Asymmetric Effects of Sell-Side Analyst Optimism and Broker Market Share by Clientele

Andrew Grant, Elvis Jarnecic and Mark Su

School of Business, University of Sydney, Sydney NSW, 2006, Australia

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ABSTRACT

Using broker level data we demonstrate that relatively optimistic and relatively pessimistic analyst earnings forecasts *both* generate trade for their brokerage firms. This relationship is found to be asymmetric as the influence of relatively optimistic analyst forecasts on own broker market share is larger than the influence of relatively pessimistic analyst forecasts. Furthermore, upgrades and downgrades in recommendations also generate significantly higher broker market share, suggesting that sell-side institutions are rewarded for providing new information to the market. This study also provides evidence for the first time on how different broker clienteles react to earnings forecast and stock recommendations. Greater trade volume is found to be associated with optimistic earnings forecasts and stock recommendations are stronger for analysts affiliated with retail brokerage firms than those affiliated with institutional brokerage firms. Further the asymmetry between trade generated by relatively optimistic and pessimistic forecasts is greater fore retail investors, consistent with retail investors facing higher short sales constraints.

Corresponding author: Elvis Jarnecic, University of Sydney, Sydney, NSW, 2006, Australia. Phone: +61 9351 8708. Email: elvis.jarnecic@sydney.edu.au

1. Introduction

The analysts' role is integral to the process by which their affiliated brokerage firms generate business. [1] In fact, most brokerage firms reward analysts based on the trading volume their reports generate. As such, analysts must balance their incentive to generate trade against their personal reputation, as well as the reputation of their firm. For example, Cowen, Groysberg, and Healy (2006) find that analysts working at reputable firms make more accurate forecasts than others. Fang and Yasuda (2009) conclude that the analyst's personal reputation is more important. In this paper, we discuss whether or not a sell-side analyst's clientele influences their degree of forecast optimism or pessimism, which helps generate trade. We show that analysts with mainly retail clientele tend to provide more extreme forecasts, on average, than analysts with mainly institutional clientele. These analysts are able to generate additional trading volume through their affiliated brokerage, either due to the inability of their investors to fully account for the bias in the analyst's message, or due to a lack of importance of their reputation.

Theoretical models (Hayes, 1998; Jackson, 2005; Beyer and Guttman, 2010) consistently predict that analysts bias their forecasts in an optimistic fashion, and deviating from the consensus forecast generates trade for the analysts' affiliated brokerage. Furthermore, these models predict that investors will respond in asymmetrically to an analyst's deviation from the consensus; due to transaction costs or short-sales constraints, optimistic forecasts will generate more trading volume than pessimistic forecasts. On the other hand, empirical studies that have examined the relationship between analyst optimism and affiliated brokerage market share have largely

[1] Ramnath, Rock, and Shane (2008) provide a comprehensive review and taxonomy of research relating to analysts in financial markets. Trade generation incentives have been investigated by, among others, Agrawal and Chen (2008), Choi, Clarke, Ferris, and Jayaraman (2009), Cowen, Groysberg, and Healy (2006), Hayes (1998), Irvine (2004), Jackson (2005), and Niehaus and Zhang (2010).

approached the issue in a linear framework (Jackson, 2005; Niehaus and Zhang, 2010).[2]

This paper is motivated by the apparent inconsistency between the common theoretical predictions and the empirical evidence found in past research. This provides an opportunity to corroborate and refine some existing evidence on the nature of the relationship between analyst forecast optimism and broker market share. We also extend the literature by considering the differential impact of analyst optimism for brokerage firms with institutional as opposed to retail clienteles. There is extensive evidence that different factors motivate trade among retail and institutional investors (Barber, Odean and Zhu, 2009). Mikhail, Walther, and Willis (2007) and Malmendier and Shanthikumar (2007) show that institutional investors (as proxied by large traders) adjust their trading response to analysts' stock recommendations appropriately. However, retail investors (small traders) are prone to taking analysts recommendations at face value. Of additional interest to this work, Malmendier and Shanthikumar (2007) show that institutional investors sufficiently discount recommendations from affiliated optimistic analysts, but retail investors do not adjust their trading reaction to analyst affiliation. As explained by Boni and Womack (2003), retail investors are less likely to realise the extent to which analysts' recommendations are already incorporated into market prices, and that institutional investors possess a greater ability to understand the subtlety of sell-side research.

Our results are pertinent to four main issues. First, we present empirical evidence to support the common theoretical predictions (Hayes, 1998; Jackson, 2005; Beyer and Guttman, 2010) that trade demand is asymmetrically responsive to optimistic versus pessimistic analyst earnings forecasts. Second, for we find that outstanding buy-type (buy and strong buy) stock recommendations generate higher broker market share than hold, sell and strong sell

[2] Irvine (2004) remains as the only published paper to our knowledge that examines the asymmetric relationship between broker market share and analyst forecast optimism in an empirical setting.

recommendations.

Thirdly, we find that both recommendation upgrades and downgrades are associated with an increase in affiliated broker market share. Furthermore, the impact of upgrades in recommendations on broker market share appears to be larger than the impact of downgrades. The difference is likely due to short sale restrictions or transactions costs that limit the extent to which investors can trade on the negative information about a stock.

Fourthly, we find evidence that analysts affiliated with retail brokerages have a larger impact on own broker market share through earnings forecasts and stock recommendations than analysts affiliated with institutional brokerages. The larger trading reaction of retail investors in response to information conveyed through analyst forecasts and recommendations is consistent with retail investors relying more heavily on information supplied by their broker. Institutional investors however are likely to consider the information released from numerous brokers and in addition are better able to de-bias information received from sell-side analysts. Furthermore, the asymmetric trading response to positive and negative messages is found to be more pronounced for retail investors than institutional investors. A likely explanation is that retail investors face higher short sales constraints than institutional investors, and therefore have less ability to trade on the negative information. It also offers an explanation the findings of Cowen, Groysberg, and Healy (2006), who find that retail brokerage firm analysts issue more optimistic earnings forecasts and stock recommendations on average than institutional brokerage firm analysts.

This remainder of this paper is structured as follows. Section 2 provides an overview of the Australian sell-side industry and discusses the important institutional considerations relevant to this paper. Section 4 sets out the hypotheses to be tested. Section 5 describes the data used and outlines the database matching procedure. Section 5 details the research design and defines the key variables. Section 6 presents the main results. Descriptions of additional robustness checks are provided in Section 7 and Section 8 concludes.

2. The Australian Sell-Side Industry

The ten largest research brokerages in the Australian market consist of global investment banks that, in addition to brokerage operations, also undertake significant corporate finance business activities in the Australian market. The focus of their brokerage operations lies on providing research for institutional investors, typically with particular emphasis on larger stocks.[3] On the other hand, research brokerages that are ranked outside the top ten in terms of size typically focus on mid market stocks, and focus mainly on retail traders.

Two institutional considerations in particular are relevant to this paper. First, sell-side analysts are employed by brokerage firms that provide analyst research to their clients. Clients typically do not pay directly for the research product, but pay indirectly via brokerage commissions. When clients receive a research report that induces them to trade, they are not obliged to deal through the broker that provided that research.

Many institutional investors construct a panel of brokers at the start of a given period in deciding how brokerage will be allocated over the subsequent period in return for access to analyst research. This arrangement may make it difficult to empirically associate brokerage firm volume with analyst actions for a given stock. Nonetheless, Jackson (2005) observed

[3] Based on the product disclosure statements, some top ten brokerages do not give retail clients access to research reports, and act instead as execution only brokers for retail clients. On the other hand, clients of smaller brokerages are allowed access to research reports after subscribing to the brokerage services provided and often paying a fixed monthly subscription fee.

after discussions with several fund managers in the Australian market that institutional investors often do trade with the broker whose analyst has provided them with an influential recent report on a stock, in order to maintain a good relationship with that analyst.

Second, retail investors are also likely to deal through the broker that provided them the analyst research. They typically have relationships with only one investment advisor, and are less informed than institutional investors. Hence, they are expected to be more reliant on the information provided by analysts employed by their designated brokers than institutional investors.

3. Hypotheses

We develop a number of hypotheses below on how earnings forecast optimism affects market share. In particular, we test whether alternative analyst messages in the form of recommendations subsume the market share-optimism relationship, and the expected differences in the relationship that occur with the brokerage clientele.

3.1 The relationship between earnings forecast optimism and affiliated brokerage market share

Applying Hayes (1998) theoretical predictions and extending Jackson's (2005) empirical findings, analysts that issue relatively optimistic earnings forecasts and analysts that issue relatively pessimistic earnings forecasts are both expected to generate higher affiliated brokerage market share. This leads to the first hypothesis:

> **H1:** Analysts who issue relatively optimistic earnings forecasts and analysts who issue relatively pessimistic analyst earnings forecasts both generate higher brokerage market share than analysts who issue relatively neutral earnings forecasts.

Second, following the theoretical models of Hayes (1998) and Beyer and Guttman (2010), and the empirical study of Irvine (2004), the presence of short sales constraints implies that the investor may not always be able to implement his desired trade after receiving a low message from a pessimistic analyst. This leads to the second hypothesis:

> **H2:** Analysts who issue relatively optimistic analyst forecasts generate higher brokerage market share than analysts who issue relatively pessimistic analyst forecasts.

Together, the two hypotheses portray a non-linear relation between analyst optimism and trading volume.

3.2 Optimistic earnings forecasts combined with optimistic recommendations

Analysts may convey messages to the market through issuing stock recommendations, which can contain incremental information beyond that of earnings forecasts alone (Francis and Soffer, 1997; Loh and Mian, 2006). In the context of stock recommendations, the Jackson (2005) model predicts that analysts have incentives to issue optimistic recommendations because short sales constraints cause trading volume to be more responsive to positive recommendations than negative recommendations (see for example, Agrawal and Chen, 2008; Clarke, Ferris, Lee, and Jayaramaran 2006). We therefore test the following hypothesis:

> **H3:** Brokerage market share generated given an outstanding buy recommendation is greater than brokerage market share given an outstanding sell recommendation.[4]

[4] Since it is widely accepted in the industry that a Hold recommendation is equivalent to a signal for investors to sell (see for example, Chan, Brown and Ho (2006)), we classify Hold, Sell and Strong Sell recommendations as sell recommendations. Affiliated analysts are known to exhibit a reluctance to provide negative

Asquith, Mikhail and Au (2005) find that upgrades and downgrades contain more significant informational content than outstanding recommendations and reiterations. This suggests that analysts may be rewarded for providing new information to the market through changes in recommendations. To provide further insights about the mechanism of rewarding analysts for providing sell-side research services and the impact of new information, we compare market share of volume during months which an analysts upgrades/downgrades his/her recommendation to market share during months in which there is no change in the outstanding recommendations. This tests the extent to which analysts get rewarded for providing new information to the market beyond the existing rewards of ongoing research coverage:

> **H4:** Affiliated brokerage market share given an upgrade or downgrade in analyst recommendation is greater than affiliated brokerage market share when the analyst does not change his/her recommendation.

3.3 Retail versus Institutional Investors

The asymmetric reaction predicted towards optimistic and pessimistic forecasts is expected to be more pronounced for retail investors than for institutional investors, since the cost of short selling is higher for retail investors.[5] Hence, the asymmetry in trading reaction predicted by the Jackson (2005) and Hayes (1998) model is expected to be stronger for brokerage firms that have a larger proportion of retail clients. This leads to the following hypothesis

> **H5:** The difference between trade generated by relatively optimistic analyst forecasts

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recommendations (e.g. Kadan et al, 2009).

[5] D'Avolio (2002) provides evidence on the costs of short-selling stock. Retail investors are more short sales constrained than institutional investors.

and trade generated by relatively pessimistic analyst forecasts is larger for brokerage firms that have a larger proportion of retail clients.

Finally, retail investors are less informed than institutional investors, and therefore are less able to de-bias the information provided by sell-side analysts. They are expected to rely more heavily (and trade more) on information conveyed through analyst earnings forecasts and stock recommendations than institutional investors. This leads to the final hypothesis:

H6: Earnings forecasts and stock recommendations of analysts affiliated with brokerage firms that have a larger proportion of retail clients have a more significant impact on broker market share.

4. Data Description

Data are acquired for the Australian equity market that matches broker identified trades with respective earnings forecasts over the period from January 2002 to December 2007. The datasets are described below.

Transaction data is obtained from a unique Australian Securities Exchange (ASX) proprietary database, consisting of unmasked broker identification codes, ASX stock codes and trade-by-trade buy and sell orders. Daily total volumes are tabulated for each broker for each stock.

The analyst fiscal year 1 (FY1) earnings forecasts data and recommendations are obtained from the Institutional Brokers Estimate System (I/B/E/S) database, for the period 1st January 2002 to 31st December 2007. Individual analyst forecast updates and revisions are obtained from the Detailed Forecast File. The Detailed Recommendations File was used to obtain analyst recommendations for all individual updates and revisions.[6]

In order to conduct empirical analysis, we matched ASX trading volume data with the I/B/E/S datasets. For the Detail Forecasts File, each broker and each analyst was assigned a unique I/B/E/S identification code. These I/B/E/S identification broker codes are first matched to the broker codes (called Broker_ID) in the ASX proprietary database.[7] The top 20 research brokers (out of 23 research brokers in total) in the Australian sell-side industry were able to be identified and successfully matched to the I/B/E/S earnings forecasts database. A similar process was applied when combining the I/B/E/S Recommendations file with the ASX trading volume data.

5. Research Design

Below we describe the measurement of variables and estimation procedures used for our analysis.

5.1 Definition of Key Variables

This section outlines the key variables used to test the hypotheses.

5.1.1 Monthly Broker Market Share

Market share is the monthly volume of shares traded by the brokerage firm normalised by the total shares traded by the complete research broker subset in the stock:

[6] I/B/E/S standardises the recommendations by establishing its own rating system – a rating of 1 reflects a strong buy recommendation, 2 a buy, 3 a hold, 4 a sell, 5 a strong sell and 6 for termination of coverage (see, e.g. Barber, Lehavy, McNichols, and Trueman, 2001).

[7] It is common for one broker to have multiple trading channels with the ASX. This results in multiple Broker_IDs for many brokerage houses that we aggregated for each broker.

$$MKTSHARE_{s,t}^{j} = \frac{BrokerVolume_{s,t}^{j}}{\sum_{j=1}^{J} BrokerVolume_{s,t}^{j}} \tag{2}$$

where $MKTSHARE_{s,t}^{j}$ equals broker *j*'s market share of volume in stock *s* during month *t*.

5.1.2 Measuring Analyst Forecast Optimism

A reliable way to measure relative forecast optimism suggested by Jackson (2005) is to examine optimism at multiple dates throughout the month, and construct a relative average optimism measure over the month.[8] On each day of the 12 months prior to the earnings announcement, we follow Jackson (2005) and take the most recent forecast for each analyst and calculate daily optimism for each analyst using the traditional optimism measure. The optimism measures across all analysts are compared each day for each stock, and each analyst is assigned a percentile rank based on their relative optimism measure.

The daily percentile rank is computed as follows. On each day, the analyst with the x^{th} highest optimism score based on equation 3 receives the rank *x*. For example, the analyst with the highest score in day *i* for stock *s* receives a rank of one, and the analyst with the lowest score (least optimistic) receives the highest rank (e.g. five when there are five live forecasts outstanding that day). When two or more forecasts are tied, we assign all those analysts the midpoint of the value of the ranks they take up (e.g., if the two highest scores are the same, then they both receive a rank of 1.5). The daily optimism rank is then calculated using the following formula:

[8] Jackson (2005) constructed an average measure over one year, whereas Niehaus and Zhang (2010) constructed the measure over one month, using the same methodology. Although their analysis was based on different markets, both obtained similar results and reached similar conclusions.

$$Optimism\_Rank_{s,t}^{j} = \left[1 - \frac{Rank_{s,t}^{j} - 1}{Number\,of\ Analysts_{s,t} - 1}\right] \quad (4)$$

Then, for each month of the 12 months prior to the earnings announcement, we calculate the average monthly optimism rank for each analyst in each stock by averaging the daily optimism ranks:

$$Avg\_Optimism\_Rank = \frac{1}{n}\sum Optimism\_Rank_{s,t}^{j} \quad (5)$$

where n = number of days in the month

Finally, each analyst receives a summary percentile rank based on this monthly average.[9] Since broker market share and brokerage commissions are both flow variables, measured over one month, this flow-based measure of optimism better captures the consistency of an analyst's relative optimism throughout the month.[10] We name this forecast optimism proxy $FY1Optimism_{s,t}^{j}$.[11]

5.1.3 Measuring Analyst Recommendation Optimism

Recommendation optimism is proxied using the dummy variable $BUY_{s,t}^{j}$. $BUY_{s,t}^{j}$ is set to one if the outstanding recommendation of an analyst affiliated with broker j for stock s is a buy or

[9] This ranking methodology is consistent with Jackson (2005) and Niehaus and Zhang (2010) for earnings forecasts optimism, and is similar to Hong and Kubik's (2003) proxy for analyst forecast accuracy.

[10] Using information from all forecasts on a high frequency (daily) allows us to match flow-based measures of trading volume to a flow-based optimism measure. Since optimism is an average deviation over time, this approach is quite analogous to the calculation of integrated volatility measures as described by Andersen et al. (2003).

[11] This paper focuses on fiscal year 1 analyst earnings forecasts (FY1 forecasts).

strong buy recommendation, and zero otherwise. Hold recommendations are classified as a 'sell type' recommendation in this paper (e.g. Chan, Brown, and Ho, 2006).

Furthermore, to examine the impact of upgrades/downgrades in analyst recommendations, we create two dummy variables. $UPGRADE_{s,t}^{j}$ ($DOWNGRADE_{s,t}^{j}$) equals one if an analyst affiliated with broker j upgraded (downgraded) stock s during month t and zero otherwise.

5.2 Other Control Variables

To isolate the effects of optimism in earnings forecasts and stock recommendations, we need to control for other variables that are likely to be correlated with brokerage market share. These are broker size, the age of the earnings forecast, the dispersion in the earnings forecasts, and the number of analysts covering the stock. Each of these are discussed below.

5.2.1 Broker Size

Larger brokerage firms are likely to have higher market share due to higher resource levels such as sales staff, research budgets, and distribution infrastructure.[12] Previous research uses the number of analysts employed by the brokerage firm as a proxy for broker size (e.g., Irvine, 2001; Hong and Kubik, 2003). However, Jackson (2005) finds that the number of analysts employed by the brokerage firm is a somewhat less effective proxy for broker size than the market share of the broker across the market. We follow Jackson (2005), and use market-wide broker market share across all stocks in a given month as the proxy for broker size.

5.2.2 Forecast Age

Forecasts issued more recently are expected to have greater impacts on broker market share (Brown, 1993; Jackson, 2005). We calculate a relative forecast age measure that ranks analysts daily based on the age of their most recent outstanding estimates. Analysts with the

[12] See Jackson (2005).

oldest estimates on average receive a percentile ranking of 1, and those with the most recent receive a rank of 0. We take the average of this measure over the month, and rank analysts based on this summary measure (similar to the ranking method used to proxy for analyst forecast optimism).

5.2.3 Dispersion in Analyst Earnings Forecasts

As the uncertainty surrounding the analyst earnings forecasts increases, the extent to which investors trade on the information conveyed by analyst forecasts decreases (see for example, Admati and Pfleiderer (1990), Allen (1990), and Brennan and Chordia (1993)). Therefore, to control for the impact of the uncertainties surrounding the earnings forecasts, we include the following dispersion measure as a control variable in the regression specification[13]:

$$Dispersion^{j}_{s,t} = \frac{STDEV_{s,t}}{\left|C_{s,t}\right|} \qquad (6)$$

where $STDEV_{s,t}$ is the standard deviation of forecasts across all outstanding analyst earnings forecasts for stock *s* in period *t* and $\left|C_{s,t}\right|$ is the absolute value of the consensus forecast for all outstanding analyst forecasts for stock *s*, again in period *t*.

5.2.4 Amount of Analyst Coverage

Analysts who cover firms with thin coverage are more likely to be in the extremes of the analyst optimism ranks used in this paper.[14] Hence, if analysts that follow few or thinly covered firms during our sample period are more or less likely to increase/decrease affiliated brokerage market share for reasons other than the relative optimism in their earnings forecasts, then we might find a spurious relationship between affiliated brokerage market

[13] This is consistent with the dispersion measure used by Diether, Malloy, and Scherbina (2002).

[14] For example, if three analysts have different outstanding forecasts in a given day the standardised ranks would be 0, 0.5 and 1; compared to 0, 0.2, 0.4, 0.6, 0.8, and 1 if there are 6 analysts (Hong and Kubik (2003)).

share and analyst optimism/pessimism.[15] This is highly possible, as the amount of analyst coverage likely proxies for the competition among analysts and brokerages for market share in a particular stock, and is expected to be negatively related to affiliated brokerage market share (Niehaus and Zhang, 2010). To control for the possible impact of thinly covered firms, we include the number of outstanding earnings forecasts per month for each stock as a control variable in the regression specification.

5.3 Estimation Procedures

The earnings forecast optimism rank (the *FY1Optimism* variable) ranges between 0 and 1 by construction. To conduct our analysis in a non-linear framework, we first partition these percentile ranks into quintiles. The lowest quintile (analysts with percentile ranks between 0 and 0.2) represents relatively pessimistic analysts that are expected to induce significant selling pressure; while the highest quintile (analysts with percentile ranks between 0.8 and 1) represents relatively optimistic analysts that are expected to induce significant buying pressure. The middle three quintiles (analyst with percentile ranks between 0.2 and 0.8) are relatively neutral analysts who are not expected to have a significant impact either buying or selling pressure. We then examine a variety of pooled regression models with the following general forms.

5.3.1 Examining Differences in Means Between Each Optimism Quintile:

We run the initial model that examines the differences in the mean monthly market share within each quintile of optimism rank:

[15] This is similar in rationale to Hong and Kubik (2003). Hong and Kubik (2003) focused on percentile rankings of analyst accuracy rather than analyst optimism. However, the standardised ranking measure is identical.

$$MKTSHARE^{j}_{s,t} = \alpha_0 + \beta_1 Q1_{Pessimistic} + \beta_2 Q2 + \beta_3 Q4 + \beta_4 Q5_{Optimistic} + \beta_5 BUY^{j}_{s,t} + \beta_6 UPGRADE^{j}_{s,t} + \beta_7 DOWNGRADE^{j}_{s,t} + \beta_8 BROKERSIZE_t + \beta_9 FORECASTAGE^{j}_{s,t} + \beta_{10} DISPERSION_{s,t} + \beta_{11} ANALYST\_COV_{s,t} + e^{j}_{s,t} \quad (7)$$

The dependent variable is the market share of broker *j* for stock *s* in month *t*. Q*n* represent a dummy variable that equals 1 if the analyst has a percentile optimism rank in the n^{th} quintile, and 0 otherwise (where *Q3* is omitted from the model as the quintile of reference); $BUY^{j}_{s,t}$ equals one if broker *j* has an affiliated analyst that has a buy type recommendation outstanding, and zero otherwise; $UPGRADE^{j}_{s,t}$ ($DOWNGRADE^{j}_{s,t}$) equals one if an analyst affiliated with broker *j* upgraded (downgraded) stock *s* during month *t* and zero otherwise. The control variable $BROKERSIZE_t$ is the total market share of the broker in month *t* across all stocks. $FORECASTAGE^{j}_{s,t}$ is a relative rank between 0 and 1, such that analysts affiliated with broker *j* with the oldest estimates on average in month *t* for stock *s* has a percentile rank of 1, and those with the most recent a rank of 0. $DISPERSION_{s,t}$ is the average of daily standard deviation of all outstanding forecasts scaled by the absolute value of the outstanding consensus for stock *s* over month *t*. $ANALYST\_COV_{s,t}$ is the number of analysts with outstanding forecasts for stock *s* in month *t*.

5.3.2 Multiplicative Interaction Effects (Estimating the Differences in Slope)

Distinct to the previous model, this model tests the slope shifts in $FY1Optimism^{j}_{s,t}$ between the relatively optimistic, relatively pessimistic and neutral values:

$$
\begin{aligned}
& MKTSHARE^{j}_{s,t} = \alpha_0 + \beta_1 D_{Pessimistic} + \beta_2 D_{Optimistic} + \beta_3 FY1OPTIMISM^{j}_{s,t} \\
& + \beta_4 FY1OPTIMISM^{j}_{s,t} * D_{Pessimistic} + \beta_5 FY1OPTIMISM^{j}_{s,t} * D_{Optimistic} \\
& + \beta_6 BUY^{j}_{s,t} + \beta_7 UPGRADE^{j}_{s,t} + \beta_8 DOWNGRADE^{j}_{s,t} + \beta_9 BROKERSIZEE_{t} \\
& + \beta_{10} FORECASTAGE^{j}_{s,t} + \beta_{11} DISPERSION_{s,t} + \beta_{12} ANALYSTCOVERAGE_{s,t} + e^{j}_{s,t}
\end{aligned} \quad (8)
$$

The dependent variable is the market share of broker *j* for stock *s* in month *t*. $FY1OPTIMISM^{j}_{s,t}$ is the proxy for analyst earnings forecast optimism, and ranges between 0 (least optimistic) and 1 (most optimistic). $D_{Pessimistic}$ equals to one if the value of $FY1OPTIMISM^{j}_{s,t}$ is in the lowest quintile (between 0 and 0.2), and zero otherwise; $D_{Optimistic}$ equals one if the value of $FY1OPTIMISM^{j}_{s,t}$ is in the highest quintile (between 0.8 and 1), and zero otherwise. $FY1OPTIMISM^{j}_{s,t} * D_{Pessimistic}$ represents the differences in slopes between forecasts ranked in the lowest quintile relative to the forecasts ranked in the middle three quintiles; and $FY1OPTIMISM^{j}_{s,t} * D_{Optimistic}$ represents the differences in slopes between forecasts ranked in the highest quintile relative to forecasts ranked in the middle three quintiles.

5.3.3 Clustered Standard Errors

We calculate *t*-statistics first using White (1980) robust standard errors to control for heteroskedasticity, and second using the Williams (2000) robust variance estimate to adjust for within-cluster correlation in residuals induced by the same analyst covering several stocks in a given year. We also calculate *t*-statistics using broker–month clusters rather than analyst–month clusters to allow for common firm-wide shocks to brokerage market shares. For brevity, only analyst-month and broker-month cluster adjusted *t*-statistics are reported in the results of this paper.[16]

[16] The results for the White (1980) robust standard errors are more significant in most cases than the clustered t-

5.4 *Classification of Retail and Institutional Brokerages*

To test whether trade generation incentives are stronger in mixed retail and institutional brokerages, we classified brokerage firms by the types of clients they served (retail or institutional). The first step in our classification was to use the description of firms' business and client mix in Bloomberg Terminal to access whether brokerage firms focused solely on institutional investors, retail clients, or some combination of both. If there was insufficient detail, we searched firms' websites of information on the type of clients served. Finally, where possible, we examined the Product Disclosure Statements of the brokerages to see whether retail clients get access to the same research reports as institutional clients.

Almost all brokerage houses in our sample service institutional clients. The full-service investment banks focus predominantly on institutional clients.[17] On the other hand, all other brokerage firms offer a mix of services to both institutional and retail clients. Hence, similar to Cowen, Groysberg, and Healy (2006), we classify the ten full-service investment banks in our sample as 'institutional brokers' who focus primarily on institutional trading, and all other brokers as 'retail brokers' who focus on a mix of institutional and retail trading.

6. RESULTS

6.1 *Descriptive Statistics*

Table 1 presents summary statistics for the 20 research brokers in the sample, showing the overall monthly average market share of the 20 brokers over the full sample period and the

statistics reported. These results are available upon request.

[17] For many banks, the retail clients do not gain access to the same research reports provided to institutional clients. Hence, while it is true that investment banks do have some retail clients, they do not trade based on the information provided by the research analysts affiliated with the bank.

average number of stocks transacted on per month over the full sample period. The table reveals that market share within the research brokers in our sample is strongly concentrated in the top 10 brokers. The top 10 brokers constitute approximately 88% of the market share in our sample, while the rest account for only approximately 12% of the market share.

The top 10 brokers in terms of average monthly market share in Table 1 are full-service investment banks with corporate finance operations in the Australian market. They offer both underwriting and brokerage services, and prior to 2003, used revenues from both services to fund research. It is common for their analysts to be remunerated on the basis of various performance criteria other than trading commissions, including feedback on research quality from institutional clients, traders and money managers. They are classified 'large brokers' who focus predominantly on institutional trading.

The brokers ranked outside the top 10 in Table 1 are brokerage firms whose primary source of income is commissions from client trade execution.[18] Brokerage firms usually reward their research analysts using a single measure of performance: trading volume in the stocks that they cover. They are classified as the 'small brokers' who has a mix of institutional and retail businesses, and focuses more on mid market stocks.

[18] A few of these brokers have relatively small corporate finance operations.

Table 1: Summary Statistics of Broker Market Share

This table presents summary statistics for the 20 research brokers in the sample. Broker names are excluded due to confidentiality constraints. The second column contains the number of months of market share data available for the broker in our sample. The third column shows the average number of different stocks in which a broker transacts per month. The fourth is the average monthly market share across the entire market in the sample.

Broker #	Months in Market Share Sample	Average Number of Different Stocks Transacted Per Month	Average Monthly Market Share (%)
Panel A: Institutional Broker Market Share			
I1	72	266.60	12.8
I2	72	329.83	12.8
I3	72	295.83	12.2
I4	72	228.86	9.0
I5	72	227.26	8.3
I6	72	197.08	8.2
I7	72	195.56	7.5
I8	72	180.75	6.7
I9	72	329.86	5.7
I10	72	211.59	5.0
Mean	72	246.32	8.8
Panel B: Retail Broker Market Share			
R1	72	260.87	2.2
R2	72	165.83	1.9
R3	72	161.08	1.6
R4	72	80.99	1.5
R5	40	168.43	1.5
R6	72	83.75	1.4
R7	72	150.27	1.1
R8	34	22.18	0.8
R9	72	62.68	0.6
R10	72	17.54	0.1
Mean	65	117.36	1.3

Table 2 presents summary statistics for the analysts' earnings forecast optimism measure. By the construction, the average monthly optimism measure has a mean close to 0.5 and a median close to 0.5. Higher overall scores correspond to higher analyst forecast optimism. The standard deviation is 0.0339. The forecast age measure is constructed in a similar manner to the relative forecast optimism measure, and has a mean and median close to 0.5, and a standard deviation of 0.3002. The mean dispersion, measured as the monthly average of daily scaled standard deviation of all outstanding forecasts is 0.1024.

Table 2: Summary Statistics for Analyst Forecasts

Table 2 provides summary statistics for the distribution of the analyst forecasts related independent variables between January 2002 and February 2007 for all, institutional and retail brokers. Column 1 contains the distribution of the FY1Optimism variable. Column 2 presents summary statistics for the forecast recency control variable; column 3 presents the summary statistics for the analyst coverage control variable; and column 4 presents summary statistics for the dispersion variable.

	FY1Optimism	Forecast Age	Analysts_Cov	Dispersion
Panel A: All Broker Analyst Forecasts				
1st Q	0.201	0.251	6	0.0035
Mean	0.498	0.500	8.36	0.1024
Median	0.500	0.510	9	0.0628
3rd Q	0.803	0.746	11	0.1220
Std Dev	0.339	0.300	3.316	2.9707
Panel B: Institutional Broker Analyst Forecasts				
1st Q	0.204	0.264	6	0.035
Mean	0.496	0.501	8.38	0.109
Median	0.500	0.492	9	0.062
3rd Q	0.782	0.743	11	0.119
Std Dev	0.334	0.295	3.220	2.964
Panel C: Retail Broker Analyst Forecasts				
1st Q	0.167	0.207	4	0.038
Mean	0.53	0.490	7.74	0.124
Median	0.550	0.470	7	0.073
3rd Q	0.902	0.798	11	0.155
Std Dev	0.373	0.337	3.971	3.260

Table 3 presents summary statistics for the 78,975 analyst recommendations in the sample. It reveals that buy and hold recommendations outnumber sell recommendations. Buy type recommendations comprise of 39.63% of the sample, while hold recommendations and sell type recommendations comprise of 47.85% and 12.52% respectively. In our sample retail broker analysts were likely to make more extreme observations. Retail broker analysts strong buy (buy) recommendations account for 38.39 (13.88) percent of their recommendations as compared to 12.64 (24.96) for institutional analysts. Analogously with respect to sell recommendations, retail broker analyst strong sell (sell) recommendations represent 6.07 (2.19) percent of their recommendations compared to 4.91 (8.29) for institutional analysts. Further, 39.48 percent of retail broker analyst recommendations are hold recommendations compared to 49.20 percent for institutional broker analysts which is again consistent with retail broker analysts recommendations being more extreme.

Table 3: Summary Statistics for Analyst Recommendations

Table 3 provides summary statistics for the distribution of the stock recommendations.

Recommendations	2002	2003	2004	2005	2006	2007	Total Per Category	% of Total
Panel A: All Broker Analyst Forecasts								
Strong Buy	1,529	1,519	1,800	1,717	2,684	3,546	12,795	16.20
Buy	2,173	3,712	3,150	2,901	2,817	3,749	18,502	23.43
Hold	3,195	7,696	7,149	5,925	6,522	7,304	37,791	47.85
Sell	519	1,156	732	988	1,286	1,201	5,882	7.45
Strong Sell	347	868	763	719	588	720	4,005	5.07
Total	7,763	14,951	13,594	12,250	13,897	16,520	78,975	100.00
Panel B: Institutional Broker Analyst Forecasts								
Strong Buy	1,307	1,090	1,312	1,157	1,795	1,936	8,597	12.64
Buy	2,065	3,489	2,985	2,786	2,471	3,188	16,984	24.96
Hold	2,961	7,233	6,703	5,318	5,631	5,628	33,474	49.20
Sell	488	1,099	732	968	1,230	1,126	5,643	8.29
Strong Sell	331	808	675	611	425	491	3,341	4.91
	7,152	13,719	12,407	10,840	11,552	12,369	68,039	100.00
Panel C: Retail Broker Analyst Forecasts								
Strong Buy	222	429	488	560	889	1,610	4,198	38.39
Buy	108	223	165	115	346	561	1,518	13.88
Hold	234	463	446	607	891	1,676	4,317	39.48
Sell	31	57	0	20	56	75	239	2.19
Strong Sell	16	60	88	108	163	229	664	6.07
	611	1,232	1,187	1,410	2,345	4,151	10,936	100.00

6.2 FY1 Analyst Forecasts and Brokerage Market Share According to Broker Clientele

6.2.1 Differences in Means Regression Analysis

Jackson (2005) and Hayes (2005) predict that analysts who issue relatively optimistic and relatively pessimistic earnings forecasts both generate higher own broker market share; and that analysts who issue relatively optimistic earnings forecasts generate higher own broker market share than analysts who issue relatively pessimistic earnings forecasts.

Consistent with the first prediction, Panel A of Table 4 demonstrates that, in the context of Fiscal Year 1 (FY1) earnings forecasts, the most optimistic and the most pessimistic analysts *both* generate higher brokerage market share. Specifically, Panel A shows that the most optimistic analysts (analysts with percentile optimism ranks in the top quintile) generate 0.45% higher market share on average than analysts ranked in the middle (3^{rd}) quintile; and the most pessimistic analysts (analysts with percentile optimism ranks in the lowest quintile) generate 0.16% higher broker market share on average relative to analysts ranked in the middle (3^{rd}) quintile. Furthermore, analysts with ranks in the 2^{nd}, 3^{rd} and 4^{th} forecast optimism quintiles generate similar levels of own broker market share on average. Hence, the results in of the coefficients on Q2 and Q4 suggest that the average brokerage market shares generated by analysts ranked the middle three forecast quintiles are lower than the average brokerage market shares generated by analysts ranked in the highest and lowest forecast optimism quintiles.

Table 4 also demonstrates the asymmetric trading reaction to relatively optimistic and relatively pessimistic earnings forecasts predicted by Hypothesis 2. The average affiliated brokerage market share when analysts are relatively optimistic (ranked in the highest forecast optimism quintile) is higher than the average affiliated brokerage market share when analysts are relatively pessimistic (ranked in the lowest forecast optimism quintile). Furthermore, relatively neutral analysts ranked in the middle three quintiles generate the lowest affiliated brokerage market share on average. Hence, the results from both dummy variable specifications in Panel A of Table 4 provide evidence in support of Hypothesis 1 and Hypothesis 2.

The coefficient on broker size in Table 4 is positive and highly significant, indicating that larger brokers have higher market shares on average, as we might expect. Additionally, the number of analysts covering the stock is inversely related to broker market share, consistent with the interpretation that the brokers face increased competition from other brokers as the number of analysts covering a stock increases, which puts downward pressure on the market share of the brokers covering the stock (Niehaus and Zhang, 2009).

The regression also considers the impact of analyst recommendations on affiliated brokerage market share.[19] Prior studies observe that analyst recommendations contain distinct information to analyst earnings forecasts (see for example, Francis and Soffer, 1997; Chan, Brown, and Ho, 2006). Hence, it is expected that analyst earnings forecasts and stock recommendations both possess significant influence on affiliated brokerage market share.[20] The 0.0175 coefficient on *BUY* is significant at the 1% level, indicating that an outstanding positive (buy) recommendation generates approximately 1.75% higher monthly brokerage market share than negative (sell) recommendations on average for the forecast stock.

[19] The analysis was also performed without considering the impact of analyst recommendations on affiliated brokerage market share and produced qualitatively similar results.

[20] Because we compare the different impacts of recommendation and earnings forecast optimism on affiliated brokers' trading volume, we include only months where an outstanding recommendation and a valid analyst earnings forecast is available. This reduces the sample size to 78,865 broker-stock pairs.

Moreover, consistent with Jackson (2005) and Niehaus and Zhang (2009), the effect of optimistic recommendations on brokerage market share appears to be larger and more significant than the effect of optimistic analyst earnings forecasts (the coefficient on *BUY* is larger and more significant). This is likely because analyst recommendations reflect a summary of all the factors that affect the value of a stock relative to its price. An alternative explanation consistent with Jackson (2005) is that analysts may prefer transmitting optimism via recommendations over earnings forecasts because recommendations are not horizon specific, and is therefore the least costly to the analysts' reputation.

In Panels B and C, the regression models specified are run across two sub samples – the 'institutional brokers' and the 'retail brokers' based on the classification procedure described in section 5.4. Panels B and C indicate that analysts employed by both institutional and retail brokerage firms appear to be able to significantly increase their own broker market share by issuing relatively optimistic or relatively pessimistic earnings forecasts. Interestingly, the coefficients on Q1 and Q5 are larger in magnitude in Panel C (retail brokers) than in Panel B (institutional brokers). Consistent with Hypothesis 6, this demonstrates that relatively optimistic and relatively pessimistic forecasts issued by analysts affiliated with retail brokerage firms seem to have a higher impact on own broker market share than forecasts issued by analysts affiliated with institutional brokerage firms.

Furthermore, the relative sizes of the coefficients of Q1 and Q5 in Panels B and C also reveal an important observation. The asymmetric investor trading reaction between relatively optimistic and pessimistic forecasts appears to be more pronounced for retail brokerage firms. Specifically, in Panel B, the coefficient on Q5 is 1.5 times larger than the coefficient on Q1, indicating that for institutional brokers, relatively optimistic analysts ranked in the highest forecast optimism quintile generate approximately 1.5 times more market share on average than relatively pessimistic analysts ranked in the lowest forecast optimism quintile. On the other hand, for the retail brokers sub sample in Panel C, the coefficient on Q5 is approximately 2.5 times bigger than the coefficient on Q1. These results provide some evidence to support the role short sales constraints in the asymmetric investor reaction to positive and negative news. As retail investors face higher short sales constraints than institutional investors, the asymmetry between trade generated by relatively optimistic forecasts and trade generated by relatively pessimistic forecast is larger for retail brokers.

Table 4: Differences in Means Models and Analyst Recommendations

The table presents the parameter estimates of the following model:

$$MKTSHARE^{j}_{s,t} = \alpha_0 + \beta_1 Q1 + \beta_2 Q2 + \beta_3 Q4 + \beta_4 Q5 + \beta_5 BUY^{j}_{s,t} + \beta_6 BROKRESIZE_{s,t} + \beta_7 DISPERSION_{s,t} + \beta_8 FORECASTAGE^{j}_{s,t} + \beta_9 ANALYST\_COV_{s,t} + \varepsilon^{j}_{s,t}$$

Panel A, B and C present the parameter estimates for all, institutional and retail brokers respectively. Q1 is a dummy variable that equals 1 if the analyst has a forecast optimism rank in the lowest quintile, and 0 otherwise. Q5 is a dummy variable that equals 1 if the analyst has a forecast optimism rank in the highest quintile, and 0 otherwise. Q2 – Q4 are dummy variables from quintile 2 to quintile 4. *Buy* equals 1 if the outstanding recommendation for the month is a 'buy type' (buy or strong buy) recommendation and 0 otherwise. *Broker Size* is the total market share of the broker in month *t* across all stocks. *Dispersion* is the monthly average standard deviation of all outstanding analyst forecasts scaled by the absolute value of the consensus. *Analyst_Cov* is the number of analysts with valid forecasts in the month for the stock. *ForecastAge* is the percentile ranking of the duration of the analysts' forecast relative to other analysts (1 = least recent, 0 = most recent). Only stocks where the broker has an analyst covering the stock are included (and where valid forecasts and recommendation for that analyst exists). The dependent variable is the market share of the broker in that stock for that month. Broker/analyst-stock-months is the unit of analysis; cluster-adjusted *t*-statistics (both analyst-month and broker-month clusters) are presented.

Dependent Variable: Broker Market Share (t)

	PANEL A (All Brokers)			PANEL B (Institutional Brokers)			PANEL C (Retail Brokers)		
	Coefficient	Cluster *t*-Statistics (Broker-Month)	Cluster *t*-Statistics (Analyst-Month)	Coefficient	Cluster *t*-Statistic (Broker-Month)	Cluster *t*-Statistic (Analyst-Month)	Coefficient	Cluster *t*-Statistic (Broker-Month)	Cluster *t*-Statistic (Analyst-Month)
Intercept	0.0559	21.62***	32.01***	0.0288	12.65***	18.81***	0.1234	17.77***	24.93***
Q5 (Optimistic)	0.0045	5.32***	5.53***	0.0021	3.11***	3.13***	0.0135	7.04***	6.82***
Q4	0.0010	1.29	1.32						
Q2	-0.0007	-0.93	-0.99						
Q1 (Pessimistic)	0.0016	1.97**	2.06**	0.0014	1.85*	1.91*	0.0053	2.79***	2.43***
Buy	0.0175	22.78***	29.92***	0.0160	20.54***	26.80***	0.0195	9.53***	11.04***
Broker Size	0.8490	53.78***	85.30***	0.9883	58.90***	92.00***	0.2181	0.96	1.29
Dispersion	-0.0001	-0.80	-0.78	-0.0000	-0.30	-0.30	-0.0003	-0.68	-0.68
Forecast Age	-0.0016	-1.40	-1.57	-0.0032	-2.66***	-3.03***	0.0020	0.67	0.65
Analyst_Cov	-0.0045	-23.29***	-37.30***	-0.0027	-14.66***	-23.76***	-0.0114	-24.15***	-32.30***
Observations	78,862			68,036			10,826		
Adjusted-R^2	21.16%			19.23%			20.99%		

***, ** and * represent significance at the 1%, 5% and 10% level, respectively

6.2.2 Testing the differences in slope – Interaction Variable Regression Analysis

The dummy variables specification presented in Table 4 examine the differences in the average affiliated brokerage market share in each forecast optimism quintile. However, it does not specifically address the question of whether the coefficient of analyst forecast optimism (*FY1Optimism*) varies between the relatively optimistic, pessimistic and neutral quintiles. To examine this issue, we conduct further analysis based on the interaction variables model given in equation 9. This model specification examines the statistical significance of the slope shift in *FY1Optimism* at the relatively optimistic, relatively pessimistic and relatively neutral levels. Forecasts with a percentile rank in the top and bottom 20% as the cut-off point for relatively optimistic and pessimistic forecasts.[21]

Table 5a reports the main regression results. Of most interest are the coefficient estimates for *FY1Optimism* and the interaction variables, $D_{Optimistic}$*FY1Optimism* and $D_{Pessimistic}$,*FY1Optimism*. The slope for relatively optimistic forecasts is calculated as the sum of the coefficient estimates on *FY1Optimism* and $D_{Optimistic}$*FY1Optimism*; and the slope for relatively pessimistic forecast is calculated as the sum of the coefficient estimates on *FY1Optimism* and $D_{Pessimistic}$,*FY1Optimism*. The slope for relatively neutral forecasts is simply the coefficient estimate on *FY1Optimism*.

For ease of interpretation, Table 5b presents the relevant slope coefficients for the relatively optimistic, pessimistic and neutral analysts based on the parameter estimates in Table 5a. In

[21] To ensure that the results are robust, we test the relationship using forecasts with percentile ranks in the top and bottom 30% as the cut-off point for relatively optimistic and pessimistic forecasts (instead of the top and bottom 20% in Table 5a). The parameter estimates of this regression produces results consistent with Table 5a, indicating that the asymmetric relationship between broker market share generated by relatively optimistic forecasts and relatively pessimistic forecasts is fairly robust to variations in the partitioning method of the forecast optimism ranks.

panel A of Table 5b, the relevant slope coefficient for relatively optimistic analyst forecasts (ranked in the highest quintile) is positive and the relevant slope coefficient for relatively pessimistic analyst forecasts (ranked in the lowest quintile) is negative, indicating that optimistic and pessimistic forecasts *both* generate higher brokerage market share. This is consistent with Hypothesis 1.

Furthermore, consistent with Hypothesis 2, the absolute size of the slope coefficient for relatively optimistic forecasts is larger than the absolute size of the coefficient on for relatively pessimistic analysts for Panel A of Table 5b, demonstrating that optimistic analyst forecasts have a stronger impact on brokerage market share than pessimistic analyst forecasts on average.

Although the coefficient on *FY1Optimism* in Panel A of Table 5a is positive and significant, it is small in absolute magnitude compared to the coefficients on both interaction terms for optimistic and pessimistic forecasts. This indicates that analysts who are relatively 'neutral' (analysts with percentile ranks between the second and the fourth quintile) have less impact on average on affiliated brokerage market share than relatively optimistic and relatively pessimistic analysts.

Including the outstanding positive (buy) stock recommendations in the regression as an additional dummy variable reduces a result that pertains to the impact of positive recommendations. Specifically, the coefficient for *BUY* is also positive and significant at the 1% level. Consistent with hypothesis 3, this indicates that analysts with outstanding positive (buy) recommendations generate 1.74% more market share per month on average than analysts with negative (sell) recommendations.[22]

[22] The model is also estimated without controlling for the effects of positive (buy) recommendations, the

In summary, the results in the differences in means regression models in Table 4 and the results in the interaction variables model in Table 5a and Table 5b are consistent with Hypothesis 1 and Hypothesis 2. Together, they provide support for the notions that a) relatively optimistic and relatively pessimistic analyst forecasts both generate higher broker market share, and b) broker market share generated by relatively optimistic forecasts is higher than broker market share generated by relatively pessimistic forecasts. Further, it is documented that positive (buy or strong buy) recommendations generate higher brokerage market share on average, relative to hold, sell and strong sell recommendations, consistent with Hypothesis 3.

To gain further insights into the nature of the relationship between affiliated brokerage market share and analyst optimism as it varies for institutional and retail brokers and clients, we present the results for each broker sub sample in Panels B and C of Table 5a. For ease of interpretation, Panels B and C of Table 5b present the relevant slope coefficients for relatively optimistic, pessimistic and neutral forecasts using the parameter estimates of the interactive variables regression. The difference (in percentage terms) between the slope coefficients for relatively optimistic and pessimistic forecasts appears to be slightly larger in Panel C than in Panel B. Hence, the asymmetry between brokerage market share generated by relatively optimistic forecasts and relatively pessimistic forecasts appears to be somewhat stronger for retail brokerage firms. In addition, for analyst recommendations, Panels B and C of Table 5a demonstrate that analysts affiliated with retail brokerages increase own broker market share by 1.97% on average per month by issuing positive (buy)

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asymmetric relationship between relatively optimistic, pessimistic and neutral forecasts portrayed by the interactive variables regression in Table 5a remaining highly significant.

recommendations (compared to only 1.59% for analysts affiliated with institutional brokers). Thus, it appears that the differential impact between positive and negative recommendations on broker market share is larger for the retail broker sub sample. This result provides some justification to the role of short sales constraints as a driver of the asymmetric trading reaction predicted by the Jackson (2005) and Hayes (1998) model.

Another interesting observation relating to broker category from the results presented in Table 4, Table 5a and Table 5b is that the clients of retail brokers are more reactive on average to both relatively optimistic/pessimistic earnings forecasts and positive (buy) recommendations. The results suggest that retail investors are likely to place more reliance on the research provided by analysts than institutional investors when making trading decisions. This is consistent with Hypothesis 6.

The parameter estimates of the control variables reveal some interesting results. The coefficient on forecast age is negative and significant at the 1% level for institutional brokers, but is insignificant for retail brokers. This is likely explained by the fact that the clientele of institutional brokers (that is, institutional investors) are able to digest and interpret the relevance and how current the information conveyed by analysts is, whereas retail investors are less adept at identifying and utilising new information. The broker size control variable is also significant for institutional brokers, and insignificant for retail brokers (which tend to have smaller market share on average). This is consistent with the descriptive statistics shown in Table 1, which indicates that market share for brokerages ranked outside the top 10 is relatively evenly distributed.

Table 5a: Interaction Variables Model and Analyst Recommendations

The following table represents the parameter estimates of the following model:

$$MKTSHARE^{j}_{s,t} = \alpha_0 + \beta_1 D_{Optimistic} + \beta_2 D_{Pessimistic} + \beta_3 FY1OPTIMISM^{j}_{s,t} + \beta_4 D_{Optimistic}{*}\ FY1OPTIMISM^{j}_{s,t} + \beta_5 D_{Pessimistic}{*}\ FY1OPTIMISM^{j}_{s,t} + \beta_6\ BUY^{j}_{s,t} + \beta_7 BROKERSIZE_{s,t} + \beta_8 DISPERSION_{s,t} + \beta_9 FORECASTAGE^{j}_{s,t} + \beta_{10} ANALYST\_COV_{s,t} + \varepsilon^{j}_{s,}$$

FY1Optimism is a percentile ranking of the analyst's FY1 EPS forecast relative to other analysts covering the stock (1 = most optimistic, 0 = least optimistic) averaged over the month. $D_{Optimistic}$ equals 1 if the value of *FY1Optimism* is between 0.8 and 1. $D_{Pessimistic}$ equals 1 if the value of *FY1Optimism* is between 0 and 0.2. *Buy* equals 1 if the outstanding recommendation for the month is a 'buy type' (buy or strong buy) recommendation and 0 otherwise. *Broker Size* is the total market share of the broker in month *t* across all stocks. *Dispersion* is the monthly average of daily standard deviation of all outstanding analyst forecasts scaled by the absolute value of the consensus. *Analyst_Cov* is the number of analysts with valid forecasts in the month. *ForecastAge* is the percentile ranking of the duration of the analysts' forecast relative to other analysts (1 = least recent, 0 = most recent). The dependent variable is the market share of the broker in that stock for that month. Broker/analyst-stock-months is the unit of analysis; cluster-adjusted *t*-statistics (both analyst-month and broker-month clusters) are presented.

Dependent Variable: Broker Market Share (t)									
	PANEL A (All Brokers)			PANEL B (Institutional Brokers)			PANEL C (Retail Brokers)		
	Coefficient	Cluster *t*-Statistics (Broker-Month)	Cluster *t*-Statistics (Analyst-Month)	Coefficient	Cluster *t*-Statistics (Broker-Month)	Cluster *t*-Statistics (Analyst-Month)	Coefficient	Cluster *t*-Statistics (Broker-Month)	Cluster *t*-Statistics (Analyst-Month)
Intercept (Mid)	0.0518	19.59***	27.93***	0.0260	10.67***	14.29***	0.1199	16.09***	21.23***
$D_{Optimistic}$	-0.0541	-7.26***	-7.37***	-0.0265	-4.13***	-4.03***	-0.0878	-5.00***	-5.28***
$D_{Pessimistic}$	0.0055	4.46***	4.48***	0.0045	3.16***	3.30***	0.0099	2.48**	2.27**
FY1Optimism	0.0042	2.45**	2.53**	0.0043	2.06**	2.15**	-0.0001	-0.02	-0.02
$D_{Optimistic}$*FY1Optimism	0.0598	7.20***	7.35***	0.0282	3.84***	3.79***	0.1069	5.34***	5.62***
$D_{Pessimistic}$*FY1Optimism	-0.0364	-4.61***	-4.58***	-0.0350	-4.69***	-4.93***	-0.0791	-3.82***	-3.48***
Buy	0.0174	22.67***	29.87***	0.0159	20.36***	26.57***	0.0197	9.53***	11.22***
Broker Size	0.8526	54.49***	86.25***	0.9882	59.07***	92.10***	0.1884	0.84	1.12
Dispersion	-0.0001	-0.80	-0.77	-0.0000	-0.33	-0.32	-0.0003	-0.63	-0.62
Forecast Age	-0.0017	-1.45	-1.63	-0.0032	-2.67***	-3.04***	0.0020	0.69	0.68
Analyst_Cov	-0.0043	-22.75***	-36.67***	-0.0026	-14.29***	-23.23***	-0.1095	-23.50***	-32.34***
Observations	78,862			68,036			10,826		
Adjusted-R^2	21.30%			19.29%			21.22%		

***, ** and * represent significance at the 1%, 5% and 10% level, respectively

Table 5b: Calculation of Relevant Coefficients

This table presents the relevant coefficients for relatively optimistic, pessimistic and neutral forecasts based on the parameter estimates of the interactive regression model in Table 5a. The intercept values are the values of the dummy variables. Neutral slope equals to the coefficient on *FY1Optimism*; optimistic slope equals to the sum of the coefficient on *FY1Optimism* and $D_{Optimistic}$**FY1Optimism*; pessimistic slope equals to the sum of the coefficients on *FY1Optimism* and $D_{Pessimistic}$**FY1Optimism*. The value is assumed to be zero in the calculations if the coefficient is not significant. The coefficient estimates of the control variables are not included.

Dependent Variable: Broker Market Share (t)			
	PANEL A All Brokers	PANEL B Institutional Brokers	PANEL C Retail Brokers
	Coefficient	Coefficient	Coefficient
Neutral Intercept	0.0518	0.0260	0.1199
Optimistic Intercept	-0.0541	-0.0265	-0.0878
Pessimistic Intercept	0.0055	0.0045	0.0099
Neutral Slope	**0.0042**	**0.0043**	**-0.0001***
Optimistic Slope	**0.0640**	**0.0325**	**0.1069**
Pessimistic Slope	**-0.0322**	**-0.0307**	**-0.0791**
Buy	**0.0174**	**0.0159**	**0.0197**

* coefficient not significantly different from zero.

6.3 The Impact of Upgrades and Downgrades in Analyst Recommendations on Broker Market Share According to Broker Clientele

6.3.1 Differences in Means Regression Analysis with Changes in Recommendations

This section presents regressions that simultaneously examine the different impacts of *changes* in analyst recommendations on affiliated brokerage market share and analyst earnings forecasts. The results provide several interesting insights.

Table 6 shows that after accounting for the impact of upgrades and downgrades in analyst recommendations, the most optimistic analyst forecasts retain significant impact on brokerage firm market share. However, different to results found in previous sections, the relatively pessimistic analysts ranked in the bottom forecast optimism quintile do not appear to generate statistically higher monthly brokerage market share on average than relatively 'neutral' forecasts ranked in the third forecast optimism quintile. This is likely because analysts reinforce downgrades in stock recommendations with negative earnings forecasts (see for example, Pattenden and Stretch (2006)). Hence, the negative impact of the pessimistic recommendations on own broker market share is likely to be captured by the *DOWNGRADE* variable instead. Nonetheless, the coefficient on optimistic earnings forecasts remains positive and highly significant in Table 6. This indicates that the influence of analysts who issue relatively optimistic earnings forecasts on own broker market share may be stronger than the influence of analysts who issue relatively pessimistic earnings forecasts.

Second, consistent with Hypothesis 5, the coefficients on *UPGRADE* and *DOWNGRADE* are positive and statistically significant at the 1% level in Table 6. This demonstrates that affiliated brokerage market share is higher for months when analysts upgrade or downgrade their recommendations. Upgrades in analyst recommendations increases affiliated brokerage firm market share by 1.15% per month on average, whereas downgrades in analyst recommendations increases affiliated brokerage firm market share by 0.72% per month on average.

A Wald test rejects the equality of the coefficients on *UPGRADE* and *DOWNGRADE* ($p <$ 0.01), indicating an asymmetric trading response to upgrades in recommendations and downgrades in recommendations. Specifically, in Panel A the coefficient on *UPGRADE* is approximately 37% larger in size than the coefficient on *DOWNGRADE*. The likely explanation for the lower impact of downgrades relative to upgrades is that many investors cannot use negative information about a stock because of short sales constraints. This is consistent with the theoretical predictions by the Jackson (2005) model. The results are also consistent with the empirical findings of Niehaus and Zhang (2009) for the NASDAQ market.

Panels B and C of Table 6 compare the different impacts of upgrades, downgrades and analyst earnings forecasts on the market share of institutional versus retail brokers. Panels B and C illustrate that upgrades and downgrades both generate significant brokerage market share across all brokers. Furthermore, it appears that upgrades/downgrades in recommendations made by analysts affiliated with retail brokerage firms have a larger impact on own broker market share on average than upgrades/downgrades made by analysts affiliated with institutional brokerage firms. Consistent with Hypothesis 6, this indicates that retail investors are more reliant on information conveyed by a single broker's analysts than institutional investors when making investment decisions.

The relative sizes of the coefficients on *UPGRADE* and *DOWNGRADE* in Panels B and C also provide some insights to support the short selling hypotheses proposed by Hayes (1998) and Jackson (2005). Specifically, the coefficient on *DOWNGRADE* is approximately two thirds the size of the coefficient on *UPGRADE* for the large brokers; whereas the coefficient on *DOWNGRADE* is only approximately one third of the size of the coefficient on *UPGRADE* for the small brokers. This suggests that the asymmetric reaction to positive and negative messages conveyed by analysts is stronger for brokerage firms that focus on retail trading than for brokerage firms that focus on institutional trading.

When included in the same regression, the impact of relatively pessimistic analyst forecasts on affiliated brokerage market share appears to become insignificant for institutional brokers. Again, we interpret this result as demonstrating that analysts at institutional brokers tend to reinforce downgrades in recommendations with relatively pessimistic earnings forecasts more often than analysts at small brokers (Pattenden and Stretch, 2006).

Table 6: Upgrades, Downgrades and Analyst Earnings Forecasts – Differences in Means

Panel A presents the parameter estimates of the following model:

$$MKTSHARE^{j}_{s,t} = \alpha_0 + \beta_1 Q1 + \beta_2 Q2 + \beta_3 Q4 + \beta_4 Q5 + \beta_5 UPGRADE^{j}_{s,t} + \beta_6 DOWNGRADE^{j}_{s,t} + \beta_7 BROKRESIZE_{s,t} + \beta_8 DISPERSION_{s,t} + \beta_9 FORECASTAGE_{s,t} + \beta_{10} ANALYST\_COV_{s,t} + \varepsilon^{j}_{s,t}$$

The explanatory variables are the same as in Table 4 except that $UPGRADE^{j}_{s,t}$ and $DOWNGRADE^{j}_{s,t}$ is added to the regression. $UPGRADE^{j}_{s,t\ t}$ equals one if in month t an analyst affiliated with market participant j raised his/her recommendation for stock s and zero otherwise. $DOWNGRADE^{j}_{s,t\ t}$ equals one if in month t an analyst affiliated with market participant j lowered his/her recommendation for stock s and zero otherwise. Only stocks where the broker has an analyst covering the stock are included (and where valid forecasts and recommendation for that analyst exists). Cluster-adjusted t-statistics (both analyst-month and broker-month clusters) are presented.

Dependent Variable: Broker Market Share (t)									
	PANEL A (All Brokers)			PANEL B (Institutional Brokers)			PANEL C (Retail Brokers)		
	Coefficient	Cluster *t*-Statistics (Broker-Month)	Cluster *t*-Statistics (Analyst-Month)	Coefficient	Cluster *t*-Statistics (Broker-Month)	Cluster *t*-Statistics (Analyst-Month)	Coefficient	Cluster *t*-Statistics (Broker-Month)	Cluster *t*-Statistics (Analyst-Month)
Intercept	0.0649	24.09***	36.28***	0.0363	16.00***	23.45***	0.1330	18.26***	26.11***
Q5 (Optimistic)	0.0052	6.22***	6.39***	0.0026	3.70***	3.76***	0.0155	7.82***	7.65***
Q4	0.0008	1.01	0.98						
Q2	-0.0014	-1.72*	-1.79*						
Q1 (Pessimistic)	0.0006	0.77	0.80	-0.0005	-0.76	-0.79	0.0048	2.54**	2.21**
Upgrade	0.0115	8.85***	10.09***	0.0084	6.88***	7.78***	0.0463	6.54***	6.80***
Downgrade	0.0072	6.61***	6.80***	0.0057	5.41***	5.44***	0.0175	3.23***	3.42***
Broker Size	0.8226	51.77***	81.64***	0.9742	59.10***	90.22***	0.1465	0.64	0.87
Dispersion	-0.0001	-1.02	-0.98	-0.0000	-0.46	-0.45	-0.0004	-0.87	-0.86
Forecast Age	-0.0022	-1.91*	-2.14**	-0.0038	-3.13***	-3.58***	0.0012	0.41	0.39
Analyst Coverage	-0.0046	-23.86***	-37.56***	-0.0028	-15.27***	-24.06***	-0.0113	-23.81***	-31.57***
Observations	78,761			67,961			10,800		
Adjusted-R^2	20.24%			18.30%			20.70%		

***, ** and * represent significance at the 1%, 5% and 10% level, respectively

6.3.2 Interaction Variables Regression Analysis with Changes in Recommendations

Table 7a reports the results of the interaction variable model that includes *UPGRADES* and *DOWNGRADES* as additional variables, and Table 7b presents the relevant slope coefficients given the parameter estimates in Table 7a. Consistent with Hypothesis 4, the coefficient on *UPGRADE* and *DOWNGRADE* are positive and significant in Table 7a, and are similar in magnitude with the coefficients reported in Table 6. Hence, overall, the evidence this table provides further support to the notion that recommendation changes provide new information to the market and that investors reward analysts for providing this new information.

Panels B and C of Table 7a present results for the interactive variables model for institutional and retail broker sub samples. Of particular interest are the respective signs and difference in the sizes of the coefficients on the interaction variables, $D_{Optimistic}$*FY1Optimism* and $D_{Pessimistic}$*FY1Optimism.* The difference between the size of the coefficients on *UPGRADE* and *DOWNGRADE* across institutional and retail brokers is also important. In Table 7b the more pronounced differences between the Optimistic slope and the Pessimistic Slope in Panel C demonstrates that the asymmetry between affiliated brokerage market share generated by relatively optimistic and relatively pessimistic analyst forecasts is larger for brokerage firms that focus on retail trading. Similar results apply for upgrades and downgrades in recommendations. Consistent with Hypothesis 5, the results suggest the asymmetry between broker market share generated by positive and negative messages is higher for brokerage firms that focus on retail rather than institutional trading, due to the higher short sales constraints faced by retail investors. This also implies that analysts affiliated with small (retail) brokerages may have higher incentives to issue optimistic forecasts and recommendations than analysts affiliated with large (institutional) brokerages, which corroborates the findings of Cowen, Groysberg, and Healy (2006).

Table 7a: Upgrades, Downgrades and Earnings Forecasts – Interaction Variables Model

The following table represents the parameter estimates of the following model:

$$MKTSHARE^{j}_{s,t} = \alpha_0 + \beta_1 D_{Optimistic} + \beta_2 D_{Pessimistic} + \beta_3 FY1OPTIMISM^{j}_{s,t} + \beta_4 D_{Optimistic}*FY1OPTIMISM^{j}_{s,t} + \beta_5 D_{Pessimistic}*FY1OPTIMISM^{j}_{s,t} + \beta_6 UPGRADE^{j}_{s,t} + \beta_7 DOWNGRADE^{j}_{s,t} + \beta_8 BROKRESIZE_{s,t} + \beta_9 DISPERSION_{s,t} + \beta_{10} FORECASTAGE^{j}_{s,t} + \beta_{11} ANALYST\_COV_{s,t} + \varepsilon^{j}_{s,}$$

The explanatory variables are the same as in Table 6 except that $UPGRADE^{j}_{s,t}$ and $DOWNGRADE^{j}_{s,t}$ is added to the equations. $UPGRADE^{j}_{s,t}$ equals one if in month t an analyst affiliated with market participant j raised his/her recommendation for stock s and zero otherwise. $DOWNGRADE^{j}_{s,t}$ equals one if in month t an analyst affiliated with market participant j lowered his/her recommendation for stock s and zero otherwise. Broker/analyst-Stock-Months is the unit of analysis. Cluster-adjusted t-statistics (both analyst-month and broker-month clusters) are presented.

Dependent Variable: Broker Market Share (t)

	Panel A (All Brokers)			Panel B (Institutional Brokers)			PANEL C (Retail Brokers)		
	Coefficient	Cluster *t*-Statistics (Broker-Month)	Cluster *t*-Statistics (Analyst-Month)	Coefficient	Cluster *t*-Statistics (Broker-Month)	Cluster *t*-Statistics (Analyst-Month)	Coefficient	Cluster *t*-Statistics (Broker-Month)	Cluster *t*-Statistics (Analyst-Month)
Intercept	0.0594	21.63***	31.38***	0.0315	13.41***	17.86***	0.1233	16.29***	22.25***
$D_{Optimistic}$	-0.0550	-7.35***	-7.45***	-0.0339	-4.38***	-4.39***	-0.0969	-4.93***	-5.12***
$D_{Pessimistic}$	0.0058	4.70***	4.70***	0.0049	3.78***	3.88***	0.0149	4.10***	3.69***
FY1Optimism	0.0062	3.55***	3.69***	0.0063	3.43***	3.56***	0.0095	1.79*	1.82*
$D_{Optimistic}$*FY1Optimism	0.0609	7.31***	7.44***	0.0360	4.20***	4.22***	0.1137	5.16***	5.40***
$D_{Pessimistic}$*FY1Optimism	-0.0389	-4.92***	-4.87***	-0.0381	-3.10***	-4.69***	-0.0637	-2.55***	-2.38**
Upgrade	0.0115	8.93***	10.17***	0.0084	6.91***	7.81***	0.0473	6.75***	6.96***
Downgrade	0.0073	6.65***	6.85***	0.0057	5.45***	5.49***	0.0173	3.19***	3.40***
Broker Size	0.8265	52.46***	82.55***	0.9743	59.23***	90.36***	0.1191	0.52	0.71
Dispersion	-0.0001	-1.02	-0.99	-0.0000	-0.47	-0.46	-0.0004	-0.85	-0.83
Forecast Age	-0.0023	-1.96**	-2.21**	-0.0037	-3.10***	-3.54***	0.0012	0.42	0.40
Analyst _Cov	-0.0043	-23.33***	-36.94***	-0.0026	-14.73***	-23.23***	-0.0109	-2.93***	-31.32***
Observations	78,761			67,961			10,800		
Adjusted-R^2	20.40%			18.38%			20.94%		

***, ** and * represent significance at the 1%, 5% and 10% level, respectively

Table 7b: Calculation of Relevant Coefficients

This table presents the relevant coefficients for relatively optimistic, pessimistic and neutral forecasts based on the parameter estimates of the interactive regression model in Table 7a. The intercept values are the values of the dummy variables. Neutral slope equals to the coefficient on *FY1Optimism*; optimistic slope equals to the sum of the coefficient on *FY1Optimism* and $D_{Optimistic}$**FY1Optimism*; pessimistic slope equals to the sum of the coefficients on *FY1Optimism* and $D_{Pessimistic}$**FY1Optimism*. The value is assumed to be zero in the calculations if the coefficient is not significant. The coefficient estimates of the control variables are not included.

Dependent Variable: Broker Market Share (t)			
	PANEL A All Brokers	PANEL B Institutional Brokers	PANEL C Retail Brokers
	Coefficient	Coefficient	Coefficient
Neutral Intercept	0.0594	0.0315	0.1233
Optimistic Intercept	-0.0550	-0.0339	-0.0969
Pessimistic Intercept	0.0058	0.0049	0.0149
Neutral Slope	**0.0062**	**0.0063**	**0.0095**
Optimistic Slope	**0.0671**	**0.0423**	**0.1232**
Pessimistic Slope	**-0.0327**	**-0.0318**	**-0.0542**
Upgrade	**0.0115**	**0.0084**	**0.0473**
Downgrade	**0.0073**	**0.0057**	**0.0173**

* coefficient not significantly different from zero.

7. Further Robustness Checks

7.1 Fixed Effects Estimation

Unlike studies by Jackson (2005) and Irvine (2004), Niehaus and Zhang (2010) use fixed effects regressions to control for 'unobserved heterogeneity in base-line market shares'. Heterogeneity in base-line market shares is likely to exist because the institutional equity market is characterised by idiosyncratic business and personal relationships between buy-side and sell-side institutions. A likely consequence of these relationships is that a buy-side client directs a disproportionate amount of its trades to the brokers with which it has a relationship, which all else equal gives these brokers a higher market share of volume for the stocks that the buy-side client trades. Since relationships vary across institutions, base-line market shares of volume in a stock also vary across brokers.

To ensure that our results are not affected by this potential bias, we follow Niehaus and Zhang (2010) and re-estimate the results of this paper using fixed effects regressions. This does not alter any conclusions of the paper.[23]

[23] The fixed effects estimators yield better results in many occasions.

7.2 Multicollinearity

When using interaction variables, it is likely that the interaction variables are correlated with each other. To ensure the inherent multicollinearity between the interaction variables is not influencing our results, we first use the partial orthogonalisation method suggested by Burrill (1977), and re-estimate the interaction terms in the multiplicative interaction regression model. We then re-run all interaction variables regressions using the new orthogonalised interaction terms. The coefficients remain identical in magnitude and sign, and the *t*-statistics are similar in significance in every case. This suggests that multicollinearity is not affecting the results of this paper.

7.3 Investment Banking Robustness

To filter out the potential impact of underwriting relations on research coverage and trading volume, we repeat the analysis after we exclude all stocks that had an IPO or SEO in the previous three years. This has a minimal effect on the results of this paper, which suggests that the fixed effects and broker-month clustered standard errors in the pooled regressions has already captured IPO and SEO related market share effects. Thus, the reported results are not likely to be driven by investment banking relations.[24] This also indicates that trade generation incentives is an important institutional factor that impacts sell-side analyst optimism.

8. Conclusion

The role of trade generation incentives in sell-side research is a topic that has gained significant interest over the past decade. However, limited academic attention was dedicated to this issue, due to relative difficulties in obtaining and combining the various datasets required. In particular no prior evidence has considered the influence that different investor clienteles have on the relationship between sell-side research and market share. The findings in this paper provide several insights into the role of trade generation incentives in the conflicts of interests faced by sell-side analysts.

Using evidence from the Australian market, this paper first examines the relationship between analyst forecast optimism and broker market share in a non-linear framework. We find that a)

[24] Due to the length constraints of the paper, the results of investment banking and multicollinearity robustness checks are not presented.

relatively optimistic and pessimistic earnings forecasts both generate higher broker market share and b) broker market share generated by relatively optimistic earnings forecasts is higher than broker market share generated by relatively pessimistic earnings forecasts. In addition to analyst forecasts, analysts who issue buy type recommendations generate higher broker market share on average than analysts who issue sell type recommendations. These findings are consistent with theoretical work by Hayes (1998) and confirm results in the empirical literature (Jackson (2005), Niehaus and Zhang (2010), Irvine (2004)), suggesting that sell-side analysts have incentives to issue optimistic recommendations in an effort to increase brokerage commissions.

This paper also presents evidence consistent with the view that analysts are rewarded when they uncover and report new information to the market through upgrades and downgrades in recommendations in the Australian market. Although both upgrades and downgrades in recommendations generate higher brokerage market share for the month of the upgrade/downgrade, upgrades appear to generate higher brokerage market share on average than downgrades. This is consistent with literatures that predict an asymmetric investor trading reaction to positive and negative messages conveyed by sell-side analysts due to short sales constraints (Irvine (2004), Jackson (2005)).

Perhaps most significantly, evidence is provided for the first time that retail investors are more reliant on information conveyed by a particular analyst through earnings forecasts and stock recommendations than institutional investors. Furthermore, they appear to be less able to take advantage of negative information because they face higher short sales constraints than institutional investors. Hence, analysts affiliated with brokerage firms that focus on retail trading are likely to have higher incentives to issue optimistic forecasts than analysts affiliated with brokerage firms that focus on institutional trading. This corroborates the results of Cowen, Groysberg, and Healy (2006), and offers a potential explanation to why brokerage firm analysts are found to be more optimistic on average than investment bank analysts.

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