Overreaction to Stock Market News and Misevaluation of Stock Prices by Unsophisticated Investors: Evidence from the Option Market*

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Overreaction to Stock Market News and Misevaluation of Stock Prices by Unsophisticated Investors: Evidence from the Option Market

This paper examines option activity on value and growth stocks before earnings announcements. The main finding is that unsophisticated investors enter option positions that load up on growth stocks relative to value stocks in the days leading up to earnings announcements. This occurs despite the fact that at earnings announcements value stocks outperform growth stocks by a wide margin. The paper's results provide evidence that unsophisticated option market investors (1) overreact to past news on underlying stocks and (2) mistakenly believe that mispriced stocks will move even further away from fundamentals at impending scheduled news releases.

One important line of stock market research maintains that growth stocks are overpriced relative to value stocks and that the mispricing is generated by unsophisticated investors overreacting to periods of mostly good or bad news about firms (e.g., DeBondt and Thaler (1985) and Lakonishok, Shleifer, and Vishny (1994)). If such overreaction is actually occurring, then trading between sophisticated and unsophisticated investors produces value and growth stock prices that settle in between their fundamental values and those which seem correct to the unsophisticated investors. Consequently, unsophisticated investors will believe (counterfactually) that growth stocks are underpriced relative to value stocks. As a result, they will expect that when important information is released about firms and the mispricing is at least partially corrected, growth stocks will experience higher returns than value stocks. A testable implication of this story is that in the days leading up to the pre-scheduled release of important information about firms, unsophisticated investors will increase their bets on growth stocks relative to value stocks.

The primary goal of this paper is to test this implication by examining the pre-earnings announcement trading of three classes of option investors: firm proprietary traders (e.g., employees of Goldman Sachs who trade options for the bank's own account), customers of full-service brokers (e.g., investors who trade options through Merrill Lynch), and customers of discount brokers (e.g., investors who trade options through Etrade). We maintain that firm proprietary traders are the most sophisticated option market participants, full-service customers have an intermediate level of sophistication, and discount customers are the least sophisticated. Later in the paper we will provide arguments, including results from previous empirical studies, which support this characterization of option market investor sophistication.

Our main result is that the least sophisticated discount customers increase their long option market positions on growth stocks relative to values stocks in the days leading up to earnings announcement dates (EADs), while the more sophisticated investors do not. The behavior of the discount customers is particularly striking, because at EADs value stocks outperform growth stocks by a wide margin (LaPorta, Lakonishok, Shleifer, and Vishny (1997)).

The behavioral view that the superior returns to value stocks arise from investor overreaction is controversial, and our findings provide valuable evidence for the debate. Fama and French (1992,1993) argue that the returns to value stocks constitute rational compensation for risk in accordance with the Merton (1973) intertemporal capital asset pricing model. Daniel and Titman (1997), however, challenge this rational interpretation by uncovering expected returns associated with value characteristics that are unrelated to the covariance structure of returns. More recently, Davis, Fama, and French (2000) argue that in the United States the Daniel and Titman (1997) result is specific to a particular data period, while Daniel, Titman, and Wei (2001) show that it extends to the Japanese stock market. We contribute to this line of research by showing that prior to EADs unsophisticated option market investors engage in option market trading which is consistent with overreaction to stock market news of the type posited by the behavioral explanation of the value premium. Although our findings do not address the behavior of stock market investors directly, they are an important addition to the pool of available evidence, because there has been no previous research on the question of whether option investors overreact to past positive and negative news on underlying stocks. In the stock market, on the other hand, there have already been a large number of studies of investor overreaction — many of which use essentially the same data. In addition, unlike the stock market studies, we provide direct evidence that investors of varying levels of sophistication overreact differentially to stock market news.

Our results also contribute more broadly to the limits to arbitrage approach to finance. In recent years an important strand of the finance literature has investigated limitations in the ability of the arbitrage activity of sophisticated investors to push the prices of misvalued assets back to fundamental values (see e.g., DeLong, Shleifer, Summers, and Waldmann (1990), Shleifer and Vishny (1997), the *Journal of Financial Economics* special issue on "Limits on Arbitrage" (Vol. 66, Nos. 2-3, 2002), or Shleifer (2000)). In models of limited arbitrage, assets typically trade at prices in between fundamental values and values that unsophisticated investors mistakenly perceive as correct (e.g., DeLong, Shleifer, Summers, and Waldmann (1990, p. 712)).[1] Consequently, in this type of framework unsophisticated investors believe that asset prices are

[1]See also Section 4.1 of Cohen, Gompers, and Vuolteenaho (2002).

too close to fundamental values and that this belief should be exploited when it is known that important information is about to be released into the market. To the best of our knowledge, our findings are the first empirical evidence that unsophisticated investors (1) believe that mispriced assets should deviate more than they do from fundamental values and (2) trade on these beliefs before scheduled information releases. Hence, our results provide important confirmation for two major implications of the limits to arbitrage approach to financial markets.

We use daily long and short open interest on calls and puts to measure the extent to which the various investor classes use the option market to load up on growth and value stocks. When interpreting our findings, we treat net long option market positions on underlying stocks as informative about net long bets on these stocks. Our discussions with option market professionals indicate that many option positions, especially those of less sophisticated investors, are indeed outright bets on the future movements of underlying stocks which suggests that treating net long option market positions in this way is justified. Nonetheless, we are sensitive to the fact that not all option positions reflect a view by their holders that the underlying stock will move in a direction that will increase their value. As a result, we perform tests to evaluate whether our findings are produced either by option positions which hedge bets in the underlying stock or by option positions that are part of combined strategies with other options.

In order to evaluate how likely it is that our results are driven by option positions established to hedge bets made directly in the underlying stock, we repeat our analysis using only long call open interest. We do this, because the most common positions that include both options and underlying stocks are those that are long the underlying stock and short calls (i.e., covered calls) and those that are long the underlying stock and long puts (i.e., protective puts.) Consequently, if our findings are produced by option positions that are entered into in order to hedge bets made directly in the underlying stock, they should weaken considerably or disappear altogether when the tests are conducted using only long call open interest. We find, however, that our main result is just as strong when the analysis employs only long call positions as when it includes the other option positions as well.[2]

[2]Another reason to believe long call positions are less likely than other positions to be hedging bets in the underlying stock is that long call positions would hedge short stock positions. Short stock positions, however, are relatively uncommon — especially among unsophisticated investors.

To assess whether our conclusions are influenced by option positions that are entered into in combination with other option positions, we repeat our analysis after delta-adjusting the option open interest. The delta-adjustment converts any combined option positions into an equivalent number of shares of the underlying stock. For example, without delta-adjusting a bear spread which consists of a short position in an out-of-the-money put and a long position in an in-the-money put would be counted as a neutral bet, because the long put and the short put would cancel one another out. After delta-adjusting, however, the bear spread will be counted as a bet that the stock price will go down, because the long in-the-money put will have a greater delta (in absolute value) than the short out-of-the-money put. Our main result does not change when the analysis is performed after delta-adjusting the option open interest. Thus, we believe that it is unlikely that we misinterpret our findings because combined option positions are present in our data.

A possible non-behavioral explanation for our results is that even though at EADs the average growth stock does more poorly than the average value stock, unsophisticated option market investors have relatively more skill at identifying particular growth stocks that will have high EAD returns. If this is the case, unsophisticated investors may load up on growth relative to value stocks prior to EADs in order to exploit their greater ability to choose individual growth stocks with high EAD returns. We test for this possibility by determining whether the various investor types disproportionately establish long option market positions leading up to EADs on growth (value) stocks that do better than the average growth (value) stock at EADs. We find no evidence that the option market positions established by unsophisticated investors prior to EADs are associated with a greater ability to identify growth than value stocks with above average EAD returns.

Another potential alternative explanation for our findings is that growth stocks might attract more attention than value stocks in the days leading up to earnings announcements, and unsophisticated investors may trade options differently when underlying stocks are in the news. We test for this possibility by splitting underlying stocks into sub-samples according to the extent to which their option market activity tends to increase prior to EADs. We re-run our tests and find that the main effect is present in each sub-sample. We conclude that it is unlikely that our findings correspond to an attention effect.

As always, a risk-based explanation for our results cannot be ruled out. Specifically, it could be the case that loading up on growth relative to value stocks in the option market prior to EADs allows unsophisticated investors to hedge some type of risk that they want to protect themselves against and that the value of the hedging outweighs the lower expected returns to the option positions. It should be kept in mind, however, that in order for an alternative risk-based explanation to work, it would have to make clear why unsophisticated investors care more about the risk — whatever it might be — than sophisticated investors.

Our findings are related to a number of papers that document suboptimal behavior by option market investors. Stein (1989) presents evidence that as a group S&P 100 index option investors overreact to trends in the volatility of the underlying index. Poteshman (2001) shows that S&P 500 index option investors do so as well. The present paper finds that unsophisticated option traders overreact to past positive and negative news about the stocks that underlie equity options as well. Finucane (1997) and Poteshman and Serbin (2003) demonstrate that irrational early exercise of Chicago Board Options Exchange (CBOE) options is a regular occurrence. Poteshman and Serbin (2003) show, in addition, that this irrational exercise activity is limited to less sophisticated investors.

Our paper is also related to studies that examine incorporation of information into option prices around public news events. Cao, Chen, and Griffin (2005) find that the option market is more conducive than the stock market to information and price discovery prior to takeovers. Amin and Lee (1997) find that option market trading volume increases several days before earnings announcements while stock market trading volume does not. They also find that active-side option traders (i.e., roughly non-market makers) initiate more option positions that represent long (short) positions in the underlying stock before earnings news that is better (worse) than the most recent Value Line forecast. Furthermore, if the option positions are closed out two days after the earnings announcements, they earn a higher profit than otherwise comparable positions entered into at times not leading up to earnings announcements. This finding suggests that in their sample option market traders as a whole initiate positions that benefit from the unexpected information at earnings announcement dates. By contrast, when we condition on earnings announcements for value and growth stocks, we find that unsophisticated option traders initiate positions that are ill-suited to the returns that are actually realized by these stocks at EADs.

Two recent papers also use option market data to examine the limits to arbitrage. Ofek, Richardson, and Whitelaw (2004) find that violations of put-call parity are asymmetric in the direction of short sales constraints and that the magnitude of the violations are related to the difficulty of shorting the underlying stock as measured by the rebate rate. Bollen and Whaley (2004) find that time variation in the implied volatility of both index options and options on individual equities is related to net buying pressure from public order flow. While these papers study the impact of limited arbitrage on option prices, we use option market information as a tool for investigating limited arbitrage in the market for the underlying securities.

Finally, our paper has connections to a literature that examines stock trading by different types of investors around earnings announcements. Lee (1992) finds no evidence of informed trading in the buy/sell imbalance of equity trades prior to earnings announcements. This is true for both small trades which are presumably more likely to be made by individual investors and for large trades which are presumably more likely to be made by professional or institutional investors. Hirshleifer, Myers, Myers, and Teoh (2003) study investors at a discount brokerage house and conclude that the trading of these types of investors does not drive post-earnings announcement drift. Besides examining the option rather than the stock market and conditioning on being a value or growth stock, our study employs data that is in some ways more informative about the various types of traders. Unlike Lee (1992), we know with certainty which type of trader is responsible for market activity. Unlike Hirshleifer, Myers, Myers, and Teoh (2003), our data set includes all of the trades made in the market by all types of investors.

The remainder of the paper is organized as follows. Section 1 describes the data. Section 2 examines the returns to value and growth stocks at earnings announcements during our data period. Section 3 investigates the extent to which different types of investors load up on growth stocks relative to value stocks through their option market positions in the days leading up to EADs. Section 4 contains robustness tests including those that check whether option positions entered into in conjunction with positions in the underlying stocks or with other options are likely to effect the interpretation of our results. Section 5 assesses two possible alternative explanations for our findings. Section 6 concludes. An appendix provides details on the estimation and testing methods employed in the paper.

1 Data

The main data for this paper were obtained from the CBOE. The data consist of a daily record of closing short and long open interest for different types of investors for all CBOE listed options from the beginning of January 1990 through the end of December 2000.[3] When a CBOE listed option is also listed on other exchanges, the data cover open interest from all exchanges at which it trades. Options that trade only at exchanges other than the CBOE, however, are not included in the data set.

The Option Clearing Corporation (OCC) assigns one of three origin codes to each option transaction: C for public customers, F for firm proprietary traders, and M for market makers. Our data covers open interest from all transactions with the C or F designation. The public customer data were further subdivided by an analyst at the CBOE into open interest for discount customers, full-service customers, or other public customers. The other customers category consists of all OCC public customers that are not designated by the CBOE analyst as discount or full-service customers. This category includes open interest from transactions that originated from registered broker-dealer's personal accounts, foreign broker-dealer accounts, CBOE floor broker error accounts, and specialists. We study the open interest from options on individual equities by the firm proprietary traders, the discount customers, and the full-service customers.

We maintain that among the three groups of option market investors, the firm proprietary traders have the highest level of sophistication, the full-service customers have an intermediate level of sophistication, and the discount customers are least sophisticated. Clear evidence that the firm proprietary traders have the highest level of sophistication is provided in Poteshman and Serbin (2003) which demonstrates that firm proprietary traders never engage in irrational early exercise of stock options while the full-service and discount customers do so with some reg-

[3]The total long open interest for any option always equals the total short open interest. For a given investor type, however, the long open interest will not in general be equal to the short open interest.

ularity. One reason to believe that full-service customers are on average more sophisticated than discount customers is that most hedge funds trade through full-service brokerage houses. In addition, Pan and Poteshman (2004) find that the option volume of full-service customers is more informative than that of discount customers which also suggests that full-service customers are more sophisticated. Further evidence that in the option market full-service customers are more sophisticated than discount customers is provided in Lakonishok, Lee, Pearson, and Poteshman (2005) which shows that during the stock market bubble of the late 1990s and early 2000 discount customer option trading was more caught up in the speculative frenzy.

Panel A of Table 1 reports the number of distinct option symbols in our data set for each of the calendar years from 1990 through 2000. The number of option symbols is monotonically increasing beginning with 321 in 1990 and ending up with 3834 in 2000. Panel B describes the average daily total open interest per option symbol by the different investor types. The average open interest per option symbol is generally increasing for the discount customers which reflects the increase in the importance of discount brokerage houses over our time period. There is no clear increasing or decreasing pattern over time for the other investor classes. Panel C, however, shows that the average daily number of option symbols with strictly positive open interest is monotonically increasing through time for each investor class. For each investor class this number is less than 300 in 1990 and greater than 2000 in 2000. Taken together, Panels B and C indicate that the total open interest for each of the investor classes was increasing throughout our data period.

Stock returns were obtained from the Center for Research in Security Prices (CRSP). For earnings announcement dates, we use the date of publication in the *Wall Street Journal* as recorded in COMPUSTAT. Data from CRSP and COMPUSTAT are used to compute book-to-market (BM) ratios for underlying firms.

2 Earnings Announcement Returns to Value and Growth Stocks

LaPorta, Lakonishok, Shleifer, and Vishny (1997) define value stocks as those in the top BM decile and growth stocks as those in the bottom BM decile. Using this classification, they find that from 1971 to 1992 portfolios of value stocks outperform portfolios of growth stocks by an average of 400 basis points around the next four quarterly earnings announcements or by about 100 basis points per earnings announcement. Before investigating option market investor behavior leading up to EADs over the 1990 to 2000 period, we will first examine whether the difference in earnings announcement returns to value and growth stocks is also present during our later data period.

We also classify firms into value and growth categories based upon their BM ratios. The universe of firms for which we compute BM is comprised of New York Stock Exchange, American Stock Exchange, and Nasdaq firms that are included in CRSP and COMPUSTAT and for which certain data items are available. We exclude real estate investment trusts, American Depository Receipts, closed-end mutual funds, foreign stocks, unit investment trusts, and American trusts. In order to ensure that we are not using accounting data to compute BM values for stocks before the data were actually available to investors, we compute BM values for June of year t to May of year $t+1$ using accounting data for all fiscal years ending in calendar year $t-1$. We include in our sample only firms for which there are sufficient data to compute BM which is defined as book equity (BE) divided by market equity (ME). ME is computed by multiplying the December of year $t-1$ CRSP share price and number of shares outstanding. BE is computed from year $t-1$ COMPUSTAT data. Following Davis, Fama, and French (2000), BE is defined as the book value of stockholders' equity, plus balance sheet deferred taxes and investment tax credit (if available), minus the book value of preferred stock. Depending on availability, we use the redemption, liquidation, or par value (in that order) to estimate the book value of preferred stock. Stockholders' equity is the value reported by COMPUSTAT, if it is available. If not, we measure stockholders' equity as the book value of common equity plus the par value of preferred stock, or the book value of assets minus total liabilities (in that order).

For the June 1990 through May 2000 period, we compute the 3-day buy-and-hold earnings announcement return for value (i.e., highest BM decile) and growth (i.e., lowest BM decile) stocks.[4] We find that value stocks outperform growth stocks by an average of 95 basis points (z-statistic = 6.02, p-value = 0.0000). We also find similar differences in earnings announcement returns for

[4]The three day window extends from the trade date before to the trade date after the *Wall Street Journal* earnings announcement date recorded in COMPUSTAT.

value and growth stocks during the 1990 to 1994 and 1995 to 2000 subperiods. Hence, during the 1990 to 2000 time period the difference in earnings announcement returns between value and growth stocks is similar to the difference documented from 1971 to 1992 by LaPorta, Lakonishok, Shleifer, and Vishny (1997).

3 Option Market Activity in Value and Growth Stocks Leading up to Earnings Announcement Dates

This section of the paper examines the option market activity of different classes of investors leading up to EADs. We focus on the question of whether unsophisticated investors load up on growth relative to value stocks prior to EADs despite the fact that value stocks substantially outperform growth stocks at EADs.

We introduce a "Net Long (Open Interest) Ratio" (NLR) variable to measure the net long positions investors take in underlying stocks through their option market positions. Let m be one of four categories of open interest: long call, short call, long put, or short put. In addition, let $OI_{s,t}^{m,i}$ be the open interest of type m, for underlying stock s, investor class i, and trade date t relative to an EAD. This variable aggregates open interest of type m for a given underlying stock across all strike prices and maturities. Similarly, let $\overline{OI}_{s}^{m,i}$ be the average of $OI_{s,t}^{m,i}$ over a period from 30 days before to 30 days after the EAD. We then define the Net Long Ratio (NLR) variable as follows:

$$NLR_{s,t}^{i} \equiv \frac{OI_{s,t}^{long\ call,i} - OI_{s,t}^{short\ call,i} - OI_{s,t}^{long\ put,i} + OI_{s,t}^{short\ put,i}}{\overline{OI}_{s}^{long\ call,i} + \overline{OI}_{s}^{short\ call,i} + \overline{OI}_{s}^{long\ put,i} + \overline{OI}_{s}^{short\ put,i}} \tag{1}$$

The numerator of the NLR variable is the net long open interest. In order to understand this variable, note that long call and short put positions appreciate when the price of the underlying stock increases, while long put and short call positions depreciate when the price of the underlying stock increases. Consequently, in the numerator of NLR we add the long call and short put and subtract the long put and short call open interest. We divide the net long open interest by the sum of the average of the four types of open interest to control for the heterogeneity in overall option market activity across underlying stocks.

In order to see whether investors load up on growth stocks relative to value stocks prior to

EADs, we compare their NLR measure in growth options with their NLR measure in value options leading up to EADs. To do this, we first run the following set of regressions (which contains one cross-sectional regression for each trade date relative to an EAD):

$$
\begin{aligned}
&\vdots \\
NLR^i_{s,-4} &= \alpha^i_{-4} + \beta^i_{-4} GrD_s + \epsilon^i_{s,-4} \\
NLR^i_{s,-3} &= \alpha^i_{-3} + \beta^i_{-3} GrD_s + \epsilon^i_{s,-3} \qquad (2) \\
NLR^i_{s,-2} &= \alpha^i_{-2} + \beta^i_{-2} GrD_s + \epsilon^i_{s,-2}
\end{aligned}
$$

GrD_s is a growth dummy which takes the value 1 if the stock s is in the first decile of BM ratio and 0 if the underlying stock is in the 8th - 10th decile of BM ratio. We define value stocks as BM deciles 8 through 10 in order to have roughly the same number of growth and value stocks with CBOE traded options. All observations that are in BM deciles 2 - 7 are excluded from the regressions. In Equations (2), i specifies the investor class and t indexes trade dates relative to the EAD (where the EAD is defined as $t = 0$). For each trade date t relative to the EAD, we have a set of observations, indexed by s, on value and growth stocks in each quarter of the time period.[5]

In these regressions α^i_t is the average NLR, for investor group i and trade date t relative to the EAD, across all value options. The coefficient β^i_t is the average difference in NLR between growth and value options, for investor group i on trade date t relative to the EAD. Consequently, an increasing (with time index t) β^i_t indicates that investors of group i increase their bets on growth options relative to value options as they approach EADs. Such an increase would be consistent with the investors in group i expecting higher return for the growth stocks relative to the value stocks at EADs.

With this framework in place, we next test whether the various investor classes increase their option market growth relative to value positions leading up to EADs. The tests compare the average β coefficients in a period close to but before the EAD (which we call the target

[5]If a stock does not have an EAD in a given quarter, it is excluded from the cross-section of data for that quarter. We also impose one additional filter on the observations included in the regressions. Note that for a given date t, each observation in the regression corresponds to an EAD. We only keep observations for which the EAD previous to and subsequent to the current EAD have a minimum distance of 10 trade days from the date of the observation. This filter reduces the effects from EADs other than the current one on the estimated coefficients. Changing the 10 trade day minimum distance to 0 to 20 trade days has little impact on the results.

period) with the average β coefficients in a period far from and before the EAD (which we call the benchmark period). In order to account for correlation through time in the β coefficients, we use the "Seemingly Unrelated Regression" (SUR) method.[6]

We begin by specifying a period $\mathcal{T}$ before EADs (which encompasses both the benchmark and target periods). In our initial test, this period covers trade dates -21 to -2 (relative to the EADs). For each investor group, we have a system of regression equations. More specifically, for each trade date in the period $\mathcal{T}$, there is a regression equation in the system, as specified in Equations (2). For this system of equations, we estimate the coefficients and their covariance matrix using the SUR method. Next, we define two sub-periods in $\mathcal{T}$, a benchmark period $\mathcal{T}_{bp}$ (containing T_{bp} days) and a target period $\mathcal{T}_{tp}$ (containing T_{tp} days). For our first estimation, $\mathcal{T}_{bp}$ covers the 5 trade dates from day -21 to day -17 (relative to the EAD), and $\mathcal{T}_{tp}$ covers the 3 trade dates from day -4 to day -2 (relative to the EAD). We end the target period at day -2, because it is possible that earnings announcement information sometimes reaches the market the day before the COMPUSTAT earnings announcement date (i.e., the information may actually reach the market on day -1). We start the target period at day -4, because a target period of three trade dates seems like a reasonable trade-off between making the period longer to cut down on noise and making it shorter to keep it close to the EAD. We end the benchmark period at day -17 in order to end it three weeks before the end of the target period. We start the benchmark period at day -21 in order to make it one week long. Although the length and the ending date of the benchmark period are somewhat arbitrary, it will be shown below that our results do not depend on our particular choice for the benchmark period. Given the benchmark and target periods, we test whether the average β in the target period is greater than in the benchmark period. That is, we perform a one-sided test of the following null and alternative hypotheses for the system of equations:

$$H_0 \ : \ \underbrace{\frac{1}{T_{tp}} \sum_{t \in \mathcal{T}_{tp}} \beta_t^i}_{\bar{\beta}_{tp}^i} - \underbrace{\frac{1}{T_{bp}} \sum_{t \in \mathcal{T}_{bp}} \beta_t^i}_{\bar{\beta}_{bp}^i} = 0 \qquad \text{vs.} \qquad H_1 \ : \ \bar{\beta}_{tp}^i - \bar{\beta}_{bp}^i \neq 0 \ . \tag{3}$$

In expression (3), $\bar{\beta}_{tp}^i$ is the average β coefficient in the target period, and $\bar{\beta}_{bp}^i$ is the the average

[6]For a discussion of the SUR models and issues related to estimation and test of hypotheses in this framework, see Amemiya (1985) and Srivastava and Giles (1987). A detailed explanation of our econometric procedure is provided in the Appendix.

β coefficient in the benchmark period (both for investor group i). If we reject H_0 in favor of H_1, then there is a significant change in the β coefficient for investor group i from the benchmark period to the target period. An increase would indicate that close to EADs investors in group i on average increase their option bets on growth stocks compared to their option bets on value stocks. We use a two-stage method to estimate the SUR system. The estimator is consistent and asymptotically normal (cf. Amemiya (1985) and Srivastava and Giles (1987)). These issues are discussed in more depth in the Appendix.

We present the results of the formal tests in Table 2. The table indicates a statistically significant increase (at the 0.5% level) in the discount customer β coefficient from the benchmark period to the target period. Consequently, there is reliable evidence that the least sophisticated option market investors load up on growth options relative to value options in the period shortly before EADs. This occurs despite the fact that value stocks outperform growth stocks by a wide margin at EADs. For full-service customers the change is essentially zero. Hence, there is no evidence they load either up or down on growth options relative to value options just before EADs.

For the firm proprietary traders, we find a decrease in the average beta coefficient from the benchmark to the target period. Although, the magnitude of the estimated coefficient is large (almost two times that of discount customers), the test statistic has a p-value of 0.577, which indicates that the difference is not statistically significant. The upshot is that the sign of this coefficient suggest that the most sophisticated investors in the option market correctly speculate on the EAD difference between growth and value returns, but the evidence is not strong enough to make a reliable inference.

4 Robustness

4.1 Benchmark Period

It is natural to ask whether the results in section 3 are sensitive to the choice of benchmark period. In order to address this question, we repeat the tests reported in Table 2, while systematically varying the benchmark period. We consider all benchmark periods starting from 26 to

16 trade dates before the EAD and ending from 22 to 12 trade dates before the EAD, subject to the constraint that the length of the benchmark period is at least 5 trade days. For the reasons discussed above, we keep the target period fixed at the interval from trade date -4 to trade date -2 relative to the EAD.

All together there are 66 test configurations, and we perform the tests from Table 2 for each of these configurations. Table 3 reports two groups of numbers: (1) The frequency across the 66 configurations of the test statistics (for the change in the average β , $\bar{\beta}^i_{tp} - \bar{\beta}^i_{bp}$,) that meet the row's criteria,[7] and (2) the average $\bar{\beta}^i_{tp} - \bar{\beta}^i_{bp}$ across configurations that meet the row's criteria. The results indicate that the main findings in Table 2 are quite robust to the choice of the benchmark period. In Table 2, the difference, $\bar{\beta}^i_{tp} - \bar{\beta}^i_{bp}$, for the discount customers is 0.028 and significant at the 0.5% level. In Table 3, the discount customer difference is significant at the 1% level for 56 of the 66 benchmark periods, with an average of 0.027. It is positive and significant at the 5% level for the other 10 benchmark periods. Table 2 indicates that the full-service group's NLR measure does not change prior to EADs: The test statistic is -0.0006 and insignificant at the 90% level. In Table 3, the test statistic is positive and insignificant at the 10% level for 44% of the configurations, and negative and insignificant at the 10% levels for the other 56% of the configurations, and the magnitude of the difference is around 0.001, on average, in both cases. Hence, changing the benchmark period does not have a major impact on the results for the full-service investors. Finally, like Table 2, Table 3 suggests that the firm proprietary traders may wisely reduce their option bets on growth stocks relative to value stocks close to EADs. In particular, for 85% of the configurations the test statistic is negative (though insignificant at the 10% level).

4.2 Hedging

So far we have implicitly assumed that changes in investor option portfolios prior to EADs reflect speculative trading. Next, we assess this assumption by examining whether it is likely that the use of options as hedging tools drives our results.

[7]Since the configurations overlap, they are not independent of each other. The frequencies reported in Table 3 should be interpreted with this in mind.

4.2.1 Options Combined with Underlying Stocks

We consider first the use of options to hedge the risk of positions held in the underlying stock. In order to understand our approach, note that the most common strategies that include both options and underlying stock are those that are long the underlying stock and short calls (i.e., covered calls) and those that are long the underlying stock and long puts (i.e., protective puts.) Consequently, if our findings are produced by option positions that are entered into in order to hedge bets made directly in the underlying stock, they should become considerably weaker or disappear when the tests are conducted without short call and long put open interest. Since, in addition, a natural way for investors to use the option market to speculate on stocks is to buy calls, we repeat our analysis using only long call open interest to measure investor speculation via the option market on value and growth stocks.[8]

We define a "Long Call (Open Interest) Ratio" LCR variable which divides the long call open interest by the sum of the four types of open interest:

$$LCR^i_{s,t} \equiv \frac{OI^{long\ call,i}_{s,t}}{\overline{OI}^{long\ call,i}_s + \overline{OI}^{short\ call,i}_s + \overline{OI}^{long\ put,i}_s + \overline{OI}^{short\ put,i}_s} \quad (4)$$

The division by total average open interest controls for heterogeneity in overall option market activity across underlying stocks. Table 4 shows the results of statistical tests like those in Table 2, but with the LCR variable. The main findings from section 3 continue to hold.

We also check the sensitivity of these results to the choice of the benchmark period by perturbing the endpoints of the benchmark period as we did for the NLR tests in Table 3. The results are presented in Table 5, which indicate that the LCR analysis is robust to the choice of the benchmark period.

4.2.2 Options Combined with Other Options

In addition to hedging underlying stocks, options can also be used to hedge other options. In order to investigate whether it is likely that this use of options produces our results, we re-run

[8] It is also worth noting that investors hold a lot more long than short stock positions. In fact, Odean (1999) reports that less than one percent of the stock sales in his data set are short sales. (His data cover records of a large number of customers at a major discount brokerage house.) Since long calls would hedge short rather than long stock positions, the lack of short stock positions also suggests that long call positions are relatively less likely than other option positions to hedge holdings in the underlying stock.

our NLR tests after delta-adjusting the option open interest. We do this because the delta-adjustment converts any combined option positions into an equivalent number of shares of the underlying stock. Therefore, the delta-adjusted net option position in a stock factors out any hedging among the options and just leaves the component of the option positions that would be speculative in the absence of positions in the underlying stock. Put differently, the delta-adjusted net open interest on a given stock measures whether the total option position on the stock becomes more or less valuable when the stock price appreciates. As a result, delta-adjusting net option positions controls for hedging among the options.

We define a $NLR\triangle$ variable to use in place of the NLR variable in our analysis:

$$NLR\triangle_{s,t}^{i} \equiv \frac{OI\triangle_{s,t}^{long\ call,i} - OI\triangle_{s,t}^{short\ call,i} - OI\triangle_{s,t}^{long\ put,i} + OI\triangle_{s,t}^{short\ put,i}}{\overline{OI\triangle}_{s}^{long\ call,i} + \overline{OI\triangle}_{s}^{short\ call,i} + \overline{OI\triangle}_{s}^{long\ put,i} + \overline{OI\triangle}_{s}^{short\ put,i}} \quad (5)$$

In this expression, $OI\triangle$ denotes the delta-adjusted open interest and $\overline{OI\triangle}$ is its average over the $[-30, 30]$ trade-day period of the relevant EAD. For example, $OI\triangle_{s,t}^{long\ call,i}$ is the delta-adjusted long call open interest of investor group i, on underlying stock s and trade date t (relative to the EAD). The delta-adjusting is accomplished by multiplying each open interest component by the absolute value of the Black-Scholes delta of the corresponding option.[9]

Table 6 presents the results for the $NLR\triangle$ variable. The main thrust of the results is not changed. The test statistic is large and positive for the discount group, close to zero for the full-service group, and large and negative for the firm proprietary traders. The test-statistic is significant at the 0.3% level for the discount investors and is insignificant for the full-service investors and the firm proprietary traders. In Table 7, we also check these results for their sensitivity to the benchmark period. Once again, varying the benchmark period does not suggest that there is anything unusual about the primary benchmark period of -21 to -17 trade dates before the EAD.

[9]We compute Black-Scholes deltas using the one month LIBOR rate as a proxy for the risk-free rate and assuming perfect foresight of the dividends paid by the underlying stock over the remaining life of the option. Since the Black-Scholes assumptions are violated in a number of ways (e.g., the options have American style exercise and the volatilities of the underlying stocks are stochastic), the delta-adjusting should be viewed as a first-order approximation. However, since the conclusions drawn from the non-delta-adjusted and the delta-adjusted statistics are similar, we believe employing more sophisticated delta-adjustments would not make much of a difference.

5 Alternative Explanations

This section of the paper examines two potential alternative explanations for our results. The first is that unsophisticated investors have a greater ability to pick growth than value stocks which do well at EADs. The second is that leading up to EADs greater attention is paid to growth than value stocks.

5.1 Stock Picking

We have shown that unsophisticated investors increase their option market positions in growth stocks relative to value stocks leading up to EADs. This finding has been interpreted as evidence that unsophisticated investors overreact to news on underlying stocks. A possible alternative explanation for our results is that unsophisticated investors have a greater ability to identify growth than value stocks with above average EAD returns. If this is the case, then it may be perfectly rational for these investors to load up on growth relative to value stocks prior to EADs, even though the average value stock significantly outperforms the average growth stock at EADs.

To test for this possibility, we run the following regression for each investor-type i:

$$Ret_{s,[-1,1]} = \gamma_0^i + \gamma_1^i \, \Delta NLR_s^i + \gamma_2^i \, GrD_s + \gamma_3^i \, GrD_s \times \Delta NLR_s^i + \epsilon_s^i \; . \qquad (6)$$

In this equation, s indexes the observations which are comprised of the cross-section of stocks repeated for each quarter in our data period subject to the following restrictions. First, only growth (BM decile 1) and value stocks (BM deciles 8-10) are included. Second, for each investor group i observations are included only if the group has non-zero total open interest at some time in the $[-30, 30]$ period. This restriction is imposed so that the ΔNLR variable is well defined (i.e., has a non-zero denominator). ΔNLR is the change in the average net long ratio from the benchmark period (trade dates -21 to -17) to the target period (trade date -4 to trade date -2) for observation s and investor class i: $\Delta NLR_s^i \equiv \overline{NLR}_{s,[-4,-2]}^i - \overline{NLR}_{s,[-21,-17]}^i$. The variable $Ret_{s,[-1,1]}$ denotes the 3-day return from the trade date before to the trade date after an EAD (for observation s), and finally GrD_s is a growth dummy (1 if s is a growth stock and 0 if it is a value stock).

The γ_0^i coefficient is the average 3-day EAD return on the subset of value stocks for which investor group i carries non-zero total option open interest at some time in the $[-30, 30]$ period.[10] For simplicity, we will refer to this subset of stocks as the value stocks that are traded by investor group i and similarly for growth stocks. The remainder of this paragraph discusses the returns to these subsets of stocks. In Equation (6), when investor group i's NLR increases by α from the benchmark period to the target period, a value stock's EAD return will increase by $\gamma_1^i \times \alpha$. A growth stock's EAD return will increase by $(\gamma_1^i + \gamma_3^i) \times \alpha$ when investor group i's NLR increases by α from the benchmark to the target period. Consequently, a significantly positive estimate for the γ_3^i coefficient indicates that investor group i has a greater ability to identify growth stocks than value stocks that perform above average at EADs. An insignificant γ_3^i indicates that there is no evidence of a difference between investor group i's ability to choose among growth and value stocks at EADs. A significant negative γ_3^i indicates that investor group i has a lesser ability to identify growth stocks than value stocks that perform above average at EADs.

Table 8 displays the coefficient estimates from regression equation (6). The γ_3 coefficient for all investor groups is negative and insignificant at the 5% level. Hence, there is no evidence that before EADs any group of investors are better at choosing growth than value stocks. In fact, insofar as the negative sign carries any information at all, it indicates that these investors may be somewhat better at choosing value stocks prior to EADs. These results suggest that it is unlikely that discount investors load up in the option market on growth relative to value stocks before EADs, because they are better at identifying growth than value stocks that do better than average.

We also check how sensitive the results in Table 8 are to the choice of the benchmark period. As in section 4, we vary the benchmark period and repeat the regression in Equation (6). The results, reported in Table 9, indicate that the conclusions do not change when the benchmark period is altered.

[10]This statement is strictly true when the change in the net long ratio of investor group i (from the benchmark period to the target period) is zero. Since the average change in NLR is very small, it can be disregarded in a first approximation.

5.2 Attention

Growth stocks may attract more attention than value stocks leading up to EADs. This would occur, for example, if growth stocks experience more media reports or internet rumors shortly before earnings releases. We assess whether our finding corresponds to an attention effect by dividing our sample of underlying stocks into two groups based upon their tendency to have increased option market activity leading up to EADs. We then check whether our result is present in each group. More specifically, we define the daily option trade volume for a stock as the sum of the absolute values of the daily difference in open interest for the options written on the stock. Next for each stock and EAD, we compute the ratio of the daily option trading volume during the ten trade dates leading up to the EAD to the daily trading volume from 30 to 20 trade dates before the EAD. The stocks are then sorted into a low and a high option market activity group depending upon whether the ratios are above or below the median. We repeat our main test from Table 2 on each group where the value (growth) stocks are defined by the highest (lowest) tercile of BM within the group.

For the discount customers, the increase in the average beta coefficient from the benchmark period to the target period is positive for both the low and high option market activity groups with p-values of less than 0.003 in both cases. For the full-service customers and the firm traders, the changes in the average beta coefficient for both the high and the low option market activity groups are insignificant. Hence, the paper's main effect is present in both the low and and high option market activity groups.[11] As a result, it appears unlikely that the paper's main effect reflects a combination of growth stocks getting more attention leading up to EADs and option market activity increases being concentrated in long option positions.[12]

[11]Furthermore, for discount customers if underlying stocks are first sorted into quintiles based on option market activity, the β coefficient increases more for the growth than the value stocks within each option market activity quintile.

[12]As an alternative way to control for any differential changes in option market activity leading up to EADs across underlying stocks, we redefined the NLR variable as

$$NLR^i_{s,t} \equiv \frac{OI^{long\ call,i}_{s,t} - OI^{short\ call,i}_{s,t} - OI^{long\ put,i}_{s,t} + OI^{short\ put,i}_{s,t}}{OI^{long\ call,i}_{s,t} + OI^{short\ call,i}_{s,t} + OI^{long\ put,i}_{s,t} + OI^{short\ put,i}_{s,t}},$$

so that the denominator accounts for any changes in levels of option activity around EADs. Changing the NLR variable in this way leaves all of the paper's main results unaltered.

6 Conclusion

This paper provides evidence that less sophisticated option market investors increase their option market bets on growth stocks relative to value stocks in the days leading up to earnings announcements. No such change is observed for more sophisticated option market investors. Our findings provide new information about the behavior of option market investors and also contribute to two major issues in the finance literature.

First, the behavior we document is consistent with unsophisticated option market investors overreacting to news on underlying stocks. Although a number of researchers have previously used stock market data to argue that unsophisticated stock market investors overreact to stock market news (e.g., DeBondt and Thaler (1985) and Lakonishok, Shleifer, and Vishny (1994)), this interpretation of the historically high returns of value compared to growth stocks has been controversial (e.g., Fama and French (1992,1993), Daniel and Titman (1997), Davis, Fama, and French (2000), Daniel, Titman, and Wei (2001).) Our evidence provides an important contribution to this debate, because it comes from a market where the question of overreaction to positive and negative stock market news has not been previously addressed. A relatively fixed pool of stock market data, on the other hand, has already been used to study this question a number of times. Our results are especially compelling, because value stocks outperform growth stocks by a wide margin at EADs. This EAD return differential makes it surprising that any group of investors would load up on growth relative to value stocks leading up to EADs.

Second, our findings make a more general contribution to the growing literature on the limits to arbitrage. In models of limited arbitrage, asset prices typically settle in between fundamental values and the values that unsophisticated investors erroneously believe are correct. This is the case, for example, in the well-known model of DeLong, Summers, Shleifer, and Waldmann (1990). Consequently, these models imply that before the scheduled release of important news about firms, unsophisticated investors will place bets that stock prices will move further away from fundamental values. Insofar as we are aware, our results provide the first empirical evidence (1) that unsophisticated investors believe that asset prices should deviate more than they actually do from fundamental values and (2) that they place bets before scheduled news releases in a misguided effort to profit from their mistaken expectations that prices will move even further away from fundamental values when the news reaches the market.

Appendix

This appendix provides details on the estimation and test methods employed in the paper.

A standard SUR model consists of T regression equations:

$$\mathbf{y}_t = \mathbf{X}_t \beta_t + \mathbf{u}_t \ , \quad t = 1, \ldots, T \tag{7}$$

where $\mathbf{y}_t \equiv (y_{t,1}, \ldots, y_{t,N})'$ is the $N \times 1$ vector of N observations on the t-th dependent variable, $\mathbf{X}_t \equiv (\mathbf{x}_t^1, \ldots, \mathbf{x}_t^K)$ is the $N \times K$ matrix each column of which, $\mathbf{x}_t^i \equiv (x_{t,1}^i, \ldots, x_{t,N}^i)'$ $i = 1, \ldots, K$, comprises the N observations on the ith regressor in the tth equation of the model, $\mathbf{u}_t \equiv (u_{t,1}, \ldots, u_{t,N})'$ is the $N \times 1$ vector of error terms in the tth equation of the model, and $\beta_t = (\beta_{t,1}, \ldots, \beta_{t,K})$ is the $K \times 1$ vector of coefficients in the tth equation of the model.

We can stack the equations:

$$\underbrace{\begin{bmatrix} \mathbf{y}_1 \\ \mathbf{y}_2 \\ \vdots \\ \mathbf{y}_T \end{bmatrix}}_{\mathbf{y}} = \underbrace{\begin{bmatrix} \mathbf{X}_1 & 0 & \cdots & 0 \\ 0 & \mathbf{X}_2 & \cdots & 0 \\ \vdots & \vdots & & \vdots \\ 0 & 0 & \cdots & \mathbf{X}_T \end{bmatrix}}_{\mathbf{X}} \underbrace{\begin{bmatrix} \beta_1 \\ \beta_2 \\ \vdots \\ \beta_K \end{bmatrix}}_{\beta} + \underbrace{\begin{bmatrix} \mathbf{u}_1 \\ \mathbf{u}_2 \\ \vdots \\ \mathbf{u}_T \end{bmatrix}}_{\mathbf{u}} , \tag{8}$$

and obtain a more compact form:

$$\mathbf{y} = \mathbf{X}\beta + \mathbf{u} \qquad (\,\mathbf{y}, \mathbf{u} : NT \times 1 \ , \ \mathbf{X} : NT \times KT \ , \ \beta : KT \times 1\,) \, . \tag{9}$$

We make the following standard SUR framework assumptions:

1. $\mathbf{X}_t$ is fixed, with rank$(\mathbf{X}_t) = K$.

2. $\lim_{N \to \infty} \left(\frac{1}{N} \mathbf{X}_s' \mathbf{X}_t \right) = Q_{st}$, where Q_{st} is non-singular with fixed and finite elements.

3. $\mathbf{E}[\mathbf{u}] = 0$.

4. $\mathbf{E}[\mathbf{u}\mathbf{u}'] = \begin{bmatrix} \sigma_{11} I_N & \cdots & \sigma_{1T} I_N \\ \vdots & & \vdots \\ \sigma_{T1} I_N & \cdots & \sigma_{TT} I_N \end{bmatrix} = \Sigma \otimes I_N \equiv \Omega$.

The error covariance in the standard regression model is a scalar times an identity matrix (i.i.d. assumption), whereas the covariance in Equation (9) is a positive definite, but not necessarily diagonal, matrix Ω. One can still apply OLS to the SUR model to obtain an unbiased estimator, $\hat{\beta}_O$. The estimator and its covariance matrix are:

$$\hat{\beta}_O = (\mathbf{X}'\mathbf{X})^{-1}\,\mathbf{X}'\mathbf{y}\,, \qquad \mathbf{Var}\hat{\beta}_O = (\mathbf{X}'\mathbf{X})^{-1}(\mathbf{X}'\Omega\mathbf{X})(\mathbf{X}'\mathbf{X})^{-1}\,. \tag{10}$$

If the error covariance, Ω , were known then one could use the Generalized Least Squares (GLS) method. The estimator, $\hat{\beta}_G$, and its covariance matrix are:

$$\hat{\beta}_G = (\mathbf{X}'\Omega^{-1}\mathbf{X})^{-1}\,\mathbf{X}'\Omega^{-1}\mathbf{y}\,, \qquad \mathbf{Var}\hat{\beta}_G = (\mathbf{X}'\Omega^{-1}\mathbf{X})^{-1} \tag{11}$$

It can be easily shown that $\mathbf{Var}\hat{\beta}_O \geq \mathbf{Var}\hat{\beta}_G$, and in general the OLS estimator is not efficient. In the special case where $\mathbf{X}_1 = \cdots = \mathbf{X}_T$, the GLS and OLS estimators are the same: $\hat{\beta}_G = (\mathbf{X}'\mathbf{X})^{-1}\,\mathbf{X}'\mathbf{y}$, and $\mathbf{Var}\hat{\beta}_G = \mathbf{Var}\hat{\beta}_O = \Sigma \otimes (\mathbf{X_1}'\mathbf{X_1})^{-1}$. Still, the usual OLS estimate of the coefficients' covariance matrix, $\sigma^2(\mathbf{X}'\mathbf{X})^{-1}$, is not consistent.

In practice, the error covariance Ω is unknown and therefore the GLS method cannot be implemented. If a consistent estimator, $\hat{\Omega}$, for the error covariance is available, then one can use the Feasible GLS (FGLS) method:

$$\hat{\beta}_F = (\mathbf{X}'\hat{\Omega}^{-1}\mathbf{X})^{-1}\,\mathbf{X}'\hat{\Omega}^{-1}\mathbf{y} \tag{12}$$

FGLS is a two-stage method: In the first step one obtains a consistent estimate of the error covariance, $\hat{\Omega}$. In the second step, Equation (12) is used for the estimation. In many cases, a good candidate for $\hat{\Omega}$ is the estimate of the error covariance from the OLS method. To apply the FGLS method to SUR models, we first estimate Σ by $\hat{\sigma}_{t,\tau} = N^{-1}\hat{\mathbf{u}}_t'\hat{\mathbf{u}}_\tau$, where $\hat{\mathbf{u}}_t = \mathbf{y}_t - \mathbf{X}_t\hat{\beta}_{t,O}$ are the OLS residuals from the tth equation. The FGLS estimator then has the following form:

$$\hat{\beta}_F = \left[\mathbf{X}'(\hat{\Sigma}^{-1} \otimes I_N)\mathbf{X}\right]^{-1}\,\mathbf{X}'(\hat{\Sigma}^{-1} \otimes I_N)\mathbf{y} \tag{13}$$

These estimate are consistent as N gets large while T is fixed. The estimators from FGLS and GLS have the same asymptotic distribution:

$$\sqrt{N}(\hat{\beta}_F - \beta_0) \sim_A \mathcal{N}[0, (\lim N^{-1}\mathbf{X}'\Omega^{-1}\mathbf{X})^{-1}] \tag{14}$$

Comparing Equation (2) in section 3 and Equation (7) here indicates that in the special case of our model (suppressing the investor group index i): $\beta_t = (a_t, b_t)'$, $\mathbf{X}_1 = \mathbf{X}_2 = \cdots = \mathbf{X}_T = (\mathbf{1}_N, GrD)$, and therefore the OLS and GLS estimates coincide. Simple algebra shows that $\hat{a}_t =$

$\overline{NLR}_t^v$ and $\hat{b}_t = \overline{NLR}_t^g - \overline{NLR}_t^v$, where $\overline{NLR}_t^v$ and $\overline{NLR}_t^g$ are average NLR in the t-th equation for the value and growth options, respectively. The estimate of an error covariance term is a weighted average of the covariance of NLR for growth and value sub-samples: $\hat{\sigma}_{t,\tau} = \frac{N^g}{N} s_{t,\tau}^g + \frac{N^v}{N} s_{t,\tau}^v$, where N^v and N^g are the number of value and growth options in the sample respectively ($N = N^g + N^v$). Also, $s_{t,\tau}^v$ and $s_{t,\tau}^g$ are the covariance of NLR in periods t and τ in the sub-sample of value and growth options, respectively. Finally, the estimate of the covariance of the coefficient estimates has the following simple form:

$$\mathbf{c\hat{o}v}(\hat{a}_t, \hat{a}_\tau) = \frac{1}{N^v}\hat{\sigma}_{t,\tau}\ ,\ \mathbf{c\hat{o}v}(\hat{a}_t, \hat{b}_\tau) = -\frac{1}{N^v}\hat{\sigma}_{t,\tau}\ ,\ \mathbf{c\hat{o}v}(\hat{b}_t, \hat{b}_\tau) = \frac{N}{N^v N^g}\hat{\sigma}_{t,\tau}\ . \tag{15}$$

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Table 1: **Descriptive Statistics for Open Interest on Chicago Board Options Exchange Listed Individual Equity Options, January 2, 1990 through December 31, 2000**

This table contains descriptive statistics by calendar year on open interest for Chicago Board Options Exchange (CBOE) listed individual equity options over the January 2, 1990 through December 31, 2000 time period. The data were obtained directly from the CBOE. When CBOE listed individual equity options also trade on other exchanges, the open interest is inclusive of all exchanges at which the options trade. Options that trade only at other exchanges are not included. Panel A reports the total number of option symbols during each calendar year. Panel B provides the average daily long and short open interest per option symbol for firm proprietary traders (Firm Proprietary), customers of discount brokers (Discount), and customers of full-service brokers (Full-Service). Panel C displays for these three investor types the daily average number of option symbols with strictly positive long or short open interest.

	1990	1991	1992	1993	1994	1995	1996	1997	1998	1999	2000
Panel A: Number of Option Symbols											
	321	389	568	786	1001	1199	1458	1934	2306	3090	3834
Panel B: Average Daily Total Open Interest per Option Symbol											
Firm Proprietary	2160	1949	1653	1609	1826	1730	1711	2220	2527	3235	4100
Discount	1518	1441	1516	1558	1635	1681	1800	1919	1890	2529	3553
Full Service	14238	11816	10404	9543	9812	8836	8560	8036	8071	9958	13360
Panel C: Average Daily Number of Option Symbols with Strictly Positive Total Open Interest											
Firm Proprietary	203	241	311	402	469	549	632	787	927	1261	2038
Discount	250	306	422	580	755	908	1102	1412	1711	2049	2646
Full Service	259	314	434	597	773	927	1125	1437	1734	2065	2662

Table 2: **Test for Increasing Net Long Ratio Before Earnings Announcement Dates, January 2, 1990 through December 31, 2000**

This table contains the results of a test for whether the Net Long Ratio (NLR) for growth relative to value stock changes prior to earnings announcement dates (EADs). The NLR variable measures the net long positions that investors take in underlying stocks through their option market positions. The test is performed separately for firm proprietary traders (Firm Proprietary), customers of discount brokers (Discount), and customers of full-service brokers (Full-Service). The tests proceed by running the following regression separately for each investor group i and trade date t (for $t = -21$ to $t = -2$) measured relative to EADs:

$$NLR^i_{s,t} = \alpha^i_t + \beta^i_t GrD_s + \epsilon^i_{s,t}$$

where $NLR^i_{s,t}$ is the net long option market position held by investor class i, for underlying stock s, on trade date t relative to an earnings announcement date and GrD_s is a growth stock dummy that is one when an underlying stock s is a growth stock (has book-to-market value in the bottom decile) and is zero otherwise. Only observations on underlying growth and value stocks are used in the regressions. The β^i_t coefficient is the average difference in the NLR variable between growth and value options for investor group i on trade date t relative to the earnings announcement date. The regression equations are estimated using the Seemingly Unrelated Regressions (SUR) methodology in order to account for correlation through time in the β coefficients. Defining $\bar{\beta}_{bp}$ as the average β coefficient during a benchmark period that runs from -21 to -17 trade dates before EADs and $\bar{\beta}_{tp}$ as the average β coefficient during a target period that runs from -4 to -2 trade dates before EADs, for each investor group the null hypothesis that $\bar{\beta}_{tp} - \bar{\beta}_{bp} = 0$ is tested against the alternative hypothesis that $\bar{\beta}_{tp} - \bar{\beta}_{bp} \neq 0$. If the null hypothesis is rejected in favor of the alternative, then there is a significant change in the β coefficient from the benchmark to the target period. A significant *increase* is consistent with the investor group loading up just prior to EADs on growth relative to value stocks through its option market positions. The statistical tests are based on the asymptotic normality of the SUR model's estimates, and the p values are two-sided probabilities from a standard normal distribution.

Investor Type	$\bar{\beta}_{tp} - \bar{\beta}_{bp}$	z- statistic	p-value
Firm Proprietary	-0.04668	-0.5576	0.577
Discount	0.02761	2.8261	0.005
Full-Service	-0.00060	-0.0859	0.932

Table 3: **Test Statistic for Increasing Net Long Ratio Before Earnings Announcement Dates as Benchmark Period is Varied, January 2, 1990 through December 31, 2000**

This table reports the distribution of a statistic used to test whether the Net Long Ratio (NLR) for growth relative to value stock changes prior to earnings announcement dates (EADs). The distribution is obtained by varying the benchmark period used to construct the statistic. The NLR variable measures the net long positions that investors take in underlying stocks through their option market positions. The test statistic is obtained separately for firm proprietary traders (Firm Proprietary), customers of discount brokers (Discount), and customers of full-service brokers (Full-Service). It is computed by running the following regression separately for each investor group i and trade date t during a benchmark period that runs from $t = -a$ to $t = -b$ and a target period that runs from $t = -4$ to $t = -2$ where t is the trade date measured relative to EADs:

$$NLR^i_{s,t} = \alpha^i_t + \beta^i_t GrD_s + \epsilon^i_{s,t}$$

The $NLR^i_{s,t}$ is the net long option market position held by investor class i, for underlying stock s, on trade date t relative to an earnings announcement date and GrD_s is a growth stock dummy that is one when an underlying stock s is a growth stock (has book-to-market value in the bottom decile) and is zero otherwise. Only observations on underlying growth and value stocks are used in the regressions. The β^i_t coefficient is the average difference in the NLR variable between growth and value options for investor group i on trade date t relative to the earnings announcement date. The regression equations are estimated using the Seemingly Unrelated Regressions (SUR) methodology in order to account for correlation through time in the β coefficients. Defining $\bar{\beta}_{bp}$ as the average β coefficient during a benchmark period that runs from $-a$ to $-b$ trade dates before EADs and $\bar{\beta}_{tp}$ as the average β coefficient during a target period that runs from -4 to -2 trade dates before EADs, for each investor group the statistic is computed for all combinations of a and b where $-26 \leq a \leq -16$ and $-22 \leq b \leq -12$ subject to the restriction that $-a \leq -b - 5$. There are a total of 66 combinations of a and b which meet these requirements. The "Freq." columns report the frequency of configurations that fall in each category and the "Av. Diff." columns report the average $\bar{\beta}_{tp} - \bar{\beta}_{bp}$ across such configurations.

	Firm-Proprietary		Discount		Full-Service	
Test Statistic Significance	Freq.	Av. Diff.	Freq.	Av. Diff.	Freq.	Av. Diff.
$\bar{\beta}_{tp} - \bar{\beta}_{bp} < 0$, insignificant at 0.10	56	-0.0416	0	—	37	-0.0016
$\bar{\beta}_{tp} - \bar{\beta}_{bp} > 0$, insignificant at 0.10	10	0.0205	0	—	29	0.0011
$\bar{\beta}_{tp} - \bar{\beta}_{bp} > 0$, significant at 0.05 insignificant at 0.01	0	—	10	0.0196921	0	—
$\bar{\beta}_{tp} - \bar{\beta}_{bp} > 0$, significant at 0.01	0	—	56	0.0271	0	—

Table 4: **Test for Increasing Long Call Ratio Before Earnings Announcement Dates, January 2, 1990 through December 31, 2000**

This table contains the results of a test for whether the Long Call Ratio (LCR) for growth relative to value stock changes prior to earnings announcement dates (EADs). The LCR variable measures the net long positions that investors take in underlying stocks through their option market positions. The test is performed separately for firm proprietary traders (Firm Proprietary), customers of discount brokers (Discount), and customers of full-service brokers (Full-Service). The tests proceed by running the following regression separately for each investor group i and trade date t (for $t = -21$ to $t = -2$) measured relative to EADs:

$$LCR^i_{s,t} = \alpha^i_t + \beta^i_t \, GrD_s + \epsilon^i_{s,t}$$

where $LCR^i_{s,t}$ is the long call position held by investor class i, for underlying stock s, on trade date t relative to an earnings announcement date and GrD_s is a growth stock dummy that is one when an underlying stock s is a growth stock (has book-to-market value in the bottom decile) and is zero otherwise. Only observations on underlying growth and value stocks are used in the regressions. The β^i_t coefficient is the average difference in the LCR variable between growth and value options for investor group i on trade date t relative to the earnings announcement date. The regression equations are estimated using the Seemingly Unrelated Regressions (SUR) methodology in order to account for correlation through time in the β coefficients. Defining $\bar{\beta}_{bp}$ as the average β coefficient during a benchmark period that runs from -21 to -17 trade dates before EADs and $\bar{\beta}_{tp}$ as the average β coefficient during a target period that runs from -4 to -2 trade dates before EADs, for each investor group the null hypothesis that $\bar{\beta}_{tp} - \bar{\beta}_{bp} = 0$ is tested against the alternative hypothesis that $\bar{\beta}_{tp} - \bar{\beta}_{bp} \neq 0$. If the null hypothesis is rejected in favor of the alternative, then there is a significant change in the β coefficient from the benchmark to the target period. A significant *increase* is consistent with the investor group loading up just prior to EADs on growth relative to value stocks through its long call positions. The statistical tests are based on the asymptotic normality of the SUR model's estimates, and the p values are two-sided probabilities from a standard normal distribution.

Investor Type	$\bar{\beta}_{tp} - \bar{\beta}_{bp}$	statistic	p-value
Firm Proprietary	-0.02029	-0.3527	0.724
Discount	0.02523	3.1156	0.002
Full-Service	0.00575	1.2287	0.219

Table 5: **Test Statistic for Increasing Long Call Ratio Before Earnings Announcement Dates as Benchmark Period is Varied, January 2, 1990 through December 31, 2000**

This table reports the distribution of a statistic used to test whether the Net Long Ratio (LCR) for growth relative to value stock changes prior to earnings announcement dates (EADs). The distribution is obtained by varying the benchmark period used to construct the statistic. The LCR variable measures the net long positions that investors take in underlying stocks through their option market positions. The test statistic is obtained separately for firm proprietary traders (Firm Proprietary), customers of discount brokers (Discount), and customers of full-service brokers (Full-Service). It is computed by running the following regression separately for each investor group i and trade date t during a benchmark period that runs from $t = -a$ to $t = -b$ and a target period that runs from $t = -4$ to $t = -2$ where t is the trade date measured relative to EADs:

$$LCR^i_{s,t} = \alpha^i_t + \beta^i_t GrD_s + \epsilon^i_{s,t}$$

The $LCR^i_{s,t}$ is the net long option market position held by investor class i, for underlying stock s, on trade date t relative to an earnings announcement date and GrD_s is a growth stock dummy that is one when an underlying stock s is a growth stock (has book-to-market value in the bottom decile) and is zero otherwise. Only observations on underlying growth and value stocks are used in the regressions. The β^i_t coefficient is the average difference in the LCR variable between growth and value options for investor group i on trade date t relative to the earnings announcement date. The regression equations are estimated using the Seemingly Unrelated Regressions (SUR) methodology in order to account for correlation through time in the β coefficients. Defining $\bar{\beta}_{bp}$ as the average β coefficient during a benchmark period that runs from $-a$ to $-b$ trade dates before EADs and $\bar{\beta}_{tp}$ as the average β coefficient during a target period that runs from -4 to -2 trade dates before EADs, for each investor group the statistic is computed for all combinations of a and b where $-24 \leq a \leq -18$ and $-20 \leq b \leq -14$ subject to the restriction that $-a \leq -b - 5$. There are a total of 66 combinations of a and b which meet these requirements. The "Freq." columns report the frequency of configurations that fall in each category and the "Av. Diff." columns report the average $\bar{\beta}_{tp} - \bar{\beta}_{bp}$ across such configurations.

	Firm-Proprietary		Discount		Full-Service	
Test Statistic Significance	Freq.	Av. Diff.	Freq.	Av. Diff.	Freq.	Av. Diff.
$\bar{\beta}_{tp} - \bar{\beta}_{bp} < 0$, significant at 0.05 insignificant at 0.01	2	-0.117835	0	—	0	—
$\bar{\beta}_{tp} - \bar{\beta}_{bp} < 0$, significant at 0.10 insignificant at 0.05	5	-0.101452	0	—	0	—
$\bar{\beta}_{tp} - \bar{\beta}_{bp} < 0$, insignificant at 0.10	45	-0.0419105	0	—	0	—
$\bar{\beta}_{tp} - \bar{\beta}_{bp} > 0$, insignificant at 0.10	14	0.00581302	0	—	47	0.00591149
$\bar{\beta}_{tp} - \bar{\beta}_{bp} > 0$, significant at 0.10 insignificant at 0.05	0	—	0	—	16	0.00874198
$\bar{\beta}_{tp} - \bar{\beta}_{bp} > 0$, significant at 0.05 insignificant at 0.01	0	—	0	—	3	0.0109686
$\bar{\beta}_{tp} - \bar{\beta}_{bp} > 0$, significant at 0.01	0	—	66	0.0134411	0	—

Table 6: **Test for Increasing Delta-Adjusted Net Long Ratio Before Earnings Announcement Dates, January 2, 1990 through December 31, 2000**

This table contains the results of a test for whether the delta-adjusted Net Long Ratio ($NLR\,\triangle$) for growth relative to value stock changes prior to earnings announcement dates (EADs). The $NLR\triangle$ variable measures the net long positions that investors take in underlying stocks through their option market positions. The test is performed separately for firm proprietary traders (Firm Proprietary), customers of discount brokers (Discount), and customers of full-service brokers (Full-Service). The tests proceed by running the following regression separately for each investor group i and trade date t (for $t = -21$ to $t = -2$) measured relative to EADs:

$$NLR\triangle^{i}_{s,t} = \alpha^{i}_{t} + \beta^{i}_{t}\,GrD_{s} + \epsilon^{i}_{s,t}$$

where $NLR\triangle^{i}_{s,t}$ is the delta-adjusted net long option market position held by investor class i, for underlying stock s, on trade date t relative to an earnings announcement date and GrD_s is a growth stock dummy that is one when an underlying stock s is a growth stock (has book-to-market value in the bottom decile) and is zero otherwise. Only observations on underlying growth and value stocks are used in the regressions. The β^{i}_{t} coefficient is the average difference in the $NLR\triangle$ variable between growth and value options for investor group i on trade date t relative to the earnings announcement date. The regression equations are estimated using the Seemingly Unrelated Regressions (SUR) methodology in order to account for correlation through time in the β coefficients. Defining $\bar{\beta}_{bp}$ as the average β coefficient during a benchmark period that runs from -21 to -17 trade dates before EADs and $\bar{\beta}_{tp}$ as the average β coefficient during a target period that runs from -4 to -2 trade dates before EADs, for each investor group the null hypothesis that $\bar{\beta}_{tp} - \bar{\beta}_{bp} = 0$ is tested against the alternative hypothesis that $\bar{\beta}_{tp} - \bar{\beta}_{bp} \neq 0$. If the null hypothesis is rejected in favor of the alternative, then there is a significant change in the β coefficient from the benchmark to the target period. A significant *increase* is consistent with the investor group loading up just prior to EADs on growth relative to value stocks through its option market positions. The statistical tests are based on the asymptotic normality of the SUR model's estimates, and the p values are two-sided probabilities from a standard normal distribution.

Investor Type	$\bar{\beta}_{tp} - \bar{\beta}_{bp}$	statistic	p-value
Firm	-0.08958	-0.8981	0.3691
Discount	0.04017	2.9933	0.003
Full-service	0.00331	0.3136	0.754

Table 7: **Test Statistic for Increasing Delta-Adjusted Net Long Ratio Before Earnings Announcement Dates as Benchmark Period is Varied, January 2, 1990 through December 31, 2000**

This table reports the distribution of a statistic used to test whether the delta-adjusted Net Long Ratio ($NLR\triangle$) for growth relative to value stock changes prior to earnings announcement dates (EADs). The distribution is obtained by varying the benchmark period used to construct the statistic. The $NLR\triangle$ variable measures the net long positions that investors take in underlying stocks through their option market positions. The test statistic is obtained separately for firm proprietary traders (Firm Proprietary), customers of discount brokers (Discount), and customers of full-service brokers (Full-Service). It is computed by running the following regression separately for each investor group i and trade date t during a benchmark period that runs from $t = -a$ to $t = -b$ and a target period that runs from $t = -4$ to $t = -2$ where t is the trade date measured relative to EADs:

$$NLR\triangle^i_{s,t} = \alpha^i_t + \beta^i_t GrD_s + \epsilon^i_{s,t}$$

The $NLR\triangle^i_{s,t}$ is the delta-adjusted net long option market position held by investor class i, for underlying stock s, on trade date t relative to an earnings announcement date and GrD_s is a growth stock dummy that is one when an underlying stock s is a growth stock (has book-to-market value in the bottom decile) and is zero otherwise. Only observations on underlying growth and value stocks are used in the regressions. The β^i_t coefficient is the average difference in the delta-adjusted NLR variable between growth and value options for investor group i on trade date t relative to the earnings announcement date. The regression equations are estimated using the Seemingly Unrelated Regressions (SUR) methodology in order to account for correlation through time in the β coefficients. Defining $\bar{\beta}_{bp}$ as the average β coefficient during a benchmark period that runs from $-a$ to $-b$ trade dates before EADs and $\bar{\beta}_{tp}$ as the average β coefficient during a target period that runs from -4 to -2 trade dates before EADs, for each investor group the statistic is computed for all combinations of a and b where $-24 \leq a \leq -18$ and $-20 \leq b \leq -14$ subject to the restriction that $-a \leq -b - 5$. There are a total of 66 combinations of a and b which meet these requirements. The "Freq." columns report the frequency of configurations that fall in each category and the "Av. Diff." columns report the average $\bar{\beta}_{tp} - \bar{\beta}_{bp}$ across such configurations.

	Firm-Proprietary		Discount		Full-Service	
Test Statistic Significance	Freq.	Av. Diff.	Freq.	Av. Diff.	Freq.	Av. Diff.
$\bar{\beta}_{tp} - \bar{\beta}_{bp} < 0$, insignificant at 0.10	64	-0.0559248	0	—	0	—
$\bar{\beta}_{tp} - \bar{\beta}_{bp} > 0$, insignificant at 0.10	2	0.0140035	0	—	66	0.00473323
$\bar{\beta}_{tp} - \bar{\beta}_{bp} > 0$, significant at 0.05 insignificant at 0.01	0	—	17	0.0305259	0	—
$\bar{\beta}_{tp} - \bar{\beta}_{bp} > 0$, significant at 0.01	0	—	49	0.0360416	0	—

Table 8: **Test for Greater Ability to Identify Growth than Value Stocks that Perform above Average at Earnings Announcement Dates, January 2, 1990 through December 31, 2000**

This table reports the result of a regression that is run to test whether the option market activity of various groups of investors indicates a greater ability to identify growth than value stocks with above average earnings announcement date (EAD) returns. The regression is run separately for firm proprietary traders (Firm Proprietary), customers of discount brokers (Discount), and customers of full-service brokers (Full-Service). The regression specification is:

$$Ret_{s,[-1:1]} = \gamma_0^i + \gamma_1^i \, \Delta NLR_s^i + \gamma_2^i \, GrD_s + \gamma_3^i \, GrD_s \times \Delta NLR_s^i + \epsilon_s^i$$

The $Ret_{s,[-1:1]}$ variable is the return on underlying stock s from the trade date before through the trade date after its EAD. The ΔNLR_s^i variable is investor group i's change in the average net long ratio (NLR) on underlying stock s from a benchmark period -21 to -17 trade dates before the EAD to a target period -4 to -2 trade dates before the EAD. The NLR variable measures the net long positions that investors take in underlying stocks through their option market positions. GrD_s is a growth stock dummy that is one when an underlying stock s is a growth stock (has book-to-market value in the bottom decile) and is zero otherwise. A positive estimate for the γ_3^i coefficient indicates that investor group i has a greater ability to identify growth than value stocks that perform above average at EADs.

Investor Type	Intercept	ΔNLR	GrD	$GrD \times \Delta NLR$	R^2
Firm Proprietary	0.0089***	0.00050	-0.0049**	-0.0021**	0.0019**
Discount	0.0077***	0.0101**	-0.0036*	-0.0131*	0.0015*
Full-Service	0.0075***	0.0162***	-0.0034*	-0.0146*	0.0017**

***: significant at the 5 % , **: significant at the 10 % , *: significant at the 20 %

Table 9: **Coefficient Estimate for Testing Whether Investors Have a Greater Ability to Identify Growth than Value Stocks that Perform above Average at Earnings Announcement Dates as Benchmark Period is Varied, January 2, 1990 through December 31, 2000**

This table reports the distribution of a coefficient used to estimate whether investors have a greater ability to identify growth than value stocks that perform above average at EADs The distribution is obtained by varying the benchmark period used to estimate the coefficient. The coefficient is obtained by estimating a regression that is is run separately for firm proprietary traders (Firm Proprietary), customers of discount brokers (Discount), and customers of full-service brokers (Full-Service). The regression specification is:

$$Ret_{s,[-1:1]} = \gamma_0^i + \gamma_1^i \, \Delta NLR_s^i + \gamma_2^i \, GrD_s + \gamma_3^i \, GrD_s \times \Delta NLR_s^i + \epsilon_s^i$$

The $Ret_{s,[-1:1]}$ variable is the return on underlying stock s from the trade date before through the trade date after the EAD. The ΔNLR_s^i variable is investor group i's change in the average net long ratio (NLR) on underlying stock s from a benchmark period $-a$ to $-b$ trade dates before the EAD to a target period -4 to -2 trade dates before the EAD. The NLR variable measures the net long positions that investors take in underlying stocks through their option market positions. GrD_s is a growth stock dummy that is one when an underlying stock s is a growth stock (has book-to-market value in the bottom decile) and is zero otherwise. A positive estimate for the γ_3^i coefficient indicates that investor group i has a greater ability to identify growth than value stocks that perform above average at EADs. The coefficient is estimated for all combinations of a and b where $-24 \leq a \leq -18$ and $-20 \leq b \leq -14$ subject to the restriction that $-a \leq -b - 5$. There are a total of 66 combinations of a and b which meet these requirements. The "Freq." columns report the frequency of configurations that fall in each category and the "Av. Diff." columns report the average γ across such configurations.

	Firm-Proprietary		Discount		Full-Service	
Test Statistic Significance	Freq.	Av. Diff.	Freq.	Av. Diff.	Freq.	Av. Diff.
$\bar{\beta}_{tp} - \bar{\beta}_{bp} < 0$, significant at 0.05	57	-0.0028221	0	—	0	—
$\bar{\beta}_{tp} - \bar{\beta}_{bp} < 0$, significant at 0.10 insignificant at 0.05	8	-0.00200625	29	-0.0160532	0	—
$\bar{\beta}_{tp} - \bar{\beta}_{bp} < 0$, significant at 0.25 insignificant at 0.05	1	-0.00166682	37	-0.012009	42	-0.0160827
$\bar{\beta}_{tp} - \bar{\beta}_{bp} < 0$, insignificant at 0.25	0	—	0	—	24	-0.0112355