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The Success of Long-Short Equity Strategies versus Traditional Equity Strategies & Market Returns

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SUBMITTED TO

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Abstract

This study examines the performance of long-short equity trading strategies from January 1990 to December 2010. This study combines two financial screens that will yield candidates for both long and short positions for each month during the aforementioned time period. Two long-short strategies are tested: (1) perfectly-hedged, or equal allocation to long and short positions, and (2) net-long. The results of this thesis reveal that if a long-short equity manager is able to successfully determine what companies are overvalued and undervalued and actively rebalance their portfolio, perfectly-hedged and net-long strategies can generate superior risk-adjusted alpha.

1. Introduction

From hedge funds to endowment funds, many institutions in the world of finance have begun to implement a new investment strategy: absolute return. Many managers disapprove of the name "absolute return" because the concept is deceptive; in the world of investing, there are no guaranteed returns. If returns could be guaranteed, investment managers would become obsolete. At the most fundamental level, absolute return strategies attempt to exploit positions on securities that possess little or no correlation to traditional asset classes such as equities and fixed income instruments (Swensen 2009). Absolute return strategies can be broken into two categories: event-driven investments such as capital structure arbitrage or merger arbitrage and value-driven investments such as hedged long-short portfolios (Swensen 2009). According to David Swensen, Chief Investment Officer of the Yale University Endowment Fund, event-driven positions hinge on the occurrence of corporate finance transactions such as two companies merging or a company emerging from bankruptcy (Swensen 2009). Value-driven investing implies a portfolio of both long and short positions, which should theoretically diversify out the majority of an investor's exposure to market risk (Swensen 2009).

Though absolute return is certainly a burgeoning concept, long-short strategies are not new to the investment world. The existence of a trading strategy called absolute return begs the question should everyone have an absolute return fund? What is stopping absolute return from becoming the new law of the land in the investment universe? The purpose of this thesis is to identify whether long-short equity strategies truly deserve their classification as absolute return.

Swensen's introduction to long-short equity strategies explains "[v]alue-driven absolute return strategies rest on the manager's ability to identify undervalued and overvalued securities, establish positions, and reduce market exposure through hedging activity" (Swensen 2009). Value-driven investing is the manager's ability to go long on undervalued stocks, as presumably these prices will go up, and go short on overvalued stocks, assuming these prices should fall. In doing so, the manager has essentially provided some insulation from market forces because of the offsetting of long and short positions. This study mimics Swensen's explanation of long-short equity strategies.

In keeping with Swensen's procedure, I will first create a portfolio of long-short positions. Companies that are undervalued will be candidates for long positions and overvalued firms will be candidates for short positions. I have identified two screens based on book-to-market ratios that I will use to determine undervalued and overvalued companies. Upon completion of the portfolio of long-short positions, I will collect return data from CRSP in order to evaluate the performance of the perfectly-hedged portfolio and net-long portfolios against traditional long-only returns and market returns. If these long-short strategies outperform the traditional long-only equity portfolios and market indices, perhaps long-short equity trading will deserve its classification as absolute return.

2. Background

2.1 The Emergence of the Long-Short Equity Strategy

A standard, all-encompassing definition of a long-short equity hedge fund does not exist. Managers can choose to operate their long-short portfolios in different ways. In order for a long-short equity strategy to bear the label market-neutral, each long position and short position must have the same dollar amount (Swensen 2009). Though market-neutral strategies do exist, most managers are typically net-long because of the added risk that comes with shorting a stock. If an investor's short position actually increases in value, or the price of the stock rises, that investment becomes a larger portion of their portfolio (Swensen 2009). With a long position, however, as stock prices decrease, the position becomes a smaller portion of the portfolio (Swensen 2009). In order for a long-short equity strategy to excel, the portfolio must be carefully constructed and actively rebalanced.

The inception of pure long-short equity hedge funds marks the increasing popularity of the investment strategy. According to a research paper published by R. Lamm (2004), Duetsche Bank's Chief Investment Strategist, the liquidity of the long-short market has increased faster than any other hedge fund strategy. In the last decade, the average long-short equity manager's total assets under management have increased by 20% (Lamm 2004). The unmatched growth of the strategy has displaced global macro strategies as the leading investment strategy for hedge funds. In the early 1990s, long-short strategies accounted for less than 10% of hedge fund portfolios but by 1999, hedge funds were allocating 45% of their funds to long-short managers (Lamm 2004).

The early success of the long-short managers reveals a heightened awareness of a money manager's ability to generate pure alpha, or return in excess of the market return. Any manager can do well if the market is doing well. The true test of a manager's alpha-generating ability is the performance of the fund through both bullish and bearish markets. Through business cycles, long-short equity strategies have historically outperformed traditional long-only managers while maintaining significantly lower risk. In the three years following the rupture of the stock market bubble in 2000, assets under management for long-short equity hedge funds increased from \$133 billion to \$205 billion, despite the fact that the S&P declined 17% during the period (Lamm 2004). The performance of long-short equity funds account for this increase in assets managed. While the S&P was incurring double-digit losses, the hedged portfolios experienced only slightly negative returns (Lamm 2004). The performance of long-short equity funds from 2000-2003 reveals the advantage of hedged portfolios: long-short portfolios capture a majority of the upside of long-only managers, and much less of the downside (Lamm 2004). As markets started to decline, long-short equity managers began to rebalance their net-long positions and hedge with more short positions. In comparison to the equity markets, long-short portfolios carry significantly less risk with virtually the same upside returns and less downside returns in bearish markets. Because long-short equity managers generate superior risk-adjusted returns, or higher overall returns with less risk, the strategy is one that should be considered in the investment universe.

One limitation to the historical performance numbers on long-short equity strategies emphasized by both Swensen and Lamm is the "survivorship bias" associated with the return streams (Swensen 2009). The long-short equity funds that research organizations collect data from are the long-short equity managers that are strong enough to have survived the market thus far; any long-short hedge funds that have failed are not incorporated in the performance results. The survivorship bias undoubtedly overestimates the positive performance of the long-short equity hedge funds. According to Lamm however, even adjusting historical long-short equity performance downward to account for the survivorship bias, the new hedge fund strategy still outperforms traditional long-only managers and market returns. This thesis will eliminate the survivorship bias because it will not test any one long-short fund or manager, but rather a general long-short portfolio across the entire market from 1990 to 2010.

2.2 Literature Review

Swensen shrewdly warned that the success of a long-short equity strategy depends on the manager's ability to select undervalued and overvalued firms. Joseph D. Piotroski and his colleague Partha S. Mohanram built two separate scores that attempt to qualify firms as overvalued or undervalued based on book-to-market ratios. Joseph D. Piotroski performed a study that uses historical financial statement analysis to predict future firms with a high book-to-market (BM) ratio that are likely to have continued growth and strong financial performance. Partha S. Mohanram built off Piotroski's research and applied it to firms with low book-to-market ratios. This study will use Piotroski's research to identify high book-to-market firms that are strong candidates for a long position and Mohanram's analysis to acquire low book-to-market firms positioned for short plays.

Joseph D. Piotroski (2000) wrote an article titled "Value Investing: The Use of Historical Financial Statement Information to Separate Winners from Losers", in which he attempts to separate a pool of high book-to-market firms into potential winners and losers. As Piotroski's colleague Mohanram explains, the BM ratio of a firm is a strong indicator of a firm's future stock performance (Mohanram 2005). Piotroski developed a score to evaluate companies to determine the overall strength of the company. High book-to-market firms are usually associated with financial distress due to consistently low profit margins, inconsistent cash flows, and increasing financial leverage ratios (Piotroski 2000). Piotroski explains that because of this, investing in high BM firms is a contrarian investment strategy because analysts usually refrain from recommending high BM firms (Piotroski 2000). In evaluating the future performance of firms, Piotroski's score uses financial indicators that examine the overall financial position of the firm. Piotroski's nine variables are derived from three areas that test the firm's financial position: profitability, liquidity, and operating efficiency. Piotroski's test, which he deems the F-Score, is a summation of nine binary financial indicators (Piotroski 2000). If the firm has a positive financial signal, such as their leverage ratio decreased from last year, the firm is rewarded a one for that variable. If the firm's financial signal is weak, the firm will receive a zero on that variable. The nine variables are summed to create the F-Score. If a firm scores a nine out of the nine binary variables on the Piotroski F-Score, this firm is a superior candidate for a long position (Piotroski 2000).

To test the firm's future profitability, or the firm's ability to generate cash flows from internal operations, Piotroski first examines the return on assets (ROA) and the firm's cash flow from operations (CFO). If the firm's ROA and CFO are positive, the firm scores a one on both of these variables: F_{ROA} and F_{CFO}. The third variable is change in ROA (ΔROA), which is the difference between the current year's ROA and the previous year's ROA. If ΔROA is greater than zero, then the firm has heightened the efficiency of its asset base and earns a one for the third variable: $F_{\Delta ROA}$. The final variable that constitutes the profitability test of the firm is the difference between the CFO and ROA. If the firm's cash flows are greater than the return on assets, then the firm is awarded a one on the final profitability variable: $F_{ACCRUAL}$ (Piotroski 2000).

Piotroski's F-Score also evaluates a firm's liquidity, or the ability to cover future debt obligations. The first ratio is the measure of a firm's long-term debt to average total assets, which measures the company's leverage. To be awarded a one for this variable, $F_{\Delta LEVER}$, the firm's current leverage ratio must be less than the previous year's leverage ratio, or $\Delta LEVERAGE < 0$ (Piotroski 8). Piotroski explains that deleveraging is a symbol of financial health for financially distressed firms, which describes most high BM firms. Another variable used to judge the financial security of the company is the current ratio, or the ratio of current assets to current liabilities, which Piotroski labels liquidity. A firm achieves a one for the variable F_{LIQUID} when the current ratio has increased since the previous fiscal year, or $\Delta LIQUIDITY > 0$. An increasing current ratio is a sign that the company is better equipped to cover their outstanding debt obligations (Piotroski 8). The final measure of financial stability is whether or not the company has issued common stock within the last fiscal year. A company earns a one on $F_{EQOFFER}$ if they have not sold common stock within the past year, because this demonstrates that the company has enough funds to cover their obligations without raising extra capital. The equity offering indicator is especially significant for potentially distressed firms because it is a sign that the company has enough cash and marketable securities to service their current debt obligations, which indicates that the firm is not in immediate danger of bankruptcy (Piotroski 2000).

The final category for measuring the financial performance of the firm is the operating efficiency. The two variables that Piotroski considers are the change in the firm's gross margin ratio and the change in the firm's total asset turnover. For both ratios, if the difference between this current year and the previous year is greater than zero, the firm earns a score of one. A rise in the firm's gross margin suggests one of two things: the firm has efficiently cut costs or raised revenues, both emblematic of financial success. Similarly, an increase in the total asset turnover ratio signifies that the firm has increased the efficiency of their asset base (Piotroski 2000).

Ultimately, Piotroski generates the final F-Score by summing each of the nine binary variables. The F-Score can be calculated as follows:

$$FScore = F_{ROA} + F_{CFO} + F_{\Delta ROA} + F_{ACCURAL} + F_{\Delta LEVER} + F_{\Delta LIQUID} + F_{EQOFFER} + F_{\Delta MARGIN} + F_{\Delta TURN} \qquad (1)$$

Firms who obtain a score of eight or nine are deemed worthy of a long position because the score predicts future financial success (Piotroski 2000).

Five years after Piotroski published his score, Partha Mohanram (2005) published a similar research paper that created a financial statement analysis score to judge the financial health of low book-to-market firms. According to Mohanram, low BM firms are typically growth-oriented, “glamour” firms that are overvalued because investors have overestimated the future growth potential of the firm due to strong current earnings and exceptional recent growth (Mohanram 2005). Mohanram examines firms whose BM ratios are equal to or below the 20^{th} percentile of the market (Mohanram 2005). The G-Score consists of ratios that aim to test the firm’s profitability and security of cash flows, but also attempts to detect if the firm is overvalued or if the firm is simply a low BM firm because of conservative accounting (Mohanram 2005).

Mohanram’s first group of ratios mimics Piotroski’s F-Score, as they are basic financial valuation ratios to test the firm’s profitability, or likelihood of future cash flow streams. Unlike Piotroski’s traditional financial statement ratio analysis however, Mohanram evaluates the firm’s financial ratios against the industry median. In Mohanram’s G-Score, the first variable considered is ROA, and the firm earns a one if their ROA is greater than the industry median: $G_{ROA} = 1 \; if \; ROA > ROA \; Industry \; Median$. The second variable Mohanram employs is a modified ROA, instead of net income scaled by total assets, Mohanram commissions a more conservative measure of ROA: cash flows scaled by total assets. Mohanram argues this measure is particularly important for firms with low BM ratios because growth firms typically make large investments in fixed or intangible assets. Like the binary condition for ROA, a firm earns a one if its cash flow ROA exceeds the industry median: $G_{ROACFO} = 1 \; if \; CFROA > CFROA \; Industry \; Median$. Just as Piotroski scored a firm on an accrual variable, Mohanram’s final profitability ratio tests the firm's accrual generating power. A firm earns a one if its cash flows from operating activities exceed the firm's net income: $G_{CFONI} = 1 \; if \; CFO > Net \; Income$ (Mohanram 2005).

Mohanram incorporates two variables to reveal whether the firm's growth has been overestimated because of inflated current earnings and exaggerated growth potentials. The first variable examines the firm's earnings variability. According to Mohanram, firms with stable earnings will separate low BM firms who have solid future prospects from those "glamour" firms that are riding on the coattails of overestimated growth opportunities. A firm earns a one for stable earnings if their earnings volatility is less than the industry median, or $G_{EarnVar} = 1 \; if \; Earn. Vol. < Industry \; Median \; EV.$ Mohanram also considers the variability in a firm's sales growth, and a firm earns a one if their sales growth volatility is less than that of the industry median: $G_{SalesGrowthVar} = 1 \; if \; Sales \; Growth \; Vol \; < Industry \; Median \; Sales \; Growth \; Vol.$ If a firm earns a one on both of these indicators, it is clear the firm's low BM ratio cannot be attributed to the high-growth glamour factor (Mohanram 2005).

The final category of ratios examines factors that may underestimate current earnings, which may depress the book value of the firm in the short-term, but will ultimately lead to future growth. An increase in Research & Development expenses (R&D), capital expenditures, and advertising expenses are factors that Mohanram identifies as possible explanations for a firm's current low BM ratio. For Mohanram, an increase in each of these expenses means the firm is deploying capital today to increase growth prospects for the future. Mohanram's score includes R&D expenses, capital expenditures, and advertising expenses as evident of future growth opportunities. Firms will be awarded a one for the variables G_{RDEx}, G_{Capex}, and G_{AdEx} if the firm's expenses exceed the industry median expenses (Mohanram 2005).

Like Piotroski's score, the Mohanram G-Score is merely a summation of the eight binary variables. The final G-Score is calculated as follows:

$$GScore = G_{ROA} + G_{ROACFO} + G_{CFONI} + G_{EarnVar} + G_{SalesGrowthVar} + G_{RDEx} + G_{Capex} + G_{AdEx} \qquad (2)$$

Firms who obtain a score of zero or one are candidates for the short position because the score reveals these firms are glamour firms that are overvalued (Mohanram 2005).

This study will combine the F-Score and the G-Score to generate a portfolio of long and short positions and then use the portfolio to test long-short equity strategies versus market returns and traditional long-only portfolios.

3 Data Methodology and Description

3.1 Updating and Combining the F-Score and G-Score

According to Piotroski, prior research reveals a portfolio of high BM firms would consistently outperform a portfolio of low BM firms (Piotroski 2000). Mohanram discusses that in general, high BM firms earn impressive positive excess returns where as low BM firms generate significant negative excess returns (Mohanram 2005). Because the F-Score better predicts high BM firms that are potential winners and the G-Score reveals potential low BM losers, this thesis aims to combine these two screens to yield a superior long-short portfolio.

The results of Piotroski and Mohanram's screens confirm the success of each of their scores and the rationale that Piotroski's F-Score (Mohanram's G-Score) should be used for long positions (short positions). The high BM firms that scored an eight or a nine on Piotroski's F-Score generated 13.4% return and the high BM firms that scored a zero or a one earned -9.6% return over the entire period of the study from 1976 to 1996 (Piotroski 2000). Similarly, firms with the highest G-Score yielded 3.1% return and firms with the lowest G-Score earned -17.5% return from 1978 to 2001 (Mohanram 2005). The portfolio constructed for this study will use low BM firms that score a zero or one on Mohanram's G-Score for short positions and will take high BM firms that earn an eight or nine on Piotroski's F-Score.

In order to obtain the data to replicate and update the F-Score and G-Score, the data set for this study began as a sample of all of the firms in the CRSP/Compustat merged data sets.[1] Data on all of the financial information necessary to calculate each of the ratios of the F-Score and G-Score was obtained from the CRSP/Compustat database. Though the preliminary data set included every company in existence since 1950, any firms that existed before 1970 had to be eliminated due to lack of populated data points.[2] This study also excludes financial firms because the F-Score and G-Score use financial ratio tests that do not accurately test the health of a financial firm.[3]

For the long positions, I generated an updated version of Piotroski's F-Score by downloading all of the required financial information necessary to score each F-Score variable. A description of each F-Score variable is available in *Table 1.1*. For F_{ROA} and $F_{\Delta ROA}$, net income is scaled by total assets, both of which were obtained from the CRSP/Compustat data. Some changes had to be made to the variables that require a measure of cash flows: F_{CFO} and $F_{ACCURAL}$. The variable CRSP/Compustat provides for operating net cash flows (oancf) was poorly populated. Upon further examination, it became evident that firms reported operating cash flows under the variable oancf after the fiscal year 1987, but had previously reported under the variable called finances from operating activities (fopt). In order to gain an accurate operating cash flow variable, I had to merge the oancf and fopt data points into one cash flow variable.

[1] The data for the F-Score and G-Score simulation was obtained from CRSP/Compustat merged data sets available through University of Pennsylvania's Wharton Research Data Services.
[2] The data was sorted by Fiscal Year and any data points before 1970 were excluded from this study.
[3] The data was sorted by SIC code and any companies between 6021 and 6411, according to the SIC database, are financial services firms and therefore had to be excluded from this study.

Piotroski used three variables to judge a firm's liquidity: $F_{\Delta LEVER}$, $F_{\Delta LIQUID}$, and $F_{EQOFFER}$. In order to obtain the change in each firm's leverage ratio, long-term debt and total assets figures were retrieved from the CRSP/Compustat database. Piotroski's liquidity variable is simply a current ratio, or current assets divided by current liabilities. For the equity offering variable, Piotroski believes that an equity offering, especially for high book-to-market firms, is a sign of poor financial health because the company is presumably raising capital to service debt obligations. To determine whether a firm issued equity the year proceeding the examined fiscal year, I used the variable sstk provided by the CRSP/Compustat merged dataset. The variable sstk describes any new sales of common or preferred stock taken from a firm's statement of cash flows.[4] If sstk was greater than zero, the firm had issued common and/or preferred stock in the previous fiscal year which would mean the firm received a zero for the $F_{EQOFFER}$ variable.

The final category of variables in the Piotroski F-Score is the operating efficiency variables: $F_{\Delta MARGIN}$ and $F_{\Delta TURN}$. To obtain each firm's change in margin, I downloaded the firm's cost of goods sold and sales and calculated the change in gross margin by scaling cogs by sales and taking the difference between the current and previous fiscal year. The change in turnover variable is defined as the change in a company's total asset turnover from year to year. Total asset turnover was calculated as total revenue over total assets.[5]

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[4] This information was obtained from the Compustat online user manual.
[5] All of the information for the operating efficiency ratios was obtained from the CRSP/Compustat merged database.

In order to select the candidates for short positions, I recreated and updated Mohanram's G-Score. A description of all of the variables that make up the G-Score is available in *Table 1.2*. Mohanram's first category of variables is a profitability test similar to Piotroski's where the only difference is Mohanram benchmarks the financial variable against an industry median.[6] The first profitability ratio, G_{ROA}, was obtained using the same data as the Piotroski F-Score return on assets calculation. The other two profitability ratios, G_{ROACFO} and G_{CFONI}, were calculated using the same cash flow variable as the Piotroski cash flow variables and were measured against industry medians. As with the F-Score, the cash flow numbers for these G-Score variables were obtained by merging the oancf and fopt variables provided by the CRSP/Compustat merged data sets.

Mohanram's second category of variables was earnings and growth variability. The earnings growth variable was generated by taking the variance of the firm's ROA based on the four previous years of annual data.[7] Like the earnings growth variable, the sales growth variable was obtained by taking the variance of sales from the previous four years of annual data.[8] The return on assets and sales growth data were obtained from the CRSP/Compustat merged data sets.

In Mohanram's G-Score, the final ratio category examines variables that will depress a firm's book value for the time being but will lead to future growth. The variables included in this category are R&D expense (G_{RDEx}), capital expenditures (G_{Capex}), and advertising expenses (G_{AdEx}). Because R&D and advertising expenses are

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[6] The industry medians were calculated by obtaining a median of each financial variable for each SIC code.
[7] Though this study uses annual data, Mohanram's G-Score variable for the earnings growth variance was calculated by taking the variance in ROA over the previous four years of quarterly data.
[8] Though this study uses annual data, Mohanram's G-Score variable for the sales growth variance was calculated by taking the variance in sales over the previous four years of quarterly data.

specific to certain industries, an adjustment had to be made for firms whose reported expenses for these income statement items were missing. If a company's R&D or advertising expenses were missing, I assume that the firm's expenses were zero. Because both of these G-Score variables are benchmarked against industry medians, in many cases this change made the industry medians zero. Therefore, the condition for the binary variable on the G-Score variables was the company would receive a one if its R&D or advertising expense was greater than or equal to zero. If a company's advertising or R&D expenses were zero and the industry average expenses were zero, I can safely assume that the industry is one that does not typically require these expenses and award these firms a 1 on the R&D or advertising variable.

After cleansing the data set, I obtained the results of the F-Score and the G-Score for every firm from 1970 to 2010, unless any firm had a missing data point.[9] Once I had obtained the F-Score and G-Scores for the firms, it was time to merge monthly returns data from CRSP. I downloaded monthly returns and price data for each company by manually entering the permno identifier for each firm.[10]

3.2 Constructing the Long-Short Portfolio

After updating and replicating the F-Score and G-Score, the final step was to combine the two scores to obtain a portfolio of long and short positions for each month since January 1970 through December 2010.[11] The long positions require a score of eight or nine on Piotroski's F-Score and must exceed the highest book-to-market quintile for its

[9] Any firm with a missing data point for any one of the nine F-Score variables or any one of the eight G-Score variables was eliminated from this study.
[10] Permno is the unique company identifier for firms in the CRSP database.
[11] This time constraint was determined by data availability.

fiscal year. The short positions were firms who received a zero or one on Mohanram's G-Score and rested in the lowest book-to-market quintile for its fiscal year. Because each firm's BM ratio was computed at a different point in time, the BM quintiles were created by sorting the observations and ranking them within their "post3month" variable designation.[12] Firms with a negative book-to-market were dropped from this study because of the ambiguities surrounding the interpretation of what a negative book-to-market ratio means for a company.

Firms with a share price of less than a dollar per share also had to be excluded from this study because of the high likelihood that a firm in that much distress would delist while holding the stock in the portfolio. In addition, in order for a month to be included in the study, it had to have at least 30 firms that were candidates for the long or short position in that month.[13] When firms with depressed share prices were excluded, the number of candidates for short positions declined significantly up until 1990. Because of this limitation, this study will examine monthly returns for the long and short positions from January 1990 to December of 2010.

The returns for each of the long and short positions had to be adjusted downward to account for transaction costs. Bollen & Busse (2006) quantify the transaction costs and commissions associated with making trades in the stock market. Bollen & Busse borrow some of their estimations from previous research, such as citing Chan and Lakonishok

[12] The variable "post3month" is generated by the mofd command in STATA of the data point's data date and adding three months to each data point. The three months account for the buffer time to allow the financial changes to influence return streams.
[13] The number thirty firms were selected because that is the size of the smallest stock exchange in the United States: the Dow Jones includes thirty firms.

(1995) to obtain transaction costs for the purchase and sale of stock. Chan and Lakonishok approximate a 1% transaction cost for purchasing a stock and a 0.35% transaction cost for selling a stock. Bollen & Busse use previous literature citing Chalmers, Elden, and Kadlec (2001) to obtain an estimate on average commission expenses. Chalmers, Elden, and Kadlec sample hedge funds between 1984 and 1991 and determine that the average commission expense is approximately 0.75%. Summing the front-end and back-end transaction costs from Chan and Lakonishok and the average commission cost from the second study, we obtain a total cost of 2.1%. However, Bollen & Busse expand on this previous literature and discover that trading costs increased post August 2001. The researchers recommend that we add an additional 0.502% to the transaction costs post August 2000. Ultimately, both the long and short positions in the portfolios generated for this study will be adjusted downward by approximately 2.602% to account for transaction costs and trading commission fees.

On the short side, there is an additional factor that has to be accounted for: the cost of borrowing (D'Avolio 2002). D'Avlio (2002) estimates that for small market capitalization stocks, of which all of Mohanram's firms are, the cost of borrowing is very high for these glamour firms, approximately 1.05% annually (D'Avolio 2002). In order to obtain a monthly borrowing cost, one must "de-annualize" the borrowing cost. The monthly transaction cost for small, glamour, low book-to-market firms is approximately 0.09%. In addition to the transaction costs, the short positions had to be adjusted for these borrowing costs, which yielded a total adjustment of approximately 0.09% to the return streams of the short positions. In addition to the 2.602% transaction costs and trade commissions, the short positions had to be adjusted downward by another 0.09% to account for borrowing costs.

3.3 Long-Short Strategies Considered

This study will consider the performance of the two main types of long-short strategies: market-neutral and net-long. A market-neutral strategy implies a perfectly-hedged portfolio, or fifty percent long and fifty percent short. A net-long portfolio, on the other hand, is comprised of a significantly higher proportion of long stocks than short because of the added costs and risks that come with shorting a stock. For the purpose of this study, the net-long portfolio will consist of seventy percent long positions and thirty percent short positions. In addition, I will test another net-long portfolio that has 60% allocated to long positions and 40% short positions to see which way the portfolio alpha moves as allocation to long positions increases and the amount invested in short positions decreases. The two long-short strategies, market-neutral and net-long, will be benchmarked against a long-only strategy and market returns.

4 Data Analysis and Results

4.1 Explanation of Descriptive Statistics

The variables generated in the final portion of this study, or the actual long-short portfolio generation, can be divided into two major categories: return variables and risk factor variables. The study has five different return variables which are described in *Table 1.3*: shortret, longret, hedgeret, netlongret7030, and netlongret6040. The variable shortret is simply a collapsed monthly mean of equally-weighted returns on individual stocks that were selected from the G-Score to be short positions.[14] Similarly, the variable longret is a collapsed monthly mean of each of the returns on individual stocks that received an eight or nine on the F-Score. The variable hedgeret is equal to the difference between longret and shortret, which renders a portfolio of equally weighted long and short positions. Hedgeret captures the return on a perfectly-hedged, market-neutral portfolio. The variable netlongret7030 describes the return of a portfolio that allocates 70% to long positions and only 30% to short positions. The variable netlong6040 represents a portfolio that is comprised of 60% long positions and 40% short positions. Hedgeret, netlong7030, and netlong6040 are the variables that describe the possible strategies of long-short equity hedge funds. The final return variable is a market return variable that was calculated from the Fama-French estimations of the market risk premium and the risk free rate.[15]

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[14] The returns were collapsed by their post3month designation.

[15] Monthly data points for market risk premium and the risk-free rate from January 1990 to December 2010 were taken from the Fama-French data library at <http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/index.html>.

The variables that quantify risk are the benchmark factors mktmrf, smb, hml, and mom, all of which were obtained from the Fama-French data library, with the exception of the momentum factor.[16] A summary of the risk factor variables is demonstrated by *Table 1.4*. Fama and French use the variables mktmrf, smb, and hml to estimate the deviations in stock market returns from the standard predictions in the Capital Asset Pricing Model (CAPM). The variable mktmrf is the Fama-French estimation of the market-risk premium, or the market return less the risk free rate (Fama-French Database). The next two variables, smb and hml, are firm-specific variables that are accepted by the industry as a proxy for macroeconomic fluctuations. The variable name smb stands for the small minus big factor and is the Fama-French adjustment for firm-size risk, or an approximation of the performance of smaller stocks in comparison to big stocks. The third variable, hml, or high minus low, quantifies the risk associated with the book-to-market ratio. The high minus low factor quantifies the amount of excess return a portfolio of high book-to-market firms has over a portfolio of low book-to-market firms. The variable hml compares the performance of high book-to-market firms, usually considered value firms, to that of low book-to-market growth firms. The market risk premium (mktmrf), size factor (smb), and market-to-book factor (hml) all make up what Fama-French deem a three-factor regression analysis.

The final risk-associated variable is the variable Carhart (1997) labeled mom, or the momentum factor. The momentum factor captures the idea of momentum in the stock

[16] Monthly data points for market risk premium, small minus big (smb), high minus low (hml), the risk-free rate, and momentum factors from January 1990 to December 2010 were taken from the Fama-French data library at <http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/ index.html>.

market: if a stock does exceedingly well one month, the stock price may continue to rise as investors flock to the big winner.

4.2 Explanation of Four-Factor Regression Model

This thesis will use the Carhart Four-Factor regression model to benchmark the alpha generated by the long-short strategies (Carhart 1997). Carhart calculates the four factor regression model as follows:

$$r = Alpha + B(R_m) + B_{SMB} * SMB + B_{HML} * HML + B_{MOM} * MOM \quad (3)$$

The variable B_{SMB} represents the beta associated with the size of the firm, so a B_{SMB} of one would be a portfolio of firms carrying firm-size risk, which would be a portfolio of largely small capitalization firms (Fama & French 1996). A portfolio with a B_{SMB} of zero on the other hand would represent a portfolio of large capitalization stocks that are fairly reflective of market risk and do not carry much excess firm-induced beta (Fama & French 1996). The variable B_{HML} represents the beta associated with the book-to-market ratio of the firm. A portfolio with a B_{HML} of one would be a firm with a high BM ratio and a portfolio with a B_{HML} of zero would be a firm with a low BM ratio (Fama & French 1996). The B_{MOM} term represents a firm that carries momentum factor risk, and would be high for a firm that tends to have directional stock market swings (Carhart 1997). The alphas generated by the portfolios in this study will theoretically be risk-adjusted because the four-factor regression model should serve as a proxy for macroeconomic fluctuations that will effect stock prices (Bodie 2011).

4.3 Regression Results and Analysis

Because this study uses market returns and long-only return streams to benchmark the returns of the long-short equity strategies, standard regressions of this data would be affected with auto-correlation, or the correlation of a variable with itself. One method of eliminating this bias is to run the regressions with a Newey-West regression, which lags the data to eliminate the autocorrelation bias. In order to employ Newey-West regressions, the data had to adjusted for time-series regressions (Newey & West 1987).[17]

In running a Newey-West regression for the long portfolio returns, as reflected in *Table 2.1*, all variables in the four-factor regression were significant in determining the returns of the long-only portfolio. However, the returns generated by the long-only portfolio were not statistically significant in the four-factor regression model. The long-only portfolio returns were positively correlated with the market risk premium at the 0.10% significance level. The market cap factor (smb) and the book-to-market factor (hml) were both positively correlated with the generation of long-only portfolio returns and were significant at the 0.10% significance level. The momentum factor was slightly negatively correlated with the long portfolio returns and were statistically significant at the 1% significance level. In the basic CAPM regression, the long portfolio generated a statistically significant beta coefficient of 0.61, which means that the long portfolio is relatively correlated with market risk. The constant coefficient for the long-only portfolio in the CAPM regression, or the portfolio alpha, is reported in *Table 2.1* as .0035, or 0.35% on a monthly basis. The annualized return of the long-only portfolio from the

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[17] The data was prepared for time-series regressions by using the tsset time series adjustment in STATA.

basic CAPM regression is approximately 4.28%. Because this number is from the CAPM regression, the 4.28% return is not risk-adjusted. It must be noted that this estimation of long-only returns is generous because the long positions incorporated in this portfolio were all rewarded an eight or nine on the Piotroski F-Score. Because of this, the long-only returns are stronger than a typical long-only strategy, which means that this an extremely strong benchmark to measure the returns of the net-long and perfectly-hedged strategies.

The Newey-West regression results for the four-factor regression of the short-only portfolio, as reflected in *Table 2.2*, reveal that the all four risk factors are statistically significant. The short portfolio returns were postively correlated with the market risk premium at the 0.01% significance level. The short-only portfolio returns have a positive correlation with the market capitalization factor (smb) that is statisically significant at the 0.10% significance level. The book-to-market factor (hml) was also statistically significant in having a negative correlation with short portfolio returns, which makes sense because a high book-to-market firm, as Piotroski and Mohanram affirm, is not a good candidate for a short position. The final statistically significant determinant of short portfolio returns is the momentum factor, which is statistically significant at the 0.10% significance level. The momentum factor is negatively correlated with short portfolio returns, because investors are less likely to join the bandwagon on the short side of a stock that is performing poorly. The alpha coefficient for the short-only portfolio was statstically significant at the 1% significance level. The alpha coefficient reported in the table is -0.0043, which reflects the monthly return of the portfolio of short positions. The annualized return risk-adjusted return of the short-only portfolio is approximately 5.28%.

In the basic CAPM regression for the short-only portfolio, the beta coefficient was approximately 0.77, a higher correlation with the market than the long-only portfolio. The raw short portfolio alpha generated by the basic CAPM regression was -0.0047 on a monthly basis. [18] After annualizing the absolute value of the monthly returns, it becomes clear that the raw alpha generated by the short portfolio is approximately 5.79%.

The perfectly-hedged portfolio, the first long-short hedge fund trading strategy we examine, is negatively correlated with the market risk premium, but the correlation is not statistically significant. The perfectly-hedged portfolio is only correlated with two of the Fama-French factors: firm size risk and book-to-market risk. As reflected in *Table 2*.3, the returns generated from the hedged portfolio were negatively correlated with the firm size risk factor (smb) at the 1% significance level. The market-to-book factor (hml) was postively correlated with hedged portfolio returns at the 1% significance level. The alpha generated by the perfectly-hedged portfolio is statistically significant at the the 1% significance level. The monthly risk-adjusted alpha reported in *Table 2.3* is 0.0066. The annualized, risk-adjusted return for the hedged portfolio generated by the four factor regression is approximately 7.44%. The basic CAPM regression in *Table 2.3* reveals that the hedged portfolio has a beta of -0.16 and is statistically significant at the 5% significance level. The hedged portfolio is the only investment strategy examined that achieved the fundamental principle behind long-short strategies: to have negative correlation to market returns. The negative beta of the hedged portfolio reveals that this

[18] The short-only portfolio returns are negative, which makes sense because when an investor shorts a stock, he is betting that the stock price will fall. The equation I use to calculate annualized return will use the absolute value of the short portfolio returns in order to reflect the positive returns that would be contributed to the overall long-short portfolio.

hedged strategy would be an excellent diversifier to any investment fund portfolio. With negative correlation to market returns, the hedged portfolio will have low correlation to the traditional asset classes such as long-only equities and fixed income instruments. The hedged portfolio is supposed to be market-neutral, and a negative beta confirms the fact that this portfolio is negatively correlated with the market.

The results generated by the first net-long strategy, a portfolio that allocates 70% of fund assets to long positions and 30% to short positions, has a positive correlation with the market risk premium at the 1% significance level. As demonstrated by *Table 2.4*, the net-long portfolio returns are also positively correlated with the firm size risk (smb) at the 5% significance level. The market-to-book factor (hml) has an even more statistically significant positive correlation with net-long portfolio returns. The fourth risk factor, the momentum factor, does not have a statsitically significant relationship with the net-long portfolio returns. As revealed by *Table 2.4*, the net-long trading strategy has a monthly risk-adjusted alpha of 0.0029 that is statistically significant at the 1% significance level. After annualizing the .29% monthly return, the risk-adjusted net-long portfolio annualized returns are approximately 3.17%. The basic CAPM regression for the net-long portfolio yields a beta coefficient of 0.20. The raw alpha of 0.0039 generated by the CAPM regression is significant at the 0.1% significance level. The annualized returns for the 70-30 portfolio under the CAPM regression was 4.78%.

The results of the 70-30 net-long trading strategy led me to test a portfolio between the net-long and perfectly-hedged. I tested the portfolio alpha and standard deviation of a portfolio with 60% of its assets dedicated to long positions and only 40%

of its assets allocated to short positions. In theory, the standard deviation of this portfolio should increase relative to the 70-30 portfolio standard deviation because the allocation to riskier assets (short positions) has increased. The results of the Newey-West four-factor regression for a net-long portfolio of 60% allocation to long positions is reflected in *Table 2.5*. The 60-40 net-long portfolio has a positive correlation with the hml factor at the 1% significance level. Both the smb factor and the momentum factor were not statistically significant in the net-long (60-40) portfolio. The alpha generated by the 60% net-long portfolio was reported as 0.0031 in *Table 2.5*, which suggests a monthly portfolio return of 0.31%. The annualized return of the 60% net-long portfolio is approximately 3.78%. The standard deviation of the 60-40 net-long portfolio did not increase from the 70-30 portfolio, which strenghtens the Sharpe ratio of the 60-40 portfolio.

The difference between the returns of each of the portfolios examined in this study can be evaluated through examining a factor that is of utmost importance to any investor: risk. An analysis of the sharpe ratios of each of the portfolios, demonstrated in *Table 3*, bolsters the conclusion that a hedged portfolio of selected long and short positions is a superior investment strategy. The sharpe ratio of the long-only portfolio is the smallest of any of the portfolios examined, which suggests that traditional long-only managers should consider diversifying with a hedged portfolio. The next highest sharpe ratio is the short-only portfolio, with a sharpe ratio of 2.18. The reward-to-risk of all three of the long-short strategies examined yield better sharpe ratios than both the long-only and short-only portfolios. The portfolio with the third best sharpe ratio is the net-long portfolio with 70% allocation to long positions, with a sharpe ratio of 2.93. Though the worst-performing strategy of all three of the long-short equity strategies, this strategy still significantly outperforms traditional long-only managers. The second best overall sharpe ratio is the net-long portfolio with 60% allocated to long positions which has a sharpe ratio of 3.14, only to be beat by hedged portfolio with a sharpe ratio of 3.22. Because the hedged portfolio claims the highest reward-to-risk ratio over the period from 1990 to 2010, it can be said that out of the strategies tested in this study, this strategy is the most effective through any market conditions.

Another element that is important to consider is the consistency of each of the portfolio returns. In other words, is the hedged portfolio hitting one or two home-runs, or are the returns fairly consistent singles and doubles. *Table 4* demonstrates the percentage of monthly returns that are positive for each portfolio. Every long-short portfolio has approximately 60% of the months yielding positive return, as does the market. Because both the market return and perfectly-hedged returns have 60% positive monthly returns, it reveals that the difference in portfolio returns comes from the magnitude of returns. The perfectly-hedged portfolio captures more of the upside and less of the downside than the market return portfolio.

Another examination of the return-to-risk ratio is the Markowitz efficient frontier (Bodie et.al. 2011). The Markowitz efficient frontier for the long-short universe is described by *Figure 5*. The red arrow marks the Global Minimum Variance portfolio for long-short strategies. The Global Minimum Variance portfolio marks the portfolio that bears the least amount of risk (Bodie et.al. 2011). Every portfolio that lies on the curve above the Global Minimum Variance portfolio represents an optimal portfolio, or a portfolio whose return has the least amount of risk (Bodie et.al. 2011). Any portfolio that lies beneath the Global Minimum Variance portfolio has a more optimal portfolio directly above it on the efficient frontier of long-short portfolios. The only long-short strategies from this study that lie on the efficient frontier are the perfectly-hedged portfolio and the 60-40 portfolio. The 70-30 portfolio and the long-only portfolios are not efficent. Essentially, the Markowitz frontier supports the conclusion that if a manager can engage in hedging, the sharpe ratio of the portfolio will increase. As the amount of hedging decreases, the more inefficient the portoflio gets.

4.4 Areas for Further Study

After the completion of this study, it is important to examine areas for further research and development. The present study used an approximate borrowing cost for low book-to-market firms presented by D'Avolio (2002) because the short positions in this study were taken from Mohanram's G-Score, which examined low book-to-market firms. To make the returns net of borrowing costs more precise, it would have been ideal to have the data on the shorting costs of each of the firms examined. If the data is not readily available, perhaps a shorting cost model could be built that would more accurately depict the borrowing costs of firms. Another avenue to consider that would require more accurate borrowing costs is examining leveraged portfolios. For instance, if we examined portfolios that were net-short, with 70% allocated to short positions and 30% allocated to long positions, would the portfolio alpha still be significant? A further study could examine at what point do borrowing costs associated with shorting a stock destroy the alpha-generating power of a hedged portfolio.

Upon examining research conducted by Boehme, Danielsen, & Sorescu (2006), other partitions could be applied to the data as robustness checks. Though firms with a price per share of less than a dollar were excluded from this study, Boehme, Danielsen, & Sorescu (2006) exclude any firm with a price per share of less than five dollars. The researchers exclude these firms because of the illiquidity associated with a firm trading under five dollars (Boehme, Danielesen, & Sorescu 2006). It would be interesting to see if this change was applied to the data set used in this study, if the alphas generated by the long-short portfolios be just as strong.

Another robustness check for this study would be to run the same Newey-West regressions with unwindsorized returns. The results in this study were obtained with windsorized returns, which means any outliers in the return stream were normalized. As most investors can attest to, the stock market is inherently abnormal and will have outliers. To account for the effect of firm-specific volatility and idiosyncratic risk, we could run the same regressions with unwindsorized returns and see the robustness of the portfolio alphas.

Finally, an area of further study would be generating the same study with value-weighted returns. The present study uses equally weighted returns, which does not accurately reflect the goals of hedge fund managers. If a stock's value goes up in this study, the next month, the excess return is sold off to rebalance and maintain equal weightings. Hedge fund managers do not strive to maintain equal weightings between the equities in their portfolios. In conducting a further study, one could create a value-weighted return where the return would be weighted by the current share price and return of the stock.

Conclusion

The results of this study bolster the hypothesis that a long-short equity manager can generate superior risk-adjusted returns to that of market returns or a traditional long-only manager. The portfolio that generated the highest risk-adjusted return and claimed the highest reward-to-risk ratio was the perfectly-hedged portfolio. After risk adjustments, transactions costs, commission fees, and borrowing costs, the market-neutral portfolio boasts an impressive 8.21% return. As the only equity portfolio in this study to yield a negative beta, it becomes clear that equity managers should consider a perfectly-hedged portfolio as it is a superior portfolio diversifier because of its negative correlation with equity markets.

Though the long-short strategies examined in this strategy were successful, it is important to qualify their success. The effectiveness of any long-short strategy rests on a manager's ability to select undervalued and overvalued companies. In addition, even generating a superior portfolio of long and short plays is not enough. As David Swensen notes, the success of long-short strategies is largely dependent on the active management and attentive rebalancing of a portfolio (Swensen 2009). In order to outpace traditional long-only portfolios, managers of long-short equity funds must actively reassess mispricings that reveal whether a company is currently undervalued or overvalued. From endowment funds to hedge funds, investment institutions should consider eliminating some of their exposure to market risk by incorporating some sort of long-short trading strategy.

Appendix of Tables and Figures

Table 1.1 – Description of Piotroski F-Score Variables for High BM Firms

F-SCORE VARIABLES	Calculation
Return on Assets	ROA > 0
Cash Flows from Operations	CFO > 0
Change in ROA	∆ROA > 0
Positive Accruals	CFO > ROA
Leverage	∆LEVERAGE < 0
Liquidity	∆LIQUIDITY > 0
Equity Offering	EQOFFER < 0
Change in Margin	∆MARGIN > 0
Change in Turnover	∆TURN > 0

Table 1.2 – Description of Mohanram G-Score Variables for Low BM Firms

G-SCORE VARIABLES	Calculation
Return on Assets	$ROA > ROA_{Ind.\ Med.}$
Cash Flows from Operations*	$CFROA > CFROA_{Ind.\ Med.}$
Positive Accruals	CFO > NI
Earnings Variability	$STDEV(ROA) < STDEV(ROA)_{Ind.\ Med.}$**
Sales Growth Variability	$STDEV(SGR) < STDEV(SGR)_{Ind.\ Med.}$**
R&D Expenses	$R\&DExp > R\&DExp_{Ind.\ Med.}$
Capital Expenditure	$Capex > Capex_{Ind.\ Med.}$
Advertising Expense	$AdEx > AdEx_{Ind.\ Med.}$

*Mohanram's CFO calculation is cash flows scaled by total assets.
**Earnings variability (sales growth variability) were calculated as the variance of ROA (Sales Growth) over the past four years of annual data.

Table 1.3 – Description of Return Variables

RETURN VARIABLES	DESCRIPTION
longret	A variable generated from the collapsed monthly mean of any firm that scored an 8 or a 9 on the Piotroski F-Score.
shortret	A variable generated from the collapsed monthly mean of any firm that scored a 0 or a 1 on the Mohanram G-Score.
hedgeret	A variable generated by taking the difference between longret and shortret. This variable represents a perfectly-hedged portfolio.
netlong7030	A portfolio generated by taking seventy percent long positions and thirty percent short positions. This represents a net long strategy.
netlong6040	A portfolio generated by taking sixty percent long positions and forty percent short positions. This represents a net long strategy.

Table 1.4 – Description of Risk Variables

RISK VARIABLES	DESCRIPTION
mktmrf	The Fama French (1995) estimation of the market risk premium.
smb	The Fama French (1995) estimation of the firm size risk factor.
hml	The Fama French (1995) estimation of the market-to-book risk factor.
mom	The Carhart (1997) estimation of the momentum factor.

Table 2.1 – Long Portfolio Return versus Market Returns

VARIABLES	Long Portfolio Return CAPM	Long Portfolio Return Four-Factor
mktmrf	0.6139***	0.5864***
	(0.0430)	(0.0375)
smb		0.3599***
		(0.0534)
hml		0.3031***
		(0.0582)
mom		-0.0643**
		(0.0292)
Constant	0.0035**	0.0024
	(0.0017)	(0.0014)
Observations	252	252
R-Squared	0.5757	0.7150
Adj. R-Squared	0.5741	0.7104

Standard errors in parentheses
*** p<0.001, ** p<0.01, * p<0.05

Table 2.2 – Short Portfolio Return versus Market Returns

VARIABLES	Short Portfolio Return CAPM	Short Portfolio Return Four-Factor
mktmrf	0.7730***	0.6111***
	(0.0519)	(0.0432)
smb		0.5799***
		(0.0663)
hml		-0.1497**
		(0.0641)
mom		-0.0944***
		(0.0345)
Constant	-0.0047*	-0.0043** [19]
	(0.0026)	(0.0020)
Observations	252	252
R-squared	0.4975	0.6813
Adj. R-Squared	0.4955	0.6761

Standard errors in parentheses
*** p<0.001, ** p<0.01, * p<0.05

[19] The returns in this regression are negative, but because the alpha is generated from short positions, the return will be added back to the total portfolio return as a positive number.

Table 2.3 – Perfectlly-Hedged Portfolio Return versus Market Returns

VARIABLES	Hedged Portfolio Return CAPM	Hedged Portfolio Return Four-Factor
mktmrf	-0.1591**	-0.0247
	(0.0675)	(0.0530)
smb		-0.2200***
		(0.0703)
hml		0.4528***
		(0.0715)
mom		0.0301
		(0.0382)
Constant	0.0082***	0.0066***
	(0.0026)	(0.0021)
Observations	252	252
R-squared	0.0377	0.2721
Adj. R-Squared	0.0339	0.2604

Standard errors in parentheses
*** p<0.001, ** p<0.01, * p<0.05

Table 2.4 – Net-long (70/30) Portfolio Return versus Market Returns

VARIABLES	Net-long Portfolio Return CAPM	Net-long Portfolio Return Four-Factor
mktmrf	0.1978***	0.2272***
	(0.0339)	(0.0275)
smb		0.0780**
		(0.0362)
hml		0.2571***
		(0.0391)
mom		-0.0167
		(0.0200)
Constant	0.0039***	0.0029***
	(0.0012)	(0.0010)
Observations	252	252
R-squared	0.2175	0.3956
Adj. R-Squared	0.2144	0.3858

Standard errors in parentheses
*** p<0.001, ** p<0.01, * p<0.05

Table 2.5 – Net-long (60/40) Portfolio Return versus Market Returns

VARIABLES	Net-long (60/40) Portfolio Return CAPM	Net-long (60/40) Portfolio Return Four-Factor
mktmrf	0.0592*	0.1074***
	(0.0332)	(0.0263)
smb		-0.0160
		(0.0343)
hml		0.2418***
		(0.0361)
mom		-0.0008
		(0.0189)
Constant	0.0040***	0.0031***
	(0.0012)	(0.0010)
Observations	252	252
R-squared	0.0244	0.2406
Adj. R-Squared	0.0205	0.2283

Standard errors in parentheses
*** p<0.001, ** p<0.01, * p<0.05

Table 3 – Sharpe Ratios of Each Portfolio Examined

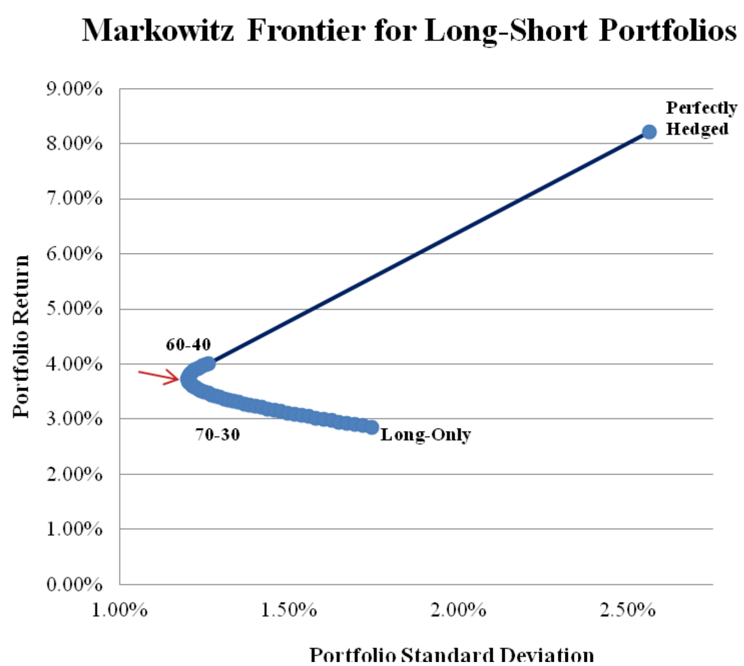
Sharpe Ratios				
Portfolio	Beta	Return - Rf	St. Dev.	Sharpe
Market Return*	1.00	6.39%	3.78%	1.69
Long-Only	0.61	2.92%	1.69%	1.72
Short-Only	0.77	5.28%	2.43%	2.18
Perfectly-Hedged	**-0.16**	**8.21%**	**2.55%**	**3.22**
Net-Long (60/40)	0.60	3.78%	1.21%	3.14
Net-Long (70/30)	0.20	3.54%	1.21%	2.93

*Market return is calculated from the Fama French estimations of the market risk premium and the risk free rate.

Table 4 – Percentage of Months with Positive Returns in Each Portfolio

Months with Positive Returns	
Portfolio	% Months
Market	60%
Long-Only	58%
Short Only	53%
Perfectly-Hedged	60%
Net-Long (60/40)	61%
Net Long (70/30)	62%

Figure 5 – Markowitz Frontier of Long-Short Portfolios



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