The Importance of Investment Strategy

March 2010

C. Thomas Howard, PhD*

Professor, Reiman School of Finance, University of Denver
CEO & Director of Research, AthenaInvest, Inc.

Do not quote without permission.

The Importance of Investment Strategy

- Abstract -

Superior stock picking is common among active equity fund managers. The reason stock picking skill is not detected by many performance studies is over-diversification, which overwhelms the superior performance of top holdings. Managers who do not over-diversify outperform by an astonishing 6% to 12% annually. The style grid is a significant contributor to this over-diversification problem. In addition, the grid does not help investors identify successful active managers, since stock characteristics, such as market-cap and PE, are unrelated to superior performance. Using self-declared investment strategy for organizing the active equity universe frees managers to pursue a narrowly defined strategy and helps in identifying successful managers within each strategy. I provide statistically significant evidence that funds are more alike within strategies than across, that strategy clustering funds is superior to either random or style grid clustering (which itself is inferior to random clustering), and that each of the 10 strategies generates returns in a unique way. Furthermore, stocks can be strategy categorized based on the collective judgment of the strategy managers who hold them. The resulting strategy stock pools move about the equity universe over time, independent of stock characteristics. Those managers who hold the largest number of own strategy stocks outperform those who hold the least by a statistically and economically significant 3.21% annually.

The Importance of Investment Strategy

I. Introduction

Superior stock picking skill is common among active equity mutual fund managers, a conclusion drawn from 20 years of academic research. This body of research uncovers strong evidence of stock picking skill by focusing on performance persistence and the specific investment decisions made by active managers. On the other hand, there is a better known stream of research, which focuses on life-of-fund performance, that claims the typical equity manager underperforms and thus lacks stock picking skill. These conflicting results are best understood in light of portfolio over-diversification. The typical fund holds 100 stocks, of which 30 or so are high-conviction stocks, while the remaining 70 or so are low-conviction stocks. The underperformance of the larger number of low-conviction stocks offsets the superior performance of high conviction stocks. This is why studies focusing on manager decisions reveal superior stock picking skill and performance, while those that focus on life-of-fund performance do not.

So why does the typical fund so dramatically over-diversify? Performance robbing over-diversification is driven by powerful industry incentives, such as compensating based on AUM, responding to legal/professional pressures to look like an index, staying in a style box in order to participate in the style grid based fund distribution system, and using stock characteristic based performance attribution. Thus the typical manager underperforms, not because of lack of investment skill, but because the industry strongly incents them to over-diversify.

Current industry practice is to categorize funds based on the average market-cap and PE (or PS or PB) of the stocks held. This characteristic based system, referred to as the style grid or style boxes, has become the language of the fund industry and infuses every corner of the industry, including forming peer groups, building multi-fund portfolios, evaluating performance, and distributing funds. Unfortunately the style grid helps little in finding successful managers and contributes to the problem of over-diversification. Funds that stay style consistent underperform, while those who style drift are top performers. Furthermore, market-cap and PE are non-actionable stock return factors and thus are of little interest to active managers. Organizing the fund universe around these two characteristics says little about how investment decisions are being made, makes it difficult to find successful managers and, most problematic, impedes managers trying to consistently pursue an investment strategy.

Instead, the active equity universe should be viewed and organized around the investment strategy being pursued by the manager. Investment strategy is the way a manager goes about analyzing, buying, and selling stocks. A manager's self-declared strategy provides information on how investment decisions are being made and provides a basis for organizing the fund universe that does not get in the way of pursuing a strategy. Successful managers are those who consistently pursue a narrowly defined strategy and as a result generate superior returns. Strategy provides a rigorous basis for forming fund peer groups, building multi-fund portfolios, evaluating performance, and organizing the fund universe. All of this is possible without getting in the way of what a manager is supposed to be doing: skillfully picking stocks and generating superior returns.

Over time, managers develop strategy-specific stock picking skills. These skills are most effectively applied to own strategy stocks. Own strategy stocks are the stocks that strategy peer managers collectively find most attractive, as evidenced by their holdings. Over time, the composition of each strategy stock pool changes as managers, responding to ever evolving economic and market conditions, alter their holdings. On average, a stock remains in a specific strategy pool for 15 months before moving on to another pool. To be successful, a manager must be ever in pursuit of own strategy stocks. On the other hand, there are many strategy stocks so the expectation that managers hold own strategy stocks does not mean managers pursuing the same strategy will end up holding the same stocks. The bottom line is that successful managers move about the equity universe over time as they track the constantly changing own strategy stock pool. Failure to do so means underperforming.

Support for the preceding statements is presented in the remainder of this paper. In Section II, the case for active equity managers being skilled stock pickers is made. In Section III, the inherent problems with using the style grid for organizing the active equity universe and for identifying successful active manager are examined. In Section IV, the value of self-declared strategy is explored. In Section V, strategy return drivers are identified and their economic and statistical significance tested. In Section VI, the novel idea of strategy categorizing stocks, based on the strategy managers who most hold them, is presented. In Section VII, a measure of strategy consistency is presented and shown to predict subsequent performance. Section VIII provides concluding remarks.

II. Stock Picking Skill

Conventional wisdom has the typical active equity mutual fund manager lacking stock picking skill and thus underperforming. There is a well known body of research that purports to show this.[1] Somewhat surprisingly, there is a substantial body of manager-decision research, stretching back 20 years, that documents just the opposite: the existence of superior equity fund performance. Included in this research stream are studies by Hendricks et. al. (1993), Grinblatt and Titman (1993), Goetzmann and Ibbotson (1994), Brown and Goetzmann (1995), Elton et. al. (1996), Daniel et. al. (1997), Zheng (1999), Chen et. al. (2000), Wermers (2000), Collins and Fabozzi (2000), Baks et. al. (2001), Pastor and Stambaugh (2002B), Wermers (2003 A and B), Bollen and Busse (2004), Avaramov and Wermers (2005), Cohen et. al. (2005), Kosowski (2006), Frazzini (2006), Mamaysky (2006), Baks (2006), Busse and Irvine (2006), Brands et. al. (2006), Kacperczyk and Seru (2007), Wermers (2007), Kacperczyk et. al. (2008), and Han et. al. (2008). Given the size and breadth of this research stream, it is somewhat surprising that it plays such a minor role in shaping the conventional wisdom regarding active equity managers.

Recent studies within this manager-decision research stream report the following:

- Baker, Litov, Wackter and Wurgler (2004): "We uncover new evidence that fund managers have at least some stock picking skill."

---

[1] For example, see Sharpe (1966), Jensen (1968), Carhart (1997), Barras et. al. (2008), and Fama and French (2008).

- Kosowski, Timermann, Wermers, and White (2006): "…a sizable minority of managers pick stocks well enough to more than cover their costs. Moreover, the superior alphas of these managers persist".

- Alexander, Cici, and Gibson (2007): "Our analysis reveals that managers making purely valuation-motivated purchases substantially beat the market but are unable to do so when compelled to invest excess cash from investor inflows. A similar, but weaker, pattern is found for stocks that are sold."

- Keswani and Stolin (2008): "… there is a robust smart money effect in the United Kingdom. The effect is caused by buying (but not selling) decisions of both individuals and institutions. Using monthly data available post-1991 we show that money is comparably smart in the United States".

- Cremers and Petajisto (2009): "…the most active stock pickers have enough skill to outperform their benchmarks even after fees and transaction costs." (where "active" is defined as willingness to look different from an index).

- Shumway et. al. (2009): "We measure the differences in beliefs between funds with high BAI and all other funds, the belief difference index (BDI). Sorting stocks based on BDI, we find that the annualized return difference between the top and bottom decile is about two to six percent."

- Pomorski (2009): "…best idea mutual fund trades… , likely generated by centralized research of fund management companies, account for about 30% of fund volume and outperform benchmarks and other trades by as much as 47 basis points per month."

Most startling are the results reported by Cohen, Polk and Silli (2009), who find, "… the U.S. stock market does not appear to be efficiently priced, since even the typical active mutual fund manager is able to identify stocks that outperform by economically and statistically large amounts." Their results, presented in Figure 1, are based on the performance of the typical manager's ranked best ideas and reveals that not only is the typical manager a superior stock picker, but so is nearly <u>every</u> equity manager. This is confirmed by the lower 2 standard deviation bound reported in Figure 1. Thus Cohen, Polk, and Silli (CPS) reveal, for the first time, that the vast majority of equity managers are superior stock pickers and, in addition, are able to rank their best ideas.

Collectively these studies reveal a universe of equity mutual fund managers who are very good at identifying profitable investment opportunities. The manager-decision research stream portrays an industry replete with superior stock picking, with those who are unable to identify top performing stocks the exception. This flies in the face of the conventional wisdom that contends such skill is a rare commodity.

<u>Why then do Managers Underperform?</u>

If stock picking skill is so widespread, then why do so many funds underperform? CSP argue that fund underperformance is the result of over-diversification. The typical manager is able to identify a handful of superior stock ideas. But rather than limiting the portfolio to these good ideas, managers purchase additional stocks that, by all accounts, hurt portfolio performance. While managers speak passionately about their best ideas, they often speak meekly, even apologetically about the additional stocks purchased to "round out" the portfolio. As discussed

below, this over-diversification is the result of powerful industry forces that even the best managers are unable to resist.

Before addressing the issue of over-diversification, it is necessary to determine how many stocks comprise a properly diversified portfolio. This number depends upon the offsetting return and risk effects of adding the next stock to a portfolio. In particular, it makes no sense to add a stock if, by doing so, expected return is reduced while volatility is little changed. As represented in Figure 1, the marginal after-the-fact alpha generated by a manager's best ideas declines as each additional stock is added to a portfolio. The top ranked stock (i.e. the stock with largest relative weight in the portfolio) produces an after-the-fact average monthly alpha of about 50bp. The second ranked best idea generates an alpha of roughly 45 bp monthly alpha. The tenth best idea produces a much lower 22 bp monthly alpha. Each additional stock reduces expected return, thus it is obvious that the number of stocks included in the portfolio should be small, since performance progressively worsens as each new stock is added.

On the other hand, adding a stock reduces portfolio volatility, as represented in Figure 2. As can be seen, adding a second typical stock to a typical portfolio reduces volatility (as measured by annual standard deviation) by roughly 25%. Note that marginal risk reduction falls off rapidly, with the incremental reduction a mere 1% by the 10th stock. This means that if the average stock standard deviation is 45%, the portfolio standard deviation falls to 20.1% from 20.6% as the result of adding the 10th stock. Thus by the 10th stock, virtually no incremental risk reduction is realized (the portfolio standard deviation approaches 15% as the number of stocks grows very large in this example displayed in Figure 2).

Combining the diminishing marginal alpha shown in Figure 1 with the diminishing marginal risk reduction shown in Figure 2, one can argue that, if risk and return optimization is the goal, a properly diversified portfolio is comprised of as few as 10 stocks. This means the typical manager should be holding a highly concentrated, best ideas portfolio, which in turn has the opportunity to generate the highest long term compound return for the investor (the annual compound return can be approximated by subtracting one half of the portfolio variance from the average annual return). Another clear message of Figure 1 is that portfolio returns decline with every stock added, so the fewer stocks added the better.

The typical active equity mutual fund holds 100 stocks, which means dramatic over-diversification is common. This creates serious fund performance problems. As a manager moves down best idea rank, stock alphas eventually turn negative (probably somewhere between ranked stock 30 and 40), so as a result, lower ranked stocks morph into "bad" idea stocks. CPS find that the monthly alpha declines to negative 25bp as stock rank approaches "last" (not shown in Figure 1). Indeed, in the typical fund portfolio bad ideas outnumber good ideas by 2 to 1. So in the mutual fund market, over-diversification is the rule while proper diversification is the exception.

Industry Driven Over-diversification

This raises the perplexing question of why managers purchase so many stocks. Why not hold a small number of stocks, maybe as few as 10 as suggested above, thus concentrating the

portfolio in best ideas. CSP and others argue that there are powerful industry forces encouraging funds to do otherwise.

- Funds are compensated based on assets under management (AUM). This provides an irresistible incentive to grow large. As the fund grows in size it becomes increasingly difficult to hold a small number of stocks. Since revenues grow dramatically as size increases, it is easy to see why a fund finds it to their benefit to invest in a large number of stocks, since the gain to increased AUM easily offsets the loss due to under-performance. Based on this relationship, Berk and Green (2004) argue that growing too large and thus over-diversifying represents profit maximizing behavior on the part of a fund attempting to extract the economic rents of superior stock picking skill.

- The current fund distribution system is based on the style grid which also encourages funds to purchase many stocks. In order to fit into the style grid distribution system the fund must be categorized in one of the style boxes, such as small-cap value. Once so categorized, the fund is loath to "style drift" since this is grounds for being excluded from or thrown off highly profitable fund platforms. Style drift is avoided by purchasing the stocks in the style index associated with the fund's style box. Thus in attempting to grow large by fitting into the style grid distribution system, the fund over-diversifies.

- Investors, advisors, and consultants place considerable importance on fund level volatility, which encourages managers to purchase many stocks. Adding stocks reduces a fund's standard deviation (or maximum drawdown or downside risk or other volatility measures), making the fund more attractive with respect to volatility. But adding many stocks in order to reduce volatility leads to over-diversification.

- To avoid criticism, or worse yet legal problems, a fund manager will construct the portfolio to look like an index or other fund portfolios. It is well known that investor regret is much higher when a unique or different investment approach does not work as compared to the regret experienced when a traditional approach does not work. This is reinforced by a legal system which at times outright requires over-diversification or leads to the same result by applying "prudent man" concepts. These rules/regulatory requirements mean that properly diversified portfolios (i.e. small, concentrated portfolios) are more susceptible to regulatory criticism and lawsuits. Managers, often following the advice of legal counsel, over-diversify in order to avoid such potential problems. This is a major issue since, as I discuss below, best ideas are very different from manager to manager and so any pressure to conform to a common portfolio will hurt performance.

Collectively these industry forces lead to dramatic over-diversification by equity fund managers. Without these forces, managers would build small portfolios concentrated in their best ideas and virtually all of them would generate positive alphas. Instead, the vast majority of managers over-diversify to the point of under-performance. So the good news is that the vast majority of equity managers are superior stock pickers, but the bad news is that industry driven over-diversification wipes out superior returns by encouraging investment in more bad ideas than good ideas.

<u>Superior Managers</u>

Industry forces encourage many but not all managers to over-diversify. Such managers can be identified in several ways, including the number of stocks held (the fewer the better based on CPS), AUM (the smaller the better as reported by Amihud and Goyenko (2008)), best fit index R^2 (the lower the better as reported by Amihud and Goyenko (2008)), active share (the higher the better as reported by Cremers and Petajisto (2009)), style drift (the higher the better as reported by Wermers (2002)), and tracking error (the higher the better as reported by Cremers and Petajisto (2009)). Each of these measures is consistent with the notion that equity managers are most successful when they concentrate on their best ideas. Those that limit over-diversification can produce superior returns.

The importance of concentrating on best ideas and avoiding over-diversification is explored by comparing the performance of the average active US equity open-end mutual fund to a sub-sample of funds selected using the methodology of Amihud and Goyenko (2008). They show that funds with the lowest quintile trailing one year market R^2 <u>and</u> the highest quintile trailing one year return significantly outperform over the subsequent year. In other words, funds with strong performance that don't hug indices (low R^2) are more likely to perform well in the future. Amihud and Goyenko further demonstrate that both selection criteria contribute to the subsequent superior performance.

<u>Test Methodology</u>

The sample includes all active US equity open-end mutual funds over the period from February 1980 through February 2009. Index, lifecycle, target date, allocation, balanced, and 529 funds

are excluded. This results in a sample of 4070 funds, with half still in existence in February 2009, for a total of 403,577 fund-month observations. The sample is survivor bias free since it includes all active US equity funds that existed in any month during this sample period. Excess monthly returns are net of the monthly S&P 500 return as well as automatically deducted management, trading, 12B-1 and other fees. Reported results are simple averages across funds. Monthly fund returns were obtained from Thomson Financial.

The first test examines the compound monthly net excess return performance of the average active US equity fund. The results reported in Figure 3 are organized by fund year, that is, the number of years since the inception of the fund. It reveals that the average life-of-fund compound net monthly excess return is -5bp for fund years 1 through 5 and declines to -13bp for fund years 26 through 30. This is consistent with a number of studies that show the average fund underperforming, with performance declining with age. Furthermore, the underperformance of the typical 26-30 year old fund is roughly equal to the average monthly management fee of 11 bp, which implies that, before fees, such funds earn index returns.

Next, the "Active R^2-R" fund selection approach, proposed by Amihud and Goyenko (2008), is applied. At the beginning of each month, from February 1981 through February 2009, funds are sorted by trailing one year S&P 500 R^2 and independently by the trailing one year return. The funds with the lowest quintile R^2 and the highest quintile return are held for the subsequent month, thus avoiding a look-ahead bias. The compound monthly excess return is calculated using continuous, trailing monthly excess returns for all months in which the fund is designated Active R^2- R. Slightly fewer than half of the 4070 funds are so designated at one time or

another during the sample period, with such funds remaining Active R^2-R an average of 11% of the months over which the fund exists. On average, 7% of funds are Active R^2-R in any particular month.

Active R^2-R performance is far superior to that generated by the buy-and-hold approach, as is shown in Figure 4. The average compound monthly excess return increases from 50bp for fund years 1 through 5 to a very impressive 118bp for fund years 26 through 30. Furthermore, in unreported results, the chance of beating the S&P 500 increases from 64% for fund years 1 through 5 to an astounding 84% for fund years 26 through 30. These results reveal superior fund performance which improves with age. This latter result is consistent with the proposition that experienced managers are better stock pickers. In fact, by expanding Active R^2-R to include those funds in the bottom three R^2 quintiles <u>and</u> the top three return quintiles (about half of the funds), the average excess return remains positive. So, over time a changing upper half of US equity managers, which can be identified ahead of time, produce superior returns.

Based on the results reported above, I come to two conclusions:

1. The typical fund starts out life underperforming after fees and gets worse with age. The declining performance is most likely the result of the powerful industry incentives described above. These incentives dictate a typical time path of declining fund performance.

2. On the other hand, if a fund continues to concentrate on best ideas and avoid over-diversifying, as measured by a low R^2, performance starts out strong and gets stronger with age. This means that such fund managers are skilled enough stock pickers to more

than cover their fees, while stock picking skill improves with fund age (and more than likely with manager experience). The average 26-30 year old fund that continues to concentrate on best ideas generates an excess net of fees return exceeding 1% monthly while beating the market an astounding 84% of the time.

The implication for investors is that it is very difficult to buy and hold so-called "active" funds and generate superior returns, since average fund returns diminish over time. Instead, it is necessary to ensure that a fund continues to be truly active and concentrate on best ideas. Diligence in this regard is rewarded with superior returns as evidenced by long time truly active managers outperforming the typical long term fund by a stunning 15% annually.

How does one go about identifying top performing managers? And within what framework should managers be categorized and evaluated? This latter question is critical in the search for superior managers. But before answering these two questions, the shortcomings of the currently popular style grid will be addressed.

III. The Style Grid

The active equity fund industry uses the market-cap, PE (or PS or PB) style grid (or style indices or factor models) for categorizing, forming peer groups, and evaluating performance. This approach assigns each active equity fund to one of nine (sometimes more, sometimes less) style boxes based on the average characteristics of the stocks held by the fund. For example, a fund holding stocks that are on average low market capitalization and low PE is categorized a small-cap value fund. Thus a fund is categorized based on the stocks held rather than by the investment approach being pursued.

Those who use the style grid believe managers pursuing the same investment "style" end up purchasing the same size and PE stocks, thus the name style grid. But why would this be the case? At the very least, it seems important to test this contention before accepting it as an industry standard. After all, the powerful and perverse affects of mislabeling are widely known and so for something as important as labeling equity managers, a careful analysis seems essential. But surprisingly, there is no foundational research supporting the usefulness of the style grid for categorizing funds, forming peer groups, or evaluating performance. On the contrary, the widespread industry acceptance of the style grid is the result of a leaderless stampede.

The underlying problem with a fund's style box is that it reveals little about how investment decisions are made. For example, what approach is being pursued by a so called "small-cap blend" manager? Does the manager analyze every aspect of the company by visiting the management team, talking with suppliers and competitors, and gauging its competitive strength? Or do the fund managers simply run the numbers and never set foot on company property? Are they looking for companies with long term profit potential or are they simply looking for a short term arbitrage opportunity? In fact, they could be doing all, some or none of the above and still be included in the same small-cap blend peer group, or any style box for that matter.

Indeed, several studies question the style grid's ability to correctly cluster managers and thus help identify the actionable return factors of importance to managers pursuing a well defined investment strategy:

- Brown and Goetzmann (1997) cluster active equity funds based on historical return time series. They end up with 8 such clusters and conclude that such clustering is superior to style grid clustering in predicting past and future fund performance.

- Studies by Wermers (2002, style drift), Cremer and Petajisto (2009, active share) and Amihud and Goyenko (2008, index R^2) each conclude that the key to generating superior returns is to move about the equity universe rather than being confined to a style box. Thus the actionable return factors of interest to fund managers are unrelated to the style grid.

- Three other studies confirm the style grid lacks explanatory power with respect to the equity manager's investment process:

  - ✓ Wermers (2000):
    "... 75 basis points per year can be attributed to the stock selection talents ... The table also shows that funds exhibit no abilities in timing the characteristics."

  - ✓ Wermers (2007):
    "The return-predictive power of the models is ...derived largely from the ability to predict firms' future operating profitability. Further, investment signals generated by the models are distinct from a large number of stock return signals documented by existing literature."

  - ✓ CSP:
    "We find that most of the abnormal performance we measure in the four and six-factor regressions comes from stock selection within a characteristic benchmark, not from holding that benchmark passively or tactically."

- Hunter et. al. (2009) reveal that the 4 factor model (i.e. market, size, PB, and momentum) does a poor job capturing across "strategy" cluster correlations.[2] Adding a "strategy" endogenous index reduces the across cluster correlations by 50% to 70%. In addition, the "strategy" index is positively priced in the vast majority of the individual fund factor regressions, while the three factors, other than the market, are inconsistently priced. Adding the "strategy" indices allows for superior forecasting of future fund alphas. That is, Hunter et. al. demonstrate that the style grid, which is based on two of the factors, does a poor job of capturing the strategy being pursued by a fund and the actionable return factors of interest to equity managers.

- The very basis of the style grid has been called into question by:

  - ✓ Phalippou (2008):
    "The value premium is driven by 7 percent of the stock market. The 93 percent of market capitalization held most by institutional investors is value premium free."

  - ✓ Fama and French (2008) who show the size premium is insignificant over the 45 year time period 1962 – 2006 and is significant only over the period 1962-1983.

The collective conclusions of these studies are 1) market-cap and PE stock characteristics do not capture actionable return factors, 2) skilled stock pickers do not stay in a style box and thus style drift, and 3) the very existence of the so called small firm effect and value premium have been called into question. Together these studies portray a style grid unable to identify the actionable return factors of interest to skilled stock pickers. Using the style grid as the lens for viewing active equity managers is looking for manager skill in all the wrong places.

---

[2] Hunter et. al. use self-declared investment objective as a way to cluster managers. Using investment objective falls somewhere in between the stock characteristic based style grid and investment strategy as defined in the next section. Thus Hunter et. al. use a quasi "strategy" approach in their study.

IV. Investment Strategy

Investment strategy is the way an active equity manager goes about analyzing, buying, and selling stocks. The manager's first step in creating an investment strategy is to identify a set of actionable return factors which can be used to generate superior performance. These economic, market and firm specific factors drive stock returns over time and determine the corresponding means, standard deviations, and correlations. If the factors upon which the manager focuses turn out to be non-actionable or if the strategy is poorly executed, the fund will underperform. On the other hand, if the factors are actionable and a narrowly defined strategy is relentlessly pursued, the fund will outperform. Factors that are actionable for one strategy will in general not be actionable for other strategies. A factor may currently be actionable, but may not remain so as its performance can be arbitraged away. Successful managers are continually adjusting the specifics of their strategy in response to the changing nature of actionable return factors.

Return factors are not directly observable. In creating an investment strategy, the manager must identify both quantitative and qualitative stock features, such as return on equity or management quality, that proxy for the unobservable actionable factors. By tracking and responding to each proxy, the manager is able to take advantage of the unobserved actionable factors. Thus the proxies used to implement an investment strategy are not the actionable factors themselves.[3] In the following discussion, these proxies are referred to as strategy

---

[3] Market-cap, PE, and other stock characteristics are often referred to as return factors and, in fact, the current four and six factor risk models are based on this convention. But this is technically incorrect. The premise is that observable stock characteristics proxy for important but unobservable return factors. It is clear that stock characteristics are one level removed and are not the return factors themselves. Thus the technically correct name is "factor proxy model". As was argued in the previous section and further confirmed later in this paper, the factors for which stock characteristics proxy are generally non-actionable.

elements, that is, the specific items upon which a manager focuses in order to implement an investment strategy.

Investment strategy encompasses both the manager's general approach to stock picking as well as the elements upon which the manager focuses. For example, a Valuation (one of the 10 strategies to be introduced shortly) manager identifies and invests in undervalued stocks. The elements used by the manager to implement the Valuation strategy might include PE ratios, valuing future cash flows, or being a contrarian. Drilling down further, the specific criteria used by the manager, such as purchasing stocks with a PE of less than 15, are not included in the strategy description and instead are considered the manager's "secret sauce". So the term investment strategy or simply strategy, as it used in this paper, provides a general understanding of the manager's investment process, but not enough information to replicate it fully.

Looking through a strategy lens reveals a world in which active equity managers produce superior returns by means of their sophisticated understanding of actionable stock return factors. More specifically, we observe each manager:[4]

- identifying a set of actionable return factors,

- developing a unique investment strategy to take advantage of these factors,

- defining a handful of elements used to implement the strategy,

- pursuing the strategy consistently over time, and

---

[4] Of course investment strategy is not limited to the stock market. Investment strategy is an important aspect in any market in which managers are attempting to actively outperform a market index.

- moving about the equity universe in response to ever changing economic and market conditions.

Equity Strategy Identification

Identifying the investment strategy being pursued by a manager allows for the formation of meaningful fund peer groups and, in turn, proper performance evaluation. Clustering managers based on self-declared strategy avoids the problem of artificially limiting the stocks which can be purchased and the attendant underperformance. Active managers are expected to consistently pursue their self-declared strategy and, in doing so, generate superior returns. The latter expectation is no different than what is expected in the current style grid system: active managers are expected to outperform.

Strategy identifying US and International active equity mutual funds was accomplished by gathering "Principal Investment Strategies" information from each fund's prospectus[5]. The resulting information was input into a strategy identification algorithm. This algorithm was developed using an iterative process involving manager interviews, gathering principal strategy information, eliminating key words that generated false signals, and creating a manageable number of strategies. In order to ensure accuracy, the strategy identifications assigned by the algorithm are subjected to a series of audits before being included in the fund data base. Over 45,000 pieces of prospectus strategy information were gathered for the 3000 (ignoring share

---

[5] The Principal Investment Strategies prospectus statement was first mandated by the SEC in 1998.

classes) US based active US and international equity mutual funds.[6] The identification

algorithm assigned specific strategy information to one of 40 elements, which were then

assigned to one of 10 equity strategies.

The 10 US and international equity strategies are described in Table 1. From this table one can

see that Competitive Position managers focus on business principles, including quality of

management, market power, product reputation, competitive advantage, sustainability of the

business model and history of adapting to market changes. On the other hand, Economic

Conditions managers take a top down approach based on economic fundamentals which might

include employment, productivity, inflation, and industrial output, then gauge where the

overall economy is in business cycle, the resulting supply and demand situations in various

industries, and the best stocks to purchase as a result. And so forth for the other 8 strategies.

Table 2 reports the November 2009 US and international equity fund population by primary

and secondary strategy. Overall, the largest strategies are Competitive Position, Valuation, and

Future Growth while Risk and Market Conditions are the smallest.

The resulting primary and secondary fund strategies, along with the corresponding elements,

make it possible to create broad or granular fund peer groups. These groupings range from the

10 primary strategy groups to the 90 primary-secondary peer groups to unique, single fund

primary-secondary-elements strategy peer groups. Only 22 of the 2801 strategy identified

funds have a primary-secondary-elements twin outside the fund family. Including same family

---

[6] About 7% of the funds could not be strategy identified because a prospectus could not be located or the prospectus did not provide useful strategy information (such a prospectus might simply state that the goal of the fund is to earn superior returns).

funds, the number of funds with a strategy twin is 348. Thus the typical fund is pursuing a unique strategy when full granularity is taken into consideration. This is consistent with the results reported in Table 2 of CPS that 75% of the top ranked best ideas are held by a single manager. This means that positive alphas are the consequence of highly idiosyncratic investment strategies being pursued by individual managers. That is, there are hundreds of managers selecting hundreds of different best idea stocks, each generating a positive alpha.

V.   Are Self-declared Strategy Statements of any Value?

There is a widely held belief, in both the academic and professional communities, that equity managers frequently deviate from their stated investment approach, which has created a general distrust of what investment managers say versus what they actually do. This begs the question of whether self-declared strategy information has any value. I test this value proposition in two ways. First, I test the ability of strategy statements to cluster funds pursuing similar investment approaches. This is important for creating meaningful peer groups and for proper performance evaluation. Second, I test the ability of strategy statements to concentrate actionable return factors in a single cluster, while distributing non-actionable factors across clusters. This allows managers to pursue their strategy without facing artificial peer group constrains as well as making it easier to identify superior strategy managers. Based on the results for each of these tests reported below, I conclude that self-declared strategy statements is a superior way to view and label active equity managers.

Forming Fund Clusters

Fund clusters should be comprised of managers who are pursuing similar investment strategies. Managers build their investment strategies in order to take advantage of a set of actionable return factors. Thus a plausible approach for testing strategy similarity is to analyze between-fund correlations (or simply fund correlations). The larger are fund correlations, the more similar are the strategies being pursued by the two fund managers. By this criteria, clustering funds based on self-declared strategy is deemed effective if the average fund correlation is greater within a strategy then across strategies.

Fund Sample

The 1988-2007 fund sample is comprised of all strategy identified US active equity funds as of December 2007. The sample includes 408 strategy identified funds in January 1988, growing to 2120 in December 2007. The sample excludes index, allocation, 529, life and style funds, thus focusing exclusively on actively managed equity funds. Fund-month returns are calculated as a simple average over all fund share class returns for that month. Monthly returns are net of management, 12B-1 and other automatically deducted fees, but not of other fees such as load charges and third party management fees. The sample is comprised of 276,317 fund-month observations.[7]

---

[7] US active equity funds were strategy identified in 2007 and 2008 so a fund that does not exist in those years is not included in the sample. The sample includes 64% of all possible fund-month observations over the 1988 to 2007 sample period. Since the same sample is used for all tests, there is little reason to believe a survivor bias exists in the comparison goodness-of-fit tests that are the focus of this test.

Testing Fund Correlations

Fund correlations are calculated using all monthly returns available for the shortest time period of the two funds. With 2120 funds, the full fund correlation matrix is impossibly large (2,245,080 unique elements to be exact!), so it is necessary to analyze the correlation matrix strategy by strategy and, in addition, draw multiple random samples when the number of funds within a particular strategy is large. Each within strategy sample is comprised of 100 randomly selected funds, which produces 9900 fund correlation estimates. When calculating across strategy average correlations, only those with the strategy of interest as part of the fund correlation are included in order to increase statistical power.

The fund correlation results are reported in Figure 5 and reveal that the average within strategy correlation exceeds the average across strategy correlation by .022 (t-value = 4.4), when funds are clustered using primary strategy alone. This difference increases to 0.035 (t-value = 7.0) when funds are clustered using both primary and secondary strategies. Thus clustering funds based on self-declared strategy means similar funds are being grouped together, while less similar funds as being assigned to different clusters. Both correlation differences are highly significant which means the results cannot be explained by chance. The fact that the correlation difference nearly doubles with the inclusion of a second piece of self-declared strategy information (i.e. secondary strategy) provides further evidence that the more one knows about a manager's strategy the better. These results provide strong support for the contention that a manager's self-declared investment strategy provides valuable information. It also provides support for the computer based algorithm and accompanying audit process used for strategy identification.

<u>Common Factors and Stock Picking Returns</u>

The results just reported show that strategy fund clustering has the desirable outcome of creating groups of managers who are pursuing similar investment strategies and, in turn, are taking advantage of similar stock return factors. In this section, two other desirable fund clustering outcomes are examined: minimizing common factors while maximizing stock picking returns. First, the lower are across-strategy common return factors the better, since this means, to the greatest extent possible, managers in each cluster are pursuing a unique strategy. Cluster uniqueness is an overriding goal of any clustering methodology. Second, the return factors upon which a strategy manager focuses are actionable, so it should be the case that greater exposure to these factors will produce higher fund returns. Unfortunately, return factor exposure is not directly measurable. But an indirect measure is provided by across-strategy return correlations or simply strategy correlations. Fund managers ignore non-actionable return factors when developing their investment strategy, so such factors are distributed randomly across strategy clusters, with their impact largely diversified away within clusters. Thus those factors concentrated enough in a strategy to produce strategy correlations must be actionable. This implies higher strategy correlations and higher fund returns should go hand-in-hand. As a consequence, two desirable fund clustering outcomes are common factor minimization combined with a positive relationship between returns and common factor exposure. These desirable outcomes are portrayed as moving northwest in Figure 6.

 Using the same 1988-2007 fund sample described in the previous section, the average monthly returns net of the across fund average return are calculated. The resulting 10 strategy, 240

month time series are used to estimate the across-cluster correlation (abbreviated cluster correlation from here on) matrix. Netting out the average monthly fund return makes it easier to focus on relative cluster performance.

The existence of common factors is measured by means of the average absolute cluster correlation (ρ^*).[8] Perfect fund clustering yields a ρ^* of zero, meaning each cluster is completely independent of other clusters. A low ρ^* means that a large portion of fund correlations are being captured within clusters and that the 10 clusters are reasonably distinct. On the other hand, a large ρ^* implies that managers in different clusters are pursuing similar investment strategies and are focused on a common set of return factors. A ρ^* of 1 means that managers in each cluster are pursuing identical strategies and are focused on an identical set of return factors. This would be the case, for example, if every manager were holding the market portfolio. So the lower is ρ^*, the more effective is fund clustering in terms of grouping managers who are pursuing a unique strategy.

The second clustering effectiveness measure is the extent to which common factors are actionable. The cluster correlations for a particular cluster provide a measure of how pervasive are common return factors within that cluster. Skilled stock pickers take advantage of higher exposure to actionable factors and thus one would expect a positive relationship between a cluster's average return and the average absolute correlation for those correlations involving

---

[8] The sign of the strategy correlation is irrelevant since both large positive and large negative correlations imply common return factors and/or a common investment strategy. If there are 10 clusters, ρ^* is calculated using the 45 non-diagonal, unique elements from the 10x10 correlation matrix.

cluster i (ρ^*_i).[9] The slope (SR) of the simple regression of strategy's average monthly return

on ρ^*_i is given by:

$$R_i = \alpha + SR\ \rho^*_i + e_i \text{ , where:} \tag{1}$$

R_i = 1988-2007 average strategy i monthly return,
SR = stock picking return (slope coefficient),
ρ^*_i = average absolute strategy correlation for strategy i, and
e_i = error term.

The higher is the stock picking return SR, the greater the collective manager skill at taking

advantage of actionable common return factors.[10] Fund clustering that produces high SR is

effective by this metric. That is, clustering has correctly concentrated, within the cluster, those

return factors that skilled stock pickers can take advantage of, while randomly distributing

factors they cannot. Combining these two measures, effective fund clustering is characterized

by low ρ^* along with high SR, as represented in Figure 6. The more effective is fund

clustering, the greater the movement to the northwest as SR increases and ρ^* decreases.

Estimating ρ^* and SR

For comparison purposes, ρ^* and SR are estimated using three different clustering approaches:

random, style grid, and strategy. Random clustering provides a numeric enumeration of the

joint ρ^*, SR sampling distribution in which the 2120 US active equity funds are randomly

assigned, in 700 independent trials, to one of 10 clusters.[11] The 1988-2007 monthly returns are

calculated for each of the 10 random clusters and then used to estimate ρ^* for each cluster,

---

[9] If there are 10 clusters, ρ^*_i is calculated using the 9 non-diagonal, unique elements involving cluster i from the 10 x10 correlation matrix.

[10] This is similar to the standard test for determining if a factor is "priced by the market". In this case, "pricing" means that the common factors are manager actionable.

[11] This number 10 was based on the number of equity strategies discussed in the previous section as well as being close to the number of style boxes (which is 9). The cluster assignment probabilities were set equal to the actual number of strategy fund-months. This was done to take into account the impact of different sized clusters so as not to give strategy clustering an unfair advantage.

while the annual SR is estimated by multiplying 12 times the slope monthly estimate from equation 1. As shown in Figure 7, the random ρ^* average is 0.27, with a range of 0.16 to 0.83. The random SR averaged 0.25%, with a range of -19.97 to 13.57. A regression of the 700 SR estimates on the corresponding ρ^* estimate revealed an inherent positive relationship between the two estimates, which is used to bias adjust the SR estimates obtained for style grid and strategy clustering. The resulting numeric joint SCC, SR sampling distribution is used to determine the statistical significance of the corresponding style grid and strategy estimates.

Style grid clustering is accomplished by assigning funds to one of four style boxes based on the fund's highest correlation (i.e. best fit index) among the four Russell style indices of large-cap value, large-cap growth, small-cap value and small-cap growth. The mid-cap and blend boxes are populated by randomly drawing from the adjacent corner boxes thus creating 9 style grid clusters. The random mid-cap, blend drawing was replicated 40 times and the resulting averages were used to ensure this aspect of style grid clustering did not bias the results.

Over the 40 style grid replications the average ρ^* was a highly significant 0.57, while the average annual SR was an insignificant 0.38%, as reported in Figure 7. This implies that style grid clustering spreads common factors across clusters rather than concentrating them within clusters and theses common factors are not actionable as evidenced by the low annual SR. This is consistent with Wermers (2000, 2002, 2007), Amihud and Goyenko (2008), CSP, and Cremer and Petajisto (2009), as discussed in Section III, who each conclude that market-cap and PE do not proxy for actionable return factors. They find that in order to be successful, an active manager must style drift and that superior returns are not the result of tactical or strategy

style tilts. Wermers (2007) goes a step further by showing that superior performance is independent of a wide range of previously identified stock characteristic return effects, not just the small firm and low PE effects. Collectively, these studies, along with the results reported here, confirm the style grid does not help in identifying skilled stock pickers. Indeed, random clustering is superior, on average, to style grid clustering which means that style grid clustering has made finding successful strategy managers much more difficult for investors. Thus style grid clustering moves the industry in the wrong direction.

Strategy clustering uses the primary strategy of each of the 2120 funds. The strategy clustering $\rho*$ is an insignificant 0.28, while the annual SR is a highly significant 7.17%, as reported in Figure 7. This means that strategy clustering has moved dramatically to the northwest and thus represents a significant improvement, since common return factors are now largely captured within clusters (since strategy $\rho*$ is small) and fund managers are able to take advantage of these factors (since annual SR is large). Based on the $\rho*$ and SR criteria, strategy clustering is superior to both random and style grid clustering, while style grid clustering is inferior to random clustering.

These results are consistent with those reported by Hunter et. al (2009) which were discussed earlier. They found that the 4 factor model (i.e. market, size, PB, and momentum) does a poor job of capturing across "strategy" cluster correlations. Adding a "strategy" endogenous index reduces the across cluster correlations by 50% to 70%. In addition, this index is positively priced in the vast majority of the individual fund factor regressions, while the three factors, other than the market, are inconsistently priced. Adding the "strategy" indices allows for

superior forecasting of future fund alphas. That is, Hunter et. al. demonstrate that the style grid, which is based on two of the factors, does a poor job of capturing the strategy being pursued by a fund manager.

The conclusion is that self-declared strategy information is superior to objective stock characteristic information for viewing and organizing active equity funds. Strategy provides a rigorous basis for forming fund peer groups, building multi-fund portfolios, evaluating performance, and organizing the fund universe. All of this is possible without getting in the way of what a manager is supposed to be doing: skillfully picking stocks and generating superior returns.

V.   What Drives Strategy Returns?

Summary statistics for the 10 equity strategies are reported in Table 3. Each of the performance statistics display considerable variation across strategies: annual return varies from a high of 12.98% (Competitive Position) to a low of 8.89% (Risk), standard deviation varies from a high of 18.89% (Future Growth) to a low of 14.11% (Opportunity), and best fit R^2 varies from a high of 0.76 (Quantitative) to a low of 0.57 (Risk). To determine if these return differences are statistically significant, a single factor ANOVA test, in which the 10 strategy monthly return series are input, was conducted. The resulting ANOVA F-test (9, 2390 df) p-value was 0.033, meaning the strategy return series are statistically different from one another and are thus not drawn from the same underlying population.

Next, I addressed the question of whether strategy return differences can be explained by risk differences. The correlation between the 10 average strategy returns and the corresponding average within strategy fund standard deviation was strongly negative (-0.44), as was the average beta-return correlation (-0.16). So strategy return differences cannot be explained by differences in risk and, in fact, higher strategy returns are associated with lower risk (as measured by standard deviation or beta). This is consistent with other studies, as discussed in Section II, which show that standard risk factor models do not explain superior stock picking returns.

The correlation matrix in Table 4 reveals that there are large as well as small positive and negative correlations, highlighting the existence of strategy varying common return factors. Recall these correlations are based on returns net of the monthly across fund average return, so are not the result of economy or market wide return factors. Instead, these correlations capture the extent to which the relative performance of strategies move together or in opposite directions. For example, the largest positive correlation, 0.73, is between the Competitive Position and Future Growth strategies. This means that managers in these two strategies focus on common underlying return factors and use similar approaches to managing their portfolios. On the other hand, the largest negative correlation, -0.86, is between Future Growth and Valuation which means again these managers focus on common factors, but respond in opposite directions.

Strategy returns were decomposed into the return associated with common factors and the return associated with unique factors. This decomposition allows for determining if returns are

being generated differently from strategy to strategy and how successful managers within each strategy are at taking advantage of both common and unique factors. Each of the average strategy returns is decomposed, based on equation 1, as follows:

$$CFR_i = \text{common factor return for strategy } i = SR \times \rho^*_i \text{, and} \qquad (2)$$

$$UFR_i = \text{unique (i.e. strategy specific) factor return for strategy } i = e_i \qquad (3)$$

Equations 2 and 3 are used to estimate CFR_i and UFR_i for each of the 10 strategies using the fund sample described above.

Figure 8 presents CFR and UFR for each of the 10 strategies. The values reported are relative to the all strategy average. For example, for Competitive Position (CP) the CFR-UFR pair is 7, 150 which means that the average CP fund generated a CFR that was 7 bps higher than the all strategy average return over the period 1988 through 2007, while it generated a UFR that was 150 bps higher. In total, the average CP fund generated a return that was 157 bp ($= 7 + 150$) higher than the all strategy average return. Thus the 157 bp of superior performance is decomposed into 7 bp in CFR and 150 bp in UFR. This is the same 157 bp obtained by subtracting the all strategy average (11.31%) reported at the bottom of column 3 in Table 3 from the CP average return (12.89%) at the top of the column.

The 10 strategies can be divided into three sub-groups: those for which CFR is the primary source of superior returns, those for which UFR is the primary source of superior returns, and those for which UFR is the primary source of inferior returns. Superior and inferior are used here to denote values greater or less than the all strategy average annual return of 11.31% over the 1988 through 2007 time period.

CFR Driven Superior Returns

Figure 8 reveals that Opportunity, Future Growth, and Valuation generate roughly the same superior returns (72, 73, and 94 bps, respectively), with the primary source being CFR (70, 81, and 90 bps respectively), and virtually no UFR (2, -8, and 4 bps, respectively). This means that managers in these strategies are successful at taking advantage of common actionable return factors in order to generate superior returns. However, the way they go about accomplishing this is quite different from strategy to strategy. The Opportunity and Valuation strategies display a high cross correlation (0.72) and so most likely they focus on a similar set of common factors and their investment strategies share common features. However, Valuation and Future Growth display a strong negative cross correlation and so most likely they focus on a similar set of common factors, but respond to them in opposite ways.

UFR Driven Superior Returns

The three strategies Competitive Position, Quantitative, and Profitability all generate superior returns (157, 96, and 41 bps, respectively), with UFR being the primary source of these returns (150, 102, and 132 bps, respectively). Both Competitive Position and Quantitative managers have an average exposure to common return factors while Profit has the lowest exposure among all 10 strategies. This means that each strategy successfully focuses on a unique and thus independent set of actionable return factors. Competitive Position managers look for strong, high quality, innovative companies; Quantitative managers rely on mathematical and statistical models to identify attractive stocks with little or no fundamental analysis; and

Profitability managers focus on strong cash flows and profit margins. Each in their own way are able to earn comparable levels of UFR (150, 102, and 132 bps, respectively).

UFR Driven Inferior Returns

The four strategies Market Conditions, Social Considerations, Economic Conditions, and Risk all generate inferior returns (-67, -96, -124, and -241 bps, respectively). For the latter three, both CFR and UFR contribute to this poor performance. For Market Conditions there is a small positive contribution made by CFR. The poor performance by these strategies begs the question of why managers do not attempt to increase exposure to actionable factors. It may be that they are not able to take advantage of common actionable factors as do managers in other strategies. It is also apparent that they are not able to take advantage of the unique factors to which they are exposed. Market Conditions managers focus on short term market imbalances using technical analysis, Social Considerations managers look for socially responsible companies, Economic Conditions managers attempt to take advantage of broad economic trends, and Risk managers focus on controlling risk with returns as a secondary consideration. Collectively these approaches are unable to generate superior returns.

So why would managers continue to pursue these strategies? For one thing, the results are based on average fund performance in each strategy so there are no doubt funds in each strategy that are doing well. For another, there are times when these strategies have done well even though their 20 year performance is poor. So investing in them at the right time produces superior returns (e.g. Economic Conditions heading into a recession and Risk when overall returns have been relatively low, such as 10 year period from 2000-2009). For another,

investors may choose to invest for reasons other than the highest return, such as investing in Social Considerations funds.

VI. Strategy Categorizing Stocks

Traditionally, active equity funds are categorized by the stocks they hold. For example, a fund is categorized small-cap value based on the fact they hold small-cap, low PE stocks. Here the opposite approach is taken, instead categorizing stocks based on the funds that hold them. The primary advantage is that the manager's strategy and investment skill are now associated with the stocks being held. For example, Competitive Position (CP) managers look for stocks of high quality companies that have a strong management team, have a defensible market position, are innovative, and are able to adapt to changing market conditions. So CP categorized stocks are those that CP managers have collectively decided meet these criteria.

Stocks are strategy categorized based on the portfolio weights within a strategy relative to portfolio weights in other strategies. Each stock's weights (weights are used rather than dollar holdings in order to neutralize the effect of fund size) are summed across funds within each strategy. The weight sums are then scaled to 1.00 within each strategy, which means that the scaled weights represent the average across fund stock weight within that strategy. The scaling neutralizes the effect of the varying number of funds across strategies. Each stock's strategy weights are rescaled to 100%, which produces the stock's strategy profile. Finally, each stock is strategy categorized based on the largest percentage within its strategy profile.

Three stock strategy profiles are presented in Table 5. These are based on the <u>relative</u> importance of each stock within each strategy. For example, Acuity's strategy profile is comprised 36.3% of Opportunity and 24.9% of Valuation, along with other less important strategies. Acuity is strategy categorized Opportunity since it represents the largest percentage in the strategy profile. This, however, does not mean 36.3% of the dollars invested in Acuity come from Opportunity funds, while 24.9% come from Valuation funds. In fact, Valuation funds had $91.7 million invested in Acuity at the time, while Opportunity funds had only $4.0 million invested, because there are many more Valuation funds than Opportunity funds and the average Valuation fund is larger than the average Opportunity fund. But Acuity is relatively more important among Opportunity funds than among Valuation funds and so it is categorized an Opportunity stock. The strategy profile and the resulting strategy categorization attempts to capture the relative bets placed by the different strategies in a stock. The supposition is that the higher is the stock's relative importance within a strategy, the more compelling is the investment case for the stock. This is a way to capture valuable information regarding the analytic conclusions and subsequent investment decisions of strategy managers.

US Stock Categorization Results

US stocks, held by strategy identified active US equity mutual funds with less than $1b in assets under management, were strategy identified monthly from January 1997 through September 2008. Larger funds were excluded because stock selection may be driven more by diversification considerations rather than by strongly held investment beliefs. This resulted in 397,364 stock-month strategy categorizations, an average of 2,818 stocks per month. Table 6 presents summary statistics for this sample.

Comparing the second column in Table 6 to the third reveals that there is some regression to the mean in the categorization process, as the strategies with fewer funds ended up with more categorized stocks, while the opposite was true for strategies with the most funds (Competitive Position, Future Growth, and Valuation). The typical stock stayed in a strategy an average of 15 months (bottom of column 4), which means that the relative attractiveness of a stock to a particular strategy lasts a little over a year. Managers, in pursuing a particular strategy, find a changing mix of stocks attractive over time. This shows the futility of trying to identify a fund's strategy by the stocks held, since a stock's strategy attractiveness lasts a little over a year. Indeed, 4 of the 10 strategies have average times in strategy of less than one year. On the other hand, there are stocks that remain in a single strategy for a long time, with the average maximum in a strategy being 118 months (out of 141 months possible). As another indication of how managers alter their stock preferences over time, roughly 67% of the stocks are categorized in two or more strategies during the sample period, with the average stock categorized in three different strategies. Thus strategy managers find an ever changing mix of stocks attractive.

Strategy Stock Pools

Strategy stocks are the ones of collective interest to managers pursuing the same strategy. For example, those stocks most attractive to Competitive Position managers are categorized Competitive Position stocks. In like manner, those stocks most attractive to Economic Conditions managers are categorized Economic Conditions stocks. Each stock becomes a member of a particular strategy stock pool based on which strategy finds the stock most

attractive. Over time, strategy pool composition changes as managers, responding to changing market and economic conditions, alter their stock holdings. Consequently, strategy stock pools move about the equity universe over time, as is stylistically represented in Figure 9. The composition of each pool is determined by the collective holdings of all of managers pursuing that particular strategy. Strategy pool stock characteristics, such as average market cap and PE, change over time as strategy managers adjust their holdings. Thus it is not possible to describe strategy stock pools using the characteristics of the stocks held. This lack of descriptive power applies to every stock characteristic, not just market cap and PE. Strategy stock pools are defined by the managers that hold them not by stock characteristics.

This is very different from the current representation in which the equity universe is locked in place by the style grid. In this paradigm, managers are categorized by the stocks they hold rather than stocks being categorized by the managers that hold them. In such a world, managers cannot fully respond to changing economic and market conditions as they are tethered to a specific style box. The problem with style box tethering becomes abundantly clear when considering the 1997- 2008 market-cap and sector variations, within the Opportunity and Social Considerations strategies, reported in Figures 10 and 11. The variations from the long term average can exceed 20% in any one year. So it is important to allow strategy managers to move about the equity universe and not artificially limit their choices by assigning them to a style box or by capping sector exposure.

VII. Measuring Strategy Consistency

Strategy managers move about the equity universe in pursuit of those stocks which they find most attractive, much as portrayed in Figure 9. Over time, managers develop strategy specific stock picking skills which yield the best results when applied to stocks of greatest interest to fellow strategy managers. That is, a strategy manager is most successful when analyzing, buying, and selling own strategy stocks. For example, Competitive Position managers are most successful when focusing on Competitive Position stocks. This notion is the basis for the objective fund strategy consistency measure presented next.

The monthly fund strategy consistency measure is based on the proportion of own strategy stocks held by the fund and is scaled to range from 10 (fewest own strategy stocks held) to 100 (most own strategy stocks held) within each strategy. The sample used to test this strategy consistency measure is comprised of 3065 strategy identified US and international equity mutual funds, resulting in 335,751 fund-month observations over the March 1997 to June 2009 time period. The performance of this measure is tested using the average subsequent month fund return net of automatically deducted fees and net of that month's average primary strategy return. The strategy consistency test results are reported in Figure 12. The most (100) strategy consistent (SC) funds outperform the least (10) consistent funds by 3.21% annually. With the exception of SC 90 funds, excess strategy returns increase monotonically over the SC range. This means that managers who adjust their portfolio to hold as many own strategy stocks as possible outperform those managers who do not. That is, those managers who are most successful in keeping their portfolios centered on the ever moving own strategy stock pool, as depicted in Figure 9, are the top performers.

<u>The Central Role Played by Strategy Stock Pools</u>

The results just presented provide strong support for the value of self-declared strategy, in that own strategy stocks are the ones upon which a manager should focus. In essence, this argues for a strategy based stock screen, in contrast to the commonly used stock characteristic based screens. The strategy screen is superior because it is based on the collective judgment of skilled stock pickers who are pursuing the same self-declared strategy. But this does not imply that two managers who are pursing, say, a Competitive Position strategy will end up holding the same stocks. There are over 600 Competitive Position stocks, so it is entirely possible for one strategy consistent Competitive Position manager to hold a completely different portfolio from another strategy consistent Competitive Position manager, and yet both generate superior returns. The consistency results imply strategy managers need to focus on own strategy stocks, but they do not say managers have to pursue identical investment processes nor hold the same stocks.

The strategy consistency results are independent of the strategy being pursued. That is, regardless of what strategy the manager is pursuing, own strategy stocks should be the focus. Stock strategy categorization forces each stock into one and only one strategy. This means the stocks in the Competitive Position pool are different from those in the Economic Conditions pool and so forth. The attractiveness of a stock is truly in the eye of the beholder. Competitive Position managers are looking for stocks with quality management, strong market positions, and are innovative. Economic Conditions managers are looking for stocks that will most benefit in the current stage of the economic cycle. These are two different pools, yet each yield

superior return opportunities that only a specific group of managers can find. Competitive Position managers are less successful at finding high return stocks in the Economics Conditions pool, while the Economic Conditions managers are less successful at finding high return stocks in the Competitive Position pool. It is as if each group of active managers views the equity universe through a pair of glasses that allows them and only them to see a unique set of actionable return factors.

When asked to describe their investment process, most managers don't mention the pursuit of own strategy stocks. However, the data reveals that it is indeed important as investing in own strategy stocks is a determinant of portfolio performance. Strategy stock pools change constantly as both the economy and markets evolve over time. While not explicitly attempting to do so, the successful manager is forever pursuing the own strategy stock pool.

Specialist versus Generalist

A manager might be tempted to become a generalist by developing the skills needed to fish in several pools rather than in just the own strategy stock pool. After all, superior return opportunities are available in each stock pool, so why not drop a line in each? The results presented in Figure 12 argue otherwise. The greater the percent of own strategy stocks held, the higher is the return. This percent can be increased by either investing in more own strategy stocks or decreasing the number of other strategy stocks. Referring back to Figure 1, we see that portfolio return decreases as stocks are added to a portfolio. Thus the latter choice, decreasing the number of non-strategy stocks, is better, since it both increases the percent of

own strategy stocks while decreasing the total number of stocks in the portfolio. The implication is that managers should be specialists and remain strategy focused.

Evidence against becoming a generalist shows up as well when manager investment strategy statements are carefully analyzed. Figure 13 shows that managers who limit their focus to own strategy elements generate 17.2 bp in annual higher return for each additional own strategy element and 3.3 bp annually for each additional 10% that are own strategy elements. Thus, based on what they both say and do, managers should consistently pursue a narrowly defined investment strategy. In other words, managers do best when they are investment specialists.

Strategy Consistency and Style Drift

The result that strategy consistency pays is just the opposite of the corresponding style grid results, which show that it is better to style drift than be style consistent. It is apparent that strategy and style, as it is currently used in the industry, are not the same. Fund strategy is identified based on the statements made by fund managers, while style is based on the average market-cap and PE characteristics of the stocks held by the fund. When the style grid was launched some 25 years ago, the supposition (hope?) was that managers pursuing the same strategy would end up buying stocks with the same characteristics. Thus, those managers holding small-cap value stocks, for example, were all pursuing the same investment strategy and thus were placed in the small-cap value style box. We now know this not to be the case. The most successful active equity managers exhibit the lowest style index correlations, the highest active share, and the greatest amount of style drift. So the things that managers do in order to generate superior returns seems to have little to do with style boxes. Strategy, on the

other hand, is key to generating superior returns. Jointly, strategy consistency and style drift successfully proxy for the stock picking skill that is so common among active equity managers, the results of which show up as the extraordinary fund returns previously documented in Figure 4. To be successful, a manager needs to be both strategy consistent and style box inconsistent. Given the importance of the ever changing stock strategy pools, it is no wonder mechanical stock characteristic regimes, such as the style grid, fail to capture the dynamic and largely unobservable interplay between managers and the market in which they invest.

Lest one despair that, by jettisoning the style gird, the world of portfolio construction and evaluation is forever damaged, be assured there is a strategy alternative for each corresponding style grid tool. Funds can be labeled using their identified primary strategy or, if necessary, the secondary strategy and elements. Portfolios can be constructed by diversifying across strategies (actually more effective than diversifying across boxes). Superior managers within a strategy can be identified using the strategy consistency measure. Fund performance can be evaluated relative to a broadly or narrowly defined strategy peer group. Performance attribution can be based on a fund's primary and secondary strategy, elements, and strategy consistency. Thus self-declared strategy can be used to create a rigorous equity portfolio construction and evaluation methodology.

On a number of occasions I have been asked whether expecting managers to be strategy consistent is just the latest version of sticking a manager in a box. Not an unreasonable question since there is an expectation that a manager state their strategy and then consistently pursue it. The strategy consistency measure shows that managers should focus on own strategy

stocks. Sounds a lot like asking a manager to purchase only stocks within their own style box. But there are critical differences. First, strategy is self-declared and no doubt represents the core competency of the manager. Second, it is not unreasonable to expect a manager to do what they say. Both of these are opposite of the style grid, in that the style box is externally imposed and then the manager is expected to abide by the resulting external constraints. Third, the strategy stock pools, the basis for strategy consistency, are an economic, market, and peer group determined target for fund managers, as compared to the fixed style boxes. What is more, being strategy consistent increases returns, while style box consistency hurts returns. Finally, knowing the manager's strategy tells investors something about how investment decisions are made, while the style box reveals little or nothing about the investment process. Therefore, expecting a manager to consistently pursue a self-declared strategy is not unreasonable as it provides insight into the management process; provides the metrics needed to analyze, evaluate, and build equity portfolios; and it improves returns. Seems a reasonable way to organize the active equity active manager universe.

VIII. Conclusions

Superior stock picking skill is common among active equity fund managers, with numerous studies reporting excess returns that can exceed 10% annually. How the active equity universe is viewed and organized should not artificially constrain a manager's execution of an investment strategy and, in addition, should aid investors in identifying superior managers. The style grid fails both of these criteria, in that keeping a manager in a style box leads to underperformance, since it thwarts strategy execution, while the basis of the style grid, the stock characteristics market cap and PE, are not important in generating superior returns. Thus

asking managers to consider these two stock characteristics forces them to take their focus off of what is really important, the consistent pursuit of a narrowly defined strategy.

Self-declared investment strategy is a superior way to think about and organize the active equity mutual fund universe. In terms of organizing the active equity universe, I find that funds within a strategy are more highly correlated than across strategies. Furthermore, fund clustering, based on self-declared strategy, is superior to both random clustering and style box clustering in terms of minimizing across-cluster correlations and isolating manager actionable return factors. The 10 strategy returns are statistically different and each is driven by a unique set of return factors. The bottom line is that self-declared strategy does not get in the way of strategy execution and helps identify superior managers.

Stocks can be categorized based on which strategy finds them most attractive. For example, a stock that is most held by Competitive Position managers is categorized a Competitive Position stock. Thus stocks are categorized based on the managers who hold them and not the other way around, as is current practice. Categorizing stocks based on the managers who find them most attractive transfers the strategy managers collective insight to the stocks. Thus it is possible to determine which strategy is purchasing a stock and why, resulting in a unique set of buy-side information not currently available. This is of importance since the buy-side puts their money where their mouth is, where other market participants present only opinion.

Stocks are strategy categorized by forcing each stock into a single strategy pool. Over time, the composition of each strategy pool changes as managers alter holdings based on ever evolving

economic and market conditions. Thus over time strategy stock pools move about the equity universe. Stock pools are a result of a collective vote, as measured by fund holdings, of all managers and are not measured by the characteristics of the stocks within the pool. Even though managers take into consideration stock characteristics, their final investment decisions are made based on a comprehensive qualitative and quantitative analytic process, the essence of which cannot be captured by reference to simplistic stock characteristics. This is confirmed in a series of recent fund manager-decision studies. Thus a reasonable way to categorize stocks is by strategy and not by characteristics. The former takes advantage of manager stock picking skill, while the latter attempts to use widely available, but largely unimportant specific stock data.

Since the strategy stock pools are formed based on the collective judgment of strategy managers and since each manager has developed a set of strategy-specific stock picking skills, it seems plausible that performance will improve when the manager focuses on own strategy stocks. I find this is indeed the case. Managers who hold the most own strategy stocks outperform those that hold the least by an economically significant 3.21% annually. This is powerful evidence regarding the value of self-declared strategy. Strategy identifying funds makes it possible to strategy categorize stocks, which makes it possible to identify those managers who are most strategy consistent as measured by the holding of own strategy stocks. The more strategy consistent a manager, the better is the fund's performance. Investment strategy is important for identifying superior managers.

The strategy evidence presented in this paper argues for moving away from the style gird and, instead, begin thinking in terms of self-declared strategy. Such a shift changes the language and, in turn, virtually every aspect of the active equity fund industry. Instead of being a "small-cap blend" fund, it is a "Competitive Position, Social Considerations" fund. Instead of ranking funds on previous performance, rank funds on strategy consistency and focus. Instead of a fund distribution system based on the style box, distribute based on primary and secondary strategy. Instead of performance evaluation based on a style box, evaluate based on strategy and elements. Instead of thinking about stocks in terms of characteristics, think of them in terms of strategy and elements. Wherever the style gird is used, there is a strategy alternative. What is more, strategy can be used for organizing any asset class in which active management plays a role. It provides a unifying framework across multiple asset classes, thus avoiding the "equity markets only" limitation of the style grid.

Thinking in terms of strategy opens up new research avenues. At the foundational level is the question of whether the primary, secondary, element structure used to strategy identify funds is the best possible. The evidence presented reveals that it is better than either random clustering or style grid clustering, but it is possible that a better approach exists. At another level, the strategy data provides a rich source of information regarding buy-side decision making. A host of new research questions can be explored using this data. Such research will play a role in shaping the future of active investment management.

References

Alexander, Gordon, Gjergji Cici, and Scott Gibson, 2007, Does Motivation Matter When Assessing Trade Performance? An Analysis of Mutual Funds. Review of Financial Studies 12, 1, 125-150.

Amihud, Yakov and Ruslan Goyenko, 2008. Mutual Fund's R^2 as Predictor of Performance. Working paper, NYU, December.

Avaramov, Doron and Russ Wermers, 2005. Investing in Mutual Funds when Returns are Predictable. working paper, University of Maryland.

Baker, Malcolm, Lubomir Litov, Jessica A. Wachter, and Jeffrey Wurgler. 2004. Can Mutual Fund Managers Pick Stocks? Evidence from Their Trades prior to Earnings Announcements. NBER Working Paper w10685 (July 28).

Baks, Klaas, Andrew Metrick, and Jessica Wachter, 2001. Should Investors Avoid All Actively Managed Mutual Funds? A Study in Bayesian Performance Evaluation. Journal of Finance. February, 45-85.

Baks, Klaas, 2006, On the performance of mutual fund managers. Journal of Finance (forthcoming).

Barras, Laurent, Olivier Scaillet, and Russ Wermers, 2008. False Discoveries in Mutual Fund Performance: Measuring Luck in Estimated Alphas, working paper, May.

Berk, J. B. and R. C. Green, 2004. Mutual Fund Flows and Performance in Rational Markets. Journal of Political Economy, vol. 112, no. 6, 1269-1295.

Bollen, Nicolas P. B., and Jeffrey A. Busse, 2001. On the timing ability of mutual fund Managers. Journal of Finance 56, 1075–1094.

Bollen, N. P. B. and J. A. Busse, 2004. Short-Term Persistence in Mutual Fund Performance. Review of Financial Studies, vol. 18, no. 2, 569-597.

Brands, S., Brown, S.J. and D.R. Gallagher, 2006, Portfolio Concentration and Investment Manager Performance, *International Review of Finance*, 149-174.

Brown, S. J. and W. N. Goetzmann, 1995. Performance Persistence. Journal of Finance, vol. 50, no. 2, 679-698.

Brown, S. J. and W. N. Goetzmann, 1997. Mutual Fund Styles. Journal of Financial Economics, vol. 43, 373-399.

Busse, Jeffery A. and Paul J. Irvine, 2006. Bayesian Alphas and Mutual Fund Persistence. The Journal of Finance. Vol. LXI, No. 5, October, 2251-2281.

Carhart, M. , 1997. On Persistence in Mutual Fund Returns. Journal of Finance, vol. 52, no. 1, 57-82.

Chen, Hsiu-Lang, Narasimhan Jegadeesh, and Russ Wermers, 2000, The value of active mutual fund management: An examination of the stockholdings and trades of fund managers. Journal of Financial and Quantitative Analysis 35, 343–368.

Chen, J. , H. Hong, M. Huang, and J. D. Kubik, 2004. Does Fund Size Erode Performance? Organizational Diseconomies and Active Money Management. American Economic Review, vol. 94, no. 5, 1276-1302.

Cohen, R. B. , J. D. Coval, and L. Pastor, 2005. Judging Fund Managers by the Company They Keep. Journal of Finance, vol. 60, no. 3, 1057-1096.

Cohen, R. B., C. Polk, and B. Silli, 2009. Best ideas. Harvard Working Paper. March.

Collins, Bruce and Frank Fabozzi, 2000. Equity Manager Selection and Performance. Review of Quantitative Finance and Accounting. 15, 81-97.

Cremers, Martijn and Antti Petajisto, 2009. How Active Is Your Fund Manager? A New Measure That Predicts Performance. Review of Financial Studies, September, pp 3329-3365.

Daniel, K. , M. Grinblatt, S. Titman, and R. Wermers, 1997. Measuring Mutual Fund Performance with Characteristic-Based Benchmarks. Journal of Finance, vol. 52, no. 3, 1035-1058.

Elton, Edwin J., Martin J. Gruber, and Christopher R. Blake, 1996. The persistence of risk-adjusted mutual fund performance. Journal of Business 69, 133–157.

Ennis, Richard M. 2001. The Case for Whole-Stock Portfolios. The Journal of Portfolio Management 27 (spring):17–26.

Fama, Eugene F. and Kenneth R. French, (2008). Mutual Fund Performance. University of Chicago Working Paper, August.

Frazzini, A., 2006. The Disposition Effect and Underreaction to News. Journal of Finance, Vol LXI, No.4 (August), pp 2017-2046.

Goetzmann, William N., and Roger G. Ibbotson, 1994. Do winners repeat? Patterns in mutual fund performance. Journal of Portfolio Management 20, 9–18.

Grinblatt, M. and S. Titman, 1993. Performance Measurement without Benchmarks: An Examination of Mutual Fund Returns. Journal of Business, vol. 66, no. 1, 47-68.

Han, Yufeng, Tom Noe, and Michael Rebello, 2008. Horses for courses: Fund managers and organizational structures, working paper, January.

Hendricks, Darryl, Jayendu Patel, and Richard Zeckhauser, 1993. Hot hands in mutual funds: Short-run persistence of relative performance, 1974–1988. Journal of Finance 48, 93–130.

Howard, C. Thomas and Craig T. Callahan, 2006. The Problematic 'Style' Grid. Journal of Investment Consulting, Winter, 44-56.

Howard, C. Thomas, 2008. Decomposing Strategy Returns. Working paper, November.

Hunter, David, Eugene Kandel, Shmuel Kandel, and Russell Wermers, 2009. Endogenous Benchmarks. University of Maryland working paper, March.

Ivkovic, Zoran, Clemens Sialm, and Scott Weisbenner, 2008. Portfolio Concentration and the Performance of Individual Investors, Journal of Financial and Quantitative Analysis, Vol. 43, No. 3, (September) , pp. 613-656.

Jensen, M. C. , 1968. The Performance of Mutual Funds in the Period 1945-1964. Journal of Finance, vol. 23, no. 2, 389-416.

Jones, Christopher S., and Jay Shanken, 2005, Mutual fund performance with learning across funds, Journal of Financial Economics, 78, 507–552.

Kacperczyk, M. T. , C. Sialm, and L. Zheng, 2005. On Industry Concentration of Actively Managed Equity Mutual Funds. Journal of Finance, vol. 60, no. 4, 1983-2011.

Kacperczyk, M. T. , and Amit Seru, 2007. Fund Manager Use of Public Information: New Evidence on Managerial Skills. Journal of Finance, April, 485-528.

Kacperczyk, M. T. , C. Sialm, and L. Zheng, 2008. Unobserved Actions of Mutual Funds. Review of Financial Studies, (November), 21, 2379 - 2416.

Keswani, Aneel and David Stolin, 2008. Which Money Is Smart? Mutual Fund Buys and Sells of Individual and Institutional Investors. Journal of Finance, February, 63-1, 85-118.

Kosowski, Robert, Allan Timermann, Russ Wermers, and Hal White, 2006. Can Mutual Fund "Stars" Really Pick Stocks? New Evidence from a Bootstrap Analysis. Journal of Finance, December , 61-6, 2551-2595.

Kothari, S. P. and Jerold B. Warner, 2001. Evaluating mutual fund performance. Journal of Finance, 56, 1985–2010.

Lakonishok, Josef, Andrei Shleifer, Richard Thaler, and RobertW. Vishny, 1991.Window Dressing by Pension Fund Managers. American Economic Review 81, 227–231.

Lakonishok, Josef, Andrei Shleifer, and Robert W. Vishny, 1992. The impact of institutional trading on stock prices. Journal of Financial Economics 32, 23–44.

Mamaysky, H. , M. Spiegel, and H. Zhang, 2006. Improved Forecasting of Mutual Fund Alphas and Betas. Yale ICF working paper.

Musto, David K., 1997. Portfolio disclosures and year-end price shifts. Journal of Finance 52, 1563–1588.

Musto, David K., 1999. Investment decisions depend on portfolio disclosures. Journal of Finance 54, 935–952.

Myers, Mary Margaret, and James M. Poterba, Douglas A. Shackelford, and John B. Shoven, 2001. Copycat Funds: Information Disclosure Regulation and the Returns to Active Management in the Mutual Fund Industry. working paper.

Pastor, L. and R. F. Stambaugh, 2002A. Mutual Fund Performance and Seemingly Unrelated Assets. Journal of Financial Economics, vol. 63, 315. 349.

Pastor, L., and R. F. Stambaugh, 2002B. Investing in equity mutual funds. Journal of Financial Economics 63, 351–380.

Phalippou, Ludovic, 2008. Where is the Value Premium?, Financial Analyst Journal, Vol 64, No2, (March/April), 41-48

Pollet, J. M. and M. Wilson, 2006. How Does Size Affect Mutual Fund Behavior?. working paper.

Pomorski, Lukasz, 2009, Acting on the Most Valuable Information: Best Idea Trades of Mutual Fund Managers, (March), University of Toronto working paper.

Sensoy, B. A. , 2006, . Incentives and Mutual Fund Benchmarks, . working paper.

Sharpe, William F., 1966. Mutual fund performance. Journal of Business 39, 119–138.

Shumway, Tyler, Maciej Sze‡er, and Kathy Yuan, 2009. The Information Content of Revealed Beliefs in Portfolio Holdings, (January) University of Michigan working paper.

Teo, Melvyn, and Sung-Jun Woo. 2004. Style Effects in the Cross-section of Stock Returns. Journal of Financial Economics, 74 (November): 367-398.

Wermers, R. , 1999. Mutual Fund Herding and the Impact on Stock Prices. Journal of Finance, vol. 54, no. 2, 581-622.

Wermers, R. , 2000. Mutual Fund Performance: An Empirical Decomposition into Stock-Picking Talent, Style, Transactions Costs, and Expenses. Journal of Finance, vol. 55, no. 4, 1655-1695.

Wermers, R. , 2002. A Matter of Style: The Causes and Consequences of Style Drift in Institutional Portfolios. (July) working paper, University of Maryland.

Wermers, R., 2003A. Are Mutual Fund Shareholders Compensated for Active Management Bets?. working paper, University of Maryland.

Wermers, R., 2003B. Is Money Really "Smart"? New Evidence on the Relation Between Mutual Fund Flows, Manager Behavior, and Performance Persistence. working paper, University of Maryland.

Wermers, R., Tong Yao, and Jane Zhao, 2007. The Investment Value of Mutual Fund Portfolio Disclosure (September), working paper, University of Maryland.

Zheng, Lu, 1999. Is money smart? A study of mutual fund investors' fund selection ability. Journal of Finance 54, 901–933.

Figure 1: Stock Subsequent Monthly (bp) Alpha by Portfolio Rank
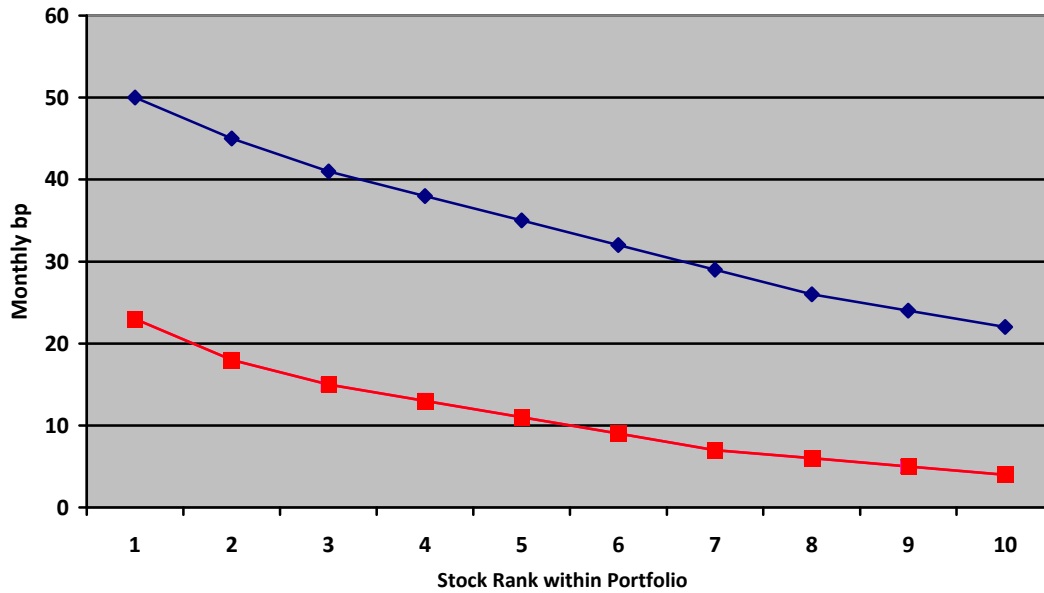
Based on Figure 3 in Cohen, Polk, and Silli (2009). The top line represents the mean bp monthly subsequent 6 factor alpha for the stock with the largest relative weight in each portfolio, the next highest and so forth. The bottom line represents 2 standard deviations below the mean.

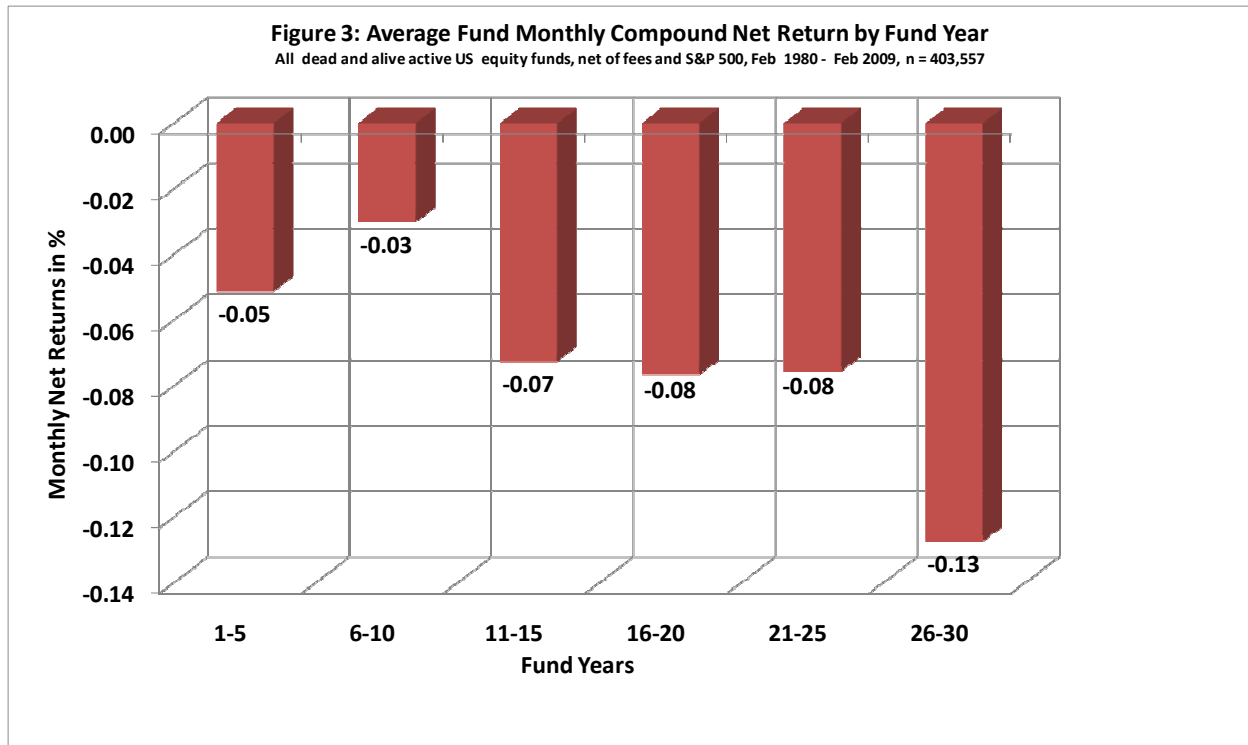**Figure 2: Incremental Reduction in Portfolio Standard Deviation**
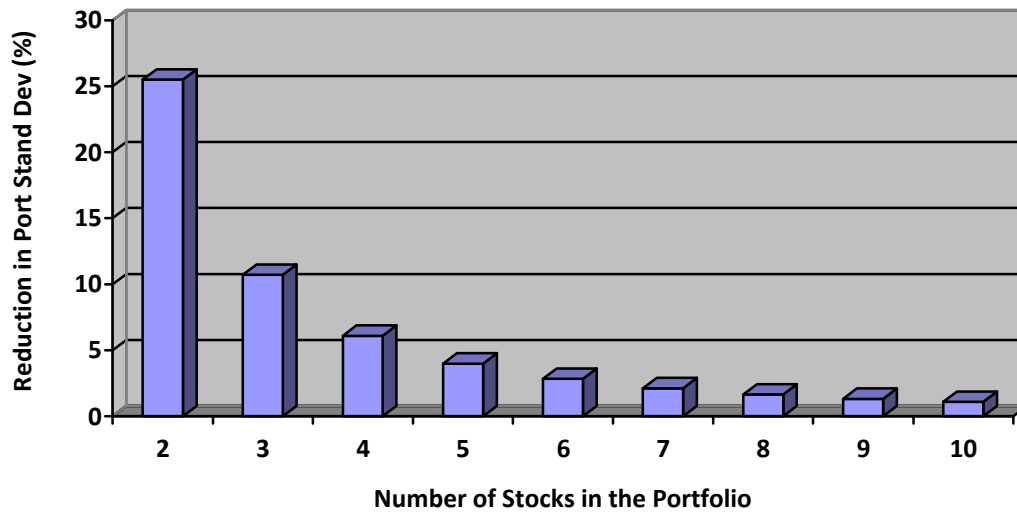
Based on the following assumptions: each stock added to the portfolio has the same standard deviation, has the same cross-stock correlation of 0.11, and is equally weighted in the portfolio.
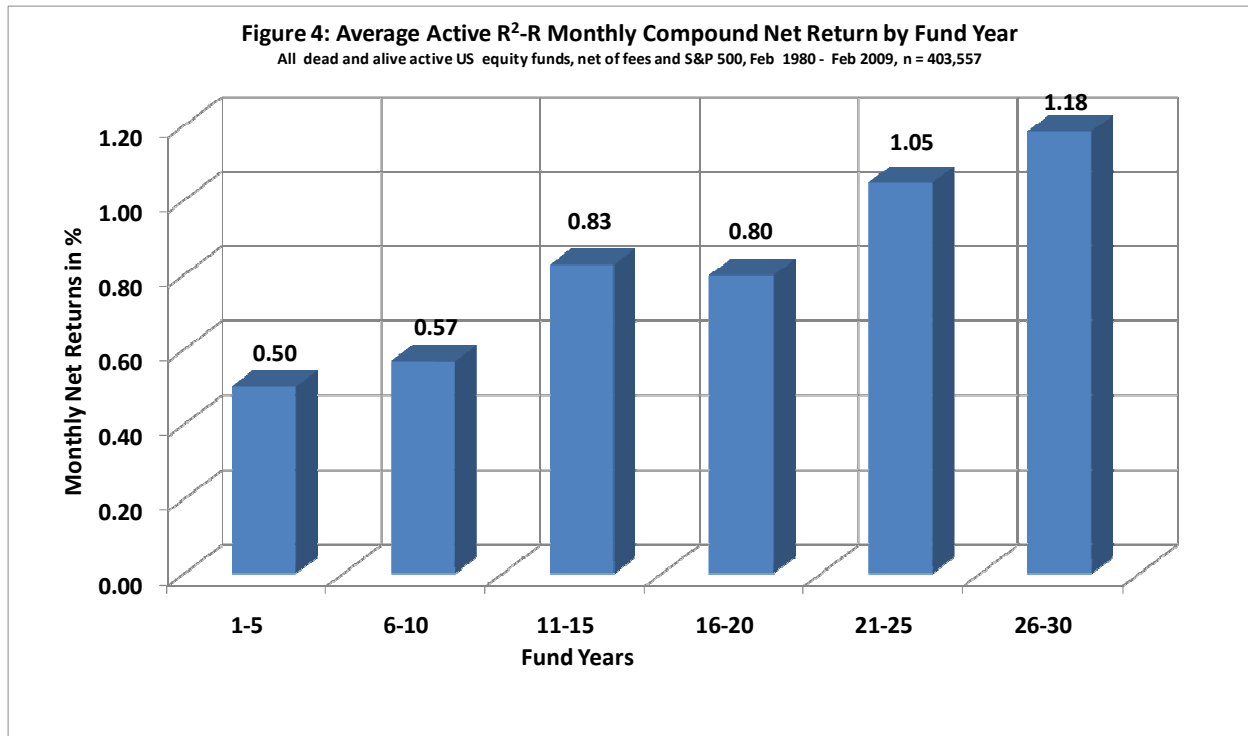
Figure 3: Average Fund Monthly Compound Net Return by Fund Year
All dead and alive active US equity funds, net of fees and S&P 500, Feb 1980 - Feb 2009, n = 403,557

Includes all active US equity open-end mutual funds over the period from February 1980 through February 2009. Index, lifecycle, target date, allocation, balanced, and 529 funds are excluded. This results in a sample of 4070 funds, with half still in existence in February 2009, for a total of 403,577 fund-month observations. The sample is survivor bias free since it includes all active US equity funds that existed in any month during this sample period. Excess monthly returns are net of the monthly S&P 500 return as well as automatically deducted management, trading, 12B-1 and other fees. Reported results are simple averages across funds.

Data source: Thomson Financial

Figure 4: Average Active R²-R Monthly Compound Net Return by Fund Year
All dead and alive active US equity funds, net of fees and S&P 500, Feb 1980 - Feb 2009, n = 403,557

Active RS1 - R1 are the funds at the beginning of each month that ranked in the bottom trailing 1 year S&P 500 R-squared quintile and the top trailing 1 year return quintile. Study methodology based on Amihud and Goyenko (2008). Sample includes all active US equity open-end mutual funds over the period from February 1980 through February 2009. Index, lifecycle, target date, allocation, balanced, and 529 funds are excluded. This results in a full sample of 4070 funds, with half still in existence in February 2009, for a total of 403,577 fund-month observations. The sample is survivor bias free since it includes all active US equity funds that existed in any month during this sample period. Excess monthly returns are net of the monthly S&P 500 return as well as automatically deducted management, trading, 12B-1 and other fees. Reported results are simple averages across funds.
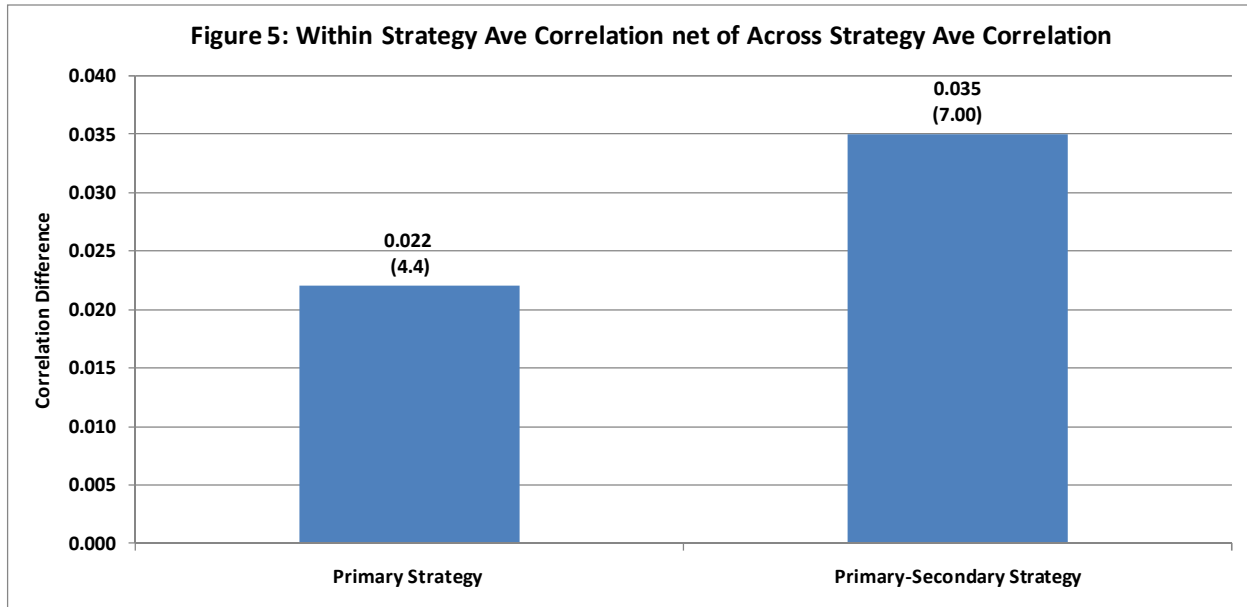
Data source: Thomson Financial.

The average across strategy correlations only include those correlations for which the strategy of interest is included in the correlation. Numbers in () are t values based on the random fund clustering standard error. Based on monthly returns for 2120 strategy identified open end funds over the period 1988-2007, resulting in 273,520 month-fund observations. Returns are net of automatically deducted fees but not load, sales, or other management fees. Fund correlations are calculated using all monthly returns available for the shortest time period of the two funds. Where number of strategy funds necessitates sampling, each sample is comprised of 100 randomly selected strategy funds and results in 9900 fund correlations.

Data sources: AthenaInvest and Thomson Financial.

Figure 6: Fund Clustering Metrics

Figure 7: SR versus Average Absolute Cluster Correlation
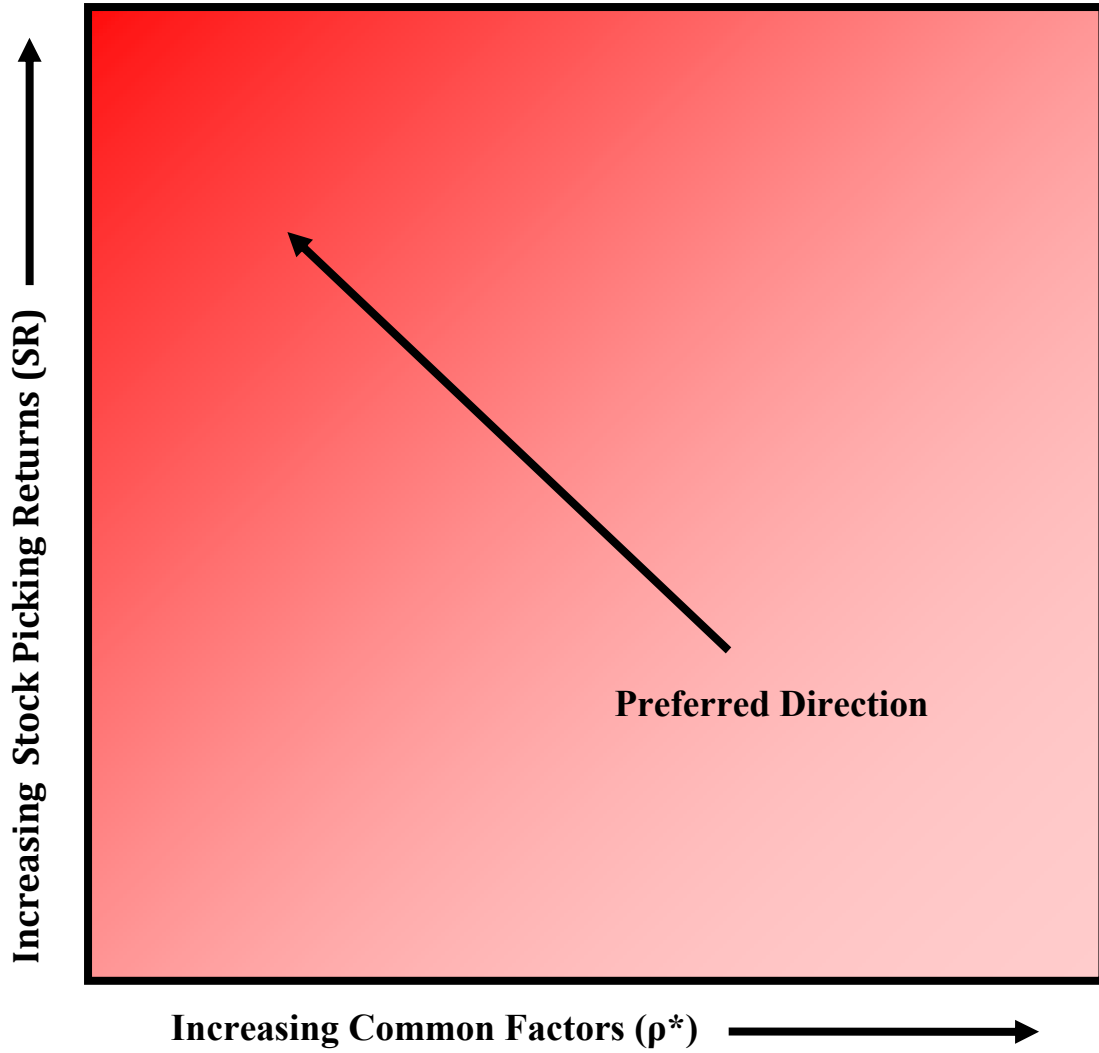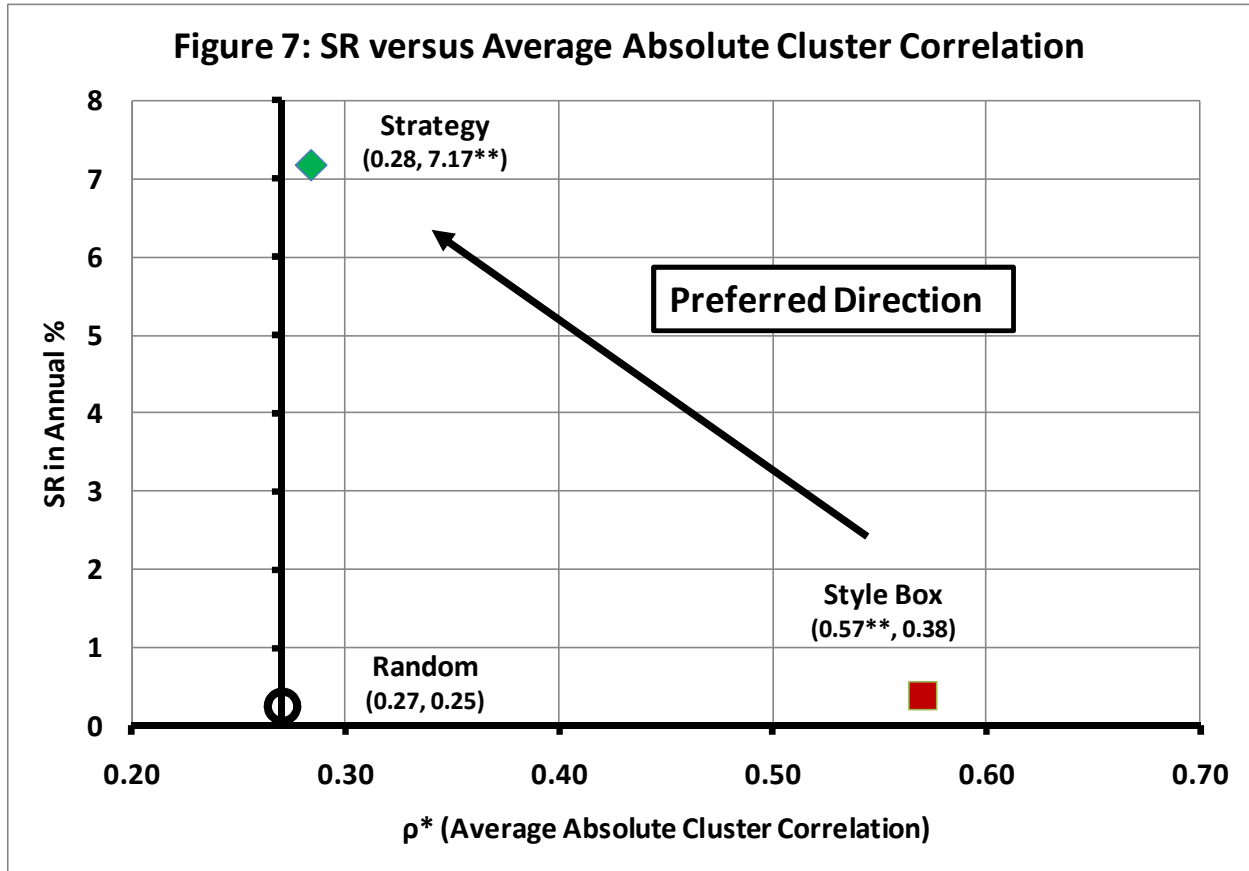
Random is random clustering of funds to one of 10 clusters. The values reported are averages over 700 trials. Style Box is clustering funds to one of 9 clusters based on their best fit market-cap/PE index. Strategy is assigning funds based one of 10 identified primary strategies. ρ^* is the average absolute across cluster correlation. Stock picking return (SR) is the s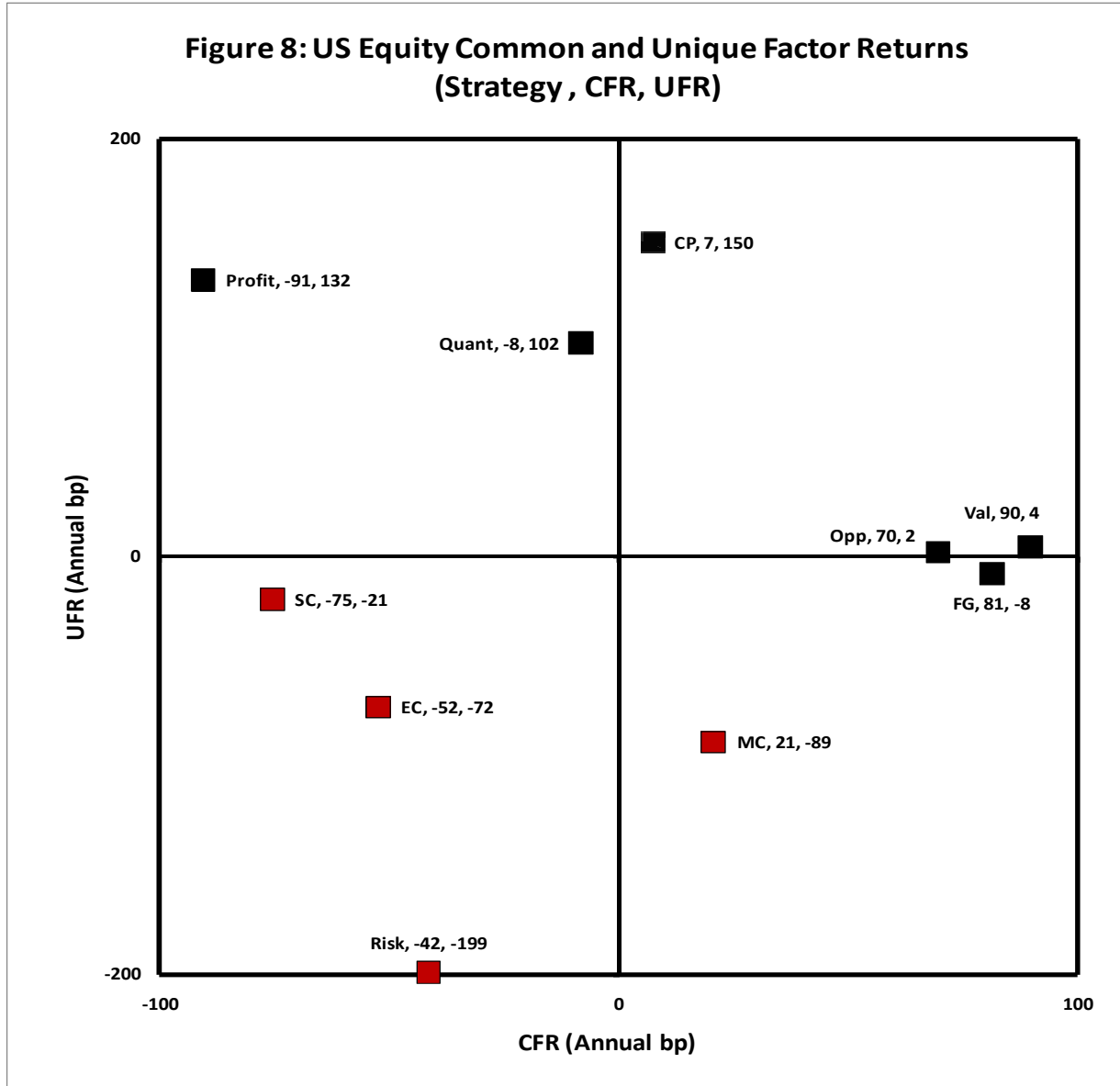lope coefficient of the regression of 1988-07 average monthly cluster returns on the average across cluster absolute correlation for which that cluster is one variable in the correlation calculation. Numbers in ()'s are average across cluster absolute correlation and skill return, respectively. ** Significantly different than the corresponding random value at the 95% confidence level. The stocking picking return (SR) estimate is biased adjusted, based on random results, using the equation: bias adjusted SR = raw SR - (ρ^* - 0.27) x 5.40. The test sample is comprised of all strategy identified US active equity funds as of December 2007. The 1988-2007 sample includes 408 strategy identified funds in January 1988, growing to 2120 in December 2007. The sample excludes index, allocation, 529, life and style funds, thus focusing exclusively on actively managed equity funds. Fund-month returns are calculated as a simple average over all fund share class returns for that month in that cluster. Monthly returns are net of the average monthly fund return and net of management, 12B-1 and other automatically deducted fees, but not of other fees such as load charges and third party management fees. Netting out the average monthly fund return makes it easier to focus on relative strategy performance. The sample includes 276,317 fund-month observations.

Data sources: AthenaInvest and Thomson Financial.

Figure 8: US Equity Common and Unique Factor Returns
(Strategy , CFR, UFR)

The 1988-2007 average annual strategy returns are decomposed , based on equation 1, into two components: CFR_i = common factor return for strategy i = SR x ρ^*_i , and UFR_i = unique (i.e. strategy specific) factor return for strategy i = e_i. The test sample is comprised of all strategy identified US active equity funds as of December 2007. The 1988-2007 sample includes 408 strategy identified funds in January 1988, growing to 2120 in December 2007. The sample excludes index, allocation, 529, life and style funds, thus focusing exclusively on actively managed equity funds. Fund-month returns are calculated as a simple average over all fund share class returns for that month in that cluster. Monthly returns are net of the average monthly fund return and net of management, 12B-1 and other automatically deducted fees, but not of other fees such as load charges and third party management fees. Netting out the average monthly fund return makes it easier to focus on relative strategy performance. The sample includes 276,317 fund-month observations.
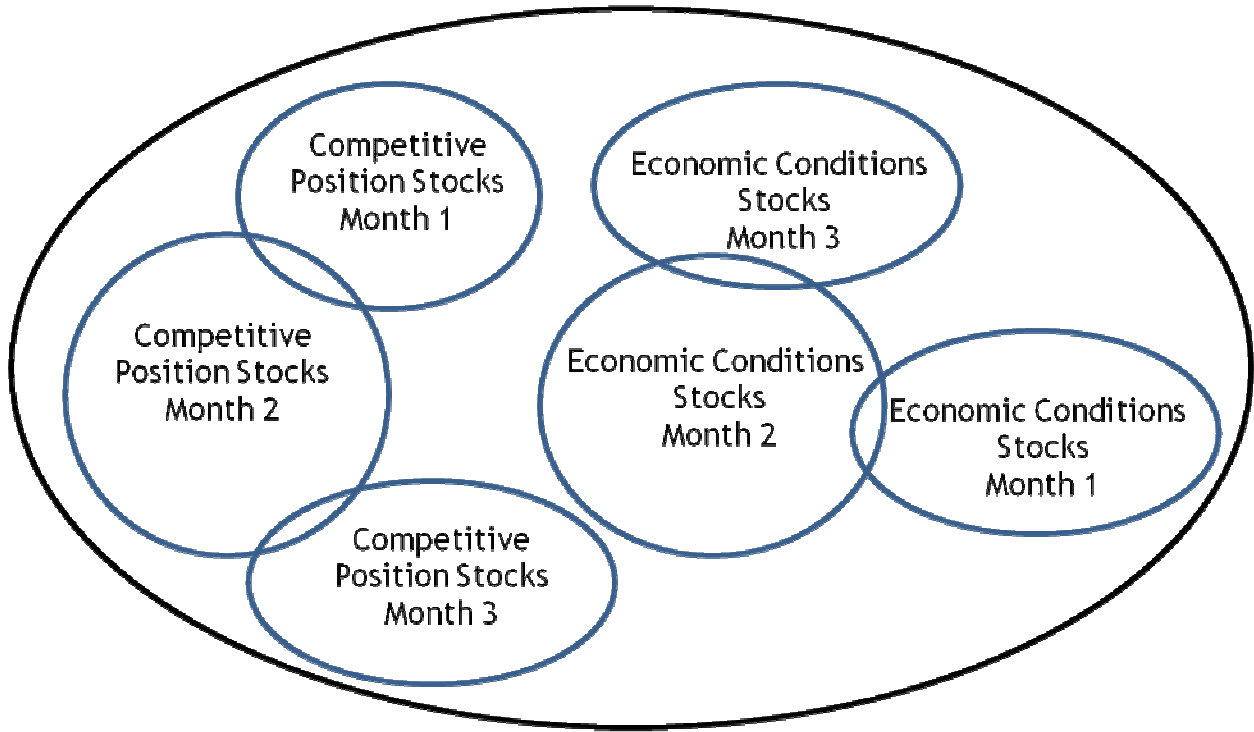
Data sources: AthenaInvest and Thomson Financial.

Figure 9: Movement of Strategy Stock Pools within the Equity Universe

Figure 10: Relative Market Cap Holdings over time for Opportunity and Social Considerations Strategies
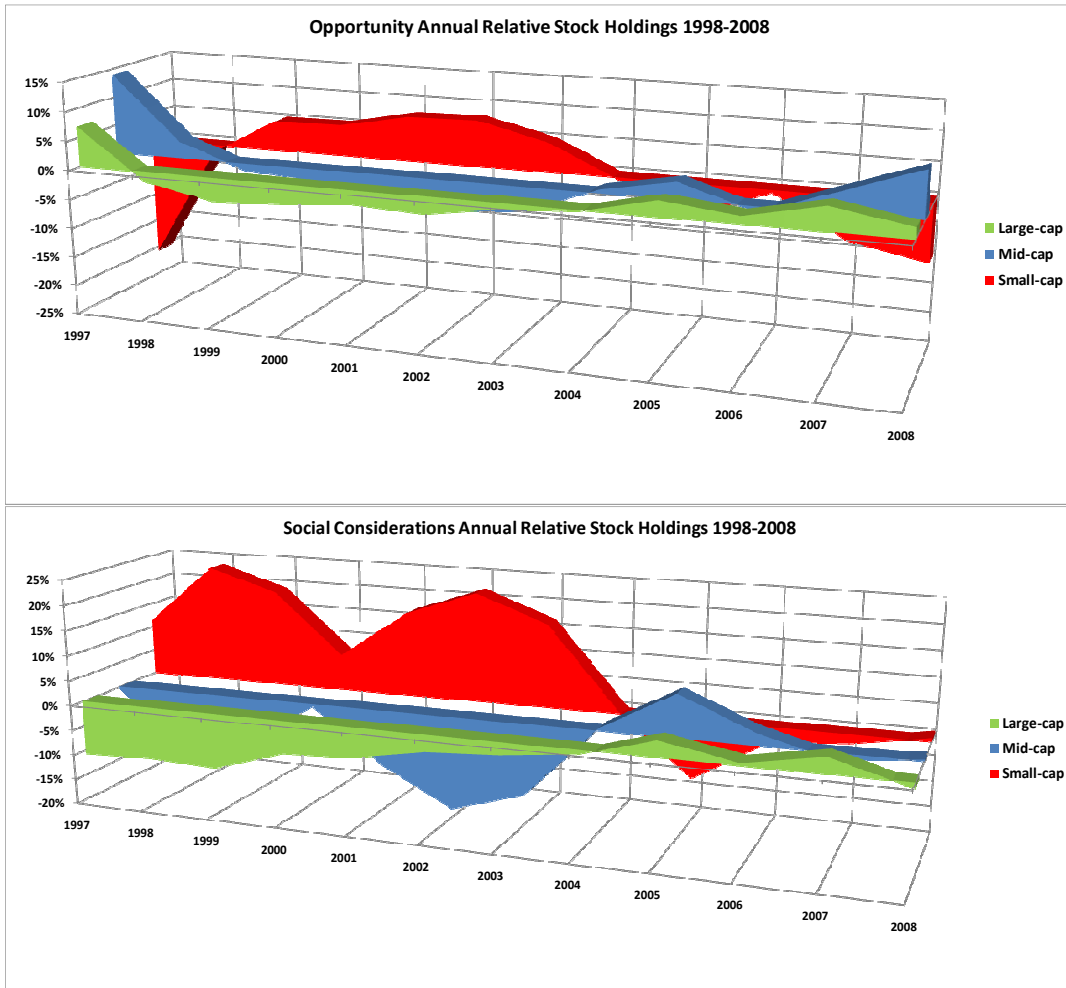
Numbers reported are annual deviations from the 12 year average holdings for each market cap within each strategy. Holdings are expressed in percent of stocks in that particular market cap category: Small-cap <$1b and Large-cap>$5b.

Data sources: AthenaInvest and Thomson Financial.

Figure 11: Relative Sector Holdings over time for Opportunity and Social Considerations strategies
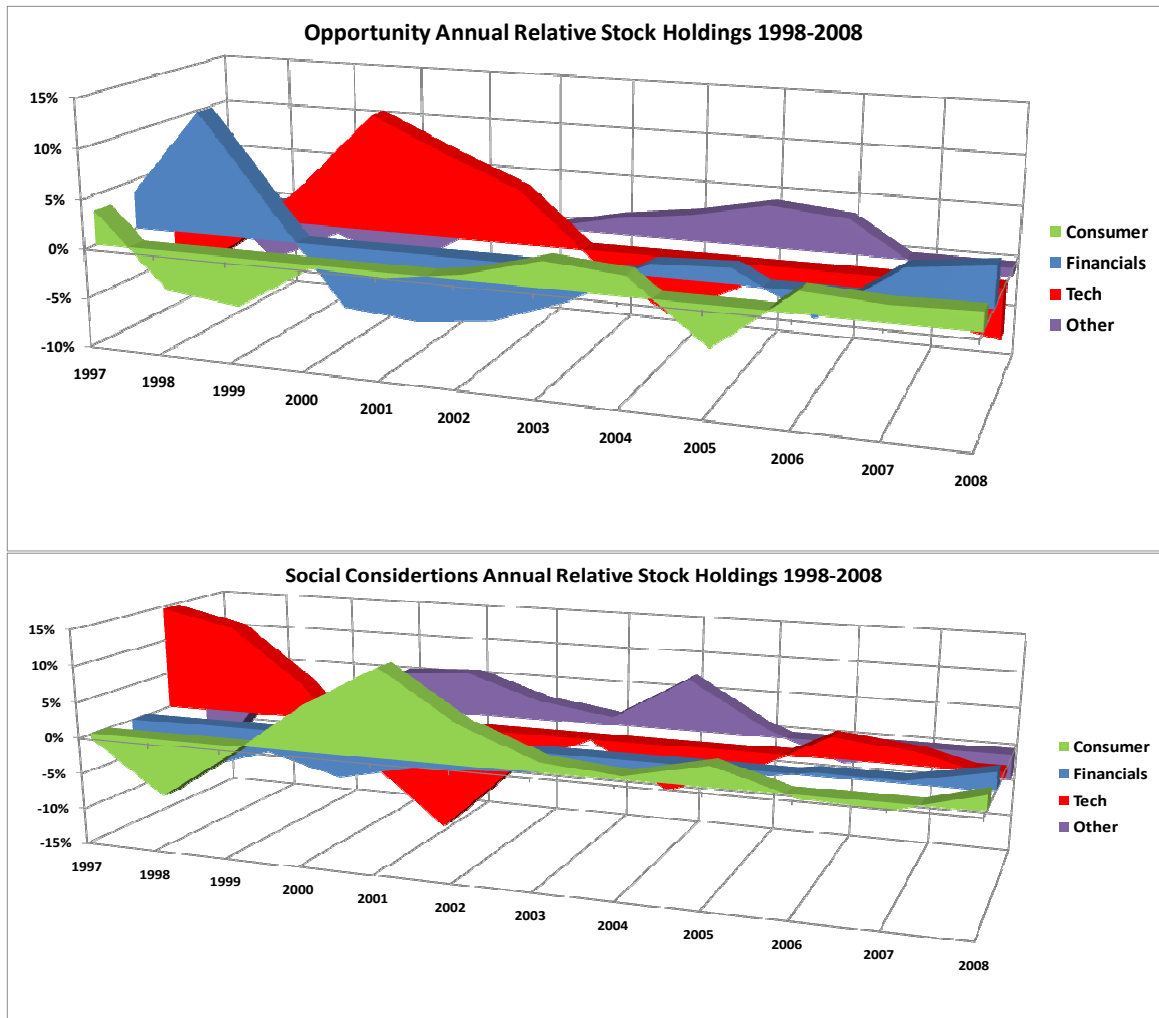
Numbers reported are annual deviations from the 12 year average holdings for each sector within the strategy. Holdings are expressed in percent of stocks in that particular sector.

Data sources: AthenaInvest and Thomson Financial.

Figure 12: Annual Excess Strategy Returns versus Strategy Consistency
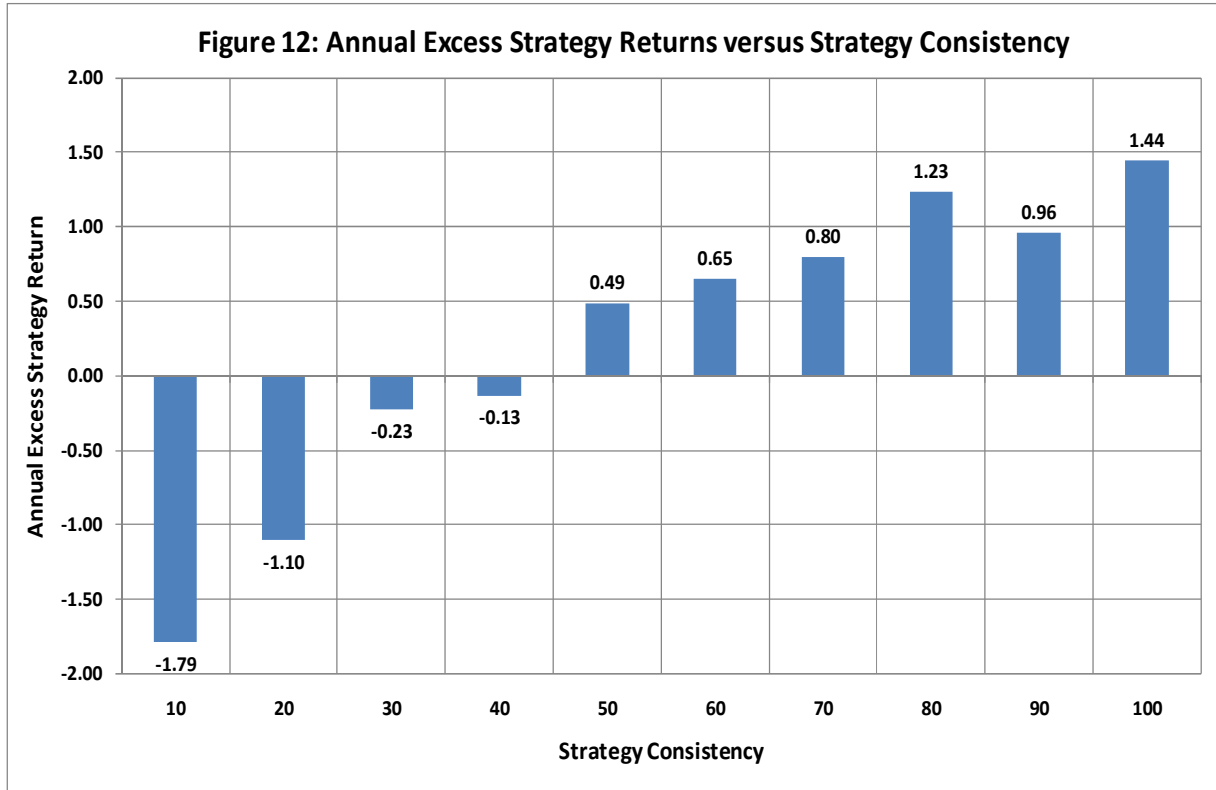
The monthly strategy consistency score is the primary strategy standard normal deviate of the percent of own strategy stocks held by the fund, scaled to be between 10 (lowest) and 100 (highest), and then rounded to the nearest 10. Based on 3065 strategy identified US and international equity mutual funds, resulting in 335,751 fund-month observations over the March 1997 to June 2009 time period. Updated monthly. The reported returns are the average subsequent month fund return net of automatically deducted fees and that month's average primary strategy return.

Data sources: AthenaInvest and Thomson Financial.

Figure 13: Annual Gains to Narrowly Defined Strategy
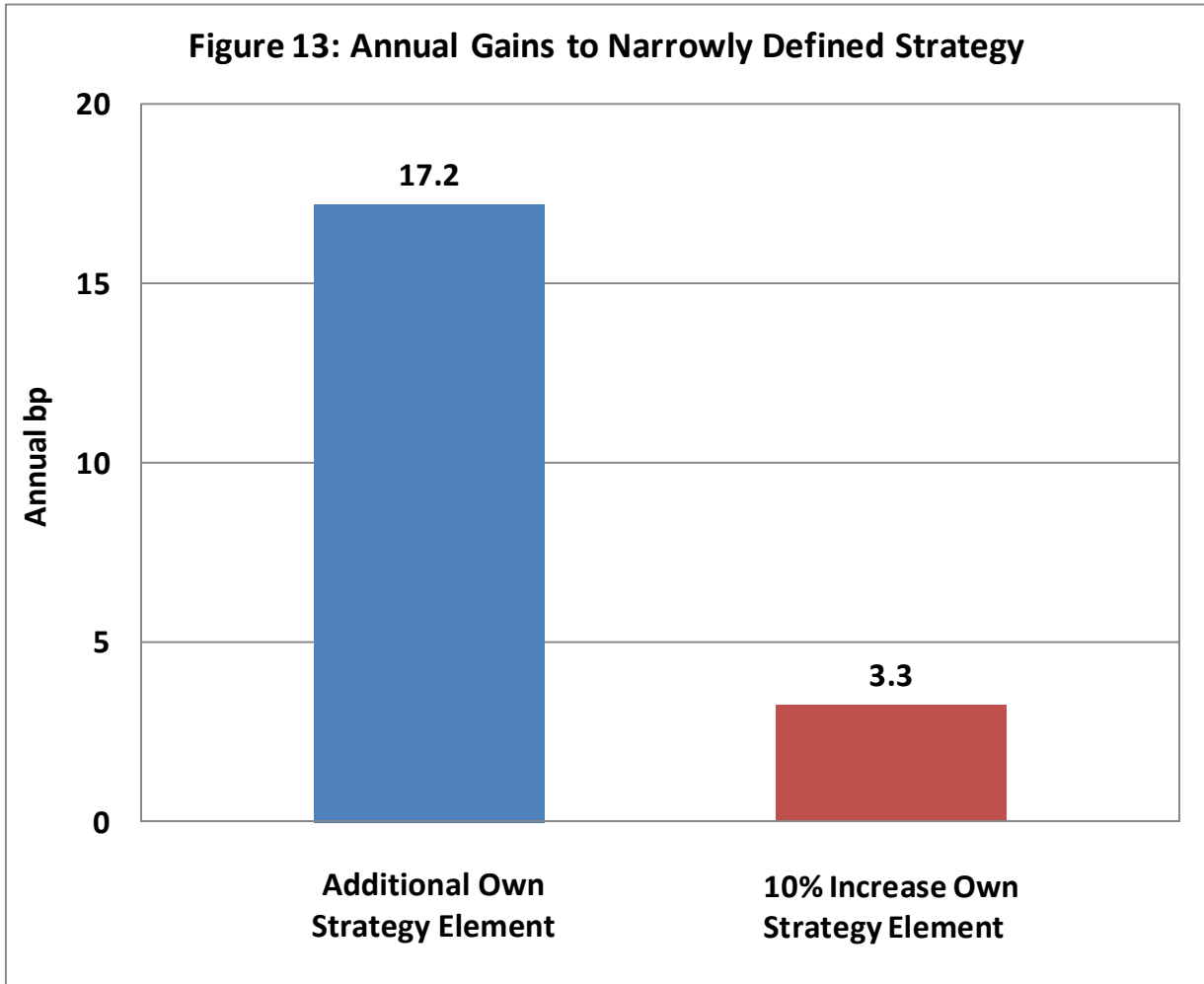
Above reports returns to an additional own strategy element (an element is a specific item upon which a manager focuses in pursuing a strategy) in absolute terms or in percent of total strategy elements. Sample includes all 2801 unique, strategy identified US equity and international equity funds. Returns are monthly average life-of-fund returns net of automatically deducted fees and net of the strategy average return for each month. Sample period January 1980 through June 2009.

Data sources: AthenaInvest and Thomson Financial.

Table 1: US and International Equity Strategies

Competitive Position: Business principles, including quality of management, market power, product reputation, and competitive advantage. Considers the sustainability of the business model and history of adapting to market changes.

Economic Conditions: Top down approach based on economic fundamentals; can include employment, productivity, inflation, and industrial output. Gauges where overall economy is in business cycle, the resulting supply and demand situations in various industries, and the best stocks to purchase as a result.

Future Growth: Companies poised to grow rapidly relative to others. The Future Growth and Valuation strategies are not mutually exclusive and can both be deemed important in the investment process.

Market Conditions: Consideration of stock's recent price and volume history relative to the market and similar stocks as well as the overall stock market conditions.

Opportunity: Unique opportunities that may exist for a small number of stocks or at different points in time. May involve combining stocks and derivatives and may involve use of considerable leverage. Many hedge fund managers follow this strategy, but a mutual fund manager may also be so classified.

Profitability: Company profitability, such as gross margin, operating margin, net margin and return on equity.

Quantitative: Mathematical and statistical inefficiencies in market and individual stock pricing. Involves mathematical and statistical modeling with little or no regard to company and market fundamentals.

Risk: Control overall risk, with increasing returns a secondary consideration. Risk measures considered may include beta, volatility, company financials, industry and sector exposures, country exposures, and economic and market risk factors.

Social Considerations: Company's ethical, environmental, and business practices as well as an evaluation of the company's business lines in light of the current social and political climate. A manager can look for these criteria or the lack of in selecting an stock.

Valuation: Stocks selling cheaply compared to peer stocks based on accounting ratios and valuation techniques. The Valuation and Future Growth strategies are not mutually exclusive and can both be deemed important in the investment process.

Table 2: US and International Active Equity Funds by Primary and Secondary Strategy

November 2009, excluding share classes

US Equity Funds by Primary and Secondary Strategy as of November 2009											
	Primary Strategy										
Secondary Strategy	**CP**	**EC**	**FG**	**MC**	**Opp**	**Profit**	**Quant**	**Risk**	**SC**	**Val**	**Total**
Competitive Position (CP)		30	231	1	8	9	20	2	25	241	567
Economic Conditions (EC)	159		22	4	4	1	8	1	3	39	241
Future Growth (FG)	209	8		1	7	11	16		8	88	348
Market Conditions (MC)	6	3	13		1		4	2	1	14	44
Opportunity (Opp)	8	2	10	2		2	3	1		55	83
Profitability (Profit)	36	2	19	1	2		2	1	4	80	147
Quantitative (Quant)	43	5	12	4	6	7		1	1	42	121
Risk	3	4	8			2	1	24		7	49
Social Considerations (SC)	2	1	2				2			2	9
Valuation (Val)	159	10	79	2	28	14	18	1	22		333
Total	**625**	**65**	**396**	**15**	**58**	**45**	**97**	**9**	**64**	**568**	**1942**

International Equity Funds by Primary and Secondary Strategy as of November 2009										
	Primary Strategy									
Secondary Strategy	**CP**	**EC**	**FG**	**MC**	**Opp**	**Profit**	**Quant**	**Risk**	**SC**	**Val**	**Total**
Competitive Position (CP)		49	38		2		8		8	69	174
Economic Conditions (EC)	97		3			1	2	4	2	17	126
Future Growth (FG)	54	13		1	1	1			1	12	83
Market Conditions (MC)		2					1	1		2	6
Opportunity (Opp)	5	3	2				2			10	22
Profitability (Profit)	6	2		1	1					25	35
Quantitative (Quant)	20	2	2	2		1		2		13	42
Risk	4	4	1		1		3		1	3	17
Social Considerations (SC)							1			1	2
Valuation (Val)	65	13	18		4		16		2		118
Total	**251**	**88**	**64**	**4**	**9**	**3**	**33**	**7**	**14**	**152**	**625**

Strategy identifying US and International active equity mutual funds was accomplished by gathering "Principal Investment Strategies" information from each fund's prospectus. The resulting information was input into the strategy identification algorithm. Over 45,000 pieces of prospectus strategy information were gathered for the active US and international equity funds (ignoring share classes) . The identification algorithm assigned specific strategy information to one of 40 elements, which were then assigned to one of ten equity strategies. The final identification algorithm was the result of a two year, iterative process involving manager interviews, gathering additional principal strategy information, and eliminating key words that generated false signals, while at the same time creating a system with a manageable number of strategies. In order to ensure accuracy, the strategy identifications assigned by the algorithm were subjected to a series of audits before being included in the data base.

Data source: AthenaInvest

Table 3: Annual US Equity Strategy Performance Statistics Based on monthly returns 1988 - 2007				
Strategy	**Fund-Mth Count**	**Ave Fund Return**	**Ave Fund SD**	**Ave Fund R^2**
Competitive Position	95,622	12.89	17.51	0.67
Economic Conditions	8,461	10.07	18.51	0.61
Future Growth	64,895	12.04	18.79	0.69
Market Conditions	1,606	10.63	18.44	0.60
Opportunity	5,798	12.03	14.11	0.63
Profitability	6,695	11.73	16.84	0.68
Quantitative	9,970	12.25	15.01	0.76
Risk	1,739	8.89	18.05	0.57
Social Considerations	5,134	10.35	16.24	0.69
Valuation	76,397	12.25	14.65	0.69
Total/Average	**276,317**	**11.31**	**16.89**	**0.68**

Average annual fund returns are annual compound returns using the 12 monthly simple average returns of all funds that existed in a particular month. The average fund standard deviation and best fit R^2 is the average over all individual fund 36 month standard deviations and best fit R^2 for that particular time period. The best fit R^2 is the best fit among the four Russell style indices. Sample includes all strategy identified funds as of December 2007. The sample includes 408 strategy identified funds in January 1988, growing to 2120 in December 2007. The sample excludes index, allocation, 529, life and style funds, thus focusing exclusively on actively managed equity funds. US active equity funds were strategy identified in 2007 and 2008 so a fund that does not exist in those years is not included in the sample. Fund-month returns are calculated as a simple average over all fund share class returns for that month. Returns are net of management, 12B-1 and other automatically deducted fees, but not of other fees such as load charges and third party management fees.

Data sources: Thomson Financial and AthenaInvest data bases, Russell Style Indices.

Table 4: Correlation Matrix for Monthly Strategy Net Returns: 1988-2007									
	CP	*EC*	*FG*	*MC*	*Opp*	*Profit*	*Quant*	*Risk*	*SC*	Val
Competitive Position										
Economic Conditions	0.11									
Future Growth	0.73	0.21								
Market Conditions	0.03	-0.18	0.36							
Opportunity	-0.42	-0.15	-0.73	-0.63						
Profitability	0.28	-0.21	-0.02	-0.26	0.12					
Quantitative	0.07	-0.23	-0.25	-0.36	0.42	0.13				
Risk	-0.45	0.16	-0.26	-0.27	-0.01	-0.22	-0.43			
Social Considerations	-0.14	-0.26	-0.14	-0.29	0.22	-0.02	0.13	-0.19		
Valuation	-0.43	-0.39	-0.86	-0.42	0.72	0.15	0.43	-0.04	0.22	

Average monthly returns net of the across fund average return that month, across all funds within a cluster that month, are calculated and the resulting monthly time series are used to estimate the above strategy correlation matrix. Netting out the average monthly fund return makes it easier to focus on relative strategy performance. Sample includes all strategy identified funds as of December 2007. The sample includes 408 strategy identified funds in January 1988, growing to 2120 in December 2007. The sample excludes index, allocation, 529, life and style funds, thus focusing exclusively on actively managed equity funds. US active equity funds were strategy identified in 2007 and 2008 so a fund that does not exist in those years is not included in the sample. Fund-month returns are calculated as a simple average over all fund share class returns for that month. Returns are net of management, 12B-1 and other automatically deducted fees, but not of other fees such as load charges and third party management fees.

Data sources: AthenaInvest and Thomson Financial.

Table 5 : Stock Strategy Categorization and Strategy Profiles											
Stock	**Strategy**	**CP**	**EC**	**FG**	**MC**	**Opp**	**Prof**	**Quant**	**Risk**	**SC**	**Val**
Acuity Brands Inc	Opportunity	17.3%	0.0%	7.4%	0.0%	36.3%	0.0%	14.1%	0.0%	0.0%	24.9%
Cameron International Corp	Economic Conditions	12.4%	70.2%	11.1%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	6.2%
Pepsico Inc	Social Considerations	13.8%	6.0%	16.7%	11.5%	5.2%	14.2%	10.4%	0.0%	20.7%	1.5%

Strategy profiles based on the <u>relative</u> importance of each stock within each strategy. For example, Acuity's strategy profile is comprised 36.3% of Opportunity and 24.9% of Valuation, along with other less important strategies. Acuity Brands is strategy categorized Opportunity since this strategy has the largest percentage in the strategy profile. This, however, does not mean 36.3% of the dollars invested in Acuity come from Opportunity funds, while 24.9% come from Valuation funds. In fact, Valuation funds had $91.7 million invested in Acuity at the time, while Opportunity funds had only $4.0 million invested, because there are many more Valuation funds than Opportunity funds and the average Valuation fund is larger than the average Opportunity fund. But Acuity is relatively more important among Opportunity funds than among Valuation funds and so it is categorized an Opportunity stock. The strategy profile and the resulting strategy categorization attempts to capture the relative bets placed by the different strategies in a stock. The supposition is that the higher is the stock's relative importance within a strategy, the more compelling is the investment case for the stock. This is a way to capture valuable information regarding the analytic conclusions and subsequent decisions made by strategy managers.

Data source: AthenaInvest

Table 6: US Stock Strategy Categorization Statistics				
Strategy	**% of Funds**	**% of Stocks**	**Months in Strategy**	
			Average	Maximum
Competitive Position	35.0%	30.1%	20	134
Economic Conditions	3.0%	6.0%	11	133
Future Growth	23.4%	16.4%	18	129
Market Conditions	0.7%	2.6%	8	93
Opportunity	1.9%	4.0%	12	97
Profitability	2.4%	3.5%	11	110
Quantitative	3.6%	8.1%	16	136
Risk	0.6%	1.7%	11	110
Social Considerations	1.8%	3.0%	13	98
Valuation	27.5%	24.6%	28	136
Average			15	118

This table provides fund and stock strategy data, as well as the average and maximum number of months a stock stayed in a strategy. US stocks held by strategy identified active US equity mutual funds with less than $1b in assets under management were strategy identified monthly from January 1997 through September 2008. The stock strategy categorization procedure is described in the notes to Table 5. Larger funds were excluded because stock selection may be driven more by diversification considerations rather than by strongly held investment beliefs. This resulted in 397,364 stock-month strategy categorizations, an average of 2,818 stocks per month.

Data source: AthenaInvest