Do Hedge Fund Managers Identify and Share Profitable Ideas?

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This draft: December 31, 2009
First draft: August 1, 2008

Job Market Paper

* I would like to thank Daniel Bergstresser, Dave Carlson, Hui Chen, John Cochrane, Lauren Cohen, Cliff Gray, Eugene Fama, Ron Howren, Andrew Kern, Carl Luft, Stavros Panageas, Shastri Sandy, Gil Sadka, Amir Sufi, Pietro Veronesi, Rob Vishny, anonymous referees for the Midwest Finance Association, and seminar participants at the University of Chicago Booth School of Business.

ABSTRACT

Evidence suggests the professional investors in my sample have significant stock-picking skills. Interestingly, these skilled investors share their profitable ideas with their competition. I test various private information exchange theories in the context of my data and determine that the investors in my sample share ideas to receive constructive feedback, gain access to a broader set of profitable ideas, and attract additional arbitragers to their asset market. The proprietary data I study are from a confidential website where a select group of fundamentals-based hedge fund managers privately share investment ideas. The investors I analyze are not easily defined: they exploit traditional tangible asset valuation discrepancies, such as buying high book-to-market stocks, but spend more time analyzing intrinsic value and special situation investments.

JEL Classification: G10, G11, G14

Key words: Value investing, abnormal returns, networks, hedge funds, market efficiency, Valueinvestorsclub.com, internet message boards.

Using a proprietary dataset of investment recommendations shared on the private website Valueinvestorsclub.com (VIC), I find robust evidence of significant stock-picking skill for a select group of small fundamentals-based hedge fund managers. Abnormal returns, calculated with a variety of methods, are economically large and statistically significant across various holding periods for long recommendations. For example, using a benchmark-portfolio BHAR (buy-and-hold abnormal return) calculation technique I find one-, two-, and three-year average abnormal returns of 9.52%, 19.03%, and 23.60%, respectively. The evidence for stock-picking skill for short recommendations, while directionally correct, is mixed and inconclusive.

To further test if the investors in my sample can identify profitable trades, I analyze the relationship between the average ratings VIC members assign to recommendations, which proxy for VIC members' ex-ante expectation of future performance, and the recommendation's ex-post abnormal returns. I find compelling evidence that the investors in my sample are able to decipher ex-ante which stocks will perform the best. This result holds for both long and short recommendations.

VIC is a new environment in which to test if there are professional managers with stock-picking skill; however, the unique context of VIC, which is a venue explicitly established so fund managers can share their private information, allows me to empirically address a fundamental question: Why does an organization such as VIC even exist? Stein (2008) questions why an arbitrageur would honestly tell another about an attractive trading opportunity when money managers are concerned with relative performance. 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.

Three theories have emerged in response to Stein's assertion. Stein proposes that fund managers may share private information because they gain valuable feedback from the person with whom they are sharing ("collaboration argument"). Gray (2009) proposes that another reason managers may share information is to promote their undervalued portfolio positions in order to get other arbitrageurs to bring additional arbitrage capital to a market overwhelmed by noise trader influence ("awareness argument"). Gray also argues that a resource-constrained arbitrageur will share profitable ideas with the competition because doing so allows the arbitrageur to diversify his portfolio among a group of arbitrage trades, as opposed to allocating all his capital into his limited set of good ideas ("diversification argument"). The empirical evidence cannot reject any of these theories and suggests that all three theories of information exchange play a role in fund managers' decisions to share their private information.

Finally, with my data, I address a basic but important economic question: How do fundamentals-based, or “value” investors, make investment decisions? Value investors are presumably the agents driving asset prices to efficient levels. Studying the value investor’s thought process may help researchers better understand the price discovery process. To date, the common assumption in academic work is that value investors are those who focus on high book-to-market stocks (e.g., Piotroski 2000). And yet Martin and Puthenpurackal (2008) show that Warren Buffett, widely known as the greatest value investor of all time, is a “growth” investor according to the Fama and French size and book-to-market classification scheme.

My results addressing how value investors make decisions are specific to the sample of investors I analyze. With that caveat in mind, I find that the value investors in my sample overwhelmingly focus on measures of intrinsic value as opposed to book value. They examine valuation models based on discounted free cash flow, use various earnings multiple measures, and often search for growth-at-a-reasonable-price (GARP) investments. To a lesser extent, these investors favor the analysis of tangible asset undervaluation, open market repurchases, net operating losses, spin-offs, turnarounds, and activist involvement. In summary, the investors in my sample are focused on investigative analysis of business fundamentals, management signals, and complicated corporate situations.

The remainder of the paper is organized as follows. Section I discusses relevant research. Section II describes the data. Section III provides the main results on the characterization of value investor decisions in my sample. Section IV tests for stock-picking skill via abnormal return analysis. Section V examines the relation between ex-ante VIC idea ratings and ex-post abnormal returns. Section VI addresses why skilled fund managers may share profitable trading opportunities, and section VII concludes.

I. Related Literature

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 (Carhart 1997, Malkiel 1995, and Daniel et al. 1997). A more recent analysis by Fama and

French (2009) 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.

Despite evidence that suggests investors would be better off investing in passive index funds, French (2008) finds that investors pay large fees to the active management industry (e.g., the industry may have cost investors over $100 billion in 2007). It would be a remarkable economic phenomenon if the active management industry was able to convince investors they provided services worth $100 billion, when in fact they provided little to no value beyond an index fund.

The size of the service fees flowing to the active investment management industry is puzzling given the studies analyzing fund managers' portfolio returns, which suggest active managers have no stock-picking skills. However, Cohen, Polk, and Silli (2009) argue that analyzing portfolio returns is not a test of stock-picking skill, or "value-added," because portfolio returns may disguise a fund manager's stock-picking ability. Their paper argues that managers have incentives to hold diversified portfolios that consist of their "best ideas" and other positions to "round out" their portfolios. Some reasons managers may include zero-alpha positions in their portfolios are to decrease volatility, price impact, illiquidity, and regulatory/litigation risk. Berk and Green (2004) formalize aspects of this argument and point out that the very nature of fund evaluation may cause managers to hold many stocks in which they have little conviction, since the managers may be punished for exposing their investors to idiosyncratic risk. Berk and Green also conclude that research analyzing fund manager portfolio returns and/or persistence in returns says little about the skill level of managers but is really a test of the efficiency of the capital allocation markets.

An alternative approach to testing the stock-picking hypothesis, which does not suffer from the issues in studying portfolio returns, is to analyze individual recommendations from superstar managers or stock analysts. These studies confirm the no-stock-picking-skill hypothesis from previous research. Desai and Jain (1995) examine the performance of recommendations made by "superstar" money managers and find little evidence of superior stock-picking skill. Barber and colleagues (2001) confirm this result and find that excess returns to the recommendations of stock analysts are not reliably positive after transaction costs.

The study of individual stock recommendations is certainly a step in the right direction for testing the stock-picking hypothesis. However, there are potential issues with testing the stock-picking hypothesis in the aforementioned studies. In the studies by Desai and Jain and Barber et al., there are no clear reasons why superstar managers or analysts would share profitable trading opportunities with the general public, so their results suggesting no stock-picking skills are not surprising.

Another angle on the stock-picking skill hypothesis has been to study the "smart money," which usually translates into studying hedge fund return databases. However, data problems plague these papers. First, hedge fund return databases suffer from survivorship bias (funds that go out of business are difficult to track) and self-selected reporting (managers may only report their returns to the hedge fund database creators when they have good performance) (Fung and Hsieh 2000). Second, hedge fund managers sometimes hold illiquid assets or engage in return smoothing, which causes their reported hedge fund returns to exhibit large autocorrelations (Asness, Krail, and Liew 2001; Getmansky, Lo, and Makarov 2004). Third, hedge fund database returns may be unreliable because the same hedge funds sometimes report different returns to different database creators (Liang 2003). Fourth, hedge fund managers often hold assets that have option-like, non-linear payoffs. This payoff profile makes it difficult for researchers to assess hedge fund performance when they analyze hedge fund manager returns using traditional linear factor models (Fung and Hsieh 2001). Finally, 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. The issue with Griffin and Xu's analysis is that they can only examine long-equity positions and they ignore intraquarter trading.

My dataset, the full sample of investment recommendations shared on the private website Valueinvestorsclub.com (VIC), although imperfect, does not suffer from many of the data biases found in previous research addressing the stock-picking skill hypothesis. Moreover, the proprietary data allow me to study individual fund manager recommendations as opposed to fund manager portfolios, which is likely a better setting in which to identify manager stock-picking skills.

II. Data

A. *Value Investors Club*

The data in this study are collected from a private internet community called

Valueinvestorsclub.com (VIC), an "exclusive online investment club where top investors share their best ideas."[1] 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*).[2] Joel Greenblatt and John Petry, both successful value investors and managers of the large 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. The VIC website mentions that it is open to any well-thought-out investment recommendation but that it focuses particularly on equity or bond-based plays (either long or short), traditional asset undervaluation plays (high B/M, low P/E, 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 to the club is based on an initial write-up of an investment idea. If the quality of the 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—the maximum exists to ensure only the member's best ideas are submitted. Members share comments and rate each other's ideas on a scale of 1 (bad) to 10 (good). In addition, a weekly prize of $5,000 is awarded to the best idea submitted (VIC management determines the winner; community ratings have no bearing on who wins the prize). Members are monitored to ensure they submit at least two credible ideas per year, and members failing to meet the high standards of the club are dismissed.

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 behind this policy is to keep individual VIC members from forming outside sharing syndicates with selected members, who could then take their valuable comments and ideas away from the broader VIC community. In addition, the anonymity requirement 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.

Unfortunately, because membership of VIC is strictly confidential, I am unable to reveal

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

detailed statistics on the subject. However, the management of VIC agreed to disclose that most VIC members are long-focused fundamentals-based hedge fund managers who have small to mid-size assets under management ($10 million to $250 million).

B. *Data Description*

I analyze all investment reports submitted to VIC since 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; ideas that subsequently do poorly are not dropped from the website and therefore the database I create does not suffer from an ex-post selection bias (although I cannot rule out disingenuous ex-post changes to the historical content of the data as described in the case of I/B/E/S analyst data by Ljungqvist and colleagues [2009]). In total, I examine 3,273 investment submissions. Report length can range from a few hundred to a few thousand words (see appendix for an example write-up). Investment ideas are wide-ranging with respect to the asset traded, where the asset is traded, and the complexity of the strategy employed.

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

All data collected are unambiguous except for the "reasons for investing." I compile a list of 16 investment criteria that are frequently cited in VIC submissions. Criteria were judged to be sufficiently common if at least 10 investment submissions acknowledged the use of the category. The 16 categories are as follows: *lack of sell-side analyst coverage*, *tangible asset undervaluation* (high book-to-market, hidden real estate assets, etc.), *insider buying/selling* (Seyhun 1988), *intrinsic value undervaluation* (e.g., discounted cash flow analysis, low P/E, EBIT/TEV, P/Sales, industry undervaluation, and hidden growth opportunities), *complicated business or taxes creating investor confusion*, *"sum-of-parts" discount, liquidation potential*, *active share repurchase programs* (Ikenberry et al. 1995), *recent restructuring or spinoff situation*, *misunderstood net operating loss tax assets*, *merger arbitrage* (Mitchell and Pulvino 2001), *stub arbitrage* (Mitchell, Pulvino, and Stafford 2002), *activist involvement* (Boyson and Mooradian 2007), *merger arbitrage trading opportunity*, *turnaround and/or bankruptcy* *emergence*, and *pair trade arbitrage* (Froot and Dabora 1999).

I read every investment idea and assign it the appropriate categories. For example, the VIC submission cited in the appendix received four category labels: *tangible asset undervaluation*, *insider buying*, *intrinsic value undervaluation*, and *net operating loss tax assets*. By assigning investment submissions discrete criteria, I capture the essence of why VIC members make their recommendations.

I then match the firms associated with a VIC recommendation to accounting and stock return data from CRSP/COMPUSTAT. For the purposes of this study, I only analyze U.S. exchange-traded long and short common stock recommendations. I 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 would bias the results (Fung and Hsieh 2001). Specifically, I eliminate all recommendations classified as merger arbitrage, stub arbitrage, pair-trade, liquidation, long/short recommendations, and non-common-equity ideas (e.g. options or preferreds). I also eliminate foreign-traded/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, I am left with 2,066 U.S.-equity long recommendations and 252 U.S.-equity short recommendations.

I must further constrain my sample to those firms with contemporaneous data available from CRSP/Compustat. The extent to which sample sizes are reduced based on data requirements on CRSP/Compustat depends on the abnormal return calculation method employed. The sample with the requisite data to perform the control-firm BHAR analysis has 1,671 long recommendations and 198 short recommendations. The sample with the necessary data to perform the benchmark-portfolio BHAR analysis consists of 1,610 long recommendations and 198 short recommendations.

C. *Potential Data Biases*

A potential criticism is that my database is biased because it represents the investment recommendations from a select group of hedge fund managers. In some sense, studying the investors most likely to have stock-picking skills is the purpose of my study—to see if *any* group of investors has skill. An obvious place to look for evidence of skilled investors is within the ranks of the so-called "smartest money."

A second criticism is that the ideas submitted to VIC might represent only the best ideas from VIC members but may not represent the performance of their overall portfolio, since their overall portfolios are presumably filled with both good ideas and bad ideas (Cohen, Polk, and Silli 2009). Embedded in this logic is the assumption that VIC members can distinguish ex-ante between "good" ideas and "bad" ideas, which in itself is a manifestation of stock-picking ability. However, because of this concern, I cannot test the hypothesis that managers' *portfolio* returns show systematic outperformance, which is a different hypothesis than the stock-picking hypothesis. Studying portfolio returns is really a test of capital allocation efficiency (Green and Berk 2004) and is beyond the scope of this paper.

On the flip side of the "best ideas bias," one may argue that fund managers will have no incentives to share their best private information with other fund managers, and instead may only submit ideas that are marginally attractive or efficiently priced. This bias will make rejecting the hypothesis that fund managers have no stock-picking skill more difficult.

Yet another possible concern is that the VIC members may use the site as a way to market their investment ideas to ignorant members and/or a gullible general public that places too much value on their investment acumen. For example, a VIC member may recommend an efficiently priced stock, but because investors believe VIC ideas are valuable, investors drive the price past fundamentals. This irrational investor behavior would confuse the underlying economics behind VIC member stock-picking skill. Instead of genuine ability to derive private information, their apparent skill could merely be a manifestation of their ability to drive stocks past their fair value.

Finally, note that the ideas under analysis are the most simple, straightforward common equity recommendations submitted to VIC and 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 (i.e., lawyers, industry specialists, and tax experts). In a Grossman and Stiglitz (1980) equilibrium where arbitrageurs are compensated for their information discovery efforts, one may hypothesize that these investments would have better gross returns (before costs of information collection) than situations requiring less effort. If this price discovery reward story is to be believed, the data under analysis will likely be biased and favor the null hypothesis that VIC members have no stock-picking skill.

III. The Characteristics of Fundamental Value Investor Decisions

Grossman and Stiglitz (1980) argue that market prices can never be perfectly efficient. If prices were always efficient, skilled investors who acquire private information (via more efficient collection and processing of available information) would never be rewarded. And if skilled investors had no incentive to engage in the price discovery process, efficient market prices would not be an equilibrium condition, but rather a case of extremely good luck.

Grossman and Stiglitz provide a compelling case that skilled investors, who are rewarded for their private information, are critical to an efficient price discovery process. However, there is little empirical evidence on where skilled investors look to generate their private information. Are these investors fixated on book value because the market cannot properly calculate asset value? Do they incorporate information from open market share repurchases, insider buying patterns, post earnings announcement drift, accruals, or use other alpha-producing strategies the academic literature documents? In this section, I examine how the value investors in my sample make investment decisions.

Using the full sample of recommendations (n=3273), I find that my sample of investors focus on U.S.-based common stock investments (82% of total recommendations) but find value in other markets as well: 13 percent of the recommended securities are internationally traded and .4 percent are non-equity investments. I also find that long recommendations in common stock represent the bulk of ideas submitted (86%) (see Table 1, Panel B).

Table 2 shows the frequency with which VIC members base their investment on various criteria.[3] I find that investors in my sample are overwhelmingly concerned with assessing intrinsic value: discounted cash flow models, earnings multiples, GARP, and other similar valuation techniques are used most frequently (87% include this analysis in their recommendation). However, approximately 24 percent of the recommendations do incorporate

[3] I analyze the full sample in this section; however, the characteristics of the sub-samples I use for the asset pricing tests are very similar.

the classic value technique of focusing on tangible asset undervaluation. Other popular tools used by VIC members are open market repurchases (12%), the presence of net operating loss assets (5%), restructuring and spin-off situations (5%), and insider trading activity (5%).

VIC members often cite more than one criterion in an investment analysis. Table 3, Panel A summarizes the frequency with which various permutations of criteria are cited. Panel A shows that although value investors are highly focused on intrinsic value, many cite additional criteria, which indicates the skilled investors in my sample are not one-dimensional. Some of the most common criteria combinations paired intrinsic undervaluation with signaling factors such as share repurchase programs, insider buying, and activist involvement.

Although the investors in my sample use a wide range of tools in their investment decisions, their analysis tends to focus on a defined set of criteria.[4] Table 3, Panel B shows that value investors typically employ up to three different criteria when making investment decisions. Ninety-eight percent of the recommendations cite three or fewer investment criteria, whereas only 2 percent cite four or more. I speculate that asset-specific issues (e.g., a liquidation trade, by its nature, exclusively focuses on tangible asset undervaluation), specialization in a specific approach to deriving private information, resource limitations, and the requirement that recommendation write-ups be concise, are the primary reasons why professional value investors in my sample focus on very few criteria when making investment decisions.

In Table 4, I present more detailed descriptive statistics of the securities recommended, segregated by type of recommendation (long versus short). In Panel A, I tabulate the sector classification: The recommendations are weighted toward manufacturing firms, representing 32.38 percent (40.91%) of the total of long (short) recommendations. Other sectors of focus for value investors are services and financial services: services represent 19.51 percent (19.19%) and financial services comprise 15.26 percent (14.65%) of the long (short) recommendations.

Panels C and D of Table 4 present a summary of the financial data pertaining to the recommended securities used in the asset pricing tests. I find that the recommended investments are typically small (see Figure 10) with a slight tilt toward value (see Figure 11). The median market capitalization is $397 million for long recommendations, and the median book-to-market ratio among long recommendations is 0.617. Based on median Fama and French size and book-

[4] I conjecture that recommendations represent a majority of the investment thesis and that members do not hold back information.

to-market breakpoints from 2000 to 2008, VIC recommendations are in the 20th percentile bin for the small to large-size portfolios, and in the 60th percentile bin for the low book-to-market to high book-to-market portfolios.

Among short recommendations the median size is $650 million (30th percentile bin for small- to large-size portfolios), which is similar to long recommendations; however, the median book-to-market for short recommendations is much lower—0.342 (25th percentile bin for low book-to-market to high book-to-market portfolios). The low median book-to-market suggests that when betting against a firm, VIC members focus on securities that would be considered "growth" on a book-to-market basis. With respect to profitability, long-recommended firms are generally less profitable than the short-recommended firms: median return on asset is 3.7 percent for long recommendations and 5.3 percent for short recommendations.

IV. Performance Analysis

In this section, I examine the performance of VIC recommendations. VIC recommendations typically state that their ideas should be considered "long-term" investments and not short-term trades. To capture this notion of long-term performance, I perform detailed calculations on holding periods of one-, two-, and three-years. I 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, traditional event-time BHARs "precisely measure investor experience" of buy-and-hold investors, the contingent most common in the value investing community. 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 and claim that the calendar-time approach has low power to detect abnormal performance associated with events that are clustered across time.

I incorporate delisting data into returns using the technique of Beaver, McNichols, and Price (2007). My abnormal return analysis accounts for delisted firms in a similar fashion to Lyons, Barber, and Tsai (1999). If a firm is delisted (either a sample firm or a control firm), I assume the proceeds of the delisted firms are invested in the control-firm or benchmark portfolio.

I also do the analysis where delisted firms' proceeds are invested in the CRSP value-weighted index, and where delisted firms are eliminated from the database. The results are similar.

Finally, as pointed out by Fama and French (1993), the three-factor model is unable to completely describe the cross-section of expected returns on the dimensions on which it is based. Their statement is validated by the handful of statistically significant intercepts for some of the low book-to-market quintile portfolios and the small-value portfolio over the July 1963 to December 1993 time period. Their analysis suggests that assuming intercepts are equal to zero will be problematic for samples tilted toward the characteristics that the three-factor model cannot price in the first place. For example, if a researcher draws a random sample of companies with small-value characteristics during 1963-1993, the portfolio is more likely to have a positive alpha, because the passive small-value portfolio from which it is drawn has a positive alpha. However, rejecting the null hypothesis is unwarranted because the model of expected returns is likely misspecified over this time period.

I use the three-factor model extensively throughout my abnormal return analysis, so it is important to understand the success (or lack thereof) of this model during my sample period. To assess whether the three-factor model of expected returns is a reliable method to describe the cross-section of expected returns during my period of analysis (January 2000 to December 2008), I replicate the analysis in Fama and French (1993). Table 5 shows the intercepts estimates from excess stock return regressions of 25 size and book-to-market equity portfolios on the Fama and French three-factor model from January 1, 2000, to December 31, 2008. The model does exceptionally well. There is only one statistically significant intercept (at the 10% level). Moreover, the small capitalization portfolios, which are most relevant to my analysis of VIC recommendations, have very small intercepts. This evidence suggests that using the Fama and French model to control for common risk factors in stock returns is less of a concern for my analysis than it is in previous time periods.

A. Control-firm BHAR

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

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

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*.

Following the methodology of Speiss and Affleck-Graves (1995), I assign each sample firm a control firm based on size (market value of equity) and book-to-market ratio. All firms in the CRSP/Compustat universe are considered potential matches. From the CRSP/Compustat universe, I 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. I 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.

I calculate the one-, two-, and three-year BHARs to 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 community. For example, if an idea is posted on January 15, I start calculating monthly returns 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 might underestimate the true returns earned by VIC members and may bias my tests in favor of the null hypothesis that fund managers have no stock-picking skills.

Table 6 presents summary statistics and results of the control-firm BHAR analysis. Abnormal returns to long recommendations are economically large and statistically significant. 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, I perform an alternate control-firm BHAR analysis. In these tests, I 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 percent. This method ensures that sample firms examined are assigned a control firm with very similar characteristics. The results from this analysis are similar to those presented in Table 6, which is not surprising given the evidence from Nekrasov et al. (2009) that the specific matching technology is immaterial to the power of a control-firm test. I also perform the control-firm BHAR analysis after eliminating the top and bottom 1 percent of observations to control for extreme outliers (see Figures 3 and 4). The results are similar to those presented in Table 6 (results not shown).

In addition to standard t-test values, I also present results in Table 6 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.

B. *Characteristics-based Benchmark-Portfolio BHAR*

Savor and Lu (2009) suggest statistical issues exist with the control-firm BHAR methodology when the sample size is small and prone to outliers (as is the case with my sample of short recommendations). A remedy to this problem is the characteristics-based benchmark-portfolio BHAR approach, where 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 by the control-firm BHAR approach. Therefore, in the analysis of statistical significance for the benchmark-portfolio BHAR approach, I account for event-time skewness bias by using the bootstrapping method Lyon, Barber, and Tsai (1999) advocate.

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

The results of this analysis are presented in Table 7. The results are consistent with the findings from the control-firm BHAR analysis. Using the benchmark-portfolio approach, I find that the investors in my sample generate statistically significant one-year BHARs of 9.52

percent, two-year BHARs of 19.03 percent, and three-year BHARs of 23.60 percent.

For short recommendations, the control-firm BHAR approach and the benchmark-portfolio approach reach the same conclusion: we cannot reject the null hypothesis once we adjust 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 percent, two-year BHAR is 18.02 percent, and three-year BHAR is 21.47 percent. Taken as a whole, the analysis of the short recommendations using the various BHAR approaches provides little statistical evidence that the investors in my sample are successful short sellers.

For robustness, I also perform the benchmark-portfolio BHAR analysis after eliminating the top and bottom 1 percent of observations to control for extreme outliers (see Figures 3 and 4). The results are similar to those presented in Table 7 (results not shown).

C. *Calendar-Time Portfolio Regressions*

To assess the robustness of the results from the BHAR analyses, I analyze the data using the calendar-time portfolio approach advocated by Mitchell and Stafford (2000) and Fama (1998). First, I create event portfolios consisting of all event firms recommended in month t to t-x, where x is the time period under analysis (e.g., one year). I then calculate the monthly returns to the event-firm portfolio in excess of the risk-free rate and regress this variable on the excess value-weighted market index return as well as the SMB (small minus big), HML (high book-to-market minus low book-to-market), and MOM (high momentum minus low momentum) pricing factors (Fama and French 1992 and Carhart 1997).[5] I perform the regression procedure using a variety of methods: portfolios constructed on both a value-weighted and equal-weighted basis using OLS, and portfolios constructed on an equal-weighted basis using WLS (weights are the number of stocks in the portfolio in a given month). Similar to Mitchell and Stafford (2000), I require that portfolios have at least 10 observations to be included as an observation in the regression.

The results of the calendar-time portfolio regressions are presented in Table 9. To be

[5] Factors obtained from Ken French's website http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html.

conservative, I focus on the three-factor results, since simulation evidence suggests four-factor calendar time regression results over-reject the null hypothesis far too often (Ang and Zhang 2004). Four-factor results (not shown) are consistent with the three-factor results, and in many cases are stronger.

The estimates in Table 9 represent the mean monthly abnormal return over the calendar-time horizon for long recommendations. The regression estimates confirm the BHAR analysis and suggest that the investors in my sample have stock-picking skills.

Panel B in Table 9 presents the results of portfolios formed from short recommendations. The evidence suggests that VIC members are successful short sellers, which is contrary to the results from the BHAR analysis, which were inconclusive based on statistical inference. Because the various abnormal return methods provide conflicting statistical evidence, I make no definitive statements regarding the short-selling ability of the investors in my sample. I 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.

Although the alphas estimated by the calendar-time portfolio regressions are large across time periods, their statistical significance depends on how the portfolios are constructed (i.e., equal weight versus value weight). Equal-weighted portfolio (both OLS and WLS) regressions produce much more significant (both economically and statistically) alphas. Because equal-weighted portfolios weight smaller firms more heavily than value-weighted portfolios, this discrepancy suggests that VIC members are more successful at developing private information among small firms than they are in the large-cap universe. Another interpretation is that the three-factor model is not capturing the true underlying risks of the VIC member recommendations and there is an asset pricing model misspecification—I cannot rule out this possibility. However, simulation evidence suggests that three-factor calendar-time portfolio regressions with large samples (i.e., $n>1000$) are well-specified and have high power to reject the null when it is false (Ang and Zhang 2004).

I also argue that the value-weighted portfolio construction effectively decrease the sample size because of the bimodal distribution of the market capitalization of VIC recommendations. Figure 10 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). The value-weighted portfolio construction will 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 regressions it was essentially the entire portfolio. Because of this value-weighted portfolio construction issue I believe the equal-weighted constructed portfolios are a more appropriate tool to assess the stock-picking skill hypothesis in my context.

D. *Additional Tests*

Figures 3 and 4 show the scatter plot of abnormal returns of long 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 submit an idea earlier in the year but then 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 are therefore less thorough, a reasonable hypothesis is that the abnormal returns should be stronger once ideas in December are eliminated. I perform this analysis using the control-firm BHAR, benchmark-portfolio BHAR, and calendar-time portfolio regression approaches, and I find that the results are essentially the same with or without the December recommendations. Figure 8 shows this result graphically for the set of long recommendations.

To better understand where VIC members are generating alpha, I divide the sample into size and book-to-market quintiles and perform the control-firm BHAR and calendar-time analysis. Table 8 shows the abnormal returns to the top and bottom size and book-to-market quintiles for long recommendations using control-firm BHAR analysis. The analysis suggests no difference in abnormal returns between size quintiles or book-to-market quintiles. The test for differences in the top and bottom quintile one-,two-, and three-year samples using a two-tailed paired t-test for difference assuming unequal variances cannot reject the hypothesis that the abnormal returns from the extreme quintiles are different. Figures 6 and 7 show this result visually. The size and book-to-market quintile BHAR estimates all fall roughly in line, which suggests VIC members have no statistically detectable skills specific to a particular market segment.

I perform a similar analysis of the size and book-to-market quintiles using the calendar-time portfolio regression approach. The results are in Tables 10 and 11. These results provide a more transparent view of where VIC members have skill. Table 10 shows that VIC members find the most alpha in the small-size quintile of recommendations; however, alphas are economically large and generally statistically significant across size quintiles.

Table 11 has the same analysis for book-to-market quintiles. Again, the results are less opaque than the BHAR analysis. The alpha estimates for high book-to-market firms are much higher and statistically significant, which suggests VIC members are especially skilled at picking “value” stocks.

E. *Performance Analysis Discussion*

Regardless of a researcher’s preference for BHAR methods or the calendar-time portfolio approach, all three methods presented in this study provide robust evidence that VIC members are successful in their long positions. The results of the various methods I use are statistically mixed with respect to VIC members’ ability to successfully short stocks. The calendar-time portfolio regressions hint that VIC members have stock-shorting skills; however, the control-firm and benchmark-portfolio BHAR analysis is indeterminate—more data are needed to make a strong statement. Nevertheless, my overall conclusion from the evidence is that VIC members appear to have stock-picking skills for buy recommendations (strong evidence), but the evidence for short-selling skill is inconclusive. Figure 5 is an intuitive way to capture these results succinctly.

A potential criticism of VIC members’ recommendations is that these ideas are not implementable. This concern is likely unwarranted. VIC is not set up for fund managers to showcase their ability to write research reports on opportunities that cannot be implemented—reports for completely illiquid names would be 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 $10mn of market capitalization and we take that into consideration when reviewing applications."

Another critique is that analyzing 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 really terrible 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 no good. Eliminating the "procrastination" ideas in December was an initial attempt to address this concern; however, the next section explores in detail how quality is related to performance.

V. The Relationship between VIC Ratings and Abnormal Returns

All VIC recommendations are not created equal. On September 14, 2009, the member "agape1095" posted a buy recommendation for Lehman Brothers, which 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. Moreover, on September 15, 2009, a VIC member posted a comment that the company had already entered 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 my sample. Although VIC membership is difficult to attain, even the best organizations can't completely screen out poor performers with certainty. To address this concern, I analyze how recommendations perform after controlling for the quality of the idea, as measured by the VIC community rating on individual investment thesis.

When investment recommendations are posted to VIC, members are given the opportunity to rate ideas 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 two weeks. (Since 2007, which is when data is available on the time of rating, 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 a 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 VIC ratings, I can perform additional tests to see if VIC members have an ability to pick stocks. In this analysis, I 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, I estimate a simple model such that a linear relation exists between abnormal returns and the VIC community rating. The model is represented as

$$\boldsymbol{BHAR_i = \delta_i + \lambda_i(Rating_i) + \varepsilon_i}, \qquad (2)$$

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. The dependent variable is calculated from t=2 to t=h to avoid an endogenous variable problem which may occur in a model that relates ratings with BHARs from t=1 to t=h. The endogenous variable problem may occur if an idea performs exceptionally well during the two-week rating period. For example, if stock X is recommended on June 20, 2008 and performs exceptionally well through July 3, 2008, members on July 3, 2008 may rate the idea extremely favorably (before the two-week rating period closes), not because they believe it will outperform in the future, but because it has performed well thus far.

In Table 12, I present coefficient estimates for the λ term in equation (2). I run regressions with the control-firm BHARs and benchmark portfolio BHARs as the dependent variable. The results suggest that VIC members have an ability to identify the best long recommendations posted to the website. Estimates for λ are positive and statistically significant across nearly all samples. I conclude from the evidence that VIC members are skilled at identifying the best and worst performing stocks within the universe of VIC recommendations.

The coefficients for the regressions performed on short recommendations also suggest the investors in my sample have an ability to discern between "good" short candidates and "bad" short candidates; however, this ability appears to be limited to a one-year horizon. The point estimates for $\hat{\lambda}$ are positive for the two- and three-year regressions; however, these estimates are not statistically significant so I cannot reject the hypothesis that VIC members cannot identify the best and worst short candidates over two- and three-year horizons.

I further analyze how ratings are related to abnormal returns by analyzing the abnormal returns associated with samples formed by rating quintiles. The results for the difference between the top and bottom rating quintile recommendations using control-firm BHAR analysis are in Table 13, and the results for the equivalent calendar-time portfolio regression analysis are in Table 14. The numbers from both tables provides strong evidence that VIC members have an ability to distinguish between "good" ideas and "bad" ideas. For example, the one-year BHAR abnormal returns associated with the top rating quintile are 21.69 percent, whereas the equivalent bottom quintile abnormal return is -.16 percent. Similarly, the average monthly alpha associated with the top rating quintile over a one-year horizon is 2.02 percent, compared to the bottom rating quintile which is –.27 percent. Figure 9 provides a visual presentation of these results.

The evidence clearly shows that VIC members have stock-picking skills. Not only is there evidence that the universe of VIC recommendations are successful on average, but there is strong evidence that members can distinguish ex-ante which stocks will outperform over the long term. This ability to distinguish between good and bad ideas is clearly a manifestation of stock-picking skill and provides ample evidence that skilled managers are in the investment management industry.

VI. Private Information Exchange in the Money Management Industry

VIC is a venue explicitly set up for fund managers to share their private information. However, the fact that VIC members are sharing their private information is puzzling. Traditional theories (Friedman 1953) suggest that arbitrageurs with private information should take full advantage of their 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 (2009) 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 (2009) 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."

A. 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 the parties involved, information exchange will occur between competitors. Stein's theory provides three basic predictions: (i) managers will share ideas in situations where 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 among 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 (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.

More anecdotal evidence suggests Stein's primary hypothesis is true. Sumzero.com, the "facebook for hedge-fund managers," is essentially a practical application of Stein's theoretical idea. A specific mission of Sumzero.com is to allow hedge fund managers to "vet out existing investment ideas."[6] Similar to VIC, the site is exclusive and caters to fundamentals-based managers. However, whereas VIC membership is anonymous within the club and to the general public, Sumzero.com membership is transparent to all members. This transparency makes private conversations on specific ideas possible. Members are also required to identify assets they have "extensively researched." This requirement facilitates the match-making process, pairing managers who follow the same assets. With 815 members and 1,211 idea submissions (as of September 20, 2009) since the site's launch in March 2008, Sumzero.com is likely the breeding ground for the value-creating conversations Stein envisioned.

To quantitatively assess Stein's primary hypothesis in more depth I analyze the comments attached to VIC recommendations (over 40,000 in total). 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 visable to the VIC community, but 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."

[6] Interview with Divya Narendra, founder of Sumzero.com. http://www.finalternatives.com/node/7348

Table 15 provides a more detailed description of the comments from VIC. I analyze the comments for all the observations used in the control-firm BHAR analysis (results are similar for other samples). In total I examine the comments on 1869 observations: 1671 long recommendations, and 198 short recommendations. I 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 percent of the recommendations receive at least 1 comment, and the typical recommendation receives 12.03 comments on average. Author comments represent 43 percent of the total comments submitted for a particular idea. 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.

I 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 I 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. I use the rating assigned to an investment recommendation as a proxy for the perceived value of an idea. I then divide the sample into quintiles formed on the percentage of total comments marked private. I estimate the statistics 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). 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.

B. *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 (2009) 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 likely 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, and/or (iii) arbitrage fund investors have a high propensity to withdraw funds following poor performance.

To test Gray's hypotheses that sharing is more likely to occur when managers have limited research resources and are capital constrained, I use a firm's assets under management as a proxy for their research and capital constraints: smaller firms have more constraints; bigger firms have fewer constraints. I analyze the size of the funds associated with the information exchange sites under analysis—VIC and Sumzero.com. I 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 members are almost exclusively small- to mid-size hedge funds ($10 million to $250 million assets under management). For more concrete data, I analyze the profile of asset managers who share ideas on Sumzero.com. Similar to VIC, the recommendations of Sumzero.com members are affiliated with funds that are overwhelmingly small (over 53% have less than $250mm assets under management). Figure 12 shows the distribution of assets under management (AUM) for managers who share ideas through Sumzero.com.

I also test Gray's prediction that sharing will occur in assets with higher noise trader risk. I find evidence in support of this hypothesis. VIC recommendations are concentrated in markets thought to have higher noise trader risk (e.g., small capitalization stocks, merger arbitrage, stub arbitrage [Mitchell, Pulvino, and Stafford 2002], and pairs/twin arbitrage [Froot and Dabora 1999]). Specifically, I find that typical long ideas submitted to VIC (89% of the sample) are recommendations for small capitalization stocks (median market capitalization is $397mm) or special situations such as stub and pair arbitrages, liquidations, and spin-offs in relatively illiquid markets (10.33% of ideas submitted). I find similar results for the submissions on Sumzero.com. Of the ideas submitted to the site, 15.5 percent are categorized as "event-driven or special situations," and the median market cap for long equity recommendations (which make up over 83% of the total equity recommendations) is $559mm.

For more concrete evidence that VIC recommendations focus on high noise trader risk assets, I analyze the institutional holdings of VIC stocks and the relationship between a calendar-time portfolio formed from VIC event firms and the change in monthly closed-end fund discounts/premiums. Lee, Shleifer, and Thaler (1991) and Barber (1994) suggest that stocks with lower institutional ownership are owned by individual stock holders who are more prone to behavioral biases that cause them to trade on "noise." These authors also contend that closed-end fund discounts are a proxy for noise trader risk; however, there is considerable debate over whether closed-end fund discounts are actually a proxy for noise-traders (Chen, Kan, and Miller 1993). Despite the controversy, I analyze both the institutional holding profile of VIC stocks and the relationship between VIC firms and closed-end fund discounts to assess the hypothesis that VIC recommendations focus on high noise trader assets.

If VIC stocks are dominated by individual investors, institutional holdings for VIC stocks should be small. I examine institutional ownership data from the Thomson Reuters Institutional Holding database (also known as the s34 database and the CDA/Spectrum 13f 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). I 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), I 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, I perform a paired t-test for unequal variances to test for differences in means and the Wilcoxson rank-sum test to test for differences in medians between the lowest quintiles and the highest quintiles.

Table 17 summarizes institutional holding for the nearest quarter for the full sample of investment recommendations submitted to VIC (1671 long observations and 198 short observations). In total, there are 1546 observations with institutional data. In order to assess how institutional ownership is related to key characteristics of VIC recommendations, I 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 percent (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 percent of the shares outstanding of all firms in the Thomson Reuters Institutional Holding database. They also find that the largest 25 percent of stocks have average institutional holdings of 79.48 percent (versus 70.47% for the large quintile of VIC recommendations). 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 Gray's notion that arbitrageurs will share ideas when there is high noise trader risk.

An interesting result from Table 17 is that BHARs are inversely related to institutional ownership. This evidence supports the much debated noise trader theory of Delong et al. (1990), which suggests that stocks with high noise trader risk will deviate from fundamental values. The evidence also supports a prediction from Gray's diversification sharing model. Gray shows that arbitrageurs who share ideas will invest more capital in arbitrage opportunities with high noise trader risk then they would invest if they were operating alone—all else equal. If BHARs are a proxy for an undervalued asset's move towards fundamentals, via price pressure from sharing arbitrageurs, then we would expect to see higher BHARs for assets with high noise trader risk.

I next perform an analysis of the relationship between VIC firms and closed-end fund discounts/premiums. Table 18 presents the results. I create calendar-time event portfolios consisting of all event firms recommended as buys in month t-11 to t. I then calculate the monthly returns to the event-firm portfolio in excess of the risk-free rate and regress this variable on the excess value-weighted market index return as well as the SMB (small minus big), HML (high book-to-market minus low book-to-market), and ΔEWD (change from month t to t-1 of an equal-weighted group of closed-end fund discounts/premiums). The closed-end fund data is from Morningstar and the funds included in the calculation of the equal-weighted discount/premium are all funds classified as non-levered general US equity. I perform the OLS regression procedure on an event portfolio constructed on an equal-weighted basis. I also require that the event portfolio has at least 10 observations to be included as an observation in the regression.

The results suggest that a portfolio of VIC recommendations has little relationship with changes in investor sentiment, as proxied by changes in closed-end fund discounts/premiums. I also break the sample into high, medium, and low institutional ownership to determine if changes in discounts/premiums are related to institutional holding percentage—again, closed-end fund discounts show no relationship to a portfolio of VIC firms.

The evidence that managers are sharing ideas for assets with high noise trader is mixed. Anecdotal evidence and the empirical institutional holdings analysis show that VIC firms are likely more affected by noise traders than the typical stock; however, there is no relationship with a portfolio of VIC firms and changes in closed-end fund discounts/premiums. More evidence and empirical analysis is needed before any definitive statements can be made with respect to Gray's hypothesis that arbitrageurs will only share ideas in assets with high noise trader risk.

Finally, I also indirectly test the hypothesis from Gray's theory which suggests that sharing will occur when a fund manager has investors who are prone to withdrawing large amounts of capital following poor performance. Baquero and Verbeek (2007) empirically identify the hedge funds that have sensitive investors: they find that investors in long/short strategies, emerging hedge funds, or smaller hedge funds are more likely to withdraw large amounts of capital following poor performance. The evidence from VIC and Sumzero.com suggests the majority of the funds sharing are small hedge funds, which Baquero and Verbeek identify as having more sensitive investors. This evidence lends preliminary credence to the hypothesis that sharing will occur when fund managers have more sensitive investors; however, more robust empirical work needs to be conducted in order to declare anything definitive.

B. *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 (δ) subsequently entering the market is high enough. If δ 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 δ is fundamental to the analysis of arbitrage chains, there is little discussion about the origins of δ and it is assumed to be exogenous. However, Gray (2009) 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, they can likely convince other arbitrageurs the idea is profitable. Another 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. Anecdotal evidence from many 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 percent 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."

One prediction from Gray's discussion of awareness sharing is that a manager who awareness shares will exchange his private information with as many arbitrageurs as possible, if the costs of sharing his private information are negligible. This prediction is in contrast to the predictions from the collaboration and diversification theories of information exchange, which suggest managers will want to keep their private information sharing limited to smaller groups. Therefore, if managers are engaging in awareness sharing, as opposed to collaboration or diversification sharing, we should see a significant overlap in ideas submitted to both VIC and Sumzero.com. The reason significant overlap would be an indicative of awareness sharing is due to the fact the sharing arbitrageur is trying to share his private information to as wide an audience as possible, as opposed to only submitting his idea to an exclusive venue like VIC (which already has a significant membership base of 250 members).

I 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 percent (19/456) of the 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. For this exercise I assume Sumzero.com submissions are done by the same individual or firm who posted the idea on VIC; however, because of the anonymous nature of VIC, I am unable to determine with certainty if the hedge fund managers submitting ideas via Sumzero.com are the same individuals submitting ideas to VIC.

Another unique prediction of awareness sharing is that large arbitrageurs will join sharing networks, but will not share ideas. The role of the large arbitrageur 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 preliminary evidence which supports the hypothesis that large funds will be members of private information groups, but will not share. Figure 12 shows that just under 5 percent of the fund population for Sumzero.com have over 20 billion assets under management. 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. 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.

Anecdotal evidence suggests awareness sharing is implemented by VIC members; however, the preliminary 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. Nonetheless, the empirical evidence from Sumzero.com also supports the awareness sharing prediction that large funds will join information sharing groups, but their participation will be limited. Overall, it is difficult to make a definitive statement with respect to the prevalence of awareness sharing as a reason for hedge fund managers sharing information with one another. Perhaps VIC members are more likely to share for collaboration and diversification benefits, whereas Sumzero.com members are likely to share for awareness reasons. Until more comprehensive data becomes available, it seems reasonable to claim that awareness sharing is used by arbitrageurs, but is limited in scope.

D. *Conclusions*

The empirical and anecdotal evidence from VIC and Sumzero.com generally support the collaboration, diversification, and awareness theories of private information exchange. I 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 is to identify unique datasets that allow the researcher to empirically identify which theory is driving sharing behavior and how these sharing actions affect asset prices. A more challenging, but perhaps more rewarding approach, would be to develop a sharing model that incorporates all three sharing theories and determines how investment managers will optimally behave. My initial hypothesis is that fund managers will engage in the following process to maximize the benefits from their own private information and the benefits from sharing: (1) identify private information, (2) take an appropriate position such that internal risk management and investment mandates are satisfied, (3) promote the position to other arbitrageurs (awareness), (4) receive constructive feedback on the idea and add or subtract to the position accordingly (collaboration), and (5) invest in the good ideas of other investment managers to lower the idiosyncratic volatility associated with holding a concentrated portfolio in only a handful of names (diversification).

VII. Conclusion

With my database, which is free from many of the biases found in databases other researchers analyze, I address three basic economic questions: (1) Where do skilled investors in my sample look to derive their private information? (2) Do the managers in my sample have stock-picking skill? (3) Why do fund managers share their private information with the competition?

With respect to question (1), I find that the skilled investors in my sample do not focus on high book-to-market stocks but instead focus on intrinsic value (discounted value of after-tax free cash flows generated by a business) and signaling factors in the market (e.g., open market repurchases, insider buying, activist activity). The analysis also suggests they spend a fair amount of time analyzing "special situations," such as liquidations, spin-offs, mergers, stub arbitrage, and pair-trade strategies, as a way to produce alpha. An interesting corollary question is why the investors on the other side of the VIC members' trade are not discovering the private information VIC members find.

The analysis answering question (2) also reveals some interesting results. The evidence suggests the fund managers in my sample have stock-picking skills for long recommendations; however, the results for short recommendations are less conclusive. These results should not be completely surprising: The recommendations I 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 (Grossman and Stiglitz 1980).

The existence of skilled investors implicitly requires the investors competing with VIC members to systematically lose money—how these investors can survive in an efficient market is puzzling. I hypothesize that systematically poor managers and investors can exist in the marketplace because the money management industry is not perfectly efficient. A manifestation of an inefficient money management industry can be inferred from the evidence in this paper that skilled investors exist who are willing to share profitable investment ideas with one another even though they are in competition for assets under management. Preliminary evidence suggests the investors in my sample are sharing for the reasons outlined in the corroboration, awareness, and diversification theories of private information exchange.

In summary, this study brings into question the broader concepts of market efficiency in the asset markets and the asset manager market; however, a key question remains concerning the magnitude of my findings. The hedge fund managers I analyze likely control a relatively small portion of the total investment capital. Moreover, the evidence suggests the investors I analyze focus their efforts in small capitalization stocks and generally illiquid arbitrage situations. These asset classes may require additional risk factors for which the asset pricing tests I utilize cannot account. However, the economic significance of the large alpha-point estimates in this study appear outsized relative to any reasonable compensation for systematic risk not accounted for with the current asset pricing models.

Appendix

The following idea to go long Sunterra Corporation was submitted on June 22, 2004, by the VIC user "ruby831" and received a club average rating of 5.8—a good, but not stellar, idea according to the community. The write-up is roughly representative of the average idea submission by VIC members.

Submission begins:

Sunterra Corporation (SNRR), a post-reorg equity, is the largest independent vacation ownership company in the world, with more than 300,000 owner families vacationing at 94 resorts in 12 countries in North America, Europe and the Caribbean. Originally founded as Signature Resorts, prior management built the company through multiple acquisitions that were never integrated. As a result, poor operations and controls, combined with an overly leveraged balance sheet, forced the company to file for bankruptcy in 2000. During Chapter 11, a new management team was assembled, with the CEO slot filled by the chief of its successful European operations. Although Sunterra emerged as a public company from bankruptcy in 2002, the company required a continued turnaround in operations, including unifying its systems, re-building its sales force, improving its credit processes and opening a new headquarters.

By the third quarter of 2003, the evidence of a turnaround clearly emerged, as operating margins improved substantially from 3% in Q3 2002 to 16% in Q3 2003. Also significant by late 2003, money losing ME operations, which had been depressing overall results, turned profitable for the first time in years. Following the release of 2003 results, management provided guidance for 2004 that projected sales growth of approximately 17%, but due to the full year impact of improved operations, margins and refinancings, an almost doubling of net income (fully taxed and excluding non-cash, reorg related expenses) from approximately $0.52/share to $0.97/share.

In addition to the positive trends specific to Sunterra, the company also benefits from positive industry fundamentals. The vacation ownership industry has shown consistent annual growth, even during recessions and the aftermath of terrorist attacks. Also significant, the industry has evolved into a more professionally managed and institutionally driven market. In addition to Sunterra, industry leaders include major lodging and leisure companies, such as Cendant, Starwood, Marriot, Hilton and Disney, among others. The vacation ownership industry should continue to enjoy strong fundamentals, with a market penetration rate of about 7% domestically and less than 3% in Europe, coupled with the positive demographics of aging baby boomers.

Furthering Sunterra's momentum will be the nationwide availability by the third quarter of a global "points-based" marketing and sales format. Currently in the U.S., customers purchase vacation ownership units through a deeded interest in a property for a certain number of weeks of usage per year at specific resorts. By selling on a global points based system, in which customers purchase points rather than weeks, Sunterra will significantly enhance its value proposition and its marketing capability to the existing customer base (the best source of new sales) and decrease marketing expenses. (The European unit has operated under a points system for many years and has historically shown marketing expenses as a percentage of sales lower than the U.S. by over 300bps.)

Other factors highlight Sunterra's solid business characteristics. These include a strong recurring revenue base (about 30% of revenues), including property management fee income (about $30mm); resort rental revenues ($11mm-$15mm); interest income on a $230mm+ receivables portfolio ($26mm+); and other income, including annual Club Sunterra, travel agency commissions and other fees ($20mm). In addition, about 40% of the balance of revenues (comprised of the sale of VOIs, or "vacation ownership interests"), comes from existing customers. Solid barriers to entry exist in the increasingly institutionalized vacation ownership industry, including the significant capital and scale required for multiple properties and global operations, as well as state regulatory hurdles in creating a global points- based system (SNRR labored for two+ years to implement it). Smaller, regional players are finding it difficult to compete, providing opportunities for Sunterra to acquire inventory, portfolios and customers at attractive prices (two deals closed in the last five months). Alternatively, since SNRR is the largest independent operator in the industry, it offers a compelling strategic asset to other lodging and leisure industry companies.

On the acquisition front, SNRR recently announced the purchase of 100% of a premier Hawaii resort that it managed and in which it owned a 23% stake. This property boosts an already impressive amount of resort inventory from about $600m at retail to $835mm at retail, representing almost 2.5 years of inventory. While the company has stated (without specifics) that this acquisition will be accretive, I estimate that it will add about $0.04 per share annually on a fully taxed basis. Importantly, there is no integration risk, since SNRR already manages and sells this property as part of its vacation network.

Based on a stock price of $12.40, a market capitalization of $248mm and net corporate debt of $135mm (excludes debt secured by the mortgage receivable portfolio), SNRR has an enterprise value of $383mm. I estimate EBITDA (my definition of which, consistent with the view of strategic buyers, is after interest expense on debt secured by mortgage receivables) to be $55mm for 2004 and $74mm for 2005, implying multiples of 7.0 and 5.2x, respectively. I estimate fully taxed EPS (excluding non-cash charges related to the reorganization and certain non-cash interest amortization) of $0.99 for 2004 and $1.44 for 2005, implying P/E multiples of 12.5x and 8.6x. A domestic NOL of $137.5mm, worth more than $1.00/share on a present value basis, makes these multiples even more attractive.

Industry transaction multiples have ranged from 7-11x EBITDA; I believe that SNRR would garner a premium multiple, but even applying the low end of the range of 7x 2005 EBITDA implies a $17.50 stock price (based on fully diluted shares included a recently issued convert, warrants and options and including corporate debt related to the Hawaii acquisition). The high end multiple would suggest a $28 stock price. Book value per share of about $10 ($7/share tangible book) also provides support for the stock. In any case, the stock appears attractively valued with earnings expected to grow organically at 25%+ for the near future.

Finally, I note that management has strong incentives to create shareholder value, with two million options struck at $15.25 per share. Following the release of Q1 earnings, management further proved its commitment and incentives, with the CEO and CFO both reporting purchases of the stock at approximately $11.00 per share.

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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: Frequency of Criteria Cited as Basis for Recommendations

This table summarizes how frequently VIC members cite various criteria as the basis for their recommendations. Each recommendation is assigned at least one reason, and many ideas receive multiple criteria. Criteria were included if there were at least 10 recommendations that cited it as a unique criterion for investing in a particular asset.

N=3273

Criteria description	% of total
Intrinsic value undervaluation	86.83
Tangible asset undervaluation	23.62
Active open-market share repurchase program	11.73
Net operating loss assets	5.13
Recent restructuring, spinoff or spinoff potential	4.77
Insider buying	4.77
Undervaluation on a “sum-of-the-parts” basis	4.58
Involvement of activist investor	3.88
Lack of sell-side analyst coverage	2.69
Turnaround and/or recent bankruptcy	2.32
Liquidation potential	2.08
Complicated business or taxes creating investor confusion	1.89
Merger arbitrage situation	1.44
“Stub” arbitrage situation	1.34
Merger arbitrage trading opportunity	0.73
Pair-trade strategy	0.70

Table 3: Criteria Analysis

This table shows summary statistics for the sample of investment recommendations submitted to VIC between January 1, 2000 and December 31, 2008. Panel A highlights the top combinations of investment criteria used by value investors. Panel B reports the number of investment criteria used by investor recommendations submitted to VIC. (n=3273).

Panel A: Most common combinations

Rank	Criteria combination	# criteria	% of total
1	Intrinsic value	1540	47.05
2	Tangible assets; intrinsic value	299	9.14
3	Intrinsic value; share repurchase program	194	5.93
4	Tangible assets	150	4.58
5	Intrinsic value; net operating loss assets	70	2.14
6	Intrinsic value; restructuring, spinoff, or spinoff potential	67	2.05
7	Intrinsic value; insider buying	66	2.02
8	Tangible assets; intrinsic value; share repurchase program	61	1.86
9	Intrinsic value; sum of parts	57	1.74
10	Intrinsic value; activist investor involvement	38	1.16
Others		731	22.33

Panel B: # of criteria used

	#	% of total
1	1827	55.80%
2	1054	32.19%
3	325	9.93%
4	61	1.86%
5+	7	0.21%

Table 4: Recommendation Descriptive Statistics

This table reports summary statistics for the control-firm sample of VIC recommendations. The control-firm sample consists of all firms that have the necessary data to conduct the control-firm BHAR analysis. Panels A and B examine the distribution of investment recommendations using four-digit Standard Industry Classification (SIC) industries. Panels C and D show the characteristics of investment ideas. Panel E 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 end of the month in which the investment is recommended. E/M is the ratio of LTM trailing earnings to the market value of equity measured at the end of the month in which the investment is recommended. ROA is the LTM return on assets. ME is the market value of equity measured at the end of the month in which the investment is recommended.

		Panel A: Industry representation for long recommendations		*Panel B: Industry representation short recommendations*	
Industry	SIC codes	Number of recommendations	Percent of sample	Number of recommendations	Percent of sample
Agriculture	< 1,000	8	0.48	4	2.02
Mining	1,000-1,499	69	4.13	4	2.02
Construction	1,500-1,999	22	1.32	4	2.02
Manufacturing	2,000-3,999	541	32.38	81	40.91
Transportation	4,000-4,999	170	10.17	10	5.05
Wholesale trade	5,000-5,199	63	3.77	8	4.04
Retail trade	5,200-5,999	199	11.91	20	10.10
Financial Services	6,000-6,999	255	15.26	29	14.65
Services	7,000-8,999	326	19.51	38	19.19
Other	> 9,000	11	0.66	0	0.00
No Data		7	0.42	0	0.00
Total		1671	100.0%	198	100.0%

Table 4: Recommendation Descriptive Statistics (continued)

Panel C: Long recommendation fundamental characteristics (n=1671)

	ME (millions)	B/M	E/M	ROA	ROE
Mean	4318	1.225	0.007	.029	0.011
25th Percentile	113	0.325	-0.006	-0.003	-0.010
Median	397	0.617	0.046	0.037	0.095
75th Percentile	1583	1.049	0.085	0.090	0.189

Panel D: Short recommendation fundamental characteristics (n=198)

	ME (millions)	B/M	E/M	ROA	ROE
Mean	2111	0.288	-0.100	0.087	0.400
25th Percentile	264	0.175	0.003	0.003	0.012
Median	650	0.342	0.037	0.053	0.121
75th Percentile	1738	0.668	0.067	0.108	0.221

Panel E: Time-series distribution of recommendations

Year	Long Recommendations	Short Recommendations
2000	95	1
2001	171	1
2002	181	10
2003	179	31
2004	190	25
2005	178	33
2006	196	30
2007	245	27
2008	236	40

Table 5: Intercepts from Fama-French 25 Excess Stock Return Regressions

This table shows the intercepts from excess stock return regressions of 25 size and book-to-market equity portfolios on the Fama and French three-factor model from January 1, 2000, to December 31, 2008. Dependent variables are 25 size and book-to-market equity portfolio returns, R_p, in excess of the 1-month Treasury-bill rate, R_f, observed at the beginning of the month. The 25 size and book-to-market equity portfolios are formed on New York Stock Exchange size and book-to-market equity quintiles. The three factors in the Fama and French model are zero-investment portfolios representing the excess return of the market, $R_m - R_f$; the difference between a portfolio of small stocks and big stocks, SMB; and the difference between a portfolio of high book-to-market stocks and low book-to-market stocks, HML. See Fama and French (1993) for details on the construction of the factors. Their empirical model is $R_{p,t} - R_{f,t} = \alpha_p + \beta_p\left(R_{m,t} - R_{f,t}\right) + \delta_p(SMB_t) + \gamma_p(HML_t) + \varepsilon_{p,t}$.

	Book-to-Market				
	Low	2	3	4	High
Intercepts:					
Value-weight portfolios:					
Small	-0.43%	0.07%	0.04%	0.30%	0.08%
2	-0.01%	-0.15%	0.33%	0.33%	0.22%
3	-0.15%	0.11%	0.42%	0.44%	0.66%
4	0.11%	0.06%	-0.40%	0.36%	-0.02%
Large	0.69%	0.04%	0.11%	-0.69%	0.13%
Equal-weight portfolios:					
Small	0.05%	0.25%	0.26%	0.23%	0.39%
2	0.07%	0.13%	0.11%	0.19%	-0.18%
3	0.40%	0.38%	0.72%	-0.13%	0.36%
4	0.07%	0.65%	-0.06%	0.32%	-0.82%
Large	0.53%	0.11%	1.09%	-0.43%	0.20%
P-Values:					
Value-weight portfolios:					
Small	0.1897	0.7577	0.7848	0.1058	0.6509
2	0.9528	0.5977	0.2559	0.1804	0.4285
3	0.6480	0.7289	0.2937	0.3172	0.0670*
4	0.7873	0.8904	0.3367	0.4812	0.9683
Large	0.1322	0.9288	0.8139	0.1800	0.8341
Equal-weight portfolios:					
Small	0.9272	0.5185	0.3367	0.3692	0.2550
2	0.7883	0.6726	0.7926	0.4701	0.5555
3	0.4661	0.2372	0.0997*	0.8328	0.3006
4	0.8764	0.2791	0.8790	0.5551	0.2051
Large	0.1514	0.8344	0.0862*	0.3119	0.7467

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

Table 6: 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 (abnormal return)	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 (abnormal return)	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 7: 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 (abnormal return)	P-value of paired t-test for difference	P-value for bootstrapped skewness-adjusted 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 (abnormal return)	P-value of paired t-test for difference	P-value for bootstrapped skewness-adjusted 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 8: Top and Bottom Size and B/M 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 size consists of the smallest (largest) 20% of the sample. The top (bottom) quintile for B/M consists of the lowest (highest) 20% of the sample. P-values associated with a two-tailed paired t-test are presented. Panel C test for difference p-values are calculated using a two-tailed paired t-test for difference assuming unequal variances.

	1(Top)			5 (Bottom)		
	One-year	Two-year	Three-year	One-year	Two-year	Three-year
Panel A: Size (Small-Large)						
N	300	260	233	271	199	155
Abnormal return	10.71%	25.93%	21.02%	4.40%	14.64%	21.96%
P-value for t-test	0.1091	0.0166**	0.1446	0.1379	0.0185**	0.0168**
P-value of sign-test	0.4530	0.0543*	0.0664*	0.5436	0.0650*	0.0157**
Panel B: B/M (Low-High)						
N	272	216	166	297	263	230
Abnormal return	11.58%	18.62%	29.55%	9.35%	16.27%	13.49%
P-value for t-test	0.0264**	0.0788*	0.0711*	0.1827	0.1982	0.4999
P-value of sign-test	0.2493	0.1174	0.0001***	0.0273**	0.0262**	0.1660
Panel C: Test for difference		Top – bottom size quintile (p-value)			Top – bottom B/M quintile (p-value)	
One-year		0.3874			0.7981	
Two-year		0.3630			0.6318	
Three-year		0.9555			0.5330	

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

Table 9: Calendar-Time Portfolio Regressions

This table reports calendar-time abnormal returns for VIC recommended stocks computed using the Fama-French three-factor model. The sample consists of all firms that have the necessary data to conduct the calendar-time portfolio regression analysis. The long-recommendations sample contains stocks recommended as a buy. The short-recommendations sample contains stocks recommended as a sell. Each month, I form portfolios consisting of all firms that were recommended within the last *n* years (where *n* is the length of the holding period). For equally weighted portfolios, I run both OLS and WLS regressions, where the weights are given by the number of stocks in the portfolio in a given month. Value-weighted portfolios weights are determined by market capitalization measured at the beginning of the month. Two-tailed p-values associated with t-statistics are presented below the intercept estimates. The time period under analysis is from January 1, 2000, to June 30, 2009, using event observations from January 1, 2000, to December 31, 2008. There are 2043 observations for the long recommendations and 248 for the short recommendations.

	Value-weight portfolio			Equal-weight portfolio			WLS		
	One-year	Two-year	Three-year	One-year	Two-year	Three-year	One-year	Two-year	Three-year
Panel A: Long recommendations									
Three-factor model alpha	0.34%	0.32%	0.22%	0.80%	0.69%	0.68%	0.63%	0.51%	0.41%
	0.3494	0.3245	0.4670	0.0009***	0.0034***	0.0050***	0.0047***	0.0173**	0.0504*
Panel B: Short recommendations									
Three-factor model alpha	0.11%	0.23%	0.21%	0.93%	0.85%	0.81%	0.77%	0.75%	0.76%
	.8498	.5504	.5637	.0059***	.0062***	.0103**	.0167**	.0126**	.0077***

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

Table 10: Calendar-Time Portfolio Regressions by Market Equity

This table reports calendar-time abnormal returns for VIC recommended stocks computed using the Fama-French three-factor model. The sample consists of all firms that have the necessary data to conduct the control-firm analysis. The long-recommendations sample contains stocks recommended as a buy. The short-recommendations sample contains stocks recommended as a sell. Each month, I form portfolios consisting of all firms that were recommended within the last *n* years (where *n* is the length of the holding period). For equally weighted portfolios, I run both OLS and WLS regressions, where the weights are given by the number of stocks in the portfolio in a given month. Value-weighted portfolios weights are determined by market capitalization measured at the beginning of the month. Two-tailed p-values associated with t-statistics are presented below the intercept estimates. The time period under analysis is from January 1, 2000, to June 30, 2009, using event observations from January 1, 2000, to December 31, 2008. There are 334 observations for quintiles 1-4 and 335 observations for quintile 5.

	Value-weight portfolio			Equal-weight portfolio			WLS		
	One-year	Two-year	Three-year	One-year	Two-year	Three-year	One-year	Two-year	Three-year
Panel A: Three-factor model									
Size quintile (small to large)									
1	0.82%	0.72%	0.65%	0.99%	0.92%	0.76%	1.22%	1.09%	0.84%
	0.0553*	0.0782*	0.0942*	0.0203**	0.0242**	0.0493*	0.0016***	0.0023***	0.0102**
2	0.96%	0.71%	0.56%	0.80%	0.64%	0.58%	0.67%	0.45%	0.38%
	0.0110**	0.0357**	0.0765*	.0301**	.0577*	.0781*	0.0528*	0.1420	0.1866
3	0.47%	0.29%	0.27%	0.36%	0.22%	0.25%	0.30%	0.15%	0.12%
	0.1738	0.3810	0.4030	0.2697	0.4314	0.3650	0.3547	0.5973	0.6754
4	0.52%	0.50%	0.50%	0.76%	0.59%	0.62%	0.60%	0.39%	0.32%
	0.0922*	0.1150	0.1041	0.0247**	0.0630*	0.0516*	0.0564*	0.2000	0.2784
5	0.06%	0.23%	-0.12%	0.68%	0.70%	0.59%	0.66%	0.66%	0.55%
	0.8968	0.5499	0.8419	0.0450**	0.0173*	0.0449**	0.0540*	0.0140**	0.0247**

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

Table 11: Calendar-Time Portfolio Regressions by Book-to-Market Equity

This table reports calendar-time abnormal returns for VIC recommended stocks computed using the Fama-French three-factor model. The sample consists of all firms that have the necessary data to conduct the control-firm analysis. The long-recommendations sample contains stocks recommended as a buy. The short-recommendations sample contains stocks recommended as a sell. Each month, I form portfolios consisting of all firms that were recommended within the last *n* years (where *n* is the length of the holding period). For equally weighted portfolios, I run both OLS and WLS regressions, where the weights are given by the number of stocks in the portfolio in a given month. Value-weighted portfolios weights are determined by market capitalization measured at the beginning of the month. Two-tailed p-values associated with t-statistics are presented below the intercept estimates. The time period under analysis is from January 1, 2000 to June 30, 2009, using event observations from January 1, 2000, to December 31, 2008. There are 334 observations for quintiles 1-4 and 335 observations for quintile 5.

	Value-weight portfolio			Equal-weight portfolio			WLS		
	One-year	Two-year	Three-year	One-year	Two-year	Three-year	One-year	Two-year	Three-year
Panel A: Three-factor model									
B/M quintile (low to high)									
1	-0.09%	0.79%	0.72%	0.41%	0.46%	0.78%	0.48%	0.31%	0.32%
	0.8419	0.1173	0.0832*	0.2529	0.1502	0.0331**	0.1530	0.2697	0.2369
2	0.06%	-0.32%	0.56%	0.69%	0.60%	0.60%	0.64%	0.53%	0.44%
	0.9047	0.4856	0.0765*	0.0383**	0.0287**	0.0224**	0.0392**	0.0301**	0.0630*
3	-0.04%	0.14%	-0.11%	0.50%	0.37%	0.30%	0.36%	0.28%	0.26%
	0.9523	0.8575	0.8811	.1677	.2254	.3009	0.2918	0.3009	0.2918
4	0.80%	0.34%	0.35%	0.62%	0.29%	0.16%	0.56%	0.25%	0.06%
	0.0401**	0.3246	0.2872	0.0340**	0.2612	0.5301	0.0528*	0.3344	0.8108
5	1.71%	1.43%	1.20%	0.91%	1.04%	0.96%	1.19%	1.10%	0.91%
	0.0099***	0.0073***	0.0254**	0.0440**	0.0102**	0.0067***	0.0049***	0.0022***	0.0036***

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

Table 12: Predicting Matched-Sample Abnormal Returns with VIC Ratings

The regression model is given by $BHAR_i = \delta_i + \lambda_i(Rating_i) + \varepsilon_i$, where $BHAR_i$ is the cumulative abnormal return to stock i from t=2 to t=h (h is holding period), and $Rating_i$ is the VIC members' rating of a particular stock i. $\hat{\lambda}$, and $\overline{Rating}$ are sample estimates for the true parameters. VIC only reports a rating if five or more members rate a recommendation. The samples used in these regressions are the same one-, two-, and three-year samples used in the control-firm and benchmark-portfolio BHAR approaches. P-values associated with t-statistics are presented below the $\hat{\lambda}$ estimates (two-tailed).

	Control Firm BHAR			Benchmark Portfolio BHAR		
	One-year	Two-year	Three-year	One-year	Two-year	Three-year
Panel A: Long recommendations						
$\hat{\lambda}$	0.0808	0.0633	0.1925	0.0797	0.0793	0.1672
	0.0053***	0.1990	0.0157**	0.0002***	0.0520*	0.0070***
$\overline{Rating}$	5.10	5.11	5.11	5.10	5.11	5.13
Number of observations	1376	1123	928	1281	962	763
Panel B: Short recommendations						
$\hat{\lambda}$	.1233	0.0371	0.0980	0.1196	0.1004	0.0932
	0.1154	0.7470	0.5103	0.0323**	0.2642	0.4744
$\overline{Rating}$	5.33	5.36	5.26	5.32	5.36	5.31
Number of observations	152	124	95	144	111	86

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

Table 13: 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. Test for difference between the top and bottom quintile p-values are calculated using a two-tailed paired t-test for difference assuming unequal variances.

Panel A: Top rating quintile

	n	Mean Sample Firm Return	Mean Control Firm Return	Difference (abnormal return)	P-value of t-test for difference	P-value of sign-test for difference	P-value of difference between top and bottom quintile
One-year	290	27.76%	6.07%	21.69%	0.0001***	0.0000***	.0017***
Two-year	255	46.59%	20.44%	26.15%	0.0028***	0.0024***	0.0536*
Three-year	221	86.86%	44.28%	42.58%	0.0054***	0.0054***	0.0061***

Panel B: Bottom rating quintile

	n	Mean sample firm return	Mean control firm return	Difference (abnormal return)	P-value of t-test for difference	P-value of sign-test for difference
One-year	254	8.56%	8.72%	-.16%	0.9736	0.8507
Two-year	202	32.26%	28.05%	4.21%	0.5737	0.8329
Three-year	168	46.25%	55.27%	-9.02%	0.4129	0.8170

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

Table 14: Calendar-Time Portfolio Regressions by Ratings

This table reports calendar-time abnormal returns for VIC recommended stocks computed using the Fama-French three-factor model. The sample consists of all firms that have the necessary data to conduct the control-firm analysis and have a rating observation. The long-recommendations sample contains stocks recommended as a buy. The short-recommendations sample contains stocks recommended as a sell. Each month, I form portfolios consisting of all firms that were recommended within the last *n* years (where *n* is the length of the holding period). For equally weighted portfolios, I run both OLS and WLS regressions, where the weights are given by the number of stocks in the portfolio in a given month. Value-weighted portfolios weights are determined by market capitalization measured at the beginning of the month. Two-tailed p-values associated with t-statistics are presented below the intercept estimates. The time period under analysis is from January 1, 2000 to June 30, 2009, using event observations from January 1, 2000, to December 31, 2008. There are 318 observations for quintiles 1-5.

	Value-weight portfolio			Equal-weight portfolio			WLS		
	One-year	Two-year	Three-year	One-year	Two-year	Three-year	One-year	Two-year	Three-year
Panel A: Three-factor model									
Rating quintile (high to low)									
1	1.37%	0.50%	0.13%	2.02%	1.16%	0.94%	1.85%	1.10%	0.81%
	0.0096***	0.2070	0.7270	0.0000***	0.0001***	0.0012***	.0000***	0.0000***	0.0018***
2	-0.15%	-0.15%	-0.32%	0.55%	0.40%	0.49%	0.47%	0.36%	0.41%
	0.8497	0.8497	0.6827	0.0430**	0.0961*	0.0552*	0.0868*	0.1292	0.0591*
3	0.39%	0.40%	0.39%	0.69%	0.53%	0.33%	0.65%	0.48%	0.43%
	0.3297	0.2294	0.1591	0.0112**	0.0359**	0.1649	0.0162**	0.0580*	0.0496**
4	-0.01%	0.15%	-0.08%	0.69%	0.50%	0.45%	0.46%	0.40%	0.24%
	0.8890	0.7955	0.8498	0.0786*	0.1296	0.1533	0.2040	0.2220	0.4145
5	-0.14%	0.05%	-0.12%	-0.27%	-0.11%	0.16%	-0.16%	0.13%	0.02%
	0.8341	0.9285	0.8419	0.4795	0.7346	0.7346	0.6828	0.7123	0.9364

*, ** 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 are1869 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 full 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: Relationship between group size and idea value

Panel A presents summary statistics for the full sample and for sample quintiles formed on the percentage of messages that are private for a given recommendation. 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 rank-sum test.

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

	Total	1(low)	2	3	4	5 (high)	1-5	P-value
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.

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 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. 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 rank-sum 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.

Table 18: Relationship between Event-Firm Returns and Changes in Closed-end Fund Discounts/Premiums

This table reports parameter estimates for the linear regression model $R_{p,t} - R_{f,t} = \alpha_i + \beta_i(R_{m,t} - R_{f,t}) + \delta_i(SMB_t) + \gamma_i(HML_t) + \theta(\Delta EWD_t) + \varepsilon_{i,t}$. The independent variables consist of the three Fama-French factors, and ΔEWD_t, which is the change from month t to t-1 of an equal-weighted group of closed-end fund discounts/premiums. The closed-end fund data is from Morningstar and the funds included in the calculation of the equal-weighted discount/premium are all funds classified as non-levered general US equity funds. The event firms consists of all long recommendation firms that have the necessary data to conduct the control-firm BHAR analysis and which have institutional holding data. Event portfolios are equal-weighted, where the weights are given by the number of stocks in the portfolio in a given month. The time period under analysis is from January 1, 2000, to June 30, 2009, using event observations from January 1, 2000, to December 31, 2008. Two-tailed p-values associated with t-statistics are presented below the intercept estimates.

	Dependent Variable: $R_{p,t} - R_{f,t}$			
	Full Sample	High Institutional %	Medium Institutional %	Low Institutional %
Constant	0.82%	0.52%	0.50%	1.16%
	0.0006***	0.1104	0.0903*	.0005***
Rm-Rf	1.095	1.100	1.074	0.974
	0.0000***	0.0000***	0.0000***	.0000***
SMB	0.696	0.792	0.681	0.710
	0.0000***	0.0000***	0.0000***	0.0000***
HML	0.411	.529	0.357	0.112
	.0000***	0.0000***	0.0000***	0.2464
ΔEWD	-0.001	-0.002	-0.000	-0.001
	0.7201	0.5011	0.8737	0.7142
Number of observations	1388	462	463	463
R^2	0.88	0.79	0.82	0.76

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

Figure 1

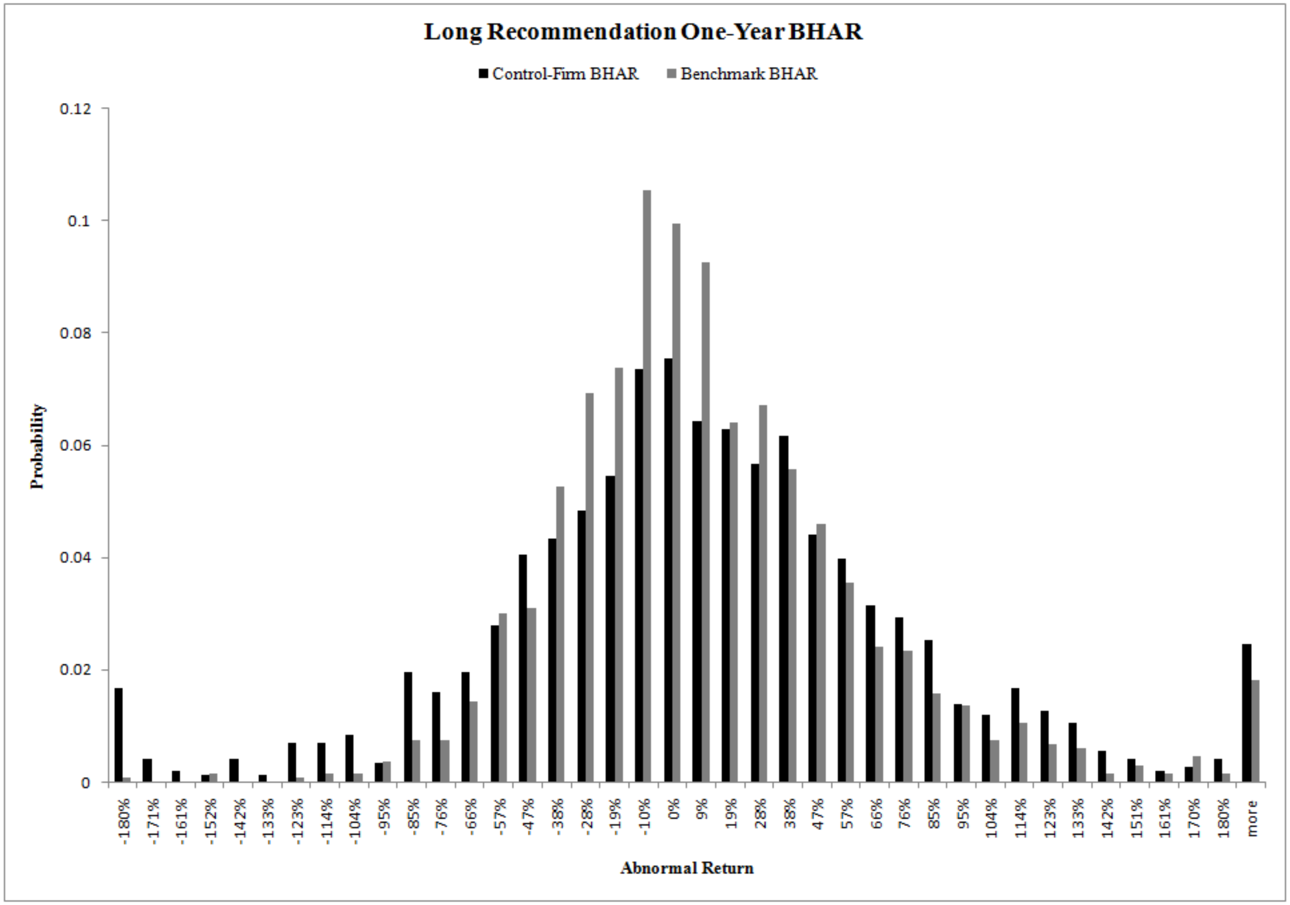


Figure 1: Long recommendation one-year BHAR. This figure represents the histogram of abnormal returns calculated from the control-firm and the benchmark-portfolio BHAR methodologies. The Y-axis represents the probability. The X-axis represents abnormal returns for long recommendations. The control-firm sample has 1,429 observations and the benchmark sample has 1,327 observations.

Figure 2

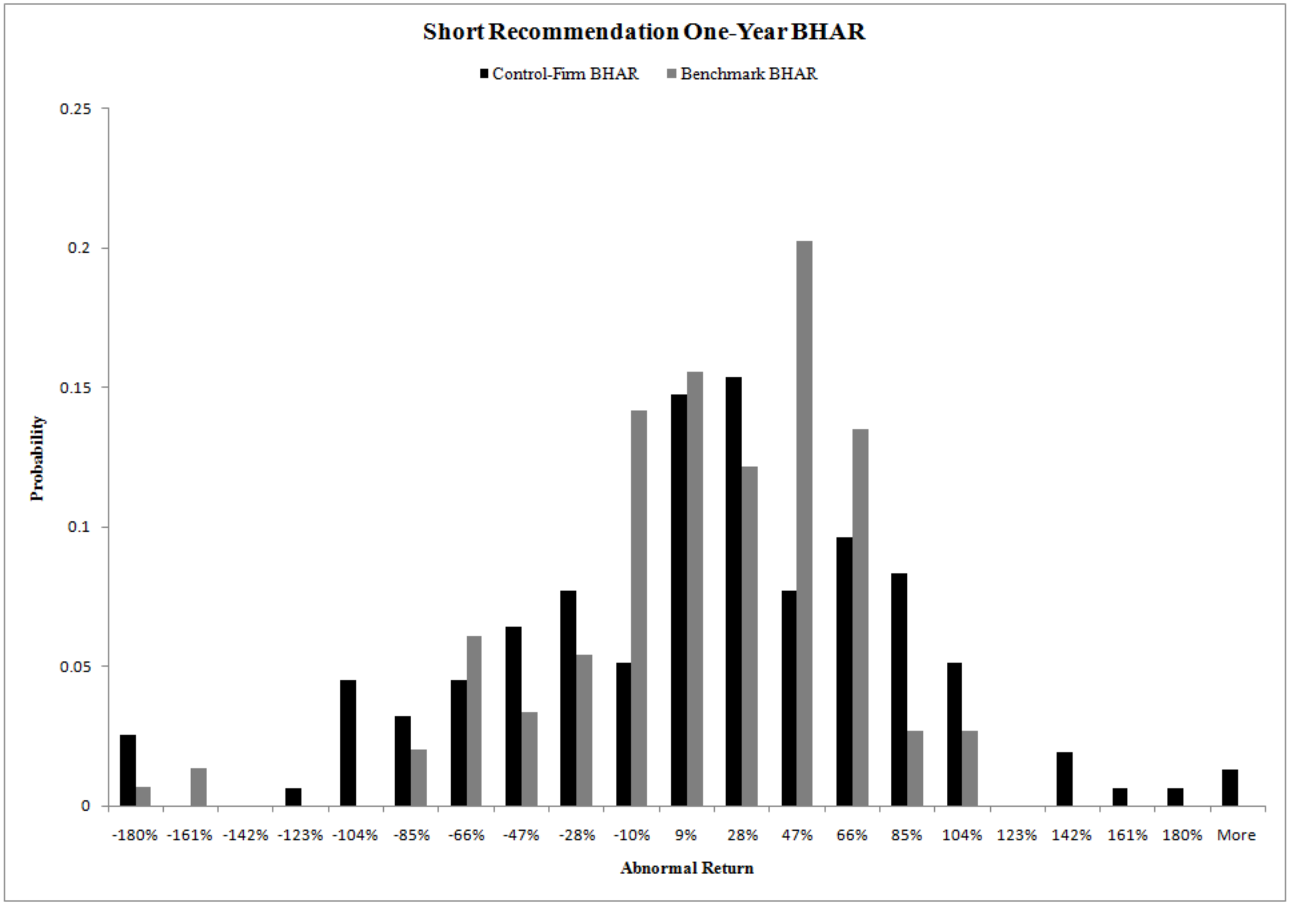
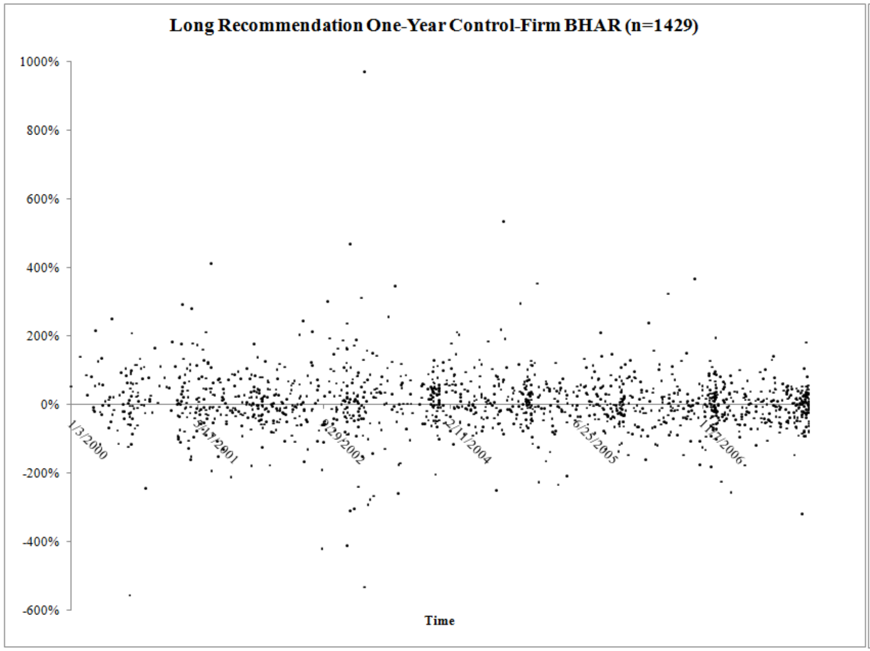


Figure 2: Short recommendation one-year BHAR. This figure represents the histogram of abnormal returns calculated from the control-firm and the benchmark-portfolio BHAR methodologies. The Y-axis represents the probability. The X-axis represents abnormal returns to a short position in short recommendations. The control-firm sample has 156 observations and the benchmark sample has 148 observations.

Figure 3



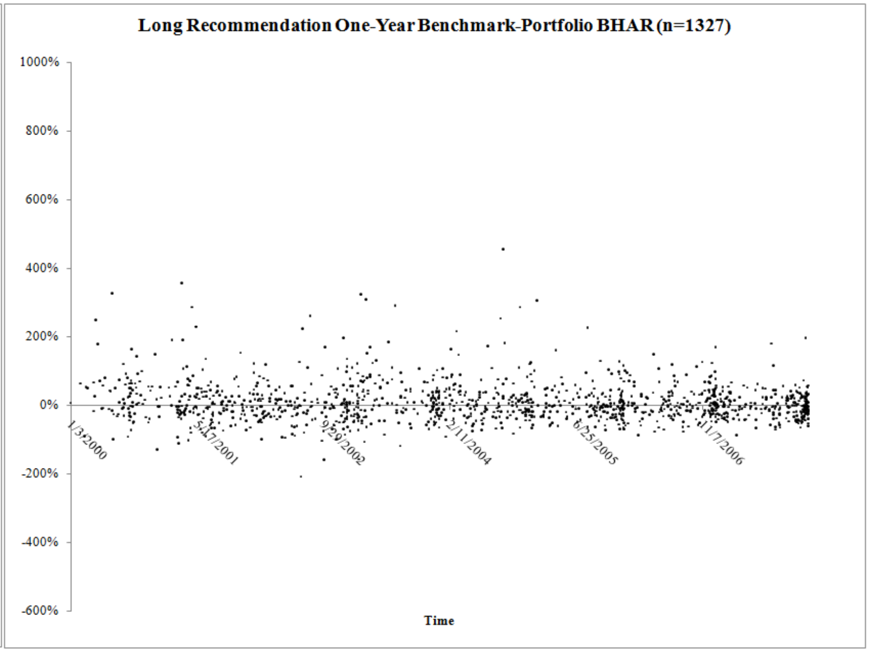


Figure 3: Scatter plot of long recommendation one-year control-firm and benchmark-portfolio BHAR. This figure represents a scatter plot of sample firm BHAR estimates. The Y-axis represents the abnormal return. The X-axis represents time.

Figure 4

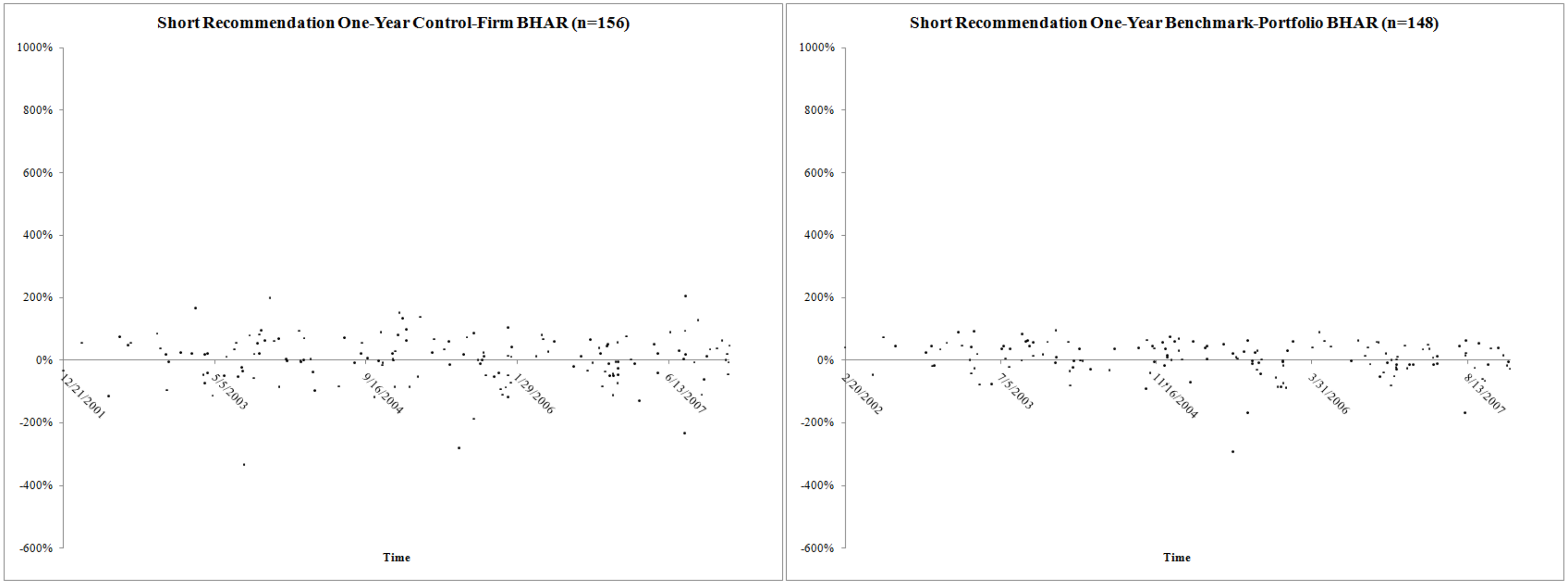


Figure 4: Scatter plot of short recommendation one-year control-firm and benchmark-portfolio BHAR. This figure represents a scatter plot of individual sample firm BHAR estimates. The Y-axis represents the abnormal return. The X-axis represents time.

Figure 5

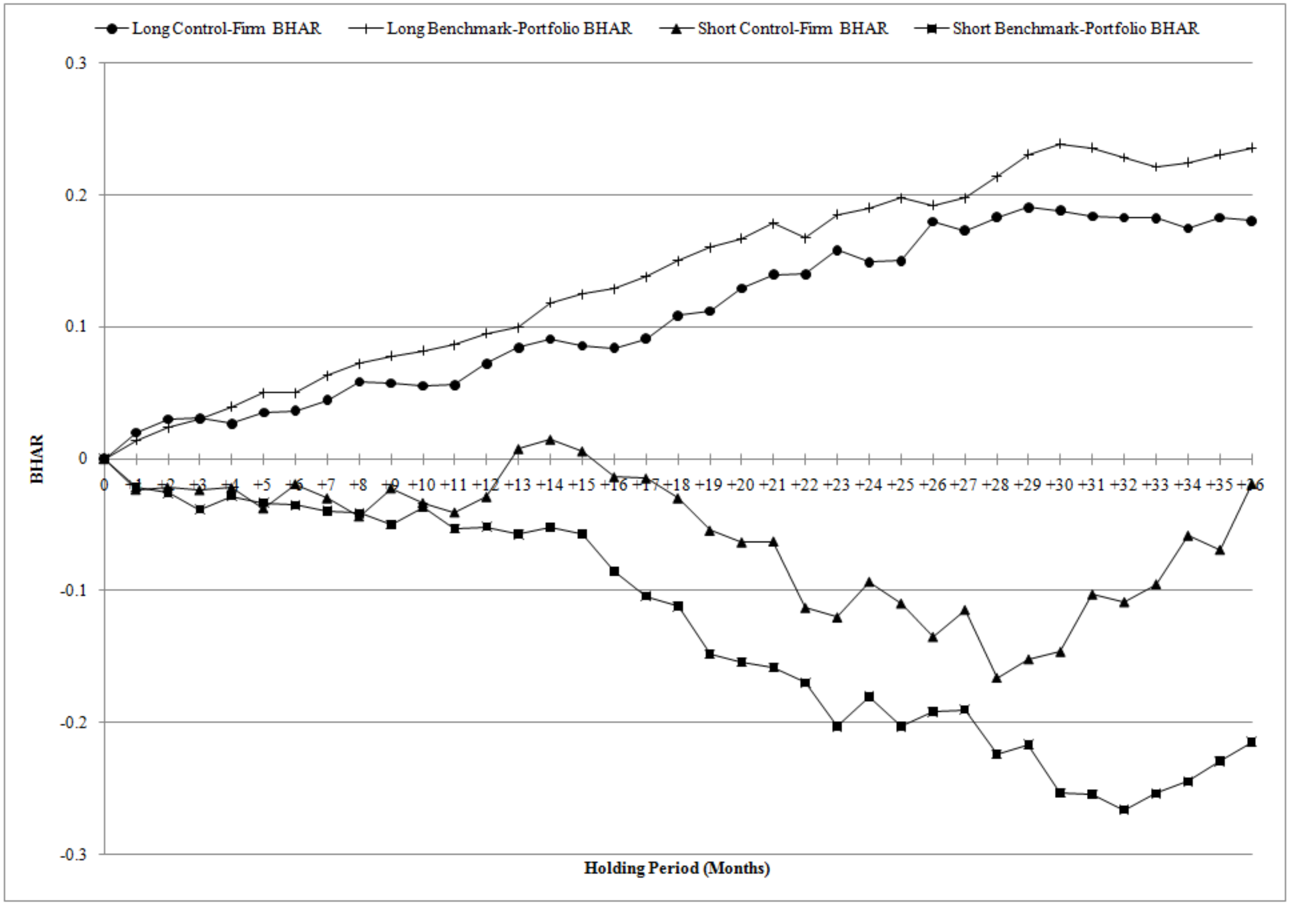


Figure 5: BHAR estimates for +1 to +36 months. This figure represents BHAR over time. The Y-axis represents the BHAR. The X-axis represents the holding period in months.

Figure 6

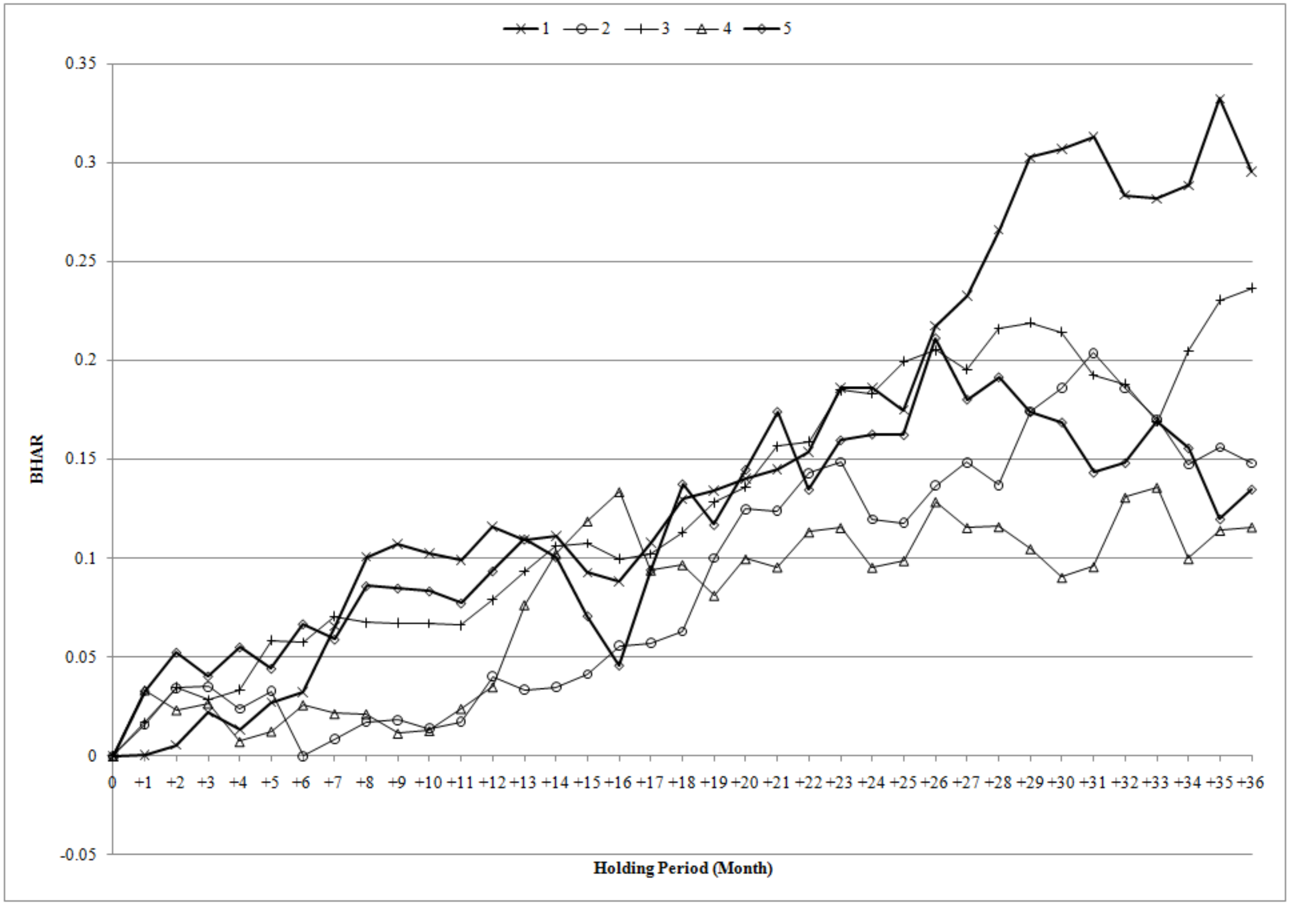


Figure 6: BHAR estimates for +1 to +36 months by book-to-market (1=low, 5=high). This figure represents BHAR over time. The Y-axis represents the BHAR. The X-axis represents the holding period in months.

Figure 7

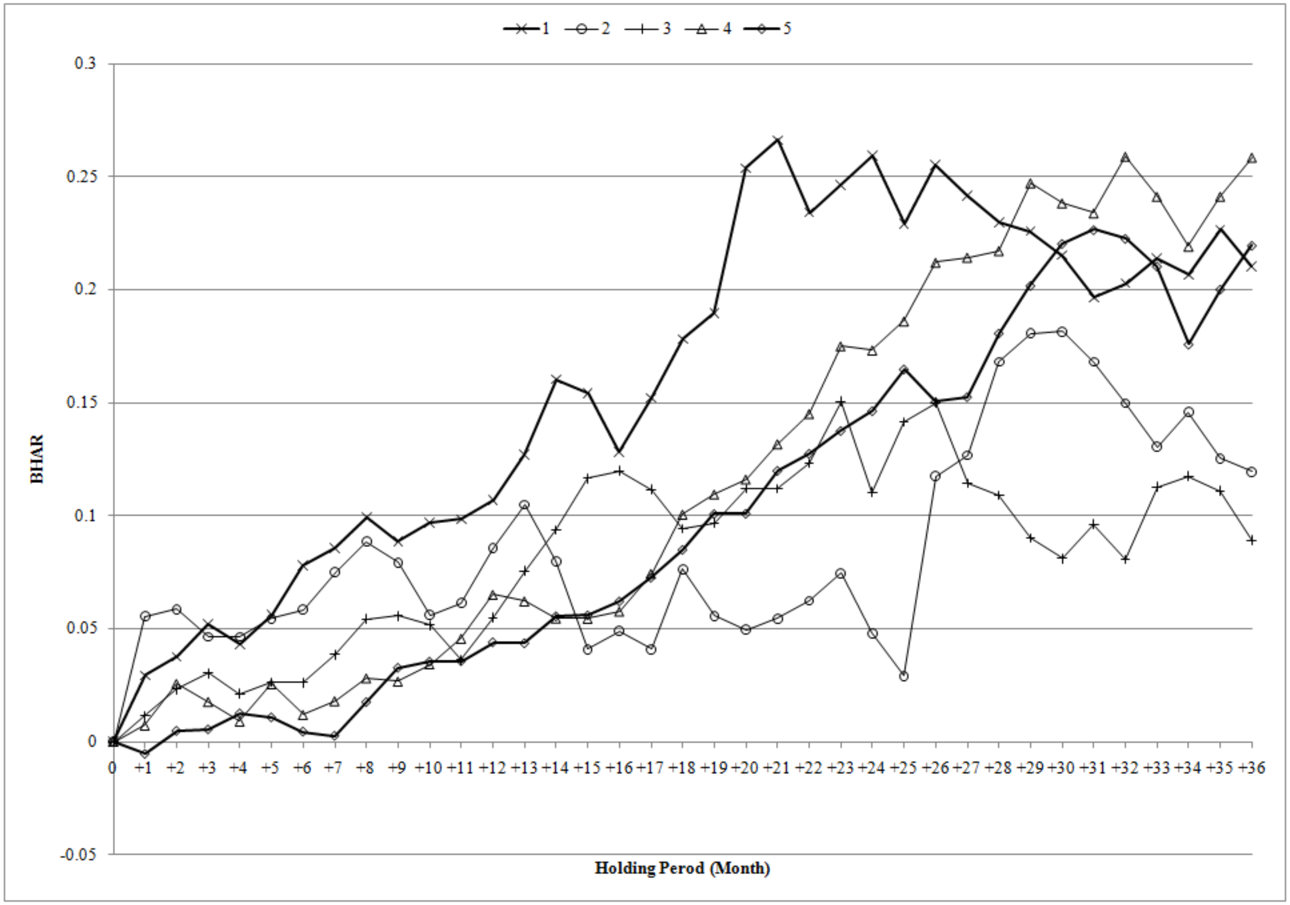


Figure 7: BHAR estimates for +1 to +36 months by size (1=small, 5=large). This figure represents BHAR over time. The Y-axis represents the BHAR. The X-axis represents the holding period in months.

Figure 8

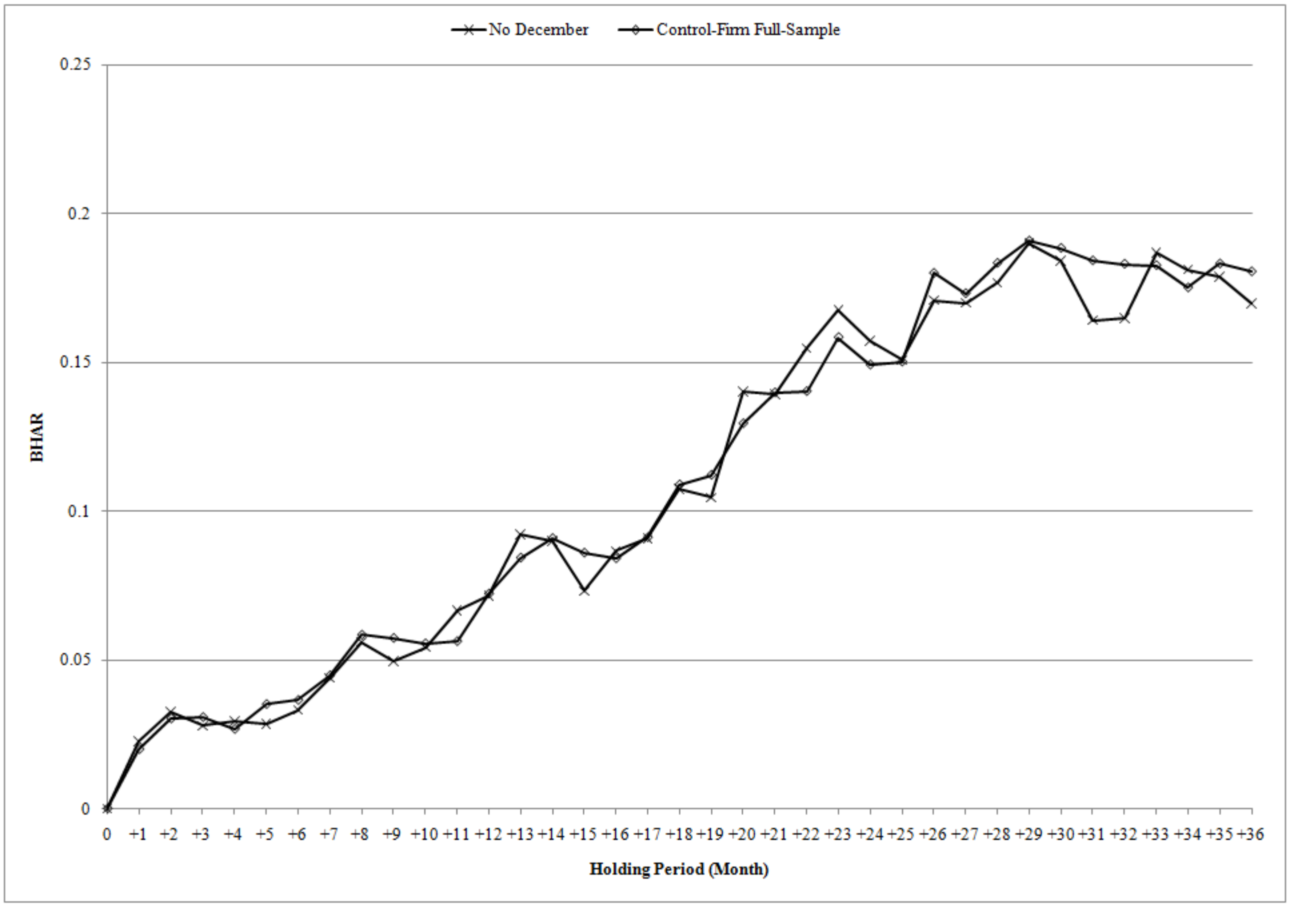


Figure 8: BHAR estimates for +1 to +36 months with and without December observations. This figure represents BHAR over time. The Y-axis represents the BHAR. The X-axis represents the holding period in months.

Figure 9

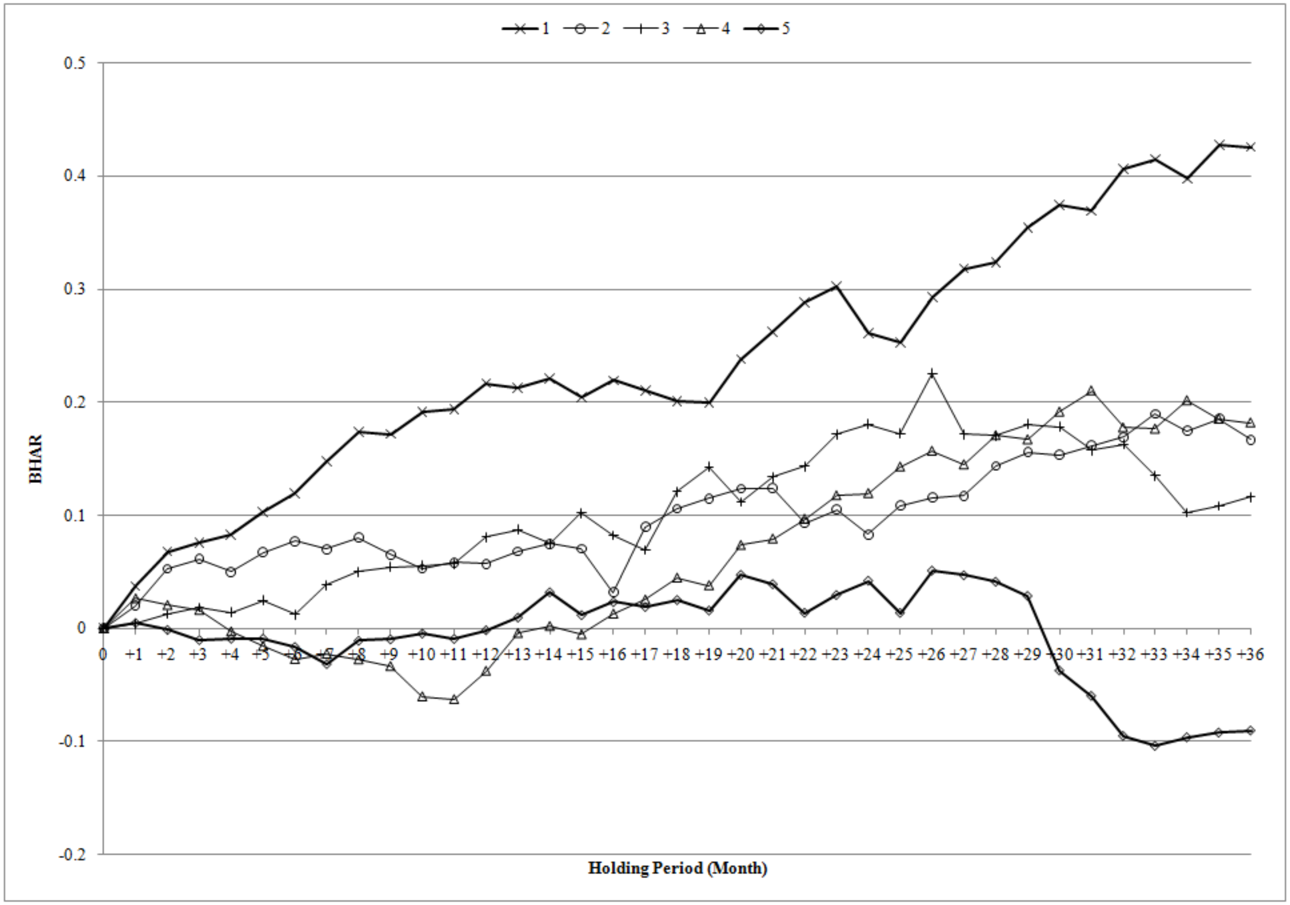


Figure 9: BHAR estimates for +1 to +36 months by rating (1=high, 5=low). This figure represents BHAR over time. The Y-axis represents the BHAR. The X-axis represents the holding period in months.

Figure 10

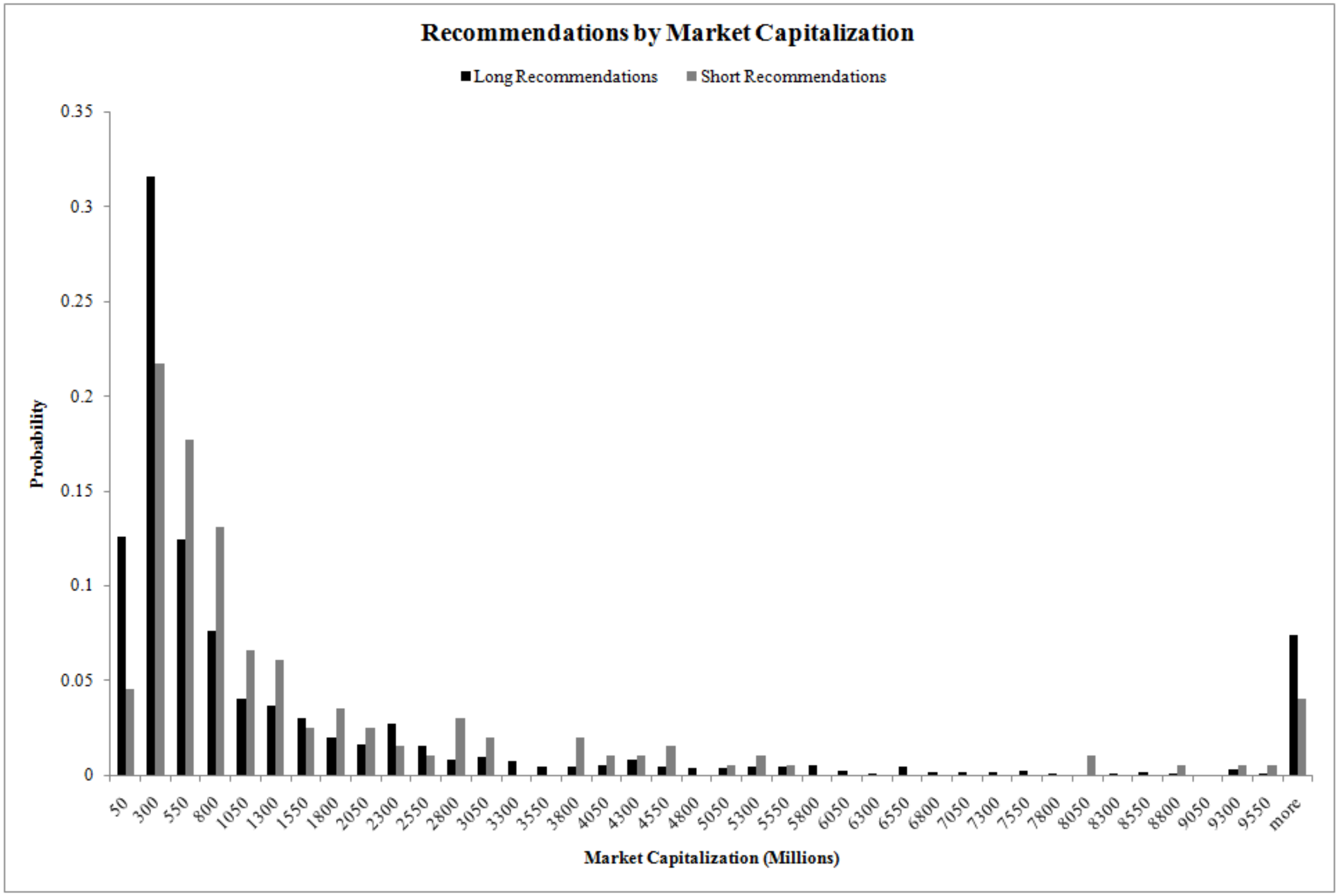


Figure 10: VIC recommendations by market capitalization. This figure represents the histogram of market capitalizations for the control-firm BHAR sample. The Y-axis represents the probability. The X-axis represents market capitalizations. There are 1671 long recommendations and 198 short recommendations.

Figure 11

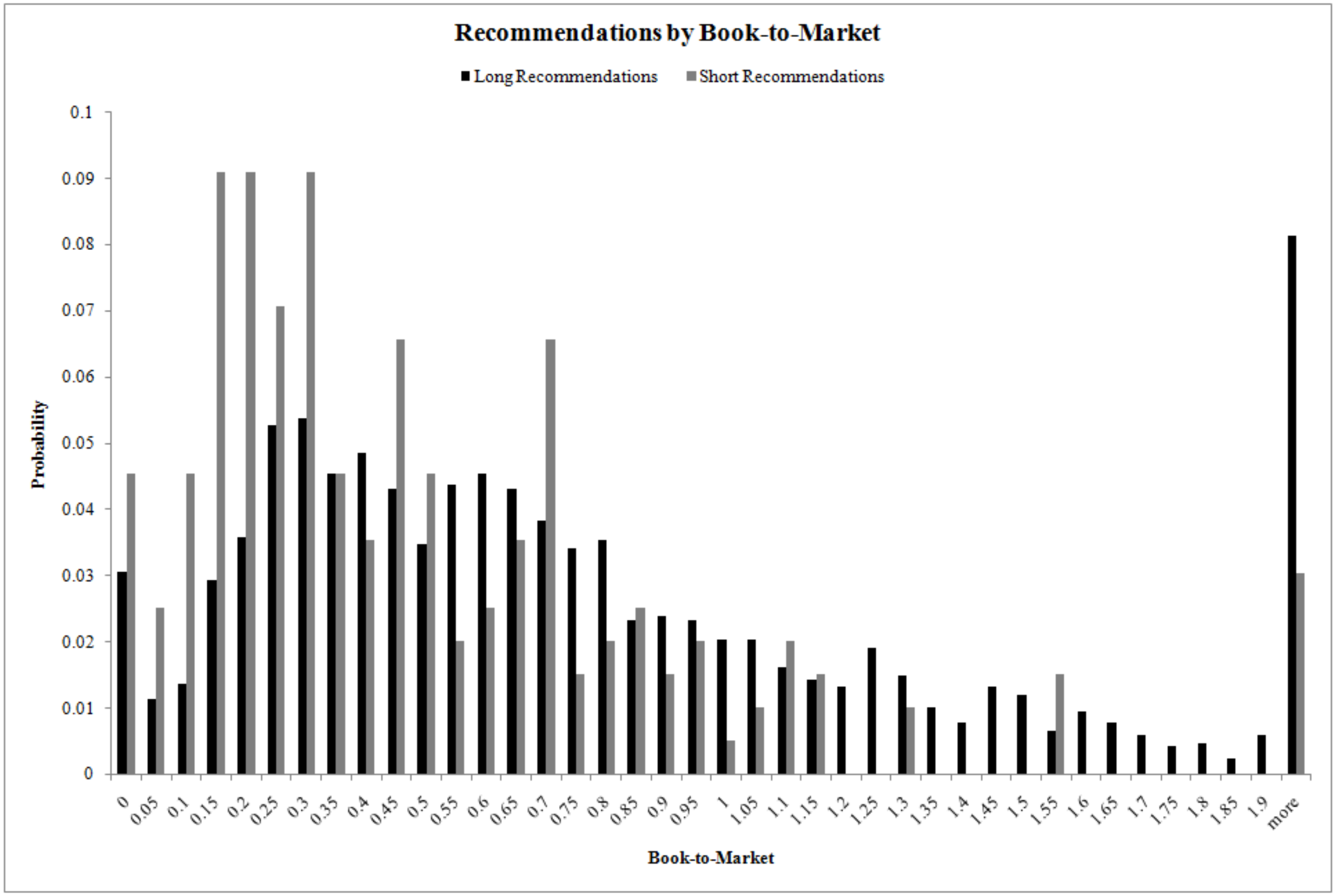


Figure 11: VIC recommendations by book-to-market. This figure represents the histogram of book-to-market ratios for the control-firm BHAR sample. The Y-axis represents the probability. The X-axis represents market capitalizations. There are 1671 long recommendations and 198 short recommendations.

Figure 12

Figure 12: 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.