**Do Fund Managers Identify and Share Profitable Ideas?[1]**

by

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ABSTRACT

We study data from an organization where fundamentals-based fund managers privately share investment ideas. Evidence suggests the professional investors in our sample have stock-picking skills. A strategy of going long (short) buy (sell) recommendations earns monthly calendar-time abnormal returns of 1.38% (-2.91%) over the January 1, 2000 to December 31, 2008 sample period. Interestingly, these skilled investors share their profitable ideas. We test predictions from private information sharing theories and determine that our sample investors share ideas to receive constructive feedback, gain access to a broader set of actionable ideas, and to attract additional arbitrager capital to their asset market.

JEL Classification: G10, G11, G14

Key words: Networks, Hedge Funds, and Market Efficiency.

[1]We would like to thank Daniel Bergstresser, Dave Carlson, Hui Chen, John Cochrane, Lauren Cohen, Cliff Gray, Eugene Fama, Ron Howren, Carl Luft, Stavros Panageas, Shastri Sandy, Gil Sadka, Amir Sufi, Pietro Veronesi, and Rob Vishny. We would also like to thank seminar participants at the University of Chicago Booth School of Business, Texas A&M, Southern Methodist Univesity, Drexel, Ohio State, University of Virginia, University of Washington, and Boston College.
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# Do Fund Managers Identify and Share Profitable Ideas?

ABSTRACT

We study data from an organization in which fund managers privately share investment ideas. Evidence suggests the investors in our sample have stock-picking skills. A strategy of going long (short) buy (sell) recommendations earns monthly calendar-time abnormal returns of 1.38% (-2.91%) over the January 1, 2000 to December 31, 2008 sample period. Interestingly, these skilled investors share their profitable ideas. We test predictions from private information sharing theories and determine that the managers in our sample share ideas to receive constructive feedback, gain access to a broader set of actionable ideas, and to attract additional arbitrager capital to their asset market.

Fundamentals-based money managers, or “value” investors, play a key role in the price discovery process. In equity markets specifically, a value manager’s job is to research a firm’s management, business, and future prospects and determine if the company is selling for less than its intrinsic value. If the value manager believes a security to be inexpensive relative to its intrinsic value, he will buy the security, driving its price towards intrinsic value. If he believes it to be expensive, he will either sell the security or sell the security short, thereby putting downward pressure on the price and driving its price to intrinsic value. This logic is the basis for the market efficiency hypothesis (Freidman, 1953). And yet, Grossman and Stiglitz (1980) argue that market prices can never be perfectly efficient: If prices were always efficient, skilled investors who acquire private information[1] would never be rewarded.

In the first part of this paper, we test the Grossman and Stiglitz prediction that price discovery agents’ compensation comes in the form of abnormal returns generated by inefficient market prices. Specifically, we study a group of specialized market participants (predominantly hedge fund managers focused exclusively on fundamental analysis) who share detailed investment recommendations on the private website Valueinvestorsclub.com (VIC). We find evidence of stock-picking skill among VIC members. Abnormal returns are economically large, statistically significant, and robust to a variety of controls. For example, the average monthly calendar-time portfolio alpha estimate (using 3-factor WLS regressions) is +1.38% for buy recommendations and -2.91% for sell recommendations.

The empirical evidence suggesting that VIC members are talented stock-pickers is interesting on its own merits. However, the unique organizational structure of VIC, which is

[1] Private information in our context refers to information derived from the effective and efficient collection and processing of publicly available information.

explicitly designed to facilitate private information exchange among professional investors, allows us to contribute to the literature by empirically addressing a question about investor behavior that has largely been ignored: Why would any investor with valuable private information share such information with others? Traditional theories suggest the process of how information flows into asset prices is straight forward. First an arbitrageur identifies a temporary mispricing, then acts on the price discrepancy with all available resources causing asset prices move to fundamental value (e.g., Friedman, 1953). However, bearing in mind this efficient pricing process, it remains unclear why a fund manager would share information about a profitable trading opportunity with other investors.

Recently, three theories have emerged that address the question of why an investor would share valuable private information. Stein (2008) proposes that fund managers may share private information because they gain valuable feedback from the person with whom they are sharing ("collaboration argument"). Gray (2010) suggests that another reason for information sharing is the promotion of managers' undervalued portfolio positions in order to attract additional capital to the market from other arbitrageurs ("awareness argument"). Gray also argues that a resource-constrained arbitrageur may share profitable ideas with the competition because doing so allows the arbitrageur to diversify his portfolio among a group of arbitrage trades, rather than allocate all his capital into his limited set of good ideas ("diversification argument").

In this paper we present the first empirical evidence to address the predictions of various information sharing theories. We determine that all three information exchange theories play a role in the sharing decision. That is, we find investors share ideas to receive constructive feedback, gain access to a broader set of profitable ideas, and to attract additional arbitragers to their asset market. These findings suggest that the mechanisms through which information flows into security prices are not as simple as traditional asset pricing models suggest.

The remainder of the paper is organized as follows. Section 1 discusses relevant research. Section 2 describes the data. Section 3 tests for stock-picking skill. Section 4 examines the relation between ex-ante VIC idea ratings and ex-post abnormal returns. Section 5 addresses why skilled fund managers share profitable trading opportunities and Section 6 concludes.

## 1. Related Literature on the "Stock-Picking Hypothesis"

Research on the collective performance of professional money managers indicates that outperforming a passive risk-adjusted index is extremely difficult. Specifically, studies of mutual fund managers have found that mutual funds, on average, do not outperform their benchmarks (e.g., Carhart, 1997; Malkiel, 1995; and Daniel, Grinblatt, Titman, and Wermers, 1997). A more recent analysis by Fama and French (2010) suggests that the aggregate portfolio of U.S. equity mutual funds roughly approximates the market portfolio and that there is little evidence for stock-picking skill among managers.

Another method of testing the stock-picking skill hypothesis is to study the performance alternative asset managers such as hedge fund managers. This research often involves analysis of hedge fund return databases. However, data pitfalls plague this research. First, hedge fund return databases suffer from survivorship bias and self-selected reporting (Fung and Hsieh, 2000). Second, hedge fund managers sometimes hold illiquid assets or engage in return smoothing, which causes the reported hedge fund returns to exhibit large autocorrelations (Asness, Krail, and Liew, 2001; and Getmansky, Lo, and Makarov, 2004). Third, researchers such as Liang

(2003) find that hedge fund database returns may be unreliable because the same hedge funds sometimes report different returns to different database operators. Finally, hedge fund managers often hold assets that have option-like, non-linear payoffs. This payoff profile makes it difficult for researchers to assess performance using traditional linear factor models (Fung and Hsieh, 2001).

Griffin and Xu (2009) address the aforementioned issues with hedge fund return database biases by analyzing hedge fund performance via their required 13F equity filings. Nonetheless, their analysis has its own shortcomings because it can only examine long equity positions and ignores intra-quarter trading.

Much of the work in this area focuses on the returns of broad portfolio returns to test for the presence of stock-picking skill. However, Cohen, Polk, and Silli (2009) argue that analyzing portfolio returns is not a test of stock-picking skill because portfolio returns may disguise a fund manager's true stock-picking ability. They argue that managers have incentives to hold diversified portfolios that consist of their "best ideas" along with other positions to "round out" their portfolios. In the end, a skilled manager may appear unskilled because of the perverse incentive structure in the fund management industry.

An alternative approach to testing the stock-picking hypothesis, which does not suffer from the inference problems associated with studying portfolio returns, is to analyze individual recommendations from superstar managers or stock analysts. These studies show little evidence in support of the stock-picking-skill hypothesis. Desai and Jain (1995) examine the performance of recommendations made by "superstar" money managers at the Barron's Annual Roundtable and find little evidence of superior stock-picking skill. Barber, Lehavy, McNichols, and

Trueman (2001) confirm this result and find that excess returns to the recommendations of stock analysts are not reliably positive after transaction costs.

We are able to avoid the inference problems associated with studying portfolio returns and directly test manager stock-picking skill by studying detailed individual stock recommendations shared on VIC. Moreover, VIC is a unique setting in which managers have incentives to share profitable ideas (see the discussion in section 5). Further, the detailed investment recommendations submitted by VIC members can be verified by the club's sophisticated membership, thereby eliminating the incentive for the promotion of efficiently priced recommendations.

The unique environment we study is different than the environment for analyst recommendations, where incentives to share good ideas may be perversely influenced by investment banking relationships, or the environment for "superstar" recommendations at the Barron's Annual Roundtable, where it is unclear that the managers sharing ideas have any incentive to share valuable ideas with the general public. Also, because the research and analysis behind superstar recommendations are never made fully available, it is unclear whether superstar recommendations are really meant to be bonafied stock-pick recommendations, or simply reflect an opportunity for the superstar manager to market his firm's brand to the general public.

Our database is not a panacea. The ideas under analysis are the simplest, most straightforward common equity recommendations submitted to VIC and we are further limited by the data available on CRSP/Compustat. The exclusion of the many complicated arbitrage trades and special situation scenarios submitted to VIC, but not analyzed due to data and analysis constraints, may bias the evidence. These sophisticated trades require advanced knowledge and understanding of niche securities and/or access to expensive resources such as lawyers, industry specialists, or tax experts. In a Grossman and Stiglitz (1980) equilibrium in which arbitrageurs are compensated for their information discovery efforts, one may hypothesize that these high information cost investments would have better gross returns than situations requiring less effort and fewer resources. If this story is to be believed, the data under analysis will likely be biased in favor of the null hypothesis that VIC members have no stock-picking skill. In general our data offer a rare opportunity to test a group of specialized managers for stock-picking skill in a relatively clean setting.

## 2. Data

### *2.1. Value Investors Club*

The data in this study are collected from a private internet community called Valueinvestorsclub.com, an "exclusive online investment club in which top investors share their best ideas."[2] Many business publications have heralded the site as a top-quality resource for those who can attain membership (e.g., *Financial Times*, *Barron's*, *BusinessWeek*, and *Forbes*).[3] Joel Greenblatt and John Petry, managers of the large fundamentals-based hedge fund Gotham Capital, founded the site with $400,000 of start-up capital. Their goal was for VIC to be a place for "the best-quality ideas on the Web" (Barker, 2001). The investment ideas submitted on the club's site are broad, but are best described as fundamentals-based. VIC states that it is open to any well-thought-out investment recommendation, but that it has particular focus on long or short equity or bond-based plays, traditional asset undervaluation plays such as high book-to-

[2] http://www.valueinvestorsclub.com/Value2/Guests/Info.aspx
[3] Ibid.

market, low price-to-earnings, liquidations, etc., and investment ideas based on the notion of value as articulated by Warren Buffett (firms selling at a discount to their intrinsic value irrespective of common valuation ratios).

Membership in the club is capped at 250 and admittance is highly selective with an approximate acceptance rate of 6%. Admittance is based solely on a detailed write-up of an investment idea (typically 1000 to 2000 words). Firm background and prior portfolio returns are not part of the application process. If the quality of the independent research is satisfactory and the aspiring member deemed a credible contributor to the club, he is admitted. Once admitted, members are required to submit two ideas per year with a maximum of six ideas per year. This maximum exists to encourage the submission of only the member's best ideas.

In addition to allowing members to comment on and rate other members' ideas, a weekly prize of $5,000 is awarded to the best idea submitted (prize is determined by VIC management). Members are monitored to ensure they submit at least two acceptable ideas per year and members failing to meet the high standards of the club are dismissed through a community-wide policing mechanism. Members are allowed to submit a thesis on a security that has been submitted in the past if the write-up is substantially unique. Otherwise, the members are required to submit their ideas in the feedback section associated with the original idea posting.

An important aspect of VIC is that members' identities are not disclosed to the general public or to the other members of the club. The intent of this policy is to keep individual VIC members from forming outside sharing syndicates with other members, who could then take their valuable research and comments away from the broader VIC community. The anonymity requirement also ensures the message board does not become a venue for hedge fund managers to signal to potential investors or market their services to the general public.[4] Finally, by keeping identifying information private, members can speak truthfully and without consequence about conversations with management, proxy situations, and other sensitive situations in which identity disclosure could lead to legal or relationship repercussions.

Because membership of VIC is strictly confidential, we are unable to publish the limited statistics on VIC members' profiles. However, the management of VIC agreed to disclose that VIC members are predominantly long-focused fundamentals-based hedge fund managers who typically have assets under management of between $50 million and $250 million.

### *2.2. Data Description*

We analyze all investment reports submitted to VIC from the time of the club's founding on January 1, 2000 through December 31, 2008. These reports represent all reports submitted to VIC over the entire time period the club has existed. That is, reports containing what ultimately prove to be poor recommendations are not deleted from the website and therefore our database does not suffer from an ex-post selection bias. In total, we examine 3,273 investment submissions. Report length can range from several hundred to a few thousand words. Investment ideas are wide-ranging with respect to the security type, trading location of the asset and the complexity of the strategy employed.

For each investment report analyzed, we record various data: date and time of submission, symbol, price at time of submission, market(s) traded, security(s) traded, strategy recommended (long, short, or long/short), and the "reasons for investing." All data collected are

[4] This would create a legal predicament for hedge fund managers who rely on Rule 506 of Regulation D in the Securities Act of 1933 to exempt them from registering their security offerings with the SEC.

unambiguous except for the “reasons for investing.” We compile a list of sixteen investment criteria that are frequently cited in VIC submissions. Criteria were judged to be sufficiently common if at least ten investment submissions acknowledged the use of the category. We then match the firms associated with a VIC recommendation to accounting and stock return data from CRSP/Compustat.

For the purposes of this study, we only analyze U.S. exchange-traded long and short common stock recommendations. We do not analyze U.S. common equity investment recommendations that have payoffs one may consider non-linear or inappropriate to analyze with linear factor asset pricing models because they may bias our results (Fung and Hsieh, 2001). Specifically, we eliminate all recommendations classified as merger arbitrage, stub arbitrage, pair-trade, liquidation, long/short pair-trade recommendations, and non-common-equity ideas such as options or preferred stock. We also eliminate foreign-traded or ADR recommendations.

Of the 3,273 observations in the original sample, 2,832 refer to U.S. securities. Of these 2,832 observations, 2,698 are recommendations on U.S. common stock securities. After the restrictions described above, we are left with 1,956 U.S.-equity long recommendations and 242 U.S.-equity short recommendations with at least one monthly return observation. Tables 1 and 2 present summary statistics of the sample.

[Insert Table 1]

[Insert Table 2]

## 3. Performance Analysis

In this section, we examine the performance of VIC recommendations. VIC members often state that their ideas should be considered “long-term investments” and not “short-term trades.” To capture this notion of long-term performance, we perform detailed calculations on holding periods ranging from one-month to three-years. We calculate abnormal returns in both event-time and calendar-time because of the considerable debate in the literature about the preferable technique for determining long-run abnormal performance. As Barber and Lyon (1997) argue, the traditional event-time buy-and-hold abnormal returns (BHAR) “precisely measure investor experience” of buy-and-hold investors, the contingent most common in the value investing community as well as among VIC membership. However, Mitchell and Stafford (2000) find that BHAR methods fail to account for cross-sectional dependence among firm abnormal returns in event-time and advocate a calendar-time approach instead. Loughran and Ritter (2000) further the debate, claiming that the calendar-time approach has low power to detect abnormal performance associated with events that are clustered across time. In this paper, we focus the discussion on results generated from the more statistically appealing calendar-time approaches.

We incorporate CRSP delisting return data using the technique of Beaver, McNichols, and Price (2007). These authors argue that the appropriate return to use for a delisted firm when no delisting return is available is the mean delisting return of those that are available among firms with the same three-digit delisting code. For instance, firms that delist as the result of merger or acquisition have a much higher mean delisting return than those that delist as the result of bankruptcy. After accounting for delisting returns, our abnormal return analysis accounts for delisted firms in a similar fashion to Lyons, Barber, and Tsai (1999). If a firm is delisted, we assume the proceeds of the delisted firms are invested in the control firm or benchmark-portfolio.

We also perform the analysis by assuming delisted firms' proceeds are invested in the CRSP value-weighted index, as well as by assuming delisted firms are eliminated from the database. The results are similar under all techniques.

### *3.1. Control-firm BHAR*

The control-firm event-time BHAR methodology we use follows that of Lyon, Barber, and Tsai (1999). The model is represented as

$$BHAR_{iT} = \prod_{t=1}^{T}[1 + R_{it}] - \prod_{t=1}^{T}[1 + E(R_{it})], \tag{1}$$

where $BHAR_{iT}$ is the buy-and-hold abnormal return to firm *i* in period *T*, $R_{it}$ is firm *i*'s return in month *t*, and $E(R_{it})$, is the appropriate expected monthly return for firm *i* in month *t*. This method allows our statistical inference to effectively control for the skewness bias in long-run abnormal returns identified by Barber and Lyon (1997).

Following the methodology of Speiss and Affleck-Graves (1995), we assign each sample firm a control firm based on size and book-to-market ratio. All firms in the CRSP/Compustat universe are considered potential matches and from this universe we select as the control firm that firm for which the sum of the absolute value of the percentage difference in size and the absolute value of the percentage difference in book-to-market ratio is minimized. We define size as the market value of equity on December 31 of the prior year and book-to-market ratio as book value of equity at the end of the last fiscal quarter of the prior calendar year divided by size.

We calculate BHARs for each recommendation using monthly CRSP data, following the advice of Brown and Warner (1985), who espouse the benefits of using monthly data rather than daily data. The event period return data begin on the first of the month following the date the recommendation was posted to the VIC community. For example, if an idea is posted on January 15, we start calculating BHARs on February 1. Because return data begins at the first of the month following the date of the recommendation, which leaves up to 30 days for VIC members to take positions, the abnormal returns presented likely underestimate the true returns earned by VIC members and may bias our tests in favor of the null hypothesis that fund managers have no stock-picking skills.

Table 3 presents the results of the control-firm BHAR analysis. Abnormal returns to long recommendations are economically large and statistically significant. We find one-year BHAR of 7.21%, two-year BHARs of 14.91% and three-year BHARs of 18.04%. The evidence from the short recommendation sample, although directionally correct, suggests we cannot reject the hypothesis that VIC members have no skill when shorting stocks. However, because the short recommendation samples are small, we should not expect a rejection of the null hypothesis, since any long-term abnormal return test lacks power in small samples (Ang and Zhang, 2004).

As a robustness test, we perform an alternate control-firm BHAR analysis. In these tests, we further require that neither the size nor book-to-market ratio of the control-firm deviates from that of the sample firm by more than 10%. This method ensures that sample firms examined are assigned a control firm with very similar characteristics. The results from this analysis (not shown) are similar to those presented in Table 3, which is consistent with the evidence presented by Nekrasov, Shroff and Singh (2009) that the specific matching technology is immaterial to the power of a control-firm test. We also perform the control-firm BHAR analysis after eliminating the observations with the highest 1% and lowest 1% of abnormal returns to control for extreme outliers seen in the BHAR scatter plots (see Figs. 1 and 2). The results (not shown) are similar to those presented in Table 3.

[Insert Table 3]

[Insert Figure 1]

[Insert Figure 2]

In addition to standard t-test values, we also present results in Table 3 from a sign test as per the recommendation by Ang and Zhang (2004), who conclude that the sign test coupled with a control-firm approach is well specified and has the highest power for detecting long-term abnormal returns among competing long-term event study methods. The conclusions from this analysis are similar.

### *3.2. Characteristics-based Benchmark-Portfolio BHAR*

A shortcoming of the control-firm BHAR approach is that, in small samples such as our sample of short recommendations, abnormal returns are very sensitive to mismatches between sample and control firms. Savor and Lu (2009) observe that in small samples only a few control firms need experience very large returns to make the mean abnormal return of the sample negative, even if the majority of sample firms experience positive abnormal returns. A remedy to this problem is the characteristics-based benchmark-portfolio BHAR approach, in which the benchmark return is the return to a portfolio of stocks with characteristics similar to those of the sample stock. Nonetheless, the use of benchmark-portfolios reintroduces the skewness bias Barber and Lyon (1997) identify, which is mitigated under the control-firm BHAR approach. Therefore, in the analysis of statistical significance for the benchmark-portfolio BHAR approach, we account for event-time skewness bias by using the bootstrapping method Lyon, Barber, and Tsai (1999) advocate.

To construct the benchmark-portfolios, we follow the characteristics-based benchmark methodology of Daniel, Grinblatt, Titman, and Wermers (1997). We assign each stock in the CRSP universe to one of 125 portfolios containing securities with similar size book-to-market and momentum characteristics. We then define benchmark-portfolio adjusted BHAR as the difference between the sample stock return and the benchmark-portfolio return, as in Eq. (1) above.

The results of this analysis are presented in Table 4. The results are consistent with the findings from the control-firm BHAR analysis. Using the benchmark-portfolio approach, we find that the investors in our sample generate statistically significant one-year BHARs of 9.52%, two-year BHARs of 19.03%, and three-year BHARs of 23.60%.

For short recommendations, both the control-firm BHAR approach and the benchmark-portfolio approach lead us to the conclusion that we cannot reject the null hypothesis after adjusting for skewness in the test statistics. However, unlike the control-firm BHAR analysis for short recommendations, the benchmark-portfolio BHARs are economically impressive: the one-year BHAR is 5.15%, two-year BHAR is 18.02%, and three-year BHAR is 21.47%. Taken as a whole, the analysis of the short recommendations using the various BHAR approaches provides little statistical evidence that the investors in our sample are successful short sellers.

For robustness, we also perform the benchmark-portfolio BHAR analysis after eliminating the observations with the highest 1% and lowest 1% of abnormal returns to control for extreme outliers. The results (not shown) are similar to those presented in Table 4.

[Insert Table 4]

*3.3. Calendar-Time Portfolio Abnormal Returns*

To assess the robustness of the results from the BHAR analyses, we analyze the data using the calendar-time portfolio approach advocated by Mitchell and Stafford (2000) and Fama (1998). Each month, the portfolios consist of all firms that were recommended in the current month *t*, and within the last *x* months (where *x* is the length of the holding period). We then calculate the monthly returns to the event-firm portfolio after adjusting for control-firm returns or benchmark-portfolio returns. We next take the time series of monthly portfolio returns to calculate a variety of relevant statistics.

We perform the analysis on equal-weight portfolios using both standard parametric and non-parametric techniques. We also perform the analysis on value-weighted portfolios and find less convincing evidence of stock-picking skill (results available upon request). However, the value-weighted portfolio construction effectively decreases the sample size and statistical power of our tests because of the bimodal distribution of the market capitalization of VIC recommendations. Fig. 3 is a histogram of market capitalization. The figure shows that the vast majority of observations are in the small-cap universe, but there is a spike in observations for very large companies (>$9.5 billion). Thus, the value-weighted portfolio construction can create portfolios that are essentially one observation. For example, in the long recommendation portfolio event month of May 2008, General Electric—a company with a $375 billion market capitalization at the time—was an event firm along with eight other companies that had an average market capitalization of $510mm, with a range of $117 million to $1.27 billion. For the remaining time General Electric was included in the portfolio it was effectively the entire portfolio. Because of this value-weighted portfolio construction issue we believe the equal-weighted constructed portfolios are a more appropriate tool to assess the stock-picking skill hypothesis in the context of our data. To address size related robustness concerns we use other standard analytical tools, which maintain the statistical power of the analysis.

The results of the calendar-time portfolio abnormal return analyis are presented in Table 5. The estimates in Table 5 represent the mean (median) monthly abnormal return over the calendar-time horizon for VIC recommendations. The estimates are consistent with the results of the BHAR analysis and suggest that the investors in our sample have stock-picking skills. The abnormal returns diminish the longer a recommendation is included in the portfolio, which is evidence that the stock market is slowly incorporating the information identified earlier by VIC members in to stock prices.

Panel B of Table 5 presents the results of portfolios formed from short recommendations. The evidence weakly suggests that VIC members are successful short sellers, contrasting with the results from the BHAR analysis which were inconclusive based on statistical inference. Because the various abnormal return methods provide conflicting statistical evidence, we draw no definitive conclusions regarding the short-selling ability of the investors in our sample. We attribute the conflicting signals to the well-known properties of small sample long-term abnormal return tests, which have low power to reject a false null hypothesis. More observations are needed to test the hypothesis for stock-picking skill on the short side of the market.

[Insert Table 5]

Table 6 presents a series of robustness checks designed to evaluate how particular characteristics affect the results. In general, the results are robust within a variety of subsamples including those formed on the basis of market capitalization, liquidity/turnover, event-time portfolio size, and those in which outliers have been eliminated.  The one area in which this analysis shows weaker robustness of our calendar-time abnormal return results is within the size-constrained sample in which market capitalization is required to be greater than $1 billion. The benchmark-portfolio adjusted calendar-time abnormal returns are persistent, but control-firm calendar-time abnormal returns vanish. This preliminary evidence suggests that VIC members' stock-picking skill may be limited to smaller companies in which the market is presumably less efficient and their research efforts are more richly rewarded.

[Insert Table 6]

### *3.4. Calendar-Time Portfolio Regressions*

To assess the robustness of the results from the BHAR and calendar-time portfolio abnormal return methodologies, we analyze the data using the calendar-time portfolio regression approach. In a similar manner to the calendar-time abnormal return approach, we form portfolios consisting of all firms that were recommended in the current month $t$, and within the last $x$ months (where $x$ is the length of the holding period). We then calculate the monthly returns to the event-firm portfolio in excess of the risk-free rate and regress this variable on a variety of linear asset pricing models which include the following variables: MKT (excess value-weighted market index return), SMB (small minus big), HML (high book-to-market minus low book-to-market), MOM (high momentum minus low momentum), INV (low investment minus high investment), ROA (high return on assets minus low return on assets), and LQD (traded liquidity factor) (Fama and French, 1993; Carhart, 1997; Pastor and Stambaugh, 2003; and Chen, Novy-Marx, and Zhang, 2010).[5] Coefficients for the various linear factor asset pricing models are presented in Table 7. The beta estimates suggest that VIC members typically recommend stocks that load positively on size and value factors and negatively on the momentum factor.

[Insert Table 7]

We perform all analyses using the single factor market model (MKT), Fama French 3-factor model (MKT, SMB and HML), Chen, Novy-Marx, and Zhang 3-factor model (MKT, INV, and ROA), Carhart (MKT, SMB, HML, and MOM), and the 5-factor model (MKT, SMB, HML, MOM, and LQD). To obtain monthly alpha estimates we perform the regression procedures using both portfolios constructed on an equal-weighted basis using OLS and portfolios constructed on an equal-weighted basis using WLS to control for heteroskedasticity issues (weights are the number of stocks in the portfolio in a given month).

The estimated alphas of these monthly regressions are presented in Table 8. The estimates in Panel A of Table 8 represent the mean monthly abnormal return over the calendar-time horizon for long recommendations. These statistically significant estimates range from 1.17% to 2.32% under the single-factor model specification and are consistent with the results of our previous analyses, providing further evidence suggesting that the investors in our sample have stock-picking skills.

[Insert Table 8]

Panel B in Table 8 presents the results of portfolios formed from short recommendations. The evidence suggests that VIC members are successful short sellers, in contrast to the results

[5] Factors obtained from Ken French's website http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html, Lubos Pastor's website http://faculty.chicagobooth.edu/lubos.pastor/research/liq_data_1962_2008.txt and Long Chen's website http://apps.olin.wustl.edu/faculty/chenl/linkfiles/data_equity.html.

from our earlier analyses which were inconclusive based on statistical inference. Because the various abnormal return methods provide conflicting statistical evidence, we conclude the data provide weak evidence for the short-selling ability of the investors in our sample.

### *3.5. Robustness Tests*

To better understand where VIC members are generating alpha, we divide the sample into size, book-to-market and turnover quintiles and perform the calendar-time portfolio regression analysis. For the sake of conservatism, we focus on the Fama-French three-factor model results because simulation evidence suggests four-factor calendar time regression results too often over-reject the null hypothesis of market efficiency (Ang and Zhang, 2004). For robustness, we also perform our tests using the alternative asset pricing models and find that the results are more compelling, but qualitatively similar to the three-factor results.

Tables 9 through 11 present the quintile analysis results. These results provide a more transparent view of how and from where VIC members derive benefits from private information collection. Not surprisingly, VIC members find the most alpha in smaller and more illiquid stocks. Alpha estimates for both the size and turnover quintiles generally decrease monotonically. In contrast to size and turnover, there is no clear indication that VIC members find value in a particular book-to-market quintile. The evidence suggests the members certainly have skill in value stocks, but there is also evidence that they have skill in the stocks tilted more towards growth.

[Insert Table 9]

[Insert Table 10]

[Insert Table 11]

Figs. 1 and 2 show the scatter plots of BHARs for long and short recommendations plotted over time. The plots suggest recommendations tend to cluster in December. According to VIC management, the reason we see more recommendations in December is because members must submit at least two recommendations per calendar year in order to fulfill their membership duties. Often, members procrastinate until the end of the year to fulfill their requirement.

Because many of these recommendations in December may be submitted due to time constraints and may be less thorough, a reasonable hypothesis is that the abnormal returns should be stronger once ideas in December are eliminated. We perform this analysis using the control-firm BHAR, benchmark-portfolio BHAR, calendar-time abnormal returns, and calendar-time portfolio regression approaches, and we find that the results are essentially the same with or without the December recommendations. Fig. 4 shows this result graphically for the set of long recommendations.

[Insert Figure 4]

### 3.6. *Performance Analysis Discussion*

Regardless of a researcher's preference for BHAR methods, calendar-time portfolio abnormal returns, or calendar-time portfolio regression approaches, all three methods presented in this study provide robust evidence that VIC members are successful long-only investors. The results of the various methods we use are statistically mixed with respect to VIC members' ability to successfully short sell stocks. The calendar-time portfolio regressions hint that VIC members have stock-shorting skills, however the BHAR and calendar-time abnormal return analysis is indeterminate. Our overall conclusion is that VIC members appear to have stock-picking skills for buy recommendations, but the evidence for short-selling skill is weak.

A potential criticism of VIC members' recommendations is that these ideas are not implementable. This concern is likely unwarranted. First, the quantitative evidence in this paper suggests that the results are robust to the addition of liquidity-related factors. Second, VIC is not designed as a means for fund managers to showcase their ability to write research reports on opportunities that cannot be implemented. Because reports are submitted under pseudonyms, reputation incentives are presumably negligible, making reports for extremely illiquid names a waste of both the author's and the membership's time. In fact, VIC has specific guidelines pertaining to the liquidity of investment recommendations submitted: "Small market capitalization ideas are fine, but as a general guideline, at least $250,000 worth of securities should trade on an average week. We understand that it is much more difficult to identify a compelling idea with $1billion of market capitalization, than one with $10mm of market capitalization and we take that into consideration when reviewing applications."

A critic may also be concerned that the full sample of VIC recommendations, without controlling for the quality of the recommendations, may bias the results in favor of the null hypothesis that investors have no stock-picking skill. For example, if a member submits a very low-quality idea because he was under time constraints, made mistakes in his analysis, or simply had no good ideas at the time, this idea may bias the results even though the VIC member submitting the idea, and the broader VIC community, can recognize the idea is not high-quality. Eliminating the "procrastination" ideas in December was an initial attempt to address this concern. The following section explores the relation between quality and performance in detail.

## 4. The Relation between VIC Ratings and Abnormal Returns

All VIC recommendations are not created equal. On September 14, 2008, the member "agape1095" posted a buy recommendation for Lehman Brothers. The report's thesis was based on a serious mistake in the writer's analysis. The idea was given a rating of 1.3 by the VIC community—the worst rating in the history of VIC and more than five standard deviations below the mean for the entire sample. Then, on September 15, 2008, a VIC member posted a comment pointing out that the company had already filed bankruptcy. Agape1095 quickly replied, "I didn't know Lehman was already bankrupted when I posted this. And this report totally deserves the low rating."

The example above highlights why analyzing the full sample of VIC recommendations may misrepresent the skill of the majority of the investors in our sample. Although VIC membership is difficult to attain, it remains difficult for the organization to completely screen out poor performers with certainty. To address this concern, we analyze how recommendations perform after controlling for the "quality" of the idea, as measured by the VIC community rating on individual investment theses.

When a report is posted to VIC, members are given the opportunity to rate it on a scale of 1 (bad) to 10 (good). Ratings are recorded if five or more members rate the idea, and the rating period is open for only two weeks to ensure members do not rate ideas based on ex-post performance. Since 2007, which is when data on the time of rating became available, 60% of ratings were submitted within 72 hours of posting. The club's guidance for ratings is that they should be objective and based purely on the quality of the investment thesis. Moreover, to encourage active participation, the club requires members to rate at least 20 ideas per year. The club also requests that extremely high (9 or 10) or extremely low (1 or 2) ratings be accompanied by some specific commentary about the investment thesis.

With the data on VIC ratings, we can perform additional tests for stock-picking skill among VIC members. In this analysis, we assume ratings approximate how favorably (or unfavorably) the VIC community believes the stock will perform in the future. To test whether VIC members can identify the best and worst recommendations within their universe of ideas, we estimate a simple model such that a linear relation exists between abnormal returns and the VIC community rating. The model is represented as

$$BHAR_i = \delta_i + \lambda_i(Rating_i) + \gamma_i controls_i + \varepsilon_i, \qquad (2)$$

where $BHAR_i$ is the abnormal return to stock *i* from *t*=2 to *t*=*h* (*h* is holding period), and $Rating_i$ is the VIC members' rating of the particular stock *i*. As the dependent variable we use both the benchmark-portfolio adjusted BHAR as well as the control-firm adjusted BHAR. We calculate the dependent variable from *t*=2 to *t*=*h* to avoid the endogeneity that may arise in a model relating ratings with BHARs that encompass the two-week rating period. That is, the rating may be endogenenously determined should an idea perform exceptionally well during the two-week rating period inducing members to rate it very highly. For example, if stock *XYZ* is recommended on June 20 and performs exceptionally well through July 3, members may rate the idea extremely favorably on July 3 not because they believe it will outperform in the future, but because it has performed well thus far.

We run Fama-Macbeth regressions to test the predictive content of ratings for abnormal returns. For each month *t*, we estimate a cross-sectional regression of the abnormal returns on the rating of the recommendation as well as controls for size, book-to-market ratio, prior six-month return, and turnover. We repeat this process for all periods to produce a set of *T* coefficient estimates (subject to the constraint that there is at least 10 observations in a given month). We then average the *T* estimates to get Fama-MacBeth coefficient estimates and t-statistics, which are robust to cross-sectional correlation.

The results from the Fama-MacBeth regressions presented in Table 12 provide weak evidence that VIC members have an ability to identify the best recommendations posted to the website as measured by ex-post BHAR. Point estimates for $\lambda_i$ are positive and statistically significant for the regression specifications of the benchmark-portfolio BHAR +2 to +6 on rating. The effect diminishes for control-firm BHARs and longer dated BHARs.

[Insert Table 12]

Because of the limited power of the Fama-MacBeth regression analysis, we further investigate how ratings are related to abnormal returns by analyzing the abnormal returns within quintiles formed on the basis of rating. In this analysis, we create calendar-time portfolios for each rating quintile. We then regress the calendar time portfolio returns for a given rating quintile on the returns to the mimicking portfolios of Fama and French (1993), where the calendar time portfolios are formed by assigning all firms that were recommended in month *t* and within the last *x* months (where *x* is the length of the holding period) to the calendar time portfolio. We present the alpha estimates of this procedure in Table 13. Alpha estimates for the highest rating quintile are large and statistically significant at the 5% level. Over one-year holding periods, the firms in the highest rating quintile have a 3.42% (t=3.14) average monthly alpha, whereas firms in the lowest rating quintile have a 0.49% (t=0.85) average monthly alpha.

This evidence suggests that VIC members are able to identify ex-ante which VIC recommendations will perform the best.

Next we investigate the ability of ratings to predict returns by examining the difference in mean BHAR between the highest and lowest rating quintile. Inference is based on both a student's t test and sign test. We present the results in Table 14. They provide strong evidence of a significant difference between the mean control-firm adjusted BHAR of the highest and lowest rated submissions. The mean one-year BHAR among the highest rating quintile is 21.69%, whereas the mean one-year BHAR to the lowest rating quintile is -0.16% (see Fig. 5). This is further evidence that VIC members can distinguish between good and bad recommendations.

[Insert Figure 5]

To summarize, we find strong evidence from both the calendar-time and the BHAR analysis that VIC members have an ability to distinguish between "good" ideas and "bad" ideas. This is further evidence in support of our stock-picking skill hypothesis; however, this analysis reveals that VIC members are successful stock pickers not only with regard to their own ideas, but in their evaluation of other members' ideas as well. The ability to distinguish between good and bad ideas is clearly a manifestation of stock-picking skill and suggests that at least some skilled managers exist in the investment management industry.

[Insert Table 13]

[Insert Table 14]

**5. Why do Managers Share Profitable Ideas?**

VIC is an organization explicitly designed to facilitate the sharing of private information among fund managers. However, the mere fact that VIC members are sharing this valuable private information at all is puzzling. Traditional theories (Friedman, 1953) suggest that arbitrageurs with valuable private information should take full advantage of the information advantage until prices reflect fundamental values. Moreover, in a market with efficient funds allocation, competing arbitrageurs should keep their valued information private so they can outperform their competition and thus attract more investor capital (Stein, 2008).

Such theories compellingly suggest that rational agents will not share private information, but few theories explain why rational agents *do* share private information in the asset management industry. Stein (2008) suggests managers might share information because they can get valuable feedback that improves their ideas ("collaboration argument"). Gray (2010) shows that a resource-constrained arbitrageur will share profitable ideas with his competition because doing so allows him to diversify his portfolio among a group of arbitrage trades. The benefits of sharing come from the fact that diversification lowers the probability the arbitrageur will experience a large negative noise trader shock in the short run and have his funds withdrawn by his investors ("diversification argument"). Finally, Dow and Gorton (1994) suggest arbitrageurs will only make investments if they believe subsequent arbitrageur demand will push the asset price higher ("arbitrage chains"). In the Dow and Gorton model, arbitrageurs are unable to reliably expect another arbitrageur to push asset prices further, and market prices end up being inefficiently priced. Gray's theory abstracts from the Dow and Gorton model and suggests that one obvious way arbitrageurs can help ensure other arbitrageurs will take a position in an asset is by sharing private information ("awareness argument"). Practitioners refer to this practice as "talking up your own book."

*5.1. Collaboration Argument*

Stein's theory of information exchange between competitors suggests that an asset manager will share his idea if it gives him access to constructive feedback that will make his idea more valuable. For example, fund manager *X* has developed a promising investment thesis, but his information set is incomplete so his idea is not worth much; however, by sharing his thesis with fund manager *Y* and receiving feedback, his investment thesis will become more valuable. As long as this give-and-take relationship is valuable for both parties involved, information exchange will occur between competitors. Stein's theory provides three basic predictions: (i) managers will share ideas in situations in which they receive constructive feedback, (ii) lower value ideas will be shared among a larger group of collaborators, and (iii) the most valuable ideas will remain localized within a small group.

Anecdotal evidence from VIC supports Stein's prediction that managers will share ideas when they can expect to receive constructive feedback. For example, on October 7, 2009, Seahawk Drilling was recommended as a long by user "ronmexico." Over the next two days, eight VIC members posted various comments relating to the investment thesis. On October 8, 2009, a detailed comment of more than 3,000 words entitled "disagree with some of the analysis" by user "ruby831" outlined the detailed short thesis for Seahawk Drilling. After some heated discussion between ronmexico and the VIC community, user "ad188" came to the following conclusion on October 9, 2009: "Excellent writeup, better Q&A—proves that VIC is worth the effort, as this would have taken me a week on my own—my conclusion [after] reading this is that HAWK [Seahawk Drilling] is not a long, at any price—however, with no debt, it doesn't seem that it is a short either." This vignette certainly suggests that one reason VIC members are sharing information is to receive valuable feedback to help develop their own ideas.

To quantitatively assess Stein's primary hypothesis in more depth we analyze the more than 40,000 comments attached to VIC recommendations. VIC has a robust infrastructure to facilitate collaboration and comments on individual ideas. Whenever an idea is posted to VIC, members receive an idea alert and are able to share their comments and thoughts on the investment thesis. Another feature of VIC is the "private" comment function. These comments are only visible to the VIC community and are not accessible by the general public (anyone can sign up for guest access to VIC, but access comes with a 45 day delay). For example, if VIC member "stockpicker" posts an idea on January 1, 2008 and another VIC member makes a comment on the idea that he designates as "private," then after February 14, 2008, all VIC members will still be able to view the private message, but anyone from the general public who is reading stockpicker's investment thesis and following the comments will not have access to the comments designated as "private."

Table 15 provides a more detailed description of the comments from VIC. We analyze the comments for the sample of observations with the necessary data to perform the control-firm analysis (results are very similar for other samples). In total we examine the comments on 1869 observations: 1671 long recommendations, and 198 short recommendations. We tabulate the total number of comments submitted, the number of unique VIC members involved in a particular conversation, the number of comments that are designated as "private," the number of comments that are author submitted, and the number of comments that are submitted within 45 days of the recommendation's posting.

Summary statistics certainly suggest that ideas submitted to VIC receive plenty of feedback. Over 91% of the recommendations receive at least 1 comment, and recommendation receives 12.03 comments on average. Author comments represent 43% of the total comments submitted for a particular idea, which suggests that the conversational, give-and-take nature of the comments between author and VIC members, fits the primary prediction of Stein's collaboration theory, that managers share their ideas to receive feedback.

We next test Stein's other hypotheses: (i) less valuable ideas will be shared among a larger group of agents, and (ii) more valuable ideas will be shared among a smaller group of agents. To assess these hypotheses we use the percentage of total comments identified as "private," as a proxy for the size of the collaboration group. For example, if idea *XYZ* has 20 comments and 15 are private, the feedback information for idea *XYZ* will be primarily limited to VIC members, whereas, if idea *ABC* has 20 comments and 0 are private, the feedback information is available to VIC members and the general public after 45 days.

We use the rating assigned to an investment recommendation as a proxy for the perceived value of an idea. We then divide the sample into quintiles formed on the percentage of total comments marked private. Table 16 presents the summary statistics and tests for differences in means and medians between the quintile of ideas with the lowest percentage of comments, and the quintile with the highest percentage of comments. The p-values associated with the t-test for differences in means and the Wilcoxson rank-sum test for differences in medians are significant at the 1% level. The evidence supports Stein's hypotheses that highly valued ideas will be shared with fewer people than lower valued ideas; the mean (median) rating for the quintile of ideas with the lowest percentage of private comments is 4.89 (5.00) versus 5.14 (5.20) for the ideas with the highest percentage of private comments. Admittedly, while the evidence from this test generally supports Stein's prediction, it is not entirely persuasive.

To further test Stein's hypothesis, we use the rating assigned to an investment recommendation as a proxy for the perceived value of an idea. We then estimate the parameters for the model

$$\%Private_i = a_i + b_i(Rating_i) + Controls_i + \varepsilon_i, \tag{3}$$

where $\%Private_i$ is the percentage of total comments marked private and $Rating_i$ is the rating of stock $i$. We estimate this model using data from January 1, 2004 to December 31, 2008 because the option to label comments "private" was rarely used prior to January 1, 2004 (10.01% of ideas had at least one private comment prior to 2004 versus 74.64% after January 1, 2004). Panel B in Table 16 shows ordinary least squares coefficient estimates as well as the maximum likelihood coefficient estimates from a logit regression model.

The regression estimates are mixed in their support for Stein's hypotheses. The estimated slopes from the OLS regressions suggest there is a positive linear relation between the quality of an idea (as proxied by rating) and the distribution of the idea (as proxied by the percentage of private comments); however, the logit regression estimates, while directionally correct, are not statistically significant from zero.

### *5.2. Diversification Argument*

If an arbitrageur is endowed with only a few great ideas in each time period, he will face difficult decisions: Does he invest all his assets under management in his handful of ideas and expose his business and investors to extreme noise trader risk? Or should he couple his few good ideas with a diversified index of efficiently priced assets and dilute his performance? Gray's theory shows that a third option is possible for arbitrageurs. Specifically, Gray finds that in a world in which investors simply focus on past returns as a rough proxy for arbitrageur skill (Shleifer and Vishny, 1997), arbitrageurs can share profitable ideas with the competition because doing so allows the arbitrageurs to diversify their portfolios among a group of arbitrage trades, which allows them to decrease their portfolio volatility, while at the same time, keeps them from diluting their performance. In addition to the basic prediction that constrained arbitrageurs will share private information, Gray's model is specific about the situations in which information exchange will occur. His model predicts that managers will share profitable ideas when (i) they have limited research resources and they are capital constrained, (ii) noise trader risk is high (i.e., market participants can drive prices from fundamentals), and/or (iii) arbitrage fund investors have a high propensity to withdraw funds following poor performance.

To test Gray's hypotheses that sharing will occur when managers have limited research resources and are capital constrained, we use a firm's assets under management as a proxy for their research and capital constraints. That is, we assume smaller firms have more constraints and larger firms have fewer constraints. To address this hypothesis, we analyze basic data from VIC and more detailed data from Sumzero.com. Sumzero.com is another exclusive buy-side-only information sharing network similar to VIC, yet it releases more detailed information on the characteristics of the 815 unique buy-side funds that make up the membership of the organization (as of September, 2009).

We find evidence that the funds sharing ideas on both VIC and Sumzero.com are predominately small. Specific data on the investor profiles of VIC members is confidential and cannot be disclosed. However, VIC management agreed to disclose that VIC members are almost exclusively small- to mid-size hedge funds ($50 million to $250 million assets under management). For more concrete data, we analyze the profile of asset managers who share ideas on Sumzero.com. Similar to VIC, Sumzero.com members are affiliated with funds that are overwhelmingly small (over 53% have less than $250mm assets under management). Fig. 6 shows the distribution of assets under management (AUM) for managers who share ideas through Sumzero.com.

[Insert Figure 6]

We next test the hypothesis that managers will share if they hold assets with high noise trader risk: we find preliminary evidence in support of this prediction. VIC recommendations are concentrated among investments thought to have higher noise trader risk such as small capitalization stocks, merger arbitrages, stub arbitrages (Mitchell, Pulvino, and Stafford, 2002), and pairs/twin arbitrage (Froot and Dabora, 1999). Specifically, we find that the long ideas submitted to VIC are recommendations for small capitalization stocks (median market capitalization is $393mm) or special situations such as stub and pair arbitrages, liquidations, and spin-offs in relatively illiquid markets (10.33% of ideas submitted). We find similar results for the submissions on Sumzero.com. Of the ideas submitted to the site, 15.5% are categorized as "event-driven or special situations," and the median market cap for long equity recommendations is $559mm.

For more evidence that sharing managers trade high noise trader risk assets, we analyze the institutional holdings of VIC stocks. If VIC stocks are dominated by individual investors, who are presumably noise traders, institutional holdings for VIC stocks should be small. We examine institutional ownership data from the Thomson Reuters Institutional Holdings database. This data source compiles the number of outstanding shares held by institutions for individual firms. The data are compiled from all SEC form 13(f) filings and are reported quarterly (March, June, September, and December). We then use CRSP price and shares outstanding data to calculate the percentage of shares outstanding held by institutions for a given firm. Similar to Chung and Zhang (2009), we exclude observations with missing variables or obvious data errors (i.e., institutional ownership greater than 100% of shares outstanding) and winsorize percent holdings at the 1st and 99th percentile to reduce the influence of extreme observations and possible data errors. Finally, we perform a paired t-test for unequal variances to test for differences in means and the Wilcoxson signed rank test to test for differences in medians between the lowest quintiles and the highest quintiles.

Table 18 summarizes institutional holding for the nearest quarter for the sample of investment recommendations submitted to VIC. In total, we have are 1546 observations with institutional data. In order to assess how institutional ownership is related to key characteristics of VIC recommendations, we present results for various quintiles related to size, B/M, and 12-, 24-, and 36-month control-firm BHARs. Average institutional ownership in the nearest quarter for VIC recommendations averages 53.13% of outstanding shares and varies widely by quintile. Chung and Zhang (2009) report that over the 2001 to 2006 period institutions held, on average, 56.31% of the shares outstanding of all firms in the Thomson Reuters Institutional Holdings database. They also find that the largest 25% of stocks have average institutional holdings of 79.48%, whereas the average within the quintile of the largest VIC recommendations is 70.47%.

Thus, relative to institutional holdings of stocks in general, and large stocks in particular, institutional ownership of VIC ideas is relatively small. If the level of noise traders and institutional ownership are inversely related, the evidence weakly supports the notion that arbitrageurs will only share ideas when there is high noise trader risk.

The initial evidence suggests that managers are sharing ideas within high-noise trader asset classes. Empirical evidence shows that the ideas submitted to both VIC and Sumzero.com are concentrated in smaller stocks and "special situation" investments, which are typically thought to have higher noise trader risk than other asset categories. Moreover, the empirical analysis of institutional holdings weakly suggests that VIC firms are sharing ideas with a higher proportion of noise traders than the typical stock in the investment universe.

### *5.3. Awareness Argument*

A key insight of the Dow and Gorton (1994) analysis of arbitrage chains is that short-horizon arbitrageurs will only make investments if the probability of another arbitrageur ($\delta$) subsequently entering the market is high enough. If $\delta$ is too low, arbitrageurs will not take an immediate position in a long-horizon arbitrage because the price will not be supported in subsequent periods and the arbitrageur will be exposed to various transaction costs. Although $\delta$ is fundamental to the analysis of arbitrage chains, there is little discussion about the origins of $\delta$ and it is assumed to be exogenous. However, Gray suggests arbitrageurs might endogenously increase the chances of future arbitrageurs coming into the market. One way arbitrageurs can help ensure other arbitrageurs take a position in an asset is by providing awareness of their investment thesis. Promotion on the basis of no information is unlikely to convince other smart investors to take a position in a particular asset; however, if investors share their private information, which can subsequently be verified by another arbitrageur, they can likely convince other arbitrageurs the idea is profitable. A distinguishing aspect of awareness sharing is that the arbitrageur shares his private information after he has already taken a full position in an asset.

Awareness sharing is likely one of the reasons investors share ideas on both VIC and Sumzero.com. In fact, at the 45$^{th}$ day after posting, VIC releases all their investment recommendations and analysis (except for comments marked as "private") to the general public, which is an explicit attempt to awareness share. Moreover, anecdotal evidence from a few of the write-ups submitted to VIC suggests the member is sharing after he has taken a full position. For example, a VIC member who recommended purchasing Aavid Thermal Technologies' 12.75% Senior Subordinate Notes states in his December 31, 2002 write-up, "Self-interest precluded me from posting the idea [earlier] because the bonds are fairly illiquid and it takes a few months to build a position."

While there certainly awareness sharing occurring after the 45$^{th}$ day after posting, it is unclear whether awareness sharing is the only dimension of the sharing decision during the 45-day period that VIC keeps recommendations private. Fortunately, one prediction from the awareness sharing theory is that a manager who awareness shares will exchange his private information with as many arbitrageurs as possible, as long as the transactional costs of sharing his private information are negligible. This prediction contrasts with the predictions of the collaboration and diversification theories of information exchange, which suggest managers will keep their private information sharing limited to smaller groups. Therefore, if managers are engaging in awareness sharing within the 45-day period that VIC keeps ideas private, as opposed to sharing for collaboration or diversification reasons, we should see a significant overlap in ideas submitted to both VIC and Sumzero.com (the null hypothesis would be 100% of ideas would be overlapping, because it is costless to post an idea to Sumzero.com after posting the idea to VIC). That is, if the sharing arbitrageur is trying to share his private information to the largest possible audience of sophisticated investors, rather than limiting his idea to an exclusive venue like VIC, he will seek to share his idea on Sumzero.com in addition to VIC.

We find that during the ten-month overlap period between the Sumzero.com and the VIC database (March 1, 2008 through December 31, 2008), 4.17% of the 456 ideas submitted on VIC are also submitted on Sumzero.com within fifteen days. Of the nineteen overlapping idea submissions to both VIC and Sumzero.com only seven are actually submitted simultaneously. This evidence rejects the awareness sharing null hypothesis during the forty-five day period in which the VIC recommendations are closed to the general public and suggest that VIC members are also using the site for collaboration and diversification benefits.

Another unique prediction of the awareness sharing theory is that large arbitrageurs will join sharing networks, but will not share ideas. The role of the large arbitrageur in the awareness sharing framework is simply to provide capital for arbitrage opportunities revealed by capital-constrained arbitrageurs. The situation is a win-win for all parties involved: capital constrained arbitrageurs win because they attract additional capital to their arbitrage situation, thus lowering the probability of a liquidation in the event of a noise trader shock, and large arbitrageurs win because they get access to arbitrage opportunities.

There is evidence to support the hypothesis that large funds will be members of private information groups, but will not share. Fig. 6 shows that just under 5% of the fund population for

Sumzero.com have over 20 billion in assets under management. Smaller funds submit 2.04 ideas per fund on average, whereas the largest funds submit 1.19 ideas on average; however, because Sumzero.com requires that members submit at least one idea a year, the marginal contribution of ideas above the mandate for small funds is 1.04 a year versus .19, or approximately zero, for the largest funds. The evidence in support of the hypothesis that large funds will not share is thin, but generally consistent with the idea that smaller funds will be the primary information sharers, and large funds will only provide arbitrage capital.

Overall, it is difficult to make an overarching statement with respect to the prevalence of awareness sharing and how it is used in practice by investors. Intuitively, one would suspect that awareness sharing is the only benefit investors care about when they share their private information with other sophisticated investors. Nonetheless, the empirical evidence shows only a small percentage of ideas submitted to VIC are actually shared with a broader audience, which suggests VIC members engage in limited awareness sharing. However, the empirical evidence from Sumzero.com does support the awareness sharing prediction that large funds will join information sharing groups, but their participation will be limited.

It appears that VIC takes a hybrid approach to awareness sharing: within the 45-day window, before the organization releases their recommendations to the public, members refrain from broad awareness sharing and likely capture the benefits from collaboration and diversification sharing. However, after the 45-day window VIC explicitly engages in awareness sharing by giving broad public access to its research. Sumzero.com appears to take a different approach. Membership of Sumzero.com is much broader in nature, so it is likely that the investors involved in this organization are primarily sharing their research to gain the benefits from awareness sharing.

### *5.4. Conclusions*

The empirical and anecdotal evidence from VIC and Sumzero.com generally support the predictions of the collaboration, diversification, and awareness theories of private information exchange. We cannot reject that members of VIC and Sumzero.com are using these networking sites to develop their own theses, create awareness of opportunities in which they have a position, and to get access to a pool of ideas that allows them to invest in a broader set of alpha-producing opportunities.

The next step in the research process would be to develop sharing models that incorporate all three sharing theories and determines how organizations will optimally behave. A good start for this research is the VIC model, which appears to be an organization that has made a first attempt at maximizing the benefits of sharing private information. VIC's approach can be summarized as follows: (1) an individual constrained agent identifies private information, (2) the agent takes an appropriate position such that internal risk management and investment mandates are satisfied, (3) the agent promotes the position to other arbitrageurs in VIC, generating the benefits of awareness, (4) the agent collaborates with other agents to receive constructive feedback on the idea, then adds to or subtracts from his current position accordingly, (5) the agent can also diversify his portfolio among the good ideas of other investment managers in VIC, and (6) after forty-five days the ideas are released to the general public to capture additional awareness sharing gains.

## 6. Conclusion

With our database, which is free from many of the biases found in databases other researchers analyze, we address two basic economic questions: (1) Do professional money managers have stock-picking skill? And, (2) why do they share their good ideas with their competition?

With respect to question (1), the evidence suggests the fund managers in our sample have stock-picking skills for long recommendations although the results for short recommendations are less conclusive. These results should not be completely surprising. The recommendations we analyze are well researched and required costly resources to develop. In equilibrium, skilled investors should be compensated for their efforts in accurately analyzing firms and driving assets to fundamental value as follows from the theory of Grossman and Stiglitz (1980).

To address question (2), we test the various predictions from the collaboration, diversification, and awareness theories of information exchange. We find that the investors in our sample appear to be sharing profitable ideas in order to increase awareness, which may mitigate inefficiencies in the securities' pricing. The investors also appear to use the VIC platform to receive constructive feedback on their analyses and gain insight on a more diverse collection of securities than they would be able to analyze if working alone. Overall, these findings suggest that the mechanisms through which information flows into security prices are not as simple as traditional asset pricing models would suggest.

In conclusion, this study brings into question the broader concepts of market efficiency in the stock market and the asset manager market. It provides evidence that some investors have skill to identify undervalued securities and are willing to share their valuable insights with their competition.

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## Figure 1

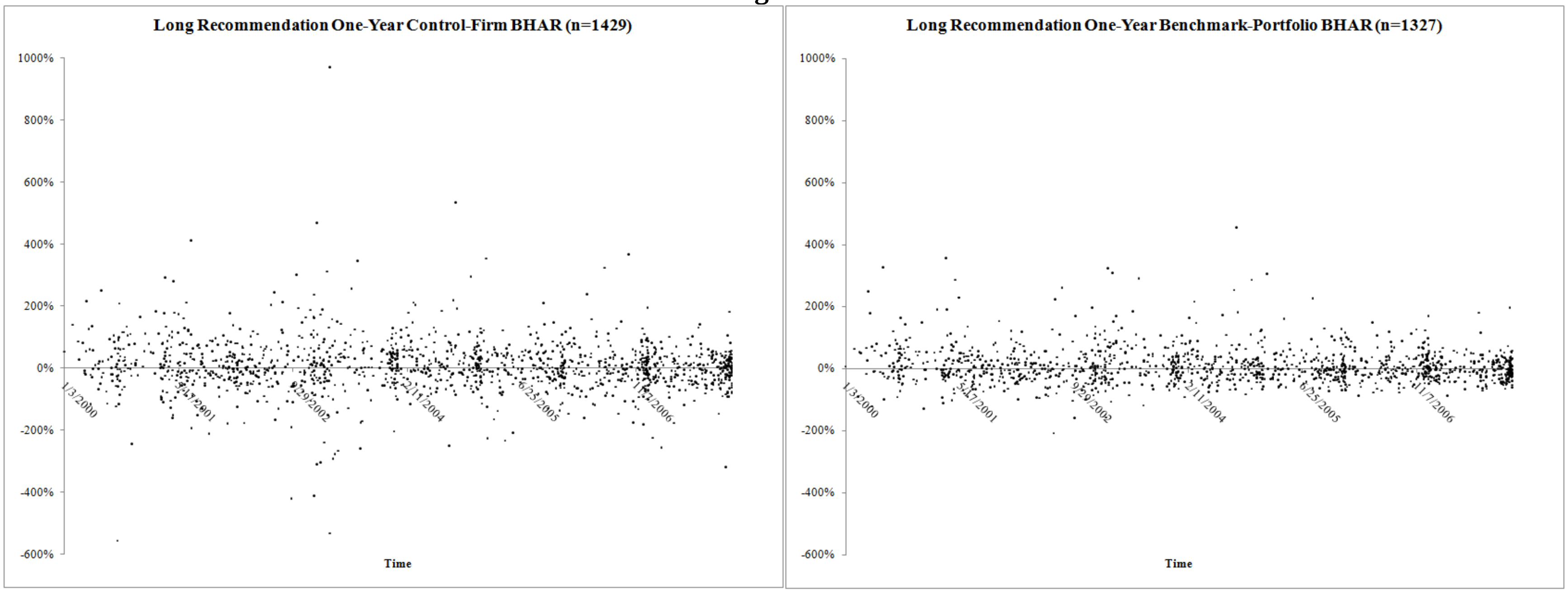


**Figure 1: Scatter plot of long recommendation one-year control-firm and benchmark-portfolio BHAR.** This figure represents a scatter plot of sample firm BHAR estimates. The Y-axis represents the abnormal return. The X-axis represents time.

## Figure 2

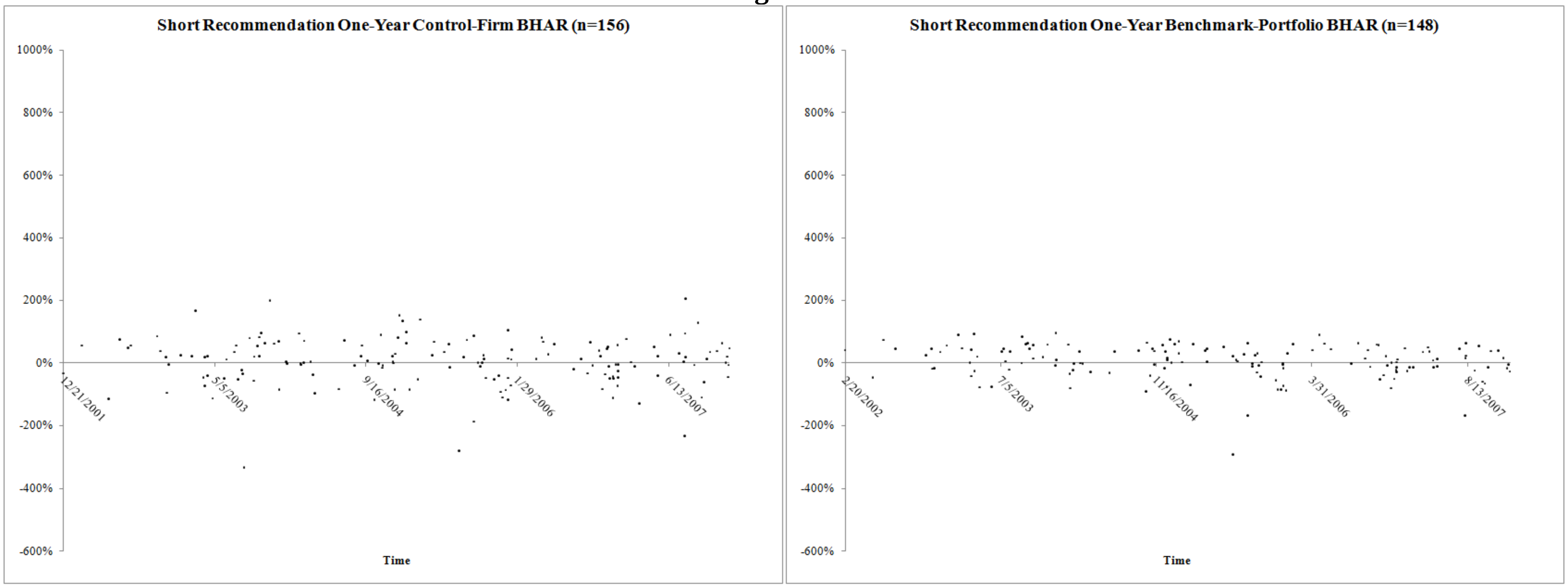


**Figure 2: Scatter plot of short recommendation one-year control-firm and benchmark-portfolio BHAR.** This figure represents a scatter plot of individual sample firm BHAR estimates. The Y-axis represents the abnormal return. The X-axis represents time.

# Figure 3

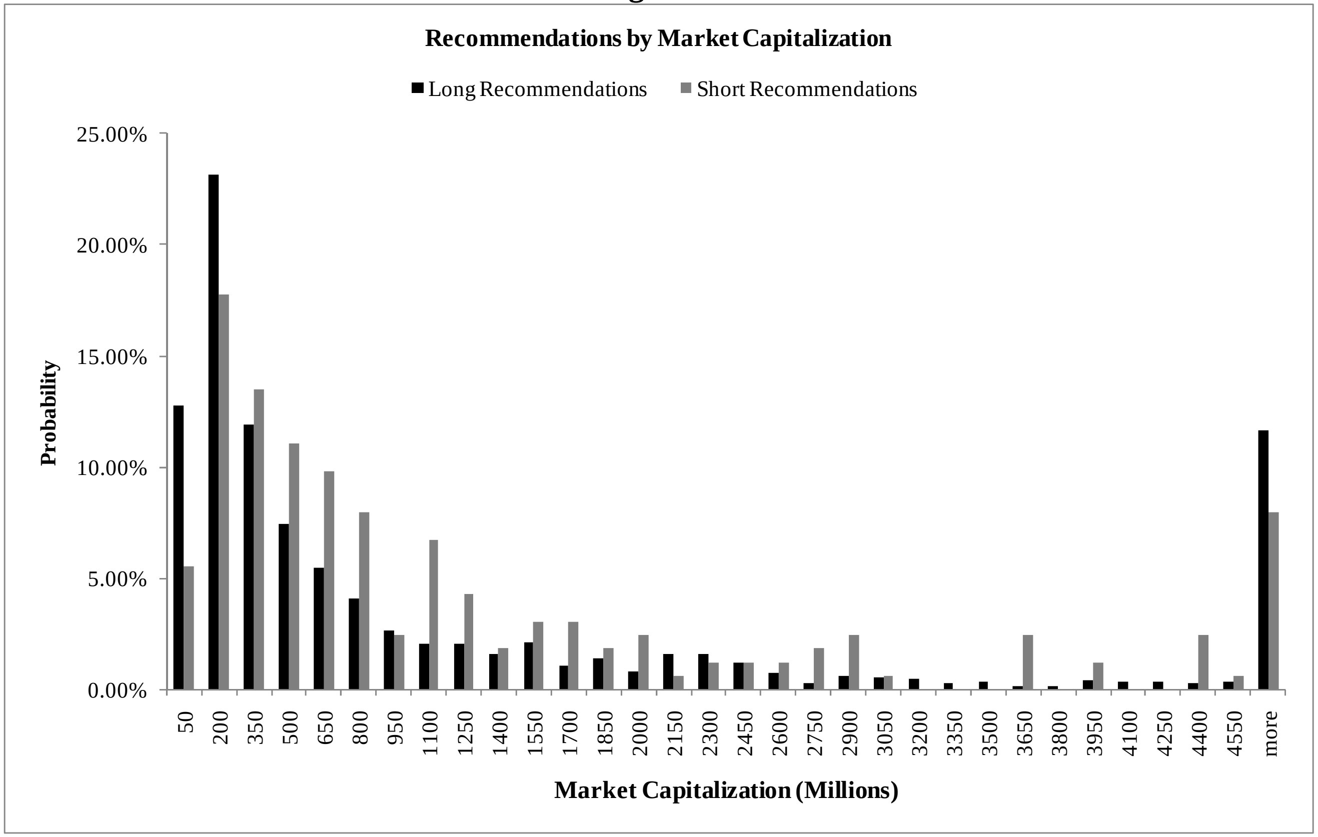


**Figure 3: VIC recommendations by market capitalization.** This figure represents the histogram of market capitalizations for the sample of firms with at least one monthly return observation. The Y-axis represents the probability. The X-axis represents market capitalizations. There are 1959 long recommendations and 242 short recommendations.

## Figure 4

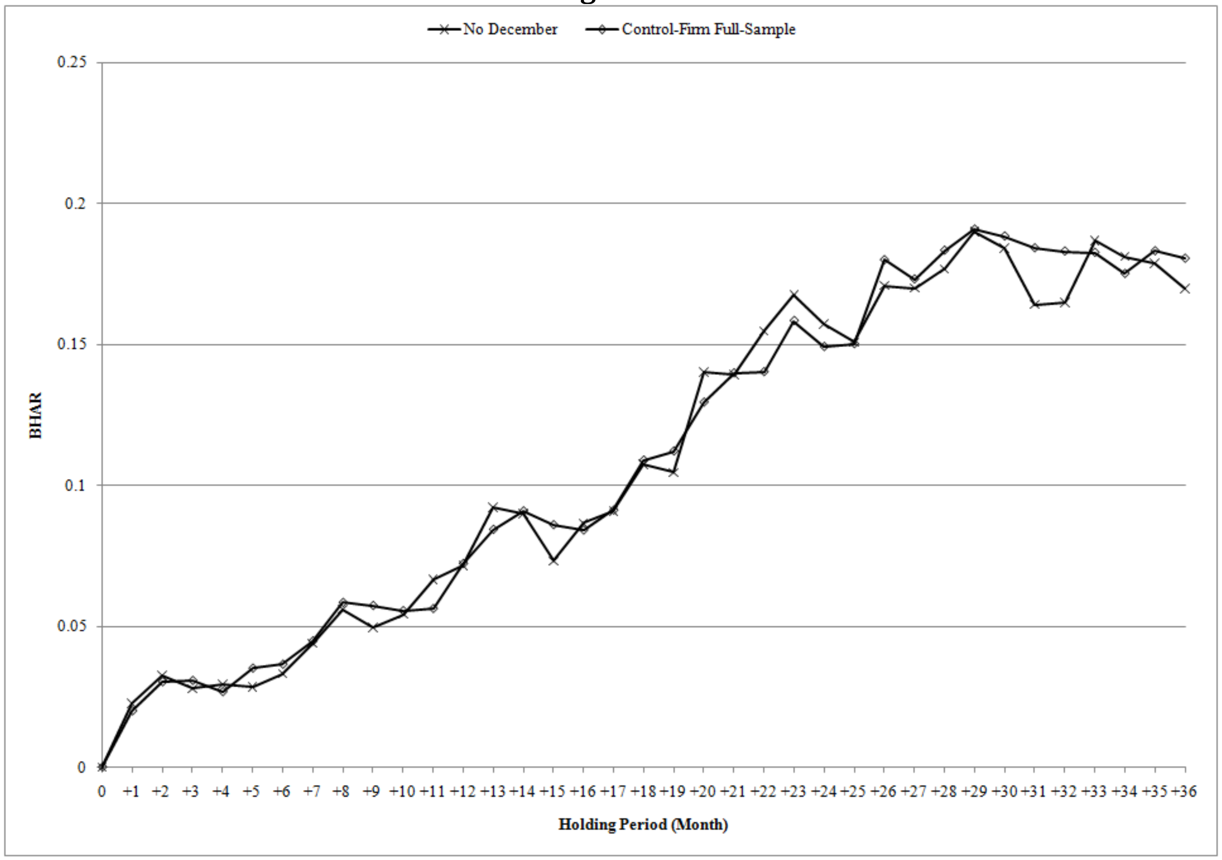


**Figure 4: BHAR estimates for +1 to +36 months with and without December observations.** This figure represents BHAR over time. The Y-axis represents the BHAR. The X-axis represents the holding period in months.

# Figure 5

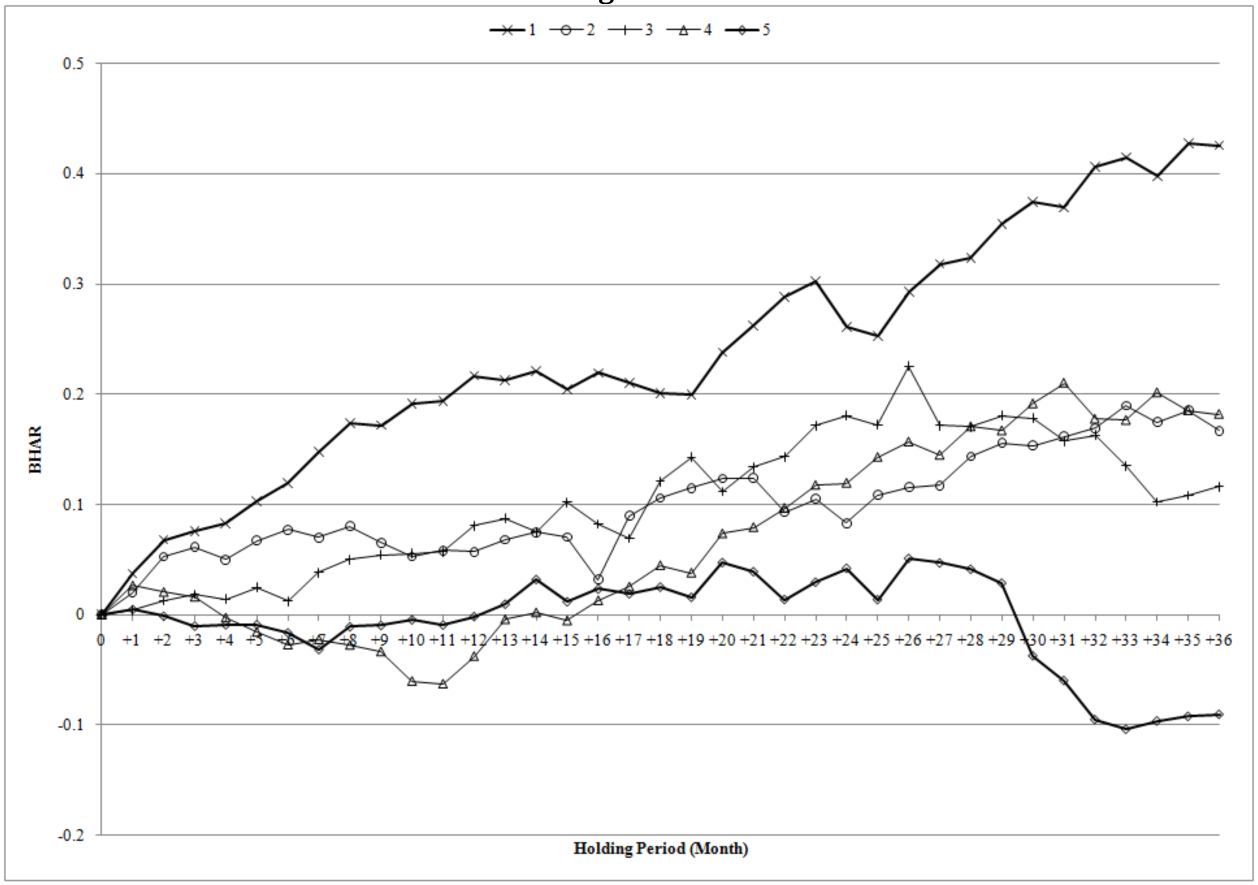


**Figure 5: BHAR estimates for +1 to +36 months by rating (1=high, 5=low).** This figure represents BHAR over time. The Y-axis represents the BHAR. The X-axis represents the holding period in months.

## Figure 6


**Figure 6: Sumzero.com Fund Manager AUM Profile.** The left axis is the percentage of funds that fit into a given asset under management (AUM) category from Sumzero.com (there are a total of 815 unique funds, but only 679 have AUM data). The right axis is the average idea submissions per fund for a given AUM category (there are 1211 ideas submissions by those funds with AUM data). The X-axis represents AUM categories. Data as of September 20, 2009.

## Table 1: Recommendation Summary Data

This table reports summary statistics for the sample of investment recommendations submitted to Valueinvestorsclub.com. The sample includes all recommendations shared with the VIC community from the time of the community's launch on January 1, 2000, through December 31, 2008. Panel A reports where assets are traded and the asset type recommended. Panel B reports the number of each long, short, and long/short recommendation by the type of asset. Panel C reports the number of each long, short, and long/short recommendation by trading location.

*Panel A: Asset type and trading location (n=3273)*

| Market | Common Stock | Bonds | Preferred Stock | Convertible Securities | Warrants | Options | Other | Total |
|---|---|---|---|---|---|---|---|---|
| US | 2698 | 46 | 32 | 12 | 7 | 7 | 30 | 2832 |
| Canada | 156 | 1 | 2 | 0 | 0 | 0 | 2 | 161 |
| UK/Europe | 149 | 3 | 0 | 0 | 0 | 0 | 1 | 153 |
| Japan | 15 | 0 | 0 | 0 | 0 | 0 | 1 | 16 |
| Hong Kong | 19 | 0 | 0 | 0 | 0 | 0 | 0 | 19 |
| Korea | 14 | 0 | 0 | 0 | 0 | 0 | 0 | 14 |
| Other | 77 | 0 | 0 | 0 | 0 | 0 | 1 | 78 |
| Total | 3128 | 50 | 34 | 12 | 7 | 7 | 35 | 3273 |

*Panel B: Recommendation by asset type (n=3273)*

| | Common Stock | Bonds | Preferred Stock | Convertible Securities | Warrants | Options | Other | Total |
|---|---|---|---|---|---|---|---|---|
| Long | 2816 | 44 | 25 | 12 | 7 | 7 | 11 | 2922 |
| Short | 274 | 1 | 3 | 0 | 0 | 0 | 5 | 283 |
| Long/Short | 38 | 5 | 6 | 0 | 0 | 0 | 19 | 68 |
| Total | 2798 | 40 | 26 | 4 | 7 | 7 | 30 | 3273 |

*Panel C: Recommendation and market location (n=3273)*

| | US | Canada | UK/ Europe | Japan | Hong Kong | Korea | Other | Total |
|---|---|---|---|---|---|---|---|---|
| Long | 2508 | 158 | 139 | 15 | 17 | 13 | 72 | 2922 |
| Short | 273 | 0 | 7 | 0 | 0 | 0 | 3 | 283 |
| Long/Short | 51 | 3 | 7 | 1 | 2 | 1 | 3 | 68 |
| Total | 2832 | 161 | 153 | 16 | 19 | 14 | 78 | 3273 |

## Table 2: Recommendation Descriptive Statistics

This table reports summary statistics for VIC recommendations. The sample consists of all firms that have at least one monthly return observation. Panels A and B show the characteristics of investment ideas. Panel C shows the frequency of recommendations by calendar year. B/M is the ratio of the LTM book value of equity to the market value of equity measured at the recommendation date. E/M is the ratio of LTM trailing earnings to the market value of equity measured at the recommendation date. ROA is the LTM return on assets. ME is the market value of equity measured at the recommendation date.

*Panel A: Long recommendation fundamental characteristics (n=1959)*

| | ME (millions) | B/M | E/M | ROA | ROE |
|---|---|---|---|---|---|
| Mean | 3806 | 1.26 | 0.00 | 0.03 | -0.05 |
| 25$^{th}$ Percentile | 112 | 0.33 | -0.02 | 0.00 | -0.01 |
| Median | 393 | 0.62 | 0.05 | 0.04 | 0.09 |
| 75$^{th}$ Percentile | 1536 | 1.06 | 0.08 | 0.09 | 0.18 |

*Panel B: Short recommendation fundamental characteristics (n=242)*

| | ME (millions) | B/M | E/M | ROA | ROE |
|---|---|---|---|---|---|
| Mean | 2010 | 0.28 | -0.11 | 0.09 | 0.41 |
| 25$^{th}$ Percentile | 251 | 0.17 | 0.00 | 0.00 | 0.01 |
| Median | 641 | 0.34 | 0.04 | 0.05 | 0.12 |
| 75th Percentile | 1672 | 0.66 | 0.07 | 0.11 | 0.22 |

*Panel C: Time-series distribution of recommendations*

| Year | Long Recommendations | Short Recommendations |
|---|---|---|
| 2000 | 110 | 1 |
| 2001 | 191 | 2 |
| 2002 | 204 | 11 |
| 2003 | 211 | 34 |
| 2004 | 226 | 31 |
| 2005 | 210 | 44 |
| 2006 | 228 | 34 |
| 2007 | 310 | 35 |
| 2008 | 269 | 50 |

## Table 3: Control-Firm Buy-and-Hold Abnormal Returns

Returns to sample firms and control firms from January 1, 2000 to December 31, 2008. Control firms are selected by choosing the firm for which the sum of the absolute value of the percentage difference in size and the absolute value of the percentage difference in book-to-market ratio is minimized. The mean sample-firm returns and mean control-firm returns in panel B are returns to a short position in the security. P-values associated with a two-tailed paired t-test and a sign-test are presented. The sample consists of all firms that have the necessary data to conduct the control-firm BHAR analysis.

*Panel A: Long recommendations*

| | N | Mean sample firm return | Mean control firm return | Difference (BHAR) | P-value of t-test for difference | P-value of sign-test for difference |
|---|---|---|---|---|---|---|
| One-year | 1429 | 17.28% | 10.07% | 7.21% | 0.0015*** | 0.1010 |
| Two-year | 1152 | 43.34% | 28.43% | 14.91% | 0.0003*** | 0.0087*** |
| Three-year | 945 | 72.34% | 54.30% | 18.04% | 0.0066*** | 0.0007*** |

*Panel B: Short recommendations*

| | N | Mean sample firm (short) | Mean control firm (short) | Difference (BHAR) | P-value of t-test for difference | P-value of sign-test for difference |
|---|---|---|---|---|---|---|
| One-year | 156 | -4.16% | -7.05% | 2.88% | 0.6421 | 0.0924* |
| Two-year | 128 | -9.06% | -18.37% | 9.32% | 0.3275 | 0.2504 |
| Three-year | 97 | -22.73% | -24.62% | 1.90% | 0.8784 | 0.1548 |

*, ** and *** denote two-tailed statistical significance at the 10%, 5% and 1% levels respectively.

## Table 4: Benchmark-Portfolio Buy-and-Hold Abnormal Returns

Returns to sample firms and benchmark-portfolios from January 1, 2000 to December 31, 2008. Benchmark-portfolio abnormal returns are calculated by assigning each stock to one of 125 benchmark-portfolios based on size, book-to-market ratio, and momentum characteristics, then subtracting the benchmark-portfolio return from the sample firm return. Mean sample returns and mean benchmark-portfolio returns in panel B represent the return to a short position in the security or portfolio. P-values associated with a paired t-test and the Lyon, Barber, and Tsai (1999) bootstrapped skewness-adjusted t-statistics are also presented (1000 resamples of size=n/4). The sample consists of all firms that have the necessary data to conduct the benchmark-portfolio BHAR analysis.

*Panel A: Long Recommendations*

| | n | Mean sample firm return | Mean benchmark-portfolio return | Difference (BHAR) | P-value of paired t-test for difference | P-value of skewness-adjusted t-test for difference |
|---|---|---|---|---|---|---|
| One-year | 1327 | 17.11% | 7.59% | 9.52% | 0.0000*** | 0.0000*** |
| Two-year | 988 | 45.02% | 25.99% | 19.03% | 0.0000*** | 0.0000*** |
| Three-year | 777 | 74.39% | 50.80% | 23.60% | 0.0000*** | 0.0013*** |

*Panel B: Short Recommendations*

| | n | Mean sample firm return (short) | Mean sample firm return (short) | Difference (BHAR) | P-value of paired t-test for difference | P-value of skewness-adjusted t-test for difference |
|---|---|---|---|---|---|---|
| One-year | 148 | -2.02% | -7.17% | 5.15% | 0.0840* | 0.4717 |
| Two-year | 115 | -3.35% | -21.37% | 18.02% | 0.0014*** | 0.1877 |
| Three-year | 88 | -12.74% | -34.21% | 21.47% | 0.0008** | 0.4906 |

*, ** and *** denote two-tailed statistical significance at the 10%, 5% and 1% levels respectively.

## Table 5: Calendar-Time Portfolio Abnormal Returns

This table reports calendar-time abnormal returns to portfolios of VIC recommended stocks. The long-recommendations sample contains stocks recommended as a buy. The short-recommendations sample contains stocks recommended as a sell. The samples consists of all firms that have at least one monthly return observation. Each month, the portfolios consist of all firms that were recommended in the current month *t*, and within the last *x* months (where *x* is the length of the holding period). Portfolios are rebalanced monthly. N represents the number of event months used in the calculations. The time period under analysis is from January 1, 2000, to December 31, 2008, using event observations from January 1, 2000, to December 31, 2008. There are 1959 (242) long (short) recommended firms with at least one monthly return observation. Average returns are in monthly percent, t-statistics are shown below the return estimates, and 5% statistical significance is indicated in bold. Non-parametric results are in median monthly percent, z-statistics from a Wilcoxon signed rank test for zero median are shown below the median return estimates, and 5% statistical significance is indicated in bold.

| | Equal-weight portfolio (parametric) | | | | | | Equal-weight portfolio (non-parametric) | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | One-month | Three-month | Six-month | One-year | Two-year | Three-year | One-month | Three-month | Six-month | One-year | Two-year | Three-year |
| Panel A: Long recommendations | | | | | | | | | | | | |
| Average/Median returns | **2.16%** | **1.61%** | **1.34%** | **1.23%** | 1.09% | 1.03% | **1.84%** | **1.45%** | **1.65%** | **1.47%** | **1.37%** | **1.37%** |
| | [2.94] | [2.41] | [2.12] | [1.97] | [1.78] | [1.67] | [3.15] | [2.75] | [2.66] | [2.64] | [2.51] | [2.44] |
| Control-firm adjusted | **2.06%** | **0.95%** | 0.48% | 0.31% | 0.27% | 0.20% | **2.54%** | **0.93%** | **0.49%** | 0.55% | 0.27% | 0.13% |
| | [3.98] | [2.86] | [1.83] | [1.34] | [1.43] | [1.14] | [3.99] | [3.03] | [2.00] | [1.68] | [1.63] | [1.22] |
| Benchmark-portfolio Adjusted | **0.81%** | **0.62%** | **0.53%** | **0.51%** | **0.39%** | 0.33% | 0.37% | **0.50%** | **0.52%** | **0.20%** | 0.27% | 0.12% |
| | [2.02] | [2.81] | [2.45] | [2.65] | [2.12] | [1.82] | [1.66] | [2.51] | [2.69] | [2.14] | [1.77] | [1.41] |
| N | 107 | 107 | 107 | 107 | 107 | 107 | 107 | 107 | 107 | 107 | 107 | 107 |
| Panel B: Short recommendations | | | | | | | | | | | | |
| Average/Median returns | **-4.03%** | **-2.10%** | -0.82% | -1.09% | -1.06% | -1.05% | **-2.94%** | -2.15% | -0.61% | -0.88% | -0.37% | -0.68% |
| | [-2.93] | [-2.01] | [-0.91] | [-1.34] | [-1.45] | [-1.6] | [-2.71] | [-1.94] | [-0.76] | [-0.94] | [-0.74] | [-1.31] |
| Control-firm adjusted | -0.69% | -1.56% | -0.69% | -0.57% | -0.54% | -0.47% | 0.69% | -0.72% | 0.25% | 0.11% | -0.06% | 0.06% |
| | [-0.42] | [-1.28] | [-0.87] | [-0.77] | [-0.78] | [-0.68] | [-0.09] | [-0.8] | [-0.2] | [-0.02] | [-0.54] | [-0.25] |
| Benchmark-portfolio Adjusted | -3.37% | **-1.99%** | **-1.39%** | **-1.19%** | **-1.24%** | **-1.28%** | -1.92% | -1.31% | -0.35% | **-0.66%** | **-0.93%** | **-0.80%** |
| | -1.33 | -2.07 | -1.99 | -2.04 | -2.28 | -2.38 | [-1.09] | [-1.87] | [-1.49] | [-1.97] | [-2.75] | [-2.88] |
| N | 76 | 76 | 76 | 76 | 76 | 76 | 76 | 76 | 76 | 76 | 76 | 76 |

## Table 6: Robustness: Calendar-Time Abnormal Returns (Long Recommendations)

This table reports calendar-time abnormal returns for VIC long recommended stocks. The sample consists of all firms that have at least one monthly return observation. Each month, the portfolios consist of all firms that were recommended in the current month *t,* and within the last *x* months (where *x* is the length of the holding period). Portfolios are rebalanced monthly. N represents the number of event months used in the calculations. The time period under analysis is from January 1, 2000, to December 31, 2008, using event observations from January 1, 2000, to December 31, 2008. Average returns are in monthly percent, t-statistics are shown below the return estimates, and 5% statistical significance is indicated in bold. TO is the past 3 months average daily trading volume divided by shares outstanding measured at the recommendation date.

| | Equal-weight portfolio | | | | | |
|---|---|---|---|---|---|---|
| | One-month | Three-month | Six-month | One-year | Two-year | Three-year |
| Panel A: ME>$1B | | | | | | |
| Control-firm adjusted | -0.19% | 0.61% | 0.11% | 0.19% | 0.12% | 0.06% |
| | [-0.19] | [1.11] | [0.25] | [0.73] | [0.57] | [0.33] |
| Benchmark-portfolio Adjusted | -0.78% | **0.76%** | 0.51% | **0.60%** | **0.55%** | **0.51%** |
| | [-1.01] | [2.04] | [1.83] | [2.75] | [2.75] | [2.65] |
| N | 74 | 103 | 103 | 103 | 103 | 103 |
| Panel B: Price >$5 & TO>1% | | | | | | |
| Control-firm adjusted | **1.35%** | **0.81%** | 0.26% | 0.25% | 0.22% | 0.16% |
| | [2.57] | [2.19] | [0.79] | [0.89] | [0.95] | [0.72] |
| Benchmark-portfolio Adjusted | **0.93%** | **0.79%** | **0.53%** | **0.57%** | **0.45%** | **0.41%** |
| | [2.23] | [3.13] | [2.51] | [2.88] | [2.48] | [2.37] |
| N | 101 | 105 | 105 | 105 | 105 | 105 |
| Panel C: Minimum 10 stocks | | | | | | |
| Control-firm adjusted | **1.62%** | **0.98%** | 0.50% | 0.33% | 0.29% | 0.22% |
| | [2.89] | [2.91] | [1.9] | [1.42] | [1.53] | [1.24] |
| Benchmark-portfolio Adjusted | **1.08%** | **0.54%** | **0.51%** | **0.50%** | **0.37%** | 0.30% |
| | [2.43] | [2.4] | [2.35] | [2.54] | [2.01] | [1.7] |
| N | 65 | 104 | 104 | 104 | 104 | 104 |
| Panel D: Windsorized Sample (5%) | | | | | | |
| Control-firm adjusted | **2.06%** | **0.97%** | **0.53%** | 0.37% | 0.31% | 0.25% |
| | [3.98] | [2.9] | [2.05] | [1.71] | [1.73] | [1.51] |
| Benchmark-portfolio Adjusted | **0.81%** | **0.62%** | **0.47%** | **0.39%** | 0.27% | 0.20% |
| | [2.01] | [2.79] | [2.19] | [2.03] | [1.47] | [1.08] |
| N | 105 | 105 | 105 | 105 | 105 | 105 |

## Table 7: Calendar-Time Portfolio Regressions, Factor Loadings 2000-2008

This table reports calendar-time abnormal returns and factor loadings for VIC recommended stocks. The long-recommendations sample contains stocks recommended as a buy. The short-recommendations sample contains stocks recommended as a sell. The samples consist of all firms that have at least one monthly return observation. Each month, the portfolios consist of all firms that were recommended in month *t*, and within the last *x* months (where *x* is the length of the holding period). Portfolios are rebalanced monthly. The time period under analysis is from January 1, 2000, to December 31, 2008, using event observations from January 1, 2000, to December 31, 2008. There are 1959 (242) long (short) recommended firms with at least one monthly return observation. Alpha is the intercept on a regression of monthly excess return from the rebalanced strategy. The explanatory variables are the monthly returns from the Fama and French (1993) and Chen, Novy-Marx, and Zhang (2010)(CNZ) mimicking portfolios, Carhart (1997) momentum factor, and Pastor and Stambaugh (2003) traded liquidity factor. Alphas are in monthly percent, t-statistics are shown below the coefficient estimates, and 5% statistical significance is indicated in bold.

| Panel A: Long recommendations (one-year portfolios) | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | Alpha | MKT | SMB | HML | MOM | LQD | INV | ROA |
| Market Model | **1.37%** | **1.18** | | | | | | |
| | [4.03] | [15.86] | | | | | | |
| Fama-French | **0.68%** | **1.13** | **0.68** | **0.49** | | | | |
| | [2.69] | [20.26] | [10.13] | [6.29] | | | | |
| CNZ | **1.54%** | **1.09** | | | | | 0.28 | -0.12 |
| | [4.38] | [11.48] | | | | | [1.82] | [-1.71] |
| Carhart alpha | **0.73%** | **1.04** | **0.75** | **0.48** | **-0.14** | | | |
| | [3.00] | [17.78] | [11.11] | [6.56] | [-3.32] | | | |
| 5-factor | **0.74%** | **1.05** | **0.75** | **0.49** | **-0.14** | -0.02 | | |
| | [2.99] | [16.19] | [10.83] | [6.22] | [-3.30] | [-0.26] | | |

| Panel B: Short recommendations (one-year portfolios) | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | Alpha | MKT | SMB | HML | MOM | LQD | MOM | LQD |
| Market Model | -1.18% | **0.84** | | | | | | |
| | [-1.67] | [4.96] | | | | | | |
| Fama-French | **-1.75%** | **0.69** | **0.80** | **1.23** | | | | |
| | [-2.86] | [4.49] | [3.00] | [4.38] | | | | |
| CNZ | -1.45% | **1.01** | | | | | 0.63 | 0.26 |
| | [-1.92] | [4.92] | | | | | [1.75] | [1.19] |
| Carhart alpha | **-1.71%** | **0.66** | **0.81** | **1.23** | -0.06 | | | |
| | [-2.75] | [3.90] | [3.00] | [4.36] | [-0.40] | | | |
| 5-factor | **-1.69%** | **0.69** | **0.81** | **1.24** | -0.06 | -0.04 | | |
| | [-2.62] | [3.23] | [2.97] | [4.27] | [-0.33] | [-0.19] | | |

## Table 8: Calendar-Time Portfolio Regressions

This table reports calendar-time abnormal returns for VIC recommended stocks. The long-recommendations sample contains stocks recommended as a buy. The short-recommendations sample contains stocks recommended as a sell. The samples consist of all firms that have at least one monthly return observation. Each month, the portfolios consist of all firms that were recommended in month *t*, and within the last *x* months (where *x* is the length of the holding period). Portfolios are rebalanced monthly. The time period under analysis is from January 1, 2000, to December 31, 2008, using event observations from January 1, 2000, to December 31, 2008. There are 1959 (242) long (short) recommended firms with at least one monthly return observation. Alpha is the intercept on a regression of monthly excess return from the rebalanced strategy. The explanatory variables are the monthly returns from the Fama and French (1993) and Chen, Novy-Marx, and Zhang (2010) mimicking portfolios, Carhart (1997) momentum factor, and Pastor and Stambaugh (2003) traded liquidity factor. Alphas are in monthly percent, t-statistics are shown below the coefficient estimates, and 5% statistical significance is indicated in bold.

| | Equal-weight portfolio | | | | | | WLS | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | One-month | Three-month | Six-month | One-year | Two-year | Three-year | One-month | Three-month | Six-month | One-year | Two-year | Three-year |
| Panel A: Long recommendations | | | | | | | | | | | | |
| Market Model alpha | **2.32%** | **1.77%** | **1.49%** | **1.37%** | **1.23%** | **1.17%** | **1.95%** | **1.43%** | **1.10%** | **0.85%** | **0.57%** | 0.42% |
| | [4.75] | [4.84] | [4.31] | [4.03] | [3.73] | [3.56] | [4.94] | [4.54] | [3.71] | [2.99] | [2.22] | [1.75] |
| Fama-French alpha | **1.59%** | **1.11%** | **0.80%** | **0.68%** | **0.57%** | **0.51%** | **1.38%** | **0.78%** | **0.47%** | 0.25% | 0.06% | -0.04% |
| | [3.6] | [3.81] | [3.00] | [2.69] | [2.29] | [2.08] | [3.79] | [3.14] | [2.1] | [1.32] | [0.38] | [-0.26] |
| CNZ alpha | **2.42%** | **1.96%** | **1.62%** | **1.54%** | **1.40%** | **1.34%** | **2.17%** | **1.69%** | **1.25%** | **0.93%** | **0.65%** | **0.52%** |
| | [4.76] | [5.21] | [4.51] | [4.38] | [4.09] | [3.95] | [5.23] | [5.07] | [4.01] | [3.14] | [2.42] | [2.09] |
| Carhart alpha | **1.64%** | **1.16%** | **0.85%** | **0.73%** | **0.61%** | **0.55%** | **1.43%** | **0.88%** | **0.55%** | 0.30% | 0.11% | 0.00% |
| | [3.73] | [4.23] | [3.26] | [3.00] | [2.56] | [2.34] | [4.14] | [3.88] | [2.63] | [1.71] | [0.7] | [0.05] |
| 5-factor alpha | **1.71%** | **1.19%** | **0.84%** | **0.74%** | **0.62%** | **0.56%** | **1.44%** | **0.90%** | **0.51%** | 0.26% | 0.09% | -0.02% |
| | [3.85] | [4.24] | [3.19] | [2.99] | [2.58] | [2.35] | [4.11] | [3.86] | [2.37] | [1.44] | [0.53] | [-0.11] |

## Table 8: Calendar-Time Portfolio Regressions (Cont.)

| | Equal-weight portfolio | | | | | | WLS | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | One-month | Three-month | Six-month | One-year | Two-year | Three-year | One-month | Three-month | Six-month | One-year | Two-year | Three-year |
| Panel B: Short recommendations | | | | | | | | | | | | |
| Market Model alpha | **-4.05%** | **-2.15%** | -0.88% | -1.18% | -1.18% | -1.19% | **-2.19%** | **-1.50%** | -0.64% | -0.95% | **-0.95%** | **-1.10%** |
| | [-3.29] | [-2.36] | [-1.17] | [-1.67] | [-1.78] | [-1.93] | [-2.03] | [-2.04] | [-1] | [-1.76] | [-2.06] | [-2.75] |
| Fama-French alpha | **-4.76%** | **-2.93%** | **-1.46%** | **-1.75%** | **-1.74%** | **-1.69%** | **-2.91%** | **-2.46%** | **-1.22%** | **-1.42%** | **-1.35%** | **-1.40%** |
| | [-4.24] | [-3.9] | [-2.21] | [-2.86] | [-3.1] | [-3.17] | [-2.78] | [-3.91] | [-2.15] | [-2.96] | [-3.48] | [-4.16] |
| CNZ alpha | **-4.08%** | **-2.21%** | -1.10% | -1.45% | **-1.41%** | **-1.33%** | -1.91% | -1.32% | -0.61% | -0.85% | -0.75% | -0.84% |
| | [-3.01] | [-2.22] | [-1.37] | [-1.92] | [-1.98] | [-1.99] | [-1.6] | [-1.61] | [-0.85] | [-1.39] | [-1.4] | [-1.78] |
| Carhart alpha | **-4.82%** | **-2.97%** | **-1.41%** | **-1.71%** | **-1.66%** | **-1.64%** | **-2.97%** | **-2.49%** | -1.09% | **-1.29%** | **-1.15%** | **-1.32%** |
| | [-4.21] | [-3.88] | [-2.09] | [-2.75] | [-2.91] | [-3.01] | [-2.76] | [-3.86] | [-1.9] | [-2.65] | [-2.94] | [-3.79] |
| 5-factor alpha | **-5.05%** | **-2.96%** | **-1.34%** | **-1.69%** | **-1.61%** | **-1.59%** | **-3.05%** | **-2.54%** | **-1.16%** | **-1.37%** | **-1.22%** | **-1.38%** |
| | [-4.29] | [-3.73] | [-1.93] | [-2.62] | [-2.74] | [-2.83] | [-2.83] | [-3.89] | [-1.98] | [-2.8] | [-3.11] | [-3.95] |

## Table 9: Calendar-Time Portfolio Regressions by Market Equity (Long Recommendations)

This table reports calendar-time abnormal returns for VIC recommended stocks. The samples consist of all firms that have at least one monthly return observation. At the beginning of every calendar month, all event firms are assigned to one of 5 quintiles based on their market capitalization at the beginning of the month. Each month, the quintile portfolios consist of all firms that were recommended in month *t*, and within the last *x* months (where *x* is the length of the holding period). Portfolios are rebalanced monthly. The time period under analysis is from January 1, 2000, to December 31, 2008, using event observations from January 1, 2000, to December 31, 2008. There are 1959 long recommended firms with at least one monthly return observation. Alpha is the intercept on a regression of monthly excess return from the rebalanced strategy. The explanatory variables are the monthly returns from the Fama and French (1993) mimicking portfolios. Alphas are in monthly percent, t-statistics are shown below the coefficient estimates, and 5% statistical significance is indicated in bold.

| | Equal-weight portfolio | | | | | | WLS | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | One-month | Three-month | Six-month | One-year | Two-year | Three-year | One-month | Three-month | Six-month | One-year | Two-year | Three-year |
| Panel A: Fama-French model | | | | | | | | | | | | |
| 1 | **4.89%** | **2.22%** | **2.60%** | **2.01%** | **1.95%** | **1.77%** | **4.17%** | **2.09%** | **1.98%** | **1.09%** | **0.91%** | 0.64% |
| (Small) | [3.19] | [2.69] | [4.11] | [3.81] | [3.75] | [3.4] | [3.62] | [2.87] | [3.62] | [2.68] | [2.4] | [1.77] |
| 2 | **2.44%** | **2.45%** | **1.86%** | **2.17%** | **1.83%** | **1.95%** | **2.15%** | **2.12%** | **1.24%** | **1.26%** | **0.75%** | **0.85%** |
| | [2.54] | [3.6] | [3.02] | [3.93] | [3.49] | [3.8] | [2.58] | [3.53] | [2.3] | [2.78] | [2.01] | [2.48] |
| 3 | 1.78% | **1.77%** | **1.88%** | **1.39%** | **1.28%** | **1.19%** | **2.36%** | **1.84%** | **1.71%** | **1.19%** | **0.96%** | **0.78%** |
| | [1.9] | [2.59] | [3.4] | [2.85] | [2.86] | [2.64] | [2.92] | [3.07] | [3.66] | [3.19] | [3.17] | [2.57] |
| 4 | **2.28%** | **1.69%** | 0.80% | 0.95% | 0.82% | 0.91% | **1.85%** | **1.39%** | 0.64% | 0.71% | 0.41% | 0.47% |
| | [2.27] | [2.65] | [1.45] | [1.86] | [1.73] | [1.94] | [2.11] | [2.38] | [1.34] | [1.89] | [1.42] | [1.85] |
| 5 | 0.92% | **1.32%** | 0.90% | 0.70% | 0.63% | 0.54% | 0.35% | 0.71% | 0.64% | 0.47% | 0.32% | 0.20% |
| (Large) | [1.16] | [2.22] | [1.72] | [1.61] | [1.61] | [1.41] | [0.51] | [1.48] | [1.48] | [1.52] | [1.38] | [1.03] |

## Table 10: Calendar-Time Portfolio Regressions by Book-to-Market Equity (Long Recommendations)

This table reports calendar-time abnormal returns for VIC recommended stocks. The samples consist of all firms that have at least one monthly return observation. At the beginning of every calendar month, all event firms are assigned to one of 5 quintiles based on their book-to-market at the beginning of the month. Each month, the quintile portfolios consist of all firms that were recommended in month *t*, and within the last *x* months (where *x* is the length of the holding period). Portfolios are rebalanced monthly. The time period under analysis is from January 1, 2000, to December 31, 2008, using event observations from January 1, 2000, to December 31, 2008. There are 1959 long recommended firms with at least one monthly return observation. Alpha is the intercept on a regression of monthly excess return from the rebalanced strategy. The explanatory variables are the monthly returns from the Fama and French (1993) mimicking portfolios. Alphas are in monthly percent, t-statistics are shown below the coefficient estimates, and 5% statistical significance is indicated in bold.

| | Equal-weight portfolio | | | | | | WLS | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | One-month | Three-month | Six-month | One-year | Two-year | Three-year | One-month | Three-month | Six-month | One-year | Two-year | Three-year |
| Panel A: Fama-French model | | | | | | | | | | | | |
| 1 | 1.44% | **3.07%** | 1.49% | **1.69%** | **1.40%** | **1.29%** | 1.11% | **2.44%** | 1.34% | **1.32%** | 0.81% | 0.73% |
| (Value) | [1.39] | [3.73] | [1.91] | [2.36] | [2.17] | [2.1] | [1.14] | [2.97] | [1.79] | [2.04] | [1.6] | [1.68] |
| 2 | 0.72% | 0.96% | 1.14% | **1.23%** | **1.01%** | 0.75% | 1.24% | 0.96% | 0.88% | **0.96%** | **0.63%** | 0.26% |
| | [0.66] | [1.51] | [1.9] | [2.68] | [2.4] | [1.78] | [1.3] | [1.65] | [1.61] | [2.47] | [2.12] | [0.91] |
| 3 | 1.05% | 1.28% | 0.84% | 0.28% | -0.11% | -0.05% | 0.34% | 0.21% | 0.41% | -0.36% | -0.91% | -0.82% |
| | [0.9] | [1.48] | [1.23] | [0.47] | [-0.17] | [-0.09] | [0.34] | [0.29] | [0.67] | [-0.7] | [-1.81] | [-1.97] |
| 4 | **3.98%** | **1.82%** | 1.27% | **1.25%** | **1.12%** | 0.93% | **2.72%** | 1.33% | 0.80% | 0.69% | 0.47% | 0.20% |
| | [3.92] | [2.43] | [1.92] | [2.16] | [2.27] | [1.9] | [2.83] | [1.89] | [1.3] | [1.42] | [1.35] | [0.61] |
| 5 | 0.46% | 0.72% | 0.44% | 0.59% | 0.40% | 0.50% | -0.19% | 0.66% | 0.46% | 0.44% | 0.22% | 0.36% |
| (Growth) | [0.33] | [1.1] | [0.73] | [1.34] | [0.99] | [1.17] | [-0.19] | [1.06] | [0.82] | [1.17] | [0.74] | [1.17] |

## Table 11: Calendar-Time Portfolio Regressions by Turnover (Long Recommendations)

This table reports calendar-time abnormal returns for VIC recommended stocks. The samples consist of all firms that have at least one monthly return observation. At the beginning of every calendar month, all event firms are assigned to one of 5 quintiles based on their turnover at the beginning of the month, where turnover is the past 3 months average daily trading volume divided by shares outstanding measured at the recommendation date. Each month, the quintile portfolios consist of all firms that were recommended in month *t*, and within the last *x* months (where *x* is the length of the holding period). Portfolios are rebalanced monthly. The time period under analysis is from January 1, 2000, to December 31, 2008, using event observations from January 1, 2000, to December 31, 2008. There are 1959 long recommended firms with at least one monthly return observation. Alpha is the intercept on a regression of monthly excess return from the rebalanced strategy. The explanatory variables are the monthly returns from the Fama and French (1993) mimicking portfolios. Alphas are in monthly percent, t-statistics are shown below the coefficient estimates, and 5% statistical significance is indicated in bold.

| | Equal-weight portfolio | | | | | | WLS | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | One-month | Three-month | Six-month | One-year | Two-year | Three-year | One-month | Three-month | Six-month | One-year | Two-year | Three-year |
| Panel A: Fama-French model | | | | | | | | | | | | |
| 1 | **2.65%** | **3.12%** | **1.49%** | **1.72%** | **1.19%** | **1.13%** | **2.34%** | **2.52%** | **0.93%** | **1.03%** | 0.24% | 0.00 |
| (Illiquid) | [3.26] | [4.82] | [3.11] | [4.01] | [2.7] | [2.68] | [3.08] | [3.99] | [2.1] | [2.56] | [0.62] | [0.35] |
| 2 | **1.90%** | **1.85%** | **1.62%** | **1.64%** | 0.92% | 0.91% | **1.95%** | **1.88%** | **1.53%** | **1.54%** | **0.80%** | **1.95%** |
| | [2.12] | [2.7] | [2.52] | [3.03] | [1.94] | [1.85] | [2.64] | [2.88] | [2.8] | [3.56] | [2.53] | [2.64] |
| 3 | **4.62%** | **2.13%** | 0.63% | 0.55% | 0.65% | 0.48% | **3.32%** | **1.52%** | 0.24% | -0.06% | -0.06% | 0.00 |
| | [3.56] | [2.98] | [1.00] | [1.07] | [1.49] | [1.06] | [3.45] | [2.5] | [0.45] | [-0.16] | [-0.23] | [-0.99] |
| 4 | 0.32% | 1.02% | 0.36% | 0.67% | 0.66% | 0.65% | -0.13% | 0.22% | 0.28% | 0.45% | 0.38% | 0.00 |
| | [0.36] | [1.39] | [0.53] | [1.19] | [1.31] | [1.35] | [-0.15] | [0.31] | [0.45] | [1.01] | [1.21] | [1.2] |
| 5 | 0.44% | 0.83% | 1.03% | 1.21% | 1.26% | **1.27%** | 0.15% | 0.53% | 0.93% | **1.06%** | **0.91%** | **0.01** |
| (Liquid) | [0.38] | [1.09] | [1.46] | [1.8] | [1.95] | [1.99] | [0.15] | [0.77] | [1.57] | [2.09] | [2.25] | [2.21] |

## Table 12: VIC Ratings and Performance

This table reports Fama-MacBeth predictive regressions of individual BHAR (buy-and-hold-abnormal-returns) on ratings. A minimum of 10 observations are required to perform a cross-sectional regression. The dependent variable in regressions (1), (2), (5), and (6) is the BHAR from *t*+2 to *t*+6. The dependent variable in regressions (3), (4), (7), and (8) is the BHAR from *t*+7 to *t*+12. Size and B/M are the natural logarithms of the firm characteristics of market equity and book-to-market of the given firm. Past 6-month returns are the return of the given firm over the prior sixth month period. Turnover is the average daily volume of the previous 3 months divided by the shares outstanding. T-statistics are shown below the coefficient estimates, and 5% statistical significance is indicated in bold.

| | Benchmark-portfolio Adjusted | | | | Control-Firm Adjusted | | | |
|---|---|---|---|---|---|---|---|---|
| | BHAR +2 to +6 | | BHAR +7 to +12 | | BHAR +2 to +6 | | BHAR +7 to +12 | |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| Panel A: Long recommendations | | | | | | | | |
| Constant | -0.16 | -0.23 | -0.13 | -0.04 | -0.19 | -0.16 | -0.19 | -0.16 |
| | [-1.82] | [-1.12] | [-1.08] | [-0.19] | [-1.37] | [-0.56] | [-1.16] | [-0.46] |
| Rating | **0.04** | **0.05** | 0.02 | 0.01 | 0.04 | 0.06 | 0.03 | 0.08 |
| | [1.96] | [2.04] | [1.09] | [0.43] | [1.37] | [1.63] | [1.01] | [1.58] |
| Ln(Size) | | -0.01 | | 0.00 | | -0.01 | | -0.02 |
| | | [-0.74] | | [0.5] | | [-0.76] | | [-0.66] |
| Ln(B/M) | | 0.01 | | 0.00 | | -0.02 | | -0.07 |
| | | [0.52] | | [0] | | [-0.48] | | [-1.54] |
| Past 6-month Returns | | 0.09 | | -0.09 | | -0.01 | | -0.11 |
| | | [1.52] | | [-1.01] | | [-0.09] | | [-0.87] |
| Turnover | | 0.55 | | -0.45 | | -0.07 | | -1.81 |
| | | [1.43] | | [-0.74] | | [-0.13] | | [-1.75] |
| Avg obs in cross-sec regs | 16.70 | 16.70 | 16.40 | 16.40 | 16.70 | 16.70 | 16.40 | 16.40 |
| Number of cross-sec regs | 52 | 52 | 48 | 48 | 52 | 52 | 48 | 48 |

## Table 13: Calendar-Time Portfolio Regressions by Ratings (Long Recommendations)

This table reports calendar-time abnormal returns for VIC recommended stocks. The samples consist of all firms that have at least one monthly return observation and a rating. At the beginning of every calendar month, all event firms are assigned to one of 5 quintiles based on their rating. Each month, the quintile portfolios consist of all firms that were recommended in month *t*, and within the last *x* months (where *x* is the length of the holding period). Portfolios are rebalanced monthly. The time period under analysis is from January 1, 2000, to December 31, 2008, using event observations from January 1, 2000, to December 31, 2008. There are 1959 long recommended firms with at least one monthly return observation. Alpha is the intercept on a regression of monthly excess return from the rebalanced strategy. The explanatory variables are the monthly returns from the Fama and French (1993) mimicking portfolios. Alphas are in monthly percent, t-statistics are shown below the coefficient estimates, and 5% statistical significance is indicated in bold.

| | Equal-weight portfolio | | | | | | WLS | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | One-month | Three-month | Six-month | One-year | Two-year | Three-year | One-month | Three-month | Six-month | One-year | Two-year | Three-year |
| Panel A: Fama-French model | | | | | | | | | | | | |
| 1 | **4.54%** | **3.62%** | **3.78%** | **3.42%** | **3.23%** | **3.18%** | **2.43%** | **2.03%** | **1.90%** | **1.23%** | **0.84%** | **0.67%** |
| (High) | [3.13] | [3.09] | [3.42] | [3.14] | [3.03] | [3.01] | [2.32] | [2.61] | [3.05] | [2.51] | [2.34] | [2.16] |
| 2 | 0.79% | 0.67% | 0.26% | 0.89% | 0.84% | 0.84% | 1.01% | **1.13%** | 0.49% | **0.92%** | **0.74%** | **0.70%** |
| | [0.89] | [1.16] | [0.49] | [1.83] | [1.8] | [1.85] | [1.24] | [2.11] | [1.14] | [2.70] | [2.66] | [2.93] |
| 3 | 0.51% | **2.06%** | 0.77% | 0.33% | 0.54% | 0.53% | 0.95% | **1.37%** | 0.62% | -0.03% | 0.10% | 0.12% |
| | [0.65] | [2.85] | [1.43] | [0.74] | [1.27] | [1.29] | [1.31] | [2.18] | [1.19] | [-0.07] | [0.31] | [0.41] |
| 4 | **1.79%** | **1.83%** | 0.35% | 0.29% | 0.37% | 0.29% | **1.78%** | **1.29%** | 0.29% | 0.23% | 0.27% | 0.16% |
| | [1.96] | [2.61] | [0.73] | [0.77] | [1.08] | [0.84] | [2.28] | [2.13] | [0.68] | [0.72] | [1] | [0.63] |
| 5 | 0.21% | -0.29% | 0.00% | 0.49% | 0.56% | 0.44% | -0.08% | -0.33% | 0.47% | **0.88%** | **0.95%** | **0.79%** |
| (Low) | [0.15] | [-0.36] | [0.01] | [0.85] | [1.07] | [0.86] | [-0.06] | [-0.47] | [0.86] | [2.11] | [2.89] | [2.79] |

## Table 14: Top and Bottom Rating Quintile Control-Firm Buy-and-Hold Abnormal Returns for Buy Recommendations

Returns to sample firms and control firms from January 1, 2000, to December 31, 2008. Control firms are selected by choosing the firm for which the sum of the absolute value of the percentage difference in size and the absolute value of the percentage difference in book-to-market ratio is minimized. The top (bottom) quintile for rating consists of the highest rated (lowest rated) 20% of the sample. P-values associated with a two-tailed paired t-test are presented. The p-values for the test for difference in BHAR between the top and bottom quintile are calculated using a two-tailed paired t-test for difference assuming unequal variances.

| | Top Rating Quintile | | | Bottom Rating Quintile | | | |
|---|---|---|---|---|---|---|---|
| | Mean sample firm return | Mean control firm return | BHAR | Mean sample firm return | Mean control firm return | BHAR | P-value of difference in BHAR |
| One-year | 27.76% | 6.07% | 21.69% | 8.56% | 8.72% | -0.16% | 0.0017*** |
| Two-year | 46.59% | 20.44% | 26.15% | 32.26% | 28.05% | 4.21% | 0.0536* |
| Three-year | 86.86% | 44.28% | 42.58% | 46.25% | 55.27% | -9.02% | 0.0061*** |

*, ** and *** denote two-tailed statistical significance at the 10%, 5% and 1% levels respectively.

## Table 15: Comments Summary Statistics

This table reports summary statistics for the analysis of the comments associated with the sample of investment recommendations submitted to Valueinvestorsclub.com. The sample includes all recommendations shared with the VIC community from the time of the community's launch on January 1, 2000 through December 31, 2008. Results are presented for the sample associated with the control-firm BHAR analysis. There are 1869 observations in total: 1671 long observations and 198 short observations. The full, long-only, and short-only samples have at least 1 comment for 91.55%, 91.02%, and 96.46% of their respective observations.

*Panel A: Summary Statistics for full sample (n=1711)*

| Market | Comments | Members | Private | % Private | Author | % Author | <45 Days | % < 45 days |
|---|---|---|---|---|---|---|---|---|
| Mean | 12.03 | 4.84 | 2.50 | 18.55% | 5.26 | 43.29% | 7.83 | 74.01% |
| Median | 8.00 | 4.00 | 1.00 | 3.85% | 3.00 | 46.15% | 6.00 | 81.25% |
| Min | 1.00 | 1.00 | 0.00 | 0.00% | 0.00 | 0.00% | 0.00 | 0.00% |
| Max | 154.00 | 28.00 | 73.00 | 100.00% | 82.00 | 100.00% | 91.00 | 100.00% |

*Panel B: Summary Statistics for long sample (n=1521)*

| Market | Comments | Members | Private | % Private | Author | % Author | <45 Days | % < 45 days |
|---|---|---|---|---|---|---|---|---|
| Mean | 11.49 | 4.71 | 2.25 | 17.58% | 5.08 | 43.42% | 7.65 | 74.44% |
| Median | 8.00 | 4.00 | 0.00 | 0.00% | 3.00 | 46.15% | 6.00 | 81.82% |
| Min | 1.00 | 1.00 | 0.00 | 0.00% | 0.00 | 0.00% | 0.00 | 0.00% |
| Max | 138.00 | 28.00 | 52.00 | 100.00% | 57.00 | 100.00% | 91.00 | 100.00% |

*Panel C: Summary Statistics for short sample (n=190)*

| Market | Comments | Members | Private | % Private | Author | % Author | <45 Days | % < 45 days |
|---|---|---|---|---|---|---|---|---|
| Mean | 16.39 | 5.86 | 4.47 | 26.34% | 6.73 | 42.32% | 9.31 | 70.57% |
| Median | 9.00 | 5.00 | 2.00 | 19.09% | 4.00 | 43.88% | 7.00 | 73.33% |
| Min | 1.00 | 1.00 | 0.00 | 0.00% | 0.00 | 0.00% | 0.00 | 0.00% |
| Max | 154.00 | 24.00 | 73.00 | 100.00% | 82.00 | 100.00% | 70.00 | 100.00% |

## Table 16: Relation Between Group Size and Idea Value

Panel A presents ratings summary statistics for sample quintiles formed on the percentage of messages that are private. P-values for difference in means are calculated using a two-tailed paired t-test assuming unequal variances. P-values for difference in medians are based on the z-test statistic from a Wilcoxson signed rank test. Panel B presents OLS estimates and maximum likelihood estimates for a logit regression. The dependent variable is the percentage of messages that are private. Total comments and number of commenters are the natural logarithms of a given firms total comments submitted and the unique number of commenters submitting comments. Size and B/M are the natural logarithms of the firm characteristics of market equity and book-to-market of the given firm. Past 6-month returns are the return of the given firm over the prior sixth month period. Turnover is the average daily volume of the previous 3 months divided by the shares outstanding. We estimate this model using data from January 1, 2004 to December 31, 2008 because the option to label comments "private" was rarely used prior to January 1, 2004 (10.01% of ideas had at least one private comment prior to 2004 versus 74.64% after January 1, 2004). T-statistics are shown below the coefficient estimates, and 5% statistical significance is indicated in bold.

*Panel A: Summary Statistics for ratings (n=1028)*

| | Total | 1 | 2 | 3 | 4 | 5 | 1-5 | P-value |
|---|---|---|---|---|---|---|---|---|
| | | (low pvt %) | | | | (high pvt %) | | |
| Mean | 5.10 | 4.89 | 5.28 | 5.17 | 5.15 | 5.14 | -0.25 | 0.0000*** |
| Median | 5.20 | 5.00 | 5.40 | 5.30 | 5.20 | 5.20 | -0.20 | 0.0000*** |
| Min | 1.30 | 3.10 | 3.50 | 3.20 | 1.30 | 3.20 | | |
| Max | 7.10 | 6.40 | 6.40 | 7.10 | 7.00 | 6.70 | | |

*, ** and *** denote two-tailed statistical significance at the 10%, 5% and 1% levels respectively.

*Panel B: Regression Analysis*

| | OLS | OLS | Logit | Logit |
|---|---|---|---|---|
| Constant | 0.76 | 0.15 | **-1.99** | **-1.59** |
| | [1.17] | [1.71] | [-3.45] | [-1.99] |
| Rating | **0.04** | **0.04** | 0.20 | 0.22 |
| | [3.06] | [3.15] | [1.78] | [1.83] |
| Ln(Total comments) | | 0.00 | | -0.02 |
| | | [-0.9] | | [-0.49] |
| Ln(Number of commenters) | | 0.00 | | 0.01 |
| | | [1.58] | | [0.87] |
| Ln(size) | | 0.00 | | -0.02 |
| | | [-0.72] | | [-0.4] |
| Ln(B/M) | | 0.00 | | -0.01 |
| | | [-0.12] | | [-0.06] |
| Past 6-month returns | | **-0.06** | | -0.31 |
| | | [-2.86] | | [-1.64] |
| Turnover | | 0.06 | | 0.24 |
| | | [0.50] | | [0.24] |
| Number of observations | 909 | 909 | 909 | 909 |

## Table 17: Institutional Ownership Summary Statistics

This table reports summary statistics for institutional ownership associated with the sample of investment recommendations submitted to Valueinvestorsclub.com. The sample includes all recommendations shared on the VIC website from the time of the community's launch on January 1, 2000, through December 31, 2008. Results are presented for the sample associated with the control-firm BHAR analysis. In total there are 1514 observations which have institutional holdings data. P-values for difference in mean institutional ownership are calculated using a two-tailed paired t-test assuming unequal variances. P-values for difference in median institutional ownership are based on the z-test statistic from a Wilcoxson signed rank test.

*Panel A: Summary Statistics for full sample (n=1514)*

| Size | Total | 1(small) | 2 | 3 | 4 | 5 (big) | 1-5 | P-value |
|---|---|---|---|---|---|---|---|---|
| Mean | 53.42% | 25.65% | 46.71% | 60.64% | 68.03% | 70.47% | -44.83% | 0.0000*** |
| Median | 57.47% | 22.78% | 47.49% | 66.83% | 73.20% | 75.72% | -52.94% | 0.0000*** |
| Min | 0.16% | 0.16% | 0.16% | 0.22% | 0.61% | 0.35% | | |
| Max | 98.36% | 98.22% | 95.26% | 98.36% | 98.26% | 98.00% | | |
| **B/M** | **Total** | **1 (low)** | **2** | **3** | **4** | **5 (high)** | **1-5** | **P-value** |
| Mean | 53.42% | 52.53% | 59.17% | 55.91% | 54.62% | 44.93% | 7.59% | 0.0010*** |
| Median | 57.47% | 58.15% | 64.08% | 61.61% | 57.79% | 41.99% | 16.16% | 0.0010*** |
| Min | 0.16% | 0.22% | 1.57% | 0.16% | 0.16% | 0.27% | | |
| Max | 98.36% | 98.25% | 98.00% | 97.77% | 98.26% | 98.36% | | |
| **CAR 12** | **Total** | **1 (low)** | **2** | **3** | **4** | **5 (high)** | **1-5** | **P-value** |
| Mean | 53.42% | 50.03% | 56.22% | 55.82% | 52.73% | 45.77% | 4.26% | 0.1095 |
| Median | 57.47% | 50.84% | 60.07% | 59.56% | 59.81% | 45.07% | 5.77% | 0.0893* |
| Min | 0.16% | 0.22% | 0.16% | 0.60% | 0.16% | 0.39% | | |
| Max | 98.36% | 97.54% | 98.22% | 98.00% | 97.72% | 97.36% | | |
| **CAR24** | **Total** | **1 (low)** | **2** | **3** | **4** | **5 (high)** | **1-5** | **P-value** |
| Mean | 53.42% | 51.62% | 55.29% | 50.71% | 51.55% | 44.19% | 7.43% | 0.0074*** |
| Median | 57.47% | 53.26% | 58.70% | 55.73% | 56.23% | 43.01% | 10.26% | 0.0082*** |
| Min | 0.16% | 1.19% | 0.22% | 0.16% | 0.39% | 0.60% | | |
| Max | 98.36% | 97.77% | 97.33% | 98.00% | 97.72% | 97.36% | | |
| **CAR 36** | **Total** | **1 (low)** | **2** | **3** | **4** | **5 (high)** | **1-5** | **P-value** |
| Mean | 53.42% | 51.66% | 52.20% | 47.77% | 48.15% | 47.49% | 4.17% | 0.1656 |
| Median | 57.47% | 52.58% | 58.40% | 47.69% | 46.22% | 49.69% | 2.89% | 0.2085 |
| Min | 0.16% | 0.22% | 0.81% | 0.16% | 0.39% | 0.70% | | |
| Max | 98.36% | 97.33% | 97.77% | 98.00% | 96.40% | 95.62% | | |

*, ** and *** denote two-tailed statistical significance at the 10%, 5% and 1% levels respectively.