Individual Investors and Broker Types

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Abstract

We study the informativeness of trades via discount and full-service retail brokers. We find that trades via full-service retail brokers are statistically and economically more informative than are trades via discount retail brokers. This finding holds in every year over the twelve-year sample period and in various subsamples. We also find that past returns, volatility, and news announcements positively relate to the net volume of discount retail brokers but these variables are unrelated to the net volume of full-service retail brokers. Our results suggest that broker type selection bias is an important consideration in studying individual investors' trades.

JEL classification: G14

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I. Introduction

This paper examines the informativeness of individual investors' trades across different broker types. Although a large literature studies individual investors' trades, the informational role of these trades in asset prices is still unclear. Odean (1998) and Barber and Odean (2000, 2002) use client level data from a US discount retail broker to study individual investors' portfolio decisions, finding that individual investors exhibit various biases and generate losses when they trade. A number of studies that extend this line of inquiry conclude that individual investors' trades are uninformative about future stock returns.[1] On the other hand, Kaniel, Saar and Titman (2008) and Kaniel et al. (2012) use the NYSE consolidated audit trail data, which tag trades originated by individual investors, and find that the intensity of individual investors' buying and selling can predict future stock returns. Similarly, Kelly and Tetlock (2012) find the buy-sell imbalance of retail orders routed through two market centers positively predicts the cross-section of stock returns.

One potential reason for the mixed results is that individual investors are a highly heterogeneous group: some subsets are likely to be highly skilled while others may be naive. We conjecture that using data from one type of broker pre-filters data and reduces investor heterogeneity. Retail brokers specialize by offering distinct services and this can lead to systematic differences in clientele and trade informativeness. Individual investors of certain characteristics are more likely to focus on minimizing brokerage costs and trade via discount retail brokers. Investors that fit this category include liquidity traders who buy or sell shares for

[1] See Feng and Seasholes (2004), Kumar and Lee (2006), Kumar (2009), and Seasholes and Zhu (2010) for studies that used the same dataset as Odean (1998). Barber, Odean and Zhu (2009), and Dorn, Huberman and Sengmueller (2008) find evidence of correlated trading among individual investors using other datasets.

saving and consumption purpose, speculators and day traders who trade and pay brokerage fees frequently, self-directed individual investors who make investment decisions independent of their stock brokers, and investors with trading ideas of lower marginal profit. The fact that discount retail brokers' popularity grew along with the internet also leads one to suspect that they disproportionately attract new and inexperienced investors. On the other hand, individual investors that have longer investment horizons and incur transaction costs infrequently, who are wealthy, or have a high opportunity cost of time, may be less concerned with brokerage cost. These investors, as well as individual investors that are cautious, may want to use a full-service broker because they think that a full-service broker may be able to provide useful information, advice, or services[2] to improve the efficiency and outcomes of their investments. Overall, the informativeness of individual investors' trades may differ across broker types due to the clientele selection effect and valuable brokers' advice.

Whether the informativeness of individual investors' trades differs significantly across broker types is ultimately an empirical question. To address this question, we use transaction data from the Australian Securities Exchange (ASX), which identifies the broker on both sides of every trade, so we know the trade direction of each broker precisely. We manually collect information on the business description of individual brokers from articles, books, commercials, and archived and current websites to identify discount retail and full-service retail brokers, among other broker types, without relying on the transaction or order data. We interpret trades via retail brokers as individual investors' trades as in Griffin, Harris and Topaloglu (2003). The informativeness of retail order flow has a strong broker specific component (Kelly and Tetlock

[2] Individual investors need not be looking for inside or private information. The broker can act as a sounding board to validate (or falsify) investment ideas and to provide information such as analyst reports, aggregate order flow of funds, or other investors for the investor to gauge sentiment.

(2012) and Linnainmaa and Saar (2012)), hence drawing inferences from trades from a small number of brokers about the population of individual investors' trades is limited by broker selection bias. We use trades from the population of pure discount retail and full-service retail brokers to reduce such broker selection bias while controlling for the broker type selection effect in this study. Our dataset offers two other desirable features. First, the ASX has been a consolidated limit order book market over the full sample period, and there is no payment for order flow and internalization practice as in the US. Internalization leads to the netting of offsetting trades before reporting. Netted trades are likely to be uninformed, and the inability to observe them causes an upward bias in the informativeness of observed trades. All trades on the ASX are reported before netting, so we avoid the trade selection bias in using US data. Second, the dataset covers thirteen calendar years from 1995 to 2007; thus, the sample period is significantly longer than those used in other studies. The long sample period allows us to check whether the results are robust across sub-periods.

Our central finding is that trades via full-service retail brokers are significantly more informative than are trades via discount retail brokers in every year over the sample period. More specifically, using the transactions-based calendar-time (TBCT) portfolio methodology of Seasholes and Zhu (2010), we find that the buys minus sells portfolio of trades via discount retail brokers consistently generates significantly negative alphas at horizons ranging from end-of-the-day to 6 months, while the trades via full-service retail brokers generate positive returns at horizons from 1 to 20 days. The largest trade informativeness difference is at the end-of-the-day horizon where the daily TBCT portfolio alpha difference across the two retail broker types is 18.41 basis points per day or 58.38[3] percent annualized. The difference shrinks to 3.02 basis

[3] Assuming 250 trading days in a year, $1.001841^{250} - 1 = 0.5838$.

points per day or 7.84 percent annualized if individual investors have a 20 day (1 month) horizon.

We perform a number of additional analyses to gain a better understanding of the trade informativeness across retail broker types. First, we separately examine both market order trades and limit order trades and find very similar effects. This finding suggests that the poor performance of discount brokers cannot be entirely attributed to the adverse selection effects associated with limit order trades. We also separately examine informativeness by stock size. We find that the trade informativeness difference across retail broker types is typically largest, and persists over longer horizons, in smaller stocks, but is also present in larger stocks. We study the determinants of individual investor net volume and discover that only the net volume of trades via discount retail brokers is related to past returns, volatility, and news announcements.

Our evidence highlights that broker type is an important filter that reduces heterogeneity amongst individual investors. This result suggests that broker type selection is an important consideration in designing and interpreting the evidence of an individual investor study. Viewed from this perspective, the diverse findings in the literature are not surprising. Earlier studies that focus on trades from discount retail brokers result in sampling trades from the less informative broker type. In general, we should be cautious about generalizing the results of a study if we do not know the composition of individual investors' trades across broker types in the data relative to the population.

The rest of the paper is structured as follows: Section II describes the ASX market and the data, Section III explains the broker type classification procedure, Section IV details the trade informativeness measurement methodology, and Section V presents the results. We discuss potential data concerns and compare methodologies in Section VI and conclude in Section VII.

II. Market and Data

The Australian Securities Exchange (ASX) is the only significant stock exchange in Australia during the sample period and there are no designated market makers. Since 1990, trading of all ASX listed stocks takes place via a consolidated electronic limit order book system. The ASX starts trading from 10:00 a.m. using an auction algorithm, then switches to operate as a continuous open limit order book until 4:00 p.m. The trading system establishes the close price in a stock with an auction shortly after 4:00 p.m.

We obtain transaction data on the ASX from the Securities Industry Research Centre of Asia-Pacific (SIRCA). The dataset covers all stock trades from 1 January 1995 to 31 December 2007. Each trade record includes the timestamp, ticker, price, the bid and ask price just prior to the transaction, trade flag, and buying and selling broker identifiers. The trade flag indicates whether the trade is a buyer- or seller-initiated trade, an auction trade, or an off-market trade. In order to compute daily returns, we collect dividends, capitalization adjustments, and month-end share market capitalization data from the Australian School of Business' Centre for Research in Finance Share Price and Price Relative database (CRIF SPPR). We also obtain financial year-end book-value data from Aspect Financial in order to compute risk-adjusted returns.

Table 1 reports the turnover velocity,[4] total turnover and the number of trades per year, as well as the average trade value. Total turnover during the thirteen-year period is AUD7.83 trillion. Annual total turnover has grown 15 times from AUD120.5 billion in 1995 to AUD1,804.9 billion in 2007. The total number of trades has increased at an even faster pace, and

[4] The turnover velocity follows the definition on the World Federation of Exchanges website (http://www.world-exchanges.org/statistics/statistics-definitions) and is calculated as the average monthly turnover of domestic shares, divided by their average month-end's total market capitalization. The monthly average figure is then annualized by multiplying by 12.

results in the average trade value falling from AUD41,000 to AUD26,000.[5] The turnover velocity of the market almost tripled in this period from 33.9 percent to 108.8 percent. The increased turnover velocity is similar to the NYSE experience during the same period where turnover velocity increased from 55.5 percent to 167.1 percent.[6]

[Insert Table 1 about here.]

III. Broker Classification

Starting with broker names, we collect information about each broker's business in order to classify the broker into one of five distinct categories: discount retail, full-service retail, institutional, mixed (full-service retail and institutional), and other. We focus on the discount retail and full-service retail brokers in this study because they represent pure retail broker types and the comparison yields clear interpretation. The steps we take to collect information on each broker are as follows:

1. Check existing broker's website or archived broker's website from the Internet Archive (http://www.archive.org/).

2. If no website exists or the broker type cannot be determined from its website, search Factiva for newspaper articles, trade journals, company announcements, or web articles on the broker.

3. If no Factiva articles exist to classify the broker, Google search the broker for any credible articles that may classify the broker. From doing this, we classified one broker from a book about the broker’s history.

[5] The trend in trade size and trade activity likely reflects the growth of practices such as algorithmic trading (see e.g. Humphery-Jenner (2011)). Our results are robust to time effects and hold across all twelve years of our sample, so any such changes in trading activity are unlikely to drive our results.

[6] Sourced from the World Federation of Exchanges website (www.world-exchanges.org).

4. If the broker still exists today but has no identifying information from a website, Factiva, or Google, we telephone the broker and ask for their clientele (institutional, mixed, or retail) and the type of services that they provide (advisory or non-advisory). We did this for two brokers.

5. If a broker's classification cannot be determined from the above steps, the broker is classified as Other.

Appendix A illustrates how we use the hand-collected data to classify brokers. For example, we classify a broker as a discount retail broker based on the broker's website if brokerage commission features prominently on its site and there is no mention of full-service or institutional sales. Our classification procedure therefore provides a direct and transparent method to classify brokers. It is also unlikely to misclassify brokers for two reasons. First, it is reasonable to believe that a broker's website or newspaper articles would focus on the broker's main strategy and clientele. For example, it is unlikely that a discount retail broker would purport to be an institutional broker or a full-service retail broker on its website or in newspaper articles. Second, we have a "mixed" category which removes ambiguity in forcing brokers to be one of the pure broker types and we also have an "other" category for broker names and identifiers for which we have not been able to obtain any information.

Our broker classification approach is most similar to Jackson (2003), who groups brokers into discount retail, full-service retail, and institutional by examining the broker's website. Without client level data of each trade, our methodology to classify brokers appears to be reasonable in comparison to the literature. [7]

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[7] Griffin, Harris and Topaloglu (2003) converse with Nasdaq and industry participants to classify brokers into whether they primarily handle institutional or individual (retail) clients. They provide support for their classification

Table 2 presents the annual statistics by broker type. Panel A shows that there are 203 unique broker identifiers during our sample period, and the first discount broker appeared in 1995. Not all brokers operate at the same time and there are approximately 90 brokers in any given year. Panel B shows that full-service brokers and discount retail brokers account for 9.44 percent of the aggregated trade value over the full sample period. While their aggregate market share is stable over time, discount retail brokers have increased their market share in turnover. This shift in market share is due to the rapid increase of the dollar turnover of discount retail brokers rather than a decline in dollar turnover of full-service retail brokers. Full-service retail brokers' turnover actually increased from AUD14.28 billion in 1995 to AUD32.31 billion in 2007.[8]

[Insert Table 2 about here.]

As an independent check of our identification of retail versus institutional brokers, Table 3 presents the dollar turnover distribution of full-service and discount retail brokers by stock size. We expect individual investors to account for a larger fraction of turnover in small stocks because the most common benchmarks for Australian equity funds during the sample period are the S&P/ASX 300 and S&P/ASX 200 indices; hence, institutional investors are much more active in trading the top 200-300 stocks. Therefore, we form three stock groups every month during 1995 to 2007 based on the market capitalization ranking of a stock at the end of the previous month: the largest 50 stocks, the 51st to 300th stocks, and stocks smaller than the 300th. We then compute the turnover share of each broker type over the entire sample period. The brokers that we classify as retail brokers account for an increasing fraction of turnover as stock

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system by showing that the trade-size characteristics of each broker conform to the separation of institutional and retail order flow.

[8] Multiply the total turnover in Table 1 in a given year by the market share in Table 2 Panel B yields these values.

size falls. Panel A shows that the two retail broker types account for 6.7 percent of the turnover in the top 50 stocks and 44.6 percent in the turnover of stocks outside the top 300 stocks. Furthermore, Panel B shows that 49.9 percent of the dollar turnover of full-service and discount retail brokers are in the top 50 stocks and 17.7 percent of their dollar turnover are in stocks outside the top 300. The corresponding turnover shares for institutional brokers are 75.2 percent and 1 percent, respectively. The statistics for the mixed brokers are indeed somewhere between those of retail and institutional brokers. Overall, the turnover-share statistics across stock size-groups supports our broker classification between retail and institutional brokers.

[Insert Table 3 about here.]

Given the five-step approach that we use and the allowance of mixed and other broker categories, we expect any residual retail broker classification errors to be random. Our goal is to quantify the trade informativeness difference across the two types of retail brokers, and random errors would reduce the likelihood of finding positive difference because they can only make the two subsets of trades less distinct.

IV. Transactions-Based Calendar-Time Portfolios

We adapt the transactions-based calendar-time (henceforth, TBCT) portfolio methodology of Seasholes and Zhu (2010) to multiple horizons in this study. The TBCT methodology corrects several issues commonly encountered in measuring individual investors' trade informativeness. It allows researchers to fully utilize all the data, and it aggregates thousands of time series across individuals and stocks into a single time series. It accounts for cross-sectional correlation across stock returns that would otherwise distort measures of statistical significance. In addition, this approach also permits the value weighting of all buys and sells over the full time series; hence, it eliminates the effect of a large number of small stocks or low volume days that are of little economic significance to the results.

The TBCT portfolio methodology requires us to add the number of shares in each buy trade to a "buys" portfolio daily and to remove the same number of shares from the portfolio holdings after a fixed period, e.g., 20 days. The portfolio's value and composition change over time as we add shares and remove holdings. We construct the "sells" portfolio analogously and compute daily value-weighted returns for these portfolios by marking the holdings and new trades to daily close prices. The informativeness of a collection of trades, e.g. trades via discount brokers, over a calendar-time horizon is measured by the mean daily difference between returns on the buys portfolio and returns on the sells portfolio. In order to assess the difference in the informativeness of trades across broker types, we use the difference-in-difference design by subtracting the buys-minus-sells TBCT portfolio returns of trades via discount retail brokers from the buys-minus-sells returns of trades via full-service retail brokers. Finally, we risk adjust returns by using the Carhart (1997) four factor model to compute alphas.

The literature measures trade informativeness at horizons ranging from 5 minutes to 1 year (see e.g. Linnainmaa and Saar (2012) and Seasholes and Zhu (2010)).[9] The wide horizon range in prior studies suggests an awareness of both short- and long-lived information. With the TBCT portfolio methodology, short horizon portfolios will not be able to capture long-lived information because the information is incorporated into the stock price slowly over many days or months. Similarly, long horizon TBCT portfolios will add noise to the measured informativeness if the information is in fact short-lived, such as those related to institutional trading-induced short-term price pressure or price adjustment following information

[9] Linnainmaa and Saar (2012) use permanent price impact over a five-minute horizon to measure informativeness. Kaniel, Saar and Titman (2008) study weekly to monthly returns conditional on past intense individual investor trading. Kaniel et al. (2012) and Linnainmaa (2010) study return at horizons ranging from end-of–the-day to 126 days. Seasholes and Zhu (2010) use horizons ranging from 3 to 12 months.

announcements. Consequently, we compute TBCT portfolio alphas using a variety of horizons from end-of-the-day to 1 year such that we can capture information of different longevity associated with individual investors' trades. In order to capture returns at the end-of-the-day,[10] we deviate from Seasholes and Zhu (2010) by using the actual transaction price of a trade instead of the end-of-the-day price in adding a trade to the portfolio. As Seasholes and Zhu point out, there are thousands of trades being added to a portfolio each day and these trades would be diversified across the bid and ask prices. Hence, our result should not be driven by bid-ask bounce despite the use of transaction prices in computing returns. We present a simplified numerical example that illustrates the construction of the buys portfolio using transaction prices in Appendix B for readers interested in the details.

V. Results

A. Discount Retail Brokers versus Full-Service Retail Brokers

Table 4 presents our main results that compare the informativeness of trades via discount and full-service retail brokers. Panel A shows the mean daily alphas of the buys-minus-sells TBCT portfolios and the difference-in-difference alphas. Panel B contains the corresponding *t*-statistics, and Panel C shows the number of years with statistically significant positive alphas minus the number of years with statistically significant negative alphas. The theoretical

[10] Returns at end-of-the-day horizon is also interesting because short-horizon individual investors such as day-traders and those that bet on short-term price trends or reversals would experience these returns frequently. Therefore, incorporating end-of-the-day returns can be important for assessing the overall returns of short horizon portfolios accurately.

maximum absolute value in Table 4 Panel C is twelve because portfolio formation consumes the first of the thirteen years of data.[11]

[Insert Table 4 about here.]

Table 4 shows that trades via discount retail brokers generate an alpha that is strikingly poor at the end-of-the-day horizon. The value at the close of the first day is in Panel A and shows that the average daily alpha is -25.93 basis points at the end-of-the-day horizon. This implies that if all of these trades are liquidated at the close price on the day of trade, the portfolio of buy trades generate a return that is 25.93 basis points lower than the return on the portfolio of sell trades after risk adjustment. This yields a compounded annual alpha of -47.75 percent,[12] which is economically extremely significant.

The large negative alpha at end-of-the-day is hypothetical in that we do not observe the actual horizon of any trade; it is most unlikely that all trades via discount retail brokers are liquidated at the end of the day. Alphas computed assuming longer holding periods show that the (lack of) informativeness of these trades increases (decreases) considerably over time. The alphas of the portfolio at 1-, 5-, and 10-day horizons remain statistically significantly negative but the magnitudes are much smaller. For example, if all trades via discount retail brokers were liquidated after 10 days, the daily alpha would be -2.48 basis points or an annualized alpha of only -6.40 percent. If these trades were held for one year, the buys-portfolio and the sells-portfolio would yield the same alpha. In other words, trades via discount retail brokers earn the

[11] Our calendar-time portfolios have a maximum horizon of one year; hence, one year of data is needed for a one year horizon portfolio to have the full spectrum of holding periods in its constituents and to reach a steady state with daily position additions and holdings liquidations.

[12] Assuming a 250 trading day year, $(1-0.002593)^{250} - 1 = -0.4775$.

required rate of returns if they hold their position for one year, and they earn less than the required return if they have shorter holding periods.

In contrast to trades via discount retail brokers, trades via full-service retail brokers exhibit informativeness at 1- to 20-day horizons in the sense that their buys-minus-sells TBCT portfolio alphas are significantly positive. Their portfolios earn the maximum average daily alpha at the 5-day horizon, where the average daily alpha is 3.53 basis points or 9.22 percent annualized. However, these trades still do not do well over the end-of-the-day horizon; the end-of-the-day alpha is -1.07 basis points, which annualizes to -2.71 percent, although it is only statistically significant at the 10 percent level. These results suggest that the individual investors who place these trades are good at anticipating returns 5 to 10 days ahead but are not good at intraday timing. Furthermore, these trades do not demonstrate informativeness over the longer horizons, exhibiting alphas that are literally zero at horizons of 3 months and beyond.

The last row in Panel A, Full-service minus Discount, shows that trades via the full-service retail brokers are significantly more informative than are trades via discount retail brokers at horizons of up to 3 months. The difference in alphas decreases as the horizon extends, starting from 18.41 basis points per day (58.38 percent annualized) when marked to the end-of-the-day through to 0.99 basis point per day (2.51 percent annualized) at the 3-month horizon. The difference in alphas is zero at the 6-month horizon and beyond. The *t*-statistics in Panel B reinforce the diminishing statistical significance as the calendar-time horizon extends. Panel C shows that trades via full-service retail brokers are more informative than are trades via discount retail brokers on average, in every year at horizons up to 5 days (one calendar week), in eleven of the twelve years at the 10-day (two calendar weeks) horizon, and in ten of the twelve years at the 20-day (one month) horizon. Overall, the results in Table 4 strongly support three points. First, trades via full-service retail brokers are systematically more informative than are trades via discount retail brokers. This difference may be due to clientele differences or the informational or execution service of the brokers. Regardless of the explanation,[13] this finding implies that broker type selection biases can severely influence the results of a study into the informativeness of individual investors' trades. Second, informativeness (or uninformativeness) of individual investors' trades is concentrated in the short term. Third, the end-of-the-day negative alphas are economically the largest and statistically the most significant relative to alphas at longer horizons. Because our methodology diversifies trades across the bid and ask prices, the end-of-the-day result should not be due to bid-ask bounce. The last two points paint the picture that individual investors are trading on short-term information, but they do so with consistent errors at the intraday level. Their intraday trading errors may reflect their information disadvantage when they are trading against institutional investors who split large orders over time and exert price pressure at intraday to short-term horizons.

B. Dissecting Trade Informativeness

While we have established that the informativeness of individual investor trades depends on the broker type, there are many unanswered questions. Is the result driven by adverse selection? How would the results change with different levels of institutional investor trading? Are trades from different types of retail brokers trend-following or contrarian? In this section, we answer these questions by studying how TBCT portfolio alphas change across market and limit order trades, across stock size, and across factors that drive the trading direction of individual investors.

[13] We do not have the data to distinguish between these explanations.

1. *Market and Limit Order Trades: Testing Whether the Results are Due to Adverse Selection*

We first address whether the performance documented in the main tests reflects adverse selection issues associated with limit order trades (the 'limit order effect'). Market order users incur the bid-ask spread in order to achieve immediate execution. Limit order users avoid paying the bid-ask spread by posting limit orders and offering to other traders to trade at their price. The costs to limit order users are that they face the non-execution risk and adverse selection (free trading option) risk. Non-execution risk arises when the limit order fails to execute and market prices drift to a less favorable level. Adverse selection risk relates to the fact that a limit order offers other traders an option to buy or sell shares and, conditional on execution, there is an increased probability that an informed trader who knows that the security is mispriced triggers the trade. This situation may arise simply because limit order users let their limit orders stay active too long by failing to update the pricing. Linnainmaa (2010) documents that the adverse selection costs associated with limit orders that are executed is significant for Finnish individual investors, and finds that this limit order effect explains a large fraction of behavioral biases. In order to control for the limit order effect, we partition trades during continuous trading hours into market order trades and limit order trades,[14] and we compare their alphas in Table 5.

[Insert Table 5 about here.]

[14] We do not have order level data; hence, we focus on trades and do not quantify non-execution cost. There is a buyer and a seller in every trade. A trade that takes place at the ask price generates a market buy and a limit sell. A trade at the bid price generates a market sell and a limit buy. We exclude trades executed in opening and closing auctions in the market and limit order trades analysis.

Market order trades offer a clear way to assess trade informativeness because market order users determine the execution of their trades; thus, market orders are not subject to adverse selection risk. Investors with a strong view or urgent trading needs are likely to use market orders. Panel A of Table 5 shows that market order trades via full-service retail brokers incur the cost of immediacy and yield negative day's close alphas. However, these trades generate positive alphas from 1- to 20-day horizons. In contrast, market order trades via discount retail brokers generate negative alphas from end-of-the-day and up to 20-day horizons, although the magnitude declines over the horizon. The alpha-difference across the two broker types is significant at horizons up to 20 days. None of the alphas is significantly different from zero at the 3-month horizon and beyond. The results in Panel A suggest that the information these trades reflect is short-lived in nature.

A comparison of the end-of-the-day alphas between Panel A and Panel B shows that limit order trades have smaller negative end-of-the-day alphas than do market order trades. This suggests that adverse selection is not too severe within the trading day in that there is a net saving in avoiding paying the bid-ask spread. The improvement in alphas is economically significant at about 10 basis points per day for both broker types. For limit order trades via full-service retail brokers, the negative alphas are still negative at the 1-day horizon but the alphas become positive at 5- to 10-day horizons and zero thereafter. The alphas of these limit order trades at 1- to 20-day horizons are all lower than the corresponding alphas for market order trades. This finding is consistent with the presence of mild adverse selection costs with the use of limit orders within the 20-day horizon. Adverse selection costs are stronger in limit order trades via discount retail brokers, with medium to long horizon alphas remaining statistically significantly negative. The difference in the informativeness of limit order trades between the two broker types is statistically significant up to the 6-month horizon.

Overall, the market and limit order trades evidence suggests that the main result in Table 4 is robust to the limit order effect. Adverse selection costs and the limit order effect exist in the data but they are not the primary drivers of the level of or difference between the informativeness of trades via the two broker types.

2. *Stock Size: Does the Informativeness of Individual Investors' Trades Depend on Stock Size?*

A stock's informational and trading environment changes with its size. Large stocks attract analysts and media coverage as well as trading by institutional investors. We have seen in Table 3 that trades via institutional brokers account for an increasing proportion of market turnover as stock size increases, whereas retail brokers have suffered a reduction in market share. This trend begs the question of whether the informativeness of individual investors' trades depends on stock size. We partition the data across stock size groups and present the alphas in Table 6.

[Insert Table 6 about here.]

The estimates in Table 6 show that informativeness of individual investors' trades depends on stock size. In small stocks, where trades via pure retail brokers account for 44.6 percent (Table 3 Panel A) of market turnover, the trades via full-service retail brokers are informative at all horizons, including the end-of-the-day. The daily alpha level at the 1-day horizon is the largest and the daily alpha difference at the end-of-the-day is the largest. In contrast, trades via discount retail brokers have negative alphas at all horizons, and the magnitude decreases steeply over the first 5 to 10 days.

The alpha pattern in medium stocks is different. Trades via discount retail brokers have alphas that are negative and decrease in magnitude over longer horizons, while trades via full-service retail brokers generate positive alphas only over 5- to 10-day horizons. Trades via full-service retail brokers are more informative than trades via discount retail brokers at end-of-the-day to 3-month horizons. Much of the difference is driven by the uninformativeness of the trades via discount retail brokers.

Trades via both retail broker types in large stocks have positive alphas at 5- to 20-day horizons, and their alphas are zeros at longer horizons. Their negative alphas at end-of-the-day are more than compensated by returns over the first few days. Trades via full-service retail brokers are the more informative trades, and they are statistically significant at horizons from 1 to 10 days.

The partition of the sample by stock size shows three patterns. First, trades via both types of retail brokers are informative in 5- to 20-day horizons in large stocks. Second, trades via full-service brokers are informative in small stocks at all horizons. Third, the smaller the stock group, the larger the economic and statistical difference between the alphas of trades across the two retail broker types and the longer is the horizon over which we find significant alpha difference.

The first pattern suggests that individual investors' trades can be informative despite institutional investors dominating trading in these stocks. The negative alphas of trades via both retail broker types followed by positive returns over short but not at longer horizons suggest that individual investors are trading on short-term information with imperfect intraday timing. The second and third patterns suggest that the contribution of trades via full-service retail brokers to information efficiency increases as stock size decreases.

3. *Determinants of Net Trading Volume*

The TBCT portfolio methodology is elegant in aggregating a vast number of trades across individual investors and stocks into one return time series. However, the interpretation of results would benefit from supplementary evidence about individual investors' trading strategies. For instance, we speculated (above) about how individual investors may be adapting to changes in the informational environment. This leads to questions about whether individual investors condition on past returns, whether they are trend-followers or contrarians, and whether past information can predict their trading direction. Subsequently, we estimate a parsimonious model of the net volume of trades via the two types of retail brokers in order to have a deeper understanding of individual investors' trading.

Our regression specification is motivated by the findings of Kaniel, Saar and Titman (2008) and Barber and Odean (2008). Kaniel, Saar and Titman (2008) study the weekly net dollar volume bought by individual investors computed from individual investor trades reported in the New York Stock Exchange audit trail data. They find that individual investors tend to buy stocks following declines and sell stocks following price increases. Barber and Odean (2008) study data from three retail brokerage firms and find that individual investors are net buyers of 'attention grabbing' stocks, e.g., stocks in the news, stocks experiencing high abnormal trading volume, and stocks with extreme one-day returns. Based on these findings, we estimate the following stock fixed effect regression specification:

(1) $$Netvol_{i,t} = \mathrm{a}_\mathrm{i} + \mathrm{b}_1\, LagNetvol_{i,t} + b_2\, LagAbvol_{i,t} + b_3\, LagAbvolDum_{i,t} + b_4\, Volatility_{i,t} + b_5\, VolaDum_{i,t} + b_6\, LagReturn_{i,t} + b_7\, LagBear_{i,t} + b_8\, LagBull_{i,t} + b_9\, News_{i,t} + e_{i,t}.$$

The stock-level fixed effects control for stock-level differences, such as stock size, and allow us to focus on the time series and attention grabbing variables. The unit of observation of the regression is a stock-day (stock *i* day *t*) and we estimate equation (1) for each broker type separately. We omit the subscripts in the following discussion. The dependent variable, *Netvol*, is net volume, calculated as the number of shares bought minus the number of shares sold by a broker type and scaled by the number of shares outstanding. *LagNetvol* is the one day lagged value of *Netvol*, which we introduce to control for persistence in trading direction. The other variables capture past returns and the attention grabbing level of a stock-day. Table 7 Panel A lists their definitions.

[Insert Table 7 about here.]

Panel B presents the regression estimates and the *t*-statistics based on standard errors clustered by date to control for cross-sectional correlation. The net volume of trades via discount retail brokers is positively auto-correlated and positively affected by the attention grabbing attributes of a stock. Specifically, the net volume of these trades is positively related to lagged abnormal volume, lagged extreme (high and low) returns, volatility, and news on the day of trade. Trades made via discount retail brokers only have lower net volumes on days of extreme volatility. That is, these trades have a tendency to sell stocks on days in which they experience extreme price movements. Furthermore, these trades are trend-following in that their net volume is positively related to the previous day's stock return. The behavior of these trades is similar to the uninformed individual investors' trades documented in Barber and Odean (2008).

The net volume of trades via full-service retail brokers behaves differently. They are not significantly affected by any past return or by attention grabbing variables. The only common significant determinant of net volume of trades via the two broker types is the lagged net volume. The adjusted r-squared in the models that examine the net volume of trades via discount retail brokers is 9.6 percent, which is twice the size of that of full-service retail brokers.

Overall, the net volume of trades via discount retail brokers is more predictable, more attracted by attention grabbing attributes of a stock, and has a higher tendency to be trend following relative to the net volume of trades via full-service retail brokers. These results confirm our interpretation of the portfolio alpha results that trades via full-service retail brokers are more informative than those of discount retail brokers.

VI. Discussion

Our study groups trades by broker identifiers and uses hand-collected information on broker type. We discussed the potential effect of classification errors in Section III but readers may suspect that our results could be an artifact of other data issues such as individual investors trading through both full-service and discount broker accounts and strategic order splitting across broker types by institutional investors.

If some individual investors have accounts across both types of retail brokers and place trades via both types of brokers, our ability to attribute the difference in trade informativeness to clientele difference would be limited. However, this possibility does not invalidate our findings per se, because we are not making claims about the source of the difference in trade informativeness. Furthermore, the best available evidence on the significance of multiple brokerage account usage, from Finland, suggests that the magnitude of the issue is small. Specifically, Linnainmaa and Saar (2012) use Finnish client-level data to study the value of using broker identifiers to predict the underlying clientele. They find that only 4.1 percent of Finnish households use multiple brokers. In addition, our finding of distinct determinants of net volume across the two broker types also affirms that our broker classification procedure identifies two types of pure retail broker trades and the multiple brokerage account issue is not evident.

With respect to strategic order splitting by institutional investors via retail brokers, we are not aware of such practice being widespread during our sample period. Furthermore, the Finnish evidence[15] also suggests that strategic order splitting is not as strong as theories would predict. Specifically, Linnainmaa and Saar (2012) study the trades of households, institutional investors, and foreigners across broker identifiers and conclude that there are significant economic frictions that limit the extent to which institutional investors can split orders across brokers. Based on this finding, we expect only a limited level of institutional investors' strategic order splitting via retail brokers. More importantly, even if institutional investors do split some orders to what we identify as pure retail brokers, economic reasoning would direct them to channel their trades to discount retail brokers. This is because discount retail brokers have the lowest trade informativeness and generate lower market impact; hence, trading via them would be a more effective camouflage for large orders. Such order splitting activity from the information-rich broker type to the information-poorest broker type would bias us against finding our results because we find trades via discount retail brokers are less informative than trades via full-service retail brokers. In summary, while our data is not perfect, our results remain robust against these data concerns and other random classification errors.

A comparison of methodologies is also in order given the diversity in the literature. Our trade informativeness methodology, which is based on Seasholes and Zhu (2010), is inclusive, conservative, and focuses on the economic significance in quantifying the overall impact of individual investors' trades on asset prices because it accounts for all trades and value-weights them. Other papers, such as Kaniel, Saar and Titman (2009), Kaniel et al. (2012), and Kelly and Tetlock (2012), focus on specific conditions or formulation of individual investor trades that generate higher stock returns prediction ability in the time series or in the cross-section such that

[15] The ASX and the Finnish Helsinki Stock Exchange are both consolidated limit order book markets. Both countries are small open economies with their own currencies and have significant institutional investor presence. These similarities provide a basis to extrapolate evidence between these markets as a first order approximation.

a substantial fraction of individual investors' trades are either netted out or unused for predicting returns. These methods also effectively equal weight observations or stocks; hence, small stocks have a relatively larger influence on the outcome in these methods than in our approach.

The alphas that we compute come from the return difference between value-weighted portfolios of buys and sells and before brokerage commissions.[16] They are positively correlated to, but are not directly comparable to, individual investors' portfolio returns in studies like Barber and Odean (2000, 2002). Individual investors buy more than they sell on average, such that the returns on their buys dominate their portfolio returns. In addition, computing statistics on individual household portfolios introduces a lot of cross-sectional correlations because the same stock-day enters the averaging process many times. The Seasholes and Zhu (2010) approach avoids this problem.

[16] Commissions are paid at the beginning and at the end of the trading horizon. Full-service brokers do not disclose their commission rate and we have no commission data at the transaction level. However, we can compute the breakeven one-way commission rate difference that full-service retail brokers may charge above the discount broker commission such that the mean alpha of trades via the two broker types would be equal. Based on the alphas differences reported in Table 4, Panel A, the breakeven additional one way commission for full-service retail brokers can be computed as $((1+\text{daily alpha})^{\text{horizon}}-1)/2$. This means 10.05 basis points at end-of-the-day horizon, 7.33 basis points at 1-day horizon, 21.25 basis points at 5-day horizon, 29.83 basis points at 10-day horizon, 40.66 basis points at 20-day horizon, and 40.3 basis points at the 3-month horizon. These are upper bounds of justifiable commission differences, as this calculation attributes all alpha differences to broker informational, execution, and other services. These breakeven commissions are not unreasonably large and there is room for future research regarding this area. An alternative source for trade informativeness difference is clientele differences such as motives and competence.

VII. Conclusion

We present systematic evidence that trades via full-service retail brokers are statistically and economically more informative than are trades via discount retail brokers on average, across time, and in various sub-samples. Our findings suggest that it is important to account for broker type in designing studies of individual investor trading and we should exercise caution in generalizing the results of a specific study of unknown broker type distribution relative to the population.

Our study also contributes to the literature by showing that the informativeness of individual investors' trades varies across horizons and in the cross-section. Individual investors' trades can be uninformative at intraday and long horizons, but informative at short horizons (5-20 days.) We observe this pattern in trades via both types of retail brokers for large stocks, where institutional investors dominate market turnover. We find that only trades via full-service brokers are informative at longer horizons (up to 1 year) in small stocks, where institutional investors' influence is lower. These results suggest that only a subset of individual investors' trades, specifically those via full-service retail brokers, consistently contribute to market information efficiency and their contribution increases as stock size decreases.

We believe that the relative effect of brokerage fee, brokerage service and clientele difference on trade informativeness is an interesting topic for future research. Another unexplored area is why and how individual investors use multiple brokers. These questions are outside the scope of our paper due to data limitations.

VIII. References

Barber, B. M., and T. Odean. "Trading is Hazardous to Your Wealth: The Common Stock Investment Performance of Individual Investors." *Journal of Finance*, 55 (2000), 773–806.

Barber, B. M., and T. Odean. “Online Investors: Do the Slow Die First?” *Review of Financial Studies*, 15 (2002), 455–488.

Barber, B. M., and T. Odean. “All That Glitters: The Effect of Attention and News on the Buying Behavior of Individual and Institutional Investors.” *Review of Financial Studies*, 21 (2008), 785–818.

Barber, B. M.; T. Odean; and N. Zhu. “Do Retail Traders Move Markets?” *Review of Financial Studies*, 22 (2009), 151–186.

Carhart, M. M. “On Persistence in Mutual Fund Performance.” *Journal of Finance*, 52 (1997), 57–82.

Dorn, D.; G. Huberman; and P. Sengmueller. “Correlated Trading and Returns.” *Journal of Finance*, 63 (2008), 885–920.

Feng, L., and M. S. Seasholes. “Correlated Trading and Location.” *Journal of Finance*, 59 (2004), 2117–2144.

Griffin, J. M.; J. H. Harris; and S. Topaloglu. “The Dynamics of Institutional and Individual Trading.” *Journal of Finance*, 58 (2003), 2285–2320.

Humphery-Jenner, M. L. “Optimal VWAP Trading Under Noisy Conditions.” *Journal of Banking and Finance*, 35 (2011), 2319–2329.

Jackson, A. “The Aggregate Behaviour of Individual Investors.” Working Paper, London Business School (2003).

Kaniel, R.; G. Saar; and S. Titman. “Individual Investor Trading and Stock Returns.” *Journal of Finance*, 63 (2008), 273–310.

Kaniel, R; S. Liu; G. Saar; and S. Titman. “Individual Investor Trading and Return Patterns around Earnings Announcements.” *Journal of Finance*, 67 (2012), 639–680.

Kelley, E. K., and P. C. Tetlock. "How Wise Are Crowds? Insights from Retail Orders and Stock Returns." *Journal of Finance*, forthcoming (2012).

Kumar, A., and C. M. C. Lee. "Retail Investor Sentiment and Return Co-movements." *Journal of Finance,* 61 (2006), 2451–2486.

Linnainmaa, Juhani. "Do Limit Orders Alter Inferences about Investor Performance and Behavior?" *Journal of Finance*, 65 (2010), 1473–1506.

Linnainmaa, J., and G. Saar. "Lack of Anonymity and the Inference from Order Flow." *Review of Financial Studies*, 25 (2012), 1414–1456.

Odean, T. "Do Investors Trade Too Much?" *American Economic Review*, 89 (1999), 1279–1298.

Seasholes, M., and N. Zhu. "Individual Investors and Location Bias." *Journal of Finance,* 65 (2010), 1987–2010.

Table 1. Summary Statistics of Market Turnover

This table reports the turnover velocity, total turnover, number of trades and average trade value of all trades on the ASX by year from 1995 to 2007. We refer to the buy (sell) side of a trade as a buy (sell) trade. We define turnover as the sum of the value of buy and sell trades divided by 2. We calculate turnover velocity as the average monthly turnover of domestic shares, divided by their average month-end's total market capitalization. We multiply average monthly figures by 12 to report the annualized value. The number of trades is the number of buy and sell trades divided by 2 and the average trade value is the turnover divided by the number of trades.

Year	Turnover Velocity (%)	Turnover (AUD bil)	No. Trades (mil)	Avg. Trade Value (AUD)
1995	33.9	120.5	2.9	41000
1996	40.6	169.2	4.3	39600
1997	43.9	212.5	5.4	39300
1998	45.1	245.8	6.2	39700
1999	48.3	308.0	9.7	31700
2000	54.2	390.0	13.8	28300
2001	68.2	487.1	12.9	37700
2002	75.1	552.3	13.6	40500
2003	80.4	582.2	15.8	36900
2004	81.6	756.0	18.6	40600
2005	88.9	973.6	26.0	37500
2006	94.4	1228.3	38.3	32100
2007	108.8	1804.9	69.4	26000
All	66.4	7830.2	236.9	33000

Table 2. Institutional and Individual Broker Count and Market Share by Year

This table presents the full sample and annual summary of the trade data between 1995 and 2007 from the ASX by broker type. We classify all brokers in the dataset into five categories: full-service retail, discount retail, institutional, mixed, and other. Section III describes the classification procedure. Panel A reports the number of brokers by broker type and Panel B reports the market share of turnover by broker type. We refer to the buy (sell) side of a trade as a buy (sell) trade. We define the market share of turnover of a type of broker as the sum of the value of buy and sell trades of a type of broker divided by the sum of the value of buy and sell trades of all brokers.

	Panel A. Broker Count						**Panel B. Market Share of Turnover (%)**				
Year	Full-service Retail	Discount Retail	Mixed	Institutional	Other	All	Full-service Retail	Discount Retail	Mixed	Institutional	Other
1995	44	4	24	10	10	92	11.85	0.70	59.57	23.26	4.63
1996	41	5	27	12	8	93	7.24	1.12	56.72	29.91	5.01
1997	42	6	24	14	8	94	6.55	1.41	44.07	43.53	4.44
1998	40	10	24	14	9	97	5.76	1.77	31.72	57.21	3.54
1999	34	11	23	16	9	93	6.35	3.69	32.87	54.80	2.29
2000	31	11	26	19	7	94	6.27	4.51	30.97	57.34	0.91
2001	31	13	27	19	7	97	4.70	3.85	31.70	58.29	1.46
2002	28	12	27	20	7	94	3.24	4.51	28.00	62.88	1.37
2003	21	10	28	18	11	88	2.57	5.96	27.76	62.14	1.56
2004	18	10	28	18	12	86	2.33	6.49	28.09	61.84	1.25
2005	19	11	30	18	8	86	2.31	7.77	27.76	61.04	1.12
2006	20	13	30	19	15	97	2.08	8.07	26.98	61.77	1.10
2007	19	12	30	22	16	99	1.79	8.12	26.35	62.44	1.30
All	57	21	49	36	40	203	3.22	6.22	29.65	59.33	1.59

Table 3. Turnover Distribution Across Stock Size and Broker Types

This table presents the dollar turnover distribution of trades by stock size and broker types. We form three stock size groups based on the prior month-end market capitalization in every month from January 1995 to December 2007: the largest 50 stocks, the 51st to 300th stocks, and stocks smaller than the 300th. Panel A shows the dollar turnover distribution of a stock size group across broker types where the percentages in Total Retail, Mixed, Institutional, and Unknown sum to 1. Panel B shows the dollar turnover distribution of a broker type across stock size groups where the percentages in Top 50, 51st-300 th and 300 th + sum to 1.

Panel A. Dollar Turnover Distribution of a Stock Size Group Across Broker Types

Size Group	Full-service Retail	Discount Retail	Total Retail	Mixed	Institutional	Unknown
Top 50	2.2%	4.4%	6.7%	27.7%	63.7%	2.0%
51 st -300 th	4.0%	7.7%	11.7%	33.6%	54.2%	0.5%
300 th +	15.2%	29.5%	44.6%	39.5%	15.3%	0.6%

Panel B. Dollar Turnover Distribution of a Broker Type Across Stock Size Groups

Size Group	Full-service Retail	Discount Retail	Total Retail	Mixed	Institutional	Unknown
Top 50	49.6%	50.0%	49.9%	65.5%	75.2%	89.5%
51 st -300 th	32.6%	32.3%	32.4%	29.6%	23.9%	9.0%
300 th +	17.8%	17.7%	17.7%	5.0%	1.0%	1.4%

Table 4. Transactions-Based Calendar-Time Buys-minus-Sells Portfolio Alphas of Brokers

This table presents the transactions-based calendar-time (TBCT) buys-minus-sells portfolio alphas of the trades via full-service retail and discount retail brokers. We refer to the buy (sell) side of a trade as a buy (sell) trade. We add the number of shares in each buy trade of a broker type to a "buys" portfolio daily and remove the same number of shares from the portfolio holdings after a fixed number of days. We construct the "sells" portfolio analogously and subtract the daily sells portfolio return from the daily buys portfolio return to form the TBCT buys-minus-sells portfolio return. We compute the alpha as the intercept in the regression of the buys-minus-sells portfolio return on the Carhart (1997) factors, i.e., market, size, value factors, and stock returns over the past 12 months. The dependent variable in the "Full-service minus Discount" alpha calculation is the buys-minus-sells portfolio return of trades via full-service retail brokers minus the return of trades via discount retail brokers. The sample covers all trades on the ASX from 1995 to 2007. Panel A reports the daily alpha in basis points at horizons ranging from End-of-the-day (i.e., each trade is held for a maximum of several trading hours) to 1 year. **,* denotes statistical significance at the 1 and 5 percent levels respectively. Panel B reports the Newey-West *t*-statistics with seven lags in parenthesis. Panel C summarizes the year-by-year results by reporting the number of years with positive buys-minus-sells alpha statistically significantly at least at the ten percent probability level minus the number of years with negative buys-minus-sells alpha statistically significantly at least at the ten percent probability level.

Panel A. Buys-minus-sells Daily Alpha (Basis Points)

Broker	End-of-the-day	1 day	5 day	10 day	20 day	3 month	6 month	1 year
Discount	-25.93**	-12.93**	-3.79**	-2.48**	-1.77**	-0.91**	-0.57*	-0.10
Full-service	-7.52**	1.07	3.53**	2.30**	1.28**	0.08	-0.26	-0.04
Full-service minus Discount	18.41**	14.00**	7.32**	4.78**	3.05**	0.99**	0.31	0.06

Panel B. *t*-statistics

Broker	End-of-the-day	1 day	5 day	10 day	20 day	3 month	6 month	1 year
Discount	(-38.69)	(-20.29)	(-7.35)	(-5.47)	(-4.60)	(-3.15)	(-2.45)	(-0.52)
Full-service	(-10.72)	(1.95)	(8.70)	(6.38)	(4.27)	(0.31)	(-1.29)	(-0.27)
Full-service minus Discount	(20.87)	(20.70)	(15.63)	(12.20)	(9.52)	(4.11)	(1.50)	(0.33)

Panel C. Number of Years with Significant Positive Returns Minus the Number of Years with Significant Negative Returns Over the 12 Years

Broker	End-of-the-day	1 day	5 day	10 day	20 day	3 month	6 month	1 year
Discount	-12	-12	-6	-2	-1	0	0	-3
Full-service	-11	2	9	6	4	0	0	0
Full-service minus Discount	12	12	12	11	9	5	2	2

Table 5. Transactions-Based Calendar-Time Buy-minus-Sell Portfolio Alphas of Brokers by Limit and Market Orders

This table presents the transactions-based calendar-time (TBCT) buys-minus-sells portfolio alphas of the trades via full-service retail and discount retail brokers by order type. We refer to the buy (sell) side of a trade as a buy (sell) trade. We add the number of shares in each buy trade of a broker type to a "buys" portfolio daily and remove the same number of shares from the portfolio holdings after a fixed number of days. We construct the "sells" portfolio analogously and subtract the daily sells portfolio return from the daily buys portfolio return to form the TBCT buys-minus-sells portfolio return. We compute the alpha as the intercept in the regression of the buys-minus-sells portfolio return on the Carhart (1997) factors, i.e., market, size, value factors, and stock returns over the past 12 months. The dependent variable in the "Full-service minus Discount" alpha calculation is the buys-minus-sells portfolio return of trades via full-service retail brokers minus the return of trades via discount retail brokers. The sample covers all trades affected on the consolidated electronic limit order book on the ASX from 1995 to 2007. We refer to the side of a consolidated electronic limit order book trade that initiated the trade as a market order trade and the other side of the trade as a limit order trade. Panel A reports the daily alpha of market order trades in basis points at horizons ranging from End-of-the-day (i.e., each trade is held for a maximum of several trading hours) to 1 year. We report the Newey-West *t*-statistics with seven lags in parenthesis. **,* denotes statistical significance at the 1 and 5 percent levels respectively. Panel B reports the results of limit order trades.

Panel A. Market Order Trades

Broker Type	Estimate	End-of-the-day	1 day	5 day	10 day	20 day	3 month	6 month	1 year
Discount	Alpha	-30.67**	-13.23**	-4.84**	-2.73**	-1.58**	-0.53	-0.25	0.93*
Full-service	Alpha	-12.35**	6.43**	4.20**	2.54**	1.34**	0.07	-0.24	0.13
Full-service minus Discount	Alpha	18.32**	19.66**	9.04**	5.27**	2.92**	0.60	0.01	-0.81
Discount	*t*-stat	(-43.99)	(-19.37)	(-9.02)	(-5.96)	(-3.98)	(-1.86)	(-1.03)	(2.24)
Full-service	*t*-stat	(-21.21)	(10.13)	(8.69)	(6.17)	(3.85)	(0.20)	(-0.91)	(0.47)
Full-service minus Discount	*t*-stat	(23.36)	(28.39)	(16.94)	(12.53)	(8.39)	(1.94)	(0.05)	(-1.92)

Panel B. Limit Order Trades

Broker Type	Estimate	End-of-the-day	1 day	5 day	10 day	20 day	3 month	6 month	1 year
Discount	Alpha	-19.91**	-12.51**	-2.64**	-2.01**	-1.89**	-1.44**	-0.97**	-0.43*
Full-service	Alpha	-2.24	-5.74**	1.44**	1.14**	0.58	-0.02	-0.33	-0.17
Full-service minus Discount	Alpha	17.67**	6.77**	4.07**	3.15**	2.47**	1.42**	0.63*	0.26
Discount	*t*-stat	(-22.87)	(-13.51)	(-3.94)	(-3.34)	(-3.94)	(-4.34)	(-3.69)	(-2.08)
Full-service	*t*-stat	(-1.60)	(-6.43)	(2.77)	(2.71)	(1.53)	(-0.06)	(-1.93)	(-1.34)
Full-service minus Discount	*t*-stat	(11.87)	(6.89)	(6.80)	(5.91)	(5.51)	(4.94)	(2.53)	(1.25)

Table 6. Transactions-Based Calendar-Time Buy-minus-Sell Portfolio Alphas of Brokers by Stock Size

This table presents the transactions-based calendar-time (TBCT) buys-minus-sells portfolio alphas of the trades via full-service retail and discount retail brokers by stock size. We group stocks by their market capitalization ranking in the prior month into Small (outside the top 300), Medium (ranked 51 to 300), and Large (the top 50). We refer to the buy (sell) side of a trade as a buy (sell) trade. We add the number of shares in each buy trade of a broker type to a "buys" portfolio daily and remove the same number of shares from the portfolio holdings after a fixed number of days. We construct the "sells" portfolio analogously and subtract the daily sells portfolio return from the daily buys portfolio return to form the TBCT buys-minus-sells portfolio return. We compute the alpha as the intercept in the regression of the buys-minus-sells portfolio return on the Carhart (1997) factors, i.e., market, size, value factors, and stock returns over the past 12 months. The dependent variable in the "Full-service minus Discount" alpha calculation is the buys-minus-sells portfolio return of trades via full-service retail brokers minus the return of trades via discount retail brokers. The sample covers all trades on the ASX from 1995 to 2007. Panel A reports the daily alpha in basis points at horizons ranging from End-of-the-day (i.e., each trade is held for a maximum of several trading hours) to 1 year. **,* denotes statistical significance at the 1 and 5 percent levels respectively. Panel B reports the Newey-West *t*-statistics with seven lags in parenthesis.

Panel A. Buys-minus-sells Daily Alpha (Basis Points)

Broker	Stock Size	End-of-the-day	1 day	5 day	10 day	20 day	3 month	6 month	1 year
Discount	Small	-48.06**	-30.10**	-13.02**	-8.26**	-5.35**	-2.48**	-1.63**	-0.65
	Medium	-30.33**	-15.38**	-4.52**	-3.21**	-2.66**	-1.39**	-0.92**	-0.64*
	Large	-12.23**	-2.43**	2.04**	1.31*	0.98*	0.26	0.31	0.21
Full-service	Small	9.62**	11.04**	6.18**	4.06**	2.21**	0.99**	0.45**	0.31*
	Medium	-13.63**	-2.50**	2.01**	1.27**	0.48	-0.34	-0.33	-0.32
	Large	-10.05**	1.00	3.60**	2.40**	1.23**	0.50	0.32	0.22
Full-service minus Discount	Small	57.67**	41.14**	19.19**	12.32**	7.56**	3.46**	2.08**	0.96**
	Medium	16.70**	12.88**	6.53**	4.49**	3.14**	1.05**	0.59	0.32
	Large	2.18	3.43**	1.56**	1.10**	0.25	0.24	0.01	0.01

Panel B. *t*-statistics

Broker	Stock Size	End-of-the-day	1 day	5 day	10 day	20 day	3 month	6 month	1 year
Discount	Small	(-33.50)	(-26.15)	(-14.93)	(-10.51)	(-8.38)	(-5.39)	(-4.14)	(-1.90)
	Medium	(-38.62)	(-19.48)	(-7.08)	(-5.64)	(-5.16)	(-3.60)	(-2.78)	(-2.20)
	Large	(-21.60)	(-3.55)	(3.43)	(2.41)	(2.06)	(0.68)	(0.95)	(0.74)
Full-service	Small	(11.02)	(14.31)	(12.05)	(9.93)	(7.24)	(4.87)	(2.70)	(2.40)
	Medium	(-24.42)	(-3.99)	(4.13)	(3.00)	(1.27)	(-1.18)	(-1.41)	(-1.76)
	Large	(-4.99)	(0.89)	(5.71)	(4.61)	(2.75)	(1.43)	(1.11)	(1.11)
Full-service minus Discount	Small	(32.85)	(29.49)	(19.73)	(14.39)	(10.96)	(7.22)	(5.10)	(2.65)
	Medium	(20.12)	(15.57)	(10.29)	(8.13)	(6.56)	(2.95)	(1.83)	(1.07)
	Large	(1.05)	(2.98)	(2.72)	(2.52)	(0.70)	(0.95)	(0.04)	(0.04)

Table 7. Determinants of Net Volume Traded by Broker Types

We group trades from 1995 to 2007 by broker type to calculate the net trading volume and estimate the following panel regression specification with stock-level fixed effects,

$$Netvol_{i,t} = a_i + b_1 LagNetvol_{i,t} + b_2 LagAbvol_{i,t} + b_3 LagAbvolDum_{i,t} + b_4 Volatility_{i,t} + b_5 VolaDum_{i,t} + b_6 LagReturn_{i,t} + b_7 LagBear_{i,t} + b_8 LagBull + b_9 News + e_{i,t}$$

The unit of observation is per stock *i* day *t*. Panel A lists the variable definitions. Panel B lists the regression estimates and *t*-stats using standard errors clustered by date. ** and * denotes statistical significance at the 1 and 5 percent levels respectively. We suppress the large number of stock specific intercept, a_i, and their corresponding *t*-statistic for presentation purposes.

Panel A. Regression Variable List

Variable	Name	Definition
Netvol	Net volume	The number of shares bought minus the number of shares sold by a broker type and scaled by the number of shares outstanding.
LagNetvol	Lagged net volume	One day lagged value of *Netvol*.
LagAbvol	Lagged abnormal volume	The lagged daily volume (unsigned total number of shares) over the previous one year's average daily volume.
LagAbvolDum	Lagged extreme volume	Equals one if the lagged daily volume is twice the standard deviation above the previous one year's average daily volume, 0 otherwise.
Volatility	Volatility	The absolute daily return on the current day.
VolaDum	Extreme volatility	Equals one if the daily volatility on the current day is two standard deviations higher than the average daily volatility in the

		previous year, 0 otherwise.
LagReturn	Lagged return	Lagged daily stock return.
LagBear	Lagged return is extremely negative	Equals one if the past day's stock return is two standard deviations or more lower than the previous one year's average daily return, 0 otherwise.
LagBull	Lagged return is extremely positive	Equals one if the past day's stock return is two standard deviations or more higher than the previous one year's average daily return, 0 otherwise.
News	News day	Equals one if the stock has at least one market sensitive news announcement on the ASX during the trading day or after trading hours on the previous trading day, 0 otherwise.

Panel B. Regression Estimates

Variables	Discount		Full-service	
	Coef ($x10^3$)	t-stat	Coef ($x10^3$)	t-stat
LagNetvol	276.44**	(10.04)	205.14**	(6.27)
LagAbvol	0.05**	(3.03)	0.00	(-0.10)
LagAbvolDum	-0.18	(-1.83)	-0.01	(-0.15)
Volatility	0.34**	(2.29)	0.02	(0.19)
VolaDum	-0.05**	(-3.06)	0.01	(1.32)
LagReturn	0.35**	(3.21)	-0.12	(-1.37)
LagBear	0.05**	(3.06)	0.00	(0.26)
LagBull	0.03**	(2.61)	-0.01	(-0.48)
News	0.15**	(11.79)	-0.01	(-0.93)
Observations	718,579		718,579	
Stocks	2,451		2,451	
Adj R^2	9.6%		4.5%	

Appendix A: Broker Classification Guide

This table lists the criteria used to classify brokers based on different data sources.

Broker Classification	Data Source	
	Broker Website or Archived Broker Website	Company Announcements, Newspapers, Books, papers, web articles
Discount Retail Broker	Site states brokerage costs (e.g. ‘trade from $19.95’) prominently and does not offer full-service or institutional sales.	States the broker is a discount broker, with no mention of the broker being institutional.
Full-Service Retail Broker	Site states the broker provides full-service or private client brokerage services and does not provide institutional sales.	States the broker is a full-service or private client broker.
Institutional	Provides only institutional or wholesale client (wealthy or high net worth individuals) brokerage services and does not provide full-service retail brokerage, or has a separate private client brokerage arm. Also includes proprietary trading desks and market makers.	States the broker is an institutional or wholesale broker.
Mixed	States that broker provides both full-service brokerage and institutional sales.	States that the broker has retail and institutional brokerage services.
Other	Clearing houses	Indeterminable brokers from articles or website.

Appendix B. Illustration of Transactions-Based Calendar-Time portfolio return calculation.

This table illustrates the mechanics of the transactions-based calendar-time portfolio methodology with an example of a 10-day buy portfolio with three buy trades. The sell portfolio can be defined analogously. There are two trades in stock A and one trade in stock B. The transaction date, size, and trade price are listed in the first five columns. Close Price represents the end of day price of the stocks. Daily Return is computed based on Close Price, dividend and capitalization adjustments. Holdings at Prior Close are the share holdings of the TBCT portfolio at the end of the previous day and they account for any new position generated in the previous day. The number of shares in new trades are included in the portfolio holdings for 10 full days. The TBCT Portfolio Base Value sum the Value of Holdings at Prior Close and the Value of New Trades. TBCT portfolio return is the value-weighted average of the Daily Return on Holdings at Prior Close and the return on the Value of New Trades computed as Close Price/Trade Price -1. For example, TBCT portfolio return on 960109 is (-0.61*58,800+80,000*(33.9/32.9-1))/(58,800+80,000)=0.0316. The portfolio formation period spans 10 days for a 10-day portfolio.

Date	Trade Size		Trade Price		Close Price		Daily Return		Holdings at Prior Close		Value of Holdings at Prior Close		Value of New Trades		TBCT Portfolio Base Value	TBCT Portfolio Return
	A	B	A	B	A	B	A	B	A	B	A	B	A	B		
960102	6,000		10.00		10.18	32.93							60,000		60,000	1.80%
960103					10.33	33.06	1.47%	0.40%	6,000		61,080				61,080	1.47%
960104					9.92	32.93	-3.97%	-0.39%	6,000		61,980				61,980	-3.97%
960105					9.99	32.87	0.71%	-0.18%	6,000		59,520				59,520	0.71%
960106					9.96	32.87	-0.30%	0.00%	6,000		59,940				59,940	-0.30%
960107					9.81	33.36	-1.51%	1.49%	6,000		59,760				59,760	-1.51%
960108					9.80	32.79	-0.10%	-1.71%	6,000		58,860				58,860	-0.10%
960109		2,500		32.00	9.74	33.90	-0.61%	3.39%	6,000		58,800			80,000	138,800	3.16%
960110					9.83	34.00	0.92%	0.30%	6,000	2,500	58,440	84,750			143,190	0.55%
960111					9.88	34.68	0.51%	2.00%	6,000	2,500	58,980	85,000			143,980	1.39%
960112					9.72	34.92	-1.62%	0.69%	6,000	2,500	59,280	86,700			145,980	-0.25%
960113	3,000		10.00		9.70	34.55	-0.21%	-1.06%		2,500		87,300	30,000		117,300	-1.56%
960114					9.48	35.09	-2.27%	1.56%	3,000	2,500	29,100	86,375			115,475	0.60%
960115					9.55	35.38	0.74%	0.83%	3,000	2,500	28,440	87,725			116,165	0.80%
960116					9.49	34.94	-0.63%	-1.24%	3,000	2,500	28,650	88,450			117,100	-1.09%
960117					9.34	34.81	-1.58%	-0.37%	3,000	2,500	28,470	87,350			115,820	-0.67%
960118					9.38	34.20	0.43%	-1.75%	3,000	2,500	28,020	87,025			115,045	-1.22%
960119					9.38	34.89	0.00%	2.02%	3,000	2,500	28,140	85,500			113,640	1.52%
960120					9.04	35.03	-3.63%	0.40%	3,000		28,140				28,140	-3.63%
960121					9.03	35.05	-0.11%	0.06%	3,000		27,120				27,120	-0.11%
960122					9.00	35.88	-0.33%	2.37%	3,000		27,090				27,090	-0.33%
960123					8.92	36.40	-0.89%	1.45%	3,000		27,000				27,000	-0.89%