The Use of Accounting Screens for Separating Winners from Losers Among the S&P 500 Stocks

Victoria Geyfman
Bloomsburg University of Pennsylvania

Hayden Wimmer
Georgia Southern University

Roy Rada
University of Maryland Baltimore County

This study uses accounting screens based on the Piotroski's (2000) F-score and the derived MagicP formulae and finds that it is an effective investment strategy, which results in risk-adjusted outperformance of stocks with high book-to-market (BM) ratios over a market weighted benchmark portfolio and its subset of growth stocks. Unlike other studies that utilized similar tests on smaller firms, we examine the performance of large value stocks within the S&P 500 between 2007 and 2014 and find evidence of the value premium. The results were robust to the time period; in fact, the highest-ranked value stocks suffered less severely during the period of market correction.

INTRODUCTION

Substantial research has been conducted on testing a well-known concept of efficient market hypothesis (EMH) that focuses on the extent to which markets incorporate information into stock prices (Fama, 1970, 1998; Malkiel, 1987, 2003, 2005, among others). Theoretically, the more efficient is the market, the more information is incorporated into stock prices and the more rapidly that information is reflected in price changes. While most studies support some degree of market efficiency (ranging from strong form or "fully reflected" information in stock prices to semi-strong and weak forms), researchers have uncovered some market anomalies that reveal patterns of trading strategies that earned higher ex-post returns than would be expected in efficient markets.

Anomalies which stray from the efficient market hypothesis may be used to garner positive abnormal returns in the market. However, supporting the EMH, is the observation that once anomalies are published, investors tend to exploit these anomalies until they disappear (Green, Hand, & Soliman, 2011). One of such anomalies is related to how stock prices react to earnings announcements. Specifically, several studies have documented a tendency for stocks to "drift" after earnings announcements in the same directions as the initial reactions. Thus, when companies report better-than-expected earnings, their stock prices jump immediately, earning positive abnormal returns. This result is consistent with investors who trade using the *momentum* strategies causing stock prices to overreact and deviate temporarily from their fundamental values (Chan, Hamao, & Lakonishok, 1993; Jegadeesh & Titman, 1993, 2001). The existence of profitable momentum trading is perpetuated by the belief that prices of past winners (known as glamour or growth stocks) will continue to rise while the prices of past losers will decline beyond their fundamental values (Jegadeesh & Titman, 2001).

A contrary to the momentum strategy, the value approach suggests that the best way to make money in the market is to invest in undervalued stocks as determined by fundamental values (low P/E ratio and high book-to-market, BM, ratio) and short-sell the overvalued growth stocks (high P/E and low BM ratios). Unlike the momentum strategy, an investor who follows the *contrarian* strategy would sell the stock that moved up and buy the stock that moved down. Extensive research has been conducted on the value investing strategy, and findings suggest that it tends to outperform investing in growth stocks (Fama & French, 1992, 1995; Lakonishok, Shleifer, & Vishny, 1994), and it holds true for diverse asset classes, markets, as well as internationally (Asness, Moskowitz, & Pedersen, 2013; Athanassakos, 2013). While it is possible that value firms have high book-to-market ratios because of high financial distress and a greater degree of risk, Piotroski (2000) proposed to screen high BM firms based on a set of financial statement criteria to separate truly financially struggling firms from those value firms that are fundamentally financially sound.

This study applies accounting screens – Piotroski's F-score and a derived variant of the Greenblatt (2006) MagicP formula – to S&P 500 firms between 2007 and 2014 in order to examine performance differences based on investment strategy (value versus growth), firm size, risk, and industry classification. The contribution of this study is the test of accounting screens on S&P 500 companies to examine whether these strategies can be applied to larger firms. Secondly, we introduce and test a new method, MagicP, to locate positive abnormal returns in the S&P 500. Thirdly, we test the robustness of these strategies using the fixed effects regression analysis to account for differences between firms and over time as the period under study includes the recent financial crisis and subsequent market recovery. Finally, we discuss the findings and implications as they pertain to individual and institutional investors who are seeking to optimize their investment strategies. The remainder of this paper is structured as follows: Section 2 provides a literature review, Section 3 describes the data collection and methodology, results appear in Section 4, finally, Section 5 concludes with the summary of findings and recommendations.

LITERATURE REVIEW

As discussed above, while growth investment is based on past performance of stocks or growth momentum (Bauman, Conover, & Miller, 1998), value investing targets investing in undervalued stocks as determined by fundamental financial analysis (Graham, Dodd, & Cottle, 1934). There is considerable evidence that value stocks earn higher long-term returns than growth stocks. Basu (1977) found abnormal returns for U.S. stocks with low price-earnings ratios. Lo and MacKinlay (1990) showed that while the momentum strategy may work for individual stocks, it will not work in a portfolio of stocks because of positive cross-autocorrelations among these stocks, which would render a contrarian strategy a success. Lakonishok et al. (1994) also provided evidence that the contrarian strategy outperform the market. They contend that the strategy is successful because investors consistently overweigh announcement, short-term information, and thus overestimate the value of glamour stocks relative to value stocks, resulting in "suboptimal" investor behavior. This theory has also been tested internationally and results confirmed the efficacy of the contrarian strategy (Chan et al., 1993; Dhatt, Kim, & Mukherji, 2004).

What are some explanations offered for better performance of value stocks? One possible explanation may be that value firms have high BM ratios because of high financial distress and increased risk; thus, higher returns may be a mere reflection of the risk premium (Chen & Zhang, 1998; Fama & French, 1992, 1995). Another explanation for market anomalies is market mispricing. In particular, investors may have too pessimistic of a view about past performance of high BM firms and have negative expectations about these firms' future performance (Lakonishok et al., 1994). Stock prices of such firms are bid down by pessimistic biases, which may be reversed in the future periods when positive earnings announcements are made (Porta, Lakonishok, Shleifer, & Vishny, 1995). There is also assertions that investors are susceptible to cognitive failures and psychological biases that include loss aversion, overconfidence, and overreaction that may result in a suboptimal investment behavior (Lo, 2004, 2009) and in stock mispricing (De Bondt & Thaler, 1985; Hirschey & Nofsinger, 2008). Others provided an alternative explanation for the returns to value investing based on data-selection bias (Kothari, Shanken, & Sloan, 1995), but this suggestion was rejected by Chan, Jegadeesh, and Lakonishok (1995), who asserted that no such bias can explain the differential performance of value and growth investing.

Piotroski (2000) proposed to use accounting signals of financial soundness for high BM value firms to differentiate truly distressed firms from out-of-favor but financially strong firms. This is consistent with findings that show that while the return on growth or glamour stocks are mainly momentum driven (Asness, 1997), the assessment of value stocks should focus on firm fundamentals based on company's financial statements. Investing based on momentum variables paired with fundamental variables have been shown to be successful (Guerard, Xu, & Gültekin, 2012). According to Piotroski (2000), financial reports are likely to provide the best and most relevant information that can be used to forecast future performance of high BM companies. We supplement the Piotroski's F-score with the derived MagicP formula to compare the performance of value stocks with the market benchmark. Greenblatt's (2006) principles suggest to buy a portfolio of 20-30 good stocks at bargain prices based on return on capital and earnings yield, and hold winners for at least one year (Lee, 2014). Unlike other studies that test accounting screens on small firms with high BM ratios (Piotroski, 2000; Woodley, Jones, & Reburn, 2011), this study tests this short-term buy-and-hold investment strategy to examine the performance of large value stocks within the S&P 500.

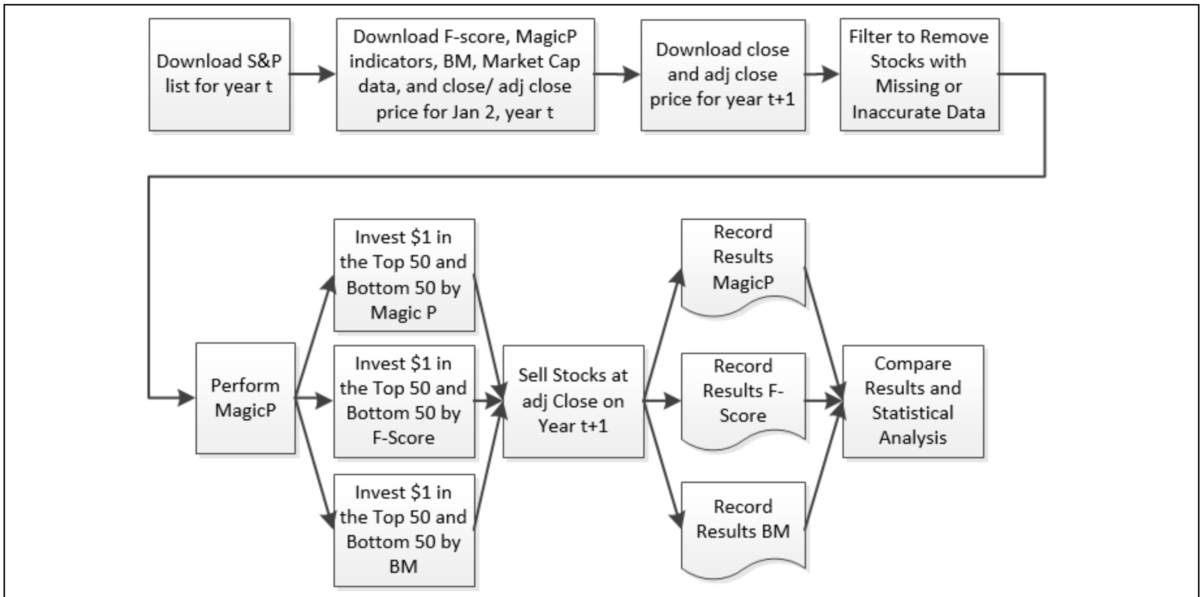
DATA AND METHODOLOGY

Data collection began with extracting of historical listings for the S&P 500. Authors regularly use the S&P 500 as a benchmark for investment style/strategy comparison (Chan, Chen, & Lakonishok, 2002; Chen & De Bondt, 2004). First, we obtained the S&P 500 constituent list from S&P Capital IQ database. Each year, the S&P 500 may change slightly with the removal and addition of new companies; thus, we retrieved a listing of the S&P firms at the beginning of each year in the study period between 2007 and 2014. The financial statement components required for the derivation of the MagicP and Piotroski's F-score were obtained from Capital IQ. We captured the share price at the beginning and the end of the trading year after the year-end financial reporting to calculate the holding period return for each stock included in our dataset. Adjusted close prices were employed to account for dividends and stock splits.

In preparing an investment strategy, stocks were screened for incorrect or missing data. Stocks were removed from the set if there was an incorrect ticker information, such as for international parent companies, a ticker that changed and was no longer on the S&P 500, or due to the M&A activity.[1] Stocks were only removed from the set for missing data in year t; however, if data for the company were missing for year $t+1$, these stocks would remain in the set for the current period t (as the hypothetical investor would not have a prior knowledge of such an event). This would be reflected in the selling of the stock in year $t+1$.

Once the data were filtered, we applied the screens and performed sorting based on each investment strategy to identify top 50 stocks as our investment targets. F-Score is sorted in descending order as our work hypothesizes that a higher F-Score indicates a strong stock; conversely, the Total Rank is sorted in ascending order as the lower the rank the stronger the stock (i.e. #1 is the strongest). It is important to note that Piotroski's screen has to be used in conjunction with the book-to-market rankings. Thus, we ranked companies by BM and utilized our screening strategies in order to choose the top 50 companies from the pool of value firms (similarly, we chose bottom 50 firms with low BM ratio, i.e., the growth stocks). Exhibit 1 presents a summary flowchart that describes the data extraction, filtering, and analysis processes.

EXHIBIT 1
DATA EXTRACTION, FILTERING, AND INVESTING FLOWCHART DIAGRAM



Flowchart A: Procedure for Data Extraction and Analysis

Piotroski F-Score Methodology

Piotroski (2000) demonstrated that by taking stocks with high BM ratios (value stocks) and then using a nine-point scale to test the financial strength of the companies, an investor can significantly outperform the market. The composite signal, denoted as F-score was calculated by summing the individual values of the binary performance scores as described in Exhibit 2.

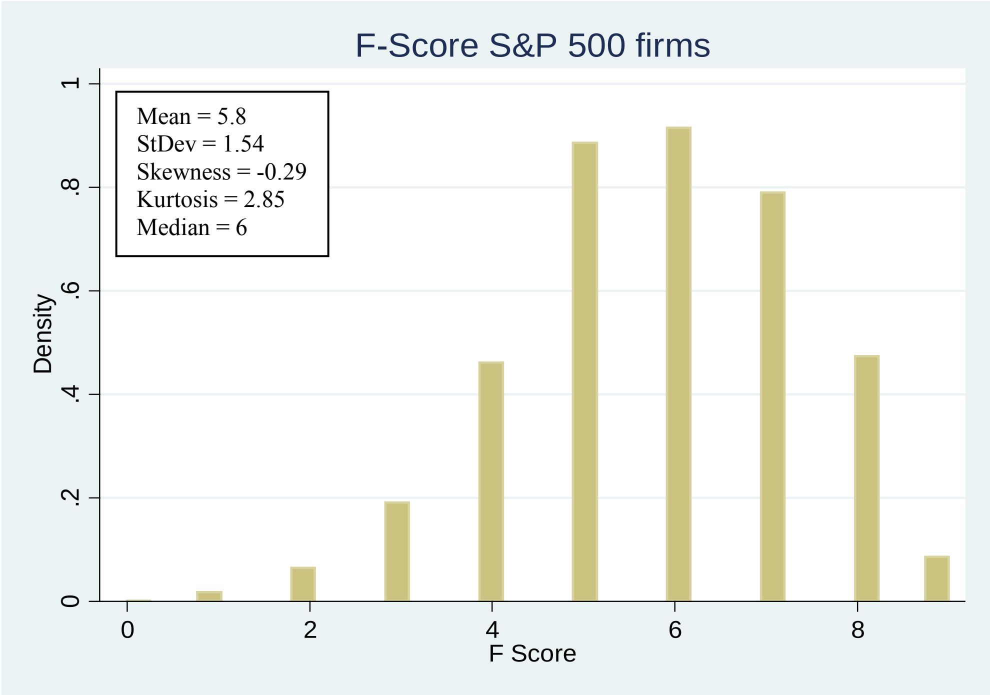
EXHIBIT 2
PIOTROSKI'S METHODOLOGY

Variable	Description	Explanation
Profitability		
F_ROA	if ROA > 0 then F_ROA = 1, else 0	Reward positive net income in t_0
F_CFO	if CFO > 0 then F_CFO = 1, else 0	Reward positive cash flow from operations in t_0
F_ΔROA	if ΔROA > 0 then F_ΔROA = 1, else 0	Reward higher ROA in t_0 vs. t_{-1}
EARN_QUALITY	if CFO > ROA then EARN_QUALITY = 1, else 0	Reward if the cash flow from operations exceeds net income
Leverage, Liquidity, and Source of Funds		
F_ΔLEVER	if ΔLEVER < 0 then F_ΔLEVER = 1, else 0	Reward decrease in leverage in t_0 compared to t_{-1}
F_ΔLIQUID	if ΔLIQUID > 0 then F_ΔLIQUID = 1, else 0	Reward increase in liquidity in t_0 compared to t_{-1}
EQ_OFFER	If no equity issued EQ_OFFER=1, else 0	Reward absence of dilution in t_0
Operating Efficiency		
F_ΔMARGIN	if ΔMARGIN > 0 then F_ΔMARGIN = 1, else 0	Reward higher gross margin in t_0 compared to t_{-1}
F_ΔTURN	if ΔTURN > 0 then F_ΔTURN = 1, else 0	Reward higher asset turnover (efficiency) in t_0 compared to t_{-1}

* where t_0 and t_{-1} refer to the current and previous years, respectively as adopted from Van Der Merwe (2013).

Piotroski awarded up to four points for profitability: one for positive return on assets, one for positive cash flow from operations, one for an improvement in return on assets over the last year, and one if cash flow from operations exceeds income. He awarded one point if the company had positive operating cash flow and up to three points for capital structure and the company's ability to meet future debt obligations. Ideally, the company would earn the highest score of nine. However, the time period investigated in this study includes a severe downturn when credit markets impaired balance sheets of many firms. According to Exhibit 3, the average F-score for our sample was 5.8 (out of 9) during the 2007-2014 period. The frequency distribution is bell shaped, relatively symmetrical and unimodal. The median was 6, which is only slightly greater than the average. The higher the F-score, the fewer are the red flags about the firm's financial health. Therefore, we hypothesize that financially strong firms with high BM ratio (value firms) will have high F-scores, which will be positively associated with their future performance and stock returns.

EXHIBIT 3
DISTRIBUTION OF F-SCORES FOR S&P 500 FIRMS, 2007-2014



S&P	2007	2008	2009	2010	2011	2012	2013	2014	AVG
F-Score	5.8	5.5	5.3	6.3	6.1	5.7	5.8	6.0	5.8

MagicP Formula

Enhanced value strategies can realize higher returns than whole market strategies (Elze, 2010). This research proposes an enhanced investment strategy titled the MagicP formula. The MagicP formula utilized in our scenarios is an adaptation of Greenblatt's Magic Formula (Greenblatt, 2006), where rankings become incorporated into the formula, market indicators, and Piotroski's F-Score. We also employ the well-tested Piotroski's F-score. This combination of F-score, market indicators, and rankings has not been explored in the financial investing literature, thereby demonstrating the novelty of this method.

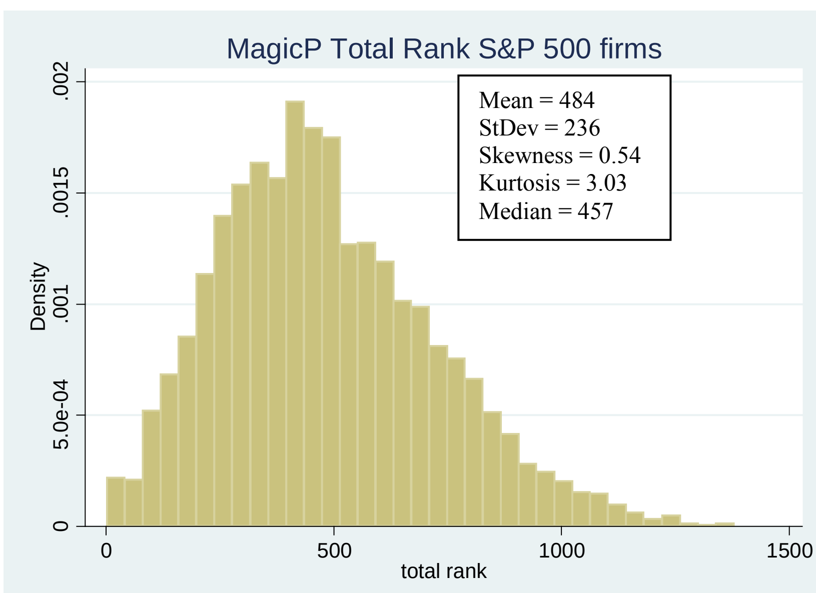
MagicP employs eight variables described in Exhibit 4. The first variable is a market indicator, and it is a ratio of closing price to earnings per share. The second variable is the return on equity. Each of the aforementioned variables is assigned a rank. The two ranks are added to produce a total indicator rank. The Piotroski F-Score is retrieved and subsequently ranked according to methodology listed above. A Final Total Rank is found by adding the total indicator rank and the Piotroski rank. It is then sorted in the ascending order and used as the key variable in making our investment selection decisions.

EXHIBIT 4
MAGIC_P METHODOLOGY

Variable	Description
Indicator 1	(Close Price)/(Earnings Per Share)
Indicator 2	Return on Equity
Rank Indicator 1	Ranking of Indicator 1
Rank Indicator 2	Ranking of Indicator 2
Total Indicator Rank	Rank Indicator 1 + Rank Indicator 2
Piotroski	Piotroski's F-Score
Piotroski Rank	Rank of Piotroski F-Score
Final Total Rank	Total Indicator Rank + Piotroski Rank

The average MagicP ranking in Exhibit 5 is 484. The total ranking ranges between a minimum of 2 and a maximum of 1378, with the median of 457. The distribution is bell shaped and relatively symmetric, with both skewedness and kurtosis minimally above the values expected for a normal distribution. Since MagicP rankings are sorted in the ascending order, we hypothesize that financially strong value firms will have a lower Total Rank measure compared to growth firms with low BM ratios.

EXHIBIT 5
DISTRIBUTION OF MAGIC_P RANK FOR S&P 500 FIRMS, 2007-2014



S&P	2007	2008	2009	2010	2011	2012	2013	2014	AVG
Total Rank	441.1	478.4	460.4	478.6	487.4	495.3	504.9	523.0	484

RESULTS

Although Piotroski's screen was originally implemented to separate winners from losers among financially distressed stocks, this study tests whether the tool can be applicable for the purposes of picking winners among the S&P 500 stocks to improve short-term portfolio returns. Table 1 reports the average market returns for S&P 500 stocks, value stocks, and growth stocks. The results indicate that the selection of financially strong firms with high book-to-market ratios (top 50 companies based on the MagicP formula and the F-score) yielded impressive results, earning average returns of 15.53% and 17.21%, respectively, compared to the overall universe of S&P 500 firms with the return of 11.46%, and growth stocks (bottom 50 companies) with 12.59% and 3.5% returns based on the same rankings. The standard deviation of returns based on MagicP is slightly greater than that of the average market, 25.12% versus 22.54%, but risk differences are statistically insignificant according to the systematic risk measures reported in Table 2. The bottom 50 firms based on the MagicP ranking performed roughly the same as the market, while the bottom firms based on the F-score metric significantly underperformed the market and top 50 F-score firms in the sample. This affirms the F-score's ability to separate "winners" from "losers".

TABLE 1
AVERAGE MARKET RETURNS FOR S&P 500, VALUE, AND GROWTH STOCKS

This table reports the average market returns and standard deviations for S&P 500, top 50 and bottom 50 firms based on MagicP and Piotroski's F-score measures over the period between 2007 and 2014. MagicP employs eight financial statement variables as described in Exhibit 4. The measures are added and ranked in ascending order resulting in the Total Rank measure. Piotroski's F-score uses a nine-point scale to test the financial strength of the companies. The composite signal is calculated by summing the individual values of the binary performance scores as described in Exhibit 2.

Market Return	S&P 500*	Top 50 MagicP	Bottom 50 MagicP	Top 50 F-score	Bottom 50 F-score
2007	1.84%	9.50%	-4.44%	9.44%	-8.21%
2008	-32.65%	-31.92%	-29.81%	-24.99%	-50.47%
2009	42.42%	50.35%	34.76%	50.89%	57.22%
2010	18.61%	17.75%	22.62%	23.86%	5.49%
2011	0.59%	0.09%	6.50%	5.22%	-11.95%
2012	18.47%	31.81%	20.40%	27.05%	7.99%
2013	29.97%	35.28%	36.54%	30.86%	25.93%
2014	11.65%	11.41%	14.17%	15.35%	1.96%
Mean	11.46%	15.53%	12.59%	17.21%	3.50%
STDEV	22.54%	25.12%	21.89%	22.20%	30.95%

*Note: The discrepancies between returns derived from this dataset and the reported S&P 500, such as Morningstar, may arise due to the fact that we excluded securities of companies that had missing or insufficient inputs for our screening formulae (see the description of this in Data Description and Methodology section).

The possibility exists that higher returns on value stocks are driven by higher risk and are only a reflection of risk premium. Table 2 reports market betas for top value stocks based on F-score and MagicP formula rankings and compares the results to the overall S&P 500 portfolio. The table shows that while value portfolio generated higher returns for top performing stocks, the market betas of the portfolios are statistically the same (1.12 for the market, 1.17 for MagicP, and 0.96 for F-score firms) based on the two-tail paired *t-test*. Thus, market risk is not an obvious explanation for the differences in returns. Similar findings were reported in Chan and Lakonishok (2004).

TABLE 2
DESCRIPTIVE STATISTICS FOR ANNUAL FINANCIAL INDICATORS, 2007-2014

This table presents financial indicators for S&P firms (S&P panel), top 50 value firms based on MagicP measure (panel A), bottom 50 firms based on Magic P (panel B), top 50 firms based on F-score (panel C), and bottom 50 firms based on F-score (panel D). *P-values* for testing of the difference between S&P firms and top 50 companies based on MagicP and F-scores (panels A and C, respectively) and p-values between top and bottom firms based on MagicP (panels A and B) and F-scores (panels C and D). ***, **, and * signify 1%, 5%, and 10% significance, correspondingly.

S&P 500 (our database)	**2007**	**2008**	**2009**	**2010**	**2011**	**2012**	**2013**	**2014**	**AVG**	***p-value*** **S&P vs. Top 50 MagicP/Fscore**
F-Score	5.8	5.5	5.3	6.3	6.1	5.7	5.8	6.0	5.8	***
Total Rank	441.1	478.4	460.4	478.6	487.4	495.3	504.9	523.0	483.7	***
Return	2.00%	-32.56%	42.39%	18.86%	0.67%	18.57%	30.05%	11.72%	11.46%	**/***
Beta	1.18	1.20	1.19	1.11	1.13	1.04	1.03	1.09	1.12	
Total Assets ($mil.)	53373	56765	54263	54039	57131	58591	60663	62794	57202	
Market Cap ($ mil.)	28699	31662	18638	22905	25433	24726	28449	35812	27040	***/*
A. Top 50 MagicP	**2007**	**2008**	**2009**	**2010**	**2011**	**2012**	**2013**	**2014**	**AVG**	**Top vs. Bottom**
Total Rank	147.72	153.12	137.5	122.28	129.98	131.74	138.12	138.4	137.36	***
Return	9.51%	-31.92%	50.35%	17.75%	0.09%	31.81%	35.28%	11.41%	15.53%	***
Beta	1.21	1.16	1.21	1.23	1.21	1.15	1.11	1.08	1.17	***
Total Assets ($mil.)	49136	24967	66843	96827	66599	98102	74833	112651	73745	***
Market Cap ($mil.)	16450	24251	15111	20005	23943	16048	18839	28793	20430	***
B. Bottom 50 MagicP	**2007**	**2008**	**2009**	**2010**	**2011**	**2012**	**2013**	**2014**	**AVG**	
Total Rank	835.8	858.22	862.26	900.18	921.78	936.2	1017.42	1055.02	923.36	
Return	-4.44%	-29.81%	34.76%	22.62%	6.50%	20.40%	36.54%	14.17%	12.59%	
Beta	1.10	1.01	1.06	1.13	1.02	0.88	1.02	1.18	1.05	
Total Assets ($mil.)	17086	18827	20530	32051	17861	20763	23714	13407	20530	
Market Cap ($mil.)	30698	57967	15269	28236	23854	30103	26269	29885	30285	

C. Top 50 F-score	2007	2008	2009	2010	2011	2012	2013	2014	AVG	Top vs. Bottom
F-score	8.2	8.14	7.84	8.24	8.3	8.28	8.08	8.24	8.17	***
Return	9.44%	-25.00%	50.89%	23.86%	5.22%	27.05%	30.87%	15.36%	17.21%	***
Beta	0.16	1.06	1.00	1.10	1.25	1.03	1.08	0.99	0.96	*
Total Assets ($mil.)	1972	25927	56758	42299	53058	76480	45744	54249	44561	**
Market Cap ($mil.)	1719	29096	13597	20161	23264	25087	22675	31437	20880	
D. Bottom 50 F-score	**2007**	**2008**	**2009**	**2010**	**2011**	**2012**	**2013**	**2014**	**AVG**	
F-score	2.98	2.48	2.6	3.38	3.6	3.26	3.3	3.44	3.13	
Return	-8.22%	-50.47%	57.22%	5.49%	-11.95%	8.00%	25.93%	1.96%	3.50%	
Beta	1.30	1.76	1.67	1.29	1.29	1.37	1.17	1.23	1.38	
Total Assets ($mil.)	150006	211641	87610	79207	47393	144526	46134	113241	109970	
Market Cap ($mil.)	29610	26216	20747	20200	15281	15777	19062	28057	21869	

The S&P panel in Table 2 reports the levels and statistical significance of various financial indicators from S&P firms and top 50 firms (value) based on MagicP and F-score rankings (panels A and C). We note that rankings, annualized market return, and market capitalization are statistically different, but beta and total assets are not. Table 2 also reports the levels and statistical significance of these measures between top 50 and bottom 50 firms based on MagicP (panels A and B) and F-score (panels C and D). All measures for top 50 MagicP firms are statistically different from their bottom 50 counterparts. Top 50 MagicP firms report better Total Rank and market returns, higher beta, and lower market capitalization. According to F-score rankings, top 50 F-score stocks have a significantly higher market return, similar betas, but insignificant differences between the size of top and bottom firms.

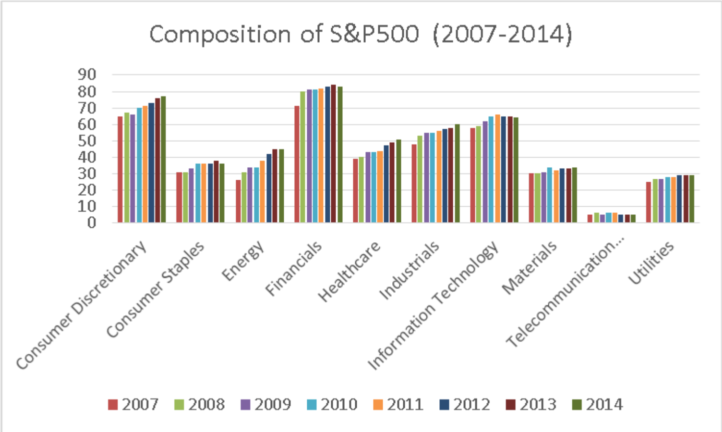
There is also a possibility that the value strategy is fundamentally riskier and should underperform relative to the growth strategy during market downturns. Both tables 1 and 2 indicate that when the market return was negative, value stocks outperformed the average market. Top 50 value stocks based on the F-score measure outperformed the market and growth stocks in each year between 2007 and 2014. The outperformance was more pronounced during the worst market environment; the bottom 50 F-score (growth) stocks performed significantly worse than other firms. When the market earned a positive return, the top 50 firms based on the MagicP ranking at least matched the market and F-score top ranking firms strongly outperformed the market in each year. This confirms that superior performance of top 50 firms does not seem to reflect their higher fundamental risk (as in Chan and Lakonishok, 2004) or the market cycle risks.

A competing explanation for the possibility of higher return on the top 50 value stocks can be drawn from the nature of industries that these stocks represent. For example, we know that a significant portion of growth-oriented stocks come from the technology industry. However, the sharp rise and decline in recent years of the technology sector call into question the argument that these stocks are less risky investments than value stocks. We decided to examine the composition of the S&P portfolio and portfolios of our top 50 firms based on MagicP and F-score strategies. Exhibit 4 shows that the composition of S&P remains quite static over time, with four largest sectors – Financials, Consumer Staples, Information Technology, and Industrials – accounting for approximately 60% of the portfolio in terms of the number of firms and their capitalization. The largest constituents of the top 50 portfolio based on MagicP are Financials, Energy, Consumer Staples, and Information Technology, while of top 50 firms based on F-score are Consumer Staples, Financials, Industrials, and Information Technology. More importantly, there is a lot of movement within these sectors as reflected in panels *b* and *c* in Exhibit 4, suggesting that the composition of the value portfolio is adjusted to reflect the changes in macroeconomic and financial markets conditions. Thus, we see the movement within the Financials sector in 2009 following the credit crisis reflecting the very nature of the value strategy of acquiring firms that become a good value (low P/E or high BM ratios) and short-sell the stocks with the high ratios.

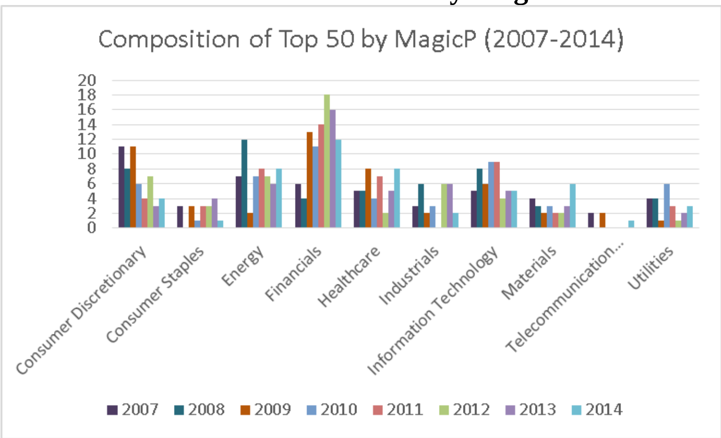
EXHIBIT 4
COMPOSITION OF S&P 500 VS. VALUE PORTFOLIOS

This exhibit presents the composition of the S&P 500 (Panel A) and value portfolios based on MagicP (Panel B) and F-score (Panel C) by industry sector between 2007 and 2014. The data are derived from S&P Capital IQ.

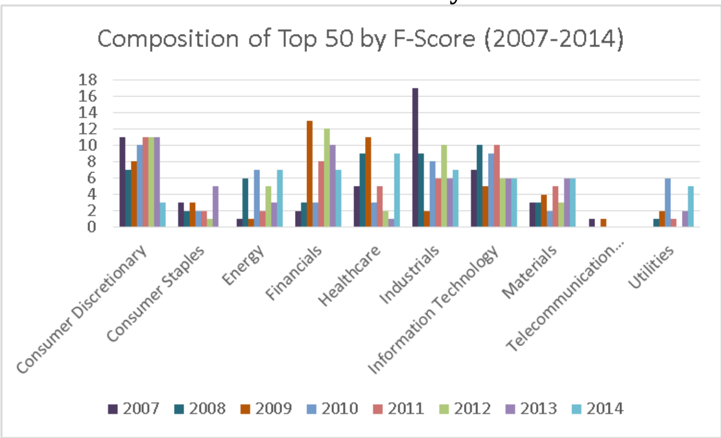
Panel A: S&P 500 Portfolio



Panel B: Value Firms by MagicP



Panel C: Value Firms by F-Score



Regression Analysis

To check the robustness of our statistical results and to formally test the relationship between the accounting screens and annual returns, we ran regression analysis of market returns on control variables comprised of firm fundamental characteristics, including company size, market value, market risk, as well as the total rank based on MagicP, and the F-score measure. There were a total of 553 distinct companies in our sample between 2007 and 2014, which comprised a panel dataset with 3605 observations. We chose to use fixed effects regressions to examine the relationship between independent control variables on market return. Fixed effects (FE) explore the relationship between predictors and outcome variable within companies. Ordinary least squares (OLS) regression is inappropriate in this case because it assumes homogeneity of firm characteristics. Our sample includes companies from ten S&P sectors and differences between companies' metrics should certainly impact the overall market performance. We need to control for that and the FE regression allows us to do that by removing the effect of time-invariant characteristics so we can assess the net effect of the predictors on the outcome variable.[2.] Another important assumption of the FE model is that each entity is different; therefore, the entity's error term and the constant (which captures individual characteristics) should not be correlated with other entities.

The equation for fixed effects model is written as:

$$Y_{it} = \alpha_i + \boldsymbol{\beta X}_{it} + \varepsilon_{it} \tag{1}$$

where Y_{it} is the dependent variable (return) for company i in year t; α_i is the unknown intercept for each company i; X_{it} represent independent control variables for each company in time t and β are their coefficients; and ε_{it} is the error term (Baltagi, 1985; Greene, 1983, 2003; Wooldridge, 2012). Another way to see the fixed effects model is by using binary variables (dummies) for firm effects, so the expanded equation becomes:

$$Y_{it} = \alpha + \beta_1 X_{1,it} + \cdots + \beta_k X_{k,it} + \gamma_2 C_2 + \cdots + \gamma_n C_n + \varepsilon_{it} \tag{2}$$

where Y_{it} is the dependent variable for company i in year t; α is the intercept; X_{it} represent independent control variables and β_k are the coefficients for independent variables; C_n are the company dummies and γ_n are the coefficients for the binary regressors associated with each company (these capture the firm effects and there are *n-1* of these observations); and ε_{it} is the error term. Control variables include F-score, total rank based on the MagicP ranking, market risk beta, the natural logarithm of total assets (ln_TA), market value (MV), and book-to-market ratio (BM). We ran the model using STATA (Allison, 2009), and the results are presented in Table 3. Column 1 shows the results of regressions with control variable and firm dummies. There is a positive relationship between F-score and total market return, but there is a negative association between MagicP total rank and market return. The coefficients are statistically and economically significant, suggesting that the higher the F-score, the more financially stable the company is, the higher is the market return, while the greater the total rank (the more removed the company is from the top), the lower the return. These findings are consistent with our hypotheses outlined in Section 3.

We also document a negative association between market returns and ln_TA, market beta, and market values indicating that a rapid growth and taking on additional risk did not necessarily translate into better performance for this sample. Finally, BM ratio is positively and significantly related to the market return, confirming that value investing strategy pays off not just for top 50 firms, but also for the entire sample. The observed R^2 is 16.71%.

We also ran the FE model that in addition to company dummies included time dummy effects (T_t where t ranges to t-1) to capture variability in performance due to economic and market cycles.[3]

$$Y_{it} = \alpha + \beta_1 X_{1,it} + \cdots + \beta_k X_{k,it} + \gamma_2 C_2 + \cdots + \gamma_n C_n + \partial_2 T_2 + \cdots + \partial_t T_t + \varepsilon_{it} \tag{3}$$

As explained above, our sample period coincides with one of the worst credit cycle phenomenon of Great Recession (2008-2010) and we wanted to capture its effects. The results are reported in the column for Model 2 of Table 3. While the levels of coefficients and their statistical significance do not change considerably compared to the first model specification, R^2 rises to 39.28%, thus including time fixed effects improved the model. In sum, the relationship between annual market returns and the accounting screen variables of F-score and MagicP remained robust after controlling for the firm and time effects.

TABLE 3
DETERMINANTS OF MARKET RETURNS BASED ON FIXED EFFECTS REGRESSION

The table reports coefficient estimates of the determinants of market returns for the entire sample of companies listed on S&P 500 between 2007 and 2014. The sample was adjusted for companies that did not include all information necessary to derive the MagicP and Piotroski F-score. The panel included 553 companies over 8 years with a total number of observations of 3605. The standard errors are in parenthesis below each estimate. The dependent variable Market Return.
Model 1: $Y_{it} = \alpha + \beta_1 X_{1,it} + \cdots + \beta_k X_{k,it} + \gamma_2 C_2 + \cdots + \gamma_n C_n + \varepsilon_{it}$
Model 2: $Y_{it} = \alpha + \beta_1 X_{1,it} + \cdots + \beta_k X_{k,it} + \gamma_2 C_2 + \cdots + \gamma_n C_n + \partial_2 T_2 + \cdots + \partial_t T_t + \varepsilon_{it}$.
***, **, and * signify 1%, 5%, and 10% significance, correspondingly.

Variable	Model 1	Model 2
F-Score	0.008947** (0.00555)	0.008152** (0.00493)
Total Rank	-0.000216*** (0.00005)	-0.000204*** (0.00004)
Beta	-0.08806*** (0.02012)	-0.0389** (0.01748)
Log of Total Assets	-0.07483*** (0.02285)	-0.19291*** (0.0222)
Market Value	-0.000186*** (0.000297)	-0.00012*** (0.00026)
Book-to-Market Ratio	0.35181*** (0.0172)	0.24729*** (0.0155)
Constant	0.85122*** (0.2221)	1.879*** (0.2131)
Company Dummies	Yes	Yes
Year Dummies	No	Yes
Number of obs.	3605	3605
R^2	0.1671	0.3928

CONCLUSIONS

Using both the Piotroski score and the derived MagicP formulae proved to be an effective screening strategy that resulted in risk-adjusted outperformance of chosen value stocks over a market weighted benchmark portfolio and its subset of growth stocks. Unlike other studies that utilized similar tests on small firms with high book-to-value (BM) ratios, we examined the performance of large value stocks between 2007 and 2014 and found that: 1) Financially strong firms selected by the means of the Piotroski F-score and the MagicP formulae outperformed the average returns of S&P 500 stocks; 2) The highest F-score and MagicP stocks consistently beat the performance of lower BM (growth) stocks, indicating that investors seeking above average returns should concentrate on investing in value stocks; 3) Using a variety of indicators, including market beta and return volatility, the chosen value stocks were not riskier than growth stocks; 4) Regarding the impacts of economic downturns, we found that value stocks suffered less severely during periods of market corrections. In fact, top 50 value stocks based on the Piotroski score outperformed S&P and growth stocks during the entire sample period, and the outperformance was more pronounced during the worst market conditions.

Since the value stock screening is based on the objective financial statement analysis, we assert that it can help investors reduce the need for complex extensive market and firm research, thus lowering a possibility of suboptimal strategies driven by judgmental biases inherent in investment behavior. This study has another implication. It is typically assumed that individual and institutional investors can choose from a diverse array of stocks; however, this screening strategy may become a valuable tool for investors or agents who are constrained to invest within a universe of large-cap stocks.

Limitations

Some of the limitations of this study include the fact that the original Piotroski screen (2000) was performed on smaller firms in financial distress and reportedly worked best for short investment time horizons in order to capitalize on the improved share price when the first good earnings announcements follow portfolio formation. However, our study was an attempt to check the strategy on S&P 500 firms that are larger and have more transparent information. The results held true for this sample implying that investors can rely on objective financial reports in an effort to differentiate the market value and intrinsic value effects of a high BM firm.

Supporting the EMH, is the observation that once anomalies are published investors tend to exploit these anomalies until they disappear (Green et al., 2011). Thus, it is necessary to test the screen's effectiveness over a longer history. This study makes a contribution to current knowledge by determining whether the accounting-based filtering process has been consistently successful during the recent past, specifically during the market downturn of 2008-2010. The study concludes that a combination of high F-score and MagicP rankings resulted in outperformance over the market weighted portfolio and growth stocks.

ENDNOTES

1. For example, Chrysler Corp. was listed as ticker "C"; however, due to mergers and acquisitions is now listed as FCAU due to the merger with Fiat. Similarly, since Chrysler relinquished ticker "C", Citicorp abandoned "CITI" in favor of "C."
2. To confirm our preference of fixed effects versus random effects, we ran a Hausman test that basically tests whether the unique error terms are correlated with regressors, which would suggest that a random effects should be used. The Hausman statistic rejected the random effects model in favor of fixed effects (Green, 2009).
3. We tested the time parameters effects to examine whether the coefficients on time dummies are jointly equal to 0, but this hypothesis was rejected according to the F statistic; therefore, time fixed effects were warranted.

REFERENCES

Allison, P. D. (2009). *Fixed effects regression models* (Vol. 160): SAGE publications.

Asness, C. S. (1997). The interaction of value and momentum strategies. *Financial Analysts Journal, 53*(2), 29-36.

Asness, C. S., Moskowitz, T. J., & Pedersen, L. H. (2013). Value and momentum everywhere. *The Journal of Finance, 68*(3), 929-985.

Athanassakos, G. (2013). Separating winners from losers among value and growth stocks in Canada another step in the value investing process. *Journal of Applied Research in Accounting and Finance (JARAF), 8*(1).

Baltagi, B. H. (1985). Pooling cross-sections with unequal time-series lengths. *Economics Letters, 18*(2), 133-136.

Basu, S. (1977). Investment performance of common stocks in relation to their price-earnings ratios: A test of the efficient market hypothesis. *The Journal of Finance, 32*(3), 663-682.

Bauman, W. S., Conover, C. M., & Miller, R. E. (1998). Growth versus value and large-cap versus small-cap stocks in international markets. *Financial Analysts Journal, 54*(2), 75-89.

Chan, L. K., Chen, H. L., & Lakonishok, J. (2002). On mutual fund investment styles. *Review of Financial Studies, 15*(5), 1407-1437.

Chan, L. K., Hamao, Y., & Lakonishok, J. (1993). Can fundamentals predict Japanese stock returns? *Financial Analysts Journal, 49*(4), 63-69.

Chan, L. K., Jegadeesh, N., & Lakonishok, J. (1995). Evaluating the performance of value versus glamour stocks The impact of selection bias. *Journal of Financial Economics, 38*(3), 269-296.

Chan, L. K., & Lakonishok, J. (2004). Value and growth investing: Review and update. *Financial Analysts Journal, 60*(1), 71-86.

Chen, H.-L., & De Bondt, W. (2004). Style momentum within the S&P-500 index. *Journal of Empirical Finance, 11*(4), 483-507.

Chen, N.-f., & Zhang, F. (1998). Risk and return of value stocks*. *The Journal of Business, 71*(4), 501-535.

De Bondt, W. F., & Thaler, R. (1985). Does the stock market overreact? *The Journal of Finance, 40*(3), 793-805.

Dhatt, M. S., Kim, Y. H., & Mukherji, S. (2004). Can composite value measures enhance portfolio performance? *The Journal of Investing, 13*(4), 42-48.

Elze, G. (2010). Value investing anomalies in the European stock market: multiple value, consistent earner, and recognized value. *The Quarterly Review of Economics and Finance, 50*(4), 527-537.

Fama, E. (1991). Efficient capital markets: II. *Journal of Finance, 46*(5), 1575-1618.

Fama, E. F. (1970). Efficient capital markets: A review of theory and empirical work*. *The Journal of Finance, 25*(2), 383-417.

Fama, E. F. (1998). Market efficiency, long-term returns, and behavioral finance. *Journal of Financial Economics, 49*(3), 283-306.

Fama, E. F., & French, K. R. (1992). The cross-section of expected stock returns. *The Journal of Finance, 47*(2), 427-465.

Fama, E. F., & French, K. R. (1995). Size and book-to-market factors in earnings and returns. *The Journal of Finance, 50*(1), 131-155.

Graham, B., Dodd, D. L. F., & Cottle, S. (1934). *Security analysis*: McGraw-Hill New York.

Green, J., Hand, J. R. M., & Soliman, M. T. (2011). Going, Going, Gone? The Apparent Demise of the Accruals Anomaly. *Management Science, 57*(5), 797-816.

Greenblatt, J. (2006). *The little book that beats the market*: John Wiley & Sons.

Greene, W. H. (1983). Simultaneous estimation of factor substitution, economies of scale, productivity, and non-neutral technical change *Developments in Econometric Analyses of Productivity* (pp. 121-144): Springer.

Greene, W. H. (2003). *Econometric analysis*: Pearson Education India.

Guerard Jr, J. B., Xu, G., & Gültekin, M. (2012). Investing with momentum: The past, present, and future. *The Journal of Investing, 21*(1), 68-80.

Hirschey, M., & Nofsinger, J. R. (2008). *Investments: analysis and behavior* (Vol. 281): McGraw-Hill Irwin.

Jegadeesh, N., & Titman, S. (1993). Returns to buying winners and selling losers: Implications for stock market efficiency. *The Journal of Finance, 48*(1), 65-91.

Jegadeesh, N., & Titman, S. (2001). Profitability of momentum strategies: An evaluation of alternative explanations. *The Journal of Finance, 56*(2), 699-720.

Kothari, S. P., Shanken, J., & Sloan, R. G. (1995). Another look at the cross-section of expected stock returns. *The Journal of Finance, 50*(1), 185-224.

Lakonishok, J., Shleifer, A., & Vishny, R. W. (1994). Contrarian investment, extrapolation, and risk. *The Journal of Finance, 49*(5), 1541-1578.

Lee, C. M. (2014). *ALPHANOMICS: The Informational Underpinnings of Market Efficiency*. School of Management, Massachusetts Institute of Technology.

Lo, A. (2004). The adaptive markets hypothesis: market efficiency from an evolutionary perspective. *The Journal of Portfolio Management, 30*, 15-29.

Lo, A. (2009). Reconciling efficient markets with behavioral finance: the adaptive markets hypothesis. *Journal of Investment Consulting, 7*(2), 21-44.
Lo, A. W., & MacKinlay, A. C. (1990). When are contrarian profits due to stock market overreaction? *Review of Financial Studies, 3*(2), 175-205.
Malkiel, B. G. (1987). Efficient market hypothesis. *The new palgrave: A dictionary of economics, 2*, 120-123.
Malkiel, B. G. (2003). The efficient market hypothesis and its critics. *Journal of economic perspectives*, 59-82.
Malkiel, B. G. (2005). Reflections on the efficient market hypothesis: 30 years later. *Financial Review, 40*(1), 1-9.
Piotroski, J. (2000). Value Investing: The Use of Historical Financial Statement Information to Separate Winners from Losers. *Journal of Accounting Research, 38*, 1-41.
Porta, R. L., Lakonishok, J., Shleifer, A., & Vishny, R. (1995). Good news for value stocks: Further evidence on market efficiency: National Bureau of Economic Research.
Van Der Merwe, C. J. (2013). The effectiveness of the Piotroski screen for value stock selection on the JSE.
Woodley, M. K., Jones, S. T., & Reburn, J. P. (2011). Value stocks and accounting screens: has a good rule gone bad? *Journal of Accounting and Finance, 11*(4), 87-104.
Wooldridge, J. (2012). *Introductory econometrics: A modern approach*: Cengage Learning.

ACKNOWLEDGEMENT

We would like to thank Jordan Boice for superb research assistance.