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Limit Order Trading Behavior and Individual Investor Performance

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Using highly detailed data from a major Australian online broker, we investigate individual investors' limit order behavior and performance. We examine relative performance categorized by number and size of limit orders placed, and by proportion of orders that execute. We find that individuals who place the most orders and have the highest number of transactions enjoy higher returns than those with the fewest orders and transactions. The best performers have the highest proportion of orders execute and place smaller orders than the worst performers. These findings are robust after controlling for stock characteristics with the Fama and French [1992] factor model.

Behavioral finance acknowledges that human beings are not the rational, mean variance-optimizing automatons of modern financial theory. Systematic behavioral biases, as documented in psychological research, have led researchers to devise various theories of individual investment behavior and the resulting performance. This study investigates some of those theories in the context of online limit order trading. In particular, we consider the phenomenon of overconfidence.

Theoretical models of overconfidence in financial markets agree that it leads to higher trading levels than would otherwise be observed. Consequently, trading activity has been the conventional proxy used to measure overconfidence. However, there is an inconsistency in the models' predictions regarding investment performance. The models of DeLong et al. [1990] and Wang [2001], for example, predict that overconfident investors will earn higher returns than less confident ones. Gervais and Odean [2001], on the other hand, predict that the excessive transaction costs incurred by overconfident investors will impair their return performance. This inconsistency in theoretical models presents an opportunity for empirical evidence.

Although most existing studies focus on overconfidence in investment professionals, we generally expect individuals to display the greatest evidence of "irrational" behavior, as they will generally have less time, fewer resources, and a lack of experience and sophistication relative to professionals. Barber and Odean [2001] propose that overconfidence is likely to be quite prevalent among individual investors, based in part on their propensity to use the internet to obtain financial information. They theorize that the volume of information available may contribute to overconfidence by providing an illusion of knowledge and control.

In psychological research, Oskamp [1965] notes that having more information may mean that people's confidence increases more rapidly than the accuracy of their forecasts. Therein lies our motivation for examining the performance of individual investors at an online discount brokerage house for the effects of possible overconfidence.

Our study is distinct from others in that we consider a limit order market. This means we can consider frequency of order placement separately from transaction frequency. Placing an order thus forms a proxy for overconfidence, but the investor does not incur a transaction cost unless it executes. Furthermore, since limit order traders choose the price at which they are willing to trade, they can mitigate the spread component of transaction costs, although at the cost of possible non-execution and a heightened hazard of trading against more informed investors. Finally, we can observe the proportion of an investor's orders that are executed, and consider the correlation between proportion and the overconfidence trait. Our study examines the effects of these features on return performance.

There are theoretical arguments regarding the effect of execution probability on returns, but empirical evidence is scant. Cohen et al. [1981] argue that a higher probability of execution minimizes non-execution costs and allows investors to capitalize on their information. Verhoeven, Ching, and Ng [2003] similarly argue that returns will increase with execution probability as the costs of trading against more informed investors are minimized. By examining the performance of individuals according to the proportion of their orders that execute, we provide empirical evidence for these theories.

We find that behavioral characteristics systematically influence investment performance after control-

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ling for firm-specific factors using the Fama and French [1992] factor model. However, our evidence regarding the overconfidence hypothesis is inconclusive. Mean comparisons reveal that individuals who place the most orders and transactions earn higher returns after transaction costs than those who place the fewest orders and transactions. We find that individuals substantially underperform the market over the sample period. Our results support the arguments of Cohen et al. [1981] and Verhoeven, Ching, and Ng [2003] that a higher probability of execution improves returns.

The remainder of the paper is organized as follows. The second section discusses our expectations for the study and the previous literature motivating those expectations. The third section describes the data, and the fourth section details our three types of methodology. The fifth section gives our results, and the final section provides our conclusions.

Hypotheses and Previous Literature

Our study focuses on the relative performance of investors exhibiting specific behavioral characteristics. Because we expect that (relatively ill-informed) individual investors will underperform the market on average, we could consider the degree of underperformance. But data constraints inhibit our calculation of risk-adjusted returns using conventional asset pricing models. Moreover, the market declines for five of the six months in our data sample. Because buy (sell) limit orders are placed below (above) current market price, they only result in a trade when the price falls (rises). They are thus predisposed to underperform during bear markets. In addition, limit orders are subject to an adverse selection cost because they may execute in response to an informed trader's order.

Linnainmaa [2003] finds the likelihood, and cost, of adverse selection is larger for individuals, as they are less informed relative to institutions. He also finds this adverse selection cost to be larger during falling markets, as most private information is likely to be negative. Since our goal is to identify behavioral patterns that influence performance, we can avoid these concerns and compare the performance of investors exhibiting more or less of a specific behavior.

We examine the following characteristics for individual investors: the number of orders, the number of transactions, the proportion of orders that execute, and the average order size, where size is the number of shares rather than the dollar value. These characteristics, in various forms, have been considered in theoretical models of overconfidence.

As noted, some critics of behavioral finance argue that the poor performance of irrational traders will eliminate them from the market, but some argue that the aggressive trading behavior of overconfident traders could result in elevated profits. Kyle and Wang [1997] model overconfidence as an overestimation of the precision of one's own information, defining an overconfident trader as one whose distribution is too tight. At equilibrium, the overconfident trader trades more aggressively than his rational opponent, and consequently may realize a higher expected profit, surviving over the long run. In a dynamic, evolutionary model of overconfidence, Wang [2001] finds that underconfidence and excessive overconfidence cannot persist into the long run. However, moderate overconfidence can survive and may dominate rational behavior.

In Benos' [1998] model, traders are overconfident in their knowledge of the signals of others and in their interpretation of a noisy signal. The model predicts that their overconfidence will lead to increased trading volume, larger depth, greater volatility, and more informative prices, since investors place larger orders as a result of overestimating the precision of their observed signal. In this model, rational traders may be squeezed out of the market, because they fear pushing the price too far in one direction. Thus, there is a first-mover advantage for overconfident traders, and there is no incentive for these traders to be rational because that would lower their expected profits. These theoretical models allow for the possibility of successful overconfident traders.

Gervais and Odean [2001] develop a dynamic theoretical model of how an investor might become overconfident. In their model, investors learn of their ability through past successes and failures, and become overconfident by taking too much credit for the successes. Their model implies that overconfidence leads to higher trading volumes, a common prediction among overconfidence models, which has some empirical support.[1] Gervais and Odean's model differs in that it predicts overconfident traders will subsequently behave suboptimally, resulting in reduced expected profits. Empirical evidence appears to support this interpretation.

Odean [1999] examines the trading behavior of individuals at a discount brokerage house and cautiously concludes that individuals display excessive levels of trading, suggestive of overconfidence. Using a sample of trades, he finds that individual gross (of transaction costs) returns are reduced through trading, even after accounting for trading motivations like liquidity demands, tax loss selling, and portfolio rebalancing. We consider both gross and net returns for individual trades, expecting to find similar poor performance for active traders.

However, note that in a limit order market, investors placing the most orders may not incur the highest transaction costs, because all of those orders may not execute. If a major cause of the observed poor performance of overconfident investors is transaction costs, then performance should be determined by the number of orders that execute, not the number placed. Similarly, those individuals who incur the most transaction costs may not have been among the most active order placers. Instead, they may tend to place orders that are more likely to execute, because the orders are closer to the market price, or because the orders are for more liquid stocks. We believe it will be more interesting, and more meaningful, to compare the performance of individuals grouped by the proportion of their orders that leads to execution.

According to Verhoeven, Ching, and Ng [2003], there is an inverse relationship between the expected execution probability of a limit order and the adverse selection component. In Cohen et al.'s [1981] model, investors face a loss from unexecuted limit orders, because they miss the opportunity to profit from possibly valuable information. Together, these arguments suggest that individuals who place orders with a high probability of execution will earn higher gross returns than those who place orders that are unlikely to execute. However, the net performance of these individuals may suffer due to transaction costs.

A last factor we consider are the return implications of the size (by volume) of individuals' orders. Brown, Thomson, and Walsh [1999] find that informed traders on the ASX chose smaller orders relative to uninformed traders, which is consistent with the stealth trading hypothesis of Barclay and Warner [1993].[2] If they are acting on private information, investors who place smaller orders are likely to have superior performance. However, for our sample period there is a confounding factor. Large volume orders are likely to be placed on lower-priced stocks, which are often the smaller firms. Over our sample period, small firms performed much more poorly than larger firms. To isolate the effect of order size, we control for share price and the poor performance of small firms with a multivariate regression.

In summary, we expect that individual limit order traders will underperform the market over the sample period, but we do not focus on the degree of underperformance. Rather, we consider whether behavioral characteristics of investors affect their realized returns. This information may provide useful investment guidance for individual investors and their advisors.

Data

The primary data used for this study come from the account details of 31,113 customers at a large discount brokerage house in Australia over the period September 1, 2000, to February 27, 2001.[3] For each order, the relevant items within the data set are: account ID number; security ID; buy/sell indicator; order size, as measured by the number of shares; share price; brokerage fees; order date and time; expiration date and time; and order value. The brokerage variable identifies the commission charged by the broker if the order executes; active traders may receive a discount. With these data, it is possible to observe the investment decisions of the individual accountholders, and, equally significantly, their realized returns net of transaction costs.

We apply a number of filters to the original data set. We delete negative and zero price orders, as well as orders totalling less than $100. We limit our analysis to orders for common stock (omitting orders on preferred stocks and warrants, for example), in line with previous studies of individual investor performance such as Barber and Odean [2000]. We eliminate orders for which the market value of equity, β, and book-to-market ratios are not available from Datastream. Finally, orders that are placed by the brokerage house trading on their own account are deleted, as the intention is to isolate the trading behavior of individuals.[4] After also removing orders on suspended companies, our sample consists of 280,119 orders placed on 1,257 ASX listed stocks by 28,569 individuals.

Table 1 presents summary statistics of the order data. All the orders are grouped in Panel A. Panels B and C display statistics solely for buy and sell orders, respectively. The distributions of all the variables are positively skewed. Panels B and C reveal that slightly more buy orders (148,204) are placed than sell orders (131,915), and at a very similar average quantity. This is consistent with the findings of Verhoeven, Ching, and Ng [2003] and the expectations of Keim and Madhavan [1995]. The mean price of sell orders ($3.94) is higher than the mean price of buy orders ($3.42), resulting in a higher mean value of sell orders ($11,004) than of buy orders ($9,517). Other characteristics of buy and sell orders are very similar.

To identify which limit orders execute and become transactions, we observe the price of the stock during the interval between the placement of an order and its expiration. Approximately 47.51% (133,069) of the orders in the sample expire at midnight of the day of placement, 4.00% (11,218) expire at midnight of the trading day after order placement,[5] and 48.49% (135,824) expire within one month of placement. If the stock price rises (falls) through the sell (buy) limit price during the life of the order, the order will execute conditional on sufficient market depth and time priority. The daily high and low prices and trading volume for each stock in the sample on each day of the sample period come from Datastream.

We assume an order executes if its price is between the high and low prices for the stock during the period between placing an order and its expiration, provided the volume traded for that stock is sufficient to cover the order volume. This procedure identifies

Table 1. *Introduction: Descriptive Statistics of Order Data*

	Mean	Lower Quartile	Median	Upper Quartile	Standard Deviation
Panel A. All Orders — 280,119 Observations					
Quantity (no. of shares)	17,850	1,250	5,000	15,000	68,284
Price ($)	3.67	0.445	1.24	4	6.18
Order value ($)	10,217	2,720	5,254	10,750	37,266
Brokerage (%)	0.89	0.24	0.53	1.06	1.34
No. of orders	9.59	1	3	8	30.07
Panel B. Buy Orders – 148,204 Observations					
Quantity (no. of shares)	17,930	1,488	5,000	14,714	78,116
Price ($)	3.42	0.45	1.16	3.87	5.73
Order value ($)	9,517	2,760	5,100	10,230	16,694
Brokerage (%)	0.84	0.25	0.54	1.04	1.08
Panel C. Sell Orders – 131,915 Observations					
Quantity (no. of shares)	17,758	1,080	4,854	15,000	55,186
Price ($)	3.94	0.445	1.34	4.19	6.64
Order value ($)	11,004	2,680	5,475	11,300	51,330.15
Brokerage (%)	0.95	0.23	0.52	1.11	1.59

137,637 orders as having executed: 82,216 buy transactions and 55,421 sell transactions. At least one order executes for 22,145 individuals, and 17,078 individuals have at least one buy transaction. The percentage of buy (sell) orders that execute is 55.47% (42.01), again very similar to the findings of Verhoeven, Ching, and Ng [2003], who report values ranging from 47.79% to 56.05% for ASX limit orders. Table 2 shows summary statistics of the transaction data. Panel A shows all the transactions, Panel B includes only those resulting from a purchase order, and Panel C includes only sell (or ask) transactions.

From Panel A, the mean (median) number of transactions for an individual during the six-month period is 6.10 (2). The mean (median) transaction price is $3.98 ($1.45), for a quantity of 13,488 (4,000) shares, at a total value of $10,598 ($5,640), and incurs a brokerage fee that represents 0.84% (0.49%) of the mean (median) transaction. As with the order level data, the transaction data are positively skewed.

Panels B and C report statistics for buy and sell transactions separately. They reveal that the average sell transaction executes at a higher price and is of a smaller quantity but larger value than the average buy

Table 2. *Descriptive Statistics of Transaction Data*

	Mean	Lower Quartile	Median	Upper Quartile	Standard Deviation
Panel A. All Transactions — 137,637 Observations					
Quantity (no. of shares)	13,488	1,100	4,000	11,000	32,642
Price ($)	3.98	0.59	1.45	4.71	6.09
Order value ($)	10,598	2,937	5,640	11,450	18,164
Brokerage (%)	0.84	0.22	0.49	1	1.30
No. of transactions	6.10	1	2	5	18.89
Panel B. Buy Transactions — 82,216 Observations					
Quantity (no. of shares)	13,759	1,300	4,500	11,628	32,691
Price ($)	3.71	0.56	1.29	4.21	5.77
Order value ($)	10,081	2,950	5,460	10,881	17,592
Brokerage (%)	0.80	0.23	0.49	0.99	1.06
Panel C. Sell Transactions — 55,421 Observations					
Quantity (no. of shares)	13,088	1,000	3,900	10,000	32,566
Price ($)	4.38	0.65	1.78	5.56	6.51
Order value ($)	11,365	2,900	5,950	12,400	18,955
Brokerage (%)	0.89	0.20	0.47	1.01	1.60

Table 3. *Firm Data Descriptive Statistics*

	Sample Mean	ASX Mean	Lower Quartile	Median	Upper Quartile	Standard Deviation	No. of Obs.
Market Capitalization ($ millions)	489.46	496.89	71.3	492.6	2,878.2	7,225	82,216
β	1.12	1	0.87	1.11	1.31	0.35	82,216
Book-to-Market Ratio	1.15	0.91	0.39	0.74	1.25	3.55	82,216

transaction. Brokerage fees as a percentage of order value are very similar for buy and sell transactions.

Firm-specific data come from two sources: Dividends, the market value of each firm,[6] and beta[7] come from Datastream; book-to-market ratios (BTM) come from Aspect Financial. Table 3 presents summary statistics. Averages are calculated at the trade level, not at the firm level, to ensure consistency between interpretation of these statistics and the results. The mean (median) market capitalization of the firms is $489.46 million ($492.60 million), which is slightly smaller than the average of all ASX listed stocks of $496.89 million.[8] The average β of firms in the sample is 1.12, and the mean BTM of 1.15 is higher than the 0.91 average for all firms in the Aspect Financial database. The individuals in our sample apparently prefer small, high-β firms.

Returns on ASX market indexes form a naive benchmark of comparison for individual investor returns.[9] The All Ordinaries Index contains the largest 500 listed companies in Australia (by market capitalization), while the S&P/ASX 200, the benchmark for institutional investors, contains the top 200 companies by market capitalization. The S&P/ASX Small Ordinaries contains those companies listed in the S&P/ASX 300 index but not in the S&P/ASX 100. The S&P/ASX Small Ordinaries is included because of the investors' disproportionate preference for small-capitalization stocks.

Table 4 shows the monthly movements for these three Australian market indexes over the sample period, which corresponds to the downturn following the "dot-com" bubble. The total market was relatively flat, although slightly down, but the small-capitalization stocks suffered heavily, falling 9.07% over the six months.

The relatively short period covered by the sample limits our ability to calculate risk-adjusted returns according to standard asset pricing models. As such, judgments of individual investment performance are restricted to comparisons with the above market indexes. Again, we focus on the relative importance of an individual's investment behavior in determining returns, rather than the characteristics of the stocks in which they invest.

Methodology

Our goal is to determine the strength of the relationship between investment characteristics and observed returns. We use three different econometric techniques to overcome the limitations of any one approach. Furthermore, consistency between the results of the three methods adds to confidence in the results.

We calculate a number of variables from the raw data. Average order size (*OS*) is the average of the number of shares in all the orders placed by each individual. The proportion of an individual's orders that execute, *PX,* is measured as:

$$PX = \frac{number\ \ of\ \ transactions}{number\ \ of\ \ orders}.$$

The daily gross return on a transaction is calculated by dividing the log gross holding period return by the number of days in the holding period, as in Equation (1):

$$r_g = \frac{\ln\left(\dfrac{end\ \ price + dividend}{buy\ \ price}\right)}{h} \tag{1}$$

where *end price* is the price of the security taken on the last day of the sample, February 28, 2001, unless the

Table 4. *Monthly Movements of Australian Market Indexes*

	Period						
Index	Sept. 2000	Oct. 2000	Nov. 2000	Dec. 2000	Jan. 2001	Feb. 2001	Total
All Ordinaries	–1.44%	–1.36%	–0.07%	–2.31%	2.69%	–0.83%	–0.15%
ASX 200	–0.98%	–1.39%	–0.07%	–2.37%	2.47%	–0.83%	–0.15%
Small Ordinaries	–5.65%	–2.46%	–0.71%	–2.81%	3.01%	–2.22%	–9.07%

Note: Source: www.asx.com.au.

security is sold prior to this date; *dividend* is the future value (the value on the "end" day) of any dividends paid during the holding period; and *h* is the number of days in the holding period. The holding period return net of transaction costs is calculated as:

$$r_n = \frac{\ln\left(\dfrac{quantity \times (end\ \ price + dividend) - brokerage}{(quantity \times buy\ \ price) + brokerage}\right)}{h} \quad (2)$$

To account for the impact of market changes on shares, we evaluate net and gross market-adjusted returns against the three previously described Australian market indexes: the All Ordinaries Index, the ASX/S&P 200, and the ASX/S&P Small Ordinaries Index. We calculate market-adjusted returns by determining the return earned by each investor over the holding period, and then subtracting the return of a market index over the corresponding period.

Figure 1 reviews the variables of investor behavior and their hypothesized signs. To test our expectations, we use correlation coefficients, a comparison of means approach, and ordinary least squares regression. The description of empirical techniques proceeds from correlation coefficients through to the regression approach.

We test first for a relationship with Spearman rank correlation coefficients. This distribution-free test determines whether there is a monotonic relationship between two variables (*x, y*) without imposing a requirement of linearity. The Spearman coefficient of correlation is calculated by ranking the two variables separately, determining the differences between the ranks of both variables, $d = rank(X) - rank(Y)$, and then summing the squares of the difference in rank order of numbers, i.e., $\sum d^2$. The Spearman rank correlation coefficient is given as in Equation (3):

$$r_s = 1 - 6\sum \frac{d^2}{n(n^2-1)} \quad (3)$$

When the sample size, n, is greater than 30, r_s is approximately normally distributed with a mean of 0 and a standard deviation of $1/\sqrt{n-1}$. Thus, for $n > 30$, the test statistic is $z = r_s \times \sqrt{n-1}$, which can be approximated by a standard normal distribution.

Our second approach is to rank the individuals based on their observed characteristics, then again based on observed returns, and to conduct a comparison of means between the extremes. Accordingly, individuals are sorted into deciles in ascending[10] order based on:

1. The number of orders placed (NO),
2. The number of transactions executed (NT),
3. The proportion of orders executed (PX),
4. Order size, as measured by the number of shares (OS),
5. Gross return (r_g), and
6. Net return (r_n).

We then compare the mean values of gross and net return for the extreme (top and bottom) deciles.

We also attempt to determine the investment characteristics of the best-performing individuals. We sort the individuals into deciles based on gross and net returns, and compare the extreme deciles to identify the characteristics of the best- and worst-performing individuals. Consistency between the two ranking procedures (on the basis of investment characteristics first and returns second) would add to the robustness of the conclusions.

The comparison of means approach improves on the correlation coefficients because it uses the trend in mean returns across deciles to determine whether a particular characteristic affects returns. It may be that overconfidence, for example, only affects returns at the extremes of behavior. If the effect of any investment characteristic is subtle and only identifiable at the extremes, a comparison of means approach will detect the effect where other approaches may fail.

We use an unequal variance *t*-test as a comparison of means, and evaluate degrees of freedom according to Satterthwaite [1946]. We consider this method to be more effective because it does not enforce any assumption about the group variances, while a simple comparison of means would require the variances to be equal. The test statistic is formed as in Equation (4):

$$t = \frac{\bar{x}_1 - \bar{x}_2}{\sqrt{\dfrac{s_1^2}{n_1} + \dfrac{s_2^2}{n_2}}} \sim t(df_{Satterthwaite}) \quad (4)$$

which is approximated by a *t*-distribution with degrees of freedom as according to Equations (5) and (6):

$$df_{Satterthwaite} = \frac{(n_1-1)(n_2-1)}{(n_1-1)(1-c)^2(n_2-1)c^2} \quad (5)$$

FIGURE 1
Predicted Directional Effects of Investment Characteristics

Variable	Predicted Sign of Coefficient
Number of orders (NO)	Negative
Number of transactions (NT)	Negative
Proportion executed (PX)	Gross: positive, Net: negative
Order size (OS)	Negative

$$c = \frac{s_1^2/n_1}{s_1^2/n_1 + s_2^2/n_2} \tag{6}$$

where $\bar{x}_i$ = the mean of group i, s_i = the standard deviation of group i, and n_i = the number of observations in group i.

The comparison of means assumes that the two groups are independent and drawn from a normal distribution. This assumption should hold for samples as large as ours. For robustness, we also estimate the non-parametric equivalent, the Wilcoxon rank sum test, also known as the Mann-Whitney test, for two independent samples, although for large samples it yields almost exactly the same results. It uses the ranks of the data rather than their raw values to calculate the statistic. The test consists of combining the two samples into one sample of size $n_a + n_b$, sorting the result, assigning ranks to the sorted values, and letting T be the sum of the ranks for the observations in the first sample. If the two populations have the same distribution, the sum of the ranks of the first sample and the second sample should be similar. The test statistic, u, is calculated using Equation (7):

$$u_a = n_a n_b + \frac{n_a(n_a+1)}{2} - T_a \tag{7}$$

where T_a = the observed sum of ranks for sample A, and

$$n_a n_b + \frac{n_a(n_a+1)}{2}$$

is the maximum possible value of T_a.

As n_a and n_b increase, the sampling distribution of T_a is approximated by a normal distribution. This approximation is valid for n_a and n_b greater than ten, which is quite appropriate for samples as large as ours.

Ordinary least squares regression is perhaps the most obvious and flexible method to test for a relationship. Regression quantifies the direction and magnitude of the relationship between variables, adding significantly to the interpretation afforded by correlation coefficients. Multivariate regression controls for the effects of other variables in determining the significance of the variable of interest.

We begin with univariate regressions for both gross and net daily returns as the dependent variable, and each of the observed investor characteristics as the independent variable. The regressions are specified as in Equation (8):

$$y = \alpha_0 + \alpha_1 x + \varepsilon \tag{8}$$

where

$$y \in [r_g, r_n],$$

and

$$x \in [NO, NT, PX, OS],$$

NO is the total number of orders placed by each individual, NT is the total number of transactions that execute for each individual, PX is the proportion of orders executed, as defined in the previous section, and OS is the average size of orders placed by an individual, measured in number of shares.

To include variables like the total number of orders and transactions for each individual, we average all the values at the account level. We are primarily interested in the sign (and significance) of each investment characteristic coefficient. The univariate regressions are exposed to a possible omitted variable problem, however, as it is unlikely that an individual's return will be substantially explained by one characteristic. Therefore the models are likely to suffer from heteroscedasticity, so we estimate all results with heteroscedasticity robust standard errors according to the White [1980] estimator of variance.

We next use multivariate regressions to determine whether individual investment behavior affects investment performance after controlling for other factors. Again, we calculate heteroscedasticity robust standard errors. We estimate regression equations including all investment characteristics to determine the effect of each controlling for the effects of the others. However, since the proportion of orders executed (PX) is a function of two other variables (NO, NT), the regression should not include all three. To identify the effects of each of the variables, we specify the regressions as in Equation (9):

$$y = \alpha_0 + \alpha_1 x_1 + \alpha_2 x_2 + \alpha_3 OS \tag{9}$$

where

$$y \in [r_g, r_n]$$

$$(x_1, x_2) \in [(NO, NT), (NO, PX), (NT, PX)]$$

In this study, any univariate findings regarding overconfidence could be explained by investor preferences for high- or low-beta stocks. Consequently, it is important to control for systematic risk factors when investigating returns. Using the Fama and French [1992] factors, we estimate the following regressions, Equations (10) to (13) inclusive:

$$r_g = \alpha_0 + \alpha_1\beta \tag{10}$$

$$r_g = \alpha_0 + \alpha_1 \ln(MV) \tag{11}$$

$$r_g = \alpha_0 + \alpha_1 \ln(BTM) \tag{12}$$

$$r_g = \alpha_0 + \alpha_1\beta + \alpha_2 \ln(MV) + \alpha_3 \ln(BTM) \tag{13}$$

where β is a firm's beta, *MV* is the average daily market value of the firm over the six-month period, and *BTM* is the firm's book-to-market ratio.

Fama and French's [1992] results suggest that the coefficient for beta should be insignificant and the coefficients for BTM should be positive. Given the movement of the market over the sample period, where small-capitalization stocks underperformed, the coefficients of market value should also be positive. For comparison, we also estimate these same regressions using net returns as the dependent variable.

With the Fama and French [1992] factors, we can consider the impact of investment behavior on returns after controlling for the stock characteristics. To test the significance of individual investment characteristics, we estimate regressions that combine the Fama and French [1992] factors with individual investment characteristics. Again, we consider three permutations to avoid including the related variables *NO, NT,* and *PX*. In addition, we add the average price of an individual's transactions, denoted by *SP,* to the regression. We expect that larger volume orders are more likely to be placed on less expensive, small-capitalization stocks, so we must control for stock price to isolate this order size effect.

The regressions are specified as in Equation (14):

$$y = \alpha_0 + \alpha_1 x_1 + \alpha_2 x_2 + \alpha_4 OS + \alpha_5 SP + \alpha_6\beta + \alpha_7 \ln(MV) + \alpha_8 \ln(BTM) \tag{14}$$

where

$$y \in [r_g, r_n],$$

and

$$(x_1, x_2) \in [(NO, NT), (NO, PX), (NT, PX)]$$

In addition to controlling for stock characteristics, we determine whether the observed effects are caused by brokerage fees by comparing the regressions in which gross return is the dependent variable to those in which net return is the dependent variable.

In summary, we use three empirical techniques to test the significance of the hypothesized relationships between individual investment characteristics and returns. First, we calculate Spearman rank coefficients. Second, we categorize individuals into investment characteristic deciles and compare the means of extreme deciles using an unequal variance t-test and its non-parametric equivalent. We also evaluate the mean of each group to determine the presence of a trend across ordered groups. Finally, we estimate regression equations, adding the ability to control for other factors while determining whether investment characteristics significantly contribute to observed returns.

Results

The results presented for each test of the hypotheses represent the full sample of transactions for 17,078 individuals. They represent the return earned by an individual over the holding period from purchase date until February 28, 2001.[11] Table 5 presents market-adjusted returns calculated as the average daily return of an individual's buy transaction over its holding period, minus the corresponding average daily return of each of the three market indexes over the same period. These values are then averaged at the account level to obtain each individual's average market-adjusted return over the six-month period. Market-adjusted figures indicate individual performance after controlling for market movements, and are therefore a very simple measure of abnormal returns.

The values in Table 5 indicate that individuals experience negative returns on average. These values are significantly different from zero at all traditional significance levels (p-values = 0.000). Compared to broad-based market indexes like the All Ordinaries or the ASX/S&P 200, individuals experience even larger negative returns (all p-values = 0.000).

For example, the average individual's daily return gross of brokerage fees over the holding period underperforms the All Ordinaries Index by a substantial 14 basis points per day. Taking into account individuals' preferences for small-capitalization stocks, and therefore using the Small Ordinaries Index for comparison, individuals still significantly underperform, by 10 basis points per day in terms of gross return, and by 17 points per day after brokerage fees. Controlling for the falling market does not account for individuals' poor performance. Although data limitations restrict the estimation of returns according to recognized asset pricing models, it seems unlikely that controlling for risk in this manner could fully explain such substantial underperformance.

Table 6 presents Spearman rank coefficients, with p-values in parentheses. As illustrated in Appendix A, the variables are not normally distributed even for the

Table 5. *Estimates of Unadjusted and Market-Adjusted Returns*

The sample is comprised of account records for 28,569 individuals at a large discount brokerage firm. This table results for the 17,078 individuals with at least one buy transaction between September 1, 2000, and February 28, 2001. The variable r_g denotes daily log returns gross of brokerage fees; r_n denotes daily log returns net of brokerage fees. Unadjusted returns are the average returns earned by sampled individuals. Market-adjusted returns are calculated as the average daily return of individuals' buy transactions over their holding periods, minus the corresponding average daily return of one of three market indexes over the same period. The three market indexes used are the All Ordinaries Index (All Ords), the ASX/S&P 200 (ASX 200), and the ASX/S&P Small Ordinaries Index (Small Ords). The numbers in parentheses are p-values and test the null hypothesis that the mean is equal to zero.

	r_g		r_n	
Return Measure	**Mean**	**Median**	**Mean**	**Median**
Unadjusted	–0.1188% (0.000)	–0.0579%	–0.1821% (0.000)	–0.1037%
All Ords	–0.1374% (0.000)	–0.0742%	–0.2007% (0.000)	–0.1199%
ASX 200	–0.1373% (0.000)	–0.0742%	–0.2006% (0.000)	–0.1198%
Small Ords	–0.1040% (0.000)	–0.0391%	–0.1673% (0.000)	–0.0836%

Table 6. *Spearman Rank Coefficients of Correlation*

The sample is comprised of account records for 28,569 individuals at a large discount brokerage firm. This table presents results for the 17,078 individuals with at least one buy transaction between September 1, 2000, and February 28, 2001. *NO* is the number of orders placed by an individual during the sample period, *NT* is the number of transactions incurred, *PX* is the proportion of orders that executed, and *OS* is the average size of all orders placed by an individual, measured as the number of shares.

	Variable			
Return Measure	***NO***	***NT***	***PX***	***OS***
Average Gross Return	–0.0690 (0.000)	–0.0493 (0.000)	0.0466 (0.000)	–0.2102 (0.000)
Average Net Return	–0.0214 (0.006)	–0.0152 (0.052)	0.0118 (0.131)	–0.1359 (0.000)

full sample of 17,078 observations. Comparing the results for the two measures of return, gross and net, shows the effect brokerage fees have on the importance of each individual characteristic. Overall, rank coefficients suggest that the relationships between investment characteristics and returns are quite significant, as all variables have p-values equal to 0.000. These results suggest that gross return increases for individuals who place fewer orders, have fewer orders execute, have a higher proportion of orders execute, and place smaller orders.

Rank correlations for returns net of brokerage fees show very similar results, and again most coefficients are significant at the 1% level, with two exceptions. Correlation with the number of transactions for an individual is accepted at the 10% level of significance, and the coefficient on the proportion of orders executed for an individual is not statistically significant. These results suggest that returns net of transaction costs are higher for individuals who place fewer orders, have fewer transactions, and place smaller orders in terms of number of shares.

Our next test involves a comparison of means analysis, for which the results are presented in Table 7. We sort individual investors into deciles based on the four observed investment characteristics, *NO*, *NT*, *PX*, and *OS*, and compare the average net and gross daily returns of extreme deciles. We also observe the means of each decile to determine whether there is a linear trend.

Our results indicate that the most active order placers experience inferior gross returns and superior returns net of brokerage fees compared to the least active order placers. This result is counterintuitive, and quite surprising. It may be, however, that the more active order placers place larger dollar value orders, so that their brokerage fees represent a smaller percentage of order value.

To aid interpretation, Figure 2 graphically represents the mean daily net (r_n) and gross (r_g) returns for each decile sorted by number of orders (*NO*) in Panel A, the number of transactions (*NT*) in Panel B, the proportion of orders executed (*PX*) in Panel C, and the order size (*OS*) in Panel D. Panel A reveals a very weak, if any, linear relationship between *NO* and r_g or r_n. Instead, the relationship appears humped, where the best-performing individuals are in the seventh decile and place an average of approximately ten orders during the six months. The worst-performing individuals in terms of gross (net) return are at the extremes, where no group underperforms the most (least) active order placers.

The distribution of mean r_g and r_n for each group in Panel B reveals no precise linear relationship between the number of transactions for an individual and observed return. It appears that individuals with large numbers of transactions actually enjoy higher returns. However, after group 4, where the average individual has approximately 4.4 trades, returns decrease as more

Table 7. *Descriptive Statistics and Comparisons of Means for Individual Deciles Sorted by Investment Characteristics*

This table presents results for comparison of means tests. The sample is comprised of account records for 28,569 individuals at a large discount brokerage firm. This table presents results for the 17,078 individuals with at least one buy transaction between September 1, 2000, and February 28, 2001. Individuals are categorized into deciles in ascending order for each of four investment characteristics. Unequal variance t-tests and Wilcoxon rank sum tests test the null hypothesis that the difference in r_g and r_n for the top and bottom groups is equal to zero. The variables are defined as follows: *NO* is the number of orders placed by an individual during the sample period, *NT* is the number of transactions incurred, *PX* is the proportion of orders that executed, *OS* is the average size of all orders placed by an individual, measured as the number of shares, r_g is the daily log returns gross of brokerage fees, and r_n is the daily log returns net of brokerage fees. The numbers in parentheses are one sided *p*-values.

Panel A. Deciles Sorted by Number of Orders

Group	Obs.	r_g	r_n	*NO*	r_g	r_n
1	2,027	–0.00124	–0.00216	1	t-test *p*-value	
2	1,942	–0.00110	–0.00190	2	H_1: diff > 0	H_1: diff < 0
3	1,674	–0.00106	–0.00179	3	(0.000)	(0.069)
4	1,289	–0.00115	–0.00183	4		
5	1,959	–0.00125	–0.00189	5.45	Wilcoxon *p*-value	
6	1,451	–0.00105	–0.00167	7.47	(0.000)	(0.000)
7	1,555	–0.00100	–0.00153	9.95		
8	1,700	–0.00111	–0.00163	14.19		
9	1,802	–0.00124	–0.00171	23.72		
10	1,679	–0.00162	–0.00198	88.75		

Panel B. Groups Sorted by Number of Transactions

Group	Obs.	r_g	r_n	*NT*	r_g	r_n
1	6,809	–0.00123	–0.00198	1	t-test *p*-value	
2	3,265	–0.00118	–0.00187	2	H_1: diff > 0	H_1: diff < 0
3	1,802	–0.00106	–0.00164	3	(0.005)	(0.016)
4	1,988	–0.00101	–0.00157	4.4		
5	1,617	–0.00112	–0.00157	7.16	Wilcoxon *p*-value	
6	1,597	–0.00144	–0.00180	25.75	(0.000)	(0.000)

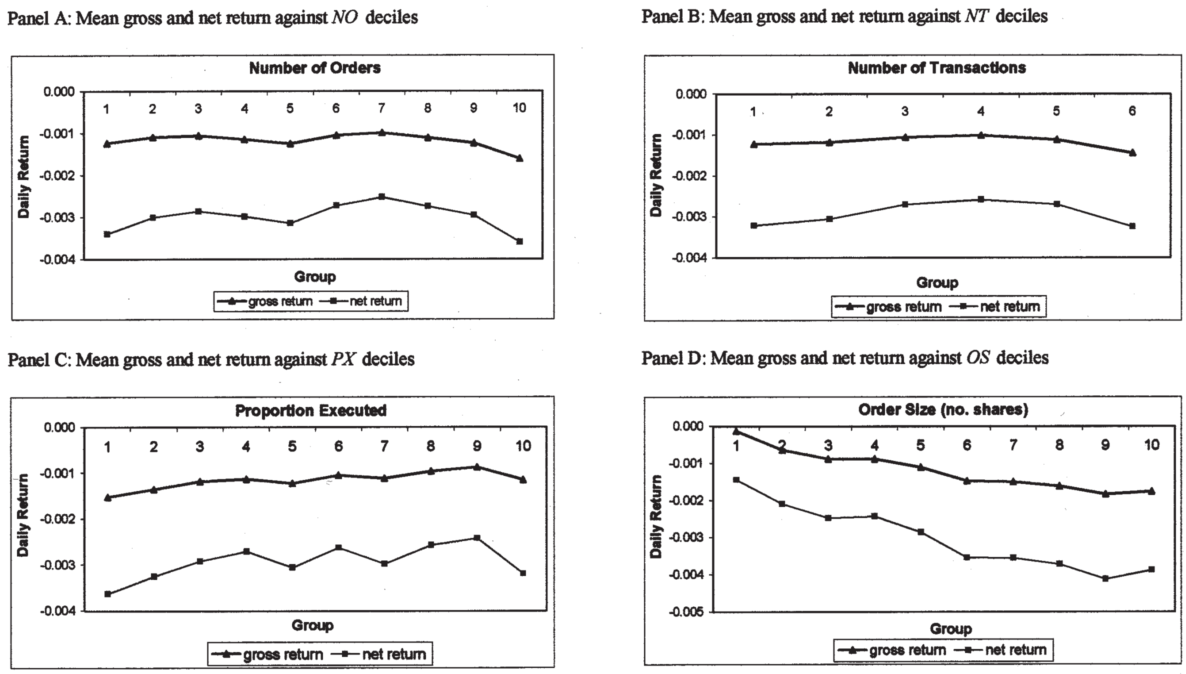
Panel C. Deciles Sorted by Proportion Executed

Group	Obs.	r_g	r_n	*PX*	r_g	r_n
1	1,735	–0.00153	–0.00210	0.1033	t-test *p*-value	
2	1,680	–0.00136	–0.00189	0.1819	H_1: diff > 0	H_1: diff < 0
3	1,708	–0.00119	–0.00173	0.2396	(0.003)	(0.336)
4	1,326	–0.00113	–0.00157	0.2906		
5	2,116	–0.00123	–0.00183	0.3419	Wilcoxon *p*-value	
6	1,464	–0.00105	–0.00157	0.4206	(0.000)	(0.028)
7	2,287	–0.00112	–0.00185	0.5000		
8	1,415	–0.00097	–0.00160	0.6257		
9	515	–0.00088	–0.00154	0.7678		
10	2,832	–0.00115	–0.00204	1.0000		

Panel D. Deciles Sorted by Order Size

Group	Obs.	r_g	r_n	*OS*	r_g	r_n
1	1,735	–0.00013	–0.00131	159	t-test *p*-value	
2	1,680	–0.00064	–0.00145	481	H_1: diff > 0	H_1: diff < 0
3	1,708	–0.00088	–0.00159	900	(0.000)	(0.000)
4	1,710	–0.00089	–0.00154	1,426		
5	1,706	–0.00112	–0.00174	2,205	Wilcoxon *p*-value	
6	1,708	–0.00148	–0.00206	3,405	(0.000)	(0.000)
7	1,708	–0.00151	–0.00204	5,247		
8	1,707	–0.00163	–0.00209	8,511		
9	1,708	–0.00184	–0.00228	15,031		
10	1,708	–0.00176	–0.00211	58,743		

FIGURE 2
Distribution of Mean Gross and Net Return Across Investor Groups



orders execute. Gross return is lower for individuals with the highest number of transactions. We expected that net return, rather than gross, would be reduced for heavy traders due to transaction costs. But perhaps those most active, overconfident traders trade on noise as if it were information, thus lowering their gross return. Theoretical models of overconfidence, however, do not consistently predict this outcome.[12]

We hypothesized that individuals would benefit from having a large proportion of orders execute. Our expectation is based on the arguments of Cohen et al. [1981], who emphasize minimizing non-execution costs, and on those of Verhoeven, Ching, and Ng [2003], who discuss adverse selection. Our results are consistent with these hypotheses, and suggest that individuals with the highest *PX* (proportion of orders executed) earn significantly higher returns than those with the lowest.

For the net return, the results are mixed: The Wilcoxon rank sum test is significant, while the standard *t*-test result is insignificant. However, the insignificance of the standard test could be a result of unusual characteristics of the high *PX* group, such as 100% of orders being executed because there was only one order for the sample period. If we substitute the penultimate decile for the highest, individuals with a higher *PX* enjoy significantly superior net performance compared to those with the lowest. These results, reinforced by Figure 2, are contrary to our expectation that having a higher *PX* would lower net return.

Our results support the hypothesis that individuals who place larger orders experience inferior return performance. The graph of mean r_g and r_n for each decile in Panel D of Figure 2 shows a strong linear relationship. Unequal variance *t*-tests reveal that individuals who place the largest volume orders experience significantly lower gross and net returns compared to those who place smaller volume orders. This result is in accordance with the findings of Brown et al. [1999] that more informed investors place smaller orders. However, it may also be the case that larger orders are likely to be placed on lower-priced stocks, usually small-capitalization stocks, which severely underperformed during the sample period. The multivariate regressions, reported later, separate these effects.

An alternative way of investigating the relationship between behavior and performance is to begin with the best- and worst-performing individuals and determine whether their behavior is systematically different. We sort individuals into deciles on the basis of observed net and gross returns and examine the distribution of the four investment characteristics. Table 8 presents the decile results and Figure 3 shows the distributions of each characteristic across the return deciles.

Figure 3 illustrates that the distribution of each investment characteristic over deciles formed on gross and net return are quite similar. Individuals experiencing the highest gross return over the sample period place the fewest orders and have the fewest orders execute of all the return deciles. They have close to the

Table 8. *Descriptive Statistics and Comparisons of Means for Individual Deciles Sorted by Net and Gross Daily Returns*

This table presents results for comparison of means tests. The sample is comprised of account records for 28,569 individuals at a large discount brokerage firm. This table presents results for the 17,078 individuals with at least one buy transaction between September 1, 2000, and February 28, 2001. Individuals are categorized into deciles in ascending order across gross (r_g) and net (r_n) returns. Unequal variance t-tests and Wilcoxon rank sum tests test the null hypothesis that the difference in investment characteristics between top and bottom groups is equal to zero. The variables are defined as follows: *NO* is the number of orders placed by an individual during the sample period, *NT* is the number of transactions incurred, *PX* is the proportion of orders that executed, *OS* is the average size of all orders placed by an individual, measured as the number of shares, r_g is the daily log returns gross of brokerage fees, and r_n is the daily log returns net of brokerage fees. The numbers in parentheses are one-sided *p*-values.

Panel A. Deciles Sorted by Gross Return

Group	Obs.	*NO*	*NT*	*PX*	*OS*	r_g
1	1,707	12.57	3.29	0.4394	12,268	–0.00881
2	1,708	24.06	6.45	0.4263	14,510	–0.00404
3	1,709	23.26	6.95	0.4314	14,196	–0.00242
4	1,707	19.21	5.70	0.4555	11,751	–0.00146
5	1,708	15.62	5.02	0.4716	9,599	–0.00083
6	1,708	16.55	5.35	0.4784	6,652	–0.00034
7	1,708	14.52	4.55	0.4884	5,843	0.00010
8	1,708	11.05	3.54	0.5120	4,793	0.00052
9	1,708	10.66	3.27	0.4690	6,510	0.00114
10	1,707	9.99	2.82	0.4392	9,987	0.00443
		H_1: diff > 0	H_1: diff > 0	H_1: diff > 0	H_1: diff > 0	
t-test *p*-value		(0.000)	(0.008)	(0.491)	(0.006)	
Wilcoxon *p*-value		(0.085)	(0.046)	(0.452)	(0.000)	

Panel B. Deciles Sorted by Net Return

Group	Obs.	*NO*	*NT*	*PX*	*OS*	r_n
1	1,707	11.59	3.10	0.4609	11,098	–0.01028
2	1,708	19.87	5.31	0.4366	12,743	–0.00479
3	1,708	22.71	6.74	0.4388	12,967	–0.00306
4	1,708	21.35	6.32	0.4633	11,593	–0.00201
5	1,708	16.29	5.14	0.4594	10,393	–0.00132
6	1,708	16.44	5.24	0.4832	8,293	–0.00079
7	1,708	15.62	4.89	0.4826	6,345	–0.00032
8	1,708	12.12	3.91	0.4904	5,424	0.00013
9	1,708	10.88	3.36	0.4739	6,258	0.00069
10	1,707	10.62	2.94	0.4221	10,996	0.00354
		H_1: diff > 0	H_1: diff > 0	H_1: diff > 0	H_1: diff > 0	
t-test *p*-value		(0.098)	(0.199)	(0.000)	(0.454)	
Wilcoxon *p*-value		(0.000)	(0.152)	(0.002)	(0.146)	

lowest proportion of orders executed of any decile (the third lowest out of ten), and place average size orders (the fifth highest).

Similarly, individuals in the top net return decile place the fewest orders and have the fewest transactions, consistent with the overconfidence hypothesis. They have the lowest proportion of orders execute and incur fewer brokerage fees. In addition, consistent with Barclay and Warner's [1993] stealth trading hypothesis, they tend to place medium-sized orders (the fifth largest out of ten deciles).

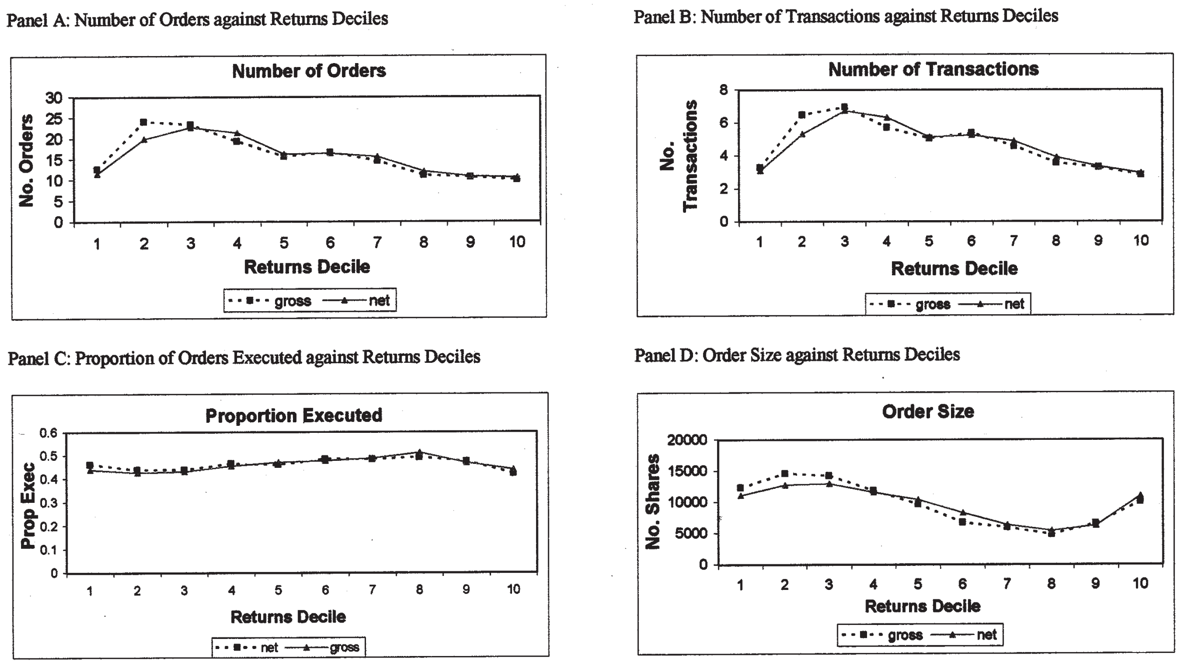
Individuals in the top gross return decile place significantly fewer orders, have fewer executions, and place smaller orders. However, the difference between the proportions of orders executed is not statistically significant, which suggests that a greater incidence of adverse selection is not necessarily a major contributor to the poorest-performing individuals.

In the case of net return, the top decile place marginally significantly fewer orders (one sided *p*-value = 0.098), and have a significantly lower proportion execute. Surprisingly, there is no significant difference in the number of transactions placed by individuals in the top and bottom return deciles, or in the size of the orders.

The final general empirical technique we used is ordinary least squares regression. Univariate regressions serve a similar purpose to the correlation coefficient approach: They identify relationships between gross (net) return and the observed investment characteristics of an individual.

Table 9 presents the results of the univariate regressions, with *p*-values in parentheses. In these gross re-

FIGURE 3
Distribution of Investment Characteristics Across Deciles Sorted by Gross and Net Returns



turn tests, all of the coefficients of investment characteristics are statistically significant at the 1% level, and all variables have the predicted signs. Interpreting each regression separately reveals that, holding all else constant, individuals who have the best performance place fewer orders, have fewer transactions, have a higher proportion of orders execute, and place smaller volume orders. Not surprisingly, explanatory power is very low: These investment characteristics viewed separately explain between 0.07% and 0.28% of the cross-sectional variation in individuals' gross returns. It is not feasible that a single behavioral characteristic would explain much of the observed cross-section of returns, particularly for the relatively undiversified portfolios we observe.

The results for net return also support our expectations. All coefficients are statistically significant at the 1% level, except the coefficient on the number of transactions for an individual, which is significant at the 5% level. As with gross returns, the better-performing individuals place fewer orders, incur fewer transaction costs, have a higher proportion of orders execute, and place smaller volume orders. Again, for the univariate models explanatory power is very low, with adjusted R^2 ranging from 0.01% to 0.12%. Somewhat surprisingly, given that brokerage fees have a consistent influence on returns, these values are lower than those of the corresponding gross return.

We estimate the Fama and French [1992] regressions as a base case against which regressions including investment characteristics can be compared. Our objective is to determine whether an individual's investment behavior contributes to the explanatory power of cross-sectional variation in return above that provided by market factors. We start with univariate regressions using gross and net return as the dependent variable, and beta (β), log of market value [*ln(MV)*], and log of book-to-market [*ln(BTM)*] as independent variables. We construct these variables by averaging company characteristics over an individual's observed portfolio. We then estimate a multivariate regression including all variables. Following Fama and French [1992], we expect that β will be insignificant, *ln(MV)* will be negative, and *ln(BTM)* will be positive. Table 10 provides the results of the univariate and multivariate Fama and French [1992] regressions.

The univariate regression results for both net and gross returns do not conform to Fama and French's [1992] results. The coefficient of β is statistically significant and negative, *ln(MV)* and *ln(BTM)* are positive, and all coefficients in the gross return regressions are significant at the 5% level. For the net return models, the results are similar, but *ln(BTM)* is no longer significant. However, during the relatively short period of analysis, the All Ordinaries Index fell by 0.15%. In a falling market, small, high-β firms would be expected to fall the furthest, so we would expect a negative coefficient on β and a positive coefficient on *ln(MV)*.

Table 11 gives the annual value-weighted returns over the previous twelve months of a portfolio of high-BTM firms minus a portfolio of low-BTM firms.[13] The high portfolio contains firms in the top

Table 9. *Univariate Regression Results*

This table presents results for the regressions as specified below. The sample is comprised of account records for 28,569 individuals at a large discount brokerage firm. This table presents results for the 17,078 individuals with at least one buy transaction between September 1, 2000, and February 28, 2001. The independent variables are defined as follows: *NO* is the number of orders placed by an individual during the sample period, *NT* is the number of transactions incurred, *PX* is the proportion of orders that executed, and *OS* is the average size of all orders placed by an individual, measured as the number of shares. The dependent variables are defined as follows: r_g is the daily log returns gross of brokerage fees, and r_n is the daily log returns net of brokerage fees. The numbers in parentheses are *p*-values based on White's [1980] heteroscedasticity robust standard errors.

$$y = \alpha_0 + \alpha_1 x + \varepsilon$$

$$y \in [r_g, r_n]$$
$$x \in [NO, NT, PX, OS]$$

Independent Variables	Dependent Variables							
	r_g	r_n	r_g	r_n	r_g	r_n	r_g	r_n
Constant	–0.00106 (0.000)	–0.00172 (0.000)	–0.00107 (0.000)	–0.00173 (0.000)	–0.00125 (0.000)	–0.00193 (0.000)	–0.00104 (0.000)	–0.00170 (0.000)
NO	–3.28E-06 (0.000)	–1.49E-06 (0.000)						
NT			–7.70E-06 (0.000)	–2.40E-06 (0.035)				
PX					0.00045 (0.001)	0.00063 (0.000)		
OS							–7.81E-07 (0.000)	–4.13E-07 (0.008)

Table 10. *Fama and French [1992] Regressions*

This table presents results for the regressions heading each pair of columns. The sample is comprised of account records for 28,569 individuals at a large discount brokerage firm. These results are for the 17,078 individuals with at least one buy transaction between September 1, 2000, and February 28, 2001. The independent variables are defined as follows: $b$is the monthly average of a firm's b during the sample period, *ln(MV)* is the natural log of average daily market value of equity, and *ln(BTM)* is the natural log of the average of 2000 and 2001 reported values of book value of equity divided by the market value of equity. The dependent variables are defined as follows: r_g is the daily log returns gross of brokerage fees, and r_n is the daily log returns net of brokerage fees. The numbers in parentheses are *p*-values based on White's [1980] heteroscedasticity robust standard errors.

Independent Variables	Dependent Variables							
	$r = a_0 + a_1\beta$		$r = a_0 + a_1 \ln(MV)$		$r = a_0 + a_1 \ln(BTM)$		$r = a_0 + a_1\beta + a_2 \ln(MV) + a_3 \ln(BTM)$	
	r_g	r_n	r_g	r_n	r_g	r_n	r_g	r_n
Constant	0.00118 (0.000)	0.00048v (0.000)	–0.00166 (0.000)	–0.00258 (0.000)	–0.00105 (0.000)	–0.00174 (0.000)	0.00057 (0.000)	–0.00042 (0.006)
β	–0.00205 (0.000)	–0.00199 (0.000)					–0.00209 (0.000)	–0.00206 (0.000)
ln(*MV*)			7.55E-05 (0.000)	1.15E-04 (0.000)			8.48E-05 (0.000)	1.23E-04 (0.000)
ln(*BTM*)					6.31E-05 (0.046)	7.21E-06 (0.834)	4.23E-05 (0.157)	–8.96E-05 (0.012)

Table 11. *Annual Returns on Portfolios of High- and Low-BTM Firms*

Portfolio	Return in Year Ending					
	Sept. 2000	**Oct. 2000**	**Nov. 2000**	**Dec. 2000**	**Jan. 2001**	**Feb. 2001**
High-BTM	–9.07%	–3.24%	5.35%	9.6%	–0.25%	–5.97%
Low-BTM	–8.55%	–1.15%	2.84%	5.27%	2.38%	–6.79%

30% of BTM; the low portfolio contains firms in the bottom 30%. The high portfolio outperforms the low portfolio in three of the six periods, so a positive coefficient is not unexpected.

The multivariate regression reveals that a portfolio's return is significantly inversely related to β and significantly directly related to the firm's market value within the portfolio. The book-to-market coefficient in the gross return model is insignificant. However, in the net return regression, the coefficient on *ln(BTM)* is significant at the 5% level. Brokerage fees may contribute some systematic component of variation, where previously the data were stochastic in nature. The adjusted R^2 values of 3.81% and 3.43% will be compared to the explanatory power of the models that include investment characteristics.

We estimate multivariate regressions, initially including only investment characteristic variables, and then adding the Fama-French factors. To avoid multicollinearity, the variables *NO*, *NT*, and *PX* are not included in the same model. These results are reported in Table 12. We again estimate robust standard errors according to White [1980], and report *p*-values in parentheses.

All coefficients for the gross return models are statistically significant at the 1% level. Together, the three estimated models consistently show that individual gross returns are higher for those who place fewer orders, have a higher proportion of orders execute, and place smaller volume orders.[14] The reliably negative constant suggests that individuals suffer negative returns on average over the sample period. Explanatory power is again low, with between 0.35% and 0.42% of cross-sectional variation in returns explained by investment behavior.

The results for the net return regressions reveal broadly similar results. All coefficients across the three models are significant at the 10% level. These regressions show that individuals with higher net returns place fewer orders, have a greater proportion of orders execute, and place smaller volume orders.

Perhaps the real test of the importance of individual investors' observed investment characteristics is whether they add any insight beyond those factors identified by Fama and French [1992]. To determine their relative importance, we include the investment characteristic variables in regressions with the Fama and French factors. We also include the average individual transaction price as a variable to isolate the effects of order size (*OS*). Table 13 gives the results.

The full sample results reveal that including investment characteristic variables adds substantially to the explanatory power of the regression model. The adjusted R^2 increases from 3.81% for the regression with only the Fama-French factors to approximately 5.6% for the full model, an increase of nearly 50%. The coefficients of the variables *NO, NT, PX*, and *OS* are significant at the 5% level. The coefficients of the

Table 12. *Multivariate Regression Results*

This table presents results for the regressions as specified below. The sample is comprised of account records for 28,569 individuals at a large discount brokerage firm. These results are for the 17,078 individuals with at least one buy transaction between September 1, 2000, and February 28, 2001. The independent variables are defined as follows: *NO* is the number of orders placed by an individual during the sample period, *NT* is the number of transactions incurred, *PX* is the proportion of orders that executed, and *OS* is the average size of all orders placed by an individual, measured as the number of shares. The dependent variables are defined as follows: r_g is the daily log returns gross of brokerage fees, and r_n is the daily log returns net of brokerage fees. The numbers in parentheses are *p*-values based on White's [1980] heteroscedasticity robust standard errors.

$$y = \alpha_0 + \alpha_1 x_2 + \alpha_2 x_2 + \alpha_3 OS$$

$$\text{where } y \in [r_g, r_n]$$
$$(x_1, x_2) \in [(NO, NT), (NO, PX), (NT, PX)]$$

	Dependent Variables					
Independent Variable	r_g	r_n	r_g	r_n	r_g	r_n
Constant	–0.00100	–0.00174	–0.00114	–0.00191	–0.00110	–0.00192
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
NO	–6.64E-06	–4.99E-06	–2.72E-06	–1.58E-06		
	(0.000)	(0.001)	(0.000)	(0.000)		
NT	1.33E-05	1.32E-05			–6.37E-06	–2.17E-06
	(0.004)	(0.002)			(0.000)	(0.063)
PX			0.00012	0.00023	0.00018	0.00019
			(0.003)	(0.050)	(0.008)	(0.098)
OS	–7.21E-09	–3.80E-09	–7.21E-09	–4.14E-09	–7.35E-09	–4.27E-09
	(0.000)	(0.016)	(0.000)	(0.009)	(0.000)	(0.007)
Adj. R^2	0.42%	0.25%	0.39%	0.32%	0.35%	0.31%

Table 13. *Combined Investment Characteristics and Fama-French Regressions*

This table presents results for the regressions as specified below. The sample is comprised of account records for 28,569 individuals at a large discount brokerage firm. This table presents results for the 17,078 individuals with at least one buy transaction between September 1, 2000, and February 28, 2001. The independent variables are defined as follows: *NO* is the number of orders placed by an individual during the sample period, *NT* is the number of transactions incurred, *PX* is the proportion of orders that executed, *OS* is the average size of all orders placed by an individual, measured as the number of shares, *SP* is the average price of an individual's transactions, *b* is the monthly average of a firm's *b* during the sample period, *ln(MV)* is the natural log of average daily market value of equity, and *ln(BTM)* is the natural log of the average of 2000 and 2001 reported values of book value of equity divided by the market value of equity. The dependent variables are defined as follows: r_g is the daily log returns gross of brokerage fees, and r_n is the daily log returns net of brokerage fees. The numbers in parentheses are *p*-values based on White's [1980] heteroscedasticity robust standard errors.

$$y = \alpha_0 + \alpha_1 x_1 + \alpha_2 x_2 + \alpha_4 OS + \alpha_5 SP + \alpha_6 \beta + \alpha_7 \ln(MV) + \alpha_8 \ln(BTM)$$

$$\text{where} \quad y \in [r_g, r_n]$$
$$(x_1, x_2) \in [(NO, NT), (NO, PX), (NT, PX)]$$

Independent Variables	Dependent Variables					
	r_g	r_n	r_g	r_n	r_g	r_n
Constant	0.00044	–0.00068	0.00055	–0.00036	0.00054	–0.00037
	(0.004)	(0.000)	(0.001)	(0.043)	(0.001)	(0.039)
NO	–3.52E-06	–1.85E-06	–2.01E-06	–1.08E-06		
	(0.007)	(0.007)	(0.000)	(0.000)		
NT	6.28E-06	5.29E-06			–4.54E-06	–1.08E-06
	(0.098)	(0.077)			(0.000)	(0.000)
PX			0.00021	0.00059	0.00032	0.00056
			(0.055)	(0.004)	(0.013)	(0.000)
OS	–3.43E-09	7.11E-10	–3.61E-09	2.79E-10	–3.72E-09	1.73E-10
	(0.027)	(0.653)	(0.020)	(0.859)	(0.016)	(0.921)
SP	8.50E-05	9.30E-05	8.60E-05	9.80E-05	8.70E-05	9.80E-05
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
β	–0.00205	–0.00203	–0.00207	–0.00206	–0.00207	–0.00206
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
ln(MV)	5.30E-05	9.59E-05	5.22E-05	9.27E-05	5.08E-05	9.09E-05
	(0.003)	(0.000)	(0.004)	(0.000)	(0.005)	(0.000)
ln(BTM)	2.41E-05	7.40E-05	2.57E-05	7.80E-05	2.34E-05	7.53E-05
	(0.257)	(0.041)	(0.257)	(0.032)	(0.279)	(0.038)
Adj. R^2	5.68%	5.14%	5.70%	5.30%	5.67%	5.29%

Fama-French factors are similar to those presented earlier, i.e., β is significantly negatively related to returns, *ln(MV)* is significantly positively related, and *ln(BTM)* is insignificant.

The investment characteristic coefficients show that, after controlling for the Fama-French factors, individuals who place fewer, smaller orders and have a higher proportion of orders execute enjoy the highest returns. Interpretation of the *NT* coefficient is again clouded by the high degree of collinearity with *NO*. However, after controlling for the number of orders that individuals place, it appears that the more transactions that execute on their behalf, the better their investment performance.

The net return regressions provide further support for the relevance of investment behavior characteristics in predicting returns. Explanatory power increases with the addition of these factors, and the adjusted R^2 value increases from 3.43% to approximately 5.3%. All the coefficients of *NO, NT,* and *PX* are significant at the 10% level. The size of an order, significant in the gross return models, has no significant effect on net return. Apparently, once we control for the effect of brokerage fees, the greater informativeness of smaller orders identified by Brown, Thomson, and Walsh [1999] no longer contributes positively to net returns. A possible explanation is that informed traders may use smaller orders, and if they tend to be lower-value orders, brokerage fees may make up a significant percentage of order value and reduce net returns. While gross return may be superior for smaller orders, the effect of transaction costs may render the effect of order size on net return insignificant.

The coefficients reveal that returns net of transaction costs are higher for individuals who place fewer orders and have a higher proportion execute after controlling for the characteristics of the stocks in which they invest. Order size has no effect on net return. After controlling for the effect of *NO*, *NT* appears to be positively related to an individual's observed return. This finding, while contrary to expectations, is consistent across the gross and net return coefficients.

Conclusion

Our aim was to discover any relationship between discount brokerage investor behavior characteristics and their return performance. We used several analytical methods, including Spearman rank correlation coefficients, difference of means tests, univariate regressions, and multifactor models, to add confidence to our results and overcome the shortfalls of any one technique.

In general, individuals' observed holding period returns within the interval were substantially and significantly negative, even after controlling for the downward trend in the market. Most overconfidence models predict that the transaction costs incurred from excessive trading will cause overconfident investors to underperform less confident investors. Our tests reveal mixed results. Correlation coefficients suggest a negative relationship between the number of orders and transactions for individuals and observed returns, in line with overconfidence model predictions. The univariate regressions indicate a significant negative coefficient for the number of orders placed. However, mean comparisons showed that the most active order placers experienced higher returns than the least active, and also showed no clear linear relationship between the number of orders placed and the returns net of brokerage fees.

Multivariate regression results are clouded by multicollinearity. However, after controlling for those effects, the number of orders placed, the number of actual transactions, and the net returns appear to be positively related. Our results do indicate that transaction costs are not the major reason for poor performance of frequent traders.

We find that investors who place orders with a high probability of execution experience superior gross returns. Spearman correlation coefficients suggest that the positive relationship between the proportion of investors' orders that execute and their returns gross of brokerage fees is statistically significant. Mean comparisons reveal that individuals with the highest proportion of orders that execute experience higher gross returns, and the relationship appears to be linear. Univariate and multivariate regressions found a statistically significant positive relationship, confirming that having a higher proportion of orders execute leads to a higher gross return. Moreover, the regression results also indicate that investors who have more executed orders earn a higher net return, although the correlation coefficient and mean comparison results were not statistically significant.

We found that investors who place smaller volume orders earn higher gross returns, in line with similar previous studies. However, when we consider transaction costs and control for Fama-French factors with the multivariate regressions, order size has no significant effect on returns.

Most work in behavioral finance focuses either on 1) applying cognitive psychology principles to the investor decision making process, and thereby identifying systematic errors that deviate from rationality, or 2) modeling the asset price discovery process in the presence of investors who are subject to these errors. In contrast, we choose observable behaviors, including the frequency with which investors place orders, the proportion of their orders that actually become transactions, and the size of their orders, and correlate those behaviors with relative return performance, both net and gross of brokerage fees. This approach may suggest an additional avenue for behavioral finance research.

Notes

1. Statman and Thorley [1998] find that trading volume is greatest after market gains, when Gervais and Odean [2001] predict overconfidence to be the greatest.
2. Barclay and Warner [1993] find that medium-sized orders contain the most information as measured by the price impact of a trade.
3. The authors thank the Capital Markets Collaborative Research Centre (CMCRC) for access to these data.
4. Aitken, Garvey, and Swan [1995] estimate that up to 33% of all brokers' trades on the ASX involve trading on their own account or taking part of an order to complete a deal.
5. All the orders that expire at midnight of the next day are placed after the close of trading, and therefore have a life of one trading day. Thus, slightly more than half the orders in the sample are day orders.
6. Market value is calculated as the average daily market value of the firm in millions over the sample period.
7. Beta is calculated as the average monthly beta during the six-month sample period. Datastream betas are calculated according to the method recommended by Cunningham, using the equation $y = ax\beta$, where y represents movement in a security, x represents movement in the market, and a and β are coefficients.
8. The source for the data is www.asx.com.au.
9. Accumulation indexes are used in each case because they include dividends, which provide consistency between index returns and individuals' returns.
10. Sorting in ascending order means that, for example, the least active order placers are in the first group and the most active are in the final group. A similar distribution applies to other variables.
11. We carried out the same empirical analysis on round-trip trades. A round-trip trade is defined as an individual buying and selling the same stock within the six-month sample period. In this data set, there were 1,580 round-trip trades from orders placed by 607 individuals. The round-trip results are not reported here for reasons of brevity, as they are not significantly different from the full sample results.

12. The model of DeLong et al. [1990] predicts that by trading on noise, overconfident investors bear higher risk and consequently earn higher returns.
13. Portfolios constructed by Kenneth French, available at http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html as of 10/09/03.
14. The coefficient on *NT* is positive in one model where *NO* is included, but negative in the model when NO is excluded. A high degree of correlation between the variables *NO* and *NT* may be a concern, so we present a correlation matrix of all the variables in Appendix A. Indeed, *NO* and *NT* are highly correlated, with a coefficient of 0.9216. No other correlations pose a concern, as they are all below absolute values of 0.2. It thus appears that collinearity between *NO* and *NT* distorts the regression.

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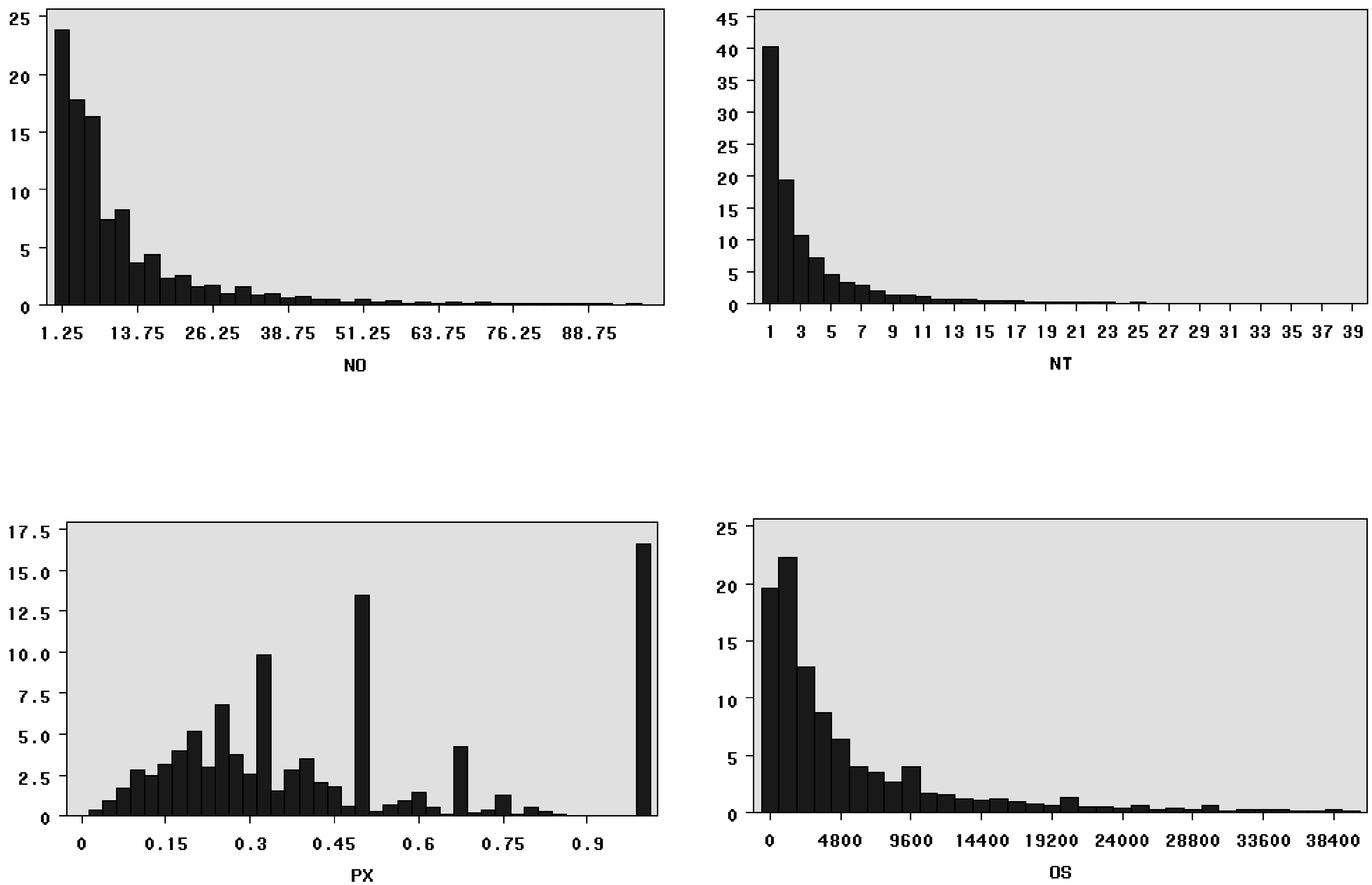
APPENDIX A
Distributions of Investment Characteristics



Note: NO is the number of orders placed by an individual, *NT* is the number of transactions incurred, *PX* is the proportion of orders that executed, and *OS* is the average size of all orders placed by an individual, measured as the number of shares.