Liquidity surrounding Sell-Side Equity Analyst Recommendation Revisions on the Australian Securities Exchange

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Abstract

The present study investigates the impact of sell-side equity analyst recommendation revisions on a time-series of liquidity measures. Our focus is on the information processing ability of analysts and their subsequent effect on transaction costs and trade volume. The empirical results indicate that bid-ask spreads do not change around revisions, but depths and trading volume increase. This finding is consistent with recommendation revisions acting as liquidity enhancing events and indicates that the market is sufficiently liquid to process this information without embedding excess information asymmetry costs. This result bodes well for the efficiency of the Australian market.

1. Introduction

Brokerages and investment banks hire sell-side equity analysts to identify mispriced securities that represent trading opportunities to their clients. These institutions distribute recommendation revisions with the intention of generating trading activity and brokerage commissions. In their role, analysts process an immense quantity of information to forecast company earnings, compare stock valuations and disseminate investment advice. This process operates under the assumption that equity analysts possess superior information processing ability and provides a valuable service to clients. The survival of analysts for many decades in a repeat game framework, under this assumption, is reason to suspect that they introduce new information to the market.

The capacity of analysts to discover new information and the requirement for brokerages to receive commissions in this repeat game framework creates the possibility that adjustments in recommendations will have an impact on liquidity and trading activity. That is, the marketing effort of large brokerages will generate trading volume and the information in new recommendations may generate additional information asymmetry risks. It becomes an empirical question whether recommendation revisions generate excess information asymmetry that is priced into the bid-ask spread (hereafter referred to as the spread). We test the strength of this impact empirically on the Australian market.

A significant amount of prior literature is dedicated to analyst recommendation revisions, with the majority of this research focusing on US analysts. Initial studies documented the price response around revisions and the subsequent performance of analyst advice. This research began with the work of Cowles (1933) and has remained an area of interest for academics with studies including Bjerring, Lakonishok and Vermaelen (1983), Stickel (1995) and Womack (1996) providing empirical evidence. In Australia, Wong (2002) examines the price response to new analyst reports. The findings of returns literature indicate that while analyst's revisions are associated with price movements around the event time, longer-term predictive ability is limited. Stickel (1995) and Barber et al. (2001), among others, find that the performance of analyst advice aligns with a high degree of market efficiency.

More recent empirical studies have looked at transaction costs and liquidity surrounding recommendation changes (Irvine, 2003, Anand et al., 2006). Documenting information flows in the securities market and the affect on transaction costs is seen as vital to establishing the profitability of trading on analyst advice (Barber et al., 2001). Transaction cost control is a major concern for institutional traders and critical to their ability to beat performance benchmarks. Analysis of the impact on transaction costs around these events provides a vital link between returns literature and the profitability of trading on recommendations, which is important to the market efficiency debate. Liquidity surrounding new recommendations on the Australian Securities Exchange (ASX) remains an open empirical question and we intend to bridge this gap to assess transaction costs and the prudence of trading at these times.

Revisiting the issue on the Australian market is justified by the microstructural differences to the US market. Inventory holding costs are less likely to exist on the Australian market as it operates without an official market maker. While unverified, there is a chance of offsetting inventory and adverse section risks on the US market that gives reason to expect differing results on the US and Australian markets. Brennan and Subrahmanyan (1995) posit that with greater financial analyst coverage, competition between informed traders on one side of the market reduces the asymmetric information component of the spread. As a result, there is an acceptable reason to suspect the Anand et al. result of unchanged spreads may differ on the

Australian market and align with an alternative hypothesis such as Brennan and Subrahmanyan (1995). Considering the need for external validation of Anand et al. and the potential benefits of testing the issue on an alternative trading mechanism, re-examination of the issue is warranted.

The paper is structured as follows. Section 2 discusses the Australian institutional setting, Section 3 reviews the relevant literature and Section 4 uses this framework to develop our hypothesis. Section 5 describes the data and provides sample selection criteria and summary statistics. Section 6 describes the methodology. We report and discuss results for interday and intraday liquidity analysis in Sections 7 and 8 respectively. Section 9 concludes.

2. Australian Institutional Setting

2.1 Australian Market Microstructure

Our price and quote data is generated on the ASX, which operates a fully automated continuous auction trading system. Traders submit market and limit orders into the electronic central limit order book, which transact based on price-time priority. Trading hours are between 10:00:00 and 16:00:00 with opening and closing call auctions commencing and concluding trade. The market operates without an official market maker, with tiered tick sizes and the ASX has pre-trade transparency of the full order book to brokers and traders.

2.2 The Sell-Side Analysts' Role

Sell-side equity analysts are market professionals that specialize in collecting and analysing the information available on public companies and summarizing this research into informed advice for the clients of a financial institution. Analyst recommendations propose a trading response to their clients. Investment banks and asset managers are the primary producers of this information and the supply of analyst reports is determined by the economic potential of covering a particular security. Securities perceived to provide opportunities to generate higher trading volume and commissions have greater analyst coverage.

Analysts are tasked with identifying discrepancies between the intrinsic and market value of listed companies. They gather economic, industry and company-specific data from public and private sources and perform perspective analysis to forecast future cash flows. Analyst valuations are compared to prevailing market value. Recommendations are based on the predicted performance of the stock against the estimated performance of the market index, or a relevant benchmark. The strength of the signal from (1) strong buy (2) buy (3) hold (4) underperform to (5) strong sell reflects the degree of the perceived mispricing.

The economic benefits derived from each individual recommendation and coverage of individual securities depends critically on the level of information asymmetry prevailing in the stock. The returns associated with each recommendation are directly correlated to the information asymmetry uncovered, which creates a track record of performance and attracts a greater clientele. It is the analyst's role to identify trading opportunities that provide excess returns and they are therefore directly compensated for the level of information asymmetry that is identified. The link between analyst information processing ability, information asymmetry and adverse selection is cause to suspect a market impact related to revisions and makes this an interesting empirical question under the assumption that analysts have timing and stock picking ability.

Persistent debate prevails concerning conflicts of interest in the analyst recommendation process. We address the possibility of such misconduct. Analysts are in a unique position to manipulate the market by using or acting upon insider information or releasing reports with deceitful motivations. The Australian Securities and Investment Commission (ASIC) govern the dissemination of analyst recommendations on the Australian market. Under the market misconduct regime, acts including insider trading, market manipulation and false, misleading and deceptive conduct are monitored and enforced. The risks of diminishing reputation coupled with legal boundaries guide analyst activity and minimize distortion from manipulation in our results.

3. Literature Review

The informativeness of analyst recommendations influences the degree of information asymmetry and the market impact of revisions. Our results rest on the assumption that analyst activity may enhance the informational efficiency of security markets. Hong et al. (2000) and Elgers et al. (2001) provide evidence that analyst following increases the rate with which prices embed public information. Prior research (Givoly and Lakonishok, 1979, Lys and Sohn, 1990, Francis and Soffer, 1997, Jegadeesh and Kim, 2006) demonstrates that analyst advice typically communicates information to securities markets. Contrarily, a number of studies (Shukla and Trczinka, 1992, Easley, O'Hara and Paperman, 1998, Cvitanic et al. 2006) have reported evidence that analyst activity is uninformative. Current empirical literature creates uncertainty over analyst's information processing ability and warrants our empirical investigation.

The assumption that analysts have information processing ability implies that they can identify information asymmetry in security markets. The process of incorporating new information into the market and the effect on transaction costs and liquidity is defined by numerous academics (Glosten and Harris, 1988, Madhavan and Smidt, 1991, O'Hara, 1995, Hasbrouck, 2007). Anand et al. are the first to study this particular event empirically. They directly investigate the impact of analyst revisions on transaction costs and liquidity by studying the time-series of liquidity around new recommendations. Their intention is to assess the rationality of institutional trading surrounding new recommendations.

Anand et al. analyse changes in spreads; depth and trading activity around recommendation revisions on NYSE and AMEX listed securities. Over the 5,863 recommendation changes investigated, transaction costs do not change, while measures of depth and volume exhibit statistically significant increases. This result is consistent after intraday analysis and several robustness checks. The authors attribute this result to the presence of contrarian traders willing to transact against analyst advice. With sufficient volume generated on both sides of the limit order book, the specialist can simply match incoming orders. This result is consistent with an inability of analysts to identify information asymmetry, the authors posit that revisions do not embody valuable information. Anand et al. conclude that this empirical finding represents a trading opportunity for institutions already resigned to trading; as they can access excess volume at spreads no greater than otherwise achieved.

Irvine (2003) studies the incremental impact of analyst initiation (the first time an analyst makes a recommendation on a firm) over continued coverage. He finds that analyst following enhances liquidity, with initiations incrementally more beneficial to liquidity. The empirical results on the NYSE and AMEX indicate that quoted and percentage spread remain relatively constant (declining slightly) with volume and the number of transactions increasing. These findings indicate that analyst coverage improves liquidity and more positive initial recommendations lead to greater improvements in liquidity. The evidence suggests that analyst coverage is positively correlated with enhanced liquidity.

Information based models state that the market will react to the arrival of valuable information. There is uncertainty concerning the degree to which recommendations are informative and the market reaction to financial analyst activity, which coupled with the requirement to study this issue on a different market mechanism, provides an interesting empirical question. For these reasons, we document the empirical findings for a time series of liquidity measures around new recommendations. This research slots nicely into the Australian literature to fill an empirical gap.

4. Research Hypotheses

Prior research uses empirical evidence to argue that the information in analyst recommendations is not sufficient to give their clients an informational advantage over the market (Anand et al.). The presence of contrarian traders, willing to trade against this information, balance the buy- and sell-side of the market removing any adverse selection. The empirical results suggest that there is sufficient liquidity to cover the arrival of this information, as new recommendations are relatively uninformative. Empirical results in Irvine (2003) confirm the liquidity enhancing attributes of analyst recommendation revisions.

Past literature suggests that trading will continue with no change in average transaction costs. A simultaneous increase in depth and trading activity is expected as the clients of sell-side analysts act on the new advice. The survival of equity analyst research on stock exchanges since Cowles (1933) seminal work implies that they provide utility to clients and trading commissions for brokerages. Analysts' continued clientele is sufficient proof that trading activity increases. Overall, this corresponds with an enhancement to liquidity, as increased size is available without an increase in transaction costs. This becomes our hypothesis.

Hypothesis 1: bid-ask spreads remain unchanged around recommendation revisions with a corresponding increase in depth and trading activity.

Contrarily, a recommendation revision by an analyst implies that in their professional opinion, the underlying stock is mispriced. Given an assumption that analysts have some skill in analysing stocks, it can then be assumed that a level of information asymmetry exists at these times. Contingent on this explanation being true, the expectation is that spreads change while metrics of liquidity also increase as traders manage information asymmetry risk. It is also a possibility that competition between informed traders reduces the asymmetric information component of the spread (Brennan and Subrahmanyan, 1995). This potential alternative to our hypothesis predicts an ambiguous effect on spreads to be verified or invalidated by our empirical analysis.

5. Data

We obtain our data from two sources. Analyst recommendations are supplied by the Institutional Brokers Estimate Service (IBES) and price data is sourced from the Securities Institute Research Center for Asia-Pacific (SIRCA), following the precedent set by past recommendations literature. This section describes the sample selection process and provides a description and summary statistics for the dataset.

5.1 Sample Selection

5.1.1 Analyst Recommendation Revisions

Our dataset of analyst recommendations is supplied by the IBES database maintained by Thomson Financial. IBES collects recommendations from subscriptions to various institutional services, which it collates and verifies on a monthly basis. Coverage commences in November 1993 and continues most recently to September 2006. Due to conflicting reporting systems between financial institutions, all recommendations are standardized by IBES into a uniform set of ratings in descending strength from (1) strong buy (2) buy (3) hold (4) underperform to (5) sell.

The dataset arrives in the form of an international analyst database encompassing all non-US recommendations. The data consists of three individual datasets; a broker identification file, a recommendation file and an initiation of analyst coverage file. We primarily use the recommendations file. Recommendations are identified as Australian by home market codes verified by home market currencies. This results in a dataset that includes the recommended firms ASX code, recommendation date and timestamp, analyst and broker names and identification numbers and the raw and adjusted analyst recommendations. Each unique observation represents a revision to the analysts' recommendation, the analyst and brokerage identification numbers allow us to create a time series of recommendations for a particular firm or analyst on a particular stock.

The event day for our analysis and the date around which all price data will be collected is defined to be the announcement date recorded by IBES using information from analysts' written and electronic reports. We contact analysts from the dataset to verify the event day recorded by IBES for a sample of recommendations. The dates and times are largely confirmed as accurate and commensurate to the date on which the advice was released. Further, electronic copies of analysts' reports are accessed to confirm the integrity of the data. IBES data on analyst recommendations closely matches actual dates.

We implement three major changes to the recommendations dataset. First, to remove the distorting effects of earnings announcements in our sample, we eliminate all recommendations that occur within a 10-day period before and after half-yearly or final earnings announcements. This follows the precedent of Stickel (1995) and Anand et al and ensures the residual effect of earnings announcements (Krinsky and Lee, 1995) will not distort the empirical results.

Second, disclosures in analyst reports indicate that hold recommendations generally imply that investors maintain their current position and refrain from trading in any direction. Hold recommendations imply that the stock will provide the market return, so under the assumption of analyst stock picking ability, superior opportunities exist. For the purpose of analyzing liquidity, a market impact would not be expected from the issuance of hold recommendations, as they may not generate trades. We do not include hold recommendations in our analysis, which follows precedent set by past literature[1]. Reiterations (where analysts release advice identical to standing advice) are retained in the sample as they convey information that mispricing in securities is persisting. To conform to past papers, we exclude holds and include reiterations in our sample.

Third, recommendations are excluded if price and trade data is unavailable or the data contains extreme or outlier observations. The criteria for these filters are outlined in Section 5.1.2. The application of these filters results in a sample of 10,959 revisions from January 1, 1994 to September 31, 2006 from the initial sample of 46,599 Australian recommendations.

Our dataset exceeds the sample size used by several seminal papers including Womack (1996) and Anand et al. A distribution of the recommendations is presented in Table 1, with percentages of total sample in parenthesis.

Table 1
Distribution of Recommendations

Strong Buy	Buy	Underperform	Sell	Total
3,947	4,245	1,370	1,397	10,959
(36%)	(39 %)	(13%)	(13%)	(100%)

5.1.2 Price and Trade Data

Price and trade data corresponding to the event windows is sourced from SIRCA. This data is extracted from ASX intraday records of market activity using variables defined in Section 6. We use event windows of 10-days surrounding the event date based on the findings of Ivkovic and Jegadeesh (2004) and Stickel (1995). This recognizes that on the Australian market, analysts often meet to discuss ratings or share recommendations with privileged clients prior to their official release to the wider public. Our study employs event windows to capture this potential market impact.

We apply a number of filters to the data to ensure that our results capture an accurate market response to analyst recommendations. Trades are deleted where transaction price or volume is not a positive number, trades with negative or zero bid-ask spreads are removed, as are negative or zero depths. Further, we exclude all off-market trades and trades that take place during the opening or closing call auctions. Where data is unavailable and we attain zero spreads or depths despite observed trading activity (due to an incomplete database) we delete the entire observation (recommendation) from our sample.

5.2 Summary Statistics

Implementation of a sample selection process that results in the application of unbiased changes to the original dataset has led to a set of recommendations that covers a diverse range of companies and situations. This is ideal for a study of this nature as it circumvents concerns about non-random sampling and the limited applicability of the findings. This was performed with a view to eliminating the likelihood of sample selection bias and survivor

[1] For the purpose of testing returns consistent with hold recommendations, Wong (2002) provides sufficient analysis on the Australian market. She finds that holds effectively supply the market return. A file is maintained in our analysis that contains hold recommendations to identify recommendation rank skips.

bias within the sample. We present summary statistics of the sample in Table 2 that demonstrates the diversity of the recommendations.

Table 2
Summary of Analyst Recommendation-Specific Variables

The sample consists of sell-side analysts strong buy, buy, underperform and sell recommendations from the IBES database. These recommendations cover a period of approximately 13-years from January 1, 1994 to September 31, 2006, inclusive.

	Mean	Median	Max	Min
Recommendation changes	10,959	-	-	-
Distinct firms	706	-	-	-
Individual analysts	1,101	-	-	-
Financial institutions	62	-	-	-
Firm size (millions)	3,439	960	65,358	3.6
Recommendations per stock	15.52	6	158	1
Investment bank recommendations	3,744	-	-	-
Recommendations rank skips	262	-	-	-
Proportion of rank skips	0.024	-	-	-
Strong recommendations	5,344	-	-	-
Proportion of strong recommendations	0.28	-	-	-
Daily av. non-event trading volume	1,181,270	514,868	29,832,225	1,355

Our sample covers 10,959 buy and sell type signals on 706 distinct firms from 1,101 analysts at 62 different financial institutions. Buy type signals outweigh sell signals by approximately 3:1. This coincides with Wong (2002) and the higher propensity for Australian analysts to make sell recommendations over their international counterparts. Stickel (1995) calculates the ratio for U.S analysts as 7:1. The sample includes recommendations on companies with market capitalisations ranging from $3.6 million to $65 billion with a mean of $3.4 billion and a median on $960 million. Given the average threshold for entry into the ASX 200 of approximately $1 billion, this demonstrates that analysts focus their recommendations on larger companies.

Our sample covers stocks with significant analyst coverage with a maximum of 158 recommendations on a single company, and those that are given less attention by analysts, with a minimum of 1. The mean of 15.52 and median of 6 recommendations per stock indicates a considerable amount of coverage for most of the 706 firms. Only 262 recommendation rank skips occur in the data, demonstrating Australian analysts move recommendations gradually, or only make large moves around significant information such as earnings announcements, which are removed. The stocks in the sample appear liquid with a mean of 1,181,270 and median of 514,868 shares traded each day in the 90-day period leading up to the recommendations. This is a useful characteristic for a study of market impacts as we largely circumvent the problem of limited liquidity on the Australian market.

6. Methodology

Documenting the time-series of liquidity before and after revisions is a direct test of whether analyst recommendation changes increases liquidity (Irvine, 2003). We implement interday and intraday analysis and apply several robustness checks to a time series of liquidity measures.

6.1 Testing the Interday Impact on Liquidity

To document the pattern of liquidity around recommendation revisions, we adopt event windows of 10-days before and after the event day, totalling 21-days. These windows are designed to take into account the potential for earlier information flows and are warranted by the results of Stickel (1995) and Ivkovic and Jegadeesh (2004). For example, Stickel (1995) finds that statistically significant abnormal returns, and accordingly, information flows, are confined to 10-day event windows. We sample various measures of liquidity within these windows and apply statistical tests to the time-series.

6.1.1 Liquidity Variable Definitions

A definitive measurement of liquidity is yet to be defined. Liquidity is often defined as the ability to quickly sell an asset for cash. Harris (2003) describes liquidity as the ability to trade large size quickly, at low cost, at any time. Under this definition, we measure liquidity using spreads, depths and trading activity with variables similar to Irvine (2003) and Anand et al. Bid-ask spreads are a visible measure of the average cost of trading. Depth is a proxy of the ability to trade at any time and at a desired size. As a post-trade measure of liquidity, we use trades and trade volume as a proxy for the availability of trading opportunities (Harris, 2003).

Our first measure of liquidity is the quoted bid-ask spread. Realized spreads (Anand et al.) are not measured, as the Australian market does not facilitate such a measure. The quoted spread is measured as the daily time-weighted average of the difference between the best bid and ask quotes. We compute the time-weighted average quoted bid-ask spread for each recommendation event *i* for each trading day *T* as follows:

$$Spread_{iT} = \left[\sum_{t=1}^{N} (Ask_{it} - Bid_{it})t \right] \Big/ N \qquad [1]$$

where Bid_{it} and Ask_{it} are, respectively, the bid and ask prices for stock *i* during period *t*, *t* is the time for which those quotes were the best quotes and *N* is the time in the trading day. Next, percentage quoted spread is used as a measure of transaction costs to account for differences in firm capitalization and stock price. We scale the quoted spread by the midpoint of the best quotes and calculate a time-weighted average for each recommendation *i* over each sample day *T*, which is defined as follows:

$$Percentage\ Spread_{iT} = \left[\sum_{t=1}^{N} \frac{Ask_{it} - Bid_{it}}{(Ask_{it} + Bid_{it})/2} \cdot 100t \right] \Big/ N \qquad [2]$$

Depth is measured using the volume available at the best bid and ask quotes. We also sample depth at the cumulative volume available at the best five bid and ask quotes. Both measures of depth are sampled for completeness and to test for changes in depth further down the limit order book. Our measure is a time-weighted average of these variables over the event-trading day. Trading activity around analyst recommendations is expected to increase. To quantify this effect, we sample the daily trades, volume and share value transacted. These are simple measures of the amount of trade activity and surveyed directly from market data and do not include off-market trading activity.

6.1.2 Statistical Tests

In order to compare these variables over the cross section, the following measurements are computed. For spreads and depths, the daily time-weighted averages are calculated over the cross section of recommendations in the sample, to obtain a single value for each day in the event window. The medians (and interquartile ranges) are then calculated over the cross section of all daily averages for each day in the 21-day event window. For trading activity, daily totals are calculated over the cross section of recommendations to obtain a daily dataset. The medians (and interquartile ranges) are then computed over the cross section of all daily totals for each day in relation to the event day. This results in a 21-day time series of each liquidity variable for all recommendations.

We employ cross sectional medians, as the distribution of the liquidity variables are skewed to the right with cross sectional means greater than cross sectional medians. We also report means (with standard deviations) as a supporting measure of central tendency. Due to the non-normality in the liquidity measures we cannot rely on a parametric test of the mean, though the mean does provide useful support for the time-series of medians.

The liquidity variables on the event day are tested against non-event days by performing statistical tests of difference of medians. We test for abnormal event day liquidity using non-parametric pairwise Wilcoxon Signed-Rank[2] tests. Days –10 and +10 are selected as the reference point representing non-event trading and we test these days against Day 0. A statistically significant value for the Wilcoxon statistic confirms that the median on the event day (Day 0) is not equal to the median on the reference day (Day –10 or Day +10). Combined with an economically significant discrepancy in the medians is evidence that the event influences the liquidity measure.

6.1.3 Robustness Checking

Several robustness tests are performed on the liquidity measures to ensure that the findings are reliable and consistent to sample selection. The analyst recommendations are partitioned in an attempt to increase the likelihood of information asymmetry. We perform additional robustness checks using rank skips, expert analysts and signal strength with justifications provided as the tests are performed. Cross sectional analysis of medians using the Wilcoxon Signed-Rank test and the previously defined liquidity variables test the robustness of the sample partitions. Analogous and statistically significant results in these samples reinforce the main findings.

6.1.4 Multivariate analysis

[2] The Wilcoxon Signed-Rank Test (Wilcoxon, 1945) is a non-parametric alternative to the paired t-test employed to test the median difference in paired data. The test involves ranking the absolute differences between measurements. These ranks are then assumed to be consistent with the normal distribution and subjected to tests for statistical significance. A statistically significant value for the Wilcoxon statistic is evidence that the medians between the two measurements are not equal.

We perform multivariate analysis on spreads to reconfirm the results of our univariate analysis. The regression, defined in McInish and Wood (1992), models spreads while controlling for determinants of spreads that include stock price (and tick sizes), trading volume and volatility. A dummy variable (the variable of interest) is included to represent the event day. We are testing the value and significance of the coefficient on the dummy variable. A statistically significant non-zero value would suggest that spreads on the event day are affected by an unspecified influence, potentially new recommendations. We apply a pooled cross sectional time series regression model defined as follows:

$$\log(spread_i) = \alpha_0 + \beta_0 \log(price_i) + \beta_1 \log(volume_i) + \beta_2 \log(volatility_i) + \beta_3 dummy + \varepsilon_i \qquad [3]$$

where the dependant variable *log(spread$_i$)*, is the natural log of the quoted spread, α_0 is an intercept term, *log(price$_i$)* is the natural log of the stock price, *log(volume$_i$)* is the natural log of the daily volume, *log(volatility$_i$)* is the natural log of the volatility measure (the log of the daily high divided by daily low price) and ε_i is an error term. The dummy coefficient takes the value of 1 if the observation is on the event day and 0 otherwise (that is, it is Day –1, +1, -10 or +10). Based on prior evidence and logical arguments (McInish and Wood, 1992), a negative sign is expected for price and volumes, and a positive sign on the coefficient for volatility. These models are run separately for buy and sell signals, on the event day against Day -1 and Day +1 and on the event day against Day –10 and Day +10.

6.2 Liquidity at an Intraday Level

Intraday analysis on liquidity is performed using the variables defined in Section 6.1.1. The variables are collected at 30-minute intervals surrounding the event with time-weighted averages for spreads and depths and market totals for trading activity. We adopt five 30-minute windows around the event for 2.5 hours before and after the event. If an event occurs within 2.5 hours of the opening or close of trade, we collect data from the preceding or following trading day.

We perform intraday analysis by computing differences between event day intraday variables and a control sample that surrounds the event. The control sample is computed as the average of the liquidity measures in the corresponding 2.5-hour segments for 30 days before and after the event (60 days in total), excluding the three days immediately preceding and following the event. That is, the event day is Day 0, so the average of the variables during the same five 30-minute time periods, between the Days –34 to –4 and +4 to +34 is computed. Event period and control period measurements are calculated as follows:

$$Event(x_t) = x_t \qquad Control\,(x_t) = \sum_{i=1}^{60} x_t \Big/ 60 \qquad [4]$$

where x_t is the liquidity measure, i represents the recommendation and t represents the 30-minute time window. The control period average is then subtracted from the event day average, which is averaged cross-sectionally over all recommendations to represent our measure of abnormal recommendation period liquidity for each of the ten time segments. The calculations are as follows:

$$D_{i,t} = Event(x_t) - Control\,(x_t) \qquad [5]$$

$$AL_t = \sum_{i=1}^{N} D_{i,t} \Big/ N$$

where $D_{i,t}$ is the difference measure and AL_t is the abnormal liquidity measure and N is the number of recommendations. To confirm that the event period variables are statistically significant we take the t-statistics for the calculation from each stock. We then average the t-statistic for each stock and event across all stocks in the sample. As a further test on the intraday time series of measurements, we compute the medians and interquartile range of the intraday variables. This is based only on the event day dataset, the control sample is not used. Wilcoxon Signed-Rank tests confirm the significance of the medians.

7. Interday Results

The medians, interquartile ranges and statistical significance of the liquidity measures are reported in Table 4a with means and standard deviations in Table 4b. Results are based on the cross section of recommendations over the 21-day window from Day –10 to Day +10. We do not report results for Days –7 to –4 and Days +4 to +7 due to space constraints as the values are intermediate to the days reported. A finding of declining spreads or increasing trading activity over the time series of liquidity measures would indicate that liquidity improves around new recommendations (Irvine, 2003).

Our evidence documents unchanged spreads around new recommendations across both measures of central tendency (means and medians) when sampled at a daily frequency. Depths do not significantly increase or decrease, with our results inconclusive. Trading activity increases significantly around the event day. These results provide evidence that there is sufficient liquidity to process the information in new sell-side recommendations without changing spreads and with a concurrent improvement in trade volume, which enhances liquidity.

Liquidity increases significantly around analyst recommendation revisions. Quoted spreads are unchanged across the sample with a median of 0.015 throughout the 21-day period. The interquartile range of quoted spreads does deviate. A Wilcoxon Signed-Rank test confirms that spreads on Day 0 are not statistically different than on Days -10 or +10 at the 10 per cent level of significance. This provides elementary evidence that there is sufficient liquidity to embed the information in new recommendations into the market with transaction costs remaining unchanged.

Table 4a
Results from Liquidity Variable Analysis: Medians and Interquartile Ranges

The medians and interquartile ranges (in parenthesis) of each variable are reported below. The cross sectional medians are computed as follows. First, the daily weighted averages of all spread measures, as well as bid and ask depths, are calculated over the cross section of the stocks in our sample to obtain a single value for each day. The medians (and inter-quartile ranges) are then computed over the cross section of all daily averages for each day in relation to the event day. For trading activity, simple daily averages are calculated over the cross section of stocks to obtain a daily dataset. The medians and inter-quartile ranges (in parenthesis) are then computed over the cross section of all daily averages for each day in relation to the event day. Cross-sectional medians are employed, as the distribution of the variables is non-normal. Days 4-7 are not presented due to space constraints, though they are comparable to the remaining days. Statistically significant differences between Day –10 and Day 0 using the Wilcoxon Signed-Rank test at a 5 per cent level of significance are represented by *A, with *B representing the significance between Day 0 and Day +10.

	-10	**-9**	**-8**	**-3**	**-2**	**-1**	**0**	**+1**	**+2**	**+3**	**+8**	**+9**	**+10**
Quoted Spread	0.015 (0.015)	0.015 (0.014)	0.015 (0.015)	0.015 (0.015)	0.015 (0.015)	0.015 (0.015)	0.015*A (0.014)	0.015 (0.014)	0.015 (0.014)	0.015 (0.015)	0.015 (0.015)	0.015 (0.015)	0.015 (0.015)
Percentage Spread	0.532 (0.785)	0.531 (0.771)	0.534 (0.776)	0.53 (0.778)	0.529 (0.771)	0.533 (0.770)	0.529 (0.786)	0.53 (0.771)	0.526 (0.767)	0.532 (0.768)	0.532 (0.785)	0.538 (0.781)	0.53 (0.767)
Best Bid Depth (‘000s)	10.9 (20.3)	10.9 (21.2)	10.8 (21.4)	11.1 (21.6)	10.9 (21.6)	10.8 (21.9)	11.0*A (21.3)	11.2 (20.9)	11.2 (21.3)	11.3 (21.6)	10.9 (20.9)	10.9 (20.9)	11.1*B (21.2)
Best Ask Depth (‘000s)	11.2 (19.6)	11.1 (19.9)	11.1 (20.4)	11.5 (20.6)	11.1 (20.1)	11.2 (20.5)	11.2 (20.3)	11.5 (20.3)	11.3 (20.3)	11.1 (20.1)	10.9 (19.6)	11.03 (19.3)	11.2*B (19.9)
Bid Depth (‘000s)	36.5 (56.4)	36.7 (58.9)	36.9 (58.6)	37.4 (58.4)	36.7 (59.1)	36.9 (60.4)	37.1*A (58.9)	37.5 (59.2)	36.9 (58.4)	37.5 (59.9)	36.5 (58.6)	36.3 (57.4)	36.6*B (57.6)
Ask Depth (‘000s)	39.7 (58.4)	39.2 (58.0)	39.4 (57.7)	40.4 (59.5)	39.4 (58.3)	39.6 (60.1)	39.2 (59.1)	40.3 (58.5)	40.1 (59.1)	39.5 (59.0)	38.9 (57.9)	39.3 (57.9)	39.5*B (58.0)
Trades	88 (237)	88 (245)	87 (240)	92 (244)	92 (244)	93 (252)	93*A (258)	96 (259)	92 (252)	91 (243)	87 (231)	87 (234)	87*B (235)
Trade Volume (‘000s)	450 (1,299)	473 (1,317)	463 (1,335)	497 (1,410)	479 (1,408)	492 (1,422)	484*A (1,427)	514 (1,451)	481 (1,417)	476 (1,367)	441 (1,291)	436 (1,284)	441*B (1,298)
Trade Value (‘000s)	1,436 (6,245)	1,470 (6,386)	1,459 (6,242)	1,550 (6,689)	1,489 (6,630)	1,557 (6,684)	1,536*A (6,878)	1,629 (6,855)	1,530 (6,614)	1,493 (6,375)	1,384 (6,034)	1,397 (5,995)	1,408*B (6,179)

Table 4b
Results from Liquidity Variable Analysis: Means and Standard Deviations

The means and standard deviations (in parenthesis) of each variable are reported below. The cross sectional means are computed as follows. First, the daily weighted averages of all spread measures, as well as bid and ask depths, are calculated over the cross section of the stocks in our sample to obtain a single value for each day. The means (and standard deviations) are then computed over the cross section of all daily averages for each day in relation to the event day. For trading volume, simple daily averages are calculated over the cross section of stocks to obtain a daily dataset. The means (and standard deviations) are then computed over the cross section of all daily averages for each day in relation to the event day. Days 4-7 are not presented due to space constraints, though they are comparable to the remaining days. No tests for statistical significance are computed due to the high level of non-normality in the data.

	-10	-9	-8	-3	-2	-1	0	+1	+2	+3	+8	+9	+10
Quoted Spread	0.0250 (0.053)	0.0244 (0.048)	0.0246 (0.061)	0.0242 (0.033)	0.0246 (0.049)	0.0249 (0.116)	0.0250 (0.065)	0.0248 (0.071)	0.0244 (0.055)	0.0239 (0.035)	0.0245 (0.056)	0.0246 (0.042)	0.0244 (0.062)
Percentage Spread	0.827 (0.91)	0.816 (1.01)	0.818 (0.88)	0.821 (0.93)	0.823 (0.96)	0.813 (0.91)	0.824 (0.95)	0.823 (0.94)	0.813 (0.90)	0.812 (0.87)	0.822 (0.94)	0.828 (0.96)	0.821 (0.94)
Best Bid Depth (‘000s)	72.3 (165.6)	74.6 (147.1)	94.7 (229.1)	216.3 (897.1)	164.9 (672.3)	193.1 (694.3)	198.5 (641.0)	200.6 (664.7)	198.3 (638.7)	218.8 (693.8)	141.3 (404.5)	138.7 (462.7)	158.0 (583.7)
Best Ask Depth (‘000s)	32.5 (99.8)	33.3 (116.4)	33.6 (112.6)	35.4 (203.9)	32.9 (140.2)	34.4 (175.6)	33.8 (125.0)	34.7 (142.4)	34.2 (134.2)	34.1 (118.0)	31.9 (90.4)	31.6 (89.0)	31.5 (83.5)
Bid Depth (‘000s)	130.3 (198.4)	133.6 (195.8)	199.6 (682.1)	285.5 (968.2)	248.8 (778.6)	332.9 (1,042)	302.1 (882.3)	293.7 (834.1)	351.3 (1,047)	340.6 (784.8)	248.3 (746.4)	215.3 (640.8)	245.3 (718.5)
Ask Depth (‘000s)	78.1 (153.9)	78.2 (150.3)	77.9 (139.5)	78.6 (138.5)	78.5 (139.6)	79.2 (147.8)	80.7 (173.2)	80.8 (163.5)	80.9 (161.6)	79.1 (158.2)	77.5 (140.1)	77.4 (146.1)	76.8 (144.2)
Trades	234 (419)	235 (421)	233 (401)	247 (461)	247 (452)	256 (467)	264 (507)	259 (472)	247 (448)	243 (440)	230 (416)	232 (418)	234 (441)
Trade Volume (‘000s)	1,407 (3,445)	1,428 (3,282)	1,399 (3,248)	1,538 (3,787)	1,517 (3,745)	1,586 (4,153)	1,594 (3,816)	1,553 (3,441)	1,483 (3,352)	1,413 (3,059)	1,324 (3,007)	1,326 (2,978)	1,337 (2,884)
Trade Value (‘000s)	8,985 (26,417)	9,041 (24,907)	8,975 (25,508)	9,915 (30,741)	9,506 (26,754)	9,821 (28,260)	10,130 (29,581)	10,144 (29,821)	9,686 (27,767)	9,189 (26,705)	8,724 (24,883)	8,666 (23,983)	8,767 (24,582)

A similar result is witnessed in percentage quoted spreads. The percentage spread (interquartile range) on Day 0 is 0.529 (0.786) per cent with analogous values of 0.532 (0.785) and 0.53 (0.767) per cent on Days –10 and +10 respectively. The Wilcoxon Signed-Rank test for equality of medians confirms that there is no statistical difference between the medians. Accounting for differences in tick sizes and stock prices, the conclusion that spreads and transaction costs remain unchanged, at a daily level, is robust.

Our results in respect to depth are inconclusive. At the best bid there is a median (interquartile range) of 11,000 (21,300) shares on Day 0 compared to 10,900 (20,300) and 11,100 (21,200) on Days –10 and +10. Similarly, for the best ask there is a median of 11,200 (20,300) shares on Day 0 compared to 11,200 (19,600) and 11,200 (19,900) on Days –10 and +10. Results for the best five bid and ask depths correspond to those at the best bib and ask. Wilcoxon Sign-Rank tests indicate that there is a statistically significant difference between the medians of pre-event bid depths and all post-event depths; though the economic value of the differences between the medians is minimal. There is no evidence at a daily level to suggest that depth changes.

Trading activity in the sample of recommendations experiences a statistically significant increase around the event day. The median (interquartile range) of the number of trades executed rises to 93 (258) on Day 0 and 96 (259) on Day +1, compared to 88 (237) and 87 (234) on Day –10 and Day +10, respectively. This increase is statistically significant at the 1 per cent level. Statistically significant increases at the 1 per cent level are also documented in trade volume and value with a median of 484,000 shares worth $1,536,000 traded on Day 0 compared to 450,000 at $1,436,000 and 441,000 at $1,408,000 on Days –10 and +10. This coincides with prior evidence and the expectation that analyst activity generates trade for financial institutions.

Our analysis of means and standard deviations as secondary measures of central tendency confirms the evidence in Table 4a. The means of the quoted and percentage quoted spread remain unchanged across the time-series of observations. However, the standard deviations of the quoted spread increase slightly towards Day –1 (0.116) and Day 0 (0.065) compared to the reference points on Day –10 (0.053) and Day +10 (0.062), with intermediate values on the remaining days. In sampling means, there is evidence that depth increases leading up to Day 0 across all bid and ask measures. This provides some reason to suspect that depth may be enhanced around recommendation revisions, which we seek to confirm with intraday analyses. Further, trading activity displays marked increases around the revision period with corresponding increases in standard deviations.

Analyst recommendations generate trades and volume on the Australian market. At daily sampling, spreads and depths exhibit no statistically significant change in response to new recommendations. The results suggest that a theoretical trader could transact excess volume without additional transaction costs and with improved immediacy. Given this evidence, recommendation revisions act as liquidity enhancing events under an acceptable definition of liquidity (Harris, 2003, Irvine, 2003).

A possible explanation for our empirical results is that analysts have a clientele, who trade on this information, but additional informed traders view this information as intrinsically uninformative and maintain equilibrium by transacting on the opposite side and offsetting the additional volume. That is, competition between informed investors is offset by contrarians and sufficient surplus market liquidity. This supports the Anand et al. contrarian hypothesis. This is an inherently interesting result as analyst recommendations generate trade in a daily window, but are not deemed to contain sufficient information to warrant a change in spreads. Our preliminary results largely align with Anand et al. (with the exception of our insignificant interday results for depth) and provide external validation of their findings

7.3 Multivariate Analysis of Spreads

One of the primary empirical results of the time-series analysis of spreads around recommendation revisions is that they do not change. This encompasses a major element of the finding that liquidity is enhanced, as transaction costs remain constant. An increase in the standard deviation of the mean spread around new recommendations noted in Section 7.1 and the importance of this finding warrant the need for further examination of spreads. We construct a pooled cross sectional time series regression model on spreads to ensure that the results are robust. The model is fully specified in Section 6.1.4. Buy and sell-type recommendations are modelled individually against Days –10 and +10 and the Days –1 and +1. The results are presented in Table 5.

Table 5
Multivariate Regression on Spreads

Regression results for the model specified in Section 6.1.4 are reported below. We run a least squares regression model with the variable of interest being the dummy variable representing the event day. Panel A models buy signals for the event day against Days –1 and +1, Panel B models sell signals against Days –1 and +1. Panel C models buy signals against Days –10 and +10, with Panel D reporting the results of a regression using Days –10 and +10 against the event day on sell signals. The model is specified as follows:

$$\log(spread_i) = \alpha_0 + \beta_0 \log(price_i) + \beta_1 \log(volume_i) + \beta_2 \log(volatility_i) + \beta_3 dummy + \varepsilon_i$$

Panel A
Buy Signals (D=1 if Event Day; D=0 if Day –1 or +1)

	Intercept	ln(price)	ln(volatility)	ln(volume)	dummy
Coefficient	-0.4488	0.4075	0.1347	-0.2264	-0.00071
t-statistic	-42.55	136.57	39.31	-145.28	-0.27
Prob Value	0.0000	0.0000	0.0000	0.0000	0.7835

Panel B
Sell Signals (D=1 if Event Day; D=0 if Day –1 or +1)

	Intercept	ln(price)	ln(volatility)	ln(volume)	dummy
Coefficient	-0.5411	0.4066	0.1353	-0.2117	-0.00058
t-statistic	-29.91	81.90	23.29	-79.68	-0.13
Prob Value	0.0000	0.0000	0.0000	0.0000	0.8930

Panel C
Buy Signals (D=1 if Event Day; D=0 if Day –10or +10)

	Intercept	ln(price)	ln(volatility)	ln(volume)	dummy
Coefficient	-0.4636	0.4095	0.1287	-0.2268	0.004368
t-statistic	-43.98	135.37	37.77	-142.89	1.65
Prob Value	0.0000	0.0000	0.0000	0.0000	0.0978

Panel D
Sell Signals (D=1 if Event Day; D=0 if Day –10 or +10)

	Intercept	ln(price)	ln(volatility)	ln(volume)	dummy
Coefficient	-0.5662	0.4033	0.1243	-0.2120	0.008592
t-statistic	-31.67	81.24	21.84	-78.81	1.95

Prob Value	0.0000	0.0000	0.0000	0.0000	0.0512

The multivariate model has significant explanatory power; R^2 values (not reported) are all between 0.50 and 0.60 and the control variables are statistically significant. The models appear well specified. The control variables coefficients are all of the expected sign, with price and volatility coefficients positive and the coefficient for volume negative. The coefficients are also of a consistent magnitude across each model.

The variable of interest (the dummy variable representing the event day) is insignificant at the 5 per cent level for all four models, suggesting that spreads do not change significantly on the event day compared to Days –10 and +10 or Days +1 or -1. The coefficient for the dummy variable is significant at the 10% level for the models employing Days –10 and +10 as the control days; however the statistical and economic significance is minimal. Our analysis does not warrant further breakdown of the spread and this evidence confirms our earlier analysis that spreads, and transaction costs, are unchanged around revisions and that recommendation changes are liquidity-enhancing events.

8. Intraday Results

Analysis at an interday level provides evidence that recommendation revisions enhance liquidity on the ASX. We perform intraday analysis to ensure that daily sampling does not overlook a transient market impact. That is, spreads could change temporarily around the release of analyst revisions. This will also establish a degree of causation to ensure that recommendation revisions drive the results. Documenting a significant market impact associated with the precise time that new recommendations are released will accomplish a level of causation.

8.1 Intraday Analysis of Liquidity

Abnormal spreads, depths and trading activity are reported in Table 6 by applying the method outlined in Section 6.4. We also conduct analysis of the event segment medians and interquartile ranges reported in Table 7 to confirm that the results derived in Table 6 are robust, due to the insignificance of several intraday variables. We find that contrary to interday analysis, there is evidence that depths increase at a statistically significant level in the intervals surrounding recommendation revisions. This new finding, when liquidity measures are sampled on a half-hourly basis, strengthens the evidence that recommendation revisions are liquidity enhancing events. Intraday results for spreads and trading activity align with the interday findings.

Table 6
Intraday Results of Liquidity Variable Analysis

Intraday periods are 30-minute intervals for 2.5 hours each side of the event, consisting of a total of 10 segments. Period +1 is the 30-minutes immediately following a revision and Period –1 is the 30-miutes immediately preceding a new recommendation. The measures are computed using time-weighted averages for spreads and depth and market observations for trades and volume within each 30-minute window. The control sample is the average of the liquidity measure for the corresponding time windows extending 30-days before and after the event (60-days total) but excluding the three days immediately preceding and following the event. We average the variables between Days –34 and –4 and +4 and +34 together. The values reported are abnormal liquidity measures where, for a given recommendation in each time period, the control period average is subtracted from the event day segment variables. These abnormal returns are then averaged cross sectionally with the average t-statistic (in parenthesis) representing the statistical difference from zero for each measure.

	-5	**-4**	**-3**	**-2**	**-1**	**+1**	**+2**	**+3**	**+4**	**+5**
Quoted Spread	-0.0013	-0.0009	-0.0004	-0.0001	0.0004	-1E-05	-0.0003	-6E-05	-0.0002	0.0004
	(-4.49)	(-2.60)	(-0.76)	(-0.18)	(0.23)	(-0.02)	(-0.39)	(-0.14)	(-0.42)	(0.44)
Percentage Spread	-0.049	-0.010	-0.012	-0.019	-0.027	-0.044	-0.016	0.071	-0.027	0.053
	(-2.36)	(-0.27)	(-0.32)	(-0.54)	(-0.42)	(-1.56)	(-0.42)	(1.02)	(-1.40)	(1.05)
Best Bid Depth	50,243	6,111	526	15,455	21,172	4,959	38,852	14,135	17,167	-4,022
	(0.91)	(0.23)	(0.02)	(0.43)	(0.67)	(0.18)	(1.04)	(0.49)	(0.58)	(-0.16)
Best Ask Depth	725	2,249	4,857	2,386	4,419	2,431	2,832	3,109	1,398	2,171
	(0.78)	(1.32)	(1.92)	(2.29)	(2.15)	(2.55)	(1.94)	(3.16)	(1.80)	(2.50)
Bid Depth (‘000s)	66,038	62,463	33,962	14,130	33,426	49,554	70,175	52,362	40,791	23,285
	(1.05)	(1.00)	(0.82)	(0.36)	(0.80)	(1.12)	(1.49)	(1.18)	(0.98)	(0.66)
Ask Depth (‘000s)	-57	892	1,249	1,846	4,398	3,439	3,803	2,945	3,122	2,997
	(-0.06)	(1.04)	(1.22)	(1.98)	(2.38)	(3.69)	(3.82)	(3.12)	(3.24)	(3.15)
Trades	0.89	1.64	1.75	1.88	2.57	4.55	3.02	2.53	2.16	1.66
	(8.42)	(9.75)	(10.07)	(10.32)	(11.36)	(13.62)	(13.13)	(13.29)	(13.21)	(12.29)
Trade Volume	-83	353	398	-71	64	122	-307	-215	129	-253
	(-0.74)	(1.37)	(1.07)	(-0.36)	(0.27)	(0.68)	(-2.06)	(-1.45)	(0.60)	(-1.93)
Trade Value	-348	299	-395	-323	-1,200	284	-1,437	-636	-481	-95
	(-1.01)	(0.60)	(-0.72)	(-0.66)	(-2.27)	(0.60)	(-3.52)	(-1.37)	(-1.10)	(-0.22)

Table 7
Intraday Results from Liquidity Variable Analysis: Medians and Inter-quartile Ranges

The medians and interquartile ranges (in parenthesis) of each variable are reported below. These are based on the event day 10-segment sample; the control sample is not used in this calculation. First, the 30-minute time-weighted averages of all spread measures, as well as bid and ask depths, are calculated over the cross section of the stocks in our sample to obtain a single value for each 30-minute window. The medians (and inter-quartile ranges) are then computed over the cross section of all 30-minute averages for each period. For trading activity, simple 30-minute totals are collected over the cross section of stocks to obtain a half-hourly dataset. The medians and inter-quartile ranges (in parenthesis) are then computed over the cross section of all 30-minute averages for each period. Cross-sectional medians are employed, as the distribution of the variables is non-normal. Statistically significant differences between Period -5 and Period -1 using the Wilcoxon Signed-Rank test at a 5 per cent level of significance are represented by *A, with *B representing the significance at the 5 per cent level between Period +1 and Day +5.

	-5	**-4**	**-3**	**-2**	**-1**	**+1**	**+2**	**+3**	**+4**	**+5**
Quoted Spread	0.01 (0.013)	0.01 (0.014)	0.01 (0.009)	0.01 (0.010)	0.01*A (0.007)	0.01 (0.010)	0.01 (0.009)	0.01 (0.009)	0.01 (0.010)	0.01*B (0.010)
Percentage Spread	0.21 (0.522)	0.24 (0.566)	0.25 (0.539)	0.26 (0.547)	0.29*A (0.588)	0.32 (0.615)	0.29 (0.58)	0.28 (0.562)	0.27 (0.557)	0.26*B (0.549)
Best Bid Depth	2,825 (10,898)	4,194 (13,830)	4,755 (15,548)	5,000 (15,643)	5,960*A (17,871)	4,646 (13,049)	4,689 (13,991)	4,711 (14,198)	4,546 (14,439)	4,036 (13,619)
Best Ask Depth	2,942 (11,350)	4,299 (13,918)	4,905 (15,276)	5,027 (15,905)	6,205*A (17,760)	4,878 (13,055)	4,726 (13,764)	4,910 (14,367)	4,781 (14,652)	4,301 (13,951)
Bid Depth	16,077 (44,114)	19,458 (48,854)	21,483 (49,019)	22,356 (49,999)	25,494*A (53,182)	21,054 (43,413)	21,281 (45,489)	21,135 (46,336)	21,197 (47,479)	20,136 (47,820)
Ask Depth	17,936 (46,762)	21,628 (51,799)	23,384 (52,100)	24,592 (53,362)	28,001*A (55,372)	23,194 (46,728)	23,313 (48,226)	23,498 (49,031)	23,373 (49,232)	22,287*B (50,172)
Trades	3 (11)	4 (17)	5 (19)	5 (22)	7*A (29)	7 (26)	6 (21)	6 (20)	5 (18)	4*B (15)
Trade Volume	610 (2,611)	996 (3,428)	1,000 (3,572)	1,000 (3,955)	1,359*A (4,831)	1,000 (3,562)	1,000 (3,454)	1,000 (3,562)	1,000 (3,588)	946*B (2,980)
Trade Value	2,560 (9,120)	3,400 (11,400)	3,560 (11,889)	3,825 (12,432)	4,806*A (15,633)	3,963 (11,227)	3,780 (10,854)	3,844 (11,232)	3,737 (11,285)	3,325*B (10,153)

The abnormal quoted spread fluctuates between positive and negative values that are both economically small and statistically significant. The largest abnormal measure is –0.0013 in Period –5 and only the Period –5 and –4 measures are statistically significant. Similarly, the percentage quoted spread is negative in all but two sample widows and is insignificantly difference from zero in every segment with the exception of Period –5. Table 7 confirms the evidence that spreads remain unchanged with the median spread constant at 0.01 across all sample windows. The empirical evidence implies that abnormal and median spreads are not significantly different their respective control measures and that transaction costs are insensitive to new recommendations at an intraday frequency.

An increase in depths is documented in intraday analysis. Depths at the bid and ask for both measures (best and best five quotes) all exhibit increased abnormal liquidity during intraday segments. Abnormal bid depth at the best bid is positive in all but one segment and there is an average abnormal depth of 16,640 additional shares available at the best bid over the 10-segment period. The abnormal ask depth measure is positive across all segments and there is an average abnormal depth of 2,658 additional shares available at the best ask over the 10-segment period. Depths at the best five quotes correspond with the improvements in the best quotes. The ask depth abnormal measures are largely statistically significant, though the bid depth measures are not significant at the 5 per cent level.

Medians and interquartile ranges reported in Table 7 confirm the evidence that depth increases leading up to the event time are statistically significant. Bid (ask) depth at the best quotes increases from 2,825 (2,942) in Period -5 to 5,960 (6,205) and 4,646 (4,878) in Periods -1 and +1 respectively, declining to 4,036 (4,301) in event Period +5. The differences in medians between Periods –5 and –1 and Periods +1 and +5 are significant at the 5 percent level for the pre-event period but not for the post-event period. This suggests that abnormal depth may persist for more than 2.5 hours after the event time. Collectively, Tables 6 and 7 provide the first documented evidence that depths increase significantly around analyst recommendation revisions.

The elevated trading activity witnessed in interday analysis is consistent when investigated at an intraday level. Abnormal trades in the event segments are positive and increase during the intraday segments, peaking around the precise event time. Excess transactions range from 0.85 to 4.55 and are statistically significant at the 1 per cent level. The intraday effect on volume and trade value is less clear. The abnormal measures for trade volume and value fluctuate between positive and negative values and are largely insignificant. However, analysis of the medians indicates that this empirical observation may be attributable to the research design. Median volume and trade value increase significantly in Periods –1 and +1 compared to Periods –5 and +5 at the 5 per cent level. Share volume (value) increases from 610 (2,560) in Period -5 to 1,359 (4,806) in Period -1 and 1,000 (3,963) in Period +1. This then falls to 946 (3,325) by Period +5.

Intraday analysis of liquidity is consistent with our interday results, with the statistically significant finding for depth increasing support for the conclusion that recommendation revisions are liquidity enhancing events. This analysis suggests that depth is sampled over an excessively large sample window in the interday tests that do not allow abnormal depth to be documented. Our evidence indicates that there is no transient affect on spreads within the event day. Compared to the control period, the intraday sample segments exhibit higher levels of liquidity. This indicates that the interday results are driven by new recommendations and not an unrelated event.

8.2 Intraday Robustness Tests of Liquidity

We apply robustness tests to the intraday data to confirm that transient effects are not evident in sample partitions where there may be additional information asymmetry. This analysis will also verify the liquidity enhancing effects of various recommendation signals at the intraday level. For example, that expert recommendations generate additional liquidity in relation to the non-expert sample or alternatively, the documented increase at an interday level was driven by an external factor. Abnormal liquidity measures for intraday Periods –1 and +1 are reported. We are testing whether abnormal liquidity in the samples where information asymmetry may be enhanced exceeds that in the reference samples. Robustness tests for recommendation type, rank skips and expert analysts are reported in Table 8.

Table 8 Panel A reports abnormal intraday liquidity measures during Periods –1 and +1 for recommendations revisions by signal type. For strong buy, buy and underperform signals, abnormal quoted and percentage spreads are statistically and economically equal to zero. Sell signals, however, exhibit statistically significant reductions of –0.001 and –0.002 in Periods –1 and +1 respectively and the percentage spread also declines at a statistically significant level for Period +1. This result is our first documented evidence that any form of analyst revision can influence spreads. These reductions, however, represent 0.1 and 0.2 per cent reductions in the spread respectively. The economic significance can be questioned, but this evidence is consistent with the Brennan and Subrahmanyan (1995) theory that competition between informed investors will, if anything, reduce spreads.

Depths across signal types are again conflicting with no general trend evident in the intraday segment abnormal measures. The four-signal types all appear to generate trades, with sell-type signals consistent with greater abnormal trading activity than buy-type signals, which aligns with our interday robustness results. There is limited evidence of a transient market impact for sell recommendations during intraday time segments, with spreads declining slightly. Partitioned by signal type, there is no other evidence of a transient market impact, which is consistent with recommendation changes acting a liquidity enhancing events. The evidence confirms that sell-type signals are more beneficial to liquidity than buy-type signals.

Table 8
Intraday Liquidity Robustness Tests

Calculations for the liquidity variables are identical to those used in Table 9, but applied to subsets of recommendations based on the potential for heightened information asymmetry. The sample partitions are identical to interday robustness tests but applied to the intraday data. The abnormal liquidity measure for Periods –1 and +1 are reported for comparison against the contrasting sample. The t-statistics for each abnormal liquidity measure are reported in parenthesis below.

Panel A: Intraday Robustness of Signal Type

	Strong Buy		**Buy**		**Underperform**		**Sell**	
	P-1	P+1	P-1	P+1	P-1	P+1	P-1	P+1
Quoted Spread	-0.0005 (-0.87)	-0.0005 (-1.12)	-0.0007 (-1.03)	0.0027 (1.23)	0.0003 (0.35)	0.0005 (0.61)	-0.001 (-1.94)	-0.002 (-3.58)
Percentage Spread	-0.04 (-0.66)	-0.09 (-2.85)	-0.03 (-0.93)	0.06 (0.77)	-0.02 (-0.76)	-0.02 (-0.65)	-0.04 (-1.08)	-0.09 (-2.33)
Bid Depth	-16,119 (-0.84)	85,515 (1.06)	10,180 (1.20)	4,452 (0.55)	-32,249 (-0.94)	-22,926 (-0.82)	713,373 (1.62)	547,411 (1.47)
Ask Depth	766 (0.17)	-178 (-0.12)	1,208 (0.96)	1,005 (0.83)	-1,063 (-0.38)	-1,874 (-0.81)	35,192 (1.30)	6,705 (1.39)

Trades	1.84 (4.44)	3.16 (5.13)	3.08 (6.72)	4.12 (6.29)	4.15 (4.27)	7.86 (4.62)	4.14 (4.48)	6.66 (4.78)
Trade Volume	-79 (-0.18)	797 (1.17)	-342 (-0.78)	-59 (-0.15)	-377 (-0.58)	-408 (-0.94)	3,736 (1.48)	-206 (-0.38)

Panel B: Intraday Robustness of Rank Skips

	All Rank Skips		**t-statistic**		**Control**		**t-statistic**	
	P-1	P+1	P-1	P+1	P-1	P+1	P-1	P+1
Quoted Spread	-0.001	-0.001	-0.56	-0.94	0.0004	-1E-05	0.23	-0.02
Percentage Spread	-0.04	0.03	-0.75	0.49	-0.03	-0.04	-0.43	-1.56
Bid Depth	579,555	-10,213	1.21	-0.09	21,172	4,959	0.67	0.18
Ask Depth	-7,401	-3,050	-1.42	-0.56	4,419	2,431	2.15	2.55
Trades	1.91	3.45	1.69	2.02	2.57	4.55	11.36	13.62
Trade Volume	-2,240	-1,672	-3.51	-2.59	64	122	0.27	0.68

Panel C: Intraday Robustness of Expert Analysis

	Expert Sample		**Non Expert Sample**	
	Period –1	**Period +1**	**Period –1**	**Period +1**
Quoted Spread	-0.0005 (-0.50)	0.0011 (0.76)	-0.0004 (-1.34)	0.0002 (0.20)
Percentage Spread	-0.014 (-0.24)	-0.101 (-2.87)	-0.04 (-2.02)	-0.001 (-0.02)
Bid Depth	149,046 (1.14)	60,285 (0.70)	53,128 (1.18)	90,188 (1.53)
Ask Depth	2,451 (1.14)	3,010 (1.42)	6,234 (1.32)	490 (0.52)
Trades	4.40 (7.81)	5.94 (6.97)	2.49 (8.07)	3.87 (8.54)
Trade Volume	623 (0.98)	-515 (-1.73)	-54 (-0.13)	429 (1.17)

Abnormal intraday liquidity measures for recommendations that skip a rank are reported in Panel B of Table 8 and align with prior results. Quoted and percentage spreads for Periods –1 and +1 are not significantly different from zero; there is no statistically significant evidence that depths change and rank skips generate fewer abnormal trades than the entire sample. There is no evidence of additional information asymmetry in recommendations that skip a rank at an intraday level. Rank skips within the sample are no more informative to liquidity than normal recommendation revisions.

Intraday robustness results for expert analysts align with previous findings. Expert analysts do not have a documented impact on spreads, with quoted and percentage spreads analogous to the non-expert sample and statistically insignificant. The results presented in Table 8 Panel C confirm the finding in interday analysis that our expert sample enhances liquidity to a greater extent than non-experts, and have a material impact on depths. Although not statistically significant, experts are associated with greater increases in abnormal depths. Further, within the sample, experts generate more trades and volume than their non-expert counterparts. The evidence suggests that expert analysts do not possess superior information, but the evidence is consistent with our expert sample having a larger clientele and enhancing liquidity to a level above that of non-experts.

Intraday robustness tests confirm that sample partitions designed to generate additional information asymmetry do not generate information asymmetry and adverse selection that influence spreads. The evidence aligns with our prior results that analyst revisions are informative to liquidity, with sell-type signals and our expert sample associated with incremental enhancements to liquidity.

9. Conclusion

We study a time-series of market liquidity measures around recommendation revisions disseminated by sell-side equity analysts. The objective is to empirically document transaction costs around this period to complete the link between prices and transaction costs on the Australian market and assess the prudence of institutional trading. This analysis also sheds light on the informational efficiency of securities markets and the information processing ability of sell-side analysts. The changing market impact of new recommendations over time is also addressed to assess the potential sensitivity of research findings to the sample period selected in empirical studies of analyst recommendation revisions.

Over our sample of 10,959 recommendation revisions, we find that transaction costs are not an issue around new trading advice. The evidence suggests that the market is sufficiently liquid to process this information without changes in transaction costs. Analyst recommendation changes enhance liquidity in our sample. Bid-ask spreads, as proxies of transaction costs, remain unchanged across numerous tests. There are documented increases in depths, particularly at an intraday level, and trading activity exhibits categorical increases. This finding is consistent across numerous empirical approaches including interday and intraday analysis and several robustness tests. Our evidence is consistent with the market overlooking the information processing ability of analysts and the absence of new information contained in these market events.

Partitions of the recommendations dataset highlight that certain signals have a greater liquidity enhancing effect. Sell-type signals including underperform and sell advice has a greater liquidity enhancing effect. The more negative the signal from strong buy to sell, the greater the incremental enhancement to liquidity. Recommendations partitioned into categories representing expert analysts also enhance liquidity to a greater extent. This evidence aligns with expert analysts being hired by institutions with a larger clientele, and is not evidence of additional information in expert recommendation. There is no evidence that any category of recommendations has an affect on the bid-ask spread, sell-type signals and our experts sample are simply more informative to liquidity enhancements.

For an institutional traders looking to trade in the stock, this represents an ideal time to take advantage of excess volume at the best quotes and transacting with consistent average transaction costs. This opportunity is consistent with the clientele generated by the marketing efforts of large financial institutions creating excess market liquidity. This represents the first study (after Brown, Ball and Chan, 2007) to use the rich Institutional Brokers Estimate

Service (IBES) database of Australian analyst recommendations, which emerge as highly accurate.

This analysis emphasizes the need for future research into the complexities of analyst advice and the information conveyed in recommendations with unique characteristics. Asquith, Mikhail and Au (2005) and Ho and Harris (2000) demonstrate the range of information embedded in individual recommendations. Each recommendation category will have a different market impact and documenting the market reaction to each specific type of recommendation will add to this literature on the Australian market. Further, we witness a statistically significant increase in trading activity around revisions in analyst recommendations. Future research should deconstruct the increase in trading activity by trade size and the initiator of the trade to gain further insight into the process.

The data tells a persuasive story that recommendation revisions have a material impact on liquidity and through trading activity, appear to be market-influencing events. Financial institutions allocate vast resources into the production of analyst recommendations, despite the assumption that there is no new information implicit in these reports. Our findings align with the notion that brokerages use their marketing expertise to generate trades and economic rents, but the wider market does not recognize the information content of analyst recommendations. This speaks greatly for the informational efficiency of the Australian market. Our analysis of liquidity provides external validation of US results reported in Anand et al. and assists in forming a more complete picture of recommendation revisions on the Australian market to complement Brown et al. and Wong (2002).

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