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Investment performance of AAII stock screens over diverse markets

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Abstract

Individual investors often rely on information services and products to compete with professional investors. To assist in this effort, the American Association of Individual Investors (AAII) offers a variety of screening tools designed to help individuals construct stock portfolios. We extend prior research on AAII screening performance by including more recent investment periods, using more rigorous factor models, and examining both median and mean returns to allow for skewing. Over a period of tumultuous markets with as little as $50,000 to invest, over 30% of the available screens achieved statistically significant excess rates of return unrelated to transaction costs and multifactor risks proposed by efficient market theorists.

JEL classification: G11; G14

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1. Introduction

As part of an investment process, investors consider the extent to which they use passive and active approaches to the equity market. Individuals often use a passive approach by investing in broadly diversified index funds rather than spend time and energy trying to pick stocks. The passive approach is supported by efficient market arguments that active trading of stocks will not consistently beat the market index on a risk-adjusted basis. The efficient

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market hypothesis is based on the view that a large numbers of rational investors with access to the same information will generate security prices that are unbiased estimates of security values. As a result, there should be no consistent abnormal returns from active trading.[1]

Active investors seek opportunities for excess rates of return that are generally linked to behavioral explanations for departures from investor rationality. Behavioral finance theories maintain that predictable irrationality in security pricing, linked to human biases and heuristics, causes predictable deviations from efficient market pricing. These predictably irrational behaviors of investors have been tested and validated in behavioral finance studies reviewed by Nofsinger (2013) and have been translated into investment strategies by Pompian (2012). Ultimately, the ability to use information and metrics about stocks to earn an excess return is an empirical issue.

Even with market inefficiencies, small investors may remain passive because they feel that professionals with large research budgets have size, diversification, technology, transaction cost, and information advantages. Empirical evidence suggests that individual investors generally do not make good stock selection decisions. Barber and Odean (2000) found that returns on stocks sold by individuals subsequently turned out to be higher than returns on stocks they bought. In the same study Barber and Odean found that the average household with an account at a large discount brokerage firm underperformed by an average 15 basis points per month even without transaction cost adjustments. Korniotis and Kumara (2013) analyzed investment accounts of over 60,000 customers of a major discount broker over the period from 1991 to 1996. They found that retail investors (less informed) underperformed wholesale investors (well informed) by over 200 basis points per year on average.

A wide range of professional services are available to help individuals overcome disadvantages relative to well informed investors. One such service available to individual investors is provided by the American Association of Individual Investors (AAII). AAII is a nonprofit investment education organization offering individual investors a set of low cost services supporting active trading strategies. Investors have access to stock screens based on what AAII believes well known and highly regarded investors use to identify attractive stocks. AAII claims that 91% of their screened portfolios beat a passive S&P 500 index but there is no information given on performance after transactions costs, risk adjustments, and tests of statistical significance.[2]

In this article we present a range of performance measures addressing both practical and theoretical issues to test the investment performance of AAII strategies. Specifically, prior tests of investment performance from using mechanical screens are extended as follows:

1. We extend AAII performance analysis in prior studies to more recent years that include the period since the 2008 market crash. Our results help establish whether or not prior findings are robust over more recent holdout periods.
2. We introduce an analysis of both the mean and median monthly returns to identify potential skewing of returns.
3. We conduct a more rigorous analysis of screened portfolio performance by using factor models. In this way we test for screened portfolios that offered significant excess returns even after more extreme risk factor hypotheses are considered.

The article offers several layers of investment analysis that may also be instructional for individual investors who have only focused on cumulative wealth, average returns, or Sharpe ratios to measure performance.

2. Literature review

We address the basic question of whether or not a mechanical screening process offered to individual investors by a third party can achieve statistically significant excess risk-adjusted returns over a long investment horizon. The relevant background literature includes both studies testing whether information is efficiently priced in general and studies testing whether there is excess return potential from following professional recommendations in particular. Even "well informed" professionals do not earn excess risk-adjusted returns net of transaction costs if security prices are efficiently valued, according to the efficient market hypothesis (EMH). AAII stock screens would be of no help to individual investors if the stock market is efficient.

The AAII screens combine types of weak-form and semi-strong form information to identify stocks. Weak-form efficiency maintains that stock prices fully reflect all historical information. Early tests of the weak-form hypothesis used correlations in short run holding period returns defined in days or weeks. Fama (1970) and Fama and MacBeth (1973) found that stock prices are not highly correlated, supporting weak form efficiency. Conrad and Kaul (1988) and Lo and MacKinlay (1988) both analyzed weekly returns of the New York Stock Exchange (NYSE) stocks and found significant positive serial correlations that were likely to be too small to allow trading opportunities. Campbell, Grossman, and Wang (1993) found momentum in short horizon data for individual transactions of stocks but the trading turnover was likely to be too high to earn excess returns. Jegadeesh (1990) constructed portfolios from one-step-ahead forecasts using a serial correlation model and found a difference in abnormal returns of 2.49% between the top and bottom portfolios. Campbell, Lo, and MacKinlay (1997) found momentum in short run holding periods but only about 12% of the daily price movement could be linked to the prior day return. Overall, momentum in stock returns tends to be found in short run holding periods but the potential improvement in returns from trading may be too small to exploit.

Jegadeesh and Titman (1993) discovered momentum in stock returns for holding periods longer than days or weeks. They demonstrated that simple strategies based on stocks ranked by cumulative returns over the past 3 to 12 months predicted relative performance over the next 3 to 12 months. They also showed that their results could not be explained by risk factors. Jegadeesh and Titman broke ranks with prior researchers at the time by suggesting that weak-form imperfections were large enough to derive excess returns. In a follow up study, Jagadeesh and Titman (2001) used out-of-sample data to show that their findings continued to hold in the decade after their original study.

For long holding period returns, DeBondt and Thaler (1985, 1987) demonstrated mean reversion where winners became losers, suggesting inefficiencies from overreaction. Shiller (1981) supported the overreaction hypothesis by finding excess volatility beyond what could be explained by material stock information. Both Metrick (1999) and Hirchleifer (2001) recognized that tension between rational (well informed) and irrational (uninformed) money movements result in long periods before full information "efficient" prices are in equilibrium, potentially allowing excess returns from trading counter to the market.

Alternative tests of weak-form efficiency used mechanical filter rules based on past data to construct portfolios. Pinches (1970) found that portfolios built on past data patterns do not outperform buy-and-hold portfolios. On the other hand, Brush (1986) found abnormal returns with rules from combinations of past data and Pruitt and White (1988) found excess returns for rules based on past data adjusted for January effects. Bessembinder and Chan (1998) used trading rules based on past price movements and found that active trading did not beat passive investing when cost of active trading were considered. Overall, the investment potential from screens based on historical data are not clearly proven or disproven. Frequency of trading and trading costs play a large role in the performance of these portfolios.

Tests of the semi-strong version of the EMH are based on performance of portfolios constructed from public information about stocks. In an efficient market, new information should be priced rapidly and there should be no excess return. Ball and Brown (1968) and Brennan (1995) demonstrated that the market prices new accounting information efficiently if the information has a real impact on the stock price. Other findings of efficient pricing in event studies occur in Fama, Fisher, Jensen, and Roll (1969) for stock splits, Jensen and Ruback (1983) for takeover information, McConnell and Muscarella (1985) for capital expenditure information, Pierce and Roley (1985) for stock market reaction to macroeconomic data announcements, and Klein (1986) for divestiture information. In contrast, Ball and Brown (1968) found that earnings announcement information was not priced efficiently. Both pre and post announcement drifts occurred for earnings surprises. Ball (1978) attributed this drift to problems in measuring abnormal returns but Rendleman, Jones, and Latane (1982) conclude that the price drift is because of behavioral under-reaction to new information.

Exceptions to efficient pricing of public information can be found in a long list of studies. Basu (1977) found excess risk-adjusted returns for portfolios of low price-to-earnings stocks. Peavy and Goodman (1983) confirmed Basu's findings after controlling for size, liquidity, and industry effects. Campbell and Shiller (1988) found that low price-to-earnings ratios can predict future abnormal returns. Dreman and Berry (1995) demonstrated that excess returns from low price-to-earnings stock portfolios were not because of inadequate adjustment for risk. Banz (1981) demonstrated a size effect where small stocks earned excess returns whereas Arbel and Strebel (1983) reached a similar conclusion for firms receiving less research attention. Peters (1991) looked at the joint effect of low price-to-earnings and growth and found excess returns for firms where the PEG (price-to-earnings ratio divided by growth) was low. Rosenberg, Reid, and Lanstein (1985) found that low market to book stocks tend to earn excess rates of return. Fama and French (1996) confirm the joint effects of market risk, size, price-to-earnings, market-to-book, and leverage on portfolio returns. However, they choose to define these effects as risk factors rather than inefficiencies. The Fama and French three factor model emerges from their study. It is impossible to tell whether the added factors are risk premiums or unpriced sources of information.

Studies of investment performance from following recommendations of professional investors have had mixed results. Oppenheimer (1981) back-tested portfolios constructed from suggestions of Benjamin Graham in periodic editions of "Intelligent Investor." The constructed portfolios beat the relevant benchmarks beyond what Graham predicted. In more recent studies, Palman, Sun, and Tang (1994) found abnormal returns in an event study based on stock recommendations from *Business Week* analysts. Anderson and Loviscek (2005) found that portfolios built from the top five picks in the book *The Best Stocks to Own in America* outperformed the market. Desai and Jain (1995) tested the performance of stocks recommended from a roundtable of "superstar" analysts published in *Barrons*. Abnormal returns were found from the date of the roundtable to the publication date but there were no abnormal returns once the recommendations were made public. Metrick (1999) tested recommendations from 153 different investment newsletters and found that neither the group of newsletters nor the 153 individual recommendations generated abnormal returns.

Several studies tested the investment performance from following recommendations of analysts appearing on television. Pari (1987); Griffin, James, and Zmijewski (1995); and Beltz and Jennings (1997) found abnormal returns for the first trading day after "Wall Street Week with Louis Rukherser" aired. However, Pari (1987) and Beltz and Jennings (1997) found negative abnormal returns measured over the longer term whereas Griffin, James, and Zmijewski (1995) found significant positive abnormal returns over the year following the Wall Street Week recommendations. Ferreira and Smith (2003) found significant positive abnormal returns for Wall Street Week recommendations in both short run and long run periods when abnormal return measures were adjusted. Bolsher, Trahan, and Venkateswarren (2012) followed the suggestions on Kramer's "Mad Man" and found positive gains for the first day after the show aired but losses occurred for the following 29 days.

Tests of public recommendations from professionals offer mixed results and it is difficult to sort unpriced information from the behavioral biases and emotions of analysts making recommendations. As an alternative, several studies test the performance from more mechanical professional recommendations. Olson, Nelson, Witt, and Mossman (1998) found significantly positive abnormal returns from trading based on *Investor's Business Daily* proprietary stock rankings. Choi (2000) found positive abnormal returns from investing in stocks with the highest *Value Line* timeliness rankings even after controlling for size, momentum, and earnings surprises. Nevertheless, Choi's findings were not likely to overcome transaction costs of trading. Loviscek and Jordan (2000) created portfolios from the top holdings of five-star mutual funds and found that the performance was too weak to recommend. Kacperczyk, Van Nieuwerburgh, and Veldkamp (2013) applied a measure of skill to 3,477 mutual funds over the period 1980 through 2005. They found that the top quintile of funds outperform by 300 to 600 basis points per year. Overall, there is no clear consensus from these studies and the possibility remains that some sources of information may offer excess returns whereas others do not.

Schadler and Cotton (henceforth noted as S&C) provided the most relevant study for the work we present here. They tested the investment performance of portfolios constructed with the AAII screens from January of 1998 to December 2005. After accounting for transaction costs, statistical significance, and the appropriate "market" index for comparison, they conclude that about 20% of the constructed portfolios and 25% of the low transaction cost portfolios beat the best fit indexes. We extend the S&C study by considering a longer investment period, measuring performance with statistical significance of excess returns from multifactor models, and considering favorable skewing of returns by using both mean and median return measures. Our approach offers a rigorous test of market efficiency in general and the performance of the AAII screened portfolios in particular.

3. AAII data and services

We first follow the basic approach used by S&C as a starting point and then extend the analysis. We use both the traditional single-factor market model and the Fama and French three-factor model to measure and test excess risk-adjusted returns (αs) after transaction costs. This approach offers more extensive tests of investment performance beyond the Sharpe ratio comparisons and statistical tests of difference in returns. Our study spans the period from the initiation of the AAII screens in January 1998 through December of 2011, whereas S&C ended their study in December of 2005. The extended period of analysis includes both investment performance leading up to the Great Recession and several years of the ongoing sluggish recovery period. These added observations help illustrate how the AAII portfolio screens tend to perform over rapidly changing markets.

The investment service provided by AAII allows investors to follow stock screens constructed with what AAII believes specific well known investors use to select stocks. AAII reports monthly returns on a total of 82 portfolios beginning with January 1998. The AAII screens are divided into the following investment styles: passive indexes, growth, value/growth, specialty/sector, and unclassified. The screen characteristics used by AAII to categorize a screen into a style represent potential market inefficiencies that might identify stocks with excess return potential. Of the 82 portfolios, 16 are stock market indices and one is the Treasury bill index. Of the remaining 65 portfolios, seven do not have complete data, leaving 56 screens for our testing purposes. Table 1 provides a listing of the screened portfolios and corresponding investment styles used in this study along with an annotation of how our list of screens is different from the list used by S&C in their study.[3]

The AAII Stock Investor Pro database is the source of data used to run through the AAII screens and create portfolios. The database includes around 8,500 actively traded stocks and ADRs from the U.S. markets. The portfolios are the result of a mechanical adherence to an investment style without emotions entering into the decisions. AAII sends CDs to members each month and current financial data on firms in the database may be downloaded each week from the AAII website. The data do not include dividend distributions. The weekly updates are from Reuters as of the end of the business day on Friday and are available to investors on Monday of the following week. At the end of each month, AAII runs the investment screens and then constructs an equally weighted portfolio of stocks passing the screen. The holding period return is calculated from the change between the price of each stock on the last trading day of the month to the price on the last trading day of the following month.

AAIIs rebalancing approach sells all securities at the end of the month and buys all securities passing the screen for the next month. The turnover approach assures that each portfolio is equally weighted. This 100% turnover of the portfolio each month is used by S&C and in our extension. The equal weighting assumption clearly results in high turnover and transaction costs. An individual investor would incur lower costs with less frequent

Table 1 Names and style classification of the 56 AAII portfolio screens in this study

Value screens[a]	Growth/value screens
Cash Rich Firms	Buffett-Hangstrom
Dividend (High Relative Yield)	Buffettology-EPS Growth
Dogs of the Dow	Buffettology-Sustainable Growth
Dogs of the Dow Low Priced 5	Fisher (Philip
Dreman	Lynch
Dividend Screen–DRPs	Muhlenkamp
Dividend Screen–Non-DRPs	O'Shaughnessy-Growth
Price-to-Free-Cash-Flow	*Oshaughnessy Small Cap Gr.& Value Price Change*[b]
Fundamental Rule of Thumb	Oberweis Octagon
Graham Defensive Investor Non-utility	Value on the Move-PEG with Est Growth
Graham Enterprising Investor IBD Stable 70	Price to Sales
Lakonishok	T. Rowe Price
Neff	Templeton
O'Shaughnessy-Value	Wanger (Revised)
P/E Rrelative	Stock Market Winners
Piotroski	Zweig
Weiss Blue Chip Dividend Yield	
MAGNET Simple Price Change[b]	Speciality/sector
Piotroski High F-score Price Change[b]	ADRs
Schloss Price Change[b]	Dual Cash Flow
Magic Formula Price Change[b]	Estimated Revisions Down
Rule #1 Investing Price Change[b]	Estimated Revisions Up
Oshaughnessy Tiny Titans Price Change[b]	Estimated Revisions Up 5%
	Graham Defensive Investor (Utility)
	Murphy Technology
Growth screens	
O'Neil's CANSLIM	Screens used in the S&C study but not this study[c]
O'Neils's CANSLIM Revised 3rd ed.	Dreman Revised (No longer in AAII data)
Foolish Small Cap 8	All DRPs (Not Classified)
Foolish Small Cap 8 Revised	Estimated Revisions Down Lowest 30 (Not Classified)
IBD Stable 70	Estimated Revisions UP top 30 (Not Classified)
Inve$tWare Quality Growth	Low Price to Book Ratio (No longer in AAII data)
Return on Equity	Dreman with Est. Revisions (Not Classified)
MAGNET Complex Price Change[b]	Estimated Revisions Down (No longer in AAII data)
Oshaughnessy Growth Mkt Leaders Price Change[b]	

[a] Screen names and classifications are determined by AAII.

[b] There are nine portfolio screens in this study that were not available in the C&S study. These portfolio screen names appear in italics. AAII added complete data for these portfolios after the S&C study was conducted.

[c] There are seven portfolio screens in the C&S study that are not used in this study. We deleted a screen if it had complete data over the entire study period or if the screen style could not be classified.

rebalancing or with an alternative weighting scheme. A key point in the analysis is that we use the same approach to transaction costs as S&C for comparison purposes.

4. Theoretical and practical issues for performance tests

To test claims made by AAII about the value of their screening services, S&C use the same portfolio performance measures that AAII provides. The measures include comparisons with the S&P Index returns, comparisons with the best-fit index returns, and Sharpe ratios. These comparisons are made with and without transaction costs. Tests for statistical differences in average portfolio returns and the benchmark indexes are also conducted by S&C. We expand the analysis of performance measures to also include a comparison of median returns of portfolios with their benchmarks to account for skewing, a single factor α with significance tests, and a three factor α with significance tests for the screened portfolios. Following S&C, we also look at the measures with and without transaction costs.

4.1. Index comparisons

AAII provides 16 different equity indexes in its database. Following S&C we identify a best-fit index for each of the AAII screened portfolios. The best-fit index for a given AAII portfolio is defined as the index with the highest correlation of monthly returns with the AAII portfolio. For each AAII portfolio we use the relevant best-fit index as the benchmark for performance measurement.

4.2. Geometric mean monthly return

Long run buy-and-hold investors who remain fully invested over the measurement period may be satisfied by beating a passive market index without risk adjustment. Risk adjustment of returns is not part of the analysis in this case since the investor will ride out the ups and downs of the market with no intention of buying or selling in response to market moves. A typical first step to analyzing performance is to simply measure the extent to which a strategy beats a benchmark over a measurement period. S&C take this approach by measuring the differences in cumulative total rates of return of AAII strategies and the relevant benchmarks. The cumulative total rate of return comparison is equivalent to measuring differences between the geometric mean monthly return (GMMR) of AAII screens and the relevant benchmark.

4.3. Mean monthly return

The arithmetic mean monthly return (AMMR) is an alternative to the GMMR measure. While the geometric mean reflects the compounded return outcome from an investment, the arithmetic mean is the expected value of a random return series. When there is skewing of returns from outliers the median monthly return (MDMR) is a better measure of the "typical" portfolio performance than the AMMR. Tests for statistical significance of the difference between the portfolio mean (or median) and the benchmark offer additional insight about performance, because a portfolio's performance may beat a benchmark because of random chance.

4.4. The Sharpe reward for risk ratio

The Sharpe index is a basic reward-for-risk measure used to evaluate portfolio performance. We use the Sharpe ratio defined as the excess return ($r_p - r_f$) divided by the portfolio standard deviation of returns (σ_p) over the measurement period.

$$\text{Sharpe Ratio} = (r_p - r_f)/(\sigma_p) \tag{1}$$

The Sharpe index in Eq. (1) measures portfolio efficiency in the sense that a higher Sharpe index reflects a better tradeoff between portfolio returns and total portfolio risk. One limitation of the Sharpe ratio is that there are no tests of statistically significant differences between Sharpe ratios.

4.5. Alpha measures of portfolio performance and factor models

In theory, good performance is measured as a statistically significant excess risk-adjusted return commonly called the portfolio's α. To measure the portfolio α there must first be a model that specifies the risk factors and risk premiums leading to an expected return (r_p). The single-factor model introduced by Sharpe (1963) is consistent with the Capital Asset Pricing Model where the portfolio is exposed to two sources of uncertainty known as systematic risk and unsystematic risk. The portfolio's systematic risk measured by β is because of portfolio exposure to movements of the overall market that affect all portfolios to some extent. The equity risk premium is the reward for taking systematic risk and is measured by the difference between the broad market index (r_m) and the risk free rate (r_f). Unsystematic risk (ε) is the second source of uncertainty for a portfolio and represents a type of residual risk that can be eliminated with diversification. The single-factor model is specified below:

$$(r_p - rf)_t = \alpha_1 + \beta(r_m - rf)_t + \varepsilon_t \tag{2}$$

Alpha represents an excess risk-adjusted return and is expected to be zero if the market prices risk efficiently.

Eq. (2) is an empirical model allowing estimation of a portfolio's α (intercept) and β (slope) by regressing (r_p – rf) on (r_m – rf) using the monthly data for the screened AAII portfolio returns, risk free rates, and market index returns. The intercept is often called Jensen's α in this formulation and the t-statistic, calculated as the estimated intercept coefficient divided by the standard error, provide tests for statistical significance of α. Statistically significant positive αs not only measure superior portfolio performance for comparison purposes but they also allow for tests of efficiency in market pricing. We would not expect to find more portfolios with statistically significant positive αs than would be generated by chance. This approach is how most of the "anomalies" to efficient market pricing have been identified.

Fama and French (1996) argue that statistically significant positive αs from the single-factor model of Eq. (2) are likely to be the result of left-out risk factors rather than excess returns. The Fama-French three-factor model augments the single-factor model with size (SMB) and value (HML) factor variables. The α in the three-factor model (α_3) represents the difference between the portfolio's return and the expected portfolio return based on the portfolio's sensitivities to the three factors. Alpha is expected to be zero if markets are pricing securities efficiently. The three-factor model is specified below:

$$(r_p - r_f)_t = \alpha_3 + \beta_1(r_m - r_f)_t + \beta_2\,\mathrm{SMB}_t + \beta_3\,\mathrm{HML}_t + \varepsilon_t \tag{3}$$

Eq. (3) is simply Eq. (2) with the two added factors SMB and HML and their βs. SMB is measured as the premium in period t for small cap minus large cap stocks and HML is the premium for high book/price stocks minus low book/price stocks at time t. If both β_2 and β_3 are not statistically different from zero we have the single-factor model of Eq. (2).

Overall, the three-factor model provides a better fit with stock returns than the single-factor model (higher adjusted R^2). We cannot say whether the additional returns due to statistically significant and positive values for β_2 and β_3 are the result of added risk premiums or are returns to inefficiencies in pricing size and value. We can say that the three factor model represents a more stringent test of portfolio performance. If the α in the three-factor model is statistically significant and positive the portfolio earned excess returns beyond what would be expected from exploiting size and valuation characteristics of stocks. The importance of including the three-factor model α in an analysis of investment performance is supported by Bodie, Kane, and Marcus (2013, *p* 0.605) as follows:

> The Fama-French (FF) three-factor model…has almost completely replaced the single-index model in academic performance evaluation, and has been gaining 'market share' in the investment services industry.

5. Transaction costs for the AAII portfolios

The AAII screens are performed each month and stocks that pass the screen are used by AAII to create equally weighted portfolios. Transaction costs are computed using the same online brokerage fee of \$7 per trade used by S&C. We do not have data on the number of trades each month so we follow S& C by using the average number of stocks in the portfolio as a proxy. With these assumptions, the AAII rebalancing approach results in a monthly roundtrip transaction cost calculated as follows:

$$(\$7)\ (2)\ (\text{average number of stocks in the portfolio}) = \$\ \text{transaction cost.} \tag{4}$$

Given the flat cost per trade, the transaction costs is higher for those screens that result in a larger number of stocks in a portfolio. The amount of the initial investment is also a relevant factor since the fixed dollar transaction costs is a higher percentage of a smaller total investment amount. This is an important consideration because the AAII screens are designed for individual investors who may not have large amounts to invest.

For the January 1998 through December 2011 investment period, Table 2 shows the

Table 2 Relationship between initial investments and the mean monthly average returns after transaction costs for AAII portfolios over the investment horizon from January 1998 through December 2011[a]

Initial investment	\$10k	\$20k	\$30k	\$40k	\$50k	\$60k	\$70k	\$80k	\$90k	\$100k
Number of funds with positive average returns	8	21	31	42	49	52	53	54	55	55
% of funds with positive average returns	14%	38%	55%	75%	88%	93%	95%	96%	98%	98%

[a] The Analysis used all 56 AAII funds. Transaction cost calculation assumes 100% turnover each month and \$7 per trade. The dollar cost each month is \$7 (2) (no. stocks in the portfolio).

number and percentage of portfolios with positive average monthly rates of return after transaction costs. For example, less than 38% of the 56 AAII portfolios in the study generated positive after-transaction cost returns if an investor put less than $20,000 into the strategy. As the amount invested goes up to $100,000 or more virtually all the AAII screens generate positive after-transaction cost monthly returns. In the performance evaluation of the AAII screens that follows we consider $50,000, $100,000, and zero initial investments with corresponding transaction cost scenarios.

6. Overall analysis of AAII portfolio screens

We analyze performance of the 56 AAII portfolios over the period from January 1998 through December 2011 by style, by transaction cost, and by different measures of performance. The total output from this analysis is too extensive to put in print but is available upon request from the authors. Table 3 provides a summary of the key findings. For each performance measure we compare findings with zero transaction costs to findings with after-cost returns for initial investments of $50,000 and $100,000. The columns in Table 3 represent six different performance measures for the AAII portfolios. The first four columns are basic performance measures much like those used by AAII and S&C plus a median monthly return (MDMR). The last two columns represent findings for single-factor (1FMM) αs and three-factor (3FMM) αs, respectively.

For GMMR relative to the best-fit index (BFI) without transaction costs we find that 79% of the portfolios beat the BFI returns with an average spread over the benchmark of 38 basis points per month. S&C had almost identical findings with 79.6% of the AAII screened portfolios beating the BFI on a raw cumulative return basis without transaction costs. Value (V) screens offered the best performance with 83% of the value portfolios beating the BFI with an average GMMR difference of 46 basis points. GMMR performance is much worse when transaction costs are introduced. When the initial investment is $100,000 only 61% of the portfolios beat the benchmark with an average GMMR margin of only 17 basis points. For an investor with $50,000 to invest only 38% of the portfolios beat the GMMR benchmark and the overall average spread is a negative eight basis points. The value style offers the best performance when investors have $100,000 invested but the growth style is the best style for the smaller $50,000 investment. A plausible explanation for this finding is linked to the difference in the number of stocks in Growth and Value portfolios. Of our 56 portfolios, growth strategy portfolios have a lower number of stocks to trade on average (16.6) than any other portfolio style. However, as the amount invested increases transaction costs as a percentage of the investment decrease to eliminate the advantage of trading small numbers of stocks in growth strategies.

The AMMR without transaction costs for 86% of the portfolios beat the BFI by an average of 51 basis points per month. However, only 39% of the portfolios are statistically significantly higher than the best fit benchmark. When transaction costs are introduced statistically significant higher AMMRs fall to 21% for $50,000 and 27% for $100,000 investments. For the statistically significant higher AMMRs the best strategy is V.

When we use median returns rather than mean returns for the AAII portfolios, perfor-

Table 3 Summary performance of AAII portfolios from January 1998 through December 2011 by performance measure, style, and transaction cost linked to size[a]

	(1) GMMR > BFI			(2) AMMR > BFI			(3) MDMR > BFI			(4) Sharpe ratios relative to BFI Sharpe ratio			(5) 1 FMM α			(6) 3 FMM α		
Initial Investment (000s)	NA	50	100	NA	50	100	NA	50	100	NA	50	100	NA	50	100	NA	50	100
Transaction costs included	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Panel A. BFI comparisons																		
% all funds > BFI	79	38	61	86	45	63	41	16	32	82	38	52						
BP difference (all funds)	38	−8	17	51	6	30	0	−49	−21									
Best style*	V	GR	V	V	GR	V	V	GRV	GRV	V	V	V						
% of funds for best style	83	44	71	92	56	75	50	24	41	92	46	67						
Best style BP difference	46	7	29	63	2	43	3	−52	−15									
Panel B. Significant Difference																		
% funds stat. sign.*	NA	NA	NA	39	21	27	29	13	16	NA	NA	NA						
Best style				V	V	V	GRV	GRV	GRV	NA	NA	NA						
Panel C. Sharpe ratios																		
Sharpe difference										.049	−.021	.017						
Best style Sharpe Difference										.06	−.003	.029						
Panel D. Factor models																		
% of funds sig. + α													80	32	59	61	29	39
Ave. significant αBP													119	121	147	163	115	126
Best Style													V	GR	GRV	GR	GR	GR
% sig. by best style													88	44	65	78	44	56

[a] Variables are defined as follows: GMMR is geometric mean monthly return; BFI is the best fit index for the given portfolio; AMMR is the arithmetic mean monthly return; BFI Sharpe ratio is the Sharpe ratio computed with the BFI return as the portfolio return; 1FMM α is the one factor market model α; 3FMM α is the three factor market model α. NA is not applicable and BP represents basis points. The asterisk (*) denotes a 5% level of significance using a one tail t-distribution. We would expect 5% of the funds to be significant because of pure chance. The factor models for all portfolios use the S&P 500 index as the market benchmark.

mance is much worse because positive skewing leads to a median lower than the mean. For no transaction costs, only 41% of AAII portfolios had MDMR higher than the BFI and only 29% had a statistically significant higher MDMR than the BFI. Only 16% of the portfolios had a MDMR higher than the BFI for a $50,000 initial investment.

The growth/value style had the highest percentage of portfolios with MDMR statistically significantly higher than the BFI. Once transaction costs are introduced the basis point spread between the MDMR for AAII portfolios and the BFI are negative overall by 49 basis points for a $50,000 investment and 21 basis points for a $100,000 investment. Even for the best style (Growth/Value) the basis point difference between the MDMR and BFI is negative. With positive skewing of returns, an investor must stick with the strategy or risk missing out on a positive "outlier" return. Portfolio strategies that look good on a mean return comparison but not a median return comparison require investors to stay with the strategy over a long period of time. Without transaction costs, 82% of the portfolios in Table 3 have a Sharpe Index higher than the BFI Sharpe Index.[4] Value portfolios offer the best overall performance with 92% of the funds beating the BFI Sharpe ratio. However, differences in Sharpe ratios tend to be small and there are no tests for statically significant differences. For smaller investors with an initial investment of $50,000, only 38% of the AAII portfolios beat their benchmark Sharpe ratios. Value style portfolios tend to have more favorable Sharpe ratio comparisons, but the spread is again negative for the $50,000 investment. For investors with $100,000 to invest the Sharpe ratio comparisons are more favorable but barely half (52%) of the AAII portfolios beat their BFI Sharpe ratios. The Value strategy is the best style across all levels of investing based on Sharpe ratio comparisons.

The results from regression analysis measuring the 1FMM α_1 and the Fama and French 3FMM α_3 appear under headings (5) and (6) in Table 3.[5] The 1FMM αs are statistically significant and positive for 80% of the AAII portfolios without transaction costs. With transaction costs, statistically significant 1FMM αs occur for 32% of the portfolios for investors of $50,000 and 59% for investors of $100,000. Since the one-tail 5% level of significance is used in the tests, we would expect 5% of the portfolios to be significant by pure chance. Even with transaction costs, the AAII screens offer more significant excess return portfolios than chance would predict. The best style varies with the size of the investment. Value dominates the zero transaction cost comparisons whereas growth dominates for the $50,000 initial investment and a growth/value blend performs best for the $100,000 initial investment. The magnitude of the statistically significant αs is very impressive with over 100 basis point excess return for every initial investment in Table 3.

When transaction costs are zero, the 3FMM α is statistically significant at the 5% level for 61% of the AAII portfolios with zero transaction costs. With transaction costs, the proportion of AAII portfolios with statistically significant 3FMM αs shrinks to 29% for a $50,000 initial investment and to 39% for an initial investment of $100,000. Statistically significant 3FMM αs average from 163 basis points for zero transaction costs to 115 basis points for the $50,000 investment. The growth style has the best performing portfolios for the 3FMM. The findings for the 3FMM are interesting because superior performance is found for a large number of the AAII portfolios even after taking out market exposure, size, and valuation factors that should reduce excess returns to zero according to Fama and French. The AAII

Table 4 Screened portfolio rankings–with transactions costs and $50k initial investment[a,b]

Portfolio name	Group	GMMR > BFI	AMMR > BFI	MDMR > BFI	Sharpe - BFI Sharpe	1FMM α	3FMM α	Average stocks held
Piotroski 9 price chg	V	1.68% (1)	2.01%* (2)	−1.02% (40)	0.130 (1)	2.71%** (1)	2.39%** (1)	4 (53)
MAGNET Simple price chg	V	1.29% (2)	2.06%* (1)	−1.03% (41)	0.097 (7)	2.45%** (2)	1.97%* (2)	3 (55)
O'Neil's CAN SLIM price chg	G	1.22% (3)	1.36%* (3)	−0.23% (14)	0.129 (2)	1.94%** (3)	1.78%** (3)	7 (50)
O'Shaughnessy: Tiny Titans price chg	V	1.14% (5)	1.14%** (6)	0.87%* (3)	0.094 (8)	1.80%** (4)	1.33%** (6)	25 (25)
Est Rev: Up 5% price chg	S	1.08% (6)	1.23%** (4)	1.00%** (1)	0.121 (3)	1.77%** (5)	1.60%** (4)	45 (9)
Piotroski: High F-Score price chg	V	1.20% (4)	0.98%* (8)	−0.25% (16)	0.070 (11)	1.66%** (6)	1.24%* (8)	24 (29)
MAGNET Complex price chg	G	0.28% (16)	0.86% (10)	−1.28% (44)	−0.003 (22)	1.66%* (7)	1.55%* (5)	2 (56)
Zweig price chg	G/V	0.76% (8)	1.17%** (5)	0.97%** (2)	0.103 (5)	1.57%** (8)	1.24%** (9)	12 (43)
Graham-Enterprising Investor price chg	V	0.93% (7)	1.11%* (7)	−1.02% (39)	0.106 (4)	1.53%** (9)	1.24%* (7)	4 (54)
Stock Market Winners price chg	G/V	0.74% (9)	0.76% (12)	−0.15% (12)	0.101 (6)	1.46%** (10)	1.19%** (10)	12 (44)
Foolish Small Cap 8 Revised price chg	G	0.47% (11)	0.79% (11)	−0.32% (21)	0.041 (15)	1.34%* (11)	1.03%* (11)	6 (51)
Neff price chg	V	0.54% (10)	0.89%** (9)	0.25%* (7)	0.087 (10)	1.28%** (12)	0.86%** (13)	23 (31)
O'Neil's CAN SLIM Revised 3rd Edition price chg	G	0.26% (17)	0.43% (17)	−0.53% (31)	0.010 (19)	1.23%* (13)	0.99%* (12)	8 (49)
O'Shaughnessy: Small Cap Growth & Value price chg	G/V	0.35% (13)	0.61%* (14)	0.67%* (4)	0.069 (13)	1.06%** (14)	0.66%* (15)	25 (27)
Price-to-Free-Cash-Flow price chg	V	0.34% (14)	0.64% (13)	−0.29% (18)	0.045 (14)	1.03%* (15)	0.51% (18)	30 (19)
Graham-Defensive Investor (Non-Utility) price chg	V	0.30% (15)	0.52%* (15)	0.35%* (6)	0.069 (12)	0.97%** (16)	0.59%* (16)	20 (35)
P/E Relative price chg	V	0.08% (18)	0.14% (23)	−0.15% (13)	0.024 (16)	0.54%* (23)	0.37% (22)	33 (13)
Buffett: Hagstrom price chg	G/V	0.46% (12)	0.48%** (16)	0.04%** (8)	0.091 (9)	0.49%** (25)	0.41%* (21)	30 (21)

[a] Rankings are for 18 screened portfolios with statistically significant 1FMM α that AAII follows over the time period 1998–2011. Each variable is given along with ranking within each variable in parentheses. Rankings are based on 56 screened portfolios. Table 4 data are sorted based on ranking of 1FMM α. Statistical significance of one-tailed test is denoted as * for 5% and ** for 1%. All statistics in table include transaction costs based on a $50,000 initial investment.

[b] Variables are defined as: GMMR is geometric mean monthly return, BFI is best fit in the table index for given fund, AMMR is mean monthly return, MDMR is median monthly return, Sharpe is Sharpe ratio, 1FMM α is the 1-factor market model monthly α, 3FMM α is the 3-factor market model monthly α, and average stocks held is average number of stocks held over entire sample time period. For Group designation G is for Growth, V for Value, S for Special.

portfolios demonstrate excess risk-adjusted returns beyond what chance would predict, supporting the argument that there are AAII screens that exploit pricing inefficiencies.

7. Top AAII portfolio strategies

The analysis up to this point focused on the overall performance of AAII portfolio strategies. We now analyze the performance of specific strategies with higher performance rankings. We first ranked all portfolios from best (1) to worst (56) for each of the six different performance measures and for the average number of stocks held in the portfolio over our period of study. Table 4 presents the ranking comparisons when returns are adjusted for transaction costs given a \$50,000 initial investment. Portfolios are presented in the rank order of statistically significant 1FMM αs using a 5% significance cutoff. We chose the 1FMM α as the base for ranking comparisons since it represents the starting point for our extension of performance measures beyond S&C's study. The portfolio's rank order for each performance measure is in parentheses, allowing a comparison of rankings across different performance measures for each portfolio strategy.

The 18 screened portfolios in Table 4 represent the AAII strategies that had statistically significant 1FMM αs over the 1998 through 2011 period. The 18 portfolios represent about 32% of the portfolios in this study, which is well above the 5% that we would expect to be significant by chance given the 5% level of significance. A few of the top 18 portfolios ranked by the 1FMM α were not statistically significant and were replaced by the next highest ranked portfolio that was statistically significant. Only the last two portfolios had statistically significant αs without being in the top 18 based on the size of α. The 1FMM αs in Table 4 are not only statistically significant but are materially attractive ranging from 271 basis points to 54 basis points.

An important first observation from Table 4 is that the (3FMM) αs and (1FMM) αs have very similar rankings. There is also consistency in statistical significance with all but two of the 3FMM portfolio αs achieving at least 5% statistical significance. Even after accounting for the added risk factors advocated by efficient market theorists, over 28% (16/56) of the AAII portfolios achieved statistically significant αs given transaction costs with a \$50,000 initial investment. Statistically significant αs from the 3FMM are also relatively large, ranging from 239 basis points to 41 basis points. These findings run counter to the efficient market hypothesis. The results in Table 4 are based on an investment of only \$50,000. As the investment is increased transaction costs become a smaller drag on returns and even higher proportions of the AAII portfolios should achieve statistically significant αs. For example, while we do not show the results here to conserve space, we replicated Table 4 with an initial investment of \$100,000 and found similar ranking patterns with statistically significant 1FMM αs for almost 60% of the AAII portfolios and a little over 39% of the AAII portfolios with statistically significant 3FMM αs. Full output with the higher initial investment is available from the authors upon request.

The Sharpe ratio ranking for portfolios in Table 4 are highly correlated with the rankings of 1FMM αs and 3FMM αs. In general, a good portfolio is a good portfolio whether the Sharpe ratio, 1FMM α, or 3FMM α is used for performance measurement. Nevertheless, there are two obvious discrepancies. The *MAGNET Complex Price Change* portfolio is a growth style portfolio and is highly concentrated with only two stocks on average. This portfolio has a Sharpe ratio rank of 22 but a much better rank of 7 for the 1FMM α and 5 for the 3FMM α. This portfolio has some attractive performance features but does not do well on a reward for total risk basis. On the other hand, *Buffett: Hagstrom Price Change* is a value/growth portfolio with an average holding of 30 stocks. The Sharpe ratio rank of nine out of 56 looks good but a much lower rank of 25 for the 1FMM α and 21 for the 3FMM does not look attractive. Even though many performance measures are highly correlated it is a good idea to consider all the risk adjusted return measures in Table 4.

Rankings of portfolios in Table 4 based on simple GMMR and AMMR measures relative to the best fit benchmark indexes are also highly correlated with all but the MDMR measure. Skewing of returns explains why a portfolio may rank high in all the other measures but low in the comparison of MDMR with the best fit index. Positive skewing because of large positive outliers makes the average higher than the median, resulting in better performance measured by the difference in the average and the BFI than the performance measured by the difference in the median and BFI. Investors may prefer positive skewing as a measure of upside potential but it takes a long term investment horizon to capture the outlier returns that play a large role in performance. The first two portfolios in Table 4 present an example of how an individual investor should use all the measures to include skewing. The *Petroski 9 Price Change* and the *MAGNET Simple Price Change* portfolios are both highly concentrated (4 and 3 stocks on average, respectively) value portfolios that top the rankings in performance measures. Both portfolios also demonstrate positive skewing of returns since average returns are much higher than the median returns relative to the benchmarks. This combination is good if the investor is looking for a long run commitment to a strategy where positive skewing is rewarded. However, the investor must also be comfortable with a highly concentrated portfolio.

8. Conclusions

As technology advances individual investor gain access to many of the same tools and strategies available to professional investors. AAII has been at the forefront of these advancements. Our study extended work by S&C to test the investment performance of AAII screens. We extended the period of analysis used by S&C (1998–2005) to include the period around the Great Recession of 2009 to see if the AAII strategies weathered the storm. Our results with performance measures used by S&C were similar to theirs. We also expanded the analysis to include the single-factor market model and the three-factor F&F model measures of excess returns (αs). Even when accounting for the view that size and market/book characteristics are really risk premiums rather than unpriced information, we find evidence of statistically significant excess returns well beyond what chance would explain. These findings do not support the efficient market hypothesis and suggest that individuals can achieve excess risk adjusted returns from following mechanical trading recommendations.

We found evidence that a good AAII portfolio based on one measure tends to be a good portfolio for other performance measures. The exception is when median returns are used and the portfolio has skewing. We found positive skewing in some AAII portfolios that long run investors might find attractive when combined with high ranking performance in other measures. For the top performing portfolios, significant αs were not because of reliance on small cap stocks or undervalued stocks based on low market to book ratios. The finding of statistically significant three-factor model αs from mechanical trading screens with relatively small amounts invested over this tumultuous financial market period is impressive. Larger investors would find even higher percentages of the 56 screens to have attractive performance since trading costs would be less of a drag on returns.

We could not control several features of this study that might make the performance of AAII screened portfolios more attractive. For example, the AAII data do not include dividends in either the portfolio return calculation or index return. Furthermore, transaction costs could be lowered if rebalancing periods could be extended from monthly to quarterly, semiannually, or annually. Rebalancing methods other than equal weighting might also affect performance for many of the AAII strategies depending on whether the strategy uses momentum or longer run value screens. In general, given the wide variety of different strategies available in the AAII service, it is likely that most strategies will do better with different combinations of holding periods and rebalancing methods. There would seem to be potential for a better service allowing individual investors to match strategies with the most appropriate holding periods and rebalancing methods. Additional work is needed on implementation of mechanical screens such as those provided by the AAII service to help individual investors gain more equal footing with professionals.

Notes

1 Fama (1970) is the generally accepted father of the efficient market hypothesis (EMH) and passive investment philosophy.

2 See www.aaii.com for more information about AAII products and services.

3 We analyzed differences between the 54 strategies used by S&C and the 56 strategies in our study. We were able to add nine new screens because AAII added complete data for these portfolios after the S&C study was conducted. We lost seven screens used in the C&S study either because there was no longer complete data over the extended study period or because the screen style could not be classified. To test for the implications of the different set of screens we first ran our analysis over the S&C period using the S&C strategies and then using our strategies. The differences were not statistically significant. We do not provide this output here to conserve space but the data are available upon request.

4 Differences in performance results in Table 3 and findings in the S&C study are small in general, but one exception occurs for the Sharpe ratio without transaction costs. We find 82% of our portfolios with no transaction costs beat the BFI Sharpe ratio while S&C find only 72% of their portfolios beat the BFI Sharpe ratio. When transaction costs are included, our findings for the Sharpe ratio are again very similar to the S&C results. Differences in our sample portfolios appear to be responsible for this outcome.

Table 1 illustrates the specific differences in our sample and the S&C sample but more specific analysis of differences in samples for the two studies is available upon request.

5 Data for the values of SMB and HML in the three factor model are available in the following website (hgttp://mba.tuck.dartmough.edu/pages/faculty/ken.french/data_library.html).

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