Equity-Style Timing with Technical Trading Rules*

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ABSTRACT

In recent years, there has been a growing concern among researchers and practitioners on the profitability of market-timing strategies. This paper addresses the issue whether short-term variations in the spreads of the U.S. value/growth Russell style indices could have been historically exploited utilizing popular technical trading strategies. In the literature this return spread is often called the "value premium". Much of the equity-style timing literature focuses on the development of either binomial or multinomial timing models based on macroeconomic and fundamental public information. Instead, in our modeling process we use daily time-series data to develop tactical market timing models based on simple and widely used technical rules. Applying different out-of-sample long-short strategies, we conjecture that the value/growth rotation is profitable at feasible levels of transaction costs. Our results demonstrate that active multi-style rotation strategies can be devised to outperform both buy and hold strategies and market as a whole. These strategies can be implemented using futures on Russell style indices.

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I. Introduction

THE CONCEPT OF EQUITY style investment is nowadays an integral part of the fund management industry. Since the mid-1980s many institutional investors have pursued focused style investment strategies. In 1987, Wilshire Asset Management introduced its equity style indices and since then investment styles have been broadly accepted in the investment community judging by the vast number of funds adopting style investing strategies and the proliferation of style indices published by several companies.

Style investing lies on one of the clearest mechanisms of human thought: classification. Classification is also diffused in financial markets where investors categorize assets in broad classes which are called “styles”. Styles serve not only as a simplified method to process huge amounts of information but also as means of evaluating money managers. Consequently, practitioners and researchers deem style allocation to be a prominent concept, as important as asset allocation.

More specifically, the performance of value and growth stocks has gained even more interest in recent years. Although a large body of empirical literature documents a strong value premium in average stock returns, the sharp changes in the differentials between value and growth stocks along with the poor performance of “pure” value strategies render absolute style rigidity a questionable strategy. There is now a growing consensus that style diversification is the optimal solution to avoid the risk associated with “pure” style investing. Given the above facts, style rotation strategies pose a great challenge to active fund managers as potential sources of added value but of course presume market timing skills.

The majority of academic research has focused on the potential benefits of style-based timing strategies using fundamental and macroeconomic factors that have been widely cited in the literature as having a predictable influence on stock returns.

To the best of our knowledge, none of the previous “timing strategy” studies have sought to investigate the performance of style-timing strategies utilizing simple technical trading rules in a daily context. In this paper we contribute to this open issue by implementing long-short strategies on small-cap, large-cap value/growth indices. Our purpose is to develop and analyze real-time strategies which are not benefited from ex post knowledge.

Our results show that active equity-style strategies are both institutionally manageable and economically viable while outperforming buy and hold strategies and beating market as a whole despite the lack of robustness in the large-cap segment. In a practical context, the availability of futures contracts on style indices enables investors to apply the suggested strategies more cost effectively, due to low transaction costs, low tracking error and high liquidity of the specific futures contracts.

The remainder of the study is organized as follows. In the following section we present a review of the literature. The next section presents a description of the data and the methodology of our technical trading strategies. In the fourth section we discuss and analyze the performance results of our dynamic market-timing strategies. The paper concludes with a summary in the last section.

II. Literature Review

A. The CAPM and Multifactor Models

The last 20 years have seen a revolution in the way financial economists understand the investment world. The backbone of financial research is to isolate those factors who determine asset prices. Until the mid-1980s, financial economist's view of the asset pricing was based on the simple one period capital asset pricing models of Sharpe (1964), Lintner (1965) and Black (1972). The CAPM states that assets can only earn a high average return if they have a high "beta" which measures the tendency of the individual asset to move up or down with the market as a whole.

Since 1980 there have been several empirical contradictions of the CAPM. In 1981 Banz (1981) was the first to observe the "small-firm effect". Forming portfolios from stocks trading in NYSE, during the period 1936-1975, he found that market equity (a stock's price times shares outstanding) adds to the explanation of the cross-section of average returns provided by market "betas". Average returns on small (low market equity) stocks are too high given their "beta" estimates, and average returns on large stocks are too low. Besides, this deviation is statistically significant. Another contradiction of the CAPM is the positive relation between leverage and average return documented by Bhandari (1988). It is plausible that leverage is associated with risk and expected return but in the CAPM model, leverage risk should be captured by market “beta”. Bhandari (1988) finds, however, that leverage helps explain the cross-section of average stock returns in tests that include size (market equity) as well as “beta”. Stattman (1980) and Rosenberg, Reid and Lanstein (1985) find that average returns on U.S. stocks are positively related to the ratio of a firm’s book value of common equity to its market value. Chan, Hamao and Lakonishok (1991) reveal a significant cross-sectional relationship between the book-to-market ratio and the expected returns in the Japanese market. They find that this variable is both statistically and economically important.

Under this mounting evidence, empirical researchers suggested that the simple one period capital asset pricing model is misspecified. That misspecification, however, does not appear to be market inefficiency but rather, the source of misspecification seems to be risk factors that are omitted from the CAPM. Thus, multifactor extensions of the CAPM started to dominate the description, performance, attribution and explanation of average returns. Multifactor models associate high average returns with a tendency to move with other risk factors in addition to movements in the market as a whole.

The size and book-to-market factors advocated by Fama and French (1992, 1996) are one of the most popular additional risk factors. Fama and French (1992, 1996) examine characteristics such as size, leverage, past returns, dividend yield, earnings-to-price ratios and book-to-market ratios and conclude that, with the exception of the momentum strategy described by Jegadeesh and Titman (1993), size and book-to-market ratio can fully explain the cross-sectional variation in expected returns. “Beta”, the traditional CAPM measure of risk, explains almost none of the cross-sectional dispersion in expected returns once size is taken into account.

B. "Value Premium" Explanations

In the light of this evidence, a broad range of influential academic writings has elaborated on the potential benefits of investing in stocks with fundamental commonalities, such as stocks with typical "value" characteristics. Value stocks can be identified by high earnings-to-price ratios, dividend yields or book-to-market ratios. Roughly speaking, value stocks are "bargain" or out of favor stocks that are inexpensive relative to company earnings or assets. On the other hand, growth stocks represent companies with the opposite characteristics. Growth stocks exhibit rapidly expanding earnings growth and are considered "glamorous". The exceptional returns of value investments are widely labeled as "value premium".

The long-term value premium has been explained in the finance literature by several parallel lines of reasoning. The traditional explanation for these observations, exposited by Fama and French (1993), is that value features of a company proxy for financial distress. Fama and French (1993) forcefully argue that value stocks are fundamentally riskier. That is, investors in value stocks, such as high book-to-market stocks, tend to bear higher fundamental risk of some sort and their higher average returns are simply compensation for this risk. In addition, they claim that value firms tend to be distressed firms who may be more sensitive to certain business cycle factors, like changes in credit conditions, than firms that are financially less vulnerable. To promote their inspiration Fama and French (1993, 1996) suggest an ad-hoc modification of the CAPM including the value-growth spread (high minus low book-to-market factor, HML) as well as the return differential between small and large capitalization stocks (small minus big factor, SMB). Liew and Vassalou (2000) show that the performance of HML and SMB contain significant information about future GDP growth. Using data from ten developed countries, they find that the predictive ability of these factors is to a large degree independent of any information contained in the market factor. Even in the presence of popular business cycle variables, HML and SMB retain their ability to predict future economic growth in some of the countries examined. Liew and Vassalou (2000) support that a risk-based explanation for the returns of HML and SMB is plausible and likely.

In sharp contrast, Lakonishok, Shleifer and Vishny (1994) give an alternative and competing view on the observed value premium. Lakonishok et al. (1994) suggest that high returns associated with high book-to-market (or value) stocks are generated by investors who incorrectly extrapolate the past earnings growth rates of firms. They argue that investors are overly optimistic about firms which have done well in the past and are overly pessimistic about those that have done poorly. They also claim that low book-to-market (or growth) stocks are more glamorous than value stocks and may thus attract naïve investors who push up prices and lower the expected returns of these securities. While Lakonishok et al. (1994) do not dispute the possibility that there may be priced factors associated with value (or growth) stocks, they argue that the return premia associated with these factor portfolios are simply too large and their covariances with macroeconomic factors are just too low to be considered compensation for systematic risk. In the same line of reasoning, Daniel and Titman (1997) show that there is neither discernible separate risk factor associated with high or low book-to-market firms nor return premium associated with any of the three factors identified by Fama and French (1993), suggesting that the high returns related to these portfolios cannot be viewed as compensation for factor risk. They find that although high book-to-market stocks do covary strongly with other high book-to-market stocks, the covariances do not result from there being particular risks associated with distress but rather reflect that high book-to-market firms tend to have similar properties. Daniel and Titman (1997) conclude that traditional measures do not, indeed, determine expected returns. Haugen and Baker (1996) also conjecture that there is no evidence that the realized fundamental return differences are risk-related and attribute these differences to biases in market pricing, or market inefficiency.

Finally, Lo and MacKinlay (1990) identify problems of data-snooping or data biases. They claim that almost all financial asset pricing studies suffer from conditioning on previous studies and therefore we should expect them to corroborate earlier findings.

C. International Evidence

Most of the empirical research on the “value premium” is based on stock market data from the United States. Fama and French (1998) and Oertmann (1999) document the existence and analyze the economics and dynamics of value-growth spreads on international equity markets.

Fama and French (1998) examine thirteen major markets during the 1975-1995 period and find that, sorting on book-to-market equity, value stocks outperform growth stocks in twelve markets. They also report a "value premium" in emerging markets. Since these results are out-of-sample, relative to earlier tests on U.S. data, they suggest that the return premium for value stocks is real. Regarding international "value premium" explanation, Fama and French (1998) argue that a two factor APT (or a one-state variable international ICAPM) model that explains returns with the global market return and a risk factor for relative distress captures the "value premium" in country and global returns.

Oertmann (1999) studies three global regions and eighteen countries over 1980s and 1990s and finds that value-growth spreads on equity markets reflect a compensation for systematic risk. Most importantly, he presents evidence that value-growth spreads are driven by global economic conditions, which is a characteristic feature of risk premiums on capital markets. His analysis of correlations of the expected value-growth spreads indicates that the underlying risk factor seems to be priced consistently across markets. He concludes that the risk factor priced in value stocks is financial distress.

D. Tactical Equity Style Strategies

Tactical Asset Allocation strategies were traditionally concerned with allocating wealth between two asset classes, typically shifting between stocks and bonds. More recently, more complex style timing strategies have been successfully tested and implemented. These strategies are based both on the recognition of the misspecifications of CAPM mentioned above and the substantial evidence that the "value premium" is not constant through time. Although, in the long-term, value stocks appear to have produced higher returns, over short investment horizons value strategies are not reliable since periods of value stock superiority alter with periods of growth stock superiority in a cyclical fashion. Thus, there is now a consensus that style diversification is the optimal solution to avoid the risk associated with "pure" style investing and to capture the potential benefits each separate style has to offer.

At the other end of this spectrum, a broad base of academic papers has explicitly elaborated on the possible benefits of style timing strategies over a style consistent approach. Although these papers may differ in methodology, they all rely on the opinion that the cyclical behavior of investment styles is correlated with systematic forces and therefore reasonable portions of value-growth spreads on equity markets are predictable by indicators of expected economic conditions.

Most empirical work on active style rotation strategies is usually concentrated on the well-documented markets in the United States and United Kingdom. Levis and Liodakis (1999) conduct simulation procedures and illustrate that forecasting the size spread with a 65-70 percent accuracy rate may be sufficient to outperform the small-cap buy-and-hold portfolio, during the thirty-year period 1968 through 1997, in the United Kingdom. In the case of value-growth rotation at least an 80 percent forecasting accuracy of the direction of the value spread would be required to beat the value strategy, which is markedly difficult to sustain in reality. Kao and Shumaker (1999) develop tactical asset allocation strategies by testing a model to explain the relationships between macroeconomic variables and the subsequent year's performance of value versus growth stocks. They confirm the efficacy of models founded on macroeconomic factors to signal style changes. Oertmann (1999) documents that reasonable portions of the value-growth return spreads, on international equity markets, are ex-ante predictable by indicators of expected global economic conditions. He concludes that this predictable variation of "value premium" is economically significant and can be exploited by active style rotation strategies. Cooper, Gulen and Vassalou (2001) suggest new trading strategies on size and book-to-market decile portfolios, constructed using the prediction of a forecast model that includes mainly business cycle related variables. Extensive out-of-sample experiments reveal that the proposed size and book-to-market strategies outperform passive strategies invested in the same portfolios, as well as SMB- and HML-type of strategies. Their results most closely support a risk-based explanation for the performance of SMB and HML. Lucas, Van Dijk and Kloek (2002) develop a framework for capturing the time-varying impact of firm characteristics like size and book-to-market ratio on excess returns. They show that both the magnitude and direction of this impact display considerable time-variation. In addition, they confirm that linking the impact to macroeconomic conditions produces consistent and robust (risk-corrected) excess returns which appear incompatible with the standard risk-compensation view.

Ahmed, Lockwood and Nanda (2002) demonstrate that portfolios formed using astute style rotation strategies considerably outperform style consistent strategies. Moreover, the potential enhancement in performance is highly significant and meaningful, especially in volatile sectors. Bauer and Molenaar (2002) develop a trading strategy in which the observed "value premium" is exploited utilizing a recursive modeling approach. Consistent with the previous studies, they estimate a universe of parsimonious models using a base set of technical and macroeconomic forecasting variables. Subsequently, they generate out-of-sample forecasts and implement their long-short strategy minimizing the look-ahead bias. They highlight the considerable variation of the relevant forecasting variables through time and conclude that the time-varying value-growth spread could be successfully forecasted and exploited in a practical context.

Furthermore, Levis and Tessaromatis (2004) assess the power of a macroeconomic model to generate forecasts about the direction and the magnitude of the value-growth spread under different benchmarks and various risk constraints. They show that style rotation strategies are both institutionally and economically viable strategies which can apply to a wide range of sectors of fund management industry. Finally, Arshanapalli, Switzer and Panju (2007) study style-timing strategies which concentrate on timing a family of style indices using a multinomial logit model. They find that investors can add substantial value to their portfolio by timing the Russell large-cap growth, large-cap value, small-cap growth and small-cap value equity style indices.

E. Technical Trading Rules

The term "Technical Analysis" is a general heading for a myriad of trading techniques. Technical trading rules have been used in financial markets for more than a century. Technical traders base their analysis on the premise that the patterns in market prices are assumed to recur in the future, and thus, these patterns can be used for predictive purposes. The motivation behind technical analysis is to be able to identify changes in trends at an early stage and to maintain an investment strategy until the weight of the evidence indicates that the trend has reversed. The techniques used to discover hidden relations in stock returns can range from extremely simple to quite elaborate.

Despite the biased attitude of academics towards technical analysis, recent findings suggest that stock returns are not fully explained by common risk measures. A line of research directly related to this work provides evidence of predictability of equity returns from past returns. When taken at face value, these results indicate that either the stock market is not efficient or that market is efficient and the predictable variation can be explained by time-varying risk premiums. From a practitioner's viewpoint, technical analysis has been enjoying a renaissance on the worldwide financial markets: all major brokerage firms publish technical commentary on the market and individual securities and many of the newsletters published by various “experts” are based on technical analysis.

Taking into account all the above, Brock, Lakonishok and LeBaron (1992) study 26 technical trading rules applied to the Dow Jones Industrial Average using 90 years of daily stock prices and their results suggest that technical rules have predictive power. They argue that the return-generating process of stocks is probably more complicated than suggested by the various studies using linear models. Specifically, they compare the returns conditional on buy (sell) signals from the actual Dow Jones Industrial Average Index to returns generated from four popular null models: the random walk, the AR(1), the GARCH-M and the exponential GARCH (EGARCH). Brock et al. (1992) find that returns obtained from buy (sell) signals are not likely to be generated by these four popular models and consider quite possible that technical rules pick up some of the hidden patterns. Nonetheless, they leave the reason why such rules might work as an intriguing issue for further studies. In response to the work of Brock et al. (1992), Sullivan, Timmermann and White (1999) apply a new methodology that allows them to control for data-snooping biases to compute the statistical significance of investment performance while accounting for the dependencies resulting from investigating several investment rules. Their findings indicate that the results of Brock et al. (1992) stand up to inspection for data-snooping effect. However, they also find that the superior performance of the best performing-trading rule is not repeated in the out-of-sample experiment covering the 10-year period 1987-1996. They conclude that, historically, the best technical trading rule did indeed produce superior performance, but that, more recently, the markets have become more efficient due to the cheaper computing power, the lower transaction costs and the increased liquidity.

F. Our Contribution to Style Rotation Issues

Unsurprisingly, previous empirical papers that attempted to predict the “value premium” relied heavily on well-established economic state indicators. These business cycle style-based results may be the consequence of the rational response of investors to changing macroeconomic and fundamental data which would change the investor opportunity set.

However, the influence of behavioral factors, as introduced in Barberis and Shleifer (2003) cannot be ruled out. Barberis and Shleifer (2003) discuss an inefficient market approach. They demonstrate that prices deviate substantially from fundamental values as styles become popular or unpopular. These inefficiencies could be exploited from a combination of momentum and contrarian trading.

Thus, in this paper, we deviate from the standard quantitative approach and examine the style-profitability of simpler technical trading rules. We believe that a simpler approach does not require complex (and often subjective) model specification which makes these strategies more appealing to the wide investment community. Furthermore, one of the reasons that make technical trading strategies interesting is the fact that they appear to be capable of capturing the short-term momentum effect which is prominent in almost every financial market.

Another issue to be considered is that regardless of overwhelming evidence from academic literature regarding the predictability and profitability of style returns, these benefits are hardly observed in practice. As pointed out by Cooper and Gulen (2006) there is a considerable gap between real-time reported results of trading strategies and the performance of rotation strategies in academic research papers. Most of these studies forecast style spreads using a fixed subset of forecasting variables that have been obtained from a setting that benefits too much from ex post knowledge. This seems rather inappropriate as no investor could have obtained these results based on the entire sample. Our aim is to ensure that a "real-time" trading strategy could be implemented in a practical context without the benefit of hindsight.

Our procedure is largely an extension of the work of Brock, Lakonishok and LeBaron (1992) who is perhaps the most comprehensive recent study of technical trading rules. Our models are aimed at forecasting the sign (direction) of index returns since, as documented by Leung, Daouk and Chen (2000), such models outperform the level estimation models in terms of predicting the direction of stock market movement and maximizing returns from investment trading. Based on these predictions we form zero-investment portfolios that are long on one style and short on the other. In the next section we present a description of the data and methodology used to predict the return spreads of the different Russell indices.

III. Data and Methodology

A. Data

We obtained daily data from June 1998 to June 2008- a collection of 10 years of data-from four different sources: DataStream, Bloomberg, the Federal Reserve Board and the site of Kenneth French. In order to implement our style-timing strategies we have selected the Russell 1000® Value, Russell 1000® Growth, Russell 2000® Value and Russell 2000® Growth indices. Returns are calculated as log differences of the indices' level.

The intuition behind using readily available indices instead of customized portfolios as used in other studies is twofold. Foremost, indices are easier and less expensive to trade both because their market acceptability as basket trades and the fact that they require less rebalancing of individual stocks in comparison to customized portfolios. Finally, readily available indices are widely used as style benchmarks either for trading or performance evaluation purposes.

B. Russell Indices Definition and Statistics

Russell indices are designed to be comprehensive representations of the investable U.S. equity market and its segments. These indices are float-adjusted and market-cap weighted and they include only common stocks belonging to corporations incorporated in the U.S. and its territories. The broadest U.S. index is the Russell 3000E™, which contains the largest 4,000 companies. Sub-indices in the Russell 3000E™ are broken out by market capitalization and style. Thus, Russell 1000® includes the first 1000 companies based on descending market capitalization. Respectively, Russell 2000® includes the subsequent 2000 companies (companies #1,001-3,000). Regarding style determination, *Russell Investments* uses a "non-linear probability" method to assign stocks to the growth and value style indices. The term "probability" is used to indicate the degree of certainty that a stock is value or growth, based on its relative book-to-price ratio and I/B/E/S forecast long-term growth mean. For each base index (Russell 1000, Russell 2000) stocks are ranked by the fore mentioned criteria. These rankings are converted to standardized units and combined to produce a score. Finally, a probability algorithm is applied to the scores' distribution to assign value and growth weights to each stock and compose Russell

1000® Value, Russell 1000® Growth, Russell 2000® Value and Russell 2000® Growth indices. All Russell indices are reconstituted annually (on May 31st) and enhanced quarterly with the addition of initial public offerings (IPOs).

There are two reasons for the use of the Russell Company style indices throughout this paper. First, institutional investors tend to rely on the Russell indices across a wide spectrum of products. In fact, according to a recent Institutional Benchmark Survey, Russell's Market Share by product for U.S. equity benchmarks used by institutional investors continues to grow and accounts for 58.5 percent. Moreover, the market share of assets benchmarked to Russell indices remains above 50 percent. Secondly, the availability of futures contracts and exchange-traded funds on the Russell indices make implementation of our timing-strategies an easily exploited and viable option for the majority of practitioners.

In Table I we report descriptive capitalization statistics and fundamental characteristics for each index of interest. The table reveals considerable market capitalization deviations between the large-cap and small-cap indices as well as notably distinct fundamental features between the value and growth style indices. In sum, the table confirms the fact that Russell indices are constructed to provide a comprehensive and unbiased barometer for the large-cap and small-cap "value premium".

Table I

Russell Indices Statistics as of May 30,2008

	R1000V	R1000G	R2000V	R2000G
Capitalization Statistics(in billions)				
Average market cap	103.657	71.038	1.328	1.693
Median market cap	5.135	5.812	0.530	0.574
Largest company by market cap	474.868	474.868	7.581	7.581
Smallest company by market cap	0.114	0.113	0.026	0.022
Fundamental Characteristics				
Price/Book	1.90	3.94	1.55	3.10
Dividend yield	2.80	1.18	2.03	0.59
P/E Ex-neg earnings	14.59	18.93	16.22	22.09
Lt growth forecast-IBES (%)	9.68	14.72	11.44	18.39
EPS growth-5 years	15.89	22.85	9.29	22.64

This table presents Russell indices capitalization statistics and fundamental characteristics. R1000V is the Russell large-cap value index, R1000G is the Russell large-cap growth index, R2000V is the Russell small-cap value index and R2000G is the Russell small-cap growth index.

Table II

Summary Statistics Value Premium

	Small-cap	Large-cap
Annualized mean (%)	2.31	1.42
Annualized standard deviation	12.43	12.92
Minimum (daily)	-5.20	-7.52
Maximum (daily)	5.57	4.40
Skewness	0.48	-0.29
Kurtosis	7.80	9.42
% Negative days	51.27	49.60

This table presents summary statistics for the large-cap value premium and the small-cap value premium. Period: 06/01/1998-06/01/2008. All numbers are daily data unless stated otherwise. Small-cap value premium is computed as returns of a long position on Russell 2000 Value index and a short position on Russell 2000 Growth index. Large-cap value premium is computed as returns of a long position on Russell 1000 Value index and a short position on Russell 1000 Growth index.

C. "Value Premium" Statistics

Table II contains summary statistics for the value spread series both for the large-cap and the small-cap segments. These series are the returns of a long position in the value index and a short position in the growth index throughout the entire sample period ranging from June 1998 to June 2008. Judging by the annualized values of mean and standard deviation, both for the large-cap and the small-cap strategies, we conclude that pure and unconditional value investing in this particular sample period was not a very attractive strategy. The analogy between mean return and risk does not produce sufficient information ratios for a demanding investor. Furthermore, we observe a high range between minimum and maximum values, which could be attributed to daily trading. Summary statistics also reveal that the spread series are strongly leptokurtic for the entire sample. Finally and most importantly, both strategies exhibit a great number of negative performance days, approximately 50 percent which indicates the potential profitability of an active style-rotation strategy based on a robust and acute timing model.

Figure 1 and Figure 2 present time-series graphs for the evolution of cumulative wealth of the large-cap and the small-cap value spread for the period 1998/06-2008/06. The spread series are the daily return of a long/short portfolio (long on the value index and short on the growth index). The initial amount invested is $100. At first glance we observe that these passive style strategies would have witnessed a highly volatile period during the first half of the sample period. For instance, during the last years of the previous decade growth stocks outperformed value stocks considerably. What is puzzling is that value stocks exhibited poor returns despite good earnings. In contrast, at the beginning of the century value stocks clearly outperformed growth stocks. This volatile period is attributed to the "dotcom bubble" and the subsequent crisis of technology stocks. The second half of the sample period could be characterized less volatile, however we observe time-varying pattern in the behavior of the "value premium" where one style seems to outperform the other for short-term horizons.

A possible explanation for the fore mentioned behavior could be the assumption that many investors allocate funds based on relative past performance, moving into styles that have performed well in the past and financing this shift by withdrawing funds from styles that have performed poorly. Thus, we assume that investment styles follow a specific life cycle. The birth of a style is often triggered by good fundamental news about the securities in the style. The style then matures as its good performance recruits new funds, further raising the prices of the securities belonging to the style. Finally, the style collapses either because of arbitrage or because of bad fundamental news. Over time, the style can be reborn. Thus, we employ a style-momentum strategy based on technical trading rules that are capable of capturing short-term trends in volatile series.

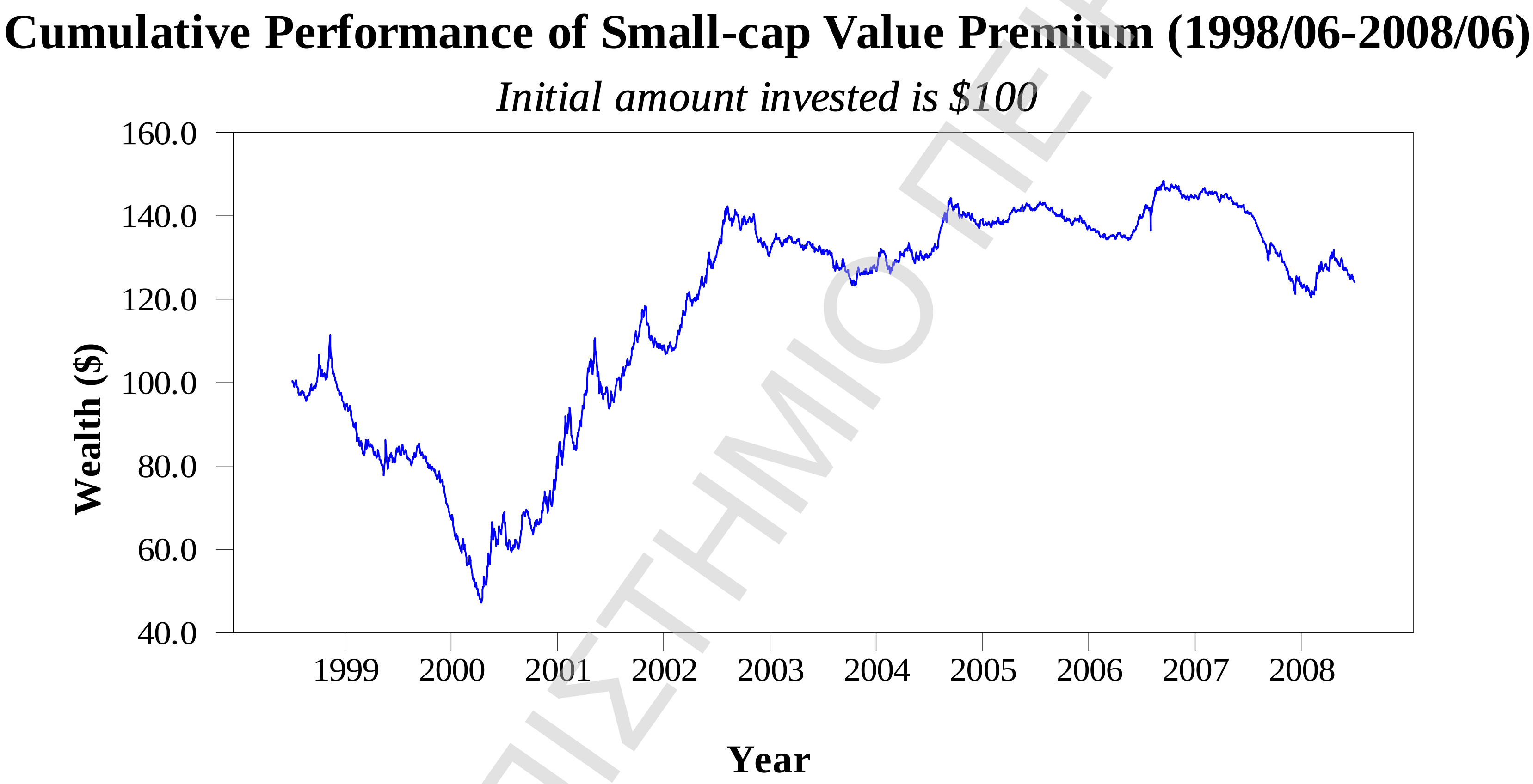

Figure 1. Cumulative performance of small-cap value premium. Period: 1998/06-2008/06. The series are the daily returns of a long position in the Russell 2000 Value index and a short position in the Russell 2000 Growth index. Initial amount invested is $100.

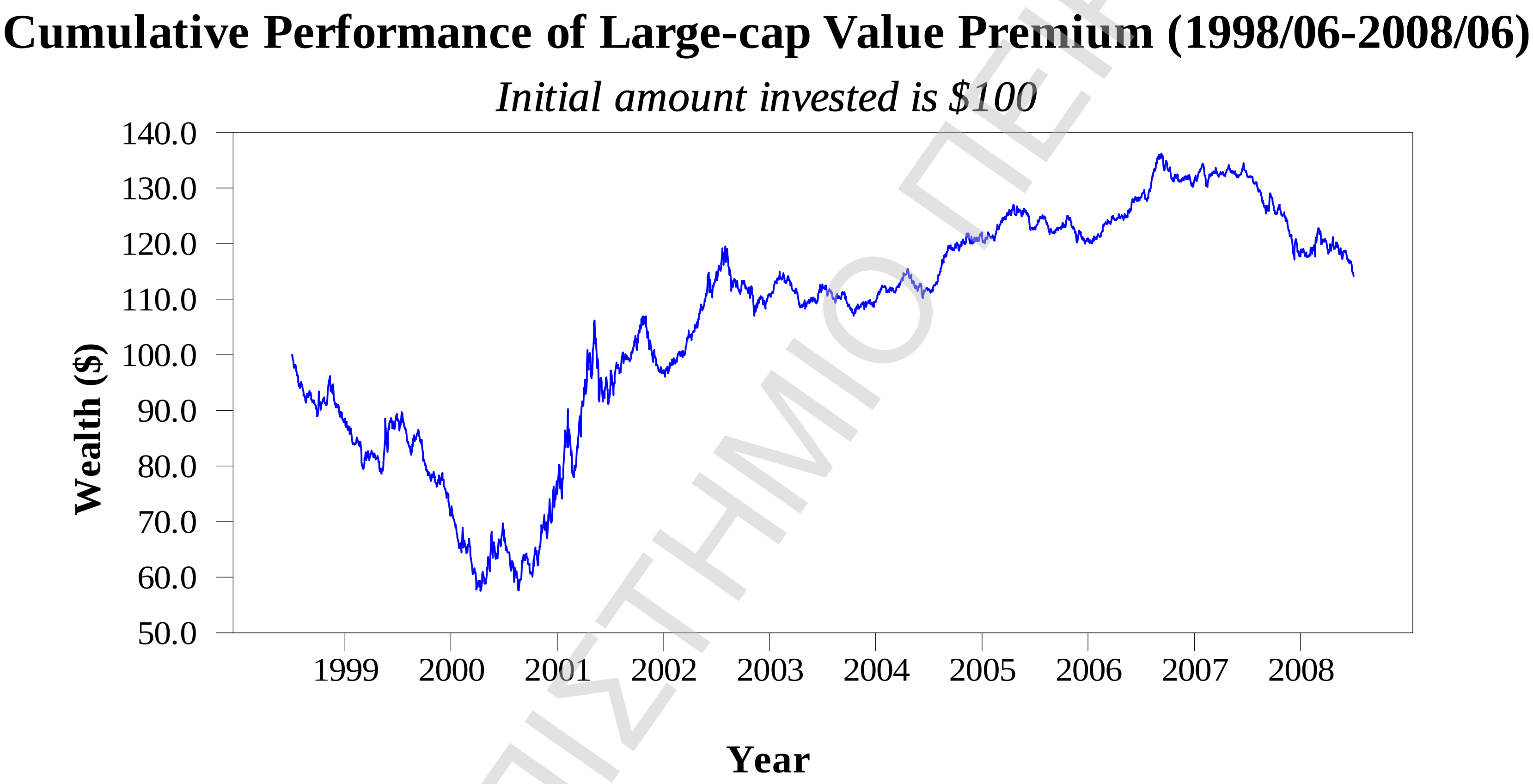

Figure 2. Cumulative performance of large-cap value premium. Period: 1998/06-2008/06. The series are the daily returns of a long position in the Russell 1000 Value index and a short position in the Russell 1000 Growth index. Initial amount invested is $100.

D. Methodology and Technical Trading Rules

Our study uses Brock et al. (1992) as a springboard for technical trading rules. One of the simplest and most widely used technical rules is investigated: moving average oscillator. The standard moving average rule, which utilizes the price line and the moving average of price, generates signals as explained in Gartley (1935):

> In an uptrend, long commitments are retained as long as the price trend remains above the moving average. Thus, when the price trend reaches a top, and turns downward, the downside penetration of the moving average is regarded as a sell signal….Similarly, in a downtrend, short positions are held as long as the price trend remains below the moving average. Thus, when the price trend reaches a bottom, and turns upward, the upside penetration of the moving average is regarded as a buy signal. (p.256)

There are numerous modifications of this rule. In this paper we use more than one moving average to generate trading signals. Besides, since we implement a long/short strategy we utilize the *price relative* of value-growth indices instead of the simple price indices to compute moving averages. *Price relative* compares the performance of one index against that of another and offers a straightforward and accurate portrayal of relative performance of different style-indices. Thus, we calculate *price relative* by dividing the large-cap (small-cap) value index's price by the value of the large-cap (small-cap) growth index.

According to the adopted moving-average rule, buy and sell signals are generated by two moving averages of the level of the *price relative* index-a long-period average and a short-period average. In its simplest form this strategy is expressed as buying (or selling) when the short-period moving average rises above (or falls below) the long-period moving average. The idea behind computing moving averages is to smooth out otherwise volatile series. When the short-period moving average penetrates the long-period moving average, a trend is considered to be initiated. The most popular moving average rule is 1-200, where the short period is one day and the long period is 200 days. While plentiful variations of this rule are used in practice we attempted to select combinations of the most popular ones: 1-50, 1-150, 5-150 and 1-200.[1] It should be noted that the main task of moving average rules is to smooth out

[1] We have also examined several other combinations. Results are essentially similar and available upon request.

data series and make it easier to identify the direction of the trend. Since past price data is used to form moving averages they are considered lagging, or trend following indicators. Moving averages will not predict a change in trend but rather follow behind the current trend.

E. Trading Strategies

Our first strategy, called the "active strategy", initiates buy (sell) signals when the short moving average is above (below) the long moving average. This method attempts to simulate a strategy where traders go long as the short moving average moves above the long and short when it is below. This strategy classifies all days into either buys or sells.

Our second strategy, called "band strategy", introduces a band around the moving average. If the short moving average is inside the band no signal is generated. The introduction of a band reduces the number of buy (sell) signals by eliminating "whiplash" signals when the short and long period moving averages are close and therefore assists in filtering out false trading signals (i.e., those signals that would result in losses). We impose a 1 percent filter and subsequently expect this method to act as shield against growing transaction costs, enhancing the net performance of this strategy. [2]

Our third strategy, called "stop-loss strategy" imposes an alternative filter on the simple "active strategy". According to this rule, the cumulated performance of the "active strategy" 15 trading days ago is compared to the current cumulated performance. In the event that the performance has declined below a certain threshold the strategy generates a neutral signal until the next trading signal (i.e., the next crossing of moving averages). We impose a threshold of -3 percent, however, many variations regarding both the look-back period and the stop-loss limit can be implemented based on the investor's personal views and tactics.[3] Concluding, this strategy is aimed at limiting an investor's loss on a specific position, especially in largely volatile markets.

Finally, our last trading rule represents a combination of the "band strategy" and the "stop-loss strategy". Under this scheme, trading signals are generated only if the

[2] Our selection of this band is influenced by the work of Brock et al. (1992).
[3] The selection of 15-day look-back period is arbitrary. We also tried 10 days and 20 days and obtained the same results. The same hold for the stop-loss limit.

short moving average is outside the band conditional upon the stop-loss threshold has not been violated. This strategy illustrates an overly defensive option, designed for risk-averse investors.

The signal functions of our technical trading strategies have a range of three values: 1 represents a long position, 0 represents a neutral position and -1 represents a short position. A long position denotes two contemporaneous positions: a long position in the large-cap (small-cap) value index and a short position in the large-cap (small-cap) growth index. Correspondingly, a short position implies a long position in the large-cap (small-cap) growth index and a short position in the large-cap (small-cap) value index. A neutral position suggests withdrawing funds from the market. In the event of a neutral signal we assume that the funds are invested in an overnight interest rate asset. In our analysis, we use the daily effective Federal funds rate as the overnight cash return, where the annualized rates reported throughout the sample, are converted to daily rates using the following formula: [4]

$$r_d = \frac{\ln(1 + r_{ann})}{252} , \tag{1}$$

where r_d is the daily interest rate, r_{ann} is the reported annualized rate, and 252 represents the average number of trading days in a year.

Another important and crucial point in our analysis relates to the look-ahead bias, which is highly intense in other studies. As mentioned above, our incentive is to attain truly practical results that explicitly account for the continuous uncertainty that "real-time" investors face regarding their trading decisions. We mitigate the impact of "hindsight" bias by generating leading signals. In particular, our model utilizes the preceding closing value of the *price relative* index in order to generate a trading signal which is implemented the following day. In this way, we ensure the forward-looking nature of the moving average rules.

Concluding, there are numerous variations of the moving average rule that we do not examine. We focus on the simplest and most popular versions. Other variants of the moving average rule also consider the slope of the long moving average in

[4] By trading government securities, the New York Fed affects the federal funds rate which is the interest rate at which depository lend balances to each other overnight. The daily effective federal funds rate is a volume-weighted average of rates on trades arranged by major brokers.

addition to whether the short-period moving average penetrated from above or below. In other versions changes in trading volume are examined before buy (sell) decisions are reached. Thus, numerous moving average rules can be designed, and some, without a doubt, will work. However, the dangers of data-snooping are immense. We present results for all the strategies examined and place emphasis on the robustness of the results over time. At last, to measure the profitability of our market-timing strategies we compare our style-rotation strategies both with a "buy and hold" strategy and with the performance of market as a whole (expressed by the performance of Standard and Poor's 500 index) in the next section.

IV. Implementation and Results of Style Rotation Strategies

A. Implementation

In theory, a style-timing strategy can be implemented by trading two instrument types: index futures or Exchange Traded Funds. In contrast to other studies which have utilized ETFs to implement style-rotation strategies we have chosen to apply our trading strategies by using index futures. There are two reasons lying behind our choice. Firstly, daily trading ETFs would incur unreasonably high transaction costs. Furthermore, the index futures market has gained sufficient liquidity the recent years. However, one main drawback of the style index futures and futures contracts, in general, is the presence of basis risk.

Starting with an initial wealth of $100, our trading simulation assumes that, at the end of each day, an investor needs to take an asset allocation decision involving the large-cap (small-cap) *price relative* Russell indices. Our trading period is common both for the buy-and-hold and the style-rotation strategies and thus ranges from June 1st 1998 to June 1st 2008.

In order to evaluate the profitability of our style-timing model, the trading strategies that implement the signals of our timing model are compared to two buy and hold strategies selected for their relevance. The first buy and hold strategy serves as a multi-style benchmark. This strategy represents a passive multi-style manager and assumes a long position on the large-cap (small-cap) value index and a short position on the large-cap (small-cap) growth index. These positions are retained until the end of the trading period (i.e. June 1st 2008). The second buy and hold strategy serves as a market proxy. This strategy illustrates the performance of the market as a whole, expressed via the performance of S&P 500 index. S&P 500 index is widely regarded as the best single gauge of the U.S. equities market, including 500 leading companies in leading industries of the U.S. economy.

B. Transaction Costs

As we have pointed out throughout this study, trading costs perform a significant role in the profitability of style-switching strategies. In fact, in order for our style-timing strategies to be a viable investment option for practitioners, those strategies, despite the fact that they are subject to a much higher turnover, need to earn a higher return than the buy-and-hold equivalents.

Russell indices futures are currently available for trading both on the New York Board of Trade (NYBOT) and on the Chicago Mercantile Exchange (CME). However, a recent deal announcement states that the IntercontinentalExchange (ICE®) has acquired exclusive licensing rights to the Russell indices for futures and options on futures contracts. Specifically, the CME has the right to list Russell U.S. index futures through contract expiration in September 2008. After September 2008 ICE will be the only exchange where Russell U.S. index-based futures and options will be available. At this moment, only Russell 2000 and Russell 1000 index futures are available. These contracts are offered in two sizes: a regular size contract ($500 times Index) and a mini-sized contract ($100 times Index) which is available only for electronic trading. The Russell indices of our interest (Russell 2000 Value, Russell 2000 Growth, Russell 1000 Value and Russell 1000 Growth) will be made available for electronic trading in the future (probably 4th quarter). Finally, these futures contracts can be traded at a relatively low cost. Suggestively, ICE exchange fees for the mini Russell 2000 futures contract range from $0.30 to $0.94 while brokerage commissions from $1 to $4 single-trip per contract.[5] Additionally, investors can achieve substantial leverage through futures trading, since initial margins are as low as 5 percent.

To verify whether our technical trading strategies could have been profitable, when implemented, accounting for realistic costs of trading and taking into account the above facts, we assume two levels of transaction costs: 10bps and 20bps of the

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[5] We are thankful to Ted Doukas for information support on Russell indices futures.

transaction value, both round-trip. There are two reasons for this discrimination. First, while the 20bps level may be high by current standards, it appears to be reasonable both for the earlier period of study and for investors who prefer ETFs as trading vehicles. Secondly, our study addresses not only to institutional and fund managers but also to individual investors and practitioners.

On the other hand, the multi-style buy-and-hold strategies could easily be implemented using ETFs, since turnover is negligible and management process is easier. When index futures mature every quarter, investors eventually have to roll futures position forward and incur associated trading costs. Moreover, ETFs can also be traded on margin and sold short. However, to attain a truly common basis for the comparison between the active and the passive strategies we choose to utilize index futures with the longest possible maturity for our buy-and-hold purposes. Anywise, as we found, net annual performance does not deviate substantially, either through the use of index futures or ETFs.[6]

C. Empirical Results of Style Rotation Strategies

In this section we analyze the results for the style timing strategies explained in the previous chapter. Our figures simulate the cumulated returns of our separate active strategies over the sample period against the buy-and-hold strategy and the market proxy. The results do not include transaction costs. Additionally, our tables provide thorough performance assessment by displaying various measures of profitability and undertaken risk. Apart form the traditional descriptive statistics we present supplementary ones in order to clarify whether our model's forecasts would have been valuable for investors accounting for risk.

Downside deviation is a value representing the potential loss that may arise from risk as measure against a minimum acceptable return. Downside deviation aims to isolate only the negative proportion of volatility and penalizes only returns that fall below the minimum acceptable return (MAR). In this paper we adopt the daily cash return series of effective fed funds rate as MAR. Moreover, we exhibit Sharpe ratios and Sortino ratios as risk-adjusted measures of return. Sharpe ratios are calculated as the quotient of the annualized excess return of the manager over the cash equivalent and annualized standard deviation of the manager return. Since there is no guarantee

[6] Four quarterly contracts are listed. Thus, trading costs for the buy-and-hold benchmarks are deducted once in a year which is, indeed, consistent with low turnover.

that our timing strategies produce symmetric returns, we further check the performance of our strategies by examining the Sortino ratio. Sortino ratio is analog to the Sharpe ratio, with the standard deviation replaced by the downside deviation. Information ratio measures the consistency with which a manager beats a benchmark. Information ratio is the ratio of the alpha component of total returns to the standard deviation of these excess alpha returns. To gauge the excess returns attributable to the skill of an active (passive) manager we specify the S&P 500 index as a benchmark.

To further evaluate the risk adjusted performance of all the models, we estimated the alpha and beta coefficients of a linear regression of the following form:

$$R_i = a_i + \beta_i R_m + e_i \, , \qquad (2)$$

where R_m are the returns of the S&P 500 index (used as a proxy for the market as a whole), R_i represent the returns of each style-timing strategy and e the random element. Both the sign and the significance of the coefficients serve as a measure of skill of an active (passive) manager since they express the sensitivity of the manager in terms of market volatility and the manager's "value added".

Regarding the significance of the regression coefficients we should point out that the null hypotheses differ. That stems from the fact that whereas a statistical different from zero alpha coefficient is desirable for a shrewd investor the same does not hold for the beta coefficient. Since beta measures the strategy's volatility, the degree to which its performance fluctuates in relation to the overall market, investors seek to insulate themselves from violent swings in equity markets by devising low-beta strategies. Thus the null hypothesis of our beta estimates focuses on whether beta is significantly negative or nearly zero, clarifying the extent to which our strategies are market-neutral.

Lastly, in order to evaluate the consistency of the performance of our strategies over time we illustrate annualized excess returns for every single year of the trading period. Annualized excess return is the annualized difference between the annualized return of the active strategy minus the annualized return of the benchmark strategy. Instead of the S&P 500 index, here, the buy-and-hold strategy serves as a benchmark, since our major purpose is to highlight the importance of active management and to contribute to the protracted debate between active versus passive types of strategies.

i. Small-cap "Value Premium"

Our analysis begins with the small-cap segment. The results in Figure 3, Figure 4, Figure 5 and Figure 6 are striking. These figures plot the cumulative wealth of the four style-rotation strategies and the simple buy-and-hold strategies (multi-style, market-proxy) over the sample period. During the period from June 1998 to June 2008, the cumulated values of our style-timing strategies are remarkably higher than the values of the buy-and-hold strategies in every case.

Obviously, the patterns illustrated vary with the combination of the moving averages and the nature of each strategy. At first glance, we can notice a disproportion between the period of the long moving average and the performance of the strategy. It is clear that the longer moving averages lack robustness and therefore achieve lower performance, ignoring the corresponding lower transaction costs. However, this phenomenon is strongly mitigated when stop-loss and band-and-stop-loss strategies are applied. The attributes of these strategies act as a cushion which secures the potential investor in cases where moving averages are incapable of capturing timely the reversal of the trend.

Another noteworthy point, is the fact that the performance of our strategies appears to evolve in an opposite fashion compare to both the buy-and-hold and the S&P 500 strategies. This is present in the first four and the last year of our trading period, as the prominent widening of the gap between the cumulative values. What is most important, our strategies' cumulative wealth is constantly above the initial wealth invested. In contrast, both the buy-and-hold and the "market" strategies experience periods of great volatility and loss of capital which, given the daily settlement of futures contracts, would absolutely lead to either bankruptcy or illiquidity.

Finally, in a rough estimation and ignoring transaction costs, we convey that 1-50 and 5-150 are the best-working trading rules. However, safer conclusions can be derived by examining the following analytic tables.

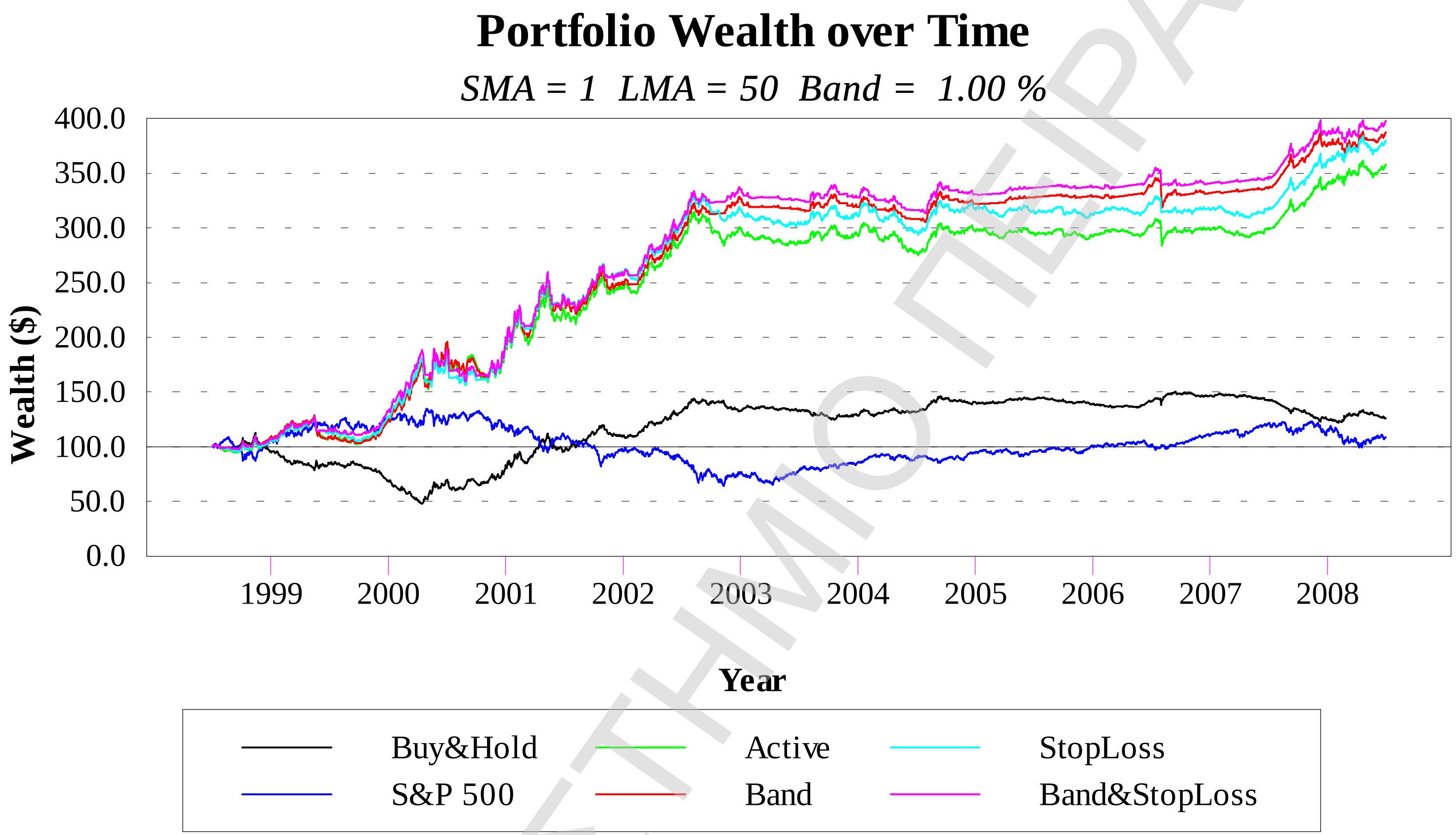

Figure 3. Portfolio wealth over time: Period (1998/06-2008/06). **Small-cap value spread.** This figure shows the cumulative portfolio wealth of the style-rotation and the buy-hold strategies over the June 1998 to June 2008 period. Initial amount invested is $100. SMA and LMA stand for the short-period moving average and the long-period moving average, respectively. Band is the percent difference that is needed to generate a signal under the "band" strategy.

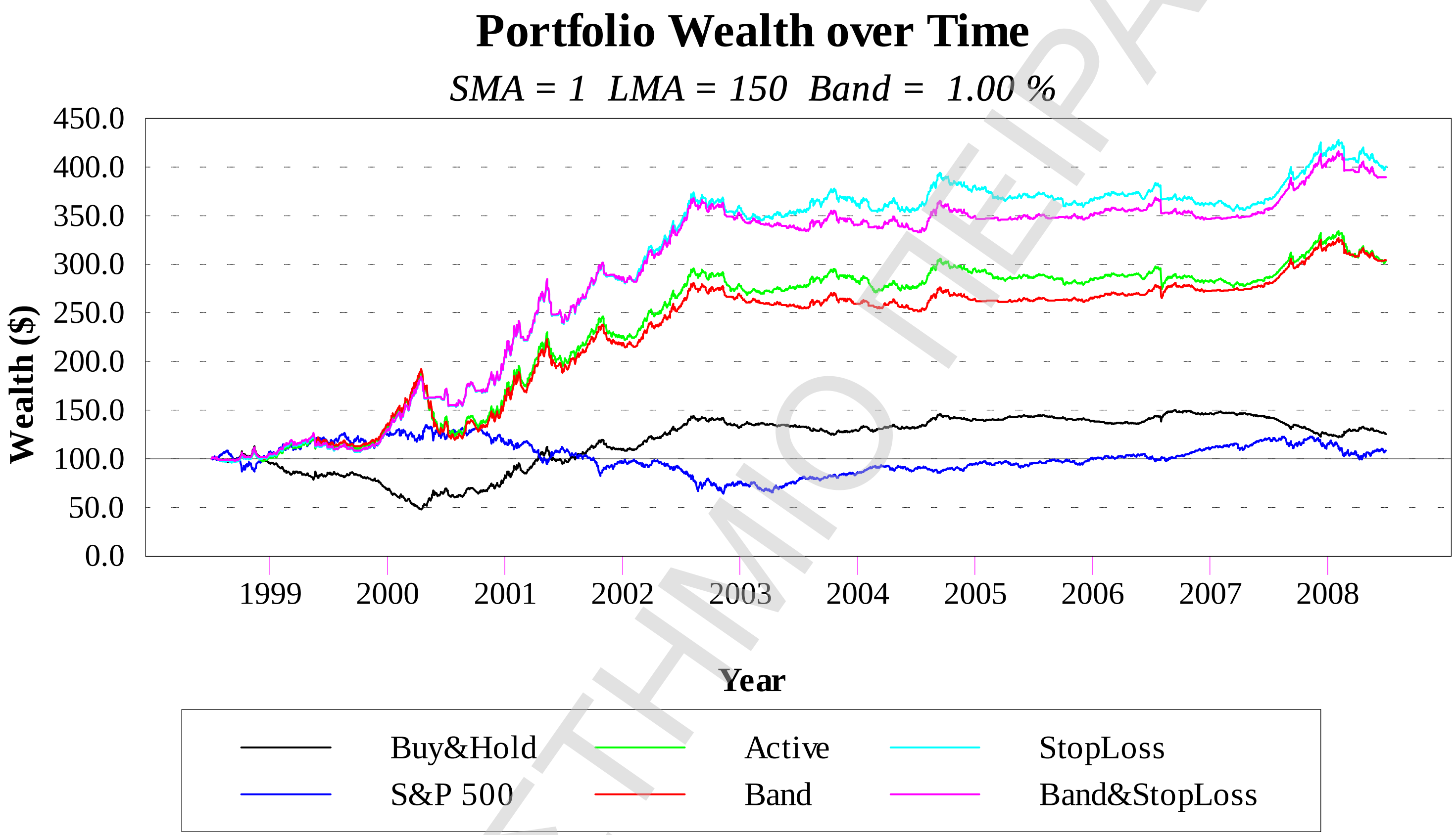

Figure 4. Portfolio wealth over time: Period (1998/06-2008/06). **Small-cap value spread.** This figure shows the cumulative portfolio wealth of the style-rotation and the buy-hold strategies over the June 1998 to June 2008 period. Initial amount invested is $100. SMA and LMA stand for the short-period moving average and the long-period moving average, respectively. Band is the percent difference that is needed to generate a signal under the "band" strategy.

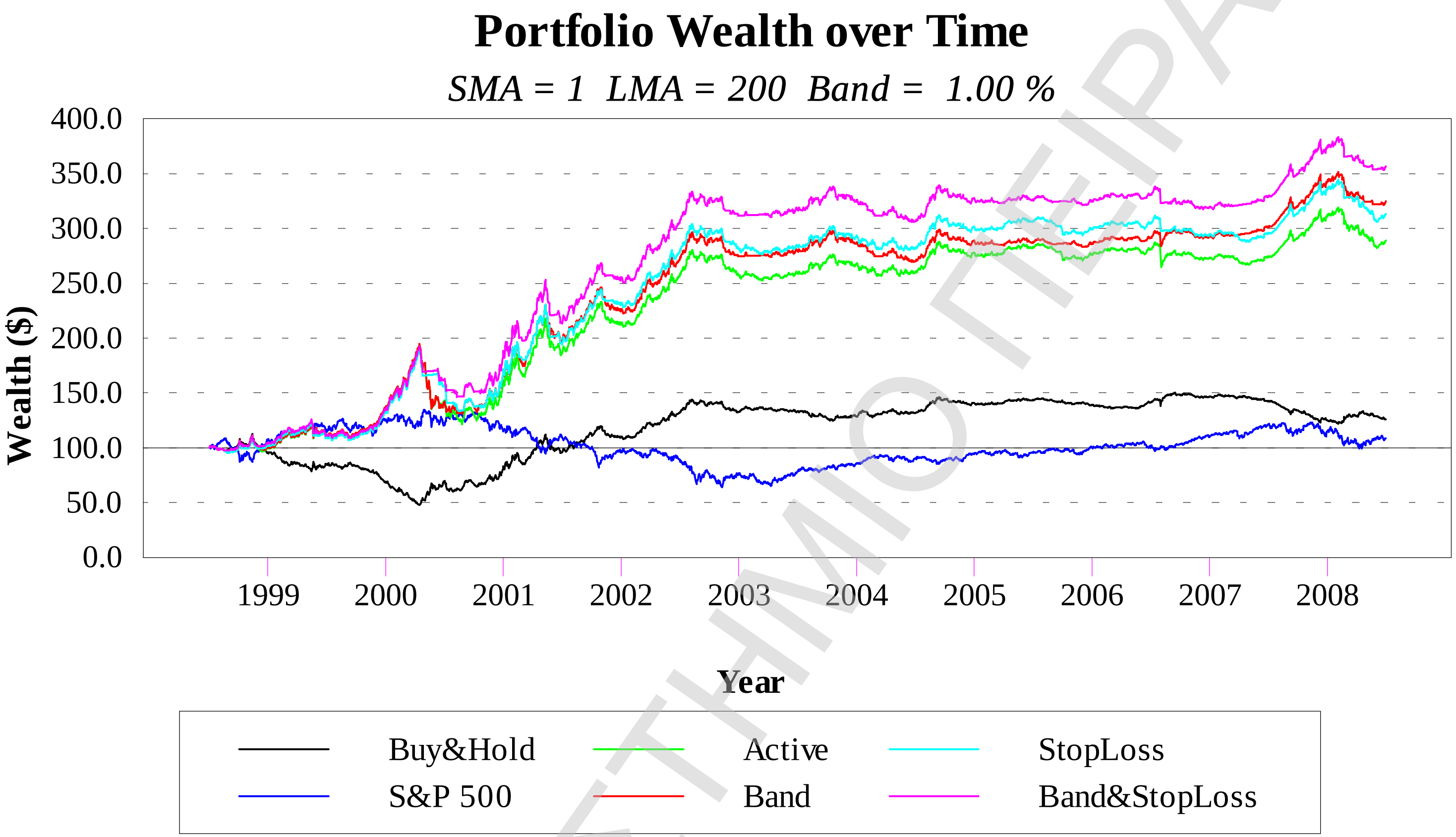

Figure 5. Portfolio wealth over time: Period (1998/06-2008/06). **Small-cap value spread.** This figure shows the cumulative portfolio wealth of the style-rotation and the buy-hold strategies over the June 1998 to June 2008 period. Initial amount invested is $100. SMA and LMA stand for the short-period moving average and the long-period moving average, respectively. Band is the percent difference that is needed to generate a signal under the "band" strategy.

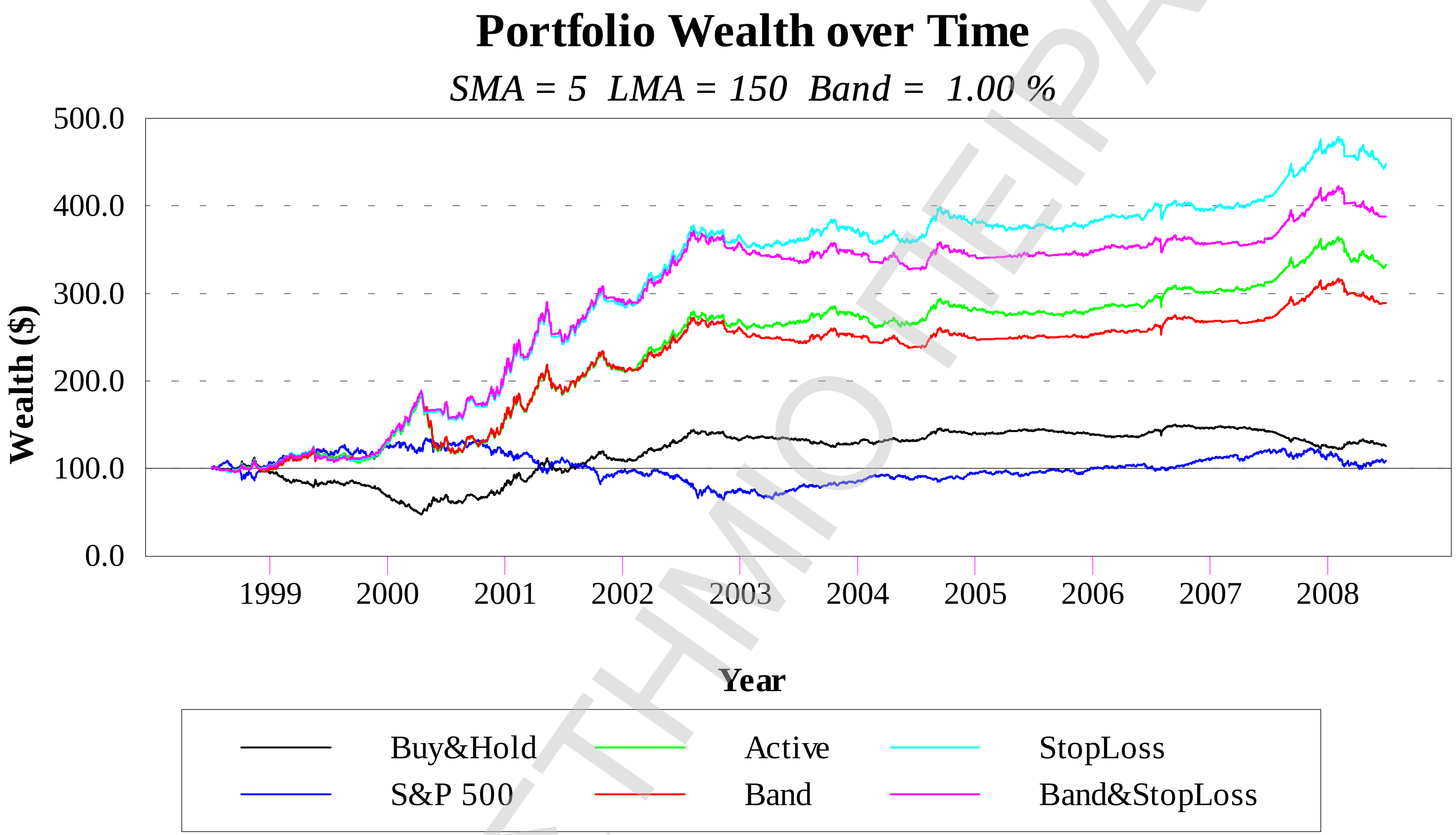

Figure 6. Portfolio wealth over time: Period (1998/06-2008/06). **Small-cap value spread.** This figure shows the cumulative portfolio wealth of the style-rotation and the buy-hold strategies over the June 1998 to June 2008 period. Initial amount invested is $100. SMA and LMA stand for the short-period moving average and the long-period moving average, respectively. Band is the percent difference that is needed to generate a signal under the "band" strategy.

Analytic results from trading strategies based on moving averages for the entire trading period are presented in Tables III through VI. The rules differ by the length of the short and the long period moving average and by the type of strategy. We compare the performance of each rotation strategy over the trading period with the buy-and-hold benchmark strategy and the market proxy (expressed via S&P 500 index). Additionally, we allow for two levels of transaction costs: 10bps and 20bps per switch round-trip to obtain a realistic basis for comparison.

The tables confirm what was previously illustrated in the graphs in a more comprehensive manner. Thus, in every case, results suggest that our rotation strategies not only perform much better than the benchmarks but also do not involve higher risk, as expressed by means of annualized standard deviation and downside deviation, excluding the “active” and the “band” strategies which demonstrate slightly higher downside deviation. A detailed examination of the tables reveals that the “stop-loss” and “band-and-stop-loss” strategies realize constantly high levels of returns, irrespectively of the moving-average rule.

The results appear to be robust even when taking into account transaction costs. The effects of incurred trading costs are negligible for the buy-and-hold and “market” strategies. On the other hand, our style-timing strategies suffer considerable deductions every time a switch is made. Thus the profits that can be derived from these trading rules depend, among other things, on the number of signals generated.

Although every strategy exhibits different sensitivity against switch recommendations we note that active and band-and-stop-loss strategies, generally, face a greater number of round-trip transactions as a result of higher turnover rates. In contrast, the stop-loss strategy generates low number of signals regardless of the moving average rule adopted. Of course it is clear, in case of longest moving averages; the signals generated by each timing-model are considerably fewer. Finally, a paradox should be mentioned: the shield against “whipsaws” the “band” strategy offers is less efficient the longer the moving average. Specifically, with the exception of 1-50 trading rule, the “band” strategy produces slightly more signals than the “active” strategy, although the opposite is expected. This phenomenon could be possibly attributed to the fact that our series mainly display trending characteristics. Nonetheless, the “band” strategy produces higher returns, which is the ultimate scope.

Our strategies’ outperformance is further eminent when looking at the risk-adjusted measures of return. Sharpe ratios, Sortino ratios and Information ratios all strongly support the superiority of style-timing strategies. In contrast to the buy-and-hold and market benchmarks, which exhibit negative values of the fore mentioned ratios our strategies achieve positive and far greater values, indicating higher excess return per unit of risk. Moreover, the percentage of negative returns is considerably lower, especially in the cases of “band” and “band-and-stop-loss” strategies indicating humble levels of downside risk.

Concluding, the last two rows of our tables illustrate the estimated alphas and betas of our strategies against the buy-and-hold benchmark. The results are akin in every circumstance, irrespective of active or passive approach. But for the statistically insignificant alpha of the buy-and-hold strategy, every single strategy demonstrates positive, significant alphas and negative, significant betas, indicating that our strategies constitute valuable hedge-tools that not only produce excess returns but also preserve potential investors from equity markets downturns.

Table III

Style Rotation Results: Small-cap Value Spread (1, 50, 1.00%)

	S&P 500	Buy & Hold	Active	Band	Stop-Loss	Band & Stop-Loss
Annualized return (%)	0.82	2.31	13.61	14.51	14.28	14.81
net of trans costs (10bps)	0.71	2.20	11.96	13.13	13.84	13.48
net of trans costs (20bps)	0.60	2.08	10.33	11.77	13.39	12.17
Annualized standard deviation	18.33	12.43	12.40	11.73	11.53	11.11
Annualized downside deviation	13.07	8.41	8.69	8.19	8.03	7.74
Sharpe ratio	-0.15	-0.11	0.80	0.93	0.92	1.00
Sortino ratio	-0.22	-0.16	1.14	1.33	1.32	1.44
Information ratio		0.06	0.53	0.57	0.56	0.59
5th centile (%)	-1.87	-1.03	-1.05	-0.98	-0.93	-0.91
Negative returns (%)	47.77	51.27	44.79	28.30	40.86	26.39
Recommended switches			146	121	39	116
Alpha		0.015	0.055**	0.058**	0.057**	0.058**
Beta		-0.318*	-0.14*	-0.156*	-0.148*	-0.153**

This table presents results of the style-rotation and buy-hold strategies for daily data from 1998/06-2008/06. Rules are identified as (SMA, LMA, Band) where SMA, LMA are the short and long moving averages, respectively, and band is the percentage difference that is needed to generate a signal under the "band" strategy. Transaction costs are expressed per switch and are round-trip. An alpha coefficient marked with * (**) indicates a 5% (1%) level of significance for a two-tailed test of H_o: $a=0$ against H_1: $a\neq 0$. A beta coefficient marked with * (**) indicates a 5% (1%) level of significance for a one-tailed test of H_o: $b=0$ against H_1: $b<0$.

Table IV

Style Rotation Results: Small-cap Value Spread (1, 150, 1.00%)

	S&P 500	Buy & Hold	Active	Band	Stop-Loss	Band & Stop-Loss
Annualized return (%)	0.82	2.31	11.76	11.77	14.89	14.57
net of trans costs (10bps)	0.71	2.20	11.03	11.02	14.49	13.68
net of trans costs (20bps)	0.60	2.08	10.29	10.28	14.09	12.80
Annualized standard deviation	18.33	12.43	12.40	11.97	11.02	10.85
Annualized downside deviation	13.07	8.41	8.88	8.64	7.71	7.60
Sharpe ratio	-0.15	-0.11	0.65	0.68	1.02	1.01
Sortino ratio	-0.22	-0.16	0.91	0.94	1.46	1.44
Information ratio		0.06	0.45	0.45	0.60	0.58
5^{th} centile (%)	-1.87	-1.03	-1.02	-0.98	-0.88	-0.87
Negative returns (%)	47.77	51.27	46.03	37.68	41.26	34.38
Recommended switches			66	67	35	78
Alpha		0.015	0.048**	0.048**	0.059**	0.057**
Beta		-0.318*	-0.169*	-0.160*	-0.144*	-0.148*

This table presents results of the style-rotation and buy-hold strategies for daily data from 1998/06-2008/06. Rules are identified as (SMA, LMA, Band) where SMA, LMA are the short and long moving averages, respectively, and band is the percentage difference that is needed to generate a signal under the "band" strategy. Transaction costs are expressed per switch and are round-trip. An alpha coefficient marked with * (**) indicates a 5% (1%) level of significance for a two-tailed test of H_o: $a=0$ against H_1: $a \neq 0$. A beta coefficient marked with * (**) indicates a 5% (1%) level of significance for a one-tailed test of H_o: $b=0$ against H_1: $b<0$.

Table V

Style Rotation Results: Small-cap Value Spread (1, 200, 1.00%)

	S&P 500	Buy&Hold	Active	Band	Stop-Loss	Band & Stop-Loss
Annualized return (%)	0.82	2.31	11.20	12.50	12.10	13.57
net of trans costs (10bps)	0.71	2.20	10.65	11.88	11.72	12.76
net of trans costs (20bps)	0.60	2.08	10.10	11.26	11.34	11.96
Annualized standard deviation	18.33	12.43	12.41	12.09	11.03	10.80
Annualized downside deviation	13.07	8.41	9.02	8.72	7.88	7.64
Sharpe ratio	-0.15	-0.11	0.61	0.73	0.77	0.92
Sortino ratio	-0.22	-0.16	0.84	1.01	1.07	1.30
Information ratio		0.06	0.44	0.49	0.48	0.55
5^{th} centile (%)	-1.87	-1.03	-1.05	-1.00	-0.93	-0.89
Negative returns (%)	47.77	51.27	45.79	39.94	41.81	36.33
Recommended switches			50	55	34	71
Alpha		0.015	0.046**	0.050**	0.049**	0.054**
Beta		-0.318*	-0.114*	-0.113*	-0.132*	-0.131*

This table presents results of the style-rotation and buy-hold strategies for daily data from 1998/06-2008/06. Rules are identified as (SMA, LMA, Band) where SMA, LMA are the short and long moving averages, respectively, and band is the percentage difference that is needed to generate a signal under the "band" strategy. Transaction costs are expressed per switch and are round-trip. An alpha coefficient marked with * (**) indicates a 5% (1%) level of significance for a two-tailed test of H_o: $a=0$ against $H1$: $a\neq 0$. A beta coefficient marked with * (**) indicates a 5% (1%) level of significance for a one-tailed test of H_o: $b=0$ against H_1: $b<0$.

Table VI

Style Rotation Results: Small-cap Value Spread (5, 150, 1.00%)

	S&P 500	Buy & Hold	Active	Band	Stop-Loss	Band & Stop-Loss
Annualized return (%)	0.82	2.31	12.78	11.19	16.18	14.53
net of trans costs (10bps)	0.71	2.20	12.55	10.83	15.83	13.98
net of trans costs (20bps)	0.60	2.08	12.33	10.48	15.48	13.43
Annualized standard deviation	18.33	12.43	12.40	12.15	11.04	10.84
Annualized downside deviation	13.07	8.41	8.96	8.82	7.71	7.60
Sharpe ratio	-0.15	-0.11	0.74	0.62	1.14	1.00
Sortino ratio	-0.22	-0.16	1.02	0.85	1.63	1.43
Information ratio		0.06	0.49	0.43	0.65	0.58
5^{th} centile (%)	-1.87	-1.03	-1.00	-0.99	-0.88	-0.87
Negative returns (%)	47.77	51.27	45.47	37.80	40.98	34.34
Recommended switches			20	32	30	48
Alpha		0.015	0.052**	0.046**	0.063**	0.057**
Beta		-0.318*	-0.148*	-0.148*	-0.144*	-0.145*

This table presents results of the style-rotation and buy-hold strategies for daily data from 1998/06-2008/06. Rules are identified as (SMA, LMA, Band) where SMA, LMA are the short and long moving averages, respectively, and band is the percentage difference that is needed to generate a signal under the "band" strategy. Transaction costs are expressed per switch and are round-trip. An alpha coefficient marked with * (**) indicates a 5% (1%) level of significance for a two-tailed test of H_o: $a=0$ against $H1$: $a\neq0$. A beta coefficient marked with * (**) indicates a 5% (1%) level of significance for a one-tailed test of H_o: $b=0$ against H_1: $b<0$.

Figures 7 to 10 present the annualized excess returns of our style-timing strategies over the buy-and-hold strategy during the 10 years of trading period. Unsurprisingly, most of the action takes place in the first and last years of the sample period.

A first glance at the figures reveals that most of the gains of our rotation strategies are obtained in “bearish” markets. This is true, since the first years of our sample period were dominated by the TMT “bubble” whereas the last year equity markets have been plunging as a result of the spillover effects of the “sub-prime” crisis. Therefore, our strategies add value during the periods when both buy-and-hold strategies and market as a whole suffer dramatically. Suggestively, in the 1999-2000 period our strategies reached their steepest level of outperformance, earning excess returns as high as 85 percent.

Contrarily, the 2000-2001 period could be characterized the worst-performing year for our models, especially for the 1-50 and 1-200 trading rules. The 1-150 and 5-150 rules seem to be able to forecast the shift in sentiment in the beginning of 2000 as they achieve either slightly higher or balanced returns compared to the buy-and-hold strategy. The same patterns are evident during the middling years, when our strategies display steady positive or hardly negative excess returns. Overall, stop-loss and band-and-stop-loss strategies exhibit a more risk-averse profile whereas the active strategy is somewhat more volatile. We could attribute this divergence to the fact that the “active” strategy is steadily in-the-market whilst the alternative strategies involve positions in the money market.

In sum, these figures underline the need of a dynamic approach during recessionary periods, despite the either modest or vaporous excessive returns during “bullish” markets.

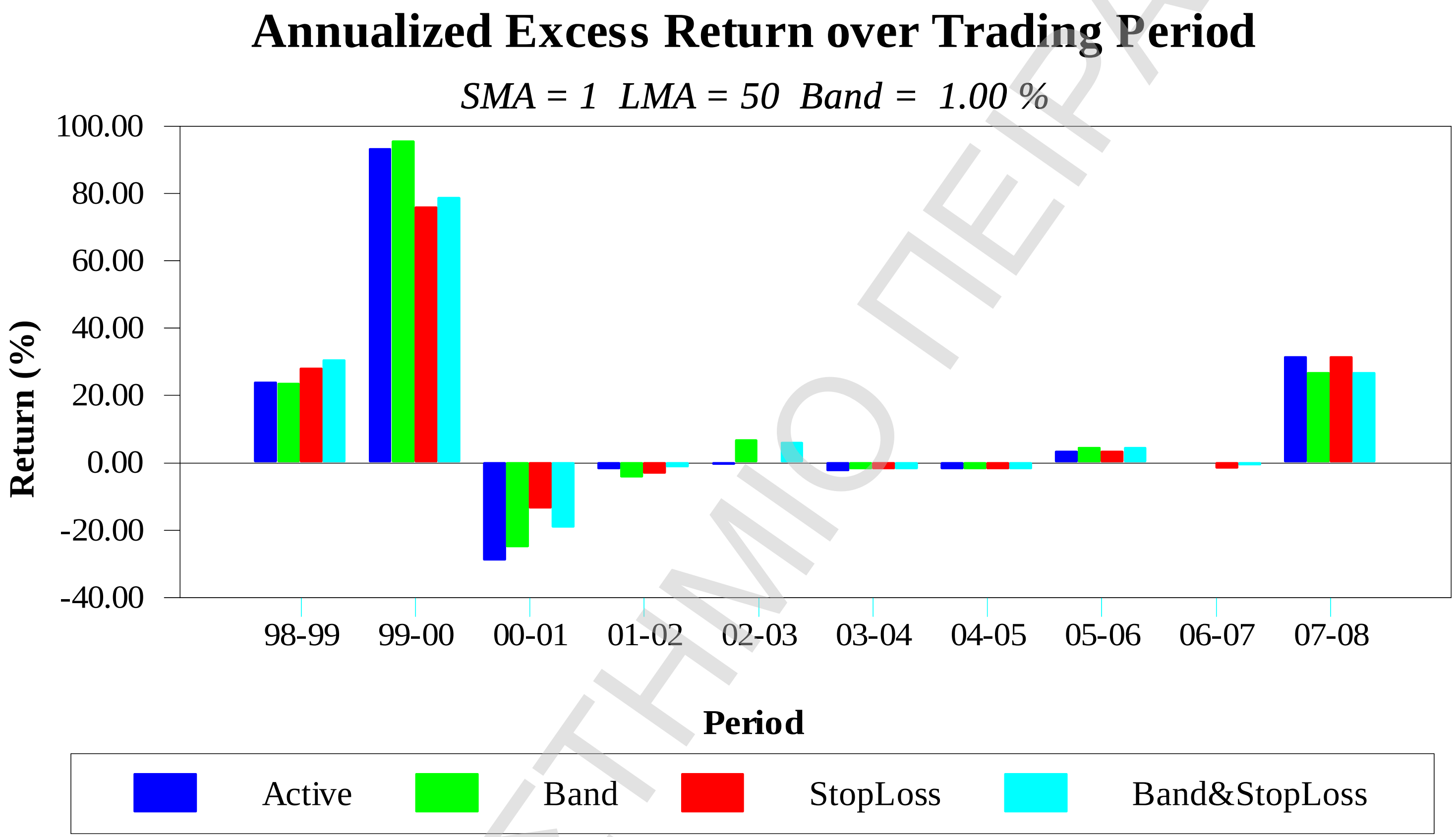

Figure 7. Annualized excess return over trading period: Period (1998/06-2008/06). Small-cap segment. This figure illustrates annualized difference between the return of the style-rotation strategies and the multi-style buy-and-hold strategy over the June 1998 to June 2008 period. SMA and LMA stand for the short-period moving average and the long-period moving average, respectively. Band is the percent difference that is needed to generate a signal under the "band" strategy.

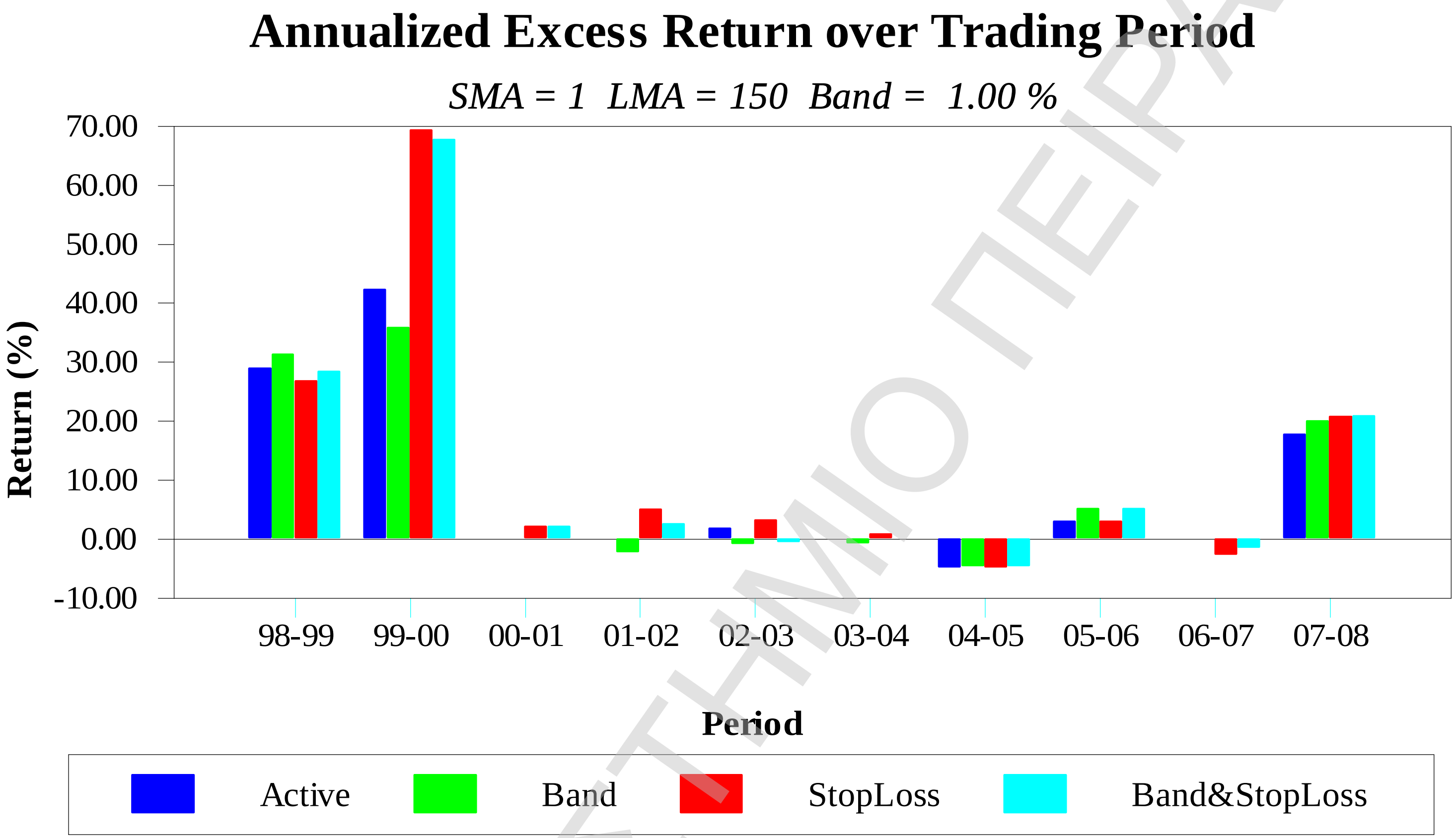

Figure 8. Annualized excess return over trading period: Period (1998/06-2008/06). **Small-cap segment.** This figure illustrates annualized difference between the return of the style-rotation strategies and the multi-style buy-and-hold strategy over the June 1998 to June 2008 period. SMA and LMA stand for the short-period moving average and the long-period moving average, respectively. Band is the percent difference that is needed to generate a signal under the "band" strategy.

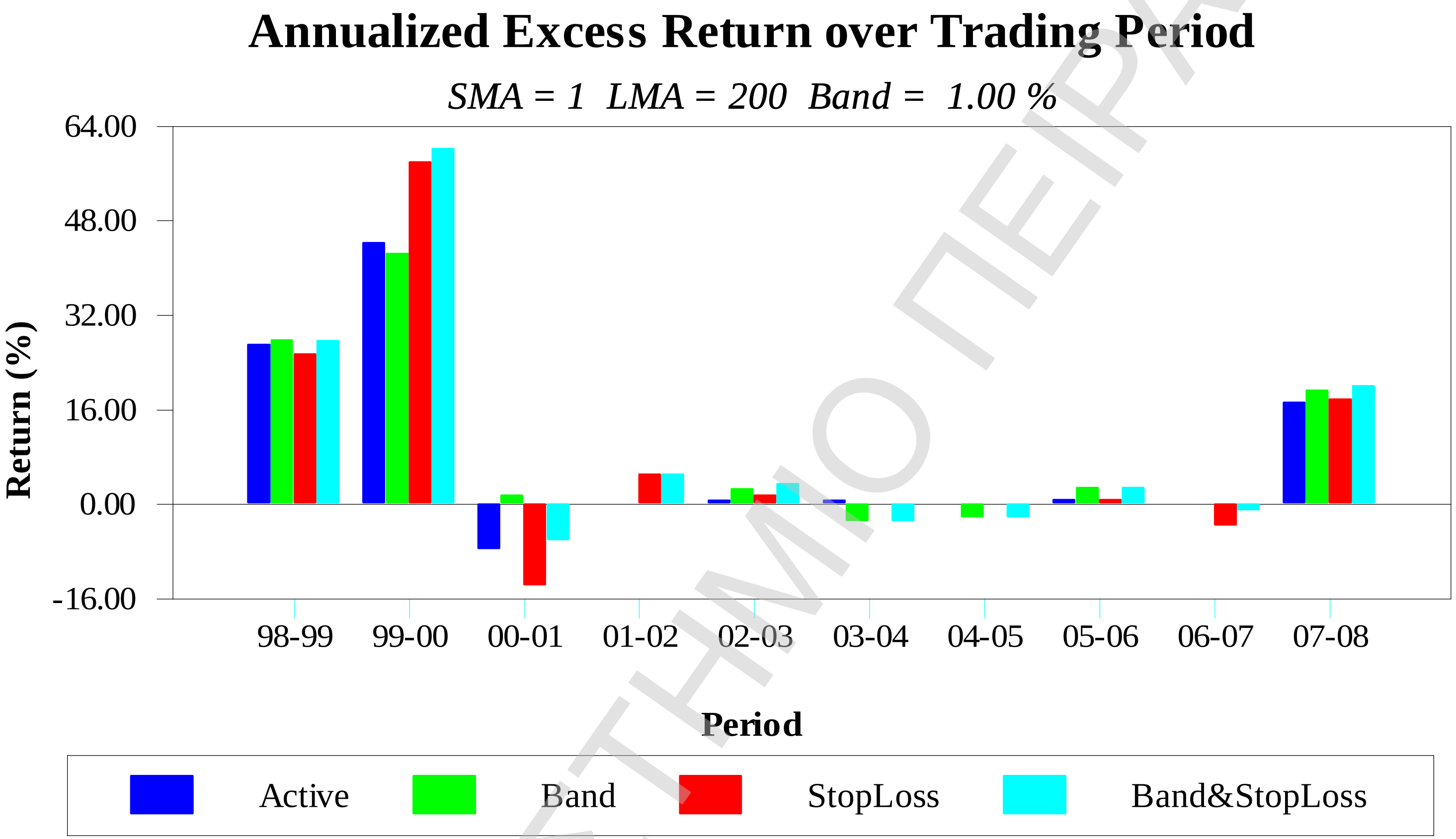

Figure 9. Annualized excess return over trading period: Period (1998/06-2008/06). **Small-cap segment.** This figure illustrates annualized difference between the return of the style-rotation strategies and the multi-style buy-and-hold strategy over the June 1998 to June 2008 period. SMA and LMA stand for the short-period moving average and the long-period moving average, respectively. Band is the percent difference that is needed to generate a signal under the "band" strategy.

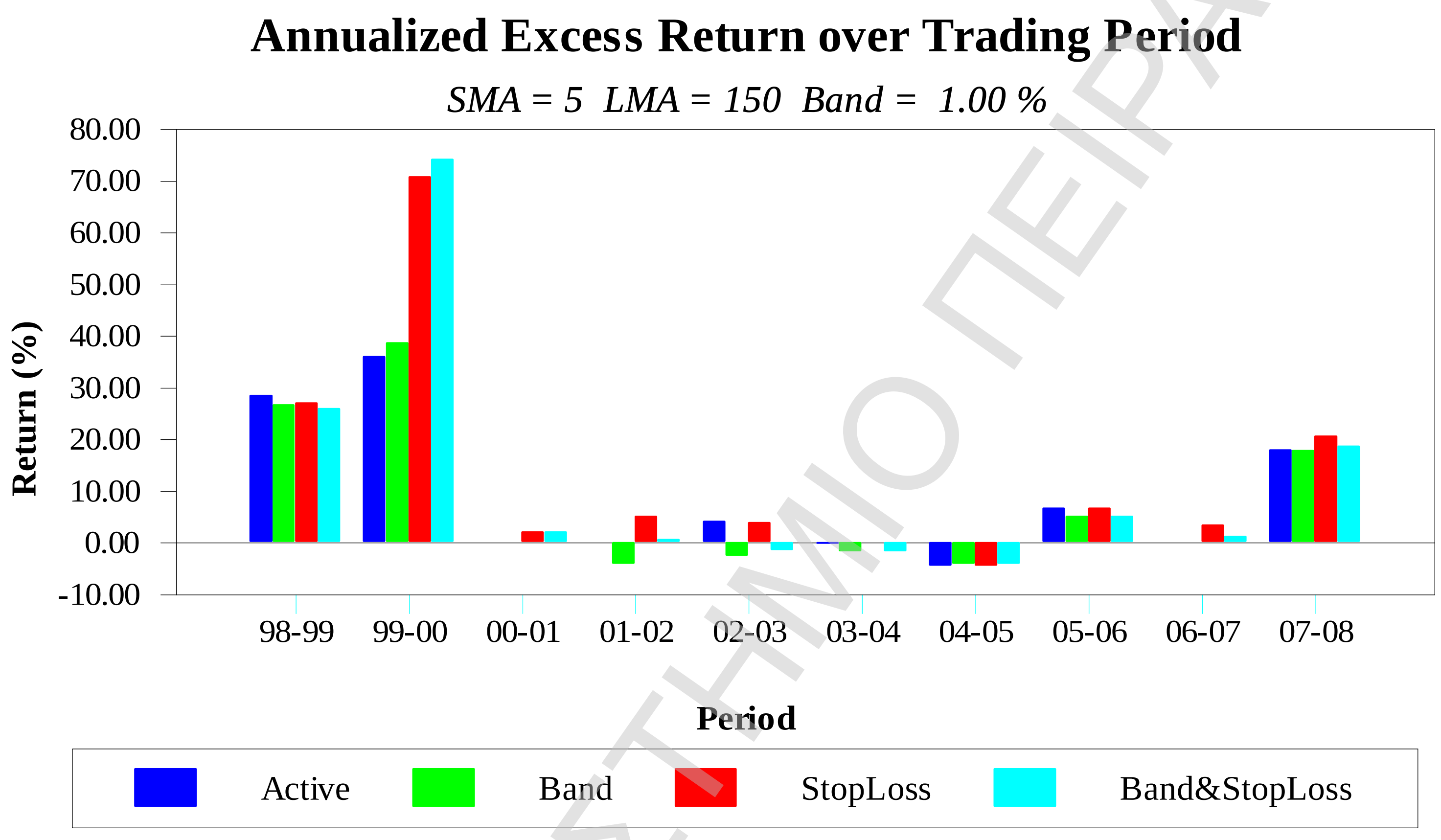

Figure 10. Annualized excess return over trading period: Period (1998/06-2008/06). **Small-cap segment.** This figure illustrates annualized difference between the return of the style-rotation strategies and the multi-style buy-and-hold strategy over the June 1998 to June 2008 period. SMA and LMA stand for the short-period moving average and the long-period moving average, respectively. Band is the percent difference that is needed to generate a signal under the "band" strategy.

ii. Large-cap "Value Premium"

This subsection reports trading results for the large-cap value versus growth rotation strategies. Figures 8 through 11 show the time development of the cumulative day-to-day returns for the dynamic trading strategies, the buy-and-hold benchmark and the market proxy. The plots evidently reveal substantial divergence between the performances of the large-cap "value premium" and the "small-cap" equivalent. Although our trading strategies persistently outperform the buy-and-hold benchmarks the cumulated wealth at the end of the period is considerably lower than that of the "small-cap" universe. Of course, the same holds for the cumulated wealth of the multi-style benchmark, thus we could roughly conclude that the small-cap segment appears more robust.

A further look at the figures shows that both the 1-150 and the 5-150 rules are rather inappropriate, since, excluding the stop-loss and band-and-stop-loss strategies, our rotation strategies hardly beat the buy-and-hold benchmark. Under these rules, for the first time, two of our trading strategies' cumulative wealth tumbles below the initial amount invested threshold.

As mentioned above, the remaining trading rules seem to perform sufficiently enough compared to the buy-and-hold benchmark. In accordance with the small-cap strategies, most of the action is observed during the first and last years of our trading period. Besides, we can observe a rather volatile period during until 2002, while thereafter the large-cap "value premium" lacks substantial momentum and its volatility is rather low until 2007. Therefore, the basis of outperformance is mainly found on the first half of the trading period, most notably between 2000 and 2001, during which the cumulative gap between the rotation strategies and the multi-style benchmark strongly widened. The returns obtained during the TMT-bubble clearly attract the attention. Under almost trading rules, the selected models quite accurately capture the negative momentum of value relative to growth. On the other hand, the incredible revival of value stocks that followed the puncturing of the bubble partially counterbalanced the gains obtained during previous period. At this point, we should note that stop-loss and band-and-stop-loss strategies performed quite efficiently despite the failure of other models to anticipate the prominent swing.

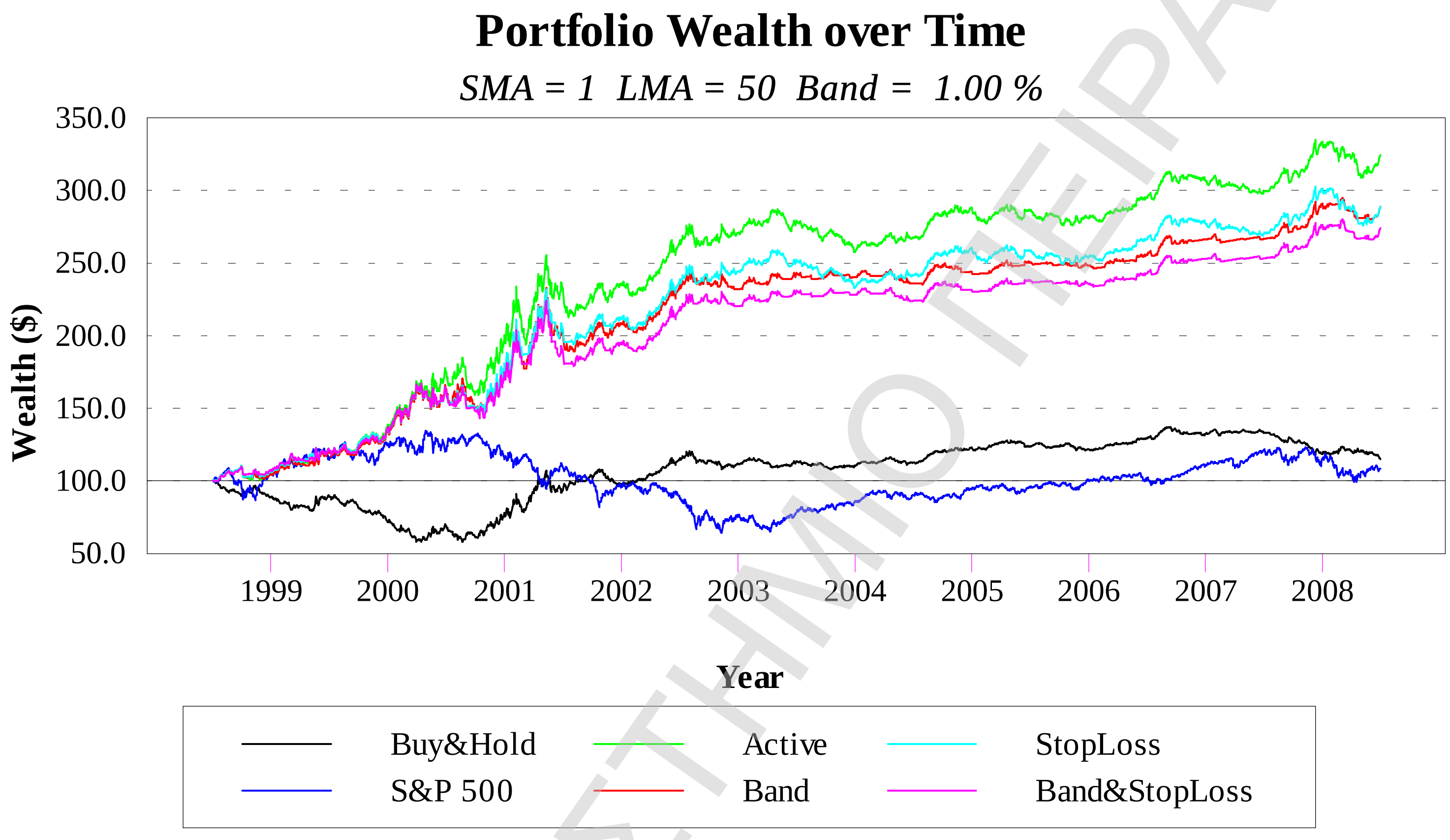

Figure 8. Portfolio wealth over time: Period (1998/06-2008/06). **Large-cap value spread.** This figure shows the cumulative portfolio wealth of the style-rotation and the buy-hold strategies over the June 1998 to June 2008 period. Initial amount invested is $100. SMA and LMA stand for the short-period moving average and the long-period moving average, respectively. Band is the percent difference that is needed to generate a signal under the "band" strategy.

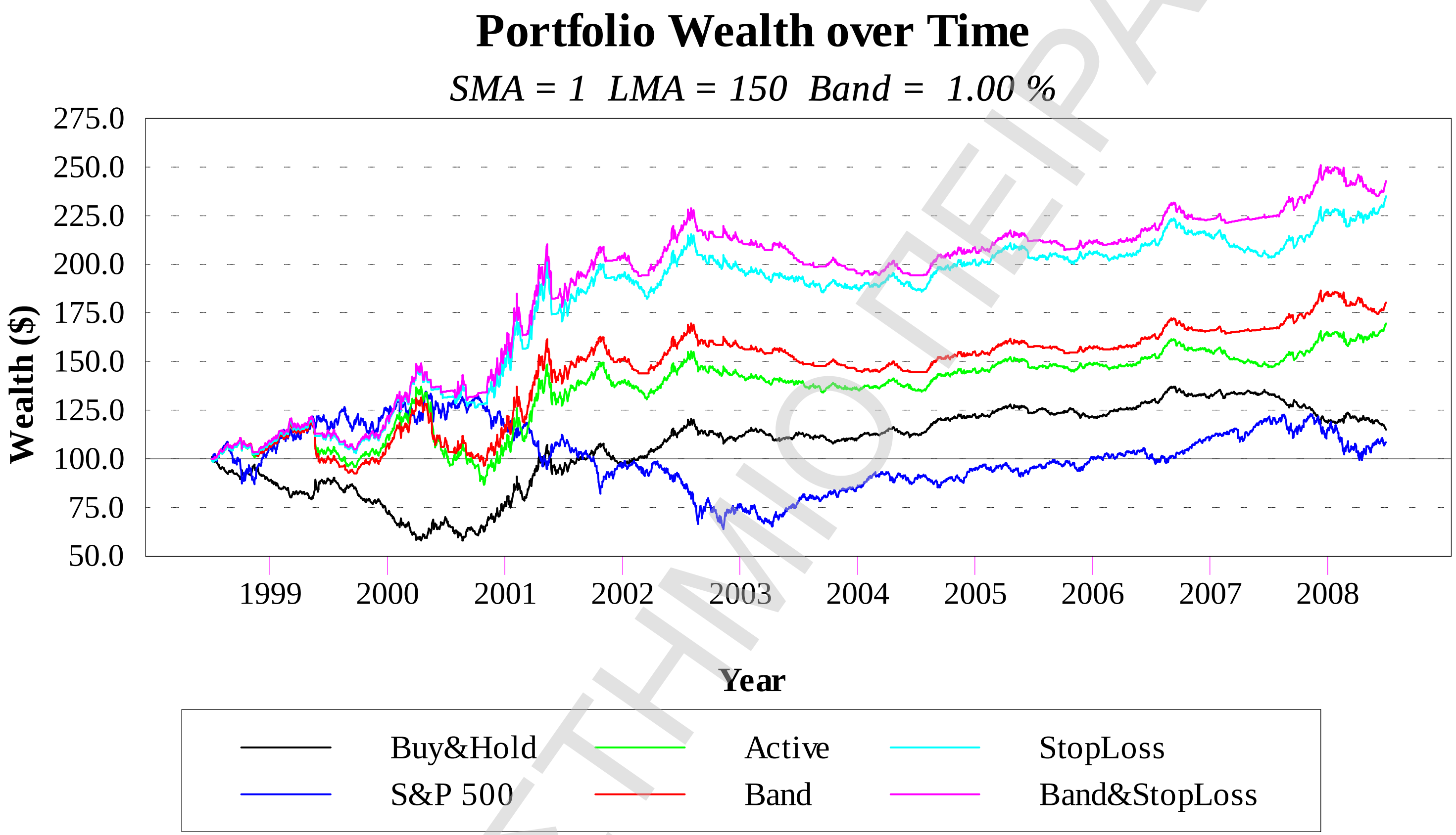

Figure 9. Portfolio wealth over time: Period (1998/06-2008/06). **Large-cap value spread.** This figure shows the cumulative portfolio wealth of the style-rotation and the buy-hold strategies over the June 1998 to June 2008 period. Initial amount invested is $100. SMA and LMA stand for the short-period moving average and the long-period moving average, respectively. Band is the percent difference that is needed to generate a signal under the "band" strategy.

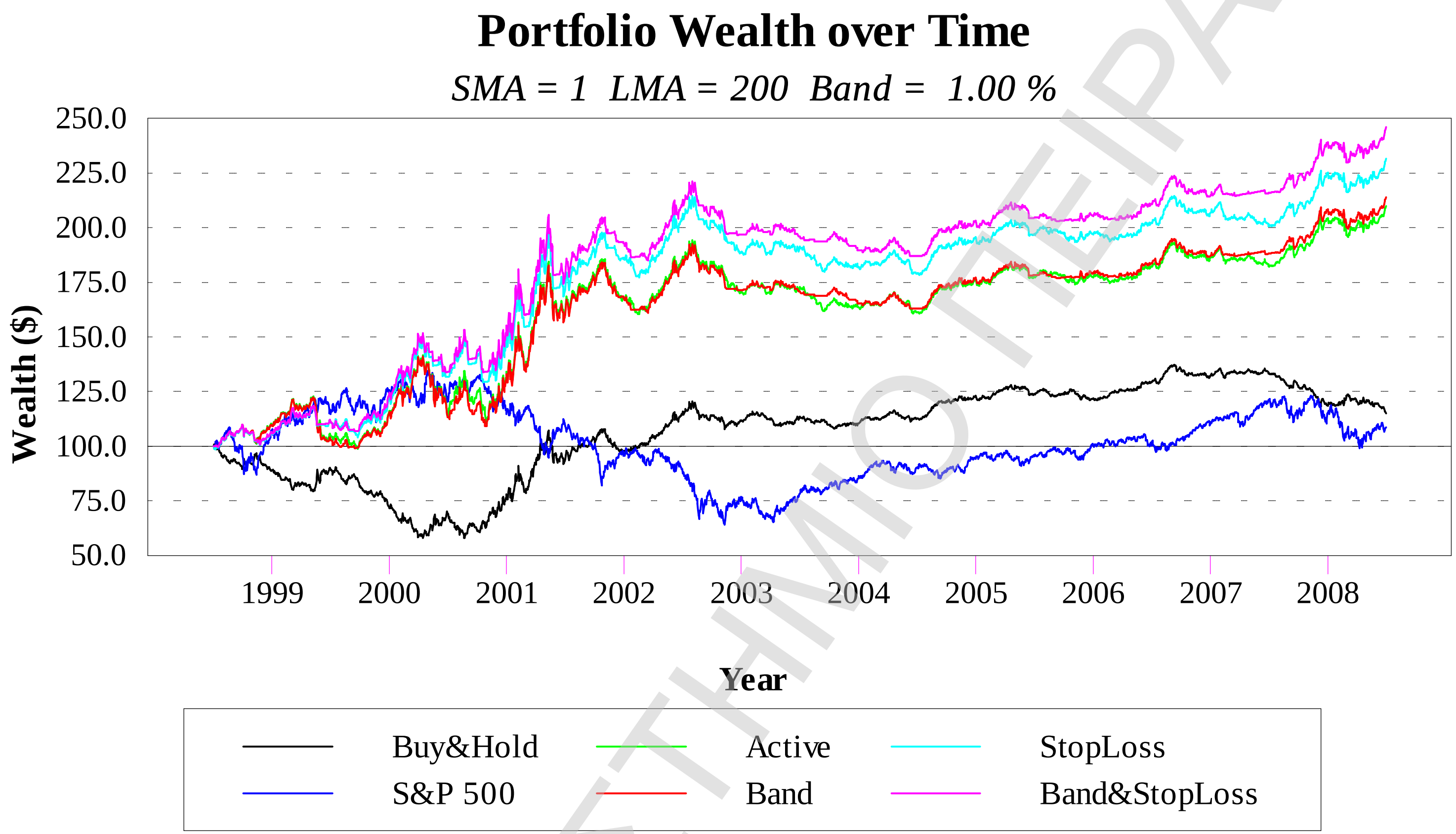

Figure 10. Portfolio wealth over time: Period (1998/06-2008/06). **Large-cap value spread.** This figure shows the cumulative portfolio wealth of the style-rotation and the buy-hold strategies over the June 1998 to June 2008 period. Initial amount invested is $100. SMA and LMA stand for the short-period moving average and the long-period moving average, respectively. Band is the percent difference that is needed to generate a signal under the "band" strategy.

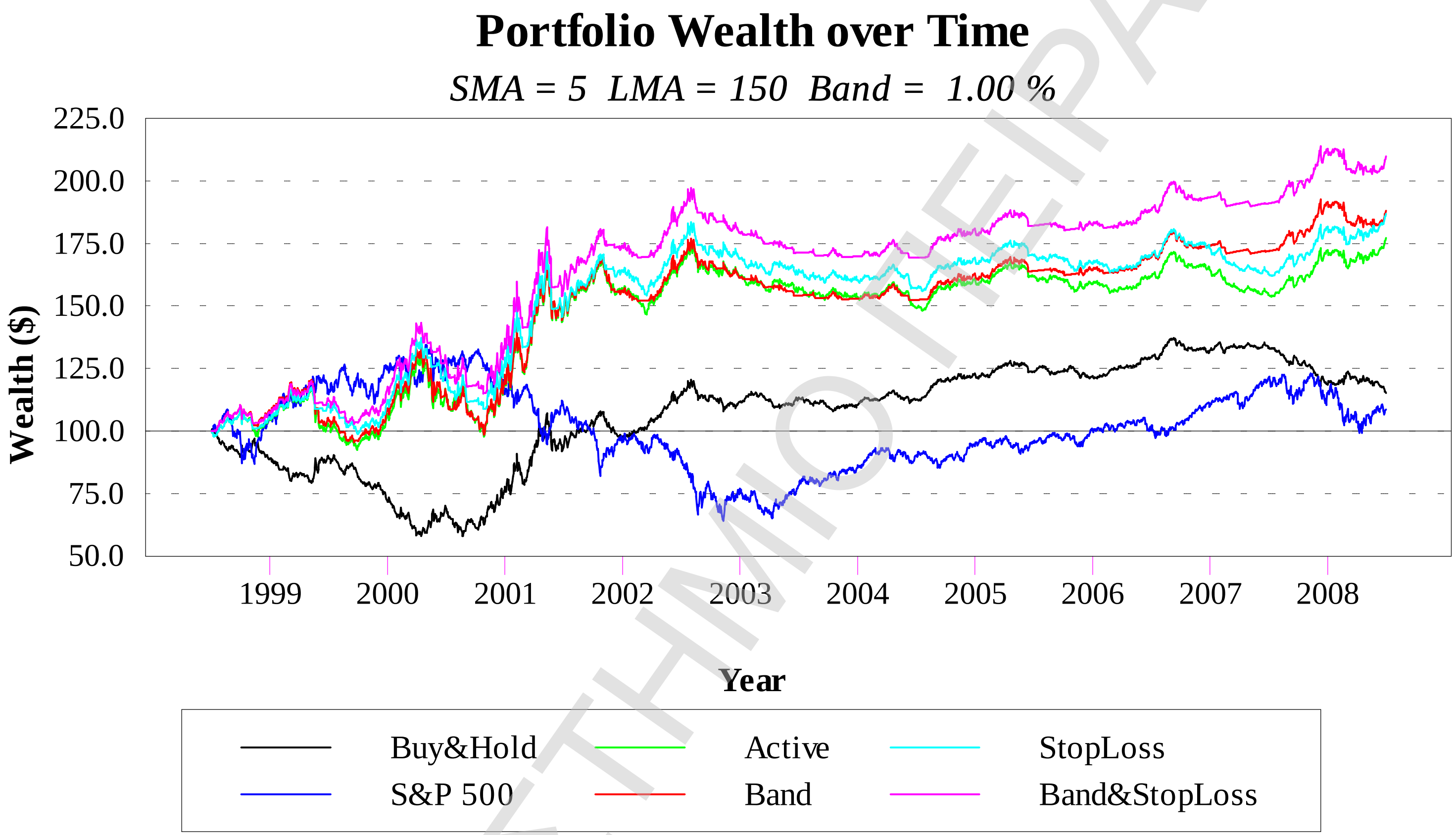

Figure 11. Portfolio wealth over time: Period (1998/06-2008/06). **Large-cap value spread.** This figure shows the cumulative portfolio wealth of the style-rotation and the buy-hold strategies over the June 1998 to June 2008 period. Initial amount invested is \$100. SMA and LMA stand for the short-period moving average and the long-period moving average, respectively. Band is the percent difference that is needed to generate a signal under the "band" strategy.

To obtain elaborate information and compare the performance of our dynamic strategies to the buy-and-hold benchmarks we summarize descriptive statistics in tables VII to X.

As mentioned earlier and judging from the annualized returns, the large-cap "value premium" performance is subordinate to the small-cap equivalent. Distinctively, the annualized return of the buy-and-hold value-growth benchmark is approximately 40 percent lower than that of the small-cap benchmark. Thus, analogous results hold for our rotation strategies, with the exception of the 1-50 trading rule, where performance is reasonable, by small-cap "standards". What is striking is the abrupt decline of performance when 1-150 and 5-150 rules are applied. By means of undertaken risk "active" and "band" strategies display slightly lower volatility, while in the cases of "stop-loss" and "band-and-stop-loss" tactics the divergence is substantial. In sum, "stop-loss" and "band-and-stop-loss" strategies exhibit a rather steady performance either from the return- or from the risk-viewpoint which is even clearer in the risk-adjusted return ratios presented below.

Nonetheless the inferior performance of the large-cap segment, our trading rules still manage to achieve adequate Sharpe, Sortino and Information ratios. This is in sharp contrast with the buy-and-hold and "market" benchmarks which keep on recording negative values of the fore mentioned ratios. A remarkable point is the fact that both "stop-loss" and "band-and-stop-loss" strategies realize acceptable ratios even in worst-case scenarios of the 1-150 and 5-150 rules, meaning that constant presence in the equity markets is not the optimal tactic.

Regarding the percentage of negative returns we observe that our rotation strategies levels are far below the approximately 50 percent level of the buy-and-hold strategy. However, the "active" strategy comprises an exception since it does not manage to diversify sizably from the buy-and-hold benchmarks. At this point, we should note that the paradox described in the small-cap section is not valid here. Thus, the "band" strategy appears to operate optimally reducing the "whiplash" signals under all trading rules. As expected, the "stop-loss" strategy is nominated winner of the turnover "category".

At last, a closer examination of the estimated alpha and beta coefficients unveils that the results are less significant in the large-cap universe. Therefore, alphas are positive and highly significant only when utilizing the "stop-loss" and "band-and-stop-loss" strategies. In other cases, alphas remain positive but are either insignificant or significant in the 5 percent level. On the other hand, betas appear consistently negative and significant under all possible scenarios. Thus, the conclusion drawn is based on the lack of robustness of the large-cap “value premium”. Although, not every of our strategies produces unsystematic returns, our rotation tactics remain not only market neutral but also hedged against market risk, due to negative and significant betas.

Table VII

Style Rotation Results: Large-cap Value Spread (1, 50, 1.00%)

	S&P 500	Buy & Hold	Active	Band	Stop-Loss	Band & Stop-Loss
Annualized return (%)	0.82	1.42	12.50	11.18	11.19	10.61
net of trans costs (10bps)	0.71	1.30	11.00	9.85	10.80	9.29
net of trans costs (20bps)	0.60	1.19	9.52	8.52	10.41	7.99
Annualized standard deviation	18.33	12.92	12.90	12.16	12.31	11.81
Annualized downside deviation	13.07	9.21	9.05	8.61	8.74	8.41
Sharpe ratio	-0.15	-0.17	0.69	0.62	0.61	0.59
Sortino ratio	-0.22	-0.24	0.98	0.88	0.86	0.83
Information ratio		0.02	0.48	0.44	0.43	0.42
5^{th} centile (%)	-1.87	-1.10	-1.15	-1.06	-1.05	-1.00
Negative returns (%)	47.77	49.60	45.59	29.89	42.93	28.58
Recommended switches			134	121	35	120
Alpha		0.011	0.051**	0.046**	0.046**	0.044**
Beta		-0.272*	-0.119*	-0.117*	-0.120*	-0.117**

This table presents results of the style-rotation and buy-hold strategies for daily data from 1998/06-2008/06. Rules are identified as (SMA, LMA, Band) where SMA, LMA are the short and long moving averages, respectively, and band is the percentage difference that is needed to generate a signal under the “band” strategy. Transaction costs are expressed per switch and are round-trip. An alpha coefficient marked with * (**) indicates a 5% (1%) level of significance for a two-tailed test of H_o: $a=0$ against H_1: $a\neq0$. A beta coefficient marked with * (**) indicates a 5% (1%) level of significance for a one-tailed test of H_o: $b=0$ against H_1: $b<0$.

Table VIII

Style Rotation Results: Large-cap Value Spread (1, 150, 1.00%)

	S&P 500	Buy & Hold	Active	Band	Stop-Loss	Band & Stop-Loss
Annualized return (%)	0.82	1.42	5.43	6.08	8.92	9.27
net of trans costs (10bps)	0.71	1.30	4.45	5.24	8.59	8.37
net of trans costs (20bps)	0.60	1.19	3.48	4.40	8.26	7.47
Annualized standard deviation	18.33	12.92	12.92	12.34	11.53	11.26
Annualized downside deviation	13.07	9.21	9.44	8.97	8.24	8.04
Sharpe ratio	-0.15	-0.17	0.14	0.20	0.46	0.50
Sortino ratio	-0.22	-0.24	0.19	0.27	0.64	0.70
Information ratio		0.02	0.19	0.22	0.35	0.37
5th centile (%)	-1.87	-1.10	-1.16	-1.09	-0.96	-0.94
Negative returns (%)	47.77	49.60	47.50	36.92	43.32	33.82
Recommended switches			93	80	30	83
Alpha		0.011	0.025	0.027	0.037**	0.038**
Beta		-0.272*	-0.108*	-0.104*	-0.097*	-0.099*

This table presents results of the style-rotation and buy-hold strategies for daily data from 1998/06-2008/06. Rules are identified as (SMA, LMA, Band) where SMA, LMA are the short and long moving averages, respectively, and band is the percentage difference that is needed to generate a signal under the "band" strategy. Transaction costs are expressed per switch and are round-trip. An alpha coefficient marked with * (**) indicates a 5% (1%) level of significance for a two-tailed test of H_o: $a=0$ against H_1: $a\neq 0$. A beta coefficient marked with * (**) indicates a 5% (1%) level of significance for a one-tailed test of H_o: $b=0$ against H_1: $b<0$.

Table IX

Style Rotation Results: Large-cap Value Spread (1, 200, 1.00%)

	S&P 500	Buy & Hold	Active	Band	Stop-Loss	Band & Stop-Loss
Annualized return (%)	0.82	1.42	7.70	7.91	8.76	9.42
net of trans costs (10bps)	0.71	1.30	6.94	7.16	8.35	8.53
net of trans costs (20bps)	0.60	1.19	6.18	6.43	7.95	7.66
Annualized standard deviation	18.33	12.92	12.91	12.53	11.75	11.49
Annualized downside deviation	13.07	9.21	9.25	9.01	8.43	8.24
Sharpe ratio	-0.15	-0.17	0.31	0.34	0.43	0.50
Sortino ratio	-0.22	-0.24	0.44	0.47	0.61	0.70
Information ratio		0.02	0.29	0.30	0.34	0.37
5^{th} centile (%)	-1.87	-1.10	-1.13	-1.09	-0.99	-0.98
Negative returns (%)	47.77	49.60	46.58	37.36	42.77	34.54
Recommended switches			71	69	37	81
Alpha		0.011	0.033*	0.034*	0.037*	0.039**
Beta		-0.272*	-0.079*	-0.082*	-0.093*	-0.092*

This table presents results of the style-rotation and buy-hold strategies for daily data from 1998/06-2008/06. Rules are identified as (SMA, LMA, Band) where SMA, LMA are the short and long moving averages, respectively, and band is the percentage difference that is needed to generate a signal under the “band” strategy. Transaction costs are expressed per switch and are round-trip. An alpha coefficient marked with * (**) indicates a 5% (1%) level of significance for a two-tailed test of H_o: $a=0$ against $H1$: $a \neq 0$. A beta coefficient marked with * (**) indicates a 5% (1%) level of significance for a one-tailed test of H_o: $b=0$ against H_1: $b<0$.

Table X

Style Rotation Results: Large-cap Value Spread (5, 150, 1.00%)

	S&P 500	Buy & Hold	Active	Band	Stop-Loss	Band & Stop-Loss
Annualized return (%)	0.82	1.42	5.88	6.52	6.45	7.69
net of trans costs (10bps)	0.71	1.30	5.34	6.09	6.06	7.12
net of trans costs (20bps)	0.60	1.19	4.81	5.67	5.67	6.55
Annualized standard deviation	18.33	12.92	12.92	12.43	11.73	11.41
Annualized downside deviation	13.07	9.21	9.27	8.96	8.47	8.24
Sharpe ratio	-0.15	-0.17	0.17	0.23	0.24	0.35
Sortino ratio	-0.22	-0.24	0.24	0.32	0.33	0.49
Information ratio		0.02	0.21	0.24	0.24	0.30
5^{th} centile (%)	-1.87	-1.10	-1.15	-1.09	-1.00	-0.97
Negative returns (%)	47.77	49.60	47.89	36.57	44.20	33.82
Recommended switches			51	40	37	53
alpha		0.011	0.026	0.029	0.028*	0.033**
beta		-0.272*	-0.094*	-0.094*	-0.105*	-0.105*

This table presents results of the style-rotation and buy-hold strategies for daily data from 1998/06-2008/06. Rules are identified as (SMA, LMA, Band) where SMA, LMA are the short and long moving averages, respectively, and band is the percentage difference that is needed to generate a signal under the "band" strategy. Transaction costs are expressed per switch and are round-trip. An alpha coefficient marked with * (**) indicates a 5% (1%) level of significance for a two-tailed test of H_o: $a=0$ against $H1$: $a\neq0$. A beta coefficient marked with * (**) indicates a 5% (1%) level of significance for a one-tailed test of H_o: $b=0$ against H_1: $b<0$.

Figures 12 through 15 illustrate the annualized excess returns of our trading strategies over the multi-style benchmark.

At first glance, we observe that the 1-50 rule performs considerably well, excluding the period 2000-2001 where almost every rotation strategy, regardless of the universe, appears incapable of catching the trend reversal. Secondly, just as in the small-cap segment, our strategies prove to be remarkably valuable during “bearish” periods. The fact that recessionary periods are periods when the marginal utility of the excess consumption is high states these strategies exceptionally valuable.

A further stake at issue are the negative-poor excess returns of our strategies during the 2001-2004 period. During that period, our strategies fail to beat the buy-and-hold benchmark which could be translated into a narrowing gap between the cumulative wealth. The next two years exhibit a rather fifty-fifty pattern while the last year our timing strategies clearly outperform the buy-and-hold benchmark. What is puzzling is the notable performance of the longest moving averages in the last year of our trading period. Specifically, both the 150- and the 200-period moving averages produce almost twofold annualized returns despite the fact that they are considered less sensitive.

Finally, neither “stop-loss” nor “band-and-stop-loss” trading strategies are successful in limiting the decline in the excess returns during the 2001-2004 period, which is in sharp contrast with the corresponding small-cap performance.

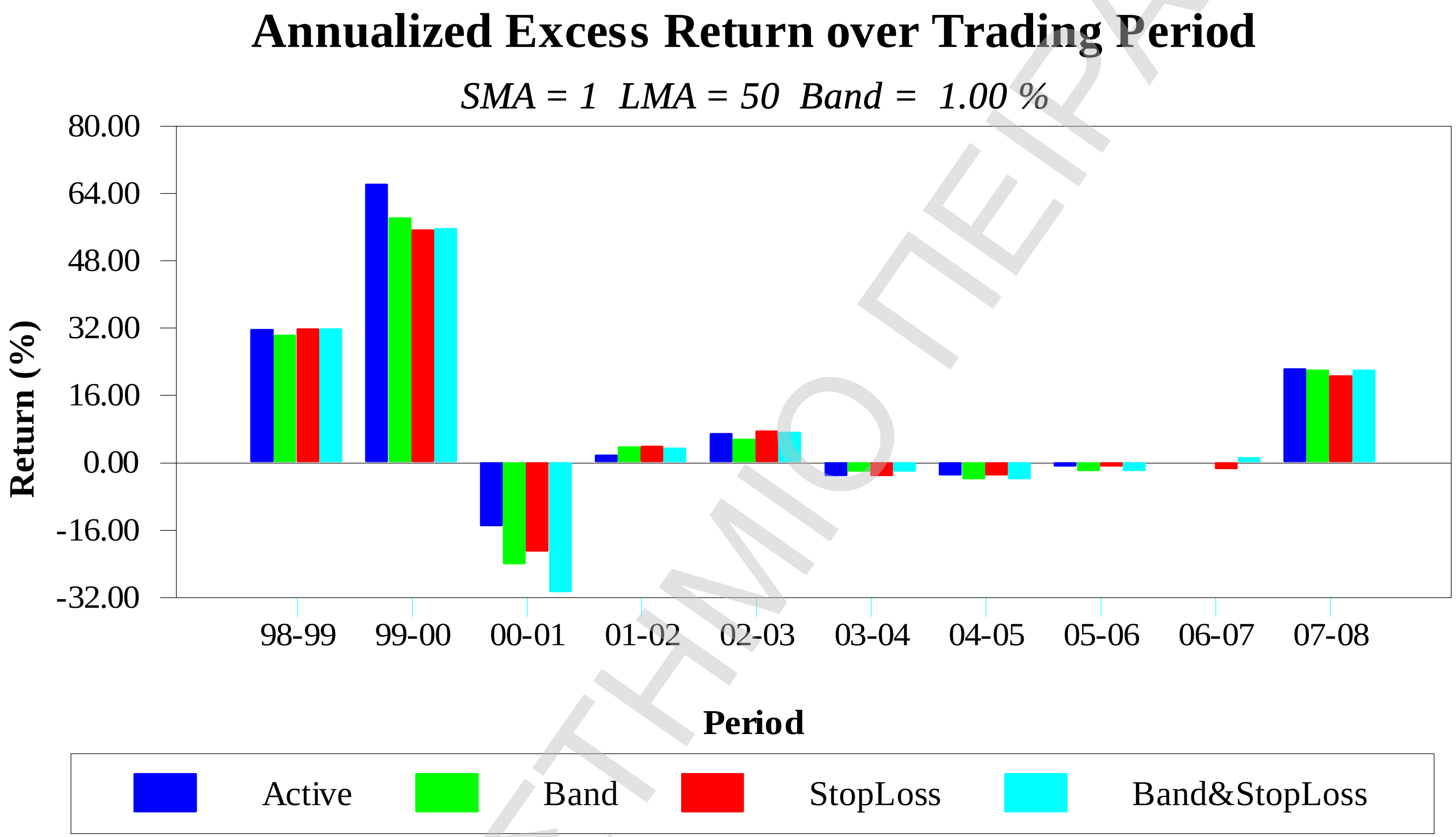

Figure 12. Annualized excess return over trading period : Period (1998/06-2008/06). **Large-cap segment.** This figure illustrates annualized difference between the return of the style-rotation strategies and the multi-style buy-and-hold strategy over the June 1998 to June 2008 period. SMA and LMA stand for the short-period moving average and the long-period moving average, respectively. Band is the percent difference that is needed to generate a signal under the "band" strategy.

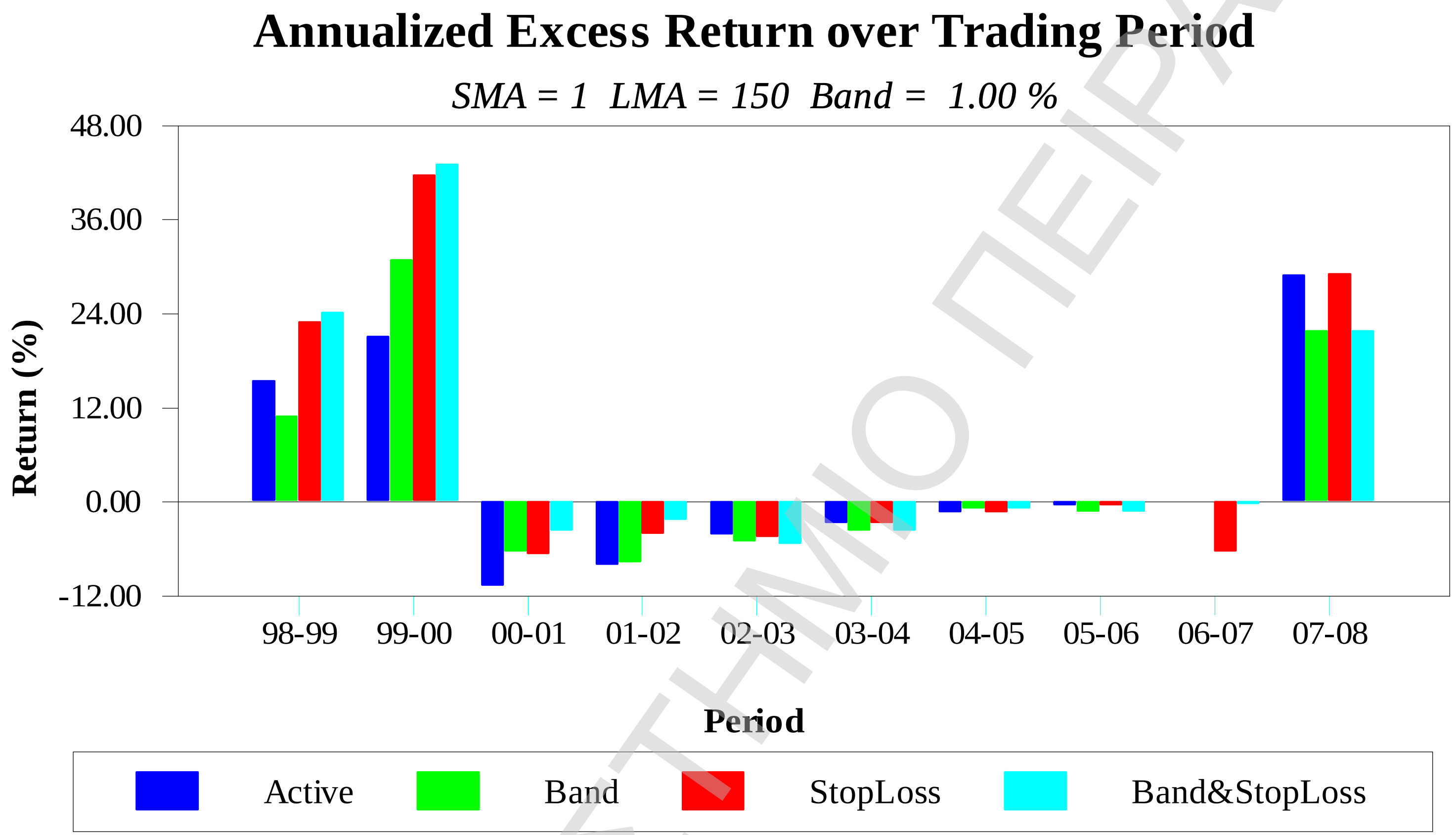

Figure 13. Annualized excess return over trading period : Period (1998/06-2008/06). **Large-cap segment.** This figure illustrates annualized difference between the return of the style-rotation strategies and the multi-style buy-and-hold strategy over the June 1998 to June 2008 period. SMA and LMA stand for the short-period moving average and the long-period moving average, respectively. Band is the percent difference that is needed to generate a signal under the "band" strategy.

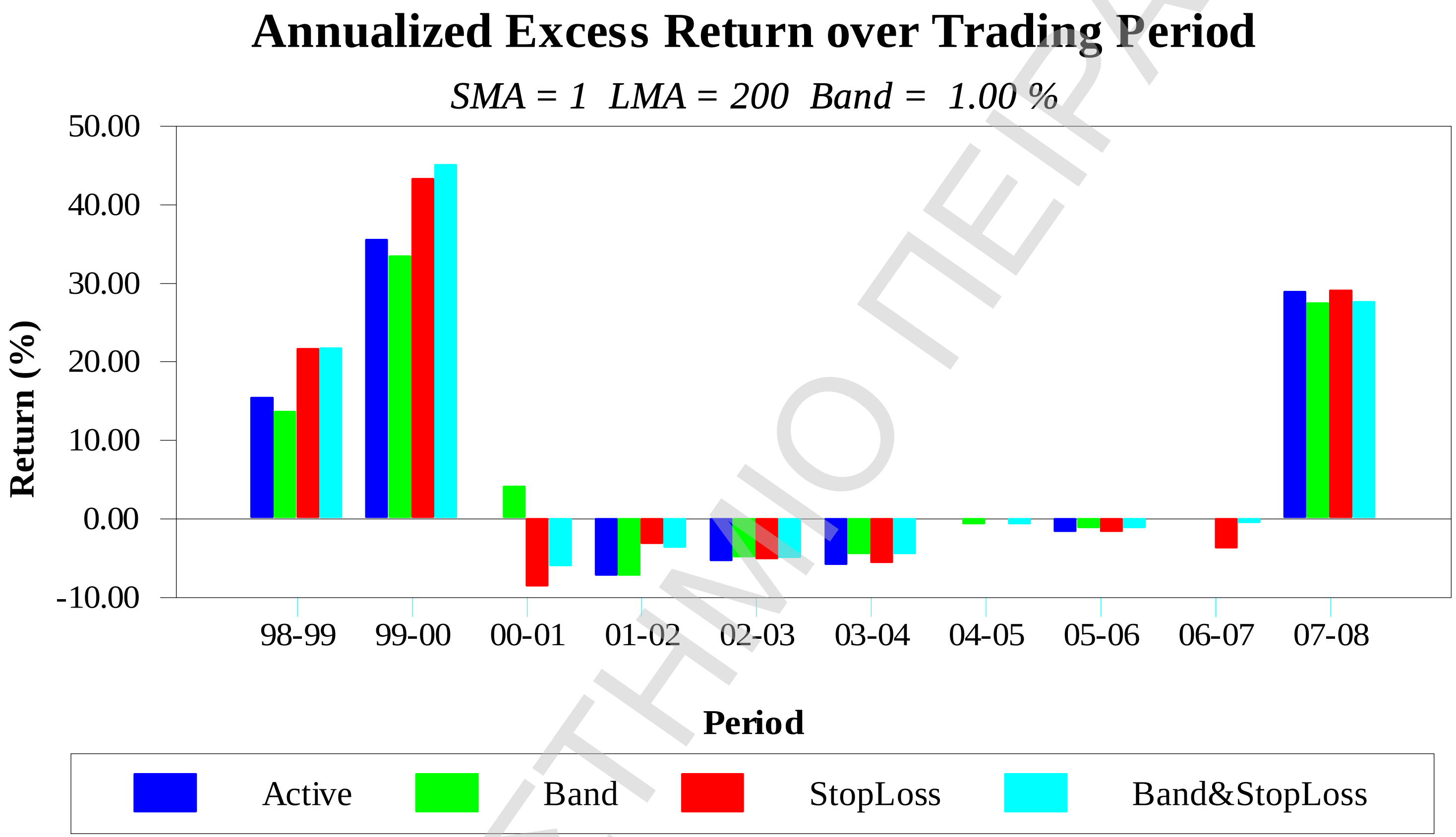

Figure 14. Annualized excess return over trading period : Period (1998/06-2008/06). **Large-cap segment.** This figure illustrates annualized difference between the return of the style-rotation strategies and the multi-style buy-and-hold strategy over the June 1998 to June 2008 period. SMA and LMA stand for the short-period moving average and the long-period moving average, respectively. Band is the percent difference that is needed to generate a signal under the "band" strategy.

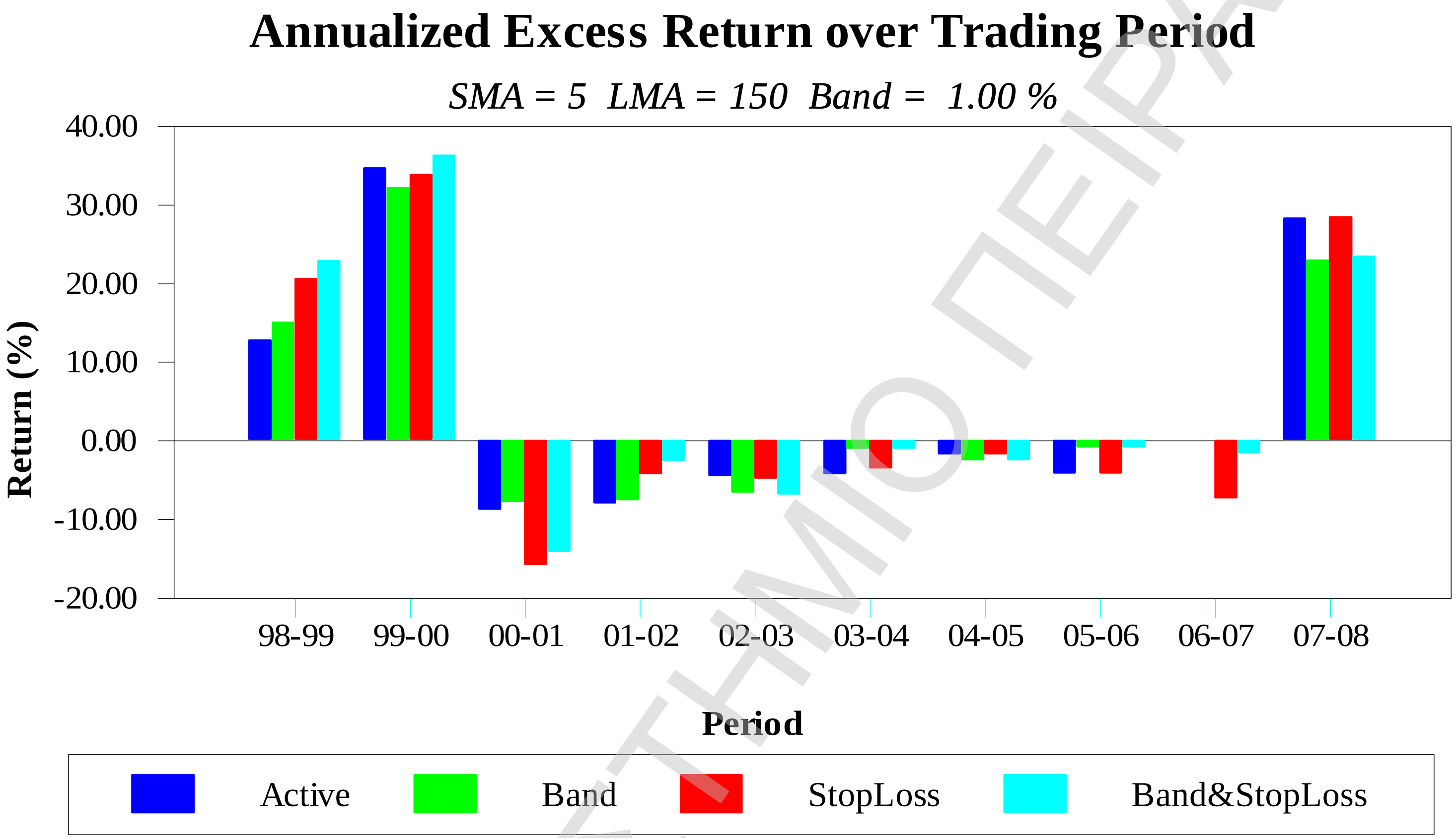

Figure 15. Annualized excess return over trading period : Period (1998/06-2008/06). **Large-cap segment.** This figure illustrates annualized difference between the return of the style-rotation strategies and the multi-style buy-and-hold strategy over the June 1998 to June 2008 period. SMA and LMA stand for the short-period moving average and the long-period moving average, respectively. Band is the percent difference that is needed to generate a signal under the "band" strategy.

D. Robustness Tests: Fama-French Three Factor Models

To further evaluate the risk-adjusted performance of our style-rotation strategies we estimated the Fama-French three factor model given by the following regression equation:

$$R_i - R_f = a + \beta_1 \, (R_m\text{-}R_f) + \beta_2 \, SMB + \beta_3 \, HML + e_i \, , \qquad (3)$$

where R_i - R_f is the excess return of our the style-timing strategy over the daily 1-month Treasury bill return, R_m-R_f is the market risk premium and SMB, HML are returns on zero-investment, factor mimicking portfolios for size and book-to-market equity, while e_i is the error term.[7]

According to Fama-French the observed difference between the returns on value and growth portfolios mirror a compensation for bearing systematic risk. Moreover, they suggest the fore mentioned three-factor model to underpin their inspiration while they argue that SMB- and HML-factors proxy for financial distress.

The main purpose of this robustness check is to address the issue whether our timing strategies produce risk-adjusted returns over-and-above the risk-factors proposed by Fama and French. If Fama-French factors completely account for risks associated with the returns, then alpha will be statistically insignificant and thus our trading rules are seriously correlated with risk. We also examine the "beta" coefficient of the HML factor to clarify the extent to which our strategies load on the specific "value" premium proxy. Finally, as a measure of goodness-of-fit we display the R-squared of each regression output.

[7] We obtained data in daily frequency for the 4-week Treasury bill rate from the Federal Reserve Bank of St.Louis.

i. Small-cap "Value Premium"

The results of the regressions for the small-cap universe are presented in Tables XI to XIV. The results reveal that alpha is statistically not different from zero for the multi-style buy-and-hold strategy. Moreover, we observe that the passive strategy exhibits a relatively high loading on the HML factor, strongly supported by an extreme t-statistic value. In accordance, the value of the square of the correlation coefficient implies a respectable goodness-of-fit. Expectedly, the buy-and hold strategy emerges well-fitted to the Fama-French risk-factor model.

On the other hand, our style rotation strategies demonstrate entirely different characteristics. Firstly, under all combinations of trading rules, the alphas are statistically significant, and thus different from zero. Most importantly, alphas are positive meaning that our dynamic strategies enhance performance, providing "added-value" which appears unexplained by the Fama-French risk-factor model. In the same line of reasoning our strategies' loadings on the HML factor, although statistically significant from zero, preserve sizably lower values than the corresponding loading of the buy-and-hold strategy. Subsequently, the r-squared values indicate that the variances of our strategies' returns remain, to a large extent, unexplained by the three-factor model.

In sum, the regression output for the small-cap segment supports the notion that technical trading rules probably capture non-risk factors since our strategies' returns do not appear to reflect risk in the context of a widely accepted multifactor model.

Table XI

Regression Results of Fama-French Factors: Small-cap Segment (1, 50, 1.00%)

	Buy & Hold	Active	Band	Stop-Loss	Band & Stop-Loss
alpha	-0.011	0.040	0.042	0.041	0.043
t-Stat	-1.366	2.668***	3.041***	2.990***	3.244***
HML-beta	0.841	0.196	0.218	0.205	0.213
t-stat	50.343***	6.540***	7.786***	7.372***	8.008***
R^2	0.719	0.087	0.112	0.097	0.111

This table presents the alpha, HML-loading and R-squared for Fama-French three-factor regression. Period: June 1998-June 2008. Small-cap segment. Rules are identified as (SMA, LMA, Band) where SMA, LMA are the short and long moving averages, respectively, and band is the percentage difference that is needed to generate a signal under the "band" strategy. The regression equation is $R_i - R_f = a + \beta_1(R_m - R_f) + \beta_2$ SMB $+ \beta_3$ HML $+ e_i$. $R_i - R_f$ is the strategy return over the daily treasury bill rate, $(R_m - R_f)$ is the market risk premium, SMB and HML are zero-investment mimicking portfolios for size and book-to-market equity. * Denotes significance at 10% level, ** denotes significance at 5% level, *** denotes significance at 1% level.

Table XII

Regression Results of Fama-French Factors: Small-cap Segment (1, 150, 1.00%)

	Buy & Hold	Active	Band	Stop-Loss	Band & Stop-Loss
alpha	-0.011	0.032	0.032	0.042	0.041
t-Stat	-1.366	2.178**	2.208**	3.222***	3.185***
HML-beta	0.841	0.222	0.228	0.220	0.228
t-stat	50.343***	7.410***	7.889***	8.313***	8.313***
R^2	0.719	0.096	0.094	0.099	0.107

This table presents the alpha, HML-loading and R-squared for Fama-French three-factor regression. Period: June 1998-June 2008. Small-cap segment. Rules are identified as (SMA, LMA, Band) where SMA, LMA are the short and long moving averages, respectively, and band is the percentage difference that is needed to generate a signal under the "band" strategy. The regression equation is $R_i - R_f = a + \beta_1(R_m - R_f) + \beta_2$ SMB + β_3 HML + e_i. $R_i - R_f$ is the strategy return over the daily treasury bill rate, $(R_m - R_f)$ is the market risk premium, SMB and HML are zero-investment mimicking portfolios for size and book-to-market equity. * Denotes significance at 10% level, ** denotes significance at 5% level, *** denotes significance at 1% level.

Table XIII

Regression Results of Fama-French Factors: Small-cap Segment (1, 200, 1.00%)

	Buy & Hold	Active	Band	Stop-Loss	Band & Stop-Loss
alpha	-0.011	0.031	0.035	0.033	0.041
t-Stat	-1.366	2.001**	2.358**	2.483**	2.941***
HML-beta	0.841	0.116	0.104	0.178	0.163
t-stat	50.343***	3.742***	3.443***	6.606***	6.186***
R^2	0.719	0.034	0.034	0.074	0.072

This table presents the alpha, HML-loading and R-squared for Fama-French three-factor regression. Period: June 1998-June 2008. Small-cap segment. Rules are identified as (SMA, LMA, Band) where SMA, LMA are the short and long moving averages, respectively, and band is the percentage difference that is needed to generate a signal under the "band" strategy. The regression equation is $R_i - R_f = a + \beta_1(R_m - R_f) + \beta_2$ SMB $+ \beta_3$ HML $+ e_i$. $R_i - R_f$ is the strategy return over the daily treasury bill rate, $(R_m - R_f)$ is the market risk premium, SMB and HML are zero-investment mimicking portfolios for size and book-to-market equity. * Denotes significance at 10% level, ** denotes significance at 5% level, *** denotes significance at 1% level.

Table XIV

Regression Results of Fama-French Factors: Small-cap Segment (5, 150, 1.00%)

	Buy & Hold	Active	Band	Stop-Loss	Band & Stop-Loss
alpha	-0.011	0.035	0.029	0.047	0.041
t-Stat	-1.366	2.358**	2.004**	3.567***	3.167***
HML-beta	0.841	0.229	0.232	0.217	0.228
t-stat	50.343***	7.599***	7.864***	8.172***	8.768***
R^2	0.719	0.079	0.082	0.099	0.105

This table presents the alpha, HML-loading and R-squared for Fama-French three-factor regression. Period: June 1998-June 2008. Small-cap segment. Rules are identified as (SMA, LMA, Band) where SMA, LMA are the short and long moving averages, respectively, and band is the percentage difference that is needed to generate a signal under the "band" strategy. The regression equation is $R_i - R_f = a + \beta_1(R_m - R_f) + \beta_2$ SMB + β_3 HML + e_i. $R_i - R_f$ is the strategy return over the daily treasury bill rate, $(R_m - R_f)$ is the market risk premium, SMB and HML are zero-investment mimicking portfolios for size and book-to-market equity. * Denotes significance at 10% level, ** denotes significance at 5% level, *** denotes significance at 1% level.

ii. Large-cap "Value Premium"

Our regression results for the large-cap segment are exhibited in Tables XV through XVIII. The results confirm our previous conclusions regarding the lack of robustness of the large-cap "value premium".

Specifically, the buy-and-hold strategy exhibits statistically significant alpha on the one hand, but the sign of the coefficient is negative. Thus, the passive strategy appears to deduct value under strong statistical support. A possible explanation for this phenomenon could the "offensive" loading of this strategy on the HML factor which is, also, significant at a remarkable level.

As we mentioned above, a closer look at the style-timing regression results unveils the robustness problems, discussed in the previous section. Excluding the 1-50 trading rule, the alpha coefficients of the remaining rules are statistically insignificant, which is in sharp contrast with the small-cap universe. However, the coefficients remain positive. Albeit, the loadings on the HML factor are greater than in the small-cap environment, they are sizably smaller than the buy-and-hold strategy's while the r-squared values are almost identical and fluctuate around the same levels compared to the small-cap segment.

Conclusively, the above results corroborate our previous findings; the large-cap outperformance of our trading strategies partially reflects risk. Yet, compared to the buy-and-hold strategy our style-timing strategies appear less risky and unexplainable in the framework of the Fama-French model which is by nature a strict test for our trading rules.

Table XV

Regression Results of Fama-French Factors: Large-cap Segment (1, 50, 1.00%)

	Buy & Hold	Active	Band	Stop-Loss	Band & Stop-Loss
alpha	-0.022	0.033	0.027	0.028	0.025
t-Stat	-2.385**	2.097**	1.845*	1.864*	1.754*
HML-beta	1.065	0.302	0.314	0.298	0.313
t-stat	56.503***	9.616***	10.618***	9.962***	10.941***
R^2	0.670	0.076	0.082	0.079	0.087

This table presents the alpha, HML-loading and R-squared for Fama-French three-factor regression. Period: June 1998-June 2008. Large-cap segment. Rules are identified as (SMA, LMA, Band) where SMA, LMA are the short and long moving averages, respectively, and band is the percentage difference that is needed to generate a signal under the “band” strategy. The regression equation is $R_i - R_f = a + \beta_1(R_m - R_f) + \beta_2$ SMB + β_3 HML + e_i. $R_i - R_f$ is the strategy return over the daily treasury bill rate, $(R_m - R_f)$ is the market risk premium, SMB and HML are zero-investment mimicking portfolios for size and book-to-market equity. * Denotes significance at 10% level, ** denotes significance at 5% level, *** denotes significance at 1% level.

Table XVI

Regression Results of Fama-French Factors: Large-cap Segment (1, 150, 1.00%)

	Buy & Hold	Active	Band	Stop-Loss	Band & Stop-Loss
alpha	-0.022	0.007	0.010	0.020	0.022
t-Stat	-2.385**	0.448	0.630	1.424	1.560
HML-beta	1.065	0.210	0.208	0.203	0.200
t-stat	56.503***	6.548***	6.813***	7.092***	7.178***
R^2	0.670	0.043	0.044	0.046	0.049

This table presents the alpha, HML-loading and R-squared for Fama-French three-factor regression. Period: June 1998-June 2008. Large-cap segment. Rules are identified as (SMA, LMA, Band) where SMA, LMA are the short and long moving averages, respectively, and band is the percentage difference that is needed to generate a signal under the "band" strategy. The regression equation is $R_i - R_f = a + \beta_1(R_m - R_f) + \beta_2$ SMB + β_3 HML + e_i. $R_i - R_f$ is the strategy return over the daily treasury bill rate, $(R_m - R_f)$ is the market risk premium, SMB and HML are zero-investment mimicking portfolios for size and book-to-market equity. * Denotes significance at 10% level, ** denotes significance at 5% level, *** denotes significance at 1% level.

Table XVII

Regression Results of Fama-French Factors: Large-cap Segment (1, 200, 1.00%)

	Buy & Hold	Active	Band	Stop-Loss	Band & Stop-Loss
alpha	-0.022	0.017	0.017	0.020	0.022
t-Stat	-2.385**	1.034	1.106	1.379	1.578
HML-beta	1.065	0.147	0.151	0.182	0.181
t-stat	56.503***	4.546***	4.815***	6.209***	6.321***
R^2	0.670	0.023	0.025	0.037	0.039

This table presents the alpha, HML-loading and R-squared for Fama-French three-factor regression. Period: June 1998-June 2008. Large-cap segment. Rules are identified as (SMA, LMA, Band) where SMA, LMA are the short and long moving averages, respectively, and band is the percentage difference that is needed to generate a signal under the "band" strategy. The regression equation is $R_i - R_f = a + \beta_1(R_m - R_f) + \beta_2$ SMB + β_3 HML + e_i. $R_i - R_f$ is the strategy return over the daily treasury bill rate, $(R_m - R_f)$ is the market risk premium, SMB and HML are zero-investment mimicking portfolios for size and book-to-market equity. * Denotes significance at 10% level, ** denotes significance at 5% level, *** denotes significance at 1% level.

Table XVIII

Regression Results of Fama-French Factors: Large-cap Segment (5, 150, 1.00%)

	Buy & Hold	Active	Band	Stop-Loss	Band & Stop-Loss
alpha	-0.022	0.010	0.012	0.011	0.015
t-Stat	-2.385**	0.598	0.763	0.742	1.089
HML-beta	1.065	0.178	0.179	0.232	0.228
t-stat	56.503***	5.529***	5.773***	8.028***	8.106***
R^2	0.670	0.032	0.034	0.055	0.057

This table presents the alpha, HML-loading and R-squared for Fama-French three-factor regression. Period: June 1998-June 2008. Large-cap segment. Rules are identified as (SMA, LMA, Band) where SMA, LMA are the short and long moving averages, respectively, and band is the percentage difference that is needed to generate a signal under the "band" strategy. The regression equation is $R_i - R_f = a + \beta_1(R_m - R_f) + \beta_2$ SMB + β_3 HML + e_i. $R_i - R_f$ is the strategy return over the daily treasury bill rate, $(R_m - R_f)$ is the market risk premium, SMB and HML are zero-investment mimicking portfolios for size and book-to-market equity. * Denotes significance at 10% level, ** denotes significance at 5% level, *** denotes significance at 1% level.

V. Conclusion

This study is, to the best of our knowledge, the first study in the style-timing “arena” that attempts to time a family of style indices utilizing simple technical trading rules. Using a dynamic approach, we implement long-short strategies, based on popular trading rules, while mitigating the look-ahead critique most academic studies on this subject suffer from. The performance of the proposed strategies is generated using only publicly available information.

We found that investors can add substantial value to their portfolio by timing the Russell large-cap value, large-cap growth, small-cap value and small-cap growth equity style indices. According to our results, trading strategies based on these tactics are able to provide at least triple annualized returns, after accounting for sensible transaction costs. Specifically, our worst performing strategy emanates from the large-cap segment, under the 1-150 rule and produces an annualized return 3.48 percent, assuming 20bps round-trip transaction costs. During the same trading period, the buy-and-hold strategy produces a mere 1.19 percent on an annualized basis.

To generalize our findings, we document a greater efficiency and performance of the small-cap “value premium”. Under every rule, our active strategies display remarkably better risk-return characteristics compared to both the multi-style benchmark and the market proxy. On the other hand, the large-cap segment demonstrates lack of robustness and experiences lower returns. However, our trading strategies actually performed quite well dominating once more the benchmarks.

A key element of the proposed strategies is the fact that they provide higher returns during recession than during expansions. As a result, they can also serve as hedges against a downturn of the economy.

Our results are consistent with technical rules having predictive power. Although, previous academic literature is the consequence of the rational response of investors to changing macroeconomic and fundamental data, we cannot rule out the influence of behavioral factors, such as momentum and sentiment. It is quite possible that technical trading rules pick up some of these hidden factors.

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