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Computerized stock screening rules for portfolio selection

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Abstract

Recent studies have uncovered several systematic patterns that increase the probability that individual investors can select stock portfolios with excess returns. This study tests the feasibility of using a commercially available computerized stock screening program for investors to take advantage of these patterns. The screening program searches the three major exchanges and selects stocks on both fundamental and technical indicators: low price-to-sales ratio, small firm size, accelerating stock prices above their 50 day moving average, high trading volume, and high earnings growth. Of the 18 models tested between 1994 and 1998, those that allow for selection between exchanges yield portfolio returns that significantly exceed the average market indices.

1. Introduction

Stock screening programs, similar to the ones used by professional portfolio managers, are becoming available on the Internet at little or no cost to the individual investor. Anderson (1998), in an article "Screening for investment gold," overviews four such sites with relatively sophisticated programs. Stock screening programs make it easier and quicker to tailor a portfolio to fit the desired style and preferences of the investor. Styles may range from investing for value to growth. But whatever the style, the goal is to develop a screening program to find systematic patterns that will increase the performance of a portfolio.

This paper investigates the use of one highly ranked investor-screening platform from Telescan, an easy-to-use software package that provides nearly 300 screening variables that cover both fundamental and technical indicators. The user can customize a model to include

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up to 40 different indicators simultaneously and can scan on relative values, e.g., the stocks with the highest relative strength, or on fundamental variables, like earnings per share momentum.

According to the efficient market hypothesis, past price movements in a competitively traded financial market do not help in predicting future prices. However, many recent articles question the efficient market hypothesis and support the notion that stock market excess returns can be predicted by publicly available information (e.g., see Gencay, 1996; Fama and French, 1995; Pesaran and Timmerman, 1995; Ferson and Harvey, 1993). Although it is still commonly believed the U.S. stock market is semi-strong efficient, Walker and Hatfield (1996) argue that financial research indicates that security prices do not reflect all publicly available information. For this reason, investors may find it worthwhile to use computerized screening programs that take advantage of large databases and advances in information technology to efficiently select stocks. A number of studies on the profitability of filter rules on exchange rates lend credibility to this hypothesis (e.g., Levich and Thomas, 1993; Taylor, 1994).

Financial gains from the use of computerized screening programs are consistent with the weak form of the efficient market hypothesis offered by Jensen (1978), i.e., prices reflect information up to the point where the marginal benefits equal the marginal costs of the information. The marginal costs of making informed investment decisions have been declining significantly due to high-speed and low-cost computer technology. This lower marginal cost may account for the increase in short-term speculative trading by individual investors. The recent literature clearly indicates that benefits, in the form of excess returns, can be realized by taking advantage of systematic patterns that seem to exist in the stock market, e.g., reaction and drift effects, earnings and forecast surprise effects, and performance persistence. A well-known study by Jegadeesh and Titman (1993), for example, documents that investment strategies which buy stocks that have performed well in the past and sell stocks that have performed poorly in the past generate significant positive returns over 3 to 12 month holding periods. This outcome is consistent with delayed price reactions to firm-specific information.

The following sections involve: (1) reviewing investment strategies for portfolio selection that have been shown to yield superior returns; (2) combining these superior strategies in a screening model to explore the possibility of any synergy gains; and (3) testing the model to assess its performance relative to the market indices.

2. Promising investment strategies

A review of the recent finance literature identifies several causal variables predicting excess returns in the market. This section will discuss these factors and their implications for use in a stock-screening model.

2.1. Price/sales ratios

Researchers have studied several indicators to identify undervalued stock and predict excess returns. These include relatively low values for price-to-earnings, price-to-book, and price-to-sales ratios. These researchers argue that stocks that have low values for these measures are not currently popular with investors and create a potential for greater price appreciation.

Recent evidence suggests the sales-to-price ratio is a more reliable indicator than other measures of undervalued stock, so this ratio is utilized in the screening model in this study. Barbee et al., (1996) offers three reasons why the sales-to-price ratio may be a more reliable predictor for stock returns than P/E ratios. First, annual sales historically are a better indicator of long-run expected profits than current reported profits. Second, earnings are more likely to be affected by short-term policies than sales revenues. Sales figures tend to be less subject to manipulation. Third, sales-to-price cannot have negative values as can P/E. Vandell (1986) argues that focusing primarily on P/E could result in two types of investment errors: (1) avoiding firms with low earnings that have a temporarily high P/E ratio but are expected to grow profitably in the future, and (2) selecting cyclical stocks when their P/E ratios are low but their profits are at their peak.

The price-to-book ratio (the inverse of book-to-market value) has received some attention in the literature, but the reviews are mixed. A low price-to-book ratio may select a company with low earnings prospects and greater risk (Kothari, Shanken, and Sloan, 1995).

2.2. Earnings momentum

Earnings prospects are considered to be an important indicator of stock returns. A study by Vandell (1986) develops a screening model for stock selection based on earnings momentum. This study finds that screening on low price-to-earnings values would be successful in predicting returns only if earnings-per-share expectations are high. More recently, Tam, Kiang, and Chi (1991) employ an induction methodology to analyze a database for commonalties. They find changes in quarterly earnings as one of the driving variables predicting the potential for excess returns. Similarly, Harris and Marston (1994) find it necessary to control for earnings prospects to predict excess returns.

Earnings momentum in this study is measured as the weighted average of quarterly growth rates in earning per share (EPS) over the past year. The recent quarters are given the most weight.

2.3. Market capitalization

Several studies support an inverse relationship between small firm size or market capitalization and stock returns. Market capitalization is the firm's stock price multiplied by the number of common shares outstanding.

Lo and MacKinlay (1988) find positive autocorrelation between weekly returns and stock portfolios grouped by size. Dennis et al., (1995) find a significant relationship between firm size, book-to-market equity and excess returns. The optimal portfolios are those with the smallest firms and highest book-to-market equity. The portfolios with the largest firms and smallest book-to-market equity underperformed the market.

2.4. Price and volume reactions

Reinganum (1988) identifies relative price as one of the primary characteristics of the 222 stock market winners between 1970 through 1983. Relative price performance is a weighted average measure of past price changes of each stock in comparison to all stocks. Advocates of this measure contend that a stock will generally lose relative strength before a significant drop in price occurs. Relative price strength is a significant factor in selecting successful stock portfolios in studies by Tam, Kiang, and Chi (1991) and Jegadeesh and Titman (1993).

Recent studies suggest that an effective investment strategy needs to examine movements in both price and volume. Kim and Verrecchia (1991) argue that price changes are associated with the market's *average* beliefs, while trading volume is the *sum* of all individual trades. Hiemstra and Jones (1994) suggest that volume serves as a proxy for information flow and that a positive relationship exists between trading volume and absolute stock returns. Stickel and Verrecchia (1994) present evidence that price changes are more likely to be reversed following low trade volume than high volume. They argue high volume reflects a greater probability that the trading stems from informed investors.

Trading volume in this study is measured by an accumulation distribution over the past 50 days. For each of these days, the stock's volume is multiplied by the change in price and summed. This indicates the amount of money moving into the stock.

2.5. Moving average rules

Technical analysts have developed numerous moving average rules. The basic rule involves calculating a moving average of past prices. The length of the period used in the moving average is commonly between 20 and 200 days. The length selected by the investor reflects the time horizon being predicted. This study uses a 50-day moving average.

The moving average model assumes that there are systematic patterns in market prices that can be used in forecasting. If the current price moves above the moving average (or some band about the average), a buy signal is generated. In this situation technical analysts believe that the mood has changed from a declining to a rising stock pattern. If the current price falls below the moving average (band), a sell signal occurs.

Until recently, technical trading rules involving moving averages were not considered to have much forecasting value. However, advances in computer technology have increased the sophistication of such models and new evidence is now being uncovered. Gencay (1996) shows substantial gains in forecast accuracy through the use of such models with a forecast horizon of 20 days. These findings are also consistent with studies showing evidence of systematic patterns in daily, weekly, and monthly returns (see Haugen and Jorian, 1996; Cutler, Poterba, and Summers, 1991).

3. Screening model and methodology

The screening model in this study attempts to find a portfolio of stocks that are not only under-valued but have relatively high growth potential. This model is developed by combining the superior investment strategies previously reviewed. Possible synergy gains are derived from the interaction of these strategies using fundamental, industry sector, and technical information.

The screening model uses *a three-step approach*. First, *fundamental* variables are used to screen for smaller companies with low price-to-sales ratios, positive returns on equity, and high earnings per share growth. Second, *strong industry* sectors are filtered, searching for positive relative price performance, because those industries do better under certain macro-economic conditions and are positioned for future growth. Stocks within these industries are then screened for high relative price performance. Third, *technical* filters are used to select stocks that are over their 50-day moving average price and have a high accumulation distribution (trading volume activity measured in dollars).

A commercially available computerized search and screening program, Prosearch from Telescan, Inc., is used to select and rank order a portfolio of stocks that most closely meet a set of criteria based on the most promising screening indicators identified in the finance literature. A methodological advantage of a screening program is that it does not require the specification of a functional form to predict returns, as is the case with linear or non-linear regression analysis.

The Telescan database universe consists of 9, 000 listed stocks on the NYSE, AMEX, and NASDAQ exchanges and is restricted by Telescan to the most recent three-year moving window. Several investment models are tested between the time frame November 1, 1994 to August 31, 1998. The rolling results cover almost four years. This period encompasses a long bull market and the sell off from the *Asian Contagion*, thereby including a mix of market conditions.

The investment strategy is designed to pick a portfolio of stocks, between 20 and 50, and rebalance on a quarterly basis. The number of different stocks is kept relatively small to make the portfolio financially accessible to the individual investor. The specific search criteria is defined below.

At the beginning of each quarter, the search program is executed and selects for purchase the top stocks from the universe that best fit the screening criteria. Dollars invested are distributed equally between the selected stocks. The total return (net of transactions costs) for the selected portfolio is compared to the market return at the end of the quarter. The portfolio is liquidated and a new search is made on the same criteria. Dollars are once again invested equally among selected stocks in the new portfolio. Transaction costs assume electronic trading with average fees between $7.50 and $15.00 per trade.

4. Screening criteria

The desired portfolio is selected using a two-step screening criteria. First, the stocks are *filtered* based on the criteria values in Table 1. Those firms that do not meet all the criteria in Table 1 are eliminated from the potential portfolio.

Second, after filtering on the above criteria, the remaining stocks are *rank ordered* based on a weighted average index of the percentile rank of the indicators in Table 2 and their respective weights. Because all criteria are weighted equally (at 100%), the index used to rank each stock is simply the average of the percentile ranking of each indicator. The ranking is done by the Prosearch program once the indicators, criteria and weights are specified.

Table 1
Screening criteria

Indicator	Screening criteria
Price/sales ratio	Between 0 and 1
Return on equity	Value greater than zero
Earnings per share momentum	Highest 50% of stocks in market
Price performance	Highest 50% of stocks in market
Industry price performance	Highest 50% of stocks in market
Accumulation distribution	Highest 50% of stocks in market

5. Results

The stock screening program is used to select a portfolio of stocks that best fit these criteria on a quarterly basis. Although only 3 to 4 years of data are available, 18 different models are tested within that timeframe and are summarized in Table 3. Models 1 to 9 search for the best stocks each quarter in all three exchanges, but have different time intervals and portfolio size, ranging between 20 and 50 different stocks. Models 10 through 18 restrict the searches to a specific exchange. The start date depends on the available three year moving window in Telescan's database, with the end date restricted to the most recent full quarter of data given the start date. Data are available from November 1994 for model 1, but are no longer accessible when the remaining models are tested.

Returns are calculated net of round trip transactions costs, assuming that trades are transacted electronically, without the direct use of a broker. Fees for trading electronically vary between $7.50 and $15.00 per transaction and are assumed to average $10.00. Assuming a 100% turnover per quarter, transaction costs for a portfolio with 20 to 50 different stocks range between $400 and $1, 000 quarterly. Overall transaction costs are calculated to average just under 1% of the portfolio, with an average portfolio size between $40, 000 and $100, 000.

The quarterly average portfolio net returns for models 1 through 9 are compared to the average return in all three exchanges, i.e., the NYSE, AMEX, and NASDAQ. In all cases, the portfolio net returns exceed the average index returns (without costs). The results are statistically significant in 7 out of the nine models.

Models 10 through 18, that arbitrarily restrict the program to select stocks within one

Table 2
Ranking criteria

Indicator	Rank criteria	Weight
Price/sales ratio	Lowest percentile in the market	100%
Earnings per share momentum	Highest percentile in the market	100%
Market capitalization	Lowest percentile in the market	100%
Price performance	Highest percentile in the market	100%
Industry price performance	Highest percentile in the market	100%
Moving avg. ratio- 50 days	Highest percentile in the market	100%
Accumulation distribution	Highest percentile in the market	100%

Table 3
Parametric tests of the screening model

Model	Exchange	Start date	End date	No. of stocks	Quarterly average portfolio net return	Quarterly average exchange return	Quarterly excess return	Test statistic
1	All	11/1/94	4/30/98	35	8.9%	5.3%	3.6%	1.78[b]
2	All	12/1/95	8/31/98	35	7.7%	2.7%	5.0%	2.75[b]
3	All	1/1/95	6/30/98	35	6.2%	3.5%	2.7%	2.09[b]
4	All	11/1/95	7/31/98	20	6.8%	4.8%	2.0%	1.36
5	All	12/1/95	8/31/98	20	7.7%	2.7%	5.0%	3.05[b]
6	All	1/1/96	6/30/98	20	6.8%	3.5%	3.3%	2.49[b]
7	All	11/1/95	7/31/98	50	6.4%	4.8%	1.6%	1.27
8	All	12/1/95	8/31/98	50	9.1%	2.7%	6.4%	3.32[b]
9	All	1/1/96	6/30/98	50	6.2%	3.5%	2.7%	1.95[b]
10	NYSE	11/1/95	7/31/98	35	5.7%	5.4%	0.3%	0.93
11	NYSE	12/1/95	8/31/98	35	4.4%	3.9%	0.5%	0.99
12	NYSE	1/1/96	6/30/98	35	5.1%	4.4%	0.7%	1.08
13	AMEX	11/1/95	7/31/98	35	6.9%	2.7%	4.2%	1.78
14	AMEX	12/1/95	8/31/98	35	6.3%	0.7%	5.6%	2.12[b]
15	AMEX	1/1/96	6/30/98	35	4.0%	1.3%	2.7%	1.36
16	NASDAQ	11/1/95	7/31/98	35	6.2%	6.3%	−0.10%	0.87
17	NASDAQ	12/1/95	8/31/98	35	9.7%	3.6%	6.1%	2.26[b]
18	NASDAQ	1/1/96	6/30/98	35	6.7%	5.0%	1.7%	1.11
Mean					6.7%	3.7%	3.0%	

[a] In models 1–9 ''All'' refers to exchanges including the NYSE, AMEX, and NASDAQ. Models 10–18 are restricted to specific exchanges. Portfolio returns are net of transactions costs.

[b] Indicates statistical significance at the 0.05 level.

exchange, do not perform as well. Although excess returns are still positive in 8 out of the 9 models, only two are statistically significant at the 0.05 level of confidence. This result is not unexpected because the flexibility of the model to choose between markets and industries is limited. This result also confirms the power of the unrestricted screening model to switch between exchanges to select the most promising companies.

Although most excess returns in models 10 through 18 are not significant, the binomial proportionality test statistic associated with all nine models together shows statistical significance at the 0.01 level. The null hypothesis tested assumes the simple fraction of profitable models (those with positive excess returns after the payment of transaction costs) should equal 0.5. The null hypothesis is rejected given 8 out of 9 models with positive excess returns.

Further evidence of support for the screening model may be found by comparing the performance of fund managers to the market indices. For the past five consecutive years, Bary (1999) finds fund managers underperformed the S & P 500. In 1998, 86% of fund managers trailed the S & P 500, whereas 90% lagged the index in 1997. Treanor (1999) reports the Combined Actuarial Performance Service (CAPS) median performance of pension fund managers for the past five years is only 13.1%, well below client requirements.

The superior portfolio returns of the screening model could not be explained by risk. The mean of the portfolio betas (obtained from the Telescan database) for models 1 to 9 is shown

Table 4
Average portfolio characteristics: models 1–9

Portfolio	Mean	Percentile (%) rank in market
Beta	0.72	—
Price/sales	0.44	24
P/E ratio	20.73	60
Price/book	2.08	57
Capitalization (mil$)	531.42	32
ROE	0.46	91
Earnings/share ($)	0.61	59
Price/rank (%)	118.50	90
MA price ratio (%)	115.35	89
Accum. distr. (mil$)	79.87	85
NASDAQ (%)	68.34	—
AME (%)	18.77	—
NYSE (%)	12.89	—

in Table 4. The average beta of the portfolios is only 0.72. Although not shown in the Table, the highest portfolio beta is 0.99 and the lowest portfolio beta is 0.48.

The betas may be biased downward owing to the selection of relatively smaller firms in the screening criteria. Scholes and Williams (1977) suggest beta adjustments to account for non-synchronous trading. However, examination of the data indicates that this is not a problem. Firm size in the portfolios, although below the market mean, have market capitalization averaging $531 million, ranking firms in the 32nd percentile. High trading volume is also a selection criteria. The average firm in the portfolio is ranked in the 85th percentile in terms of accumulation distribution.

The other characteristics of the portfolio, displayed in Table 4, are consistent with the a priori screening criteria. The price-to-sales ratio averages 0.44, which is in the lower 24% of the market in ranking, considering all exchanges (NYSE, NASDAQ, and American). The price-to-earnings (P/E) and price-to-book ratios are not considered in the selection criteria, but average in the middle range of the market, i.e., 57–60% ranking. The size of the firms in the market, measured by market capitalization, is in the lower end. The average firm's total market capitalization in the portfolio is $531.42 million, which places it in the lower 32% in market rank. The earnings per share are $0.61, which is in the middle of the market in percentile ranking at 59%. However, the portfolio ROE is relatively high, placing it at 91% in market rank. Price performance, that measures the relative price increases over a year, is in the top 90% of all stocks in the market. The moving average price ratio ranks in the top 89%, confirming that the price at selection is relatively high in relation to its 50-day moving average. Trading volume measured as accumulation distribution is relatively high, ranking in the top 85%.

The selected exchanges are shown at the bottom of Table 4. Most stocks in the portfolios are selected consistently from the NASDAQ exchange. The NASDAQ averaged 68.34% of the portfolio dollars, but it is as low as 49.4% in some quarters and as high as 86.1% in others. On average, only 12.89% of the portfolio stocks are from the NYSE and 18.77% from the AME. This tracks well with the ranking criteria that gives priority to industries with high relative price growth. Because the NASDAQ had a concentration of high growth stocks during the study period, it confirms the power of the model to switch to high growth industries.

6. Conclusions

Advances in communication and technology now place powerful screening tools in the hands of serious investors. They can rapidly search large databases in real time with complex screening rules to select the best stocks in the universe that fit a set of criteria and they can find results in seconds. The costs of using professional screening programs have been declining, making these programs accessible to the individual investor. The screening model in this study is robust enough to work well with as little as 20 different stocks in the portfolio, requiring an investment of only \$40, 000. Without considering any tax consequences, the portfolio returns of the screening models significantly exceed the average exchange indices and are almost twice the median returns achieved by professional fund managers.

What accounts for the success of the screening model in this study? Four considerations are important. First, the evidence is consistent with delayed price reactions to firm-specific information. Perhaps the market is slow to react because large institutional investors' costs (both direct and indirect) are too high, leaving an opportunity for the efficient individual investor to move more rapidly by taking advantage of recent developments in information technology. Second, the indicators are selected based on a review of the empirical literature. Only included are those indicators that proved successful in prior studies. Third, both fundamental and technical filters are linked to take advantage of synergistic effects. Finally, strong industry sectors are given priority to account for current and changing macroeconomic conditions.

Although the results are favorable, the data is limited, covering only a three-to-four year time horizon. The time interval includes the Asian crisis and a market decline, but most quarters are in a growth market. More work is needed to confirm the model, especially in declining markets.

References

Anderson, J. A. (1998). Screening for investment gold. *Black Enterprise, 29*(3), 93–97.

Bamber, L. S.(1995). Differential price and volume reactions to accounting earnings announcements. *Accounting Review, 70*(3), 417–441.

Barbee, W. C., Jr., Mukherji, S., & Raines, G. A. (1996). Do sales-price and debt-equity explain stock returns better than book-market and firm size? *Financial Analysts Journal* (March/April), 56–60.

Bary, A. (1999). The trader: indexers trounce active managers and roil market, too. *Barrons, 79*(1), 3–5.

Cutler,D. M., Poterba, J. M., & Summers, L. H. (1991). Speculative dynamics. *Review of Economic Studies, 58*, 529–546.

Dennis, P., Perfect, S. B., Snow, K.N., & Wiles, K. W. (1995). The effects of rebalancing on size and book-to-market ratio portfolio returns. *Financial Analysis Journal* (May-June), 47–56.

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.

Ferson, W. E., & Harvey, C. R. (1993). The risk and predictability of international equity returns. *Review of Financial Studies, 6*, 527–566.

Gencay, R. (1996). Non-linear prediction of security returns with moving average rules. *Journal of Forecasting, 15*, 165–174.

Grundy, B., & McNichols, M. (1989). Trade and the revelation of information through prices and direct disclosure. *Review of Financial Studies, 2*, 495–526.

Harris, R., & Marston, F. (1994). Value versus growth stocks: book-to-market, growth, and beta. *Financial Analysts Journal, 50*(5).

Haugen, R., & Jorion, P. (1996). The January effect: still there after all these years. *Financial Analysts Journal,* (Jan.-Feb.), 27–31.

Hiemstra, C., & Jones, J. D. (1994). Testing for linear and non-linear granger causality in the stock price-volume relation. *The Journal of Finance, XLIX*(5), 1639–1664.

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

Jensen, M. C. (1978). Some anomalous evidence regarding market efficiency. *The Journal of Financial Economics, 6*, 95–101.

Kim, O., & Verrecchia, R. (1991). Trading volume and price reactions to public announcements. *Journal of Accounting Research, 29,* 302–321.

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.

Levich, R. M., & Thomas, L. R. (1993). The significance of technical trading-rule profits in the foreign exchange market: a bootstrap approach. *Journal of International Money and Finance, 12*, 451–474.

Lo, A. W., & MacKinlay, A. C., (1988). Stock market prices do not follow random walks: Evidence from a simple specificationtest. *Review of Financial Studies 1*, 41–66.

Pesaran, H. .M., & Timmermann, A. (1995). Predictability of stock returns: robustness and economic significance. *The Journal of Finance, L*(4), 1201–1228.

Reinganum, M. R. (1988). The anatomy of a stock market winner. *Financial Analysts Journal,* (March/April), 16–28.

Scholes, M., & Williams, J. (1977). Estimating betas from nonsynchronous data. *Journal of Financial Economics, 5*, 309–327.

Stickel, S. E., & Verrecchia, R. E. (1994). Evidence that trading volume sustains stock price changes. *Financial Analysts Journal, 50*(6), 57–67.

Tam, K. Y., Kiang, M. Y., & Chi, R. T. H. (1991). Inducing stock screening rules for portfolio construction. *Journal of the Operational Research Society, 42*(9), 747–756.

Taylor, S. J. (1994). Trading futures using a channel rule: a study of the predictive power of technical analysis with currency examples. *Journal of Futures Market, 14,* 215–235.

Treanor, J. (1999, March 21–22). Most fund managers fail the test. *The Guardian.*

Vandell, R. P. (1986). A purposeful stride down wall street. *Journal of Portfolio Management, 12*(2), 31–39.

Walker, M. M., & Hatfield, G. B. (1996). Professional stock analysts' recommendations: implications for individual investors. *Financial Services Review, 5*(1), 13–29.