the empirical market microstructure literature (see Huang and Stoll 1996; Bessembinder and Kaufman 1997) as well as by regulators.[3] This measure more reliably reflects adverse selection risk than other commonly used proxies such as bid-ask spreads and the Probability of Information-based Trading (PIN) developed by Easley, Hvidkjaer, and O'Hara 2002.[4]

3. Since September 2001, the SEC has required each U.S. stock ''market center'' to compile and disseminate, on a monthly basis, various standardized measures of execution quality to provide traders with information on the execution quality of their trades (SEC Rule 605, formerly 11Ac1-5). These measures include the effective spread and the price impact of trade metrics (Boehmer 2005).

4. Evidence in recent studies (Duarte and Young 2009; Mohanram and Rajgopal 2009) raises doubts regarding the ability of the PIN measure to capture information risk that is priced by investors. A limitation of bid-ask spreads as a proxy for information asymmetry is that it captures both information and non-information (e.g., inventory risk) components of liquidity provision.

The rest of the paper is organized as follows. Section 2 discusses the background literature and develops the study's testable hypothesis. Section 3 describes the empirical proxies of earnings quality and information asymmetry, and also presents the study's research design. Section 4 describes our data and our sample. The empirical results are reported in Section 5. Section 6 provides concluding remarks.

2. Prior literature and hypothesis development

Literature on disclosure quality and information asymmetry

Theoretical models (e.g., Diamond 1985; Diamond and Verrecchia 1991) predict that higher-quality disclosures lower information asymmetry between market participants, and as a result reduce the cost of capital. Welker (1995) is the first empirical study to document an inverse association between disclosure quality and bid-ask spreads. Heflin et al. (2005) also find that higher-quality disclosures are associated with greater liquidity using AIMR scores as a proxy for disclosure and trading costs as a proxy for information asymmetry. In a recent study, Brown and Hillegeist (2007) find an association between disclosure quality (based on AIMR scores) and the probability of informed trade (PIN) measure.

Healy et al. (1999) and Leuz and Verrechia (2000) adopt a time series approach to examine the association between disclosure quality and information asymmetry. Healy et al. (1999) examine firms with sustained improvements in disclosure quality (using AIMR scores) and document capital market benefits such as improved stock performance, improved liquidity and greater analyst following. Leuz and Verrecchia (2000) document that the improved disclosure standards for a sample of German firms that switch from German GAAP to either U.S. GAAP or International Accounting Standards (IAS) are associated with lower bid-ask spreads.[5]

In summary, extant research indicates that a firm's overall disclosure quality is associated with information asymmetry. However, it is difficult to reliably infer the association between earnings quality and information asymmetry from research that primarily examines a firm's overall disclosure quality. A firm's overall disclosure quality is a nebulous construct because a firm has numerous financial and nonfinancial attributes, and extant proxies of disclosure quality aggregate these attributes in an ad hoc fashion because there is no theoretical guidance on how to compute a composite metric. Neither theoretical models nor empirical studies establish that firms' overall disclosure quality and accrual-based earnings quality are close substitutes, although it is likely that the two constructs are positively related.[6] In this study, we undertake a focused examination of an important component of a firm's overall disclosure quality, namely accruals-based earnings quality.

Moreover, accruals-based measures of earnings quality can be constructed for a broad cross-section of firms and can easily be updated for more recent sample periods. In contrast, AIMR scores are available for a very small and select subset of firms (generally large firms with significant analyst following), and these scores are not available after 1996. For these reasons, we believe that prior research on the relation between overall disclosure quality and information asymmetry does not preempt an inquiry on the association between earnings quality and information asymmetry.

5. Note, however, that firms that voluntarily adopt either IAS or U.S. GAAP also simultaneously cross-list on foreign exchanges. Lang, Lins, and Miller (2003) show that analyst following increases when foreign firms cross-list on the NYSE. Therefore, cross-listing can lead to informational effects that are unrelated to improved disclosure.
6. See, for example, Verrecchia 1990, Tasker 1998, and Francis, Nanda, and Olsson 2008.

Literature on various earnings attributes and information asymmetry

Our study contributes to a small but growing literature on the linkage between various earnings attributes and the liquidity cost in financial markets. Affleck-Graves, Callahan, and Chipalkatti (2002) document that firms with less predictable earnings, measured as the higher dispersion in analysts' forecasts, have higher bid-ask spreads. However, forecast dispersion is not an attribute of accounting information but rather an outcome of financial reporting quality.

In a recent study, Jayaraman (2008) documents an association between accruals volatility and bid-ask spreads and PIN. Our study differs from Jayaraman 2008 in important ways. We examine a number of issues related to the association between earnings quality and information asymmetry that Jayaraman 2008 does not. Specifically, we examine the impact of two key determinants of earnings quality — innate factors and discretionary factors — and document that the impact of the two factors on information asymmetry is different. These results should be of interest to corporate managers who have greater control over the latter but not the former, at least in the short run. We also document cross-sectional differences in the association between earnings quality and information asymmetry based on the firm's information environment, which provides empirical support for recent theoretical work. Furthermore, we show that poor earnings quality is associated not only with information asymmetry during non–earnings-release days, but also contributes to the increase in adverse selection risk around the time of earnings releases.[7]

Testable hypothesis

Evidence in Sloan 1996 suggests that earnings of firms with large accruals are mean reverting but that the marginal investor fails to fully incorporate this information into prices resulting in these firms being overpriced. Recent research also suggests that sophisticated investors (e.g., short sellers) can discern that the reported earnings of firms with high accruals are not sustainable and assume short positions to arbitrage the overpricing (Desai, Krishnamurthy, and Venkataraman 2006; Hirshleifer, Teoh, and Yu forthcoming). An implication of the above evidence is that informed traders are sensitive to the quality of reported earnings, which is consistent with the models in Diamond 1985 and Diamond and Verrecchia 1991. If investors differ in their ability to process earnings-related information, poor earnings quality can contribute to the information asymmetry among market participants. We formalize our expectation in the form of the following hypothesis:

HYPOTHESIS 1. *Poor earnings quality is associated with higher information asymmetry.*

3. Empirical proxies and research design

Measures of information asymmetry

We measure information asymmetry as reflected in the adverse selection component of the trading cost (see Stoll 2000 for a review of this literature). The adverse selection component of trading cost compensates the market maker for the risk of losing money to informed traders. The intuition for the measure is as follows. The market maker expects informed traders to submit buy market orders before periods of good news and sell

7. In a recent study, Bhattacharya, Ecker, Olsson, and Schipper (2012) (BEOS) use an econometric technique called *path analysis* to investigate the relative strengths of the various linkages between earnings quality and the cost of equity. However, path analysis does not, in and of itself, determine causality. Rather, researchers have to rely on extant theoretical and empirical research to establish, ex ante, the various causal links among variables of interest. BEOS rely on the evidence in our study to posit a link between earnings quality and cost of equity that is mediated by information asymmetry.

market orders before periods of bad news. Assuming that uninformed (liquidity) traders are equally likely to submit buy and sell orders, the order flow imbalance of liquidity demanders will tend to be positive (buys exceed sells) when the security is undervalued and negative (sells exceed buys) when the security is overvalued. The market maker incorporates the information observed from order flow by adjusting quotes upward (downward) when the imbalance is positive (negative). The magnitude of the quote adjustments reflects the market maker's interpretation of the order imbalance signal. It reflects both the market maker's assessment of the proportion of informed traders vs. liquidity traders and the extent of superior information about security value held by the informed traders.

To capture the adverse selection risk perceived by the market makers, we estimate the *percentage price impact*, proposed by Huang and Stoll 1996:

$$\textit{Percentage price impact} = 2 \times D_{it} \times (V_{i,t+30} - Mid_{it})/Mid_{it} \times 100 \qquad (1),$$

where:

$V_{i,t+30}$ = Measure of the economic value of the asset after the trade proxied by the mid-point of the first quote reported at least 30 minutes after the transaction.

Mid_{it} = The mid-point of the quoted ask and bid prices immediately prior to the transaction at time t.

D_{it} = A binary variable that equals 1 for market buy orders and −1 for market sell orders.[8]

The *percentage price impact* measure is a direct measure of information asymmetry as it captures the magnitude of market makers' quote revisions following market orders.[9] Note that D_{it} serves to convert price movements associated with market sell orders (where, on average, we expect $V_{i,t+30}$ to be below Mid_{it}) into a positive number, while the multiplication by 2 accounts for information-related trading cost for a round trip trade.

As an alternative measure, we estimate the percentage effective spread, a widely used measure of trading costs. The effective spread captures both the non-informational (inventory costs, order processing costs, and possibly market maker rents) and informational (adverse selection) costs of liquidity provision and is estimated as follows:

$$\textit{Percentage effective spread} = 2 \times D_{it} \times (Price_{it} - Mid_{it})/Mid_{it} \times 100 \qquad (2),$$

where $Price_{it}$ is the price at which the transaction takes place at time t for security i. In estimating the measures, we follow the approach recommended by Bessembinder 2003a for recent data from NYSE and NASDAQ, which modifies the approach proposed by Lee and Ready 1991.

Measures of earnings quality

Our primary measure of earnings quality is the modified Dechow and Dichev 2002 (DD) model used in FLOS. The DD measure is based on the extent to which working capital accruals map into realized cash flows from operations. The model relies on the intuition

8. Extant research also considers various time horizons (from 5 minutes up to 30 minutes) to estimate an asset's post-trade economic value. Werner (2004) reports that spread measures obtained in large samples are relatively insensitive to the choice of the post-trade benchmark. For trades in the last half-hour of trading, we use the 4 p.m. quotation mid-point, following Bessembinder 2003a. To control for the effect of intervening trades, we construct an alternative price impact measure following Venkataraman 2001 that weighs each trade by the inverse of the number of transactions in 30 minutes. The conclusions based on the alternative measure are unchanged.
9. The *price impact of trade* has been used extensively in empirical market microstructure literature to quantify information asymmetry (see, e.g., Bessembinder and Kaufman 1997; Stoll 2000; Venkataraman 2001). Also, as mentioned earlier in footnote 5, this measure is used by the SEC to assess execution quality of trades at each U.S. stock "market center" under SEC Rule 605.

that accruals involve estimates of cash flow and that estimates are likely to contain measurement errors, either intentional or otherwise. As per DD, the higher the magnitude of the estimation error, the lower the quality of reported earnings, ceteris paribus. The specification in FLOS, based on modifications to the DD model suggested by McNichols 2002, is as follows:

$$TCA_{j,t} = \beta_{0j} + \beta_1 * CFO_{j,t-1} + \beta_2 * CFO_{j,t} + \beta_3 * CFO_{j,t+1} + \beta_4 * \Delta REV_{j,t} + \beta_5 * PPE_{j,t} + \upsilon_{j,t} \quad (3),$$

where:

$TCA_{j,t}$ = Total current accruals for firm *j* in year *t*.
CFO = Cash flow from operations (COMPUSTAT annual item 308).
$\Delta REV_{j,t}$ = Change in net sales from $t - 1$ to t (COMPUSTAT annual item 12).
$PPE_{j,t}$ = Gross property, plant and equipment in year *t* (COMPUSTAT annual item 7).

TCA is computed as (ΔCA – ΔCL – $\Delta Cash$ + $\Delta STDEBT$) where ΔCA is the change in current assets (COMPUSTAT annual item 4), ΔCL is the change in current liabilities (COMPUSTAT annual item 5), $\Delta Cash$ is the change in cash (COMPUSTAT annual item 162), and $\Delta STDEBT$ is the change in debt in current liabilities (COMPUSTAT annual item 34).

(3) is estimated separately for each industry group based on the 2-digit SIC code in a given year. The industry-specific cross-sectional regressions in a given year generate firm-specific residuals for that year. The standard deviation of firm *j*'s residuals, $\upsilon_{j,t}$, calculated over years $t - 5$ through $t - 1$, serves as our primary measure of earnings quality (hereafter, the FLOS EQ measure). In this formulation, the higher FLOS EQ measure (higher standard deviation) denotes lower earnings quality.

We recognize that the FLOS EQ measure has some limitations. In particular, it contains measurement errors due to omission of firm characteristics; it imposes a survivorship bias; and the estimation assumes that the firm level parameters remain constant over time (see Dechow, Ge, and Schrand 2010). We therefore replicate our primary analysis using two additional measures — the coefficient on the accruals quality factor-mimicking portfolio (e-loading) developed in Ecker, Francis, Kim, Olsson, and Schipper 2006 and the magnitude of industry-adjusted operating accruals scaled by total assets (OPACCIND). Ecker et al. (2006) show that e-loading is positively and significantly correlated with other proxies of earnings quality.[10] The motivation for using operating accruals as a proxy for earnings quality is from Sloan 1996, who shows that earnings of firms with extreme values of accruals are not sustainable. We calculate the operating accruals (OPACC) for a firm as:

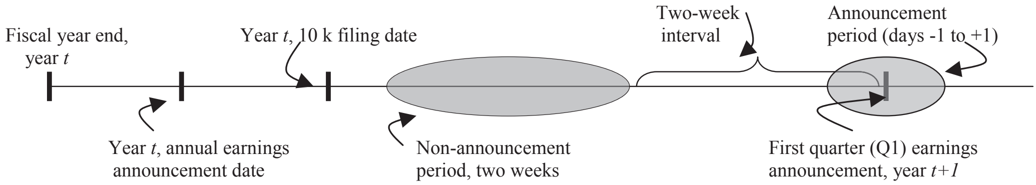
$$OPACC = (Earnings - CFO)/(AverageAssets) \quad (4),$$

where:

Earnings = Income before extraordinary items (COMPUSTAT annual data item 18).
CFO = Cash flow from operations from the statement of cash flows.
AverageAssets = Mean of beginning and ending total assets (COMPUSTAT annual data item 6).

10. E-loading is the coefficient on the accrual quality (AQ) mimicking factor portfolio in a four-factor Fama and French 1993 regression that also includes the market factor (RM-RF), the size factor (SMB) and the book-to-market factor (HML). The e-loading can thus be interpreted as the firm's exposure to earnings quality. This procedure is described in detail in Ecker et al. 2006; we thank Frank Ecker for providing the factor values.

Figure 1 Time line of events



To control for the systematic differences in the magnitude of accruals across industries, we calculate industry-adjusted operating accruals for each firm (OPACCIND), defined as the difference between the firm-specific OPACC and the median OPACC for firms in the same 2-digit SIC code. Because firms with extreme positive and negative OPACCIND values (i.e., extreme departures from industry medians) are considered to have poor earnings quality, we use the absolute value of OPACCIND in our analysis.[11]

Research design

We examine the association between earnings quality and information asymmetry during non-earnings announcement periods. As an additional test, we examine whether earnings quality is associated with the increase in adverse selection risk around earnings releases. In the latter analysis, the firm acts as its own control and therefore mitigates the concern that any omitted firm-specific determinants of earnings quality could be driving the association between earnings quality and information asymmetry. Figure 1 illustrates our research design. The earnings announcement period is a 3-day window (days –1 through +1) centered on the first-quarter (Q1) earnings announcement date of year $t + 1$. The non-announcement period is a two-week window (10 trading days) ending exactly two weeks prior to the Q1 earnings announcement of year $t + 1$. This design ensures that, for the vast majority of sample observations, the information contained in annual reports and 10-K filings for the year t is publicly available to market participants when information asymmetry is estimated prior to or around year $t + 1$ first-quarter (Q1) earnings announcements. Specifically, the earnings quality measures are estimated using fiscal year-end data of year t, while we investigate information asymmetry before and surrounding the firm's Q1 earnings announcement of year $t + 1$. For example, information asymmetry surrounding Q1 earnings announcement of 1998 is paired with FLOS EQ measure as of 1997, which in turn is computed using COMPUSTAT financial statement data over 1991 through 1997.[12] Our conclusions are unchanged when information asymmetry is examined before and surrounding the firm's Q2 earnings announcement of year $t + 1$.

4. Data and sample selection

The initial sample consists of all NYSE and NASDAQ firms with available data on the CRSP, COMPUSTAT, and Trades and Quotes (TAQ) databases. The earnings quality measures are based on firm-year observations obtained from COMPUSTAT annual tapes

11. Apart from the above proxies of earnings quality, we have replicated our analyses using the DD measure and reach similar conclusions. These results are not tabulated but available from the authors on request.
12. As described earlier, FLOS EQ measure in year t is based on the standard deviation of the firm's residuals from annual industry-level regressions over the years $t - 5$ through $t - 1$. Thus, FLOS EQ as of 1997 is based on the standard deviation of firm-specific residuals from five annual industry-level regressions over the years 1992 to 1996. Note that, because the industry-level regression (3) for year t requires CFO for years $t - 1$, t and $t + 1$, financial statement data from 1991 to 1997 are required to estimate the five annual regressions for the years 1992 to 1996.

for the years 1997 through 2006. The first-quarter (Q1) earnings announcement dates are obtained from COMPUSTAT quarterly tapes for the years 1998 through 2007.[13] Firms on both NYSE and NASDAQ experienced a significant decline in tick size due to decimalization in 2001 (see Bessembinder 2003b). We eliminate the year 2001 to avoid problems arising from comparing non-announcement and announcement periods in different tick size regimes. We use several filters to eliminate trades and quotes obtained from the TAQ database that are nonstandard or are likely to contain errors.[14] Further, in order to avoid drawing inferences using estimates based on a small number of transactions in thinly traded issues, we eliminate firm-years with less than 50 trades during the two-week non-announcement period, or less than 20 trades during the three-day announcement period.

The sample firms also meet the following selection criteria: (a) the stock is not listed as an American Depository Receipt (ADR), close-end investment fund, or real estate investment trust (REIT); (b) the firm has total assets that equal or exceed \$1 million; (c) the firm does not belong to the financial or utilities industry; (d) the firm belongs to a two-digit SIC code with at least 20 observations; (e) the stock has a market price greater than \$5;[15] (f) the firm has all the necessary COMPUSTAT data for calculating earnings quality measures. The final sample for the primary analyses contains 14,389 firm-years.

5. Empirical results

Descriptive statistics

Table 1 reports descriptive statistics for the sample firms. Panels A and B report descriptive statistics for select financial statement variables and the earnings quality measure, FLOS EQ. Panel A shows that, although the average assets and net revenues are large, there is significant skewness in their distributions, likely due to the inclusion of relatively small NASDAQ firms in the sample.[16] Mean and median operating accruals are negative, consistent with prior research. Panel B shows that the mean (median) value of the earnings quality measure, FLOS EQ, is 15.1 percent (7.7 percent). The mean of FLOS EQ is higher than the corresponding number reported in FLOS, which can be partly attributed to the observed trend of increased volatility of earnings beginning in the late 1980s (e.g., Givoly and Hayn 2000). Panel C reports descriptive statistics on firm characteristics, including trading activity. As expected, market capitalization and trading volume are highly skewed as the mean is much larger than the median.

Panels D and E report descriptive statistics on trading cost metrics — effective spreads and price impact of trade — on earnings announcement (TC_{ANN}) and non-announcement days (TC_{NONANN}). Prior research finds that information asymmetry increases and liquidity deteriorates around earnings announcement (Lee et al. 1993).

13. Sample coverage described above is based on COMPUSTAT's fiscal-year convention which is often different from the actual calendar year of a company's accounting period end.
14. Trades are omitted if they are out of time sequence, are coded as an error or cancellation, involve a non-standard settlement, are exchange acquisitions or distributions, have negative trade prices or involve a price change (since the prior trade) greater than 10 percent in absolute value. Quotes are deleted if the bid or ask is nonpositive, the bid-ask spread is negative, the change in the bid or ask price is greater than 10 percent in absolute value, the bid or ask depth is nonpositive, or the quotes are disseminated during a trading halt or during a delayed opening.
15. The conclusions are unchanged when we screen stocks based on price being greater than \$10 or less than \$500.
16. To mitigate the effects of outliers and data errors, all variables are winzorized at the 1 percent and 99 percent levels. The conclusions are unchanged if variables are winzorized at the 0.5 percent and 99.5 percent level, or no winzorization is implemented.

Consistent with earlier research, we find that both the effective spread and the price impact of trade increase around earnings announcements (significant at the 1 percent level). However, the percentage increase in price impact (panel E) surrounding earnings announcements is appreciably larger than the percentage increase in effective spread (panel D). This is because the effective spread can change over time for reasons unrelated to information risk whereas the price impact of trade is a direct measure of the adverse selection risk faced by liquidity providers as reflected in trading costs. For this reason, all the tabulated results in the study are based on the price impact of trade as the proxy for information asymmetry.

Univariate analysis of information asymmetry by earnings quality groups

We begin the empirical investigation with an univariate analysis of the association between earnings quality and information asymmetry. The sample firms are placed in quintiles based on the magnitude of FLOS EQ each year. We define five indicator variables, G1 through G5, based on the quintile ranking of FLOS EQ. Specifically, the indicator variable G1 equals one for firms in Quintile 1 (the group with smallest FLOS EQ) and equals

TABLE 1
Descriptive statistics for sample firms

	Mean	**Median**
Panel A: Financial statement variables		
Average assets (Millions)	2,260	376
Net revenue (Millions)	2,233	387
Gross property, plant and equipment (Millions)	1,413	145
Return on assets (ROA)	0.9%	4.6%
Cash flow from operations over total assets	0.07	0.09
Operating accruals over total assets	−0.07	−0.05
Annual earnings per share before extraordinary items	0.59	0.62
Absolute unexpected first-quarter earnings (random-walk)	0.21	0.10
Panel B: Earnings quality		
FLOS EQ measure	15.1%	7.7%
Adjusted R^2 values from FLOS industry-specific regressions	38.1%	34.3%
Panel C: Firm characteristics		
Stock price	35.8	26.5
Return volatility	2.9	2.2
Market capitalization (Millions)	3,492	467
Daily Trading Volume (Thousands)	5,680	1,520
Average trade size	771	527
Panel D: Percentage effective spread		
Average non-announcement period (TC_{NONANN})	0.6992	0.3268
Average announcement period (TC_{ANN})	0.7150	0.3330
Percentage increase around earnings announcements	2.26%	1.90%
Panel E: Price impact of trade		
Average non-announcement period (TC_{NONANN})	0.4085	0.2246
Average announcement period (TC_{ANN})	0.4447	0.2339
Percentage increase around earnings announcements	8.86%	4.14%

(The table is continued on the next page.)

TABLE 1 (Continued)

Notes:

The table presents the descriptive statistics on our final sample of 14,389 firm-years. The financial statements data reported in panel A are obtained from COMPUSTAT, as follows: book value of assets (annual data 6), revenues (annual data 12), property plant and equipment (annual data 7), annual and quarterly diluted earnings per share before extraordinary items (annual data 18 and quarterly data 9) and cash flow from operations (annual data 308). Absolute first-quarter (Q1) random-walk earnings surprise is computed as the absolute value of the first quarter (Q1) EPS for year t minus the Q1 EPS for year $t - 1$. Earnings quality in panel B, FLOS EQ, is the accruals quality measure proposed in Francis et al. 2005. Panel C reports firm characteristics and trading activity. The mean and median stock price, return volatility, market capitalization (millions), average trade size (shares) and cumulative number of trades (shares) values are obtained from Trade and Quote (TAQ) database. Market capitalization, stock price, trading volume and return volatility are measured over the non-announcement period. The non-announcement window is a two-week period (10 trading days) ending exactly two weeks prior to earnings announcement date. Panel D reports effective spreads while panel E reports price impact of trade during earnings announcement windows (TC_{ANN}) and non-announcement windows (TC_{NONANN}) estimated from the TAQ data. Announcement window is defined as days –1 to +1 surrounding earnings announcement date. The price impact of trade is computed as $[2 \times D_{it} \times (V_{i,\ t+30} - Mid_{it}) / Mid_{it} \times 100]$, where $V_{i,\ t+30}$ is the mid-point of the quote observed 30 minutes after the trade, Mid_{it} is the quote mid-point for firm i at time t, and D is an indicator variable that equals 1 for a market buy and -1 for a market sell. The effective spread is computed as $[2 \times D_{it} \times (Price_{it} - Mid_{it}) / Mid_{it} \times 100]$ where $Price_{it}$ is the transaction at time t for security i. The effective spreads and price impact of trade is estimated using the approach outlined in Huang and Stoll 1996.

zero otherwise, while G5 equals one for firms in Quintile 5 and equals zero otherwise. Because higher values of FLOS EQ denote lower quality, Hypothesis 1 predicts a steady increase in the price impact of trade from Quintile 1 to Quintile 5.

Panel A of Table 2 reports coefficients from a regression of price impact on the five FLOS EQ indicator variables and a decimal indicator variable that equals one during the period after decimalization and equals zero otherwise.[17] Consistent with Bessembinder 2003b we find that decimalization has reduced the price impact of trade. Consistent with Hypothesis 1, we observe a monotonic increase in the price impact of trade from Quintile 1 to Quintile 5. For example, the price impact of trade increases from 0.47 percent in Quintile 1 to 0.65 percent in Quintile 5. We find that the difference in price impact for firms in all the higher quintiles as compared to the firms in Quintile 1 is statistically significant at the 1 percent level.

Panel B reports a similar analysis based on the increase in price impact around earnings announcement. We find that the increase in price impact around earnings releases is more pronounced for firms in higher EQ quintiles as compared to the increase in price impact for firms in Quintile 1. Collectively, the results in Table 2 suggest that both the

17. We estimate all our regression models, reported in various tables, using the *generalized method of moments* (GMM) approach that corrects for heteroskedasticity and also for autocorrelation in regression errors, using the Newey-West covariance estimation technique. Further, the study's main inferences remain unchanged when we estimate the model using weighted least squares to control for heteroscedasticity and include indicator variables for each year to control for time period fixed effects.

TABLE 2
Univariate association between information asymmetry and earnings quality

	G1	G2	G3	G4	G5	Decimal indicator
Panel A: Price impact of trade, by earnings quality groups						
% Price impact	0.4666	0.5492	0.5976	0.6310	0.6453	−0.2604
Diff. from G1		0.0826***	0.1310***	0.1643***	0.1787***	
p-value		*(0.00)*	*(0.00)*	*(0.00)*	*(0.00)*	
Panel B: Increase in price impact around earnings announcements, by earnings quality groups						
% increase in price impact	0.0145	0.0295	0.0297	0.0467	0.0496	
Diff. from G1		0.0151*	0.0152*	0.0322***	0.0352***	
p-value		*(0.06)*	*(0.07)*	*(0.00)*	*(0.00)*	

Notes:

Table 2, panel A reports the price impact of trade by earnings quality groups. Table 2, panel B reports the *abnormal* price impact of trade surrounding earnings announcements grouped by earnings quality. *Abnormal* price impact is announcement period price impact minus non-announcement period price impact for the same firm in the same quarter. The announcement window is defined as days –1 to +1 around the earnings announcement. The non-announcement window is a two-week period (10 trading days) ending exactly two weeks prior to earnings announcement date. The price impact of trade is computed as $[2 \times D_{it} \times (V_{i,\ t+30} - Mid_{it}) / Mid_{it} \times 100]$, where $V_{i,\ t+30}$ is the mid-point of the quote observed 30 minutes after the trade, Mid_{it} is the quote mid-point for firm i at time t, and D is an indicator variable that equals 1 for a market buy and −1 for a market sell. The price impact of trade is estimated using the approach outlined in Huang and Stoll 1996. Earnings quality is the measure proposed in FLOS. Firms are grouped into quintile portfolios every year based on earnings quality. Indicator variable G1 equals one for firms in Quintile 1 (the group with best earnings quality) and equals zero otherwise, while G5 equals one for firms in Quintile 5 and equals 0 otherwise. Reported are the regression coefficients of price impact of trade (panel A) and the change in price impact surrounding earnings announcements (panel B) on earnings quality indicator variables and a decimal indicator variable. The decimal indicator variable equals one for the period after decimalization and equals zero otherwise. ***, **, * denote statistical significance at the 1 percent, 5 percent and 10 percent levels, respectively.

level of information asymmetry on non-earnings announcement days as well as the increase in information asymmetry on earnings release dates are inversely associated with earnings quality.

Regression analysis of earnings quality on information asymmetry

In this section, we examine the relation between earnings quality and information asymmetry after controlling for firm characteristics known to be systematically associated with information asymmetry. Specifically, we control for the effects of market capitalization, share price, trading volume, stock return volatility, institutional ownership, and analyst following (see Stoll 2000 for a detailed discussion). Firm size, trading volume, institutional ownership, and analyst following are associated with the quality and the quantity of information production in financial markets. Stock price serves as a proxy for the higher risk associated with low priced securities and the discreteness in the pricing grid. Return volatility captures the possibility that informed traders are more active in securities with higher uncertainty.[18] Prior research finds that NYSE's floor-based market structure is better at resolving information asymmetry than NASDAQ's dealer / ECN structure (e.g., Heidle and Huang 2002). We include a NYSE indicator variable that equals one for an NYSE firm and equals zero otherwise. We also include an indicator variable to capture the effects of decimalization.

Although return volatility is associated with trading costs, we exercise caution in controlling for its effects in our investigation. This is because Rajgopal and Venkatachalam (2011) show that poor earnings quality is associated with return volatility. Moreover, other studies (e.g., Leuz and Verrecchia 2000) consider return volatility to be a proxy for information asymmetry. For these reasons, we include "orthogonalized volatility" as a control variable in the regressions. Specifically, we regress return volatility on the FLOS EQ measure, and the residual from this regression provides the component of return volatility that is independent of the effect of earnings quality.[19] For the same reason, we use orthogonalized trading volume in regressions.

Although our hypothesis predicts an inverse association between information asymmetry and earnings quality, the functional form of the mapping is not specified by theory. We therefore implement both a linear and a nonlinear specification.[20] The linear specification includes the magnitude of FLOS EQ, while the nonlinear specification includes the FLOS EQ quintile indicator variables (i.e., Q2 to Q5) described earlier.

Table 3 reports the results of the regression of price impact on earnings quality and other economic determinants of information asymmetry. The predicted sign for each coefficient is indicated adjacent to the variable name. Consistent with prior research, we find that information asymmetry is significantly lower for firms with higher trading volume, larger market capitalization, higher stock price, higher institutional ownership, greater analyst following, and lower return volatility. Information asymmetry is lower for NYSE-listed firms and it declines during the time period after decimalization.

Turning to earnings quality, we find that the coefficient on FLOS EQ in the linear specification (reported in column 2) is 0.13 and statistically significant at the 1 percent level, suggesting that earnings quality is significantly and incrementally associated with information asymmetry. The inference from the nonlinear specification (reported in column 3) is similar. In this specification, the model intercept captures the price impact estimated for the benchmark portfolio with the highest earnings quality (Quintile 1). Relative to Quintile 1, the positive coefficients on each of the quintile indicator variables (i.e., G2 to G5) suggests that lower earnings quality is associated with higher information asymmetry. It is noteworthy that the coefficients exhibit a monotonic increase in magnitude from Quintile 2 to Quintile 5.[21]

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18. In results not reported in tables, we also include average trade size and a measure of (signed) imbalance between number of buyer-initiated and the number of seller-initiated transactions as control variables and find similar results.
19. The Spearman correlation between FLOS EQ and return volatility is 0.32 (significant at the 1 percent level). Our conclusions are unchanged when unorthogonalized return volatility is included as an explanatory variable.
20. One possibility is that extremely poor quality earnings might prevent even informed investors from generating precise signals, which could result in lower informed trading in these firms and hence lower information asymmetry, ceteris paribus. If this is the dominant effect, then we should find a nonlinear (inverted U-shaped) relationship between FLOS EQ and information asymmetry.
21. We perform a number of additional tests. We reject the null hypothesis that all of the quintile coefficients are jointly equal to zero (i.e., joint test of G2 = G3 = G4 = G5 = 0) at the 1 percent level. We also reject the null of a joint test that all the coefficients are equal (i.e., joint test of G1 = G2 = G3 = G4 = G5) at the 1 percent level. Finally, we reject the null hypothesis in two of the four cases that the adjacent EQ coefficients are equal, as follows: G1 = G2 (p-value = 0.00), G2 = G3 (p-value = 0.44), G3 = G4 (p-value = 0.95) and G4 = G5 (p-value = 0.04).

TABLE 3
Regression of information asymmetry on firm characteristics and earnings quality

	Price Impact of Trades (%)						
				Firm Size		Institutional Ownership	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Intercept	0.7336***	0.6921***	0.6862***	0.6881***	0.6727***	0.6865***	0.6648***
p-value	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Market Capitalization (-)	−0.3360***	−0.3440***	−0.3410***	−0.3400***	−0.3320***	−0.3420***	−0.3310***
p-value	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Stock Price (−)	−0.0012***	−0.0012***	−0.0012***	−0.0012***	−0.0011***	−0.0012***	−0.0012***
p-value	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Trading Volume (ortho) (−)	−0.1379***	−0.1405***	−0.1396***	−0.1391***	−0.1360***	−0.1403***	−0.1384***
p-value	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Volatility (ortho) (+)	5.6482***	5.7725***	5.6608***	5.7520***	5.6026***	5.7699***	5.6492***
p-value	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Institutional Holdings (−)	−0.0447***	−0.0426***	−0.0437***	−0.0421***	−0.0433***	−0.0413***	−0.0394***
p-value	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Analyst Following (−)	−0.0212***	−0.0203***	−0.0206***	−0.0188***	−0.0176***	−0.0196***	−0.0191***
p-value	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
NYSE Exchange Ind. (−)	−0.0934***	−0.0746***	−0.0788***	−0.0744***	−0.0725***	−0.0750***	−0.0765***
p-value	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Decimal Indicator (−)	−0.0906***	−0.0863***	−0.0892***	−0.0871***	−0.0909***	−0.0862***	−0.0886***
p-value	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Earnings quality							
EQ (+)		0.1335***		0.1632***		0.1487***	
p-value		(0.00)		(0.00)		(0.00)	
EQ * High Information Envr (−)				−0.0910*** ^^^		−0.0425* ^^^	
p-value				(0.00)		(0.09)	

(The table is continued on the next page.)

TABLE 3 (Continued)

	Price Impact of Trades (%)						
				Firm Size		Institutional Ownership	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Earnings quality quintiles							
G2			0.0291***		0.0579***		0.0383**
p-value			(0.00)		(0.00)		(0.03)
G2 * High Information Envr (−)					−0.0461**		−0.0147 ^^^
p-value					(0.02)		(0.39)
G3			0.0382***		0.0601***		0.0662***
p-value			(0.00)		(0.00)		(0.00)
G3 * High Information Envr (−)					−0.0368** ^^^		−0.0496*** ^^
p-value					(0.03)		(0.00)
G4			0.0390***		0.0580***		0.0551***
p-value			(0.00)		(0.00)		(0.00)
G4 * High Information Envr (−)					−0.0322** ^^^		−0.0293* ^^^
p-value					(0.05)		(0.07)
G5			0.0633***		0.0832***		0.0733***
p-value			(0.00)		(0.00)		(0.00)
G5 * High Information Envr (−)					−0.0403*** ^^^		−0.0258* ^^^
p-value					(0.01)		(0.08)
Adjusted R^2	40.77%	41.06%	40.87%	41.09%	40.91%	41.06%	40.90%
Number of Observations	14389	14389	14389	14389	14389	14389	14389

(The table is continued on the next page.)

TABLE 3 (Continued)

Notes:

Table 3 presents the regression coefficients of the price impact of trade on firm characteristics and earning quality. The price impact of trade, the earnings quality measure, and the control variables are defined in the previous tables. The control variables are calculated over the non-announcement period, which is a two-week period (10 trading days) ending exactly two weeks prior to earnings announcement date. Orthogonalized volatility is the component of return volatility that is independent of earnings quality effects. Specifically, we regress return volatility on the EQ measure and use the residuals from the regression as orthogonalized volatility. Similarly, orthogonalized volume is the component of trading volume that is independent of earnings quality effects. *Institutional Ownership* aggregates the holding by institutions reported in the Thomson/Reuters database during the quarter preceding and closest to the annual earnings announcement date. *Analyst Following* is the number of individual analysts providing forecasts on I/B/E/S in the 90-day pre-announcement window ending one day before each earnings announcement date. *NYSE Exchange* is an indicator variable that equals one for an NYSE firm and equals zero otherwise. For the nonlinear specification, we define five indicator variables G1 through G5, based on the quintile ranking of earnings quality. Indicator variable G1 equals one for firms in Quintile 1 (the group with best earnings quality) and equals zero otherwise, while G5 equals one for firms in Quintile 5 and equals 0 otherwise. The nonlinear specification excludes G1 (the highest earnings quality quintile). Expected signs on the coefficients on the explanatory variables are in parenthesis. ***, **, * denote statistical significance at the 1 percent, 5 percent and 10 percent levels, respectively, for the hypothesis that the coefficient is zero. ^^^, ^^, ^ denote statistical significance at the 1 percent, 5 percent and 10 percent levels, respectively, for the hypothesis that the sum of the earnings quality coefficient and the corresponding interaction coefficient with *High Information* firms is zero.

Theoretical models predict that large firms have incentives to provide better disclosures because they enjoy greater benefits from improving disclosures (Diamond 1985). This implies that the information advantage of informed traders will be greater in firms operating in relatively poor information environments. In a recent paper, Lambert and Verrecchia (2011) predict that the adverse consequences of information asymmetry depend on the degree of investor competition in the stock. Larger firms and firms with high institutional ownership are associated with more information production and higher investor participation. Thus, these firm characteristics also serve as reasonable proxies for the degree of investor competition in a stock.[22] We test these predictions by interacting the FLOS EQ with a dummy variable (High Information Environment) that equals one for firms above the median value of firm size and institutional ownership, respectively, and zero otherwise.[23]

The results in column 4 show that the coefficient on EQ is positive (0.16) and statistically significant at the 1 percent level, suggesting that poor earnings quality is associated with higher information asymmetry for the subsample of small firms. Results also suggest that poor earnings quality is associated with higher information asymmetry for the subsample of large firms. The coefficient on the interaction term between EQ and *Size* is negative (−0.09), implying that the earnings quality coefficient estimate for large firms is 0.07 (0.16 + (−0.09)), which is statistically significant at the 1 percent level. Our evidence that earnings quality affects information asymmetry even for firms operating in richer information environment (large firms) is important, as prior research (Botosan 1997) does not find an association between disclosure quality and cost of capital for firms with rich information environments (firms with high analyst following).

We also find that the magnitude of the association between earnings quality and information asymmetry differs between small and large firms. The negative and significant coefficient (−0.09) on the interaction term suggests that the association between earnings quality and information asymmetry is less pronounced for larger firms. Specifically, the magnitude of the association between earnings quality and information asymmetry is more than twice as large for small firms (0.16) compared to large firms (0.07). The inference from column 5 which reports the results of the nonlinear specification is similar and shows that for each of the EQ quintiles, the relation between EQ and information asymmetry is less pronounced for large firms. In columns 6 and 7, we use Institutional Ownership to proxy for the information environment and find similar results.

Overall, the results show that the association between earnings quality and information asymmetry is related to a firm's information environment and that poor earnings quality is especially costly for smaller firms and those with low institutional ownership. These findings support the prediction in Lambert and Verrecchia 2011 that adverse consequences of information asymmetry depend on the degree of investor competition in a stock.

Economic significance of the impact of earnings quality on information asymmetry

We briefly comment on the economic significance of our results reported thus far. The nonlinear specification in column 3 of Table 3 reports that the adverse selection component of trading cost for firms in EQ Quintile 5 exceed those for firms in EQ Quintile 1 by more than six basis points. Alternatively, based on the linear specification (FLOS EQ

22. Two recent studies, Akins, Ng, and Verdi (forthcoming) and Armstrong, Core, Taylor, and Verrecchia (2011) examine the impact of investor competition on pricing of information asymmetry. Their results show that the impact of information asymmetry on cost of capital is inversely related to the degree of investor competition in a stock.

23. In the interest of brevity, we report the results for size and institutional ownership but find that the conclusions are similar when analyst following serves as proxy for the firm's information environment. Our results are also similar when we use the information environment dummy to proxy for the main effect of information environment instead of the continuous variable.

coefficient of 0.13 in column 2 of Table 3), the change from the 5th percentile to the 95th percentile of the FLOS EQ distribution yields estimates of similar economic magnitude, approximately 6.5 basis points.

The survey article by Biais, Glosten, and Spatt 2005 provides some perspective on interpreting these economic magnitudes. They note that while the cost of any individual transaction can seem small, the overall economic effect of trading cost on the cost of capital for corporations and the portfolio allocations for investors is nontrivial, due to huge volume of transactions. As an example, they report that a trading cost of only five cents for a \$25 stock (approximate trading costs of 20 basis points) in 2002 implies a corresponding flow of 18 billion dollars for NYSE-listed firms alone. Amihud, Mendelson, and Pedersen (2005) estimate that the difference in expected returns for a stock with 1 percent spread compared to a same-risk category stock with 0.5 percent spread (i.e., difference in spread of 50 basis points) amounts to about 1.8 percent on an annualized basis. Extrapolating these findings to our setting, the impact of poor earnings quality *alone*, controlling for other economic determinants of trading costs, on the adverse selection component of liquidity cost appears to be economically nontrivial.

Decomposition of the FLOS EQ measure into innate and discretionary components

The evidence reported thus far shows that poor accruals (earnings) quality is associated with higher adverse selection risk. This raises the obvious question — why do corporate managers not improve earnings quality? To understand this issue, it is important to recognize that the extent to which a firm's accruals map into cash flows is affected, not only by the discretionary reporting choices made by the managers (discretionary factors), but also by the firm's operating environment and its business model (innate factors). This distinction is important because managers have little control over the innate factors, at least in the short run. To assess the relative contribution of each of the above factors to information asymmetry, we decompose earnings (accruals) quality into an innate component and a discretionary component, following the approach outlined in FLOS. Specifically, we estimate the following regression:

$$FLOS\ EQ_{j,t} = \lambda_0 + \lambda_1 * Size_{j,t} + \lambda_2 * \sigma(CFO)_{j,t} + \lambda_3 * \sigma(Sales)_{j,t} + \lambda_4 * OperCycle_{j,t} + \lambda_5 * NegEarn_{j,t} + \varepsilon_{j,t} \quad (5),$$

where:

$Size_{j,t}$ = The book value of total assets of firm j in year t.

$\sigma(CFO)_{j,t}$ = The standard deviation of firm j's cash flow from operations, computed over the past 10 years.

$\sigma(Sales)_{j,t}$ = The standard deviation of firm j's revenues, computed over the past 10 years.

$OperCycle_{j,t}$ = The log of firm j's operating cycle.

$NegEarn_{j,t}$ = The number of years during the past 10 years that firm j had net income before extraordinary items that were less than zero.[24]

Both the standard deviation measures are scaled by total assets. In (5), the explanatory variables account for innate factors that influence accruals quality; consequently, the predicted values from annual estimation of (5) capture the innate component of FLOS EQ, while the unexplained portions (the residuals) capture the discretionary component.[25]

24. Operating cycle equals (360*Avg. Accounts Receivable/Sales) + (360*Avg. Inventory/Cost of Goods Sold).

25. The adjusted R^2 from estimating (5) is 28.12 percent. The coefficient (t-statistic) on *Size* is −0.03 (−15.59), standard deviation of *CFO* is 0.68 (38.32), standard deviation of *Sales* is 0.10 (14.16), *OperCycle* is 0.02 (13.49) and *NegEarn* is 0.013 (18.45).

It is important to recognize that discretionary accruals reflect a combination of three distinct effects (Guay, Kothari, and Watts 1996) — earnings management, managerial efforts to convey information about firm performance, and pure noise. Because we are analyzing a broad cross-section of firms, we expect discretionary accruals to reflect elements of earnings management as well as attempts by managers to convey information. It is, however, difficult to disentangle managerial efforts to manage earnings from managerial efforts to convey information except in some specific settings where managers have a strong ex ante incentive to manage the reported earnings. The purpose of this study is to examine the association between earnings quality and information asymmetry for a broad cross-section of firms, and consequently this paper does not explore the motivation behind managers' discretionary reporting choices.

Table 4 reports the results of the regression of price impact on the innate and the discretionary components of FLOS EQ. The innate factor coefficient in the linear specification (column 1) is 0.26 (significant at the 1 percent level). In the nonlinear specification (column 2), the coefficient on the innate factor quintile indicator variable increases monotonically from Quintile 2 to Quintile 5. This evidence suggests that informed investors have a greater advantage in firms that operate in volatile and uncertain environments.

Turning to the discretionary factor, we find that in the linear specification (column 3), the coefficient is positive (0.07) and significant at the 1 percent level. However, this evidence should be interpreted with caution because the nonlinear specification reported in column 4 suggests that the functional form of the association between discretionary accruals and information asymmetry is U-shaped. Note that the Quintile 5 coefficient is positive but not significant suggesting that the price impact for firms in Quintile 1 and Quintile 5 are similar. Further, the coefficients for Quintiles 2 through Quintile 4 are negative suggesting that firms in Quintile 2 to Quintile 4 have *lower* information asymmetry relative to firms in Quintile 1. Additions tests reject the null (at the 1 percent level) that the Quintile 5 coefficient is equal to the Quintiles 2, 3 and 4 coefficients. Thus, it appears that information asymmetry is high both for firms in Quintile 1 and firms in Quintile 5.

In column 5, we build on this investigation and separately examine the impact of positive and negative discretionary accruals on information asymmetry. The coefficient on negative discretionary accruals is negative (−0.13) suggesting that as discretionary accruals become more negative, we observe an increase in information asymmetry. In contrast, the coefficient on positive discretionary accruals is positive (0.22) suggesting that higher values of positive discretionary accruals are associated with higher information asymmetry.

Because the earnings quality measure is based on the FLOS model and is estimated using industry-level regressions, the interpretation is that high FLOS EQ is associated with poor earnings quality. Therefore, we expect negative discretionary accruals to improve earnings quality because they improve the mapping of accruals to cash flows (i.e., reduce volatility in this association) relative to other firms in the same industry. In the same vein, positive discretionary accruals increase the volatility in the mapping and as a result reduce earnings quality. Although, the ex ante expectation is an inverse and linear relationship between discretionary accruals and information asymmetry, our results suggest a U-shaped association between the two constructs wherein both large positive discretionary accruals (Quintile 5) and large negative discretionary accruals (Quintile 1) are associated with higher information asymmetry. One interpretation of this evidence is that discretionary reporting choices that introduce a substantial deviation in the mapping of accruals to cash flows relative to other firms in the industry can befuddle investors and increase information asymmetry, ceteris paribus.

The analyses reported thus far suggest that earnings quality has a strong association with the level of adverse selection risk as reflected in trading costs. The impact of earnings quality is more pronounced for firms with relatively poor information environments. Both

TABLE 4
Regression of information asymmetry on components of earnings quality

	Price Impact of Trades (%)				
	(1)	(2)	(3)	(4)	(5)
	INNATE component of earnings quality		DISCRETIONARYcomponent of earnings quality		
					Pos Disc Acc
Intercept	0.6684***	0.6955***	0.7295***	0.7416***	0.7108***
p-value	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Market Capitalization (−)	−0.3630***	−0.3550***	−0.3310***	−0.3290***	−0.3380***
p-value	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Stock Price (−)	−0.0012***	−0.0012***	−0.0012***	−0.0012***	−0.0012***
p-value	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Trading Volume (ortho) (−)	−0.1417***	−0.1404***	−0.1382***	−0.1389***	−0.1390***
p-value	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Volatility (ortho) (+)	5.6084***	5.6394***	5.7595***	5.6803***	5.7277***
p-value	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Institutional Holdings (−)	−0.0433***	−0.0446***	−0.0450***	−0.0448***	−0.0445***
p-value	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Analyst Following (−)	−0.0164***	−0.0185***	−0.0218***	−0.0205***	−0.0202***
p-value	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
NYSE Exchange Ind. (−)	−0.0798***	−0.0846***	−0.0865***	−0.0842***	−0.0865***
p-value	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Decimal Indicator (−)	−0.0895***	−0.0917***	−0.0866***	−0.0887***	−0.087***
p-value	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Earnings quality					
EQ (+)	0.2624***		0.0672***		
p-value	(0.00)		(0.00)		
EQ *Negative Disc. EQ					−0.1306**
p-value					(0.02)
EQ *Positive Disc. EQ					0.2163***
p-value					(0.00)
Earnings quality quintile groups					
G2		0.0112		−0.0344***	
p-value		(0.30)		(0.00)	
G3		0.0285**		−0.0295**	
p-value		(0.02)		(0.01)	

(The table is continued on the next page.)

TABLE 4 (Continued)

	Price Impact of Trades (%)				
	(1)	(2)	(3)	(4)	(5)
	INNATE component of earnings quality		DISCRETIONARY component of earnings quality		Pos Disc Acc
G4		0.0550***		−0.0226*	
p-value		(0.00)		(0.05)	
G5		0.0621***		0.0090	
p-value		(0.00)		(0.47)	
Adjusted R^2	40.89%	40.82%	40.88%	40.80%	40.94%
Number of Observations	14221	14221	14221	14221	14221

Notes:

Table 4 presents the regression coefficients of price impact of trade on innate and discretionary component of earnings quality. The models also include known attributes controlling for cross-sectional variations in firm characteristics. The decomposition of the earnings quality into innate and discretionary component follows the approach in FLOS (316). The innate component captures the innate, firm-specific drivers of earnings quality while the discretionary component captures managerial discretions and manipulations. Positive discretionary accrual is an indicator variable that equals one if discretionary accrual is positive and equals zero otherwise. The price impact of trade, the earnings quality, and the control variables are defined in the previous tables. The control variables are calculated over the non-announcement period, which is a two-week period (10 trading days) ending exactly two weeks prior to earnings announcement date. Expected signs on the coefficients on the explanatory variables are in parentheses. ***, **, * denote statistical significance at the 1 percent, 5 percent and 10 percent levels, respectively, for the hypothesis that the coefficient is zero.

innate and discretionary components of earnings quality have a significant impact on information asymmetry; however the relationship is not similar. In particular, both extreme positive and extreme negative discretionary accruals are associated with higher information asymmetry.

Alternative measures of earnings quality

In this section, we investigate whether the association between earnings quality and information asymmetry is robust to alternative measures of earnings quality. The robustness analysis is important because there is no universally accepted ‘‘best’’ measure of earnings quality and it is, therefore, important to assess the main tenor of results using reasonable surrogates of earnings quality. The first measure is the loading on accruals quality factor-mimicking portfolio (e-loading) developed in Ecker et al. 2006. The second measure is the absolute value of the magnitude of industry-adjusted operating accruals scaled by total assets (OPACCIND).[26]

26. The Pearson correlation between FLOS EQ and e-loading is 0.30 and between FLOS EQ and the absolute value of industry-adjusted operating accruals is 0.27.

Table 5 reports the results based on the two alternative measures of earnings quality. The coefficient on e-loading measure in column 1 is positive (0.14) and significant, confirming that poor earnings quality is associated with higher information asymmetry. The inference from the nonlinear specification reported in column 2 is similar. We observe a monotonic increase in information asymmetry from the lower quintiles to the higher quintile of e-loading. The results in columns 3 and 4 show that although the adverse effect of poor earnings quality on information asymmetry is higher for smaller firms, the coefficients on the interaction terms are not significant.

The next four columns (columns 5 through 8) report on the association between the industry-adjusted operating accruals and information asymmetry. Because extreme positive and extreme negative values of industry-adjusted accruals represent poor earnings quality, we define OPACCIND as the absolute value of industry-adjusted accruals. Thus, as OPACCIND increases, earnings quality declines. The results of the linear specification reported in column 5 show that the coefficient on OPACCIND is positive (0.52) and significant, thereby confirming the association between earnings quality and information asymmetry documented in Table 3. The nonlinear specification based on OPACCIND (column 6) shows that the coefficients on Quintile 4 and Quintile 5 are significantly positive suggesting that firms with poor earnings quality are associated with higher price impact. The results in column 7 confirm prior findings that the association between earnings quality and information asymmetry is more pronounced for small firms. Overall, the results using the two alternate measures of earnings quality are consistent with earlier results.

Controlling for potential endogeneity inherent in the determination of earnings quality

Our analysis thus far assumes that earnings quality is exogenous. However, earnings quality could be endogenous in the sense that certain firm characteristics that affect earnings quality might also affect the consequences of poor earnings quality (Cohen 2008). For example, firm characteristics such as cash flow volatility can affect both earnings quality and information asymmetry and would bias regression estimates in the absence of proper controls. Thus, we employ the two-stage instrumental variable (IV) approach to correct for such endogeneity between earnings quality and information asymmetry. In the first stage, we model the firm-specific determinants of earnings quality, closely following the approach outlined in Cohen 2008.[27] In the second stage, the measures of information asymmetry are regressed on the predicted value of earnings quality from the first stage (FLOS EQ IV) and other known determinants of trading costs. The FLOS EQ IV acts as an instrument for the component of earnings quality that is unrelated to firm characteristics that influence information asymmetry.

Panel A of Table 6 reports the regression analysis that models the determinants of earnings quality. The coefficient on *Growth* is positive and significant suggesting that high growth firms have poor earnings quality. The coefficient on *Issue* is positive but not significant. The coefficients on *Lit* and *OC* are significantly positive indicating that firms in industries with high litigation risk and those with long operating cycles have poor earnings quality. The coefficients on *Owner* and *Herf* are negative implying that firms with higher ownership concentration and those operating in concentrated industries tend to have

27. Specifically, the firm-specific determinants of earnings quality include: *Owner* (log of number of shareholders), *Growth* (annual growth in sales), *Herf* (Herfindahl index for the industry in which the firm operates), *Issue* (indicator variable for debt or equity issuance), *Lit* (indicator variable denoting if the firm operates in a "high-litigation" industry), *Leverage* (debt over average assets),*OC* (operating cycle of the firm), *Size* (log of market capitalization), and *Age* (the number of months the firm has been listed on CRSP). Cohen (2008) discusses how each of these firm characteristics may affect earnings quality.

TABLE 5
Regression of information asymmetry on alternative measures of earnings quality

	E-loading Measure				OPACCIND Measure			
			Firm Size				**Firm Size**	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Intercept	0.6710***	0.6256***	0.6700***	0.6255***	0.6960***	0.7169***	0.6930***	0.7085***
p-value	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Market Capitalization (−)	−0.3370***	−0.3380***	−0.3370***	−0.3360***	−0.5320***	−0.5160***	−0.5210***	−0.5090***
p-value	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Stock Price (−)	−0.0011***	−0.0011***	−0.0011***	−0.0011***	−0.0011***	−0.0011***	−0.0010***	−0.0010***
p-value	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Trading Volume (ortho) (−)	−0.1415***	−0.1397***	−0.1414***	−0.1399***	−0.1333***	−0.1312***	−0.1317***	−0.1293***
p-value	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Volatility (ortho) (+)	5.7109***	5.6614***	5.7079***	5.6741***	5.7062***	5.6560***	5.6862***	5.6352***
p-value	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Institutional Holdings (−)	−0.0403***	−0.0416***	−0.0401***	−0.0412***	−0.0468***	−0.0479***	−0.0464***	−0.0473***
p-value	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Analyst Following (−)	−0.0163***	−0.0193***	−0.0160***	−0.0190***	−0.0183***	−0.0210***	−0.0166***	−0.0189***
p-value	(0.00)	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)
NYSE Exchange Ind. (−)	−0.0576***	−0.0570***	−0.0578***	−0.0589***	−0.0696***	−0.0726***	−0.0674***	−0.0690***
p-value	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Decimal Indicator (−)	−0.0938***	−0.0942***	−0.0939***	−0.0938***	−0.0950***	−0.0981***	−0.0961***	−0.0992***
p-value	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)

(The table is continued on the next page.)

TABLE 5 (Continued)

	E-loading Measure				OPACCIND Measure			
			Firm Size				Firm Size	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Earnings quality								
EQ (+)	0.1448***		0.1486***		0.5233***		0.5919***	
p-value	(0.00)		(0.00)		(0.00)		(0.00)	
EQ * High Information Envr (−)			−0.0119 ^^^				−0.2671*** ^^^	
p-value			(0.39)				(0.00)	
Earnings quality quintile groups								
G2 (+)		0.0230**		0.0076		0.0003		0.0047
p-value		(0.02)		(0.69)		(0.98)		(0.81)
G2 * High Information Envr (−)				0.0241				−0.0077
p-value				(0.21)				(0.67)
G3 (+)		0.0514***		0.0414**		0.0054		0.0090
p-value		(0.00)		(0.02)		(0.61)		(0.62)
G3 * High Information Envr (−)				0.0185 ^^				−0.0057
p-value				(0.29)				(0.74)
G4 (+)		0.1001***		0.1037***		0.0285**		0.0417**
p-value		(0.00)		(0.00)		(0.01)		(0.02)
G4 * High Information Envr (−)				−0.0097 ^^^				−0.0262*^
p-value				(0.58)				(0.09)
G5 (+)		0.1883***		0.1928***		0.0914***		0.1142***
p-value		(0.00)		(0.00)		(0.00)		(0.00)

(The table is continued on the next page.)

TABLE 5 (Continued)

	E-loading Measure				OPACCIND Measure			
			Firm Size				Firm Size	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
G5 * High Information Envr (−)				−0.0222 ^^^				−0.0613***^^^
p-value				(0.19)				(0.00)
Adjusted R^2	41.53%	41.33%	41.53%	41.33%	40.80%	40.62%	40.83%	40.65%
Number of Observations	14666	14666	14666	14666	14596	14596	14596	14596

Notes:

This table reports coefficients from the regression of the price impact of trade on two alternative measures of earnings quality. The price impact of trade and the control variables have been defined in the previous tables. The alternative earnings quality measures are (1) the loading on accruals quality factor-mimicking portfolio developed in Ecker et al. 2006 (e-loading), and (2) the *absolute value* of industry-adjusted operating accruals scaled by total assets (OPACCIND). E-loading is the coefficient on the accrual quality (AQ) mimicking factor portfolio in a four-factor Fama and French 1993 regression that also includes the market factor (RM-RF), the size factor (SMB), and the book-to-market factor (HML). The e-loading can thus be interpreted as the exposure to a firm's earnings quality. For calculating the OPACCIND measure, we first compute operating accruals as earnings minus cash flow from operations, scaled by average assets. Next, we control for the systematic difference in accruals across industries by taking the difference between the firm-specific operating accruals and the median operating accruals for firms in the same 2-digit SIC code. Firms with extreme positive and negative OPACCIND values (i.e., extreme departures from industry medians) are considered to have poor earnings quality. Expected signs on the coefficients on the explanatory variables are in parentheses. ***, **, * denote statistical significance at the 99 percent, 95 percent and 90 percent levels respectively for the hypothesis that the coefficient is zero. ^^^, ^^, ^ denote statistical significance at the 99 percent, 95 percent and 90 percent levels respectively for the hypothesis that the sum of the earnings quality coefficient and the corresponding interaction coefficient with *High Information* firms is zero.

TABLE 6

Regression of the information asymmetry on earnings quality instrumental variable

Panel A: Firm-specific determinants of earnings quality

	Intercept	Owner	Growth	Herf Index	Issue	Lit	Leverage	OC	Size	Age
Parameter estimate	0.5936***	−0.0024**	0.1022***	−0.1527	0.0041	0.0635***	−0.1032***	0.0002***	−0.0049**	−0.0758**
p-value	(0.00)	(0.02)	(0.00)	(0.64)	(0.27)	(0.00)	(0.00)	(0.00)	(0.02)	(0.00)

Panel B: % Price impact of trade on Earnings Quality (FLOS) Instrument

			Firm Size	
	(1)	(2)	(3)	(4)
Intercept	0.6809***	0.7006***	0.6614***	0.6819***
p-value	(0.00)	(0.00)	(0.00)	(0.00)
Market Capitalization (−)	−0.3473***	−0.3419***	−0.3247***	−0.3278***
p-value	(0.00)	(0.00)	(0.00)	(0.00)
Stock Price (-)	−0.0012***	−0.0012***	−0.0011***	−0.0011***
p-value	(0.00)	(0.00)	(0.00)	(0.00)
Trading Volume (ortho) (−)	−0.1374***	−0.1385***	−0.1325***	−0.1352***
p-value	(0.00)	(0.00)	(0.00)	(0.00)
Volatility (ortho) (+)	5.5413***	5.5172***	5.4708***	5.4685***
p-value	(0.00)	(0.00)	(0.00)	(0.00)
Institutional Holdings (−)	−0.0444***	−0.0437***	−0.0428***	−0.0424***
p-value	(0.00)	(0.00)	(0.00)	(0.00)
Analyst Following (−)	−0.0231***	−0.0232***	−0.0179***	−0.0197***
p-value	(0.00)	(0.00)	(0.00)	(0.00)

(The table is continued on the next page.)

TABLE 6 (Continued)

			Firm Size	
	(1)	(2)	(3)	(4)
NYSE Exchange Ind. (−)	−0.0737***	−0.0729***	−0.0672***	−0.0696***
p-value	(0.00)	(0.00)	(0.00)	(0.00)
Decimal Indicator (−)	−0.0839***	−0.0839***	−0.0853***	−0.0852***
p-value	(0.00)	(0.00)	(0.00)	(0.00)
Earnings quality				
EQ IV (+)	0.2600***		0.3903***	
p-value	(0.00)		(0.00)	
EQ IV * High Information Envr (−)			−0.3108*** ^^^	
p-value			(0.00)	
Earnings quality quintile groups				
IV2		−0.0089		0.0021
p-value		(0.45)		(0.90)
IV2 * High Information Envr (−)				−0.0107
p-value				(0.55)
IV3		−0.0150		−0.0176
p-value		(0.21)		(0.26)
IV3 * High Information Envr (−)				0.0203
p-value				(0.25)
IV4		0.0333***		0.0693***
p-value		(0.01)		(0.00)
IV4 * High Information Envr (−)				−0.0428*** ^
p-value				(0.00)

(The table is continued on the next page.)

TABLE 6 (Continued)

			Firm Size	
	(1)	(2)	(3)	(4)
IV5		0.0778***		0.1184***
p-value		(0.00)		(0.00)
IV5 * High Information Envr (−)				−0.0708*** ^^
p-value				(0.00)
Adjusted R^2	40.63%	40.80%	40.78%	40.98%
Number of Observations	13842	13842	13842	13842

Notes:

This table reports the results of a two-stage instrumental variable (IV) approach to account for endogeneity of earnings quality and information asymmetry. In panel A, we model the firm-specific determinants of earnings quality following the approach outlined in Cohen 2008. The firm-specific determinants include: *Owner* (log of number of shareholders), *Growth* (annual growth in sales), *Herf* (Herfindahl index for the industry in which the firm operates), *Issue* (indicator variable for debt or equity issuance), *Lit* (indicator variable denoting if the firm operates in a "high-litigation" industry), *Leverage* (debt over average assets), *OC* (operating cycle of the firm), *Size* (log of market capitalization), *Age* (the number of months the firm has been listed on CRSP). Panel B reports the results of the second-stage regression of the price impact of trade on first stage instrumental variable (FLOS EQ IV) and control variables. The price impact of trade and the control variables are defined in the previous tables. Expected signs on the coefficients on the explanatory variables in panel B are in parentheses. The adjusted R^2 value from the first-stage model estimation is 33.13 percent. ***, **, * denote statistical significance at the 99 percent, 95 percent, and 90 percent levels respectively for the hypothesis that the coefficient is zero. ^^^, ^^, ^ denote statistical significance at the 1 percent, 5 percent and 10 percent levels, respectively, for the hypothesis that the sum of the earnings quality coefficient and the corresponding interaction coefficient with *High Information* firms is zero.

better earnings quality. Finally, as expected, the coefficients on *Size* and *Age* are negative, suggesting that larger and older firms generally have better earnings quality. Overall, the results reported here are consistent with extant research and those reported in Cohen 2008.

Panel B of Table 6 presents regression coefficients from the second-stage analysis. In the linear specification reported in column 1, the coefficient on FLOS EQ IV is positive (0.26) and highly significant. In the nonlinear specification (column 2), we find that firms in Quintile 4 and Quintile 5 have significantly higher information asymmetry than firms in Quintile 1. In column 3 and column 4, we note that the interaction term of high information environment with FLOS EQ IV is negative, suggesting that earnings quality has a more pronounced impact on information asymmetry for smaller firms. Overall, the inverse relation between earnings quality and information asymmetry reported in Table 3 can be observed after controlling for endogeneity using an instrumental variable approach.

Impact of earnings quality on the increase in information asymmetry around earnings announcements

We also address the endogeneity concern by investigating the association between earnings quality and the *change* in information asymmetry around earnings announcements. In this analysis, the price impact surrounding earnings announcements is compared with the price impact surrounding a recent non-earnings announcement period for the same firm. This research design allows the firm to act as its own control, thereby minimizing the possibility that the association can be attributed to omitted firm-specific attributes. Nonetheless, we control for firm characteristics that may be correlated with the increase in information asymmetry around earnings release dates. Our investigation provides for a better understanding of the well-known result in the literature that information asymmetry increases around earnings releases (Lee et al. 1993, among others).[28] We investigate whether earnings quality is an important determinant of the increase in information asymmetry surrounding earnings releases.

It is important to note that the advantages of the research design come at the cost of low power. This is because the event study approach effectively eliminates the impact of earnings quality on the cross-sectional variation in the *level* of information asymmetry in the non-announcement (benchmark) period. A related observation is that, because information asymmetry is already higher for firms with poor earnings quality, as documented earlier, the increase in information asymmetry around earnings releases for these firms is likely to be small.

Prior research documents that price and volume reactions surrounding earnings announcements are larger for firms with relatively poor information environments.[29] Consequently, we include stock price, market capitalization, trading volume, institutional ownership, and analyst following to capture the cross-sectional variation in information production. To capture the information flow around earnings releases, we include the level of (orthogonalized) return volatility and the increase in trading volume surrounding earnings releases relative to a non-announcement period for the same firm. We also include a seasonal random-walk earnings surprise variable (scaled by stock price) to control for magnitudes of earnings surprises (e.g., Affleck-Graves et al. 2002).

28. Using recent data, Eleswarapu, Thompson, and Venkataraman (2004) show that information asymmetry, manifested as adverse selection component of the bid-ask spread, is higher on earnings announcement days relative to a non-announcement period. Along similar lines, Bhattacharya, Black, Christensen, and Mergenthaler (2007) document significant abnormal trading by sophisticated and less sophisticated investors during the three days surrounding an earnings announcement. The accruals anomaly first identified in Sloan 1996 appears to be concentrated on trading days surrounding earnings announcements.
29. See, for example, Bamber 1987, Bamber, Barron and Stober 1997, and Bhattacharya 2001, among others.

Table 7 reports the regression coefficients of the change in price impact surrounding earnings announcements on earning quality measures and the control variables. Consistent with prior work, the increase in information asymmetry around earnings announcements is higher for smaller firms and low-priced firms. Many of the other coefficients are not significant. In particular, the coefficient on unexpected earnings is not, possibly due to the presence of several variables in the specification that also capture earnings-related information flow.[30]

The linear specification reported in column 1 does not show a significant association between EQ and the change in price impact, but a significant association can be observed in the nonlinear specification reported in column 2. We find that firms in Quintile 2 through Quintile 5 have larger increases in information asymmetry around earnings releases as compared to the increase in information asymmetry observed for firms in Quintile 1 (significant at the 5 percent level). The results using alternative measures of earnings quality are broadly supportive of the results using FLOS EQ. The coefficient on the e-loading measure in column 3 (linear specification) is positive and weakly significant at the 10 percent level. Consistent with results in column 2, the nonlinear specification using the e-loading measure in column 4 finds evidence of an association between e-loading and change in information asymmetry. The general tenor of results and hence inference using industry-adjusted accruals (OPACCIND) is similar.

In summary, although the relationship is weak (as conjectured earlier), the inverse relation between earnings quality and the increase in information asymmetry around earnings releases is observed for all measures of earnings quality. In untabulated results, we also find that the association between earnings quality and the increase in information asymmetry is more pronounced for small firms. We conclude that poor earnings quality is associated with both the level of information asymmetry during non-earnings release periods as well as an increase in information asymmetry around earnings releases.

6. Conclusions

A fundamental role of financial reporting is to serve as a basis for capital allocation. However, the quality of reported earnings is influenced by a firm's fundamentals, such as its operating environment and business model, as well as by the discretionary reporting choices made by the managers. To the extent investors differ in their ability to process this information, poor earnings quality can lead to differentially informed investors. Higher information asymmetry is costly as it increases the adverse selection risk for market participants and lowers liquidity. For these reasons, standard-setters and regulators are concerned about the quality of accounting information and its consequences for capital allocation decisions.

In this paper, we investigate the association between earnings quality and information asymmetry. For a broad sample of NYSE and NASDAQ firms over the period 1998–2007, we document that poor earnings quality is significantly associated with higher information asymmetry as manifested in the adverse selection component of trading cost. The impact of earnings quality on information asymmetry is affected by the firm's information environment and is more pronounced for firms operating in a relatively impoverished disclosure environment.

Both innate and discretionary components of earnings quality are significantly associated with information asymmetry. However, the association between discretionary accruals

30. We find that firm size, analyst following, institutional ownership, and volatility are highly correlated, which can explain the negative coefficient on volatility. In a specification where we drop the correlated variables, we find that the increase in price impact surrounding earnings announcement is positively correlated with volatility.

TABLE 7

Regression of change in information asymmetry surrounding earnings announcements on earnings quality measures and firm characteristics

	FLOS		E-Loading		OPACCIND	
	(1)	(2)	(3)	(4)	(5)	(6)
Intercept	0.0602***	0.0283*	0.0457***	0.0396**	0.0482***	0.0203
p-value	(0.00)	(0.08)	(0.00)	(0.03)	(0.00)	(0.22)
Market Capitalization (−)	−0.2960**	−0.2820**	−0.2230*	−0.2440**	−0.6150***	−0.5830***
p-value	(0.02)	(0.02)	(0.07)	(0.04)	(0.00)	(0.00)
Stock Price (−)	−0.0002***	−0.0002***	−0.0002***	−0.0002***	−0.0002***	−0.0002***
p-value	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Trading Volume (ortho) (−)	0.0022	0.0013	0.0010	−0.0003	−0.0002	−0.0005
p-value	(0.55)	(0.72)	(0.80)	(0.94)	(0.96)	(0.89)
Change in Trading Vol. (+)	−1.0700**	−1.0400**	−1.2700***	−1.3800***	−0.8624	−0.8954
p-value	(0.02)	(0.02)	(0.01)	(0.01)	(0.26)	(0.26)
Volatility (ortho) (+)	−1.1444***	−1.1568***	−1.1792***	−1.1829***	−1.1062***	−1.0932***
p-value	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Institutional Holdings (−)	−0.0036	−0.0029	−0.0011	−0.0015	−0.0021	−0.0018
p-value	(0.27)	(0.38)	(0.73)	(0.64)	(0.52)	(0.58)
Analyst Following (−)	−0.0050	−0.0045	−0.0030	−0.0038	−0.0018	−0.0014
p-value	(0.26)	(0.30)	(0.49)	(0.37)	(0.68)	(0.75)
Unexpected Earnings (+)	6.6694	7.2831	4.2634	4.7452	1.3739	1.3682
p-value	(0.36)	(0.30)	(0.54)	(0.49)	(0.32)	(0.32)
NYSE Exchange Ind. (−)	0.0018	0.0115**	0.0026	0.0012	−0.0006	0.0030
p-value	(0.76)	(0.05)	(0.64)	(0.83)	(0.91)	(0.59)
Earnings quality						
FLOS (+)	0.0037		0.0144*		0.0317	
p-value	(0.81)		(0.09)		(0.48)	
Earnings quality decile groups						
G2 (+)		0.0202**		0.0139*		0.0269***
p-value		(0.01)		(0.07)		(0.00)
G3 (+)		0.0187**		0.0080		0.0308***
p-value		(0.03)		(0.34)		(0.00)
G4 (+)		0.0439***		0.0221**		0.0393***
p-value		(0.00)		(0.02)		(0.00)

(The table is continued on the next page.)

TABLE 7 (Continued)

	FLOS		E-Loading		OPACCIND	
	(1)	(2)	(3)	(4)	(5)	(6)
G5 (+)		0.0372***		0.0245**		0.0349***
p-value		(0.00)		(0.04)		(0.00)
Adjusted R^2	0.70%	0.86%	0.84%	0.85%	0.70%	0.85%
Number of Observations	13478	13478	13747	13747	13736	13736

Notes:

Table 7 presents the regression coefficients of *abnormal (*or *increase* in) price impact of trade surrounding earnings announcements on alternative measures of earning quality. *Abnormal* price impact is defined as the announcement period price impact less non-announcement period price impact for the same firm, where non-announcement period is defined as a two-week period (10 trading days) ending two weeks before earnings announcement. The regression models include firm-specific attributes that explain cross-sectional variations in information asymmetry surrounding earnings announcements. The variables include market capitalization, share price, trading volume, institutional ownership, analyst following and volatility. Measures of price impact, earnings quality, and control variables are defined in the previous tables. Additional control variables are change in trading volume and unexpected or seasonal random-walk change in earnings. The change in trading volume is the increase in trading volume around earnings announcement relative to non-announcement period for the same firm. Unexpected earnings is computed by taking the absolute value of the first quarter (Q1) EPS for year t minus the Q1 EPS for year $t-1$, and scaling this difference by stock price. The table reports results of a linear specification and a nonlinear specification based on quintile ranks of earnings quality. Expected signs on the coefficients on the explanatory variables are in parentheses. ***, **, * denote statistical significance at the 1 percent, 5 percent and 10 percent levels, respectively.

and information asymmetry is U-shaped suggesting that managerial choices that cause accruals volatility to be too high or too low relative to industry norms increase information asymmetry. The results are robust to alternative measures of earnings quality, alternative model specifications, and the correction for potential endogeneity between earnings quality and information asymmetry. Further, poor earnings quality appears to be a determinant of the elevated information asymmetry around earnings releases.

Overall, our study provides empirical support for the concerns articulated by regulators that an important adverse consequence of poor earnings quality is increased information asymmetry and reduced liquidity.

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