Hanging out on the Sell-Side

Evidence on analyst and broker rewards from forecasting on the ASX*

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January 2006

Draft only: do not quote

* We acknowledge the assistance of Francis Carlow and Paul Martin of SIRCA in obtaining confidential data on broker ids. We also wish to thank the ASX for allowing us to use this proprietary data.

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Abstract

This paper presents evidence on the association between sell-side analyst forecasts, recommendations and brokerage-firm market share. It uses confidential data to document results across distinct market conditions and the largest 100 stocks.

We find that buy and sell recommendations *both* impact broker market share. There is evidence that analysts reinforce sell recommendations with large downside deviations from consensus view – far more than they support buy recommendations with upside deviations.

There is evidence that smaller brokers produce *more* accurate forecasts in aggregate than larger firms. The accuracy of *all* brokers has improved significantly since the introduction of stringent continuous disclosure obligations on firms.

The sell-side of the stockbroking industry is the title given to the brokers and their research departments who provide a suite of services to clients under typically well-known financial services brands. The research analysts of sell-side firms cover stocks over which they issue forecasts, upgrades and downgrades to trading recommendations, target prices and industry sector opinions to the market. The finance literature has devoted considerable energy over the past decade in an effort to better understand the relationship between sell-side analysts and their employing brokers. In part, such interest has been shaped by the emergence and growth of 'soft-dollar' payments for research services and the practice whereby brokers are paid for their research services in allocated brokerage commission.

This paper presents evidence from the Australian Stock Exchange on the complex relationship that exists between sell-side analyst forecasts, recommendations and brokerage-firm market share. Using a unique, confidential data set, it documents results across three distinct periods of market performance and the top 100 stocks by market capitalisation.

In 2001, the financial industry in the United States was substantially and forcibly reshuffled following an investigation by New York Attorney-General Elliot Spitzer into conflicts of interest at Wall Street investment firms[3]. The result was an imposed "clear separation of the research and investment banking divisions at (brokerage) firms"[3]. The global reach of these institutions meant the changes enforced in the United States flowed in a domino-like effect into other equity markets around the world, including Australia – as these major investment houses reorganised

[3] For details of the settlement reached between the banks and U.S. regulators, see http://www.oag.state.ny.us/press/statements/global_resolution.html.

their organisations globally around a geographically scaleable model (Boni and Womack (2002), Conrad, Johnson, and Wahal (2001)).

The imposition of the enforced divorce, following the Spitzer view of the world, creates a vacuum in performance benchmarking. The result is that the incentive for analysts to generate investment banking deal flow is replaced by, perhaps an even stronger incentive, to generate trading commissions and higher market share in the trading of stocks they cover. Clearly, the simplest and most obvious way that sell-side analysts can differentiate themselves in a competitive broking research market is through their earnings forecasts and trade recommendations being divergent from the consensus.

This paper offers evidence on how earnings forecasts and recommendations (in terms of their magnitude and their position relative to consensus) change the market share of brokers in the trading market; and hence the commissions and brokerage-levels payable to them. The Australian market is an ideal academic research platform for studies of this type, given the representation of all the major, global brokerage firms and their operation within a highly developed, electronic screen-traded market on the Australian Stock Exchange (ASX).

The paper looks at the capacity of analysts to influence own-broker market share in different trading periods, both pre and post the release of forecasts and recommendations. In addition, the hypotheses test whether the market capitalisation of the stock covered, or changes in the economic climate, is important in affecting how market share changes. Finally, given the interest in the accuracy of the forecasts, the thesis tests the impact of changes to continuous disclosure regulations in January 2003 on the accuracy of analyst forecasts. The final sample of 55,152 analyst forecasts originates from 23 brokers over a six year time interval.

We find that the impact of analyst earnings forecasts on both the magnitude and direction of changes in broker market share varies dependent on the market capitalisation of the stock. The results offer support for the view that buy and sell recommendations are *both* significantly accretive to broker market share (contrary to Francis and Soffer (1997)), meaning analysts who adopt a neutral stance are penalising themselves in market share terms. However, analysts strongly reinforce their sell recommendations with large downside deviations from the consensus view – far more strongly then they support their buy recommendations with upside deviations. This supports the contention that a strong sell recommendation is perceived as being riskier than a strong buy even in the more accountable environment post 2001.

The structure of this paper is as follows. Section two discusses the relevant prior literature and reviews the Australian market in terms of its structure, regulatory, institutional environment. Section three details the three sets of hypotheses to be tested. Section four describes the data sample and methodology. Section five sets out the results and section six concludes.

2. Research context and the Australian environment.

There is a significant literature addressing the issues surrounding analysts and brokers individually; however, there is a comparatively small quantity of literature in the way of theoretical and empirical studies of the business relationship *between* these two related partners. The present paper seeks to address a number of key aspects of this relationship that are of interest to both academics and the industry. Since the Spitzer enforced separations of business units, the incentives to produce earnings forecasts and recommendations that fitted a specific profile had been substantially relieved (Boni and Womack (2002), Lee and Nicolas (2003), Gintschela and Markov (2004)). However, post-2002 it would seem that instead of fitting earnings forecasts and recommendations to a profile aligned with institutional preferences and incentives, sell-side analysts have substituted trade-generation incentives in their place (Irvine (2004), Jackson (2005)). The result is that the nature of earnings forecasts and trade recommendations remains unclear.

To this end we are interested in examining whether or not analysts are able to influence own-broker market share through their forecasts and research. The main vehicle for this influence if any exists is the earnings forecasts. A number of papers have demonstrated an association between forecasts and broker income from clients such as Lin and McNichols (1998) who reviewed the effect of underwriting relationships on analysts' forecasts and recommendations and find that investors are aware of natural biases in the recommendations of analysts whose brokerage-firms have an underwriting relationship with the company. Similarly, Ellis, Michaely and O'Hara (2000) consider how the underwriting and broking businesses of a firm are connected, highlighting the imperative for underwriters to have the support of the analyst for analytical and report writing purposes. Irvine (2004) and Jackson (2005) both find strong associations between these characteristics of the analyst industry. In the present paper we seek to cast further light on the issue of whether or not there is an incentive for analysts to offer forecasts that distinguish them from their peers in terms of in house trade volume.

In the pursuit of fees and rewards to information another area we address is that of firm size. Market practice is to expend more resources on large firms which are of interest to intuitional investors. Chung (2000) showed that using Standard and

Poors common stock rankings as empirical proxies for firm quality, more analysts followed highly rated stocks than poorly rated ones. The study also explained that analysts assist the marketing efforts of brokerage companies by focusing their analysis on such stocks.

This perception that the analysts and brokers work together as an inseparable team to benefit the company leads to the possibility of conflicts of interest, incentives and commissions in the industry.

Sell-side analysts employed by brokerage houses have several bosses – for example, corporate finance, institutional sales and retail sales. To corporate finance, the analyst owes a deal; to institutional sales, the analyst owes information first; and to the retail sales force, they owe a few stock tips. The conflicts of interest that exist prima facie are further exacerbated by endogenous incentives and commissions, such as bonuses paid from profit-share. The increased regulation of company disclosure in Australia as elsewhere in the world must therefore have a direct impact on these incentives and hazards. The third question we address is what impact has the introduction of stringent continuous disclosure requirements on firms had on the quality of the earnings forecasts published by the research brokers. We expect and find that in a more regulated environment the degree of error in forecasts is reduced inferring that there is less incentive to give unsupported forecasts that stand out from the consensus opinion.

The final area we look at is that of optimism in forecast generation. How sell-side analysts actually process information has been the subject of extensive investigations, both theoretical and empirical. Dimson and Marsh (1984) and Womack (1996) show that analysts' forecasts do appear to contain valuable private information. However, there is significant evidence to suggest that the earnings forecasts, on average, tend to be upwardly biased (Dugar and Nathan (1995)). The traditional explanation for why earnings forecasts are biased (termed 'optimism bias'), especially at the start of the year, has been found in the alignment of analyst incentives with investment banking interests (Lin and McNichols (1998), Michaely and Womack (1999) and management relations (Francis and Philbrick (1993)). We examine this question assuming that the degree of optimism must change through time as more information is available across the market, also that the external monitors on quality of information also play a role in the degree of exuberance an analyst can express!

2.2 The Australian Equity Market

The overall size of the equities brokerage industry has changed little over the past ten years, with the number of active ASX members steady at a count of around one hundred – up slightly from 88 in 1990, and 92 in June 2001. However, the competitive environment has changed considerably due to the emergence of online brokers. Online brokers have put downward pressure on brokerage rates and now account for about fifteen to twenty percent of the number of ASX trades compared with one-quarter of all trades in the U.S., and around four percent of European trades.

The market structure of the Australian market is also significant. The ASX has a very high concentration of companies that operate in the financial services and resource sectors. For example, of the largest ten stocks listed on the ASX over the study period, the 'big four' banks (ANZ, Commonwealth Bank, National Australia Bank and Westpac) together with BHP (now BHP Billiton) and Rio Tinto represent approximately thirty percent of the All Ordinaries index market capitalisation at that time.

2.2.1 Sell-side Microstructure

Sell-side analysts are employed by brokerage firms to provide analyst research to their clients. Brokerage clients (such as fund managers, both domestic and international) do not use direct, upfront cash remuneration for the research product, but rather pay indirectly via brokerage commissions.

Whilst there is no contractual obligation for clients to trade with the broker whose research analyst provided them with the research report or other information that induced their trade (McNichols (1990)) clients *do* wish to maintain a good relationship with research analysts (in particular, the top-rated ones) and as a result, will attribute the trading business to the firm whose analyst provided the information. It is common practise in the Australian market for the majority of institutional investors to each construct a 'panel' of brokers periodically to determine how brokerage commissions will be allocated over the subsequent period, in return for access to analyst research.

Given this loose association, one objective of this study is to contribute new empirical evidence on whether analysts and their employing brokers are able to benefit from incremental commission payments around the release of forecasts and recommendations. That is, is it possible for analysts and brokers to be strategic in release of their private signals?

Hayes (1998) assumes that analysts, through increased trading commissions, capture benefits around the time at which they release their forecasts and recommendations. The Australian market is also heavily reliant on 'soft-dollar' research services (Jackson, 2005), consistent with the findings of Irvine (2000) who reports that the market for analysts' research in both the U.S. and Canada is contingent on the receipt of ‘soft-dollar’ payments. This system of remuneration for analysts and brokers utilises trading commissions paid by institutional investors as payment for research services, in lieu of cash for specific or customized reports.

However, industry observations and discussions with fund managers based in the Australian market confirm that research ‘tags’ (where a broker is paid a lump-sum amount for particularly noteworthy or valuable research) is a practice increasing in popularity and a source of a growing percentage of total broker revenue. This finding is consistent with Irvine (2000) who shows that, as a consequence of the ‘soft-dollar’ market, analyst coverage of a particular stock is associated with higher brokerage-firm market share in the covered stock.

3. Hypotheses

The hypotheses to be tested are designed to provide insight into the role of sell-side analyst forecasts in the contemporary Australian equity market. They are ordered into three categories: the response to analyst forecasts, the role of market cycles and an analysis of the regulatory environment.

3.1 The Response to Analyst Forecasts

The Hayes (1998) partial equilibrium model constructs a framework of demand for the purchase and sale of securities. The model concludes that the more positive an analyst’s earnings forecast ($m_A > 0$), conditional on the forecast exceeding the consensus earnings expectation of x, the more stock investors wish to purchase. The more negative an analyst’s earnings forecast, conditional on the forecast falling below the consensus earnings expectation of x, (i.e. $m_A < 0$), the more investors wish to sell. Irvine (2004) tested this outcome in the Canadian market and found support for the model's demand functions.

Following Irvine (2004), the expectation is that analysts are able to increase their own broker market share by strategically moving their earnings forecast away from the consensus. That is, by distinguishing their forecast from the consensus, they are rewarded for taking a definitive view on the stock's future period earnings. To evaluate if this behaviour also occurs in the Australian market, the first hypothesis is:

Hypothesis 1 *– Increases in absolute forecast deviation from consensus lead to increases in broker market share in the stock.*

However while investors may respond to an individual analyst's deviation from consensus, the overall volatility in forecasts (a measure of instability or uncertainty) is undesirable. Hayes (1998) demonstrates that the demand for the number of shares investors wish to buy and sell is decreasing in s_A^2 (the variance of all analysts' expectations of the consensus forecast error, (m_A). The second hypothesis tests the assumption of Hayes (1998) and Irvine (2004), as well as the common theoretical prediction that the extent to which investors trade on information decreases as the uncertainty of that information increases (Admati and Pfleiderer (1990), Allen (1990) and Brennan and Hughes (1991)):

Hypothesis 2 *– Reduced total uncertainty in the forecast increases broker market share.*

Hayes (1998) also shows that the marginal return from analysts' efforts in gathering forecast information is greater for stocks that the analyst expects to perform relatively well. As a result, it is expected that analysts reinforce their expectations of performance with a strong recommendation. Hypothesis 3 states:

> ***Hypothesis 3*** *– Trade generated, given a buy recommendation, is greater than the trade generated, given a sell recommendation.*

If analysts are going to gain market share and hence income from having forecast deviating from the consensus we hypothesise that this is more likely to occur in those forecasts that are further way form the actual earnings announcement. The rationale for this is that there is less information in the market regarding the earnings and that there is greater uncertainty around the expected earnings. DeBondt and Thaler (1990) find that analysts revise their forecasts downward and reduce variation as they get closer to the actual earnings announcement. Therefore we assume that we would see more market share trading in response to a deviation from consensus earlier rather than later in the earnings cycle.

> ***Hypothesis 4*** *– Trade generated on a forecast further away from the actual announcement will be greater and have a more significant association with deviation in forecast than a forecast closer to actual earnings announcements.*

3.2 The Role of Market Cycles

The extant literature does not specifically address the impact of market cycles and economic factors on the nature of forecasts and their inherent uncertainty. It would not be unreasonable to suggest that in periods of high market volatility one would expect to observe greater uncertainty in forecasts. Furthermore, it would be natural for analysts to reinforce their departures from the consensus by complementing their forecasts with 'off the fence' recommendations – a buy or sell call. This is tested by the following hypotheses:

Hypothesis 5A *– Forecast errors on sells will not equal forecast errors on buys over the market cycle.*

Hypothesis 5B *– Forecast uncertainty on buys will not equal forecast uncertainty on sells over the market cycle.*

Consistent with the empirical literature (Jackson, 2005), it is expected that analysts associated with larger brokers have access to the resources needed to help generate more accurate forecasts across all market conditions.

Hypothesis 6 *– Analysts employed by larger brokers produce more accurate forecasts.*

3.3 The regulatory environment

The final hypothesis is designed to test the impact of the regulatory environment on the accuracy of analyst forecasts. Of specific interest are the continuous disclosure requirements introduced in January 2003 that are assisting (and forcing) analysts to be more accurate earlier in the forecast year. As part of its role in regulating the continuous disclosure practices of Australian companies, the ASX developed a policy on improved disclosure and earnings guidance which is set out in the ASX Discussion Paper on Enhanced Disclosure[4]. In accordance with that policy,

[4] *Continuous Disclosure – The Australian Experience (ASX, 20 February 2002)* can be found at: http://www.asx.com.au/about/pdf/Continuousdisclosure-TheAustExperience.pdf.

the ASX amended the Listing Rules with effect from 1 January 2003 to strengthen the obligation on companies to prevent a false market[5].

> ***Hypothesis 7*** *– The accuracy of forecasts changes in response to the new regulatory environment.*

4. Data and methodology

4.1 Data

The data obtained is for the top one hundred listed stocks (by market capitalisation) as at 1 January 1998, 1 June 2000 and 1 June 2002[6]. These top 100 firms represent approximately 82% of the Australian Stock Exchange market capitalisation and are the main stocks traded by institutions and pension funds. The data sample is constructed from a range of sources and the broker identifications are confidential[7].

Transaction data was obtained from the Australian Stock Exchange (ASX) through the Securities Industry Research Centre of Asia-Pacific (SIRCA), consisting

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[5] See http://www.aar.com.au/corpgov/iss/cont.htm for further details on the rationale and detail surrounding the changes to the continuous disclosure regulations.

[6] The market capitalisations of these firms were obtained from the Securities Industry Research Centre of Asia-Pacific (SIRCA).

[7] All brokers are tagged anonymously with a randomly assigned identification code for the purposes of data constitution and manipulation.

of buy volume, buy value, sell volume and sell value for each SEATS[8] broker identification code were obtained for each trading day in the sample period. Analyst earning forecasts were obtained from I/B/E/S[9]. The I/B/E/S database contained 517,323 forecasts for the total Australian market back to 1987. The ASX broker data, price data and the I/B/E/S broker data were matched and a list of 'research brokers'[10] constructed. For these brokers their earnings forecasts, daily aggregate trading around the forecast dates, as well as closing price on the forecast date for the firm in question across the sample period for the top 100 firms was recorded. After the removal of missing and erroneous values there remains a data sample of 55,152 observations, over 23 brokers and 100 firms for the sample period.

The ASX transaction data was tabulated with a record, on each trading day, for the buy and sell activity of each individual research broker in each stock. Total volume of trade for a broker is calculated as:

$$TotalVolume_t^{k,j} = BuyVolume_t^{k\ j} + SellVolume_t^{k\ j}$$

Where k is each stock and j is each broker, for each day t.

4.1.1 Forecast and Recommendation Characteristics

Using the I/B/E/S forecasts issued by the research brokers for the sample stocks, duration of 'forecast life' is calculated as the period from the date a forecast is issued to the date it is superseded Hence, *Forecast Duration* (*FCSTDUR*) measures

[8] SEATS (Stock Exchange Automated Trading System) is the electronic order processing system utilised by the Australian Stock Exchange.

[9] The I/B/E/S database is provided through Thompson Analytics.

[10] *Research Brokers* are the brokers that constitute the final sample, brokers are included if they issue I/B/E/S forecasts for at least one stock.

the time that each issued forecast remained the 'live forecast' for a broker. The consensus view on the stock's forecast earnings from all analysts in the I/B/E/S dataset was constructed at each forecast date. Similarly, the number of outstanding forecasts at the time of a new forecast being issued was computed (*NumberofBrkrFcsts*). Finally, the standard of deviation (*STDDEV*) and variance of all broker forecasts in the dataset was calculated for each stock at the time of forecast release.

Different brokers use unique scales and titles for their stock recommendations, the I/B/E/S standardised recommendation codes and titles are used as the basis for the recommendation dataset. In a fashion consistent with the treatment of analyst forecasts, the end date of a recommendation is defined as the date it is superseded by a new recommendation from that broker.

4.2 Methodology

The primary research question of this paper is whether or not there is a positive association between the deviation from consensus of analyst forecasts and changes in broker market share. In this section we detail the proxy variables and statistical methods used to test the hypotheses outlined above.

4.2.1 Broker Market share

A benchmark measure of broker market share is needed, which can be assumed to be unaffected by forecast announcements. After discussions with several research analysts and sales directors, it was decided to use days -10 to -6 relative to the forecast announcement date (day 0) as the benchmark period. Periods where a trading effect in response to a forecast announcement (day 0) were identified as: days

+1 to +5 to capture the trade in the short term post the announcement, and days +6 to +10 to examine if there are extended responses. Trading on day 0 is recorded to measure the immediate response. Days -5 to -1 are included to test for leakage prior to the public announcement. This may occur in a scenario where analysts release their forecasts (or suggestion of their likely change) to priority clients before they are released to the broader market. This is consistent with the findings of Brown et al. (1991), who find that clients of brokers can only trade profitably if clients receive analyst forecasts prior to their public release.

Market share is the volume of shares traded by the brokerage firm normalised by the total shares traded by the complete research broker subset in the stock (Irvine (2004)). Specifically, the market share on day i, of brokerage firm j, for stock k, is the total volume traded by brokerage firm j in stock k on day i, divided by the total volume traded in stock k on day i by all the research brokers:

$$MKT\_SHARE_{j,i}^{k} = \frac{\text{Broker Volume}_{j,i}^{k}}{\sum_{j=1}^{J} \text{Broker Volume}_{j,i}^{k}}$$

The present study uses *changes* between the benchmark period market share (b) and each of the market share windows of interest in the statistical analysis. The use of *changes* in market share controls for the naturally high levels of market share of large brokers. It is also a proxy better suited to addressing the research question: how do forecasts *change* brokerage-firm market share?

$$\Delta MKT\_SHARE_{j,i}^{k} = \frac{\text{Broker Volume}_{j,i}^{k}}{\sum_{j=1}^{J} \text{Broker Volume}_{j,i}^{k}} - \frac{\text{Broker Volume}_{j,b}^{k}}{\sum_{j=1}^{J} \text{Broker Volume}_{j,b}^{k}}$$

In summary, the statistical tests are based on market share *changes* between the benchmark window (days -10 to -6) market share and sequentially days -5 through

-1; days +1 though +5; days +6 though +10. In addition, change in mean market share from the benchmark window to day zero is included to capture any difference in trading at the announcement window, as opposed to the pre or post-announcement period. Table 1 presents summary statistics for broker market share over these event windows.

[Table 1 here]

4.2.2 Analyst Deviations from Consensus

The absolute deviation between an analyst's earnings forecast and the consensus earnings forecast (*ABSDEV*) is constructed as the difference between the forecast announced and the mean of 'live' forecasts for each broker one month prior to the forecast release (consensus forecast). To control for size effects the deviations are scaled by the closing stock price on the forecast day (Irvine (2004)).

$$ABSDEV = \left| \frac{Forecast_t^k - \dfrac{\sum_{j=1}^{n} Forecast_{t-1}^j}{n}}{Shareprice_t} \right|$$

Where k is the analyst (broker) issuing the forecast in question;

t is the time at which this forecast is released to the market (*as recorded in the I/B/E/S database*);

t-1 is t exactly one month prior;

n is the total number of broker forecasts in the market exactly one-month prior to the present forecast by broker k.

The Hayes (1998) model predicts that the greater the price-deflated absolute deviation (*ABSDEV*), between the analyst's earnings forecast and the consensus forecast, the greater the demand for trade in the stock. *ABSDEV* is expected to be positively associated to changes in brokerage-firm trading in the forecast stock. A secondary variable, *DEV*, is constructed to proxy for the direction, as well as the magnitude, of the earnings forecast relative to the consensus value

$$DEV = \left(\frac{Forecast_t^k - \frac{\sum_{j=1}^{n} Forecast_{t-1}^j}{n}}{Shareprice_t} \right)$$

Where k is the analyst (broker) issuing the forecast in question;

t is the time at which this forecast is released to the market (*as recorded in the I/B/E/S database*);

t-1 is t exactly one month prior;

n is the total number of broker forecasts in the market exactly one-month prior to the present forecast by broker k.

4.2.3 Total Uncertainty in Forecasts

Following Irvine (2004), a proxy for total uncertainty around an earnings forecast is adopted from Barron and Stuerke (1998). Total uncertainty is comprised of both (1) uncertainty in the consensus, and (2) idiosyncratic uncertainty (dispersion across all analysts' forecasts).

$$\text{Uncertainty} = \left(1 - \frac{1}{N}\right)D + SE$$

Where N is the number of 'live' forecasts;

D is the sample variance of analysts' forecasts;

SE is the error in the consensus forecast relative to actual earnings;

D, the proxy for dispersion across the analysts, is defined as:

$$D = \frac{1}{N-1}\sum_{a=1}^{N}\left(F_a - \overline{F}\right)^2$$

SE, the sample squared error in the consensus forecast, is defined as:

$$SE = \left(A - \overline{F}\right)^2$$

Where A is the actual reported earnings;

F_a is the forecast by analyst 'a'; and

$\overline{F}$ is the consensus forecast.

The assumption is that the uncertainty variable captures investors' *total* uncertainty surrounding the analyst's forecast, and therefore *Uncertainty* will be negatively associated with changes in broker-firm market share.

4.2.4 Other variables and controls

Once a company announces its actual earnings for the forecast period, the retrospective error in each forecast is calculated by subtracting actual reported earnings per share from the forecast earnings estimate. An *absolute* forecast error is also calculated by taking the absolute value of this error. Both the forecast error and the absolute forecast error are scaled by the closing share price obtained on the day of the earnings forecast.

$$FCSTERROR = \frac{\left(F_{a,t} - A\right)}{Shareprice_t}$$

Where $F_{a,t}$ is the forecast by analyst *'a'* at time *t*;

A is the actual reported earnings; and

$Shareprice_t$ is the stock price on the forecast date (t).

Dummy variables

In order to capture an analyst's buy or sell recommendation, two dummy variables are used. *BUY* has value equal to one for all recommendations that are classed as positive and *SELL* has value equal to one for those classed as negative[11]. The type of recommendation is assessed as the active recommendation on the day of the issue of the analyst's forecast. In the scenario where a recommendation is changed on the same date as the release of a new forecast, the new recommendation associated with the new forecast is used (see below).

It is common practice in the broking industry for sell-side analysts to release investment or trading recommendations alongside their earnings forecasts. Within the Hayes (1998) framework, positive (buy) and negative (sell) recommendations would be expected to generate more brokerage-firm trading than neutral (hold) recommendations.

Francis and Soffer (1997) find that both analysts' earnings forecasts and stock recommendations contain *distinct*, price-relevant information. Therefore it is

[11] See Appendix 7 for the treatment of the different terminology used in broker recommendations.

expected that both forecasts *and* recommendations each contain unique, accretive price-relevant information. Investors recognise this, and the marginal trade occurs according to the exclusive information revealed by both the forecast and the recommendation.

In addition to the information value of both buy and sell recommendations, there is also information contained within the decision of an analyst to change their recommendation on the day of the release of a forecast. Therefore, the dummy variable *ChgonFcstDay* has value equal to one when the release of a new forecast coincides with a change in the analyst's recommendation on the same date.

With the benefit of more analysts and wider distribution networks, it is likely that the impact of forecasts originating from the analysts of larger brokers will be different to those originating from smaller, independent brokers (Boni and Womack, 2002). Within this sample, large brokers are identified as those whose average value traded per day per stock is greater than both the mean and median values traded per day per stock in the dataset. From a total of 23 research brokers, nine brokers are identified as large. The dummy variable, *BigBroker*, is equal to one when the forecast is the product of a large broker.

4.2.5 Estimation procedures

Analyst market share and recommendations

The associations between changes in market share and analyst forecasts and recommendations are tested with robust regression which utilises a fitting criterion based on *M-estimation* (Huber, 1964). This class of estimator can be regarded as a generalisation of maximum-likelihood estimation.

The dependent variable for each regression is the change in market share, as measured from the benchmark window (control period). The explanatory variables are *ABSDEV*, *Uncertainty*, analyst recommendations are included as dummy variables for buy and sell recommendations, as well as for changes in recommendation on the forecast day. A control variable for the influence of large brokers is included as a one for a larger broker, otherwise zero.

$$\begin{aligned}\Delta MKTSHARE = b_1 + b_2 ABSDEV + b_3 UNCERTAINTY + b_4 BigBrkr +\\ b_5 Buy + b_6 Sell + b_7 ChgFcstDay + e_i\end{aligned} \quad (1)$$

The regression is run over market share windows days [-5 to -1], [+1 to +5], [+6 to +10] and [Day 0] respectively.

Whether or not there is more incentive to deviate from consensus at a greater distance from the actual earnings announcement is tested using the regression:

$$\begin{aligned}\Delta MKTSHARE = b_1 + b_2 ABSDEV_{-1} + b_3 ABSDEV_{-4} +\\ b_4 UNCERTAINTY + b_4 BigBrkr +\\ b_6 Buy + b_7 Sell + b_8 ChgFcstDay + e_i\end{aligned} \quad (2)$$

Where $ABSDEV_{-1}$ is the measure one month prior to the actual earnings and $ABSDEV_{-4}$ is four months prior. We expect that the slope estimate on the 4 month out values will be significantly larger than that on the one month out estimate.

Robustness Tests of Analyst Recommendations

In order to test the findings of Francis and Soffer (1997), the association between a buy or sell recommendation and the other variables of interest is assessed using a logistic regression. .

Market cycles and regulatory environment

In order to test the hypotheses for role of market cycles and the impact of changes to the regulatory environment the sample is divided into three sub-periods. The first time period is 1 January 1998 through 31 December 1999. This time period represents the appreciation of the Australian market, associated with the 'dot-com' boom. The second time period is 1 June 2000 through 31 May 2002. During this period, the market was in a significant downturn. The third time period is 1 January 2003 through 31 December 2004. This period represents one of the strongest periods of performance in the history of the ASX. In addition, the introduction of the enhanced continuous disclosure requirements coincided with the start of the last period.

The tests of the second and third set of hypotheses are conducted by testing for significance in the differences between means (t-test) and variances (F-test) for the *DEV*, *UNCERTAINTY* and *FCSTERROR* variables across the different time periods. Sub samples are also used to control for the forecasts of large brokers, small brokers, and buy and sell recommendations.

Finally, for the tests of the regulatory environment hypothesis, the forecast sample is partitioned into the three time periods and the mean, median and variance of the *FCSTERROR* variable are tested for significant differences across time as noted above.

5. **Results**

5.1 Descriptive Statistics

Table 2 presents summary statistics for the 55,152 analyst forecasts in the sample across all time periods and stock categorisations. Mean *ABSDEV* is 0.8 percent, while the mean (median) difference between analyst forecasts and the actual reported earnings (*FCSTERROR*) is 7.7 percent (1.1 percent). Mean *UNCERTAINTY* is AUD$0.125 per share squared, and the median is significantly lower at AUD$0.011 per share squared. The average number of analysts covering a stock is 7.9 and the mean (median) forecast 'life' (*FCSTDUR*) is 39 (28) days.

[Table 2 here]

5.2 Market share Analysis

The results of the regression equation 1 (see table 3) demonstrate that, across the whole sample, there is an inverse association between changes in market share and the analysts' forecast deviation from consensus in the days immediately after the forecast release [Days +1 to +5]. For each 1% of absolute deviation in the released forecast, broker-firm market share is lower by 1.448% (t-statistic -4.937). In an apparent contradiction to Irvine (2004), this suggests that brokers do not obtain market share value by deviating from the generally held view.

[Table 3 here]

The control variables reveal that broker size and buy and sell recommendations accompanying analyst forecasts are all positively associated with an increase in market share. As expected, large brokers have more substantial increases in market share, with broker market share rising by 17.6% (t-statistic 11.404). Buy and sell recommendations accompanying analyst forecasts *both* increase market share by 4.1% (t-statistic 4.673) and 4.7% (t-statistic 3.443) respectively. This result is consistent with the conclusions of both Irvine (2004) and Francis and Soffer (1997) that analysts' forecasts and recommendations each contain distinct price-relevant information. In this dataset, it is clear that recommendation levels generate a stronger trading response than actual forecast values. An F-test fails to reject the equality of the *Buy* and *Sell* coefficients, suggesting an indistinguishable trading response to either recommendation. However, a change in analyst recommendations on the release day of the forecast reduces broker-firm market share by 3.1% (t-statistic -2.059). This is likely caused by investors taking time to digest the new information contained in the changed recommendation.

The impact of the variables on broker-firm market share appears to continue up to ten days after the release of the analyst's forecast (see Panel C in Table 8.3), although the associations are weaker in the [Day +6 to +10] post-announcement window. This finding, together with the results in Panel D for announcement day trading, suggests that the market extracts value from the analyst forecast deviation over an extended trading period (up to ten days) rather than in one event window (such as Day 0). This behaviour, combined with the falling significance of the variable association, could give support to the microstructure literature such as Kyle (1985) that argues that informed traders 'trade down' an information curve to extract the maximum possible value.

In order to test for systematic leakage of analyst forecasts to the market prior to their official release, the regression is run across the change in market share from the control window to the days prior to the forecast release date [Days -5 to -1] (Panel A, Table 8.3). The results suggest the inverse correlation between changes in market share and *ABSDEV* is strongest in this period (t-statistic -5.37). The *BigBroker* result is also strongest in Panel A. This result for the *ABSDEV* and *BigBroker* variables, in a time period where the association between the upcoming forecast and broker-firm market share should be small, suggests some leakage of upcoming forecasts by analysts to priority clients.

[Results for equation 2 to come.]

5.2.1 Sensitivity Analysis

As shown in the previous section, the results for the total sample demonstrate that the nature of analyst forecasts impacts upon broker-firm market share. The Australian stock market is characterised by high concentrations of interest and trading in the top 20 stocks. Thereafter, these characteristics decline such that below the top 10 stocks, there is reduced analyst following and significantly less liquidity. To control for these characteristics, the regressions were repeated across four sub-samples consisting of the top 10, 11-20, 21-50 and 51-100 stocks by market capitalisation.

(a) Top 10 Stocks

The results for this sub-sample are not consistent with those obtained over the full sample (see table 4). *BigBroker* is the only variable that provides a statistically significant result across all market share windows. The variable of particular interest, *ABSDEV*, in the post-announcement period, has no statistical significance. These are the top ten firms on the Australian market and they are subject to minute and continuous scrutiny by many interested parties. It is to be expected, therefore, that there is a high level of information efficiency across market participants and as a result, little reward for analysts deviating from consensus forecasts.

[Table 4 here]

Since it can be assumed that there will be few or no surprises in an analyst's forecast announcement for these large and widely held companies, there is no intrinsic value in waiting for forecasts when timing trading in these stocks. Indeed, there may be value in trading *before* the announcement to avoid noise contamination of the prevailing price generated by uninformed traders trading on the basis of the announcement. In the period leading up to the forecast release, including Day 0, there is a significant negative association at the 5% level. This view is supported by the finding of a significant association between the variables in the days leading up to, and including, the announcement date. As the association is negative, this finding reinforces conclusions drawn in the previous section that research analysts are penalised rather than rewarded for deviating from consensus in this group of highly scrutinised firms.

It is interesting that changes in the recommendation on the forecast announcement day result in a significant positive association with changes in market share in the [Days +1 to +5] window (t-statistic 4.266). This may suggest that a change of analyst opinion on firms' expected performance carries a high level of short-lived, distinct information for these large firms.

(b) 11 to 20 Stocks

The noteworthy difference in the results for this section, compared to the full sample and the top ten firms, is that market share at days [0], [+1 to +5] and [+6 to +10] is significantly positively associated with *ABSDEV* (tstat 2.16 and 2.047

respectively). This is consistent with the prior literature (notably Irvine (2004)) which posited that analysts are able to increase their market share by moving their forecasts away from the consensus. Other results are either consistent with those previously noted or else heterogeneous (see table 5).

[Table 5 here]

(c) 21 to 50, and 51 to 100 Stocks

For the 21 to 50 stocks, the results in Days [+1 to +5] are consistent with the full sample: *ABSDEV* is weakly negatively associated; *BigBroker* is positively associated; and *Buy* is also weakly positively associated with changes in market share. However, outside this window and across all the windows in the 51 to 100 stock sub-group, there is little consistent association between the explanatory variables and changes in market share[12].

5.2.2 Recommendation effects

The results of the *Buy* logistic regression (Table 6) suggest a strong probability of a buy when deviation from consensus is positive (t-statistic 14.37), and when there is a strong negative association with uncertainty (t-statistic -2.77). This result is consistent with the Hayes (1998) model, which suggests that strong optimistic forecasts reinforce buy recommendations. In addition, buy recommendations are significantly negatively associated with top 10 companies, with investors most likely seeing little value in their use. Further, these recommendations need to be as accurate as possible to carry value to the investor community.

[Table 6 here]

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[12] The full results are available upon request from the authors.

Sell recommendations are accompanied by negative deviations from the consensus forecast (t-statistic -9.589). *Uncertainty* is negative (t-statistic -4.298) for sell recommendations. This would seem to give support to the argument that analysts will only make sell recommendations when they possess a high level of certainty regarding the forecast and the outlook for the company. A comparison of the significance of uncertainty, with respect to buys and sells, lends further support to this argument (confirmed via an F-test on the coefficients): buy recommendations are associated with a greater degree of uncertainty than are sell recommendations. This suggests analysts are far quicker to reach a threshold where they report a stock as a buy recommendation even with a high level of uncertainty, relative to the low level of uncertainty that must be amassed before issuing a sell recommendation.

In contrast to the negative result for the top 10 companies for buy recommendations, there is a positive value in sell recommendations (t-statistic 4.269). This result points to an acknowledgement (and reward) for the difficult position in which analysts place themselves when issuing a sell recommendation for a top 10 company. Analysts are likely to place strains on both their relationships with their corporate finance divisions and also the covered company's management, making forecasting and other research products more difficult to produce in the future.

5.3 Analysts and Market Cycles

Through time and across different market conditions, uncertainty about firm performance will vary. Also, exogenous factors such as the introduction of regulation to force conformity in firms' disclosure requirements would be expected to lead to differences in the dispersion of the forecasts. In order to test for the impact of these factors, the sample is divided into three sub-periods representing three different types of market conditions and two different regulatory environments.

Descriptive statistics for deviation from the consensus forecast, and uncertainty around deviations, across buys and sells within the three time periods (rising market; falling market, rising market with new regulation requirements for disclosure by firms) are documented in Table 7.

Within each period the deviation from consensus on sell recommendations is statically larger than that on buys. Similarly between periods sells deviations are larger than buy deviations . These results give strong support for an argument that analysts reinforce their sell recommendations more aggressively than they do their buy recommendations, in terms of the absolute deviation of the forecast from consensus. One way of explaining this behaviour is that there are large direct and indirect costs for both the analyst and the broker of issuing sell recommendations. For example, relations between the analyst and the company are likely to be more difficult and may lead to the analyst being frozen out of information circles. As a result, if the analyst makes the decision to issue a sell recommendation, they do so in a comprehensive manner that includes aggressive downside earnings forecasts.

[Tables 7 and 8 here]

As well as the deviation from consensus, it is important to measure the impact of dispersion in the forecasts around the consensus and from the actual earnings reported, captured by the *Uncertainty* variable. In table 7 it can be seen that the mean of the uncertainty variable is small in each period relative to the mean deviation from consensus. However, uncertainty also appears to be a function of market conditions.

From table 7 it can be seen that in time period 2 buy recommendations have a small mean deviation from consensus (approximately -2%) whereas the uncertainty of the forecast for the same recommendation in the period is18.9%. this is not unreasonable in a period of falling markets after the bubble of the tech era and reflects a lack of confidence in predicting upward market movements. Likewise, Panel B in Table 8 reports the reduction in standard deviation around uncertainty in the third time period relative to both earlier periods. This reduction in volatility would appear to be a direct result of the introduction of the continuous disclosure regulations that came into effect at the beginning of the third time period and distinguishes it from the earlier ones.

5.4 Forecast Accuracy and Broker Size

The results in Tables 9 and 10 provide evidence to reject the hypothesis that large broker forecasts are more accurate than small broker forecasts. From Table 10, it can be seen that the mean small broker forecast error is significantly less than the mean error of the large brokers across periods one and three (tstats significant at 1% level), for time period two where they are statistically indistinguishable.

[Tables 9 and 10 here]

5.5 Analysis of the Regulatory Environment

More stringent continuous disclosure regulations came into effect at the start of time period three. A specific test for the impact of this change in the regulatory environment is conducted, and the results reported in Tables 11 and 12. From these tables it can be seen that there is a significant improvement in the forecasting accuracy of analysts between time periods one and two, and period three. The mean forecast error for the first time period was 4.5%, period two was 15.5% and period three was -2.2%. These results are all statistically significant at the 1% level (table 12).

[Tables 11 and 12 here]

The results support the contention that the continuous disclosure regulations would constrain analyst forecast deviations and curtail analysts from introducing unsubstantiated error into their forecasts. The results in time period three suggest a significant tightening in the aggregate forecast errors of analysts over time period three – the 1 January 2003 through 31 December 2004 interval. On the basis of these tests, the null hypothesis is rejected and it is concluded that there has been a significant improvement in the accuracy of analyst forecasts following the changes to the regulatory environment. This suggests either an improvement in the ability of analysts to forecast company earnings, or more likely, a significant change in the information environment in which they are generating their forecasts.

6. Conclusion

The research motivation of this dissertation was to test within the Australian market a model of analyst-broker relations across three distinct types of market conditions and a significant proportion of total market capitalisation. There are few empirical studies of this type as a result of the difficulties in obtaining the necessary data. However, the structure of the Australian market is highly conducive to examining the empirical efficacy of these analyst-broker models as noted previously.

The study makes several contributions to the literature in terms of methodology. The sample size is a large progression on Irvine's (2003) study of the

Canadian market (less than 1,000 forecasts) and by structuring the analysis around the release of forecasts instead of recommendations (Aitken et al, 2001), a broader spectrum of analysis becomes possible. This is important as analyst forecasts are the driver of recommendations. The use of a robust estimation procedure and the partitioning of the sample into three discrete time periods also makes an incremental contribution to the area. In addition, by conducting the tests with time period controls for forecast deviations from consensus, uncertainty and forecast errors, the study incorporates the realisation that behavioural differences in bull markets vis-à-vis bear markets extends to all market participants, including the analysts. Finally, the sub-sampling of the stocks by market capitalisation is unique in acknowledging the availability of near homogenous information for the largest companies, as against the permeating information asymmetry for stocks subject to far less daily scrutiny.

The research hypotheses addressed the capacity of analysts to influence own-broker market share in different trading periods, pre and post the release of forecasts and recommendations. In addition, they were structured to test whether the market capitalisation of the stock covered affected how market share changes. The final question delineated the impact of changes to continuous disclosure regulations in January 2003 on the accuracy of analyst forecasts.

The results of the study suggest the impact of analyst earnings forecasts on both the magnitude and direction of changes in broker market share varies dependent on the market capitalisation of the stock. For example, analyst forecasts over the top ten companies on the ASX did *not* statistically increase market share with forecast deviations from consensus. Interestingly, the results offer support for the view that buy and sell recommendations are *both* significantly accretive to broker market share meaning analysts who adopt a neutral stance are penalising themselves in market share terms. However, analysts strongly reinforce their sell recommendations with large downside deviations from the consensus view – far more than they support their buy recommendations with upside deviations.

Finally, it appears that large brokers are able to 'ramp up' their market share far more easily than small brokers, as would be expected. Yet smaller analysts have significantly more accurate forecasts across all sample time periods. In support of the arguments in favour of an enhanced regulatory environment, the results find that the accuracy of *all* brokers has significantly improved over the 1998 to 2005 interval, in particular since January 2003. This finding is attributed to the success of more robust continuous disclosure obligations on firms in the Australian market that is assisting analysts in arriving at more accurate estimates earlier in the forecast year.

In conclusion, there remains significant scope for further research in this area. For example, it may be useful to restrict the data set to large brokers only in order to help streamline the dataset and remove a number of outlying forecasts. Finally, the impact of the changes to continuous disclosure regulations will need a further, more extensive review ata later date; however, this research presents a useful starting point.

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Table 1
Summary Statistics for Broker Market share

This table presents summary statistics on the *levels* of market share for all brokers in each window, grouped into the three time periods. The windows presented here are days *[-10 to -6]* (the benchmark period) and days *[-5 to -1]* prior to the forecast. Days *[1 to 5] and [6 to 10]* post the forecast, and the single-day window, Day [0].

Time Period 1					
January 1998 to January 2000					
Day Window	**-10 to -6 (%)**	**-5 to -1 (%)**	**1 to 5 (%)**	**6 to 10 (%)**	**0 (%)**
Min:	0.00	0.00	0.00	0.00	0.00
1st Qu.:	2.74	2.64	2.55	2.63	0.67
Mean:	9.27	9.15	8.94	9.24	6.87
Median:	6.30	6.05	5.87	6.12	2.68
3rd Qu.:	11.90	11.90	11.50	12.20	7.81
Max:	100.00	100.00	99.60	99.80	100.00
Variance:	1.08	1.05	1.05	1.05	1.25
Std Dev.:	10.40	10.20	10.30	10.30	11.20
Skewness:	2.84	2.75	2.86	2.70	3.29
Kurtosis:	12.20	11.30	12.10	11.00	14.00

Time Period 2					
June 2000 to June 2002					
Day Window	**-10 to -6 (%)**	**-5 to -1 (%)**	**1 to 5 (%)**	**6 to 10 (%)**	**0 (%)**
Min:	0.01	0.01	0.01	0.00	0.00
1st Qu.:	3.49	3.55	3.56	3.51	0.72
Mean:	9.65	9.82	9.87	9.75	6.88
Median:	7.10	7.35	7.32	7.29	3.04
3rd Qu.:	12.60	12.90	12.90	12.80	8.48
Max:	100.00	100.00	100.00	100.00	98.70
Variance:	0.88	0.87	0.93	0.90	1.10
Std Dev.:	9.39	9.32	9.66	9.48	10.50
Skewness:	2.43	2.36	2.66	2.61	3.25
Kurtosis:	8.93	9.35	11.60	11.30	14.40

Time Period 3					
January 2003 to January 2005					
Day Window	**-10 to -6 (%)**	**-5 to -1 (%)**	**1 to 5 (%)**	**6 to 10 (%)**	**0 (%)**
Min:	0.01	0.01	0.00	0.00	0.00
1st Qu.:	4.59	4.65	4.65	4.53	1.61
Mean:	10.70	10.70	10.70	10.70	8.29
Median:	8.33	8.37	8.42	8.39	4.55
3rd Qu.:	14.00	13.80	13.70	13.90	10.60
Max:	100.00	100.00	100.00	100.00	97.40
Variance:	0.87	0.90	0.95	0.88	1.13
Std Dev.:	9.30	9.49	9.74	9.38	10.60
Skewness:	2.41	2.68	3.06	2.51	2.72
Kurtosis:	10.30	12.90	16.80	11.40	10.40

Table 2
Summary Statistics: All Stocks, Periods and Brokers

This table presents summary statistics for the sample of all stocks, periods and brokers. *FCSTDUR* is the 'life' of the analysts forecast (measured as the number of days between its release and when it is superseded by a new forecast). *EPS Estimate* is the earnings per share forecast issued by the analyst. *FcstError* is the percentage difference between the forecast and the reported EPS result (*AbsFcstError* is the absolute value). *ABSDEV* is the absolute deviation, as a percentage, between the each analyst's forecast and the consensus forecast exactly one-month prior to the issue of that forecast. *DEV* is the actual deviation, positive or negative and expressed as a percentage, between each analyst's forecast and the consensus forecast exactly one-month prior to the issue of that forecast. *NumberofBrokerFcsts* is a count (inclusive) of the number of forecasts on issue at the time of the forecast. *Consensus* is a cross-sectional mean calculation of the live forecast for earnings by all analysts exactly one-month prior to the release of this forecast. *StdDev* is the standard of deviation in the forecasts at the time of the consensus calculation. *ActualEPS* is the reported earnings per share of the stock. *UNCERTAINTY* is the total uncertainty in and around the forecast.

Forecast Variables

	FcstDur (Days)	EPS Estimate (cps)	AbsFcst Error (%)	Fcst Error (%)	DEV (%)	ABSDEV (%)	Number of broker Fcsts	Consensus (cps)	StdDev (%)	Actual EPS (cps)	Uncertainty (%)
Min:	1.000	-0.455	0.000	-0.991	-0.741	0.000	2.000	-0.408	0.000	-2.239	0.000
1st Qu.:	13.000	0.261	0.027	-0.048	-0.004	0.001	4.000	0.267	0.016	0.210	0.002
Mean:	39.000	0.630	0.189	0.077	-0.001	0.008	7.930	0.632	0.053	0.554	0.125
Median:	28.000	0.447	0.081	0.011	0.000	0.004	7.000	0.447	0.034	0.404	0.011
3rd Qu.:	55.000	0.814	0.219	0.125	0.003	0.008	11.000	0.810	0.070	0.768	0.057
Max:	180.000	3.816	2.970	2.970	0.806	0.806	37.000	3.478	0.781	2.488	8.680
Variance:	1291.800	0.317	0.085	0.115	0.000	0.000	24.760	0.312	0.003	0.307	0.222
Std Dev.:	35.900	0.563	0.292	0.339	0.018	0.016	4.980	0.558	0.059	0.554	0.471

Table 3
Robust regression: ABSDEV and Uncertainty, Big Broker, Recommendation and Changes to Recommendation, All Stocks

This table presents the results of the robust regression, with this sample of forecasts being across all stocks. The regression is run multiple times, with each of the respective market share windows as the dependent variable. The market share window [Days -10 to -6] is the control period market share, and each of the windows included as a dependent variable reflects percentage *changes* in market share from the control period market share to each respective window. *ABSDEV* is the absolute deviation, as a percentage, between each analyst's forecast and the consensus forecast exactly one-month prior to the issue of that forecast. *UNCERTAINTY* is the total uncertainty in and around the forecast. *BigBroker* is a dummy variable, which has value equal to 1 if the forecast is generated by a large broker (as defined in Appendix 3). *ChgonFcstDay* is a dummy variable, which has value equal to 1 if the forecast is accompanied by a change in trade recommendation on the date of release. *BUY* is a dummy variable, which has value equal to 1 if the trade recommendation is a buy, and *SELL* is a dummy variable, which has value equal to 1 if the trade recommendation is a sell.

$$MKTSHARE\_WINDOW = b_1 + b_2 ABSDEV + b_3 UNCERTAINTY + b_4 BigBrkr + b_5 Buy + b_6 Sell + b_7 ChgFcstDay + e_i$$

	Dependent Variables			
	Change from base market share window to the following windows:			
	Panel A	**Panel B**	**Panel C**	**Panel D**
Independent Variable	**-5 to -1**	**+1 to +5**	**+6 to +10**	**0**
Intercept	-0.508	-0.55	-0.497	-0.767
	*-30.439****	*-34.218****	*-28.998****	*-78.421****
ABSDEV	-1.904	-1.448	-1.008	-0.754
	*-5.37****	*-4.937****	*-3.214****	*-4.497****
Uncertainty	0.015	0.049	0.027	0.004
	1.251	*4.127****	*2.193***	*0.629*
BigBroker	0.184	0.176	0.148	0.052
	*11.467****	*11.404****	*8.994****	*5.463****
Buy	0.03	0.041	0.03	-0.007
	*3.236****	*4.673****	*3.203****	*-1.297*
Sell	0.012	0.047	0.032	-0.004
	0.833	*3.443****	*2.21***	*-0.468*
ChgonFcstDay	-0.006	-0.031	-0.057	-0.007
	-0.39	*-2.059***	*-3.425****	*-0.783*
Explanatory Power				
Adjusted R^2	0.0163	0.0159	0.00991	0.00474

* T-statistic significant at the 10% level
** T-statistic significant at the 5% level
*** T-statistic significant at the 1% level

Table 4
Robust regression: ABSDEV and Uncertainty, Big Broker, Recommendation and Changes to Recommendation, Top 10 Stocks

This table presents the results of the robust regression, with this sample of forecasts being across the top 10 stocks by market capitalisation. The regression is run multiple times, with each of the respective market share windows as the dependent variable. The market share window [Days -10 to -6] is the control period market share, and each of the windows included as a dependent variable reflects percentage *changes* in market share from the control period market share to each respective window. *ABSDEV* is the absolute deviation, as a percentage, between each analyst's forecast and the consensus forecast exactly one-month prior to the issue of that forecast. *UNCERTAINTY* is the total uncertainty in and around the forecast. *BigBroker* is a dummy variable, which has value equal to 1 if the forecast is generated by a large broker (as defined in Appendix 3). *ChgonFcstDay* is a dummy variable, which has value equal to 1 if the forecast is accompanied by a change in trade recommendation on the date of release. *BUY* is a dummy variable, which has value equal to 1 if the trade recommendation is a buy, and *SELL* is a dummy variable, which has value equal to 1 if the trade recommendation is a sell.

$$MKTSHARE\_WINDOW = b_1 + b_2 ABSDEV + b_3 UNCERTAINTY + b_4 BigBrkr + b_5 Buy + b_6 Sell + b_7 ChgFcstDay + e_i$$

	Dependent Variables Change from base market share window to the following windows:			
	Panel A	**Panel B**	**Panel C**	**Panel D**
Independent Variable	**-5 to -1**	**+1 to +5**	**+6 to +10**	**0**
Intercept	-0.522	-0.573	-0.505	-0.708
	*-12.256****	*-15.147****	*-11.555****	*-30.07****
ABSDEV	-4.75	-1.437	-1.235	-2.588
	*-2.092***	*-0.735*	*-0.58*	*-2.101***
Uncertainty	0.001	-0.022	0.033	0.029
	0.014	*-0.496*	*0.652*	*0.962*
BigBroker	0.346	0.379	0.336	0.145
	*8.888****	*10.965****	*8.424****	*6.7****
Buy	0.044	0.025	-0.004	-0.054
	*1.669**	*1.129*	*-0.155*	*-3.615****
Sell	0.057	-0.018	0.011	0.011
	1.549	*-0.558*	*0.29*	*0.52*
ChgonFcstDay	-0.038	0.176	-0.038	-0.21
	-0.827	*4.266****	*-0.803*	*-0.785*
Explanatory Power				
Adjusted R^2	0.0578	0.0739	0.0504	0.0387

* T-statistic significant at the 10% level
** T-statistic significant at the 5% level
*** T-statistic significant at the 1% level

Table 5
Robust regression: ABSDEV and Uncertainty, Big Broker, Recommendation and Changes to Recommendation, 11-20 Stocks

This table presents the results of the robust regression, with this sample of forecasts being across the stocks ranked 11 to 20 by market capitalisation. The regression is run multiple times, with each of the respective market share windows as the dependent variable. The market share window [Days -10 to -6] is the control period market share, and each of the windows included as a dependent variable reflects percentage *changes* in market share from the control period market share to each respective window. *ABSDEV* is the absolute deviation, as a percentage, between each analyst's forecast and the consensus forecast exactly one-month prior to the issue of that forecast. *UNCERTAINTY* is the total uncertainty in and around the forecast. *BigBroker* is a dummy variable, which has value equal to 1 if the forecast is generated by a large broker (as defined in Appendix 3). *ChgonFcstDay* is a dummy variable, which has value equal to 1 if the forecast is accompanied by a change in trade recommendation on the date of release. *BUY* is a dummy variable, which has value equal to 1 if the trade recommendation is a buy, and *SELL* is a dummy variable, which has value equal to 1 if the trade recommendation is a sell.

$$MKTSHARE\_WINDOW = b_1 + b_2 ABSDEV + b_3 UNCERTAINTY + b_4 BigBrkr + b_5 Buy + b_6 Sell + b_7 ChgFcstDay + e_i$$

	Dependent Variables **Change from base market share window to the following windows:**			
	Panel A	**Panel B**	**Panel C**	**Panel D**
Independent Variable	**-5 to -1**	**+1 to +5**	**+6 to +10**	**0**
Intercept	-0.484	-0.578	-0.552	-0.809
	*-15.409****	*-20.008****	*-16.429****	*-52.157****
ABSDEV	-0.06	2.1	2.293	1.302
	-0.055	*2.16***	*2.047***	*2.364***
Uncertainty	0.024	0.023	-0.103	0.021
	0.356	*0.371*	*-1.469*	*0.61*
BigBroker	0.223	0.164	0.212	0.059
	*7.278****	*5.752****	*6.575****	*3.92****
Buy	-0.057	0.043	0.034	0.002
	*-2.873****	*2.256***	*1.636*	*0.148*
Sell	-0.137	0.045	-0.073	-0.016
	*-4.419****	*1.511*	*-2.232***	*-0.989*
ChgonFcstDay	0.082	-0.066	-0.054	-0.009
	*2.47***	*-2.114***	*-1.536*	*-0.478*
Explanatory Power				
Adjusted R^2	0.0316	0.0259	0.0271	0.00669

* T -statistic significant at the 10% level
** T -statistic significant at the 5% level
*** T -statistic significant at the 1% level

Table 6
Logistic Regression: Recommendations

In this logistic regression, *BUY* or *SELL* is defined as the dependent variable. *DEV* is the actual percentage difference (positive or negative) between each analyst's forecast and the consensus exactly one-month prior. *BIGBROKER* is a dummy variable, which has value equal to 1 if the forecast is generated by a large broker (see Appendix 3 for the calculation of this variable). Three market share windows (*Chg-5to-1, Chg0-5, Chg6-10)* capture the change in market share from the control period market share[Days -10 to -6] to each of these windows. *UNCERTAINTY* measures the total uncertainty in and around the forecast. *ASX10, ASX20, ASX50 and ASX100* are dummy variables that have value equal to 1 if the stock being forecast falls into their categorization (i.e. a top 10 stock will set *ASX10* equal to 1 only; and a stock ranked 55th by market capitalisation will set *ASX100* equal to 1 only.) Panel A sets out the results for the *BUY* dummy and panel B for the *SELL*.

$$\text{Buy/Sell} = DEV + \text{BigBroker} + \text{Chgnegfivenegone} + \text{Chgzerofive} + \text{Chgsixten}$$
$$+ \text{Uncertainty} + ASX10 + ASX20 + ASX50 + ASX100$$

Panel A: Buy recommendations

Coefficients	Value	Std. Error	t-Value	Pr(>|t|)
Intercept	0.363	0.071	5.112***	0
DEV	3.016	0.21	14.37***	0
BigBroker	-0.048	0.012	-4.126***	0
Chg-5to-1	0.001	0.001	0.604	0.546
Chg0-5	-0.002	0.002	-1.544	0.123
Chg6-10	0.001	0.001	1.002	0.317
Uncertainty	-0.025	0.009	-2.77***	0.006
ASX10	-0.057	0.01	-5.551***	0
ASX20	0.111	0.009	12.419***	0
ASX50	0.012	0.008	1.396	0.163
ASX100	0.126	0.07	1.794*	0.073

Adjusted R² 0.0204
F-statistic 49.5 on 10 and 23823 degrees of freedom

Panel B: Sell recommendation

Coefficients	Value	Std. Error	t-Value	Pr(>|t|)
Intercept	0.066	0.046	1.445	0.148
DEV	-1.305	0.136	-9.589***	0
BigBroker	0.018	0.008	2.378**	0.017
Chgto-5to-1	-0.001	0.001	-1.226	0.22
Chgto0-5	0.001	0.001	0.534	0.593
Chgto6-10	-0.001	0.001	-1.647*	0.1
Uncertainty	-0.025	0.006	-4.298***	0
ASX10	0.029	0.007	4.269***	0
ASX20	0.009	0.006	1.619	0.106
ASX50	-0.034	0.005	-6.292***	0
ASX100	0.053	0.046	1.161	0.246

Adjusted R² 0.0078
F-statistic 18.7 on 10 and 23823 degrees of freedom

*T-statistic significant at the 10% level
** T-statistic significant at the 5% level
*** T-statistic significant at the 1% level

Table 7
Forecast Deviations and Uncertainty:
Mean, Median and Variance

This table presents the results for the calculations of mean, median and variance for the *DEV* and *UNCERTAINTY* variables. *DEV* is the actual percentage difference (positive or negative) between each analyst's forecast and the consensus exactly one-month prior. *UNCERTAINTY* measures the total uncertainty in and around the forecast. *T1, T2 and T3* are the time periods of analysis, *'B'* and *'S'* represent *Buy* and *Sell* recommendations respectively.

Variable	Time Period	Classification	Observations	Mean	Median	Std. Dev.
Panel A: H4A - Deviations from Consensus (DEV)						
DEV.T1.B	1	Buy	6081	0.0984	0.0200	0.0136
DEV.T1.S	1	Sell	1791	-0.3636	-0.2000	0.0125
DEV.T2.B	2	Buy	3833	-0.0197	0.0100	0.0097
DEV.T2.S	2	Sell	717	-0.4386	-0.1900	0.0278
DEV.T3.B	3	Buy	1721	0.0344	0.0100	0.0087
DEV.T3.S	3	Sell	354	-0.2662	-0.1600	0.0153
Panel B: H4B - Uncertainty (UNC)						
UNC.T1.B	1	Buy	6893	0.0781	0.0081	0.2685
UNC.T1.S	1	Sell	1953	0.0834	0.0068	0.3514
UNC.T2.B	2	Buy	4717	0.1892	0.0209	0.4925
UNC.T2.S	2	Sell	758	0.0957	0.0121	0.3000
UNC.T3.B	3	Buy	2379	0.0499	0.0076	0.1157
UNC.T3.S	3	Sell	451	0.0612	0.0077	0.1322

Table 8
Forecast Deviations and Uncertainty:
Tests for Significance in Mean, Median and Variance

This table reports the results for tests of the difference between mean, median and variance for the *DEV* and *UNCERTAINTY* variables associated with buy and sell recommendations between each time period in the study. *DEV* is the actual percentage difference (positive or negative) between each analyst's forecast and the consensus exactly one-month prior. *UNCERTAINTY* measures the total uncertainty in and around the forecast. *T1, T2 and T3* are the time periods of analysis, '*B*' and '*S*' represent *Buy* and *Sell* recommendations respectively.

Panel A: H4A - Deviations from Consensus (DEV)

Recommendation			**Buy**		
	Statistic	**Time Period**	**T1**	**T2**	**T3**
	Mean		12.891***	11.251***	10.925***
	Median	**T1**	183.205***	147.48***	114.884
	Variance		1.176***	1.659***	2.087***
	Mean		8.673***	7.265***	6.365***
Sell	Median	**T2**	35.38	32.034	28.293
	Variance		4.189***	8.175***	10.284***
	Mean		4.879***	4.307***	5.096***
	Median	**T3**	22.666	21.635	17.395
	Variance		1.276***	2.490***	3.133***

Panel B: H4B - Uncertainty

Recommendation			**Buy**		
	Statistic	**Time Period**	**T1**	**T2**	**T3**
	Mean		0.714	8.627***	4.364***
	Median	**T1**	8.945	176.027***	2.871
	Variance		1.713***	1.964***	9.223***
	Mean		1.696*	5.074***	6.150***
Sell	Median	**T2**	34.769	47.45	38.746
	Variance		1.248***	2.695***	6.722***
	Mean		1.330	5.501***	1.844**
	Median	**T3**	0.116	11.004	0.047
	Variance		4.125***	13.877***	1.306***

* Test statistic significant at the 10% level
** Test statistic significant at the 5% level
*** Test statistic significant at the 1% level

Table 9
Forecast Errors (Brokers)

This table presents the significance results for statistical difference test results on the calculations of mean, median and variance for the *FCSTERROR* variable. *FCSTERROR* measures the percentage difference between the analyst's forecast and the actual reported earnings of the company. *T1, T2 and T3* are the time periods of analysis and *'BB'* and *'SB'* represent *Big Broker* and *Small Broker* respectively.

H5: Forecast Errors (FCSTERR)

Time Period	Classification	Observations	Mean	Median	Std. Dev.
1	Big Broker	20030	0.0540	0.0130	0.3173
1	Small Broker	3719	0.0190	0.0030	0.3143
2	Big Broker	17269	0.1558	0.0410	0.3901
2	Small Broker	2260	0.1472	0.0510	0.3730
3	Big Broker	8253	-0.0242	-0.0174	0.2187
3	Small Broker	399	0.0149	-0.0140	0.2804

Table 10
Forecast Errors (Brokers):
Tests for Significance in Mean, Median and Variance

This table presents results tests of difference between mean, median and variance of small broker errors and large broker errors across time as well as within each time period *FCSTERROR* measures the percentage difference between the analyst's forecast and the actual reported earnings of the company. *T1, T2 and T3* are the time periods of analysis and *'BB'* and *'SB'* represent *Big Broker* and *Small Broker* respectively.

H5: Forecast Errors (FCSTERR)

			Big Brokers		
	Statistic	**Time Period**	**T1**	**T2**	**T3**
Small Brokers	Mean	**T1**	6.197***	20.030***	8.671***
	Median		30.527	275.187***	179.009***
	Variance		1.020***	1.541***	2.065***
	Mean	**T2**	12.985***	0.985	27.806***
	Median		108.403	5.636	540.861***
	Variance		1.382***	1.094***	2.910***
	Mean	**T3**	2.446**	7.171***	3.438***
	Median		19.576	34.369	0.561
	Variance		1.280***	1.935***	1.645***

* Test statistic significant at the 10% level
** Test statistic significant at the 5% level
*** Test statistic significant at the 1% level

Table 11
Forecast Errors (Time Periods)

This table reports mean, median and variance for the *FCSTERROR* variable across the three time periods. *FCSTERROR* measures the percentage difference between the analyst's forecast and the actual reported earnings of the company. *T1, T2 and T3* are the time periods of analysis.

Variable	Time Period	Observations	Mean	Median	Std. Dev.
H6: Forecast Errors (FCSTERROR)					
ERR.T1	1	20031	0.045	0.01	0.313
ERR.T2	2	19529	0.155	0.042	0.388
ERR.T3	3	8652	-0.022	-0.017	0.222

Table 12
Forecast Errors (Time Periods):
Tests for Significance in Mean, Median and Variance

This table presents results tests of difference between mean, median and variance of forecast errors across time as well as within each time period. *FCSTERROR* measures the percentage difference between the analyst's forecast and the actual reported earnings of the company. *T1, T2 and T3* are the time periods of analysis.

H6: Forecast Errors (FCSTERROR)

Statistic	Time Period	T1	T2	T3
Mean		-	30.994***	18.142***
Median	**T1**	-	468.744***	906.612***
Variance		-	1.535***	1.991***
Mean		30.994***	-	39.683***
Median	**T2**	468.744***	-	2045.979***
Variance		1.535***	-	3.057***
Mean		18.142***	39.683***	-
Median	**T3**	906.612***	2045.979***	-
Variance		1.991***	3.057***	-

* Test statistic significant at the 10% level
** Test statistic significant at the 5% level
*** Test statistic significant at the 1% level