ACCOUNTING & FINANCE

afaanz

Accounting and Finance 52 (2012) 743–765

Audit quality and information asymmetry between traders

Greg Clinch[a], Donald Stokes[b], Tingting Zhu[c]

[a]*Department of Accounting and Business Information Systems, University of Melbourne, Melbourne, Australia*
[b]*Department of Accounting and Finance, Monash University, Melbourne, Australia*
[c]*School of Finance and Statistics, East China Normal University, Shanghai, China*

Abstract

In this study, we investigate the association between audit quality and information asymmetry between informed and uninformed traders. We employ three proxies for information asymmetry – absolute price differences, absolute volatility differences, and absolute differences in the long/short ratio of trades – between US stock and options markets and represent audit quality through the appointment of Big *n* and industry specialist auditors. For a sample of 4062 firm-years between 2002 to 2005, our results indicate that the appointment of Big *n* and industry specialist auditors is associated with lower information asymmetry measures. Our results are consistent with audit quality playing a role in the quality of financial reporting information and flowing through to the allocation of information among traders.

Key words: Audit quality; Information asymmetry; Earnings quality

JEL classification: M42

doi: 10.1111/j.1467-629X.2011.00411.x

1. Introduction

In this study, we investigate the association between audit quality and information asymmetry between informed and uninformed traders. Our

This paper draws from the results of Tingting Zhu's PhD thesis at the University of Technology Sydney (UTS) with financial support for the research provided by the School of Accounting at UTS and the Capital Markets Co-Operative Research Centre (CMCRC). Data support for the study has been provided by CMCRC, UTS, the Securities Industry Research Centre for Asia Pacific (SIRCA) and the University of New South Wales (UNSW).

Received 25 June 2010; accepted 12 February 2011 by Robert Faff (Editor).

broad objective is to provide new evidence relating to potential benefits from higher-quality audits. Traditional audit quality research has emphasised potential information asymmetry benefits within securities markets, with a focus on how audit quality lowers information asymmetry between firms and outside investors. In contrast, we focus on information asymmetry *between* investors in two connected markets – the stock and option markets – and investigate whether audit quality is linked to lower information asymmetry between informed and uninformed investors across these markets. Thus, our research represents a new line of inquiry and a departure from existing audit quality research.

Existing studies have demonstrated the value of higher-quality auditing through enhanced earnings quality for investors (Francis *et al.*, 1999; Ruddock *et al.*, 2006). Other studies show higher-quality audits are associated with lower cost of capital in equity markets (Willenborg, 1999; Khurana and Raman, 2004) and in debt markets (Mansi *et al.*, 2004; Dhaliwal *et al.*, 2008), higher earnings response coefficients (Higgs and Skantz, 2006) and lower post-earnings announcement drift (Ferguson and Matolcsy, 2004). Godbey and Mahar (2004) demonstrate audits are valued in options markets by finding that the implied stock price volatilities of Andersen audited clients increased after the disclosure of Enron's scandal.

In a departure from and extension to this work, we rely on literature that argues higher disclosure quality leads to lower information asymmetry between traders. There are several reasons why this might be so. First, improved public disclosure effectively brings at least some informed traders' private information into the public domain and therefore reduces the information imbalance between traders (Levitt, 1998). Second, the release of public information makes the beliefs of traders more homogeneous and reduces the magnitude of speculative positions taken by informed traders (Diamond, 1985). Third, enhanced disclosure quality reduces investors' incentives to search for private information by reducing the expected benefits from obtaining private information (Diamond, 1985; Verrecchia, 2001).[1] Because audit quality is a component of the quality of accounting information disclosed, these arguments suggest that higher audit quality could lower the information asymmetry between traders. We investigate whether the evidence is consistent with this possibility.

We also rely on studies that suggest that stock and options markets have different proportions of informed traders and use the divergence in opinions of the two markets as a proxy for information asymmetry between informed and uninformed traders. Black (1975) argues informed traders are attracted to the options market because options offer them the most leverage in exploiting any potential gains from their private information. In addition, the built-in downside protection in options and fewer short selling restrictions potentially make

[1] Empirical evidence lends support to these arguments – for example, Heflin *et al.* (2001).

options trading more appealing to informed traders (Black, 1975). Options also are claimed to provide savings in both transaction costs and time, especially for large positions (DeJong and Donders, 1998). These observations are countered by others like Fleming *et al.* (1996) who point out that the stock market is more liquid and has a smaller bid-ask spread and therefore offers lower trading costs than the options market. In addition, the lack of anonymity could make option trading less attractive to informed traders (Lee and Yi, 2001).

To date, the weight of empirical evidence tends to suggest options trading is more appealing to informed traders (Manaster and Rendleman, 1982; Bhattacharya, 1987; Anthony, 1988; Clinch *et al.*, 2005) with a smaller number of studies suggesting they prefer the stock market (Stephan and Whaley, 1990) or that there is little difference in preference between the markets (Chan *et al.*, 1993; Jarnecic, 1999). Manaster and Rendleman (1982) find that option-implied prices contain information that is not incorporated in stock prices. Similarly, Bhattacharya (1987) and Anthony (1988) report results suggesting that private information arrives in the options market first. Amin and Lee (1997) report that option traders initiate a greater proportion of long (or short) positions immediately before 'good' (or 'bad') earnings news. Christensen and Prabhala (1998) investigate the relation between implied and realised volatility, showing that implied volatility is superior in information to realised volatility for explaining future volatility. Clinch *et al.* (2005) examine approximately 20 years of US option trading data and find that stock portfolios with persistently high implied price differences (IPD hereafter) significantly outperform stock portfolios with persistently low IPDs, for up to seven weeks after formation. Stephan and Whaley (1990) obtain different results using data from the first quarter of 1993 for 43 firms with actively traded options. They report that stock prices lead option prices by 15 min, and the lead is even longer for trading volumes. However, Chan *et al.* (1993) replicate Stephen and Whaley's work and show that the result is due to differences in relative tick size. Jarnecic (1999) conducted a study on Australian data and found no significant lead–lag relationship between stock volume and options volume.

The majority of studies suggesting that the two markets have different proportions of informed traders motivate us to employ the divergence in opinions across the two markets to capture information asymmetry between informed and uniformed traders. Prior investigation of divergence in opinions between the stock and options markets has focused on cross-market metrics including volume (Stephan and Whaley, 1990; Jarnecic, 1999), long/short ratio of trades (Amin and Lee, 1997), price (Manaster and Rendleman, 1982; Bhattacharya, 1987; Anthony, 1988; Stephan and Whaley, 1990; Clinch *et al.*, 2005) and volatility (Christensen and Prabhala, 1998). Similarly, we employ three distinct measures of differences in opinion across the two markets: the difference between the long/short ratio of trades, the difference between actual stock price and an implied stock price recovered from the option price, and the difference between stock return volatility and implied return volatility recovered from option prices.[2] We use these measures to capture differences in the level of information asymmetry among (informed and uninformed) investors and investigate the extent to which they vary with different levels of audit quality.[3]

We follow prior research in the audit literature and employ two audit quality signals: whether the auditor is a Big *n* auditor (DeAngelo, 1981; Willenborg, 1999; Khurana and Raman, 2004; Francis and Lennox, 2008) and an industry specialist (Francis *et al.*, 2005; Ferguson *et al.*, 2006). We investigate whether higher audit quality measured with these two constructs is associated with smaller long/short ratio, absolute price and volatility differences across stock and options markets.

Our research setting is the US stock and options markets. Using a sample of 4062 firm-year observations from years 2002 to 2005, we find that both the appointment of Big *n* and industry specialists are significantly negatively correlated with our divergence in opinion proxies for information asymmetry between traders. Thus, our results are consistent with higher-quality auditors enhancing the quality of information reported by companies and reducing the level of information asymmetry among investors.

The remainder of the paper is organised as follows. Section 2 outlines the research design, sample selection and model specifications. Results and additional analyses are provided in Sections 3 and 4 concludes the paper.

2. Research design

2.1. The model

Chakravarty *et al.* (2004) examine price discovery in the options market relative to the stock market by using a regression model with three explanatory variables: volume ratio, spread ratio and stock volatility. We employ the same explanatory variables as our control variables to investigate the association

[2] We do not use a volume-based asymmetry measure because it requires all the trading volumes of the underlying options. As trading volume data is only available for the Chicago Board Options Exchange (CBOE) and is not available in our databases for all markets in which options are traded, we are unable to construct volume-based asymmetry measures.

[3] An alternative proxy for information asymmetry between traders is the probability of informed traders (PIN). PIN was designed by Easley and O'Hara (1992) to measure information asymmetry between informed and uninformed *equity* traders and is built on a structural sequential trade model introduced in 1987 by Easley and O'Hara. However Duarte and Young (2009) suggest that the PIN measure is more related to liquidity than information asymmetry between traders. As a practical matter, the PIN measure is not available for our sample period, and so we do not employ it in our research.

between audit quality and our proxies for information asymmetry among investors. Specifically, the following model is used:

$$\begin{aligned}\text{INFOASYM} = {} & a_0 + a_1\text{VOLUMERATIO} + a_2\text{SPREADRATIO} \\ & + a_3\text{VOLATILITY} + a_4\text{AQ} + e\end{aligned} \tag{1}$$

where:

INFOASYM is one of three proxies for differences in information asymmetry between the stock and option markets: (i) LogLSD is the natural log of the absolute difference between the long/short ratios of stock and option trades; (ii) LogIPD is the natural log of the absolute difference between the stock price and option-implied stock price scaled by stock price; or (iii) LogIVD is the natural log of the absolute difference between stock volatility and implied volatility.

VOLUMERATIO is the ratio of stock trading volume to option trading volume.

SPREADRATIO is the ratio of effective spread of stock trades to that of option trades.

VOLATILITY is stock return volatility.

AQ is one of two proxies for audit quality: (i) Big n (= 1 if audited by a Big n auditor and 0 otherwise); or (ii) industry specialist (= 1 if the incumbent auditor has the largest or second largest national market share based on audit fees in the industry and 0 otherwise).

2.1.1. Long/short ratio difference

As noted in the previous section, the ratio of long to short trades in a market has been employed in prior research as a proxy for the degree of asymmetry among traders in that market (Amin and Lee, 1997). As a result, we employ the difference in this ratio between the stock and options markets as a measure of the difference in information asymmetry between the markets. Following Amin and Lee (1997), long or short positions of option trades are defined in terms of positions initiated by active-side traders on the underlying stock. A long position is the purchase of a call option (a buyer-initiated call) or the sale of a put (a seller-initiated put); a short position is the purchase of a put (a buyer-initiated put) or the sale of a call (a seller-initiated call). The long or short position of stock trades is defined as buyer-initiated or seller-initiated stock trades. Specifically, a trade is classified as a buyer-initiated (seller-initiated) trade if the trade price is closer to the bid (ask) price (Amin and Lee, 1997). The ratios are measured over the period one week prior to the annual earnings announcement to one week after the release of the proxy statement.

2.1.2. Price difference

If the degree of asymmetry among investors differs between the stock and option markets, then this is likely to be reflected in differences in the prices in each market. Following Manaster and Rendleman (1982), price difference is defined as the difference between the actual stock price and the implied stock price recovered from an associated call option price, scaled by stock price. Prior literature suggests calculating implied stock price and implied volatility simultaneously using data from several options on the same stock to mitigate measurement error (Manaster and Rendleman, 1982). Thus, the implied price and the implied volatility pair are chosen to minimise the mean squared error of the following function:

$$\sum_{i=1}^{N_{jt}} [W^i - W^i(S_{jt}, V_{jt})]^2 \tag{2}$$

where, W^i is the observed midpoint option price, W^i (S_{jt}, V_{jt}) is the calculated option price, N_{jt} is the number of options on security j at time t, S_{jt} is the implied price, V_{jt} is the implied volatility.

Midpoint price is used instead of the actual option trade price as it has been suggested that this method can mitigate options' infrequent trading problem (Chan *et al*., 1993). As all the stock options investigated in this study are of American type, we employ the binomial option pricing model (which allows for the early exercise of American options) to calculate the implied stock price. The daily price difference is calculated over the sample period by matching the closing stock price with the contemporaneous option implied price and then taking the average of these daily price differences.

2.1.3. Volatility difference

Because different degrees of asymmetry among investors between markets will result in different patterns of information incorporation in prices, it is also likely that the two markets will exhibit different levels of volatility. As a result, we employ the difference in estimated volatility and implied volatility between the stock and option markets as our third proxy for asymmetry differences. The volatility difference is defined as the difference between the stock return volatility and the option-implied volatility. Conventionally, stock return volatility is calculated by the following formula:

$$V_{\text{daily}} = \sqrt{\frac{1}{n-1}\sum_{t=1}^{n}(r_t - \bar{r})^2} \tag{3}$$

where n is the number of observations, $r_t = \ln(P_t/P_{t-1})$, where P_t is the closing stock price of day t,

$$\bar{r} = \frac{1}{n}\sum_{t=1}^{n} r_t.$$

The option-implied volatility is estimated using the same procedure for calculating the implied stock price described earlier.

We log transform each of the information asymmetry measures to counter the potential influence of skewness of the measures on our results. Log transformation is a common procedure used in the audit research literature, for similar reasons (Larcker and Richardson, 2004). As a result of the transformation, the Anderson–Darling A-squared statistic for normality, applied to our regression residuals, decreases substantially for each of our regressions after logging. For example, when LogIPD is used as the INFOASYM measure, and Big *n* is used as the audit quality proxy, the Anderson–Darling statistic decreases from 1493.5 to 9.8. The other regression specifications exhibit similar decreases. However, we estimated all regressions using both logged and unlogged values for the information asymmetry proxies with no qualitative impact on our inferences.

2.1.4. Control variables

Chakravarty *et al.* (2004) suggest that the relative trading volume (VOLUMERATIO) and relative effective spread (SPREADRATIO) of the stock and options markets reflect the relative trading costs of the two markets. They show that the higher the trading cost of the options market relative to the stock market, the less price discovery occurs in the options market. This indicates that the trading cost difference of the two markets is related to the price difference between the two markets. In addition, they suggest that stock volatility (VOLATILITY) reflects the level of uncertainty and can be used as a control variable for information asymmetry because greater uncertainty stimulates the acquisition of private information, which leads to a higher degree of information asymmetry. Following Amin and Lee (1997), we measure effective spread in each of the options and stock markets (used in the calculation of SPREADRATIO) as follows:

$$\text{Effective spread} = 2|\text{Trade Price} - \text{Midspread}|,$$

where Midspread is the midpoint of the bid-ask price.

2.1.5. Audit quality (AQ) proxies

The extant literature suggests audit quality is multidimensional (see, for example, Francis, 2004). DeAngelo (1981) argues that auditor size is positively related to audit quality (auditor independence) because a large auditor has more clients and is less fee dependent on a single client. Therefore, a large auditor has a greater reputation to lose (their entire clientele) from low-quality audits. By contrast, a small auditor with fewer clients has greater incentive to 'cheat' to retain any one client (DeAngelo, 1981). Dye (1993) further points out that large auditors, who have more wealth at risk ('deep pockets') from litigation, have more incentive to issue accurate reports and therefore produce higher-quality outcomes. In addition, empirical evidence supports the use of Big *n* auditor as a proxy for high audit quality (Willenborg, 1999; Khurana and Raman, 2004; Francis and Lennox, 2008). Accordingly, we employ auditor size (Big *n* versus non-Big *n*) as a proxy for high audit quality.

Another strand of research suggests that industry specialist auditors make investments in industry-specific contracting technologies to enhance financial reporting credibility and to reduce the risk of litigation. Their industry expertise allows them to differentiate themselves from others and therefore earn above normal rates of return on their higher investments in industry expertise (Ferguson *et al.*, 2006). Specialist auditors are able to recognise various risks within a particular industry and gain a deeper understanding of the accounting rules and reporting requirements for that industry (Kwon, 1996). We follow this research and also use the appointment of an industry specialist auditor as a proxy to capture high audit quality (Francis *et al.*, 2005; Ferguson *et al.*, 2006).

2.2. Sample

We employ data from the US market for the years 2002 to 2005. The US options market is by far the largest of its kind in the world with the Chicago Board Options Exchange (CBOE hereafter). However, because US firms have been required to disclose the audit fee data only from 2001 onwards, our sample starts from year 2002 so that we can measure our industry specialisation proxy for audit quality.

The sample consists of non-financial service firms that trade options on the CBOE and have stock and option trade and quote data available in the Securities Industry Research Centre for Asia Pacific (SIRCA) database. In addition, financial statement data and auditing information for the analysis are required. Specifically, the financial statement items and auditor identity are from the Compustat database. Audit fee data are obtained from the Audit Analytics database.

For each firm-year in our sample, we focus on the period from one week before the annual earnings announcement to one week after the release of the proxy statement. The reason for this selection is that the value of auditing is largely attached to the accounting information and its effect, if any, on information asymmetry between traders will be exerted through affecting the quality of disclosed accounting information. It is reasonable, therefore, to concentrate on the period in which accounting and auditing information is released to the market. Prior studies suggest that option trading is active before the earnings announcement (Amin and Lee, 1997; Donders *et al.*, 2000). Amin and Lee (1997), for example, report that option market activity increases significantly in the four days before the earnings release, suggesting that option traders have advance knowledge of earnings news. Donders *et al.* (2000) find that option trading volume is higher around announcement days and the effective spread increases on the event day and on the first two days following the announcement. As these studies suggest that informed traders have advance knowledge of earnings news (prior to the earnings announcement), it is possible that they also trade on the audit quality signal attached to this information. Our sample period extends to one week after the release of the proxy statement to allow for the relevant accounting and auditing information to be released to the market.

Table 1 Panel A shows the industry composition of the sample. The 4062 firm-years span many sectors of the economy. The industries most represented in the sample are chemicals and applied products (546 out of 4062 observations, or 13.44 per cent of the sample), electronic and other electrical equipment (463 out of 4062, 11.4 per cent of the sample) and business services (392 out of 4062, 9.65 per cent of the sample). Among the 4062 firm-year observations, there are 1244 unique firms, and 744 out of the 1244 firms have observations in all four years. In this sense, the sample is relatively stable. We also compare the sample firms to all Compustat US firms in in Panel B of Table 1. The sample firms are on average larger (total assets), less leveraged (total long-term debt to total assets) and more profitable (earnings before interest and tax to total assets) than the population of Compustat US firms over the same time period.

The descriptive statistics for firm-years with non-missing values are presented in Panel A of Table 2. Panel A shows that some variables exhibit large divergences across the firms in the sample. The minimum and maximum values of the three dependent variables show that they all have a wide range, indicating that there is a high degree of variation in the information asymmetry proxies across the sample. For the AQ proxies, over 96 per cent of the sample firms chose Big *n* auditors and 57 per cent selected industry specialist auditors. Some variables have extreme values (e.g. VOLUMERATIO), but this does not influence the robustness of the regression results as conventional outlier diagnostics are applied. When observations with the absolute value of studentised residuals >2 or Cook's D >4 divided by the number of observations (with non-missing data for the particular model estimated) were deleted, this reduced the sample size available for estimating Equation (1) to 3945, 3991 and 4053 when Big *n* was employed as the audit quality (AQ) proxy and LogIPD, LogIVD and LogLSD, respectively, were the information asymmetry (INFOASYM) proxies. When Industry Specialist was employed as the AQ proxy, the corresponding numbers of observations were 3930, 3988 and 4053. However, results based on these reduced samples yield the same inferences as for the full sample. As a result, we report results based on all 4062 sample observations.

Table 2, Panel B, provides the correlation matrix between variables. As there are both continuous and dichotomous variables, different correlation coefficients are calculated whenever applicable. Specifically, for correlations between two continuous variables, the Pearson correlation coefficient is calculated. But for the association between two dummy variables, a phi coefficient is provided. For

Table 1
Industry composition and descriptive statistics

Panel A: Number of firms in each 2 digit SIC industry over the 2002–2005 period

		Year				
2-Digit SIC	Industry	2002	2003	2004	2005	All
1	Agricultural Production-Crops	1	1	1	1	4
2	Agricultural Production-Livestock	0	0	1	1	2
7	Agricultural Services	0	1	1	1	3
10	Metal Mining	12	18	21	21	72
12	Coal Mining	5	4	8	8	25
13	Oil & Gas Extraction	43	45	65	67	220
16	Heavy Construction Except Building	2	2	3	3	10
17	Construction-Special Trade Contractors	1	2	4	5	12
20	Food & Kindred Products Mfrs	23	23	26	27	99
21	Tobacco Products Mfrs	2	2	4	4	12
22	Textile Mill Products Mfrs	1	1	1	1	4
23	Apparel & Other Finished Products Mfrs	6	4	5	6	21
24	Lumber & Wood Prods	3	4	4	3	14
25	Furniture & Fixtures Mfrs	8	8	9	9	34
26	Paper & Allied Products Mfrs	9	9	10	10	38
27	Printing Publishing & Allied Industries	7	7	10	9	33
28	Chemicals & Allied Products Mfrs	113	136	148	149	546
29	Petroleum Refining & Related Inds Mfrs	16	16	20	20	72
30	Rubber & Miscellaneous Plastics Mfrs	6	6	6	6	24
31	Leather & Leather Products Mfrs	2	2	3	3	10
32	Stone Clay Glass & Concrete Prods Mfrs	5	6	8	8	27
33	Primary Metal Industries Mfrs	15	18	23	23	79
34	Fabricated Metal Products Mfrs	8	9	9	8	34
35	Industrial & Commercial Machinery Mfrs	59	68	70	70	267
36	Electronic & Other Electrical Equip Mfr	102	112	125	124	463
37	Transportation Equipment Mfrs	19	22	23	20	84
38	Measuring & Analyzing Instruments Mfrs	55	68	77	68	268
39	Miscellaneous Manufacturing Inds Mfrs	6	6	7	6	25
40	Railroad Transportation	6	6	6	6	24
42	Motor Freight Transportation/Warehouse	6	5	6	6	23
44	Water Transportation	5	9	13	11	38
45	Transportation By Air	7	8	7	8	30
46	Pipelines Except Natural Gas	0	0	0	1	1
47	Transportation Services	2	3	3	4	12
48	Communications	32	46	51	38	167
49	Electric Gas & Sanitary Services	38	40	43	43	164
50	Wholesale Trade-Durable Goods	12	13	17	18	60
51	Wholesale Trade-Non-durable Goods	7	6	10	9	72
52	Building Materials & Hardware	4	4	4	4	16
53	General Merchandise Stores	14	13	13	12	52
54	Food Stores	9	9	9	9	36
55	Automotive Dealers & Service Stations	6	7	7	7	27
56	Apparel & Accessory Stores	16	18	19	19	72

Table 1 (continued)

2-Digit SIC	Industry	Year 2002	2003	2004	2005	All
57	Home Furniture & Furnishings Stores	7	7	7	7	28
58	Eating & Drinking Places	10	12	12	12	46
59	Miscellaneous Retail	20	21	28	30	99
70	Hotels Rooming Houses & Camps	3	3	3	3	12
72	Personal Services	2	2	2	3	9
73	Business Services	84	97	105	106	392
78	Motion Pictures	2	3	3	4	12
79	Amusement & Recreation Services	11	11	13	12	47
80	Health Services	16	19	20	19	74
82	Educational Services	3	4	5	4	16
83	Social Services	1	1	1	1	4
87	Engineering & Accounting & Mgmt Svcs	12	14	15	17	58
99	Non-classified Establishments	1	2	3	3	9
	All	865	983	1117	1097	4062

Panel B: Descriptive statistics for sample firms versus all Compustat firms for 2002–2005 sample period

Variable	N	Mean	StDev
Total Assets			
Sample firms	4062	8229.0	20,960.0
All Compustat firms	20,278	3417.0	12,993.0
Leverage			
Sample firms	3994	0.200	0.201
All Compustat firms	20,278	0.212	0.261
Return on Assets			
Sample firms	3994	0.054	0.254
All Compustat firms	20,278	0.002	0.307

The sample consists of non-financial service firms that trade options on the CBOE and have stock and option trade and quote data available in the Securities Industry Research Centre for Asia Pacific (SIRCA) database. In addition, required financial statement data and auditing information for the analysis must be available on the Compustat and Audit Analytics databases. The value of total assets is in US$ millions. Leverage is the ratio of long-term debt to total assets and return on assets is the ratio of earnings before interest and tax to total assets. Compustat descriptive results are after removing any firm-years with total assets < $10 m. The reduced sample observations for leverage and return on asset results are because of missing data.

correlations between a dummy and a continuous variable, point-biserial correlation is calculated (Glass and Hopkins, 1995).

The correlation matrix shows that among the three information asymmetry proxies, implied price difference (LogIPD) has a significantly strong positive correlation with long/short ratio difference (LogLSD) with a coefficient of 0.481. It is also significantly positively related to implied volatility difference (LogIVD),

Table 2
Descriptive statistics

Panel A: descriptive statistics (n = 4062)

Variable	Mean	StdDev	Min	Q1	Median	Q3	Max
Dependent Variables							
LogIPD	−5.30	0.94	−9.07	−5.96	−5.40	−4.76	7.54
LogIVD	−3.06	1.39	−12.09	−3.78	−2.94	−2.23	1.77
LogLSD	0.18	1.78	−8.52	−1.08	0.45	1.50	7.18
Control Variables							
VOLUMERATIO	216.5	306.7	0.5	95.5	153.7	244.2	6741.6
SPREADRATIO	0.19	0.17	0.01	0.14	0.17	0.22	9.10
VOLATILITY	0.43	0.27	0.02	0.27	0.37	0.52	6.26
AQ Proxies							
Big *n*	0.96	0.19	0	1	1	1	1
Industry Specialist	0.57	0.50	0	0	1	1	1

Panel B: correlation matrix (n = 4062)

	LogIPD	LogIVD	LogLSD	VOLUME-RATIO	SPREAD-RATIO	VOLATILITY	Big *n*
LogIVD	**0.166**						
LogLSD	**0.481**	0.005					
VOLUMERATIO	**0.067**	**0.060**	−0.052				
SPREADRATIO	**0.050**	**0.051**	−0.004	**−0.045**			
VOLATILITY	**0.288**	**0.595**	0.026	**0.074**	**0.104**		
Big *n*	**−0.100**	**−0.042**	−0.006	**0.039**	**−0.033**	**−0.074**	
Industry Specialist	**−0.067**	−0.024	**−0.037**	**0.046**	**−0.054**	**−0.043**	**0.222**

See Appendix for a summary of the variable definitions. In Panel B, the Pearson correlation is calculated between any two continuous variables. The phi coefficient is calculated between two dummy variables. The point-biserial correlation is calculated between a dummy variable and a continuous variable. Bold text in Panel B indicates significance at the 0.05 (two-tailed) level or lower.

but less strongly with a correlation coefficient of 0.166. However, implied volatility difference (LogIVD) and long/short ratio difference are not significantly correlated. These results indicate that the three information asymmetry proxies are positively correlated with each other to some extent. Implied price difference and long/short ratio difference seem to capture similar aspects of information asymmetry between traders.

Panel B also shows that there is no serious correlation between the AQ proxies and the three control variables: none of the correlation coefficients between AQ proxies and control variables is >0.2. This indicates that multicollinearity is unlikely to be an issue. Finally, the panel shows there is only low correlation between the AQ proxies. This is consistent with either substantial noise in the two proxies and/or the possibility that each proxy reflects different dimensions of audit quality. We further investigate these possibilities in Section 3.2., below.

3. Results

3.1. Main results

Regression estimation results for the association between information asymmetry proxies and audit quality are shown in Table 3.[4]

The table consists of three panels, one for each of the three information asymmetry measures, respectively. Table 3 suggests that almost all the regressions of the model are significant as can be seen from the low model *P*-values. The results for the two AQ proxies (Big *n* and Industry Specialist) are broadly consistent. Neither AQ proxy is associated with the volatility difference information asymmetry measure. However, both AQ proxies are significantly negatively related to the implied price difference information asymmetry measure, while the Big *n* proxy (but not Industry Specialist) is significantly related to the long/short difference measure. This provides some evidence that firms engaged with high-quality auditors (Big *n* or industry specialist auditors) exhibit lower information asymmetry among traders. Control variables generally have consistent significant signs with volume ratio and stock volatility positively related to information asymmetry and spread ratio negatively associated with information asymmetry.

3.2. Additional analysis

3.2.1. Alternative audit quality proxies

As mentioned previously, the low correlation between Big *n* and Industry Specialist indicates the existence of substantial noise in one or both of the proxies and/or the possibility that the proxies reflect different dimensions of audit quality. We conducted two sets of additional analyses to investigate these possibilities. First, we estimated model (1) using alternative measures of auditor industry specialisation. Specifically, an alternative measure of Big *n* auditors, Barton's (2005) definition of auditor identity (BartonAC) was used, which classifies auditors into three groups – Big *n* auditor, national auditor and local auditor with the numerical coding from 3 to 1. We also considered alternative measures of industry specialist auditors. Based on prior studies noted earlier, which use arbitrary market share thresholds (typically 10 or 20 per cent) and apply these percentages across all industries to denote industry specialist, 10 and 20 per cent cut-off values to define industry specialists (IndSpe1 and IndSpe2) were

[4] Standard errors for regression coefficients are based on Newey–West adjustment for possible heteroskedasticity and serial-correlation. We also estimated cluster robust standard errors with observations clustered according to year and industry. Our inferences remained unchanged. We also estimated all regressions including industry and year dummies, again with no material impact on our inferences.

used. In addition, Godfrey and Hamilton's (2005) continuous measure of auditor industry market share (IndSpe3) was utilised.

In addition, we also employed four audit fee-based proxies of audit quality in our additional analyses. The first three – audit fee scaled by total assets (AF/TA), NAS fee scaled by total assets (NAS/TA) and total fee scaled by total assets (TF/TA) – are based on Firth (2002). The fourth – unexpected audit fee (UAF) – is based on Ferguson *et al.* (2006).[5] Higher audit fees, or unexpected audit fees, might indicate higher effort by the audit firm and reflect greater audit quality, thus lowering uncertainty over the quality of the accounting disclosures and contributing to lower information asymmetry between traders (Hope and Langli, 2010). That is, it could signal potential irregularities in the accounts that required the auditor's attention and the additional audit effort resolved them. Alternatively, during the period of this study, Arthur Andersen's demise and the collapse of Enron potentially heightened awareness of audit independence risk such that higher fees from audit and/or non-audit services and higher than expected audit fees could also suggest greater fee dependence of the auditor on the client and lower auditor independence creating further uncertainty over the quality of the company disclosures. These arguments create incentives for informed traders to search for private information about the company and produce an information imbalance between traders making the beliefs of traders less homogeneous and lead to greater divergence in opinions of the stock and options markets as reflected in our three measures of information asymmetry in model (1). This line

[5] Specifically, unexpected audit fee was calculated as the ratio of the audit fee to expected audit fee, where we used the anti-log of the fitted value of the audit fee model from Ferguson *et al.* (2006) for the expected audit fee:

$$\begin{aligned}\text{LogAF} = {} & a_0 + a_1\text{LogTA} + a_2\text{LogSeg} + a_3\text{CATA} + a_4\text{Quick} + a_5\text{DE} + a_6\text{ROI} \\ & + a_7\text{Foreign} + a_8\text{Opinion} + a_9\text{YE} + a_{10}\text{Loss} + a_{11}\text{Joint-Leader} \\ & + a_{12}\text{National-Only} + a_{13}\text{City-Only} + \text{fixed effects} + e\end{aligned}$$

where: LogAF is the natural log of audit fees in dollars; LogTA is the natural log of total assets in millions of dollars; LogSeg is the natural log of the number of unique business segments; CATA is the ratio of current assets to total assets; Quick is the ratio of current assets (less inventories) to current liabilities; DE is the ratio of long-term debt to total assets; ROI is the ratio of earnings before interest and tax to total assets; Foreign is the proportion of total sales from foreign operations; Opinion is the indicator variable, 1 is the qualified audit opinion; YE is the indicator variable, 1 is the non-December 31 year-end; Loss is the indicator variable, 1 is the loss in current fiscal year; Joint-Leader is the indicator variable for auditors that are both national industry leaders and city-specific industry leaders; National-Only is the indicator variable for auditors that are national industry leaders but not the *city-specific industry* leaders; City-Only is the indicator variable for auditors that are not national industry leaders but are the city-specific industry leaders; Fixed effects is the industry dummy variables for 2-digit SIC industry classifications; and e is the error term.

Table 3
OLS regressions of information asymmetry measures on control variables and audit quality proxies
INFOASYM = $a_0 + a_1$VOLUMERATIO + a_2SPREADRATIO + a_3VOLATILITY + a_4AQ + e

	Expected sign	Big *n*		Industry Specialist	
		Coeff	*P*-value	Coeff	*P*-value
Panel A: Dependant variable is LogIPD (n = 4062)					
Intercept		−5.375	0.000	−5.714	0.000
VOLUMERATIO	+	0.000	0.122	0.000	0.133
SPREADRATIO	−	0.120	0.252	0.115	0.283
VOLATILITY	+	0.951	0.000	0.964	0.000
AQ	−	−0.410	0.000	−0.107	0.000
R^2-adj		0.091		0.088	
Model *P*-value		0.000		0.000	
Panel B: Dependant variable is LogIVD (n = 4062)					
Intercept		−4.391	0.000	−4.385	0.000
VOLUMERATIO	+	0.000	0.358	0.000	0.357
SPREADRATIO	−	−0.085	0.541	−0.085	0.540
VOLATILITY	+	3.051	0.000	3.050	0.000
AQ	−	0.006	0.955	0.000	0.200
R^2-adj		0.354		0.354	
Model *P*-value		0.000		0.000	
Panel C: Dependant variable is LogLSD (n = 4062)					
Intercept		0.198	0.185	0.252	0.000
VOLUMERATIO	+	0.000	0.011	0.000	0.013
SPREADRATIO	−	−0.100	0.363	−0.116	0.308
VOLATILITY	+	0.204	0.060	0.196	0.069
AQ	−	−0.021	0.882	−0.122	0.041
R^2-adj		0.003		0.004	
Model *P*-value		0.004		0.003	

See Appendix for a summary of the variable definitions. All *P*-values are Newey–West adjusted for both heteroskedasticity and serial correlation. The first row header in each panel indicates the specific AQ proxy used in each regression. *P*-values are two tailed.

of reasoning suggests a positive association between information asymmetry and audit fee-based measures. Because of these conflicting stories, we view the association between fee-based proxies and INFOASYM as an empirical issue.

Table 4 summarises the results of tests using all alternative AQ metrics. It shows that BartonAC, IndSpe1, IndSpe2 and IndSpe3 are significantly negatively associated with the same two information asymmetry measures (implied price difference and long/short ratio difference) as are Big *n* and industry specialist auditors in Table 3. Thus, our main results are reinforced. Table 4 also indicates that each of the audit fee-based measures are positively associated with the information asymmetry proxies, consistent with the possibility that high audit fees signal quality concerns on the part of investors that provide incentives for private information gathering and thus increased information asymmetry.

Table 4
Summary of regression results of information asymmetry measures on control variables and additional audit quality proxies
$\text{INFOASYM} = a_0 + a_1\text{VOLUMERATIO} + a_2\text{SPREADRATIO} + a_3\text{VOLATILITY} + a_4\text{AQ} + e.$
The table summarises the regression results for the coefficient on AQ (a_4) for various audit quality proxies described below. *P* values are in parentheses

AQ Proxy	LogIPD	LogIVD	LogLSD
BartonAC	−0.232*** (0.000)	−0.03 (0.551)	−0.164* (0.057)
IndSpe1	−0.204*** (0.000)	−0.051 (0.360)	−0.254** (0.015)
IndSpe2	−0.119*** (0.000)	−0.042 (0.183)	−0.149*** (0.009)
IndSpe3	−0.264** (0.013)	0.026 (0.829)	−0.513** (0.042)
AF/TA	89.673*** (0.000)	23.47*** (0.001)	83.548*** (0.000)
NAS/TA	113.68*** (0.000)	24.983* (0.098)	201.04*** (0.000)
TF/TA	74.375*** (0.000)	19.48*** (0.001)	82.179*** (0.000)
UAF	0.03** (0.046)	0.041** (0.015)	0.07* (0.071)

See Appendix for variable definitions. *, **, *** denote significance at 1, 5 and 10 per cent level, respectively, two tailed. All results are Newey–West adjusted for both heteroskedasticity and serial correlation.

3.2.2. A combined information asymmetry proxy

Table 3, together with associated robustness analyses, indicates a consistently significant association between information asymmetry (INFOASYM) and audit quality (AQ) when either LogIPD or LogLSD is used as the INFOASYM proxy. In contrast, no significant association is observed for LogIVD. Because LogIPD and LogLSD exhibit relatively strong positive correlation (Panel B of Table 2), while LogIVD is less strongly correlated with each of these proxies, it is possible that the different proxies reflect different underlying factors. To explore this possibility, we conducted factor analysis to identify common factors underlying the proxies. As might be expected, two primary factors were uncovered, the first (second) explaining approximately 50 per cent (33 per cent) of total variation in the three proxies. Moreover, the first factor loaded significantly on LogIPD and LogLSD, while the second factor loaded significantly on LogIVD. We employed these two factors as alternative proxies for INFOASYM in estimating Equation (1). Untabulated results indicate that the first factor is significantly negatively associated with both Big *n* and Industry Specialist, while the second factor is not significantly associated with either audit quality proxy, consistent with the results reported in Table 3.

3.2.3. The effect of earnings quality (EQ)

As discussed in the Introduction, previous research suggests that disclosure quality will be associated with information asymmetry among investors. Our focus in this research is on audit quality as a component of disclosure quality, with the results presented in Tables 3 and 4 consistent with higher audit quality being associated with lower information asymmetry. However, it is possible that our audit quality proxies are also correlated with earnings quality and that our results are largely because of this omitted effect rather than to audit quality itself. To investigate this possibility, we follow prior research (Francis *et al.*, 2005) and employ absolute accruals (Absolute Total Accruals[6]) as a proxy for earnings quality and include it as an additional explanatory variable in our regressions.

Table 5 indicates that, after controlling for absolute total accruals, the results for AQ remain consistent with those reported in Table 3. Absolute Total Accruals is significantly positively correlated with one information asymmetry measures, implied price difference (LogIPD), consistent with the expectation. However, it is not significantly associated with either of the other information asymmetry measures.

3.2.4. Good and bad earnings news

The management earnings forecast literature indicates that bad earnings news is more informative or believable than good earnings news (Hutton *et al.*, 2002). That is, there is more uncertainty associated with good news than with bad news (Ferguson and Matolcsy, 2004), and this reduces the ability of high-quality audits to reduce noise attached to bad earnings news. Therefore, AQ is likely to matter more in the context of good news than in bad news.

We performed an analysis of the two key AQ proxies in good and bad earnings sub-samples. Earnings news is defined as good news if the actual earnings meet or beat analysts' forecasted earnings and bad news otherwise (Bartov *et al.*, 2002). The analyst forecast information, which is used to calculate unexpected earnings, comes from I/B/E/S.

Untabulated results show that audit quality matters more in good earnings contexts in reducing information asymmetry, with the results using the two AQ proxies in the good news sub-sample consistent with those reported in Table 3. Only Big *n* is significantly correlated with LogIPD in the bad news sub-sample.

3.2.5. Information environment

Implicitly, we assume that the information environment, aside from AQ and EQ, for all audit clients is the same. However, independent of AQ and EQ, some firms face richer information environments than others, and these differences could affect the incentives of investors to acquire private information. For example, in a rich information environment where public information is plentiful,

[6] Absolute Total Accruals are measured as the absolute value of the difference between income before extraordinary items and operating cash flows deflated by the lagged value of total assets (Dechow *et al.*, 1996).

Table 5
OLS regressions of information asymmetry measures on control variables, audit quality proxies, and absolute total accruals

$$\text{INFOASYM} = a_0 + a_1\text{VOLUMERATIO} + a_2\text{SPREADRATIO} + a_3\text{VOLATILITY} + a_4\text{AQ} + a_5|\text{Total Accruals}| + e$$

	Expected sign	Big *n*		Industry Specialist	
		Coeff	*P*-value	Coeff	*P*-value
Panel A: Dependant variable is LogIPD (n = 4062)					
Intercept		−5.396	0.000	−5.722	0.000
VOLUMERATIO	+	0.000	0.001	0.000	0.001
SPREADRATIO	−	0.113	0.181	0.107	0.206
VOLATILITY	+	0.936	0.000	0.945	0.000
AQ	−	−0.395	0.000	−0.105	0.000
|Total Accruals|	+	0.160	0.035	0.191	0.012
R^2-adj		0.092		0.089	
Model *P*-value		0.000		0.000	
Panel B: Dependant variable is LogIVD (n = 4062)					
Intercept		−4.386	0.000	−4.383	0.000
VOLUMERATIO	+	0.000	0.209	0.000	0.209
SPREADRATIO	−	−0.084	0.431	−0.084	0.431
VOLATILITY	+	3.054	0.000	3.054	0.000
AQ	−	0.003	0.978	0.000	0.994
|Total Accruals|	+	−0.034	0.726	−0.034	0.723
R^2-adj		0.354		0.354	
Model *P*-value		0.000		0.000	
Panel C: Dependant variable is LogLSD (n = 4062)					
Intercept		0.208	0.201	0.256	0.000
VOLUMERATIO	+	0.000	0.001	0.000	0.001
SPREADRATIO	−	−0.097	0.567	−0.113	0.504
VOLATILITY	+	0.211	0.045	0.204	0.052
AQ	−	−0.028	0.855	−0.122	0.031
|Total Accruals|	+	−0.073	0.630	−0.077	0.610
R^2-adj		0.003		0.004	
Model *P*-value		0.009		0.001	

See the Appendix for a summary of the variable definitions. All *P*-values are Newey–West adjusted for both heteroskedasticity and serial-correlation. The first row header in each panel indicates the specific AQ proxy used in each regression. *P*-values are two-tailed.

investors could have less incentive to acquire private information even if AQ is low. On the other hand, if the information environment is weak, the marginal benefit of acquiring private information increases whether AQ is high or low. Bhushan (1989) shows that analyst following, a common proxy for the information environment, is positively related to firm size, institutional holdings, the correlation between the firm's and market's return, and the firm's return volatility, and negatively related to the percentage of insiders and firm complexity. Although the empirical model in this research does have a control for stock volatility, there still can be other cross-sectional differences in the information environments of clients in the sample. Therefore, we performed a sensitivity test that included firm size (the natural log of total assets) as an additional explanatory variable in Equation (1). The regression results remain consistent with those reported in Table 3.[7]

3.2.6. Endogeneity

Estimation of Equation (1) raises potential endogeneity concerns between information asymmetry and audit quality. In particular, it is possible that companies choose the quality of their auditors, in part, based on factors relating to the degree of information asymmetry among their investors. For example, firms with high information asymmetry among investors could be motivated to choose high-quality auditors in an attempt to mitigate the asymmetry. Under these circumstances, estimation of (1) using OLS is potentially contaminated. We investigated this possibility by employing 2SLS estimation, with the first stage employing an auditor choice model using the log of firm size (total assets) as the exogenous factor reflecting information asymmetry (as above). The fitted values from the first stage regression were then used as the AQ proxy in estimation of (1). Untabulated results are consistent with those reported in Table 3 – LogIPD and LogLSD are significantly associated with both fitted proxies for AQ (based on Big *n* and Industry Specialist), while LogIVD is not significantly associated with either fitted AQ measure. Also, following Francis and Lennox (2008), we employed a 'matched propensity scores' approach as an alternative. The objective is to create a control sample of non-Big *n* clients that is matched to the observations in the Big *n* sample of clients based on the predicted propensity score (i.e. the predicted probability from the first stage auditor choice model) with the key assumption being that the selection of the auditor takes place on the basis of this choice model. By so matching, we have firms that are used in estimations of AQ on the INFOASYM proxies that are similar in their underlying drivers of Big *n* auditor choice and thus controlled for selectivity with respect to the companies endogenous characteristics associated with choosing to use Big *n* auditors. We estimated the first-stage auditor choice model, and each non-Big *n* client was matched (where matching is undertaken with replacement) to a Big *n* client that had the closest auditor choice probability. Untabulated results show that in estimations of the INFOASYM models, the matched sample yields similar results to those reported in Table 3 (where the samples are unmatched), suggesting that there is no strong endogeneity threat regarding the auditor choice variables we employ.

[7] Firm size is significant and has a negative sign suggesting larger firms have lower information asymmetry.

4. Conclusions

In this study, we investigate the association between audit quality and information asymmetry between informed and uninformed traders. We are motivated in part by linking two strands of research. The first strand demonstrates that high-quality auditing increases information quality for capital markets, while the second strand of research suggests that the difference in opinions of the stock and options markets can be used to proxy for information asymmetry between traders. With the disclosure literature suggesting that higher information quality leads to lower levels of information asymmetry between traders, we investigate whether high-quality auditing increases information quality and lowers information asymmetry between traders.

Using a sample of 4062 firm-year observations from years 2002 to 2005 in the US market, our results show that employing a Big *n* auditor and an industry specialist auditor is associated with lower information asymmetry between traders. The results are robust to alternative measures of these audit quality variables, and additional controls for the richness of the information environment of a company. The association between AQ and information asymmetry between traders remains after controlling for the influence of earnings quality (absolute total accruals), suggesting the AQ effect is not simply proxying for an omitted earnings quality effect. Finally, we find some additional evidence to suggest that industry specialist auditor matters more in good earnings contexts in terms of reducing information asymmetry between traders. Our results are robust to controlling for endogeneity.

These results are consistent with audit quality playing a role in the quality of financial reporting information and flowing through to the allocation of information among traders. Our study is a departure from and an extension to the extant research showing that audit quality is valuable to investors.

References

Amin, K., and C. Lee, 1997, Option Trading, Price Discovery and Earnings News Dissemination, *Contemporary Accounting Research* 14, 153–192.

Anthony, J. H., 1988, The Interrelation of Stock and Options Market Trading-Volume Data, *Journal of Finance* 43(4), 949–964.

Barton, J., 2005, Who Cares about Auditor Reputation? *Contemporary Accounting Research* 22(3), 549–586.

Bartov, E., D. Givoly, and C. Hayn, 2002, The Rewards to Meeting or Beating Earnings Expectations, *Journal of Accounting and Economics* 33, 173–204.

Bhattacharya, M., 1987, Price Changes of Related Securities: The Case of Call Options and Stocks, *Journal of Financial and Quantitative Analysis* 22, 1–15.

Bhushan, R., 1989, Firm Characteristics and Analyst Following, *Journal of Accounting and Economics* 11(2), 255–274.

Black, F., 1975, Fact and Fantasy in the Use of Options, *Financial Analysts Journal* July–August, 36–72.

Chakravarty, S., H. Gulen, and S. Mayhew, 2004, Informed Trading in Stock and Option Markets, *Journal of Finance* 59(3), 1235–1258.
Chan, K., P. Chung, and H. Johnson, 1993, Why Option Prices Lag Stock Prices: A Trading Based Explanation, *Journal of Finance* 48, 1957–1967.
Christensen, B. J., and N. R. Prabhala, 1998, The Relationship between Implied and Realized Volatility, *Journal of Financial Economics* 50, 125–150.
Clinch, G., J. Lyon, and G. Twite, 2005, *Anticipated returns implicit in option prices*, Working paper (University of Technology, Sydney).
Craswell, A. T., and S. L. Taylor, 1991, The Market Structure of Auditing in Australia: The Role of Industry Specialization, *Research in Accounting Regulation* 5, 55–77.
Craswell, A. T., J. R. Francis, and S. Taylor, 1995, Auditor Brand Name Reputations and Industry Specializations, *Journal of Accounting and Economics* 20(3), 297–322.
DeAngelo, L. E., 1981, Auditor Size and Audit Quality, *Journal of Accounting and Economics* 3, 183–199.
Dechow, P., R. Sloan, and A. Sweeney, 1996, Causes and Consequences of Earnings Manipulation: An Analysis of Firms Subject to Enforcement Actions by the SEC, *Contemporary Accounting Research* Spring, 1–36.
DeJong, F., and M. Donders, 1998, Intraday Lead-Lag Relationships between the Futures-, Options and Stock Market, *European Finance Review* 1, 337–359.
Dhaliwal, D., C. Gleason, S. Heitzman, and K. Melendrez, 2008, Auditor Fees and Cost of Debt, *Journal of Accounting, Auditing and Finance* 23(1), 1–22.
Diamond, D. W., 1985, Optimal Release of Information by Firms, *Journal of Finance* 40(4), 828–862.
Donders, M., R. Kouwenberg, and A. C. F. Vorst, 2000, Options and Earnings Announcements: An Empirical Study of Volatility, Trading Volume, Open Interest and Liquidity, *European Financial Management* 6, 149–171.
Duarte, J., and L. Young, 2009, Why is PIN Priced? *Journal of Financial Economics* 9, 119–138.
Dye, R., 1993, Auditing Standards, Legal Liability and Auditor Wealth, *Journal of Political Economy* 101, 887–914.
Easley, D., and M. O'Hara, 1992, Time and the Process of Security Price Adjustment, *Journal of Finance* 47(2), 577–605.
Ferguson, A., and Z. Matolcsy, 2004, Audit Quality and Post Earnings Announcement Drift, *Asia-Pacific Journal of Accounting & Economics* 11(1), 121–137.
Ferguson, A., J. Francis, and D. Stokes, 2006, What Matters in Audit Pricing, Industry Specialization or Overall Market Leadership? *Accounting and Finance* 46, 97–106.
Firth, M., 2002, Auditor-provided Consultancy Services and Their Associations with Audit Fees and Audit Opinions, *Journal of Business Finance and Accounting* 29(5/6), 661–694.
Fleming, J., B. Ostdiek, and J. Whaley, 1996, Trading Costs and the Relative Rates of Price Discovery in Stock, Futures and Option Markets, *Journal of Futures Markets* 16, 353–387.
Francis, J. R., 2004, What Do We Know About Audit Quality? *The British Accounting Review* 36(4), 345–368.
Francis, J., and C. Lennox, 2008, *Selection models in accounting research*, Working paper (University of Missouri-Columbia and Hong Kong University of Science and Technology).
Francis, J., E. Maydew, and H. Sparks, 1999, The Role of Big 6 Auditors in the Credible Reporting of Accruals, *Auditing: A Journal of Practice and Theory* 18(2), 17–34.
Francis, J., R. LaFond, P. Olsson, and K. Schipper, 2005, The Market Pricing of Accruals Quality, *Journal of Accounting and Economics* 39, 295–327.

Glass, G. V., and K. D. Hopkins, 1995, *Statistical Methods in Education and Psychology*, 3rd edn (Allyn & Bacon, UK).

Godbey, J. M., and J. W. Mahar, 2004, Implied Volatilities and Auditor Reputation: The Andersen Case, *Research in Finance* 21, 93–111.

Godfrey, J. M., and J. Hamilton, 2005, The Impact of R&D Intensity on Demand for Specialist Auditor Services, *Contemporary Accounting Research* 22(1), 55–93.

Heflin, F., K. W. Shaw, and J. J. Wild, 2001, *Disclosure quality and market liquidity*, working paper (Purdue University).

Higgs, J., and T. Skantz, 2006, Audit and Nonaudit Fees and the Market's Reaction to Earnings Announcements, *Auditing: A Journal of Practice and Theory* 25(1), 1–26.

Hope, O.-K., and J. C. Langli, 2010, Auditor Independence in a Private Firm and Low litigation Risk Setting, *The Accounting Review*, 85(2), 573–605.

Hutton, A., G. Miller, and D. Skinner, 2002, *The role of supplementary statements in the disclosure of management earnings forecasts*, Working paper (Harvard Business School).

Jarnecic, E., 1999, Trading Volume Lead/Lag Relations between the ASX and ASX Option Market: Implications of Market Microstructure, *Australian Journal of Management* 24(1), 77–94.

Khurana, I., and K. Raman, 2004, Litigation Risk and the Financial Reporting Credibility of Big 4 versus Non-Big 4 Audits: Evidence from Anglo-American Countries, *The Accounting Review* 79(2), 473–495.

Kwon, S., 1996, The Impact of Competition within the Client's Industry on the Auditor Selection Decision, *Auditing: A Journal of Practice and Theory* 15, 53–70.

Larcker, D., and S. Richardson, 2004, Fees Paid to Audit Firms, Accrual Choices, and Corporate Governance, *Journal of Accounting Research* 42, 625–658.

Lee, J., and C. H. Yi, 2001, Trade Size and Information-motivated Trading in the Options and Stock Markets, *Journal of Financial and Quantitative Analysis* 36, 485–501.

Levitt, A., 1998, The Importance of High Quality Accounting Standards, *Accounting Horizons* 12, 79–82.

Manaster, S., and R. Rendleman, 1982, Option Prices as Predictors of Equilibrium Stock Prices, *Journal of Finance* 37, 1043–1058.

Mansi, S. A., W. F. Maxwell, and D. P. Miller, 2004, Does Auditor Quality and Tenure Matter to Investors: Evidence from the Bond Market, *Journal of Accounting Research* 42, 755–793.

Ruddock, C., S. Taylor, and S. Taylor, 2006, Nonaudit Services and Earnings Conservatism: Is Auditor Independence Impaired? *Contemporary Accounting Research* 23(3), 701–746.

Stephan, J. A., and R. E. Whaley, 1990, Intraday Price Change and Trading Volume Relations in the Stock and Stock Option Markets, *Journal of Finance* 45, 191–220.

Verrecchia, R. E., 2001, Essays on Disclosure, *Journal of Accounting and Economics* 32(1–3), 97–180.

Willenborg, M., 1999, Empirical Analysis of the Economic Demand for Auditing in the Initial Public Offerings Market, *Journal of Accounting Research* 37(1), 225–239.

Appendix

Variable names, definitions and literature sources

Variable Name	Definition	Literature Source
Dependent Variables: |Difference|		
LogIPD	Natural log of absolute difference between option-implied stock price and actual stock price scaled by stock price	Manaster and Rendleman (1982)
LogIVD	Natural log of the absolute difference between option-implied volatility and stock volatility	Christensen and Prabhala (1998)
LogLSD	Natural log of the absolute difference between long/short ratio of option trades and that of stock trades	Amin and Lee (1997)
Control Variables		
VOLUMERATIO	Ratio of stock volume to option volume	Chakravarty, Gulen, and Mayhew (2004)
SPREADRATIO	Ratio of stock effective spread to option effective spread	
VOLATILITY	Stock volatility	
Audit Quality (AQ) Proxies		
Big *n*	Equals 1 if the incumbent auditor is a Big *n* auditor and 0 otherwise	DeAngelo (1981)
Industry Specialist	Equals 1 if the incumbent auditor has the largest or second largest national market share based on audit fees in the industry and 0 otherwise	Francis *et al.* (2005)
BartonAC	Barton auditor code, which equals 1 if the incumbent auditor is a local auditor, 2 if it's a national auditor and 3 if it's a Big *n* auditor (Barton, 2005)	Barton (2005)
IndSpe1	Equals 1 if the incumbent auditor has over 10 per cent of the total national market share (based on audit fees) in the industry and 0 otherwise	Craswell and Taylor (1991)
IndSpe2	Equals 1 if the incumbent auditor has over 20 per cent of the total national market share (based on audit fees) in the industry and 0 otherwise	Craswell *et al.* (1995)
IndSpe3	Percentage of shares an auditor has in an industry based on client sales	Godfrey and Hamilton (2005)
AF/TA	A firm's audit fee scaled by total assets	Firth (2002)
NAS/TA	A firm's NAS fee scaled by total assets	Firth (2002)
TF/TA	A firm's total audit fee scaled by total assets	Firth (2002)
UAF	Unexpected audit fee, which is the ratio of actual audit fee to model estimated audit fee	Ferguson, Francis, and Stokes (2006)