

When to Pick the Losers: Do Sentiment Indicators Improve Dynamic Asset Allocation?

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Abstract

Recent finance research that draws on behavioral psychology suggests that investors systematically make errors in forming expectations about asset returns. These errors are likely to cause significant mis-pricing in the short run, and the subsequent reversion of prices to their fundamental level implies that measures of investor sentiment are likely to be correlated with stock returns. A number of empirical studies using both market and survey data as proxies for investor sentiment have found support for this hypothesis.

In this paper we investigate whether investor sentiment (as measured by certain components of the University of Michigan survey) can help improve dynamic asset allocation over and above the improvement achieved based on commonly used business cycle indicators. We find that the addition of sentiment variables to business cycle indicators considerably improves the performance of dynamically managed portfolio strategies, both for a standard market-timer as well as for a momentum investor. For example, sentiment-based dynamic trading strategies, even out-of-sample, would not have incurred any significant losses during the October 1987 crash or the collapse of the dot.com bubble in late 2000. In contrast, standard business cycle indicators fail to predict these events, so that investors relying on these variables alone would have incurred substantial losses. However, our strategies do not simply follow market sentiment, but instead systematically exploit investor over-reaction. They are active alpha strategies with low betas and high alphas, in contrast to business cycle based strategies which are effectively index-trackers with high betas and considerably lower alphas.

JEL Classification: C32, F39, G11, G12

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"Modern markets show considerable micro efficiency . . . I [hypothesize] considerable macro inefficiency, in the sense of long waves in the time series of aggregate indexes of security prices below and above various definitions of fundamental values."

Paul Samuelson, quoted in Shiller (2000), *Irrational Exuberance*.

1. Introduction

Recent finance research invokes investor sentiment, which reflects cognitive heuristics, to suggest that investors systematically make errors in forming expectations about asset returns. These errors are likely to cause significant mis-pricing in the short run, as documented by Shleifer (2000), and Hirshleifer (2001). The subsequent reversion of security prices to their fundamental levels then implies that measures of investor sentiment are likely to be correlated with stock returns. Fisher and Statman (2000), and Charoenrook (2005), among others, find evidence that such measures indeed predict stock returns.

In this paper, we investigate whether the predictive information contained in a specific set of investor sentiment indicators can be used to improve dynamic asset allocation. We test both simple market-timing strategies as well as strategies that allow the investor to allocate funds between two momentum portfolios (winners and losers). We focus in particular on two main aspects; first we investigate if sentiment indicators can help avoid losses in market crashes or reduce portfolio risk during periods of high volatility. Second, we study whether sentiment is useful in active alpha management, i.e., we ask if dynamic strategies can consistently beat the market in the long run. The answer to both questions is affirmative: first, even out-of-sample our strategies would not have incurred any losses during the October 1987 crash or the collapse of the internet bubble in 2000. Second, in the long-run our strategies achieve consistent out-performance with (annualized) alphas in excess of 15%. The improvement in performance is statistically significant in all cases.

Behavioral theories draw on experimental psychology, which shows that individuals tend to form beliefs that are inconsistent with the economic paradigm of rational expectations. DeBondt and Thaler (1985) cite *over-reaction* in explaining return predictability based on long-term past returns. Their explanation is motivated by the observation that individuals tend to misinterpret observed events as representative descriptions of the population moments, while underestimating the randomness of observed outcomes (Kahneman and Tversky 1973). Investors mistakenly extrapolate extreme news events into the future, causing them to update their beliefs irrationally, thus leading to over-reaction.

On the other hand, Barberis, Shleifer, and Vishny (1998) rely on the conservatism bias (Edwards 1968) to motivate *under-reaction*. Because individuals tend to be excessively conservative in updating their expectations, securities prices do not adjust instantaneously to the arrival of new information. This price stickiness leads to trends in returns over short horizons and hence might be a factor in explaining the momentum effect, first documented by Jegadeesh and Titman (1993). In contrast, Daniel, Hirshleifer, and Subrahmanyam (2001) focus on the self-attribution bias. As Shefrin (1999) writes (page 101), "self-attribution bias occurs when people attribute successful outcomes to their own skill but blame unsuccessful outcomes on bad luck." In the short run, information arrival will lead investors to become over-confident and result in over-reaction. The continued flow of information will eventually drive prices back to their fundamental levels, thus creating short-run predictability.

Recent empirical studies using direct measures¹ of investor sentiment provide some evidence for these theories. Fisher and Statman (2000) find that investor sentiment is a reliable contrarian predictor of S&P 500 returns, and Charoenrook (2005) documents the predictive power of the University of Michigan Consumer Sentiment index. Amromin and Sharpe (2005), using similar data, find that returns over medium horizons appear to be extrapolated from past returns, providing evidence for the under-reaction hypothesis.

In this paper we use changes in specific components of the University of Michigan Consumer Sentiment survey data as a measure of aggregate investor sentiment. The Michigan survey is closely watched by economists and investors alike, who believe it to convey information relevant to the stock market.² We focus here on that component of the index that measures consumers perceptions of current business conditions and their

¹ - As opposed to market-based measures such as, the closed-end fund discount, book-to-market ratios, or firms decisions to issue stock rather than bonds.

² - Some articles in the financial press claim that the survey actually moves rather than predicts markets.

predictions of business conditions in the near future, as this component seems to contain information most directly relevant to the stock market. We also include different lags of these variables to see whether revisions in forecasts or perceptions, or the match (or mismatch) between past forecasts and current perceptions, also matter. Our approach thus differs from that in Charoenruek (2005), who uses the information in all the other components of the survey. As both theory and empirical evidence suggest that the predictive content of investor sentiment is not significantly related to the business cycle, we analyze whether sentiment indicators can improve the performance of market-timing strategies over and above the improvement achieved based on commonly used business cycle variables,³ which are known to be correlated with the business cycle.

We first investigate whether, investor sentiment out-of-sample, can predict extreme market movements and thus help avoid losses in market crashes or periods of high volatility. We find that sentiment-based dynamic trading strategies would not have incurred any significant losses during the October 1987 crash or the collapse of the dot.com bubble in late 2000. In contrast, standard business cycle indicators fail to predict these events, so investors relying on these variables alone would have incurred significant losses. A possible explanation is that strategies based on business cycle variables typically have very high betas, which amplify market movements in either direction. Thus, these are fair-weather-strategies, making good gains in bull markets but incurring excessive losses in market downturns. In contrast, sentiment indicators seem to allow asset managers to decouple their portfolios from the business cycle (with betas as low as 0.2) and thus successfully time the market.

In addition to pure market-timing strategies, we also consider strategies that allow the investor to allocate funds between two momentum portfolios (winners and losers) based on past performance. While momentum investing improves performance relative to pure market-timing, we also find an interesting difference in the behavior of portfolio weights. While market-timing strategies are forced to move in and out of the market, often taking short or leveraged positions, we find that momentum strategies behave much more like hedge funds: in periods of market turmoil, they remain fully invested in the risk-free asset while taking spread (long-short) positions in the momentum portfolios. Our momentum strategies remain profitable even when the transaction costs of re-balancing the momentum portfolios are taken into account.

To assess the statistical significance of our results, we use a test based on the difference in the slope of the efficient frontiers with and without the optimal use of predictive information. As this test has a known statistical distribution (both in finite sample as well as asymptotically), we can assess whether the expansion of the frontier due to predictability is statistically significant or just a product of sampling error. We find that the improvement due to the use of sentiment variables is significant (at the 5% level in all cases), while business cycle variables alone lead only to insignificant performance gains (with p -values around 20-30% at best). This is consistent with the finding that business cycle variables explain only about 1% of the return variation for the momentum portfolios, while the (adjusted) R^2 increases to about 7% when the sentiment variables (and some of their lags) are added. Omitting the lags reduces the R^2 considerably, indicating that it is not current perceptions and forecasts that predict momentum returns, but *revisions* to these perceptions.

We find that these strategies achieve their superior performance by systematically exploiting over-reaction. For example, in the market-timing strategies, the weight on the market index is negatively correlated with consumers expectations of future business conditions. Similarly, the momentum strategies pick losers when consumers expect business conditions to improve.

The performance of the market-timing strategies deteriorates if we remove the business cycle variables, indicating that it is the interaction between these sets of variables that leads to the improved portfolio performance, relative to the fixed-weight strategies.

We draw three main conclusions from our empirical findings. First our out-of-sample experiment shows that the addition of sentiment variables to business cycle indicators considerably improves the performance of dynamically managed portfolio strategies, both for standard market-timing as well as momentum investing. In contrast, strategies based on the business cycle variables alone out perform buy-and-hold strategies only

3 - We use the short rate, the slope of the Treasury yield curve, as well as the credit yield spread.

slightly and under-perform the market index in several cases. Second, our in-sample test shows that these results are statistically significant and not just artifacts of the chosen sub-period. Finally, the strategies based on the sentiment variables systematically exploit investor over-reaction leading to active alpha strategies with low betas and high alphas, in contrast to business cycle based strategies, which are effectively index-trackers with high betas and lower alphas.

The remainder of this paper is organized as follows; in section 2, we describe the data we use and our empirical methodology. The results of our empirical analysis are reported in section 3. Section 4 concludes. Detailed descriptions of the portfolio strategies used in this study, and the measures and tests used to assess their performance, are given in the appendix.

2. Data and Methodology

In this section we describe the predictive instruments and base assets used in our empirical analysis, as well as the portfolio strategies and the performance measures used to evaluate our results. We give here only an intuitive description; details can be found in appendix A.

2.1. Data

For our empirical analysis, we use monthly data covering the period from January 1980 until December 2004. The choice of sample period is mainly dictated by the availability of the predictive instruments we wish to use.

Sentiment Indicators

Each month, the Survey Research Center at the University of Michigan conducts a minimum of 500 phone interviews, which are used for the computation of a number of commonly cited gauges of the economy, such as the Index of Consumer Sentiment. The Michigan survey includes several questions regarding the respondents perception of financial and business conditions, as well as their own economic prospects, over horizons varying from one to five years. We focus here on two questions that pertain to consumers perception of current business conditions and their expectations of business conditions in six months. The responses can be good, bad, or normal for the current situation, and better, worse or unchanged for the future. As predictive instruments, we use the percentage of respondents who think conditions are currently good minus those who think they are bad (net good, NG) and similarly the percentage of those who think conditions will improve in six months minus those who think they will get worse (net better, NB). We also include different lags of each of these variables (NBxL, NGxL). These data have been available at a monthly frequency since 1978. Our sample period begins in January 1980 (to accommodate all required lags of the instruments) and ends in December 2004.

Business Cycle Predictors

The business cycle predictors we use are the 1-month US Treasury bill rate (TB1M), which has been shown to be a proxy for future economic activities (Fama and Schwert 1977), the term spread (TSPR, defined as the difference in yield on the 10-year and 1-year Treasury bond), which has been shown to be closely related to short-term business cycles (Fama and French 1988), and the credit spread (CSPR, the difference in yield between a 10-year AAA-rated corporate bond and the corresponding Treasury bond), which tracks long term business cycle conditions (Fama and French 1988).⁴

Investible Assets

The base assets are the 1-month Treasury bill and, for the market-timing strategies, the CRSP value-weighted index. For the momentum selection strategies, we replace the index by two portfolios sorted on past returns (winners and losers). To construct these, we use monthly US data of all NYSE, AMEX, and NASDAQ equities, obtained from the Center for Research in Security Prices (CRSP). We exclude all stocks with prices below \$5 as in Jegadeesh and Titman (1993). At each re-balancing point from January 1980 to December 2004, we form three equally-weighted momentum portfolios by sorting stocks on their past 6-month compounded returns. The stocks within the top 30% of past returns comprise the winner portfolio (M03) and stocks within the bottom 30% of past returns comprise the loser portfolio (M01). Portfolio returns are calculated for the six months following re-balancing. We construct non-overlapping momentum portfolios, thus reducing trading

4 - Other macroeconomic predictors, such as for example the Experimental and Recession Coincident Indices of Stock and Watson (1989), were tried but found to be inferior to the market-based variables used here.

frequencies and hence transaction costs implicit in portfolio construction.⁵ To assess the robustness of our results relative to the way in which the momentum portfolios are constructed, we also consider a variety of alternative momentum portfolios. A comparison of the findings is given in Section 3.2.

2.2. Dynamically Efficient Trading Strategies

Most of the existing literature on predictability and market-timing focuses on *myopically optimal* strategies. In contrast, we focus here on *dynamically optimal*, i.e., unconditionally efficient strategies, as studied in Ferson and Siegel (2001). While the portfolio weights of the former are determined *ex-post* on the basis of the conditional return moments, the weights of the latter are determined *ex-ante* as functions of the predictive instruments. In this sense, dynamically optimal strategies are truly actively managed, while myopically optimal strategies can be thought of as sequences of one-step-ahead efficient *static* portfolios. Because dynamically optimal strategies are designed to be efficient with respect to their long-run unconditional moments, they display a more conservative response to changes in the predictive instruments.⁶ This is an important consideration in particular with respect to transaction costs.

Most studies that have examined market-timing and the use of predictive variables such as the short rate (Breen, Glosten, and Jagannathan 1989), or time-variation in the conditional Sharpe ratio (Whitelaw 2005), have employed naive portfolio strategies related to conditional efficiency. In contrast, unconditionally efficient strategies optimally utilize both the predictive information and the time-variation in the conditional Sharpe ratio (Cochrane 1999), and can significantly outperform naive market-timing strategies.

We provide precise specifications of the weights of dynamically efficient strategies in appendix A.1. In our empirical applications, we consider both efficient minimum-variance strategies (designed to track a given target average return), as well as efficient maximum-return strategies (designed to track a given target volatility). The former are particularly useful in risk management as they provide portfolio insurance against crashes and periods of excess volatility. The latter can be thought of as active alpha strategies, designed to achieve maximum performance at a tolerable level of risk.

2.3. Measuring the Value of Return Predictability

To assess the long-run performance of dynamically managed strategies based on business cycle and sentiment indicators, we use a variety of standard *ex-post* portfolio performance measures. These include Sharpe ratios, Jensens alpha, and information ratios.

Measures of Statistical Significance

To capture the incremental gains due to the optimal use of predictive information, we compare the performance of optimally managed portfolios with that of traditional fixed-weight strategies, those for which the portfolio weights do not depend on the predictive instruments. We wish to measure the extent to which the optimal use of predictive information expands the efficient frontier, and hence the opportunity set available to the investor. Because the location of the global minimum-variance (GMV) portfolio is virtually unaffected by the introduction of predictive variables (see also figure 5), we use the asymptotic slope of the frontier (i.e. the Sharpe ratio relative to the zero-beta rate associated with the mean of the GMV) as such a measure. Because we can show that the difference in (squared) slopes of the frontiers with and without the optimal use of predictability has a known (χ^2) distribution, we are able to assess the statistical significance of any gains due to predictability. A precise definition of our test statistic is given in appendix A.2.

3. Empirical Analysis

Denote by $R_t = (r_t^1 \dots r_t^n)'$ the n-vector of risky asset returns. We estimate a linear predictive model of the form,

$$R_t = \mu_0 + B \cdot Z_{t-1} + \varepsilon_t,$$

where Z_{t-1} is the vector of (lagged) predictive instruments. We assume that the residuals ε_t are serially independent and independent of Z_{t-1} . This implies that the conditional variance-covariance matrix Σ does not

⁵ - These non-overlapping strategies have an average profit of 0.47% per month with t-ratio of 3.19.

⁶ - See also Ferson and Siegel (2001).

depend on Z_{t-1} . However, because we will estimate (1) jointly across all assets, we do not assume the ε_t to be cross-sectionally uncorrelated, i.e., we do not assume Σ to be diagonal.

In-Sample Results

Tables 1 and 2 show the in-sample estimation results, using the market index (table 1) as well as the momentum portfolios (table 2) as base assets. In each table, Column (1) reports the results using only business cycle variables as predictors, while column (2) includes all instruments. While business cycle variables seem to possess very little predictive power (explaining only about 1% of the variation for the momentum portfolios), the adjusted R^2 increases to about 7% when all the sentiment variables are added. If we add only NB and NG, then the R^2 on the winners portfolio decreases sharply to about 4%, while that on the losers reduces slightly, indicating that the three- and six-month lags are important for predicting the performance of the winners portfolio. This is also reflected in the theoretically maximum Sharpe ratios, which are increased only marginally (from 0.79 to 0.88 in the case of the momentum portfolios) by the use of macro indicators, the increase not being statistically significant (with a p-value of almost 0.3). In contrast, the addition of sentiment indicators more than doubles Sharpe ratios (to 0.98 and 1.43, respectively). This increase is statistically significant (at the 5% level for both the market-timing and momentum strategies). The benefit of adding sentiment to the set of predictive variables is also illustrated in figure 5, which shows the efficient frontiers with and without predictability. Clearly, business cycle indicators enlarge the investors opportunity set only marginally (panel A), while the addition of sentiment indicators has a much more dramatic effect (panels B and C). Finally, while allowing the investor to pick between winner and loser does improve performance, this increase is much less dramatic.

3.1. Do Sentiment Indicators Protect Against Crashes?

To begin, we conduct several out-of-sample experiments, focusing on times of high volatility or extreme market movements. We estimate the predictive model using data up to several months preceding the event in question, and then study the performance of the resulting dynamically managed portfolio strategy during the following months.

October 1987 Stock Market Crash

In our first experiment, we focus on the October 1987 market crash. Panel (A) of figure 2 shows the cumulative returns of the market index and a dynamically optimal minimum-variance market-timing strategy, using only the business cycle variables as predictors. The bottom graph in Panel (A) shows the portfolio weights of the market-timing strategy. Although the market-timing strategy loses much less than the market index in the two months following the crash, it is evident that business cycle indicators alone cannot provide full insurance against the crash. Panel (B) of figure 2 shows the performance of the corresponding market-timing strategy when the sentiment indicators are added to the set of predictors. First we note that the strategy in this case does not incur any losses in the months around the crash (in contrast to a loss of about 15% for the business cycle strategy). In fact, the sentiment strategy exhibits positive returns throughout the entire out-of-sample period. The bottom part of the figure shows that the sentiment-strategy achieves its performance by cutting its losses, by shorting the index just before the crash. In contrast, the business cycle strategy remains heavily invested in the index throughout. The performance of the strategy over the period from January 1987 to December 1992 is reported in table 3. The strategy achieves a Sharpe ratio of 0.94 relative to 0.28 for the index over the period and has a similar information ratio of 0.93. It has a low CAPM beta of 0.15 and a reasonable annualized alpha of 2.35% relative to the CAPM. Interestingly, the alpha relative to the four-factor Carhart (1997) model (where the additional factors are the Fama-French size and book-to-market factors, and Carharts momentum factor) is higher at 3.07%, indicating that this strategy is negatively correlated with at least some of the additional factors.

Finally, panel (C) of figure 2 shows the performance of the optimal strategy in the case where the investor is allowed not only to time the market but also to allocate funds between the risk-free asset and the winner and loser portfolios. This strategy incurs virtually no losses around the crash. It has higher Sharpe and information ratios of 1.36 and 1.41 (Table 4). It has a low CAPM beta of 0.06, a CAPM alpha of 3.55%, and a higher alpha

of 4.01% relative to the four-factor model, just as for the market-timing strategy. The strategy is almost fully invested in the risk-free asset over most of the period, while actively managing a position in the spread between winners and losers.

Figure 3 reports the analogous results for the three maximum-return strategies. Because of the bullish conditions preceding the crash, the business cycle strategy (panel A) in fact takes a leveraged position in the market index, and fails to reduce its exposure until almost two years after the crash. As a consequence, it experiences losses in excess of the index. In contrast, the strategies using sentiment indicators (panels B and C) not only avoid losses but record steady gains throughout (with the momentum strategy closing at more than twice its initial value in 1989). The bottom graph of panel B shows that the sentiment market-timing strategy, although having been heavily invested in the market index, switches entirely to the risk-free asset just before the crash, but reverts very soon thereafter. Comparing this to panel A shows that sentiment information induces a much more active market timing than do business cycle indicators.

However, figure 3 also shows that at least part of the gains made by the sentiment strategies rely on being able to take short positions. This is particularly the case for the momentum portfolio, where the constrained (long-only) strategy in fact does not even match the market benchmark. Over this period, it appears that pure market-timing strategies work better.

Collapse of the dot.com Bubble in 2000

We repeat the above experiment, this time focusing on the collapse of the Internet bubble in late 2000. The results are shown in figure 4. From panel (A) we see that the market-timing strategy based on business cycle variables alone performs only marginally better than the market index itself. This is largely due to the fact that the strategy is very heavily invested in the index, indicating that the business cycle indicators fail to predict the bear market. In contrast, the inclusion of sentiment indicators (panel B) dramatically improves the portfolio insurance aspect of the strategy. The portfolio weights show a pattern to that shown similar as around the 1987 crash, moving out of the market during the periods of sharpest decline. Over the May 2000 to December 2004 period it achieves a Sharpe ratio of 0.25, (table 3) but a much higher information ratio of 0.79, due to the prolonged bear market. It has a moderate CAPM beta of 0.33 with an alpha of 3.85%, while the four-factor alpha is higher at 4.27%. Finally, the strategy that uses winner and loser portfolios incurs virtually no losses throughout the entire bear market. Although designed to minimize variance, this strategy achieves a cumulative return of 80% over the 2000-2004 period. It achieves a considerably higher Sharpe and information ratios (1.07 and 1.11, respectively) than the market-timing strategy (table 4). It has a high CAPM alpha of 11.70%, but a considerably lower alpha of 5.22% when we use the four-factor model.⁷ For most of the out-of-sample period, the strategy maintains a stable position in the winners portfolio, trading off the losers against the risk-free asset, while in the later part of the period it mainly trades the spread between winners and losers.

3.2. Other Momentum Portfolios

The analysis presented in the preceding section uses non-overlapping momentum portfolios, obtained by sorting all stocks on the basis of their past 6-month returns and then forming equally-weighted portfolios of the top and bottom 30%. Other popular choices are to use the top and bottom decile portfolios, or to construct value-weighted portfolios. To ensure the robustness of our findings with respect to the method of portfolio formation, we repeat our empirical analysis with these alternative momentum portfolios. The results are qualitatively very similar in all cases, with minor differences in portfolio characteristics.

When we use the top and bottom deciles, the results over the 1987 crash period are very similar, but over the 2000-2004 period this strategy has a slightly lower mean and considerably higher volatility than for the 30% momentum portfolios. This makes intuitive sense, as over this period the difference between the returns on both sets of portfolios was very similar, while the decile portfolios had considerably higher volatilities. The difference in volatility between the two sets of portfolios was much lower during the 1987-1992 period.

7 - The strategy based on business cycle variables alone also performs quite well over this period, but its four-factor alpha is much lower at 2.58%.

When we use value-weighted portfolios, the mean return on the strategies over both periods is lower than that of the equally weighted portfolios, with the difference being more pronounced over the 2000–2004 period. Here, the strategy using equally weighted portfolios had a mean of 15.0% with a volatility of 10.8%, while the value-weighted portfolios achieved a lower mean of 8.0%, albeit at a much lower volatility of 7.8%. Finally, the results are very similar using overlapping portfolios, while these would incur significantly higher transaction costs due to more frequent re-balancing.

Thus, while all the strategies avoid losses during both bear markets, the strategies based on equally weighted top and bottom third portfolios perform best overall. The strategies based on sentiment variables alone do not work as well, suggesting that the interaction between sentiment and business cycle variables is important.

3.3. Transaction Costs

Our strategies are all dynamic and thus involve frequent re-balancing due to changes in portfolio weights, and thus the issue of transaction costs incurred by these strategies is of significance. The market timing strategies could be executed in the futures markets where the costs for a single transaction are around 5 basis points. Even assuming that the entire portfolio is moved into or out of the risky asset at each re-balancing, the strategies transaction costs are no more than 12 basis points for either of them, and thus do not affect overall profitability. It is far more of an issue for momentum portfolios, for which re-balancing involves opening and closing positions in potentially illiquid stocks. Such transactions lead to substantial costs, which are estimated in Lesmond, Schill, and Zhou (2004). We estimate the average transaction cost as the product of the average change in portfolio weight of the risky asset as a percentage of the total position in each period multiplied by the cost of executing that position. For example if the average change is 10% and the cost of executing that position is 10%, then the average transaction cost is 1% (of the total position). For the winner and loser portfolios, which are based on Jegadeesh and Titman (1993), the costs of re-balancing are estimated to be 4% and 5% respectively.

The profitability of our momentum strategies thus depends crucially on the nature of the portfolio weights, with large movements leading to high transaction costs. For the first out-of-sample period we find that the average change in portfolio weights for the loser portfolio is about 1%, while for the winner portfolio it is about 8%. The average transaction cost is then 45 basis points per transaction, which leads to transaction costs of about 75 basis points or 0.75% per year. The average return of our market timing strategy over the first period was 10.37%, so it would still deliver a substantial return after these transaction costs were accounted for. Over the second period, May 2000–2004, the average change in loser portfolio weights is still around 1%, but increases to 9% for the winner portfolio. The average transaction costs increase to 50 basis points per transaction, and the costs are more substantial at 1.34% per year. However, the strategy has a high return of 14.98%, so again remains profitable even after these substantial costs. Finally, for the long-only strategy involving small stocks with high prior return, the transaction costs are higher and estimated at around 12% in Lesmond, Schill, and Zhou (2004). The average change in portfolio weight for this strategy is 8%, leading to an average transaction cost of 1%. The average transaction cost for this strategy comes to about 0.95% per year, around 10% of its overall return, so that the strategy continues to remain profitable. The unconditionally efficient strategies are crucial here as they do not vary as much as conditionally efficient strategies, due to the conservative response to extreme signals noted in Ferson and Siegel (2001).⁸ For the long-only strategy the average change in portfolio weights for the conditionally efficient strategy was 17%, and the conditionally efficient strategy would have incurred transaction costs of over 4% a year, seriously affecting its profitability. Thus these unconditionally efficient strategies remain profitable in spite of their dynamic nature due to the low variation in portfolio weights and their high returns.

3.4. How Do the Strategies Work?

First, we note (tables 3 and 4) that the market timing strategies based on sentiment tend to have much lower betas (between 0.1 and 0.4) than those based on business cycle variables alone. In other words, business cycle strategies are effectively "index-trackers", their high betas amplifying market movements in either direction. Thus, these are "fair-weather-strategies", performing well in bull markets but incurring excessive losses during market downturns. In contrast, sentiment indicators seem to allow asset managers to "de-couple" their portfolios

8 - The maximum change in portfolio weights was 100% for the conditionally efficient long-only strategy, compared to 35% for the dynamically efficient long-only strategy.

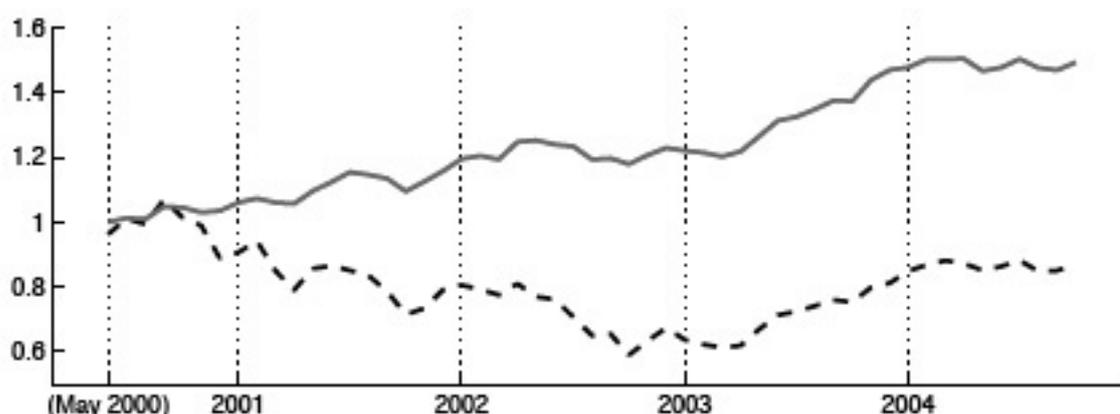
from the business cycle and thus successfully time the market. The strategies tend to perform particularly well during sharp and relatively short market declines. A good example of this is the Russian crisis in August 1998. We estimate the market-timing strategy with all variables until December 1997 and study the performance of the strategy until the end of 1999. The strategy avoids any losses during the period of sharpest decline and has a Sharpe ratio of 1.64, an information ratio of 1.88 and CAPM and four-factor alphas of 6.05% and 6.54% respectively. The momentum strategy, by contrast, does not perform quite as well, with Sharpe and information ratios of 1.43 and 1.67, and although the CAPM alpha is 8%, the four-factor alpha is a lot lower at 1.89%.

We find that the market-timing strategies run with the sentiment variables alone perform much less well. Over the 1987-199 period the sentiment-only strategy had a volatility of 5.61% (relative to 3.57% with all variables) with similar means, while over the 2000-2004 period the sentiment-only strategy achieved a mean of only 2.21% (relative to 4.86% when all variables are used) with similar volatility. The weights of the sentiment-only strategy are quite volatile and it seems that adding the business cycle variables smooths them out, leading to better performance. Thus, it is the interaction between these variables that leads to the superior performance of the managed strategies.

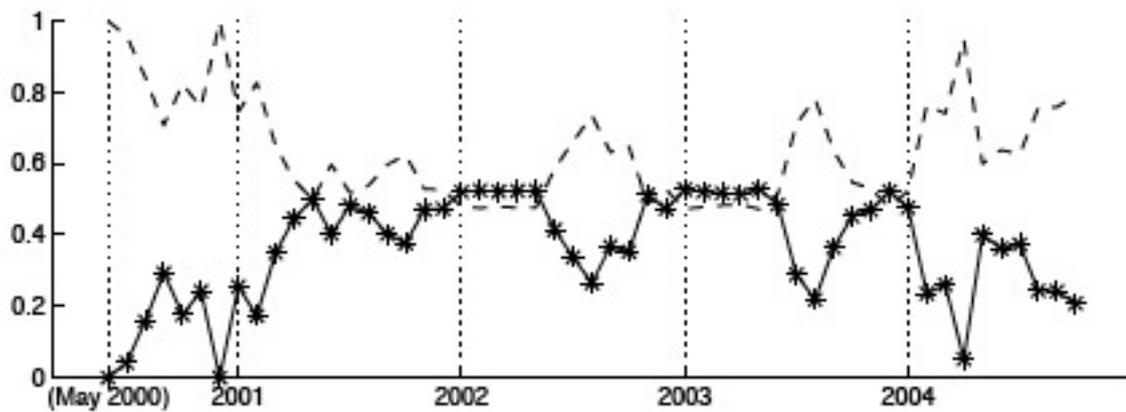
The momentum strategies perform much better during longer periods of decline. While market-timing strategies are forced to move in and out of the market, often taking short or leveraged positions, momentum strategies behave much more like hedge funds: during the 1987 crash this strategy remained fully invested in the risk-free asset while taking spread trades (i.e., long-short positions) in the momentum portfolios. During the collapse of the Internet bubble, they maintained a relatively stable position in winner stocks, while taking spread positions between losers and the risk-free asset. The difference in performance between market timing and momentum strategies is most pronounced during the 2000-2004 period, as we have observed earlier, and the profitability of the momentum strategy seems to be due to its ability to time the loser portfolio. It is interesting also to analyze the profile of the momentum strategy over this period. The betas relative to the four-factor model are 0.24 relative to the market, 0.04 relative to the size factor, 0.28 for the value factor, and 0.33 for the momentum factor. The positive betas on the size and value factors show that the strategy has a "small-value" bias while the positive beta on the momentum factor shows that it is positively correlated with the winner portfolio.

One criticism of our momentum strategy above is that its performance seems to rely on shorting the loser portfolio which may prove difficult in practice. Motivated by the style characteristics of the portfolio, in particular the positive betas on the size and momentum factors, we replace the winner and loser portfolios with a portfolio of small-winner stocks⁹ and consider the performance of the long-only minimum-variance strategy. We find that this strategy has an annualized mean of 9.91% and a volatility of 6.80%, leading to a Sharpe ratio of 1.03. It has an information ratio of 2.03 and a CAPM alpha of 8.37%, but a lower four-factor alpha of 3.20%. This strategy would be much easier to implement and realizes most of the gains of the strategy involving the momentum portfolios.

Figure 1: Total Return (Minimum-Variance Long-Only Strategy)



9 - This is the "HS" portfolio in a set of six portfolios sorted by size and past returns available on Ken French's web-site.



This figure shows the total cumulative returns of the market index (dashed line), and the minimum-variance long-only strategy, using all variables and the "HS" portfolio defined above.

3.5. What can we Learn from Investor Sentiment?

An inspection of the coefficients on the sentiment variables (table 1) shows that bullish investor sentiment ($NB > 0$) actually represents bad news: in the optimal market-timing strategy, the weight on the market index is negatively correlated with NB . In other words, *when the majority of investors expect economic conditions to improve, get out of the market!* This result is consistent with the over-confidence hypothesis (Shefrin 1999) and shows that our strategy exploits this investor over-reaction by taking the opposite position. The correlation is higher over the 1987 crash period than over the 2000-2004 period, which might explain why the market-timing strategy did better during the crash. In the period leading up to the crash, NB rose quite sharply, and the strategy's response was to become fully invested in the risk-free rate. For momentum-strategies, we find a similar pattern: in the optimal strategies, NB is negatively correlated with the weight on the winner portfolio, although the magnitude of the correlations are lower. Thus it seems that NB tells us more about when to be in or out of the market.

We next focus on the variables $NB - NGxL$ for $x = 1, 3, 6, 12$. If this difference is positive, business conditions are expected to get better in the near future than they were x months ago. If, for example, $NGxL \leq 0$, conditions were perceived to be bad in the past, but expected to improve in the future. Conversely, if $NGxL \geq 0$, investors considered business conditions to be good in the past but expect them to get even better in the future. We find that in both cases $NB - NGxL$ is positively correlated with the weight on the loser portfolio, and the correlations are very similar for all lags x (between 0.55 and 0.65). We find a negative relation between $NB - NGxL$ and the weight on the winner portfolio, although the magnitude of the coefficient is lower. In other words, *if conditions are good but are expected to get even better, sell the winners!* Our interpretation is that winner stocks are those that have over-reacted to the past good news. Conversely, *if perceptions are bad but are expected to improve, buy losers*, as the loser stocks are the ones that are likely to be under-priced due to over-reaction to past bad news.

Finally, we find that $NBxL - NG$ is negatively correlated with the weights on winners, and positively correlated with losers, for all lags x of NB , for both out-of-sample periods. In other words, *if investors did expect business conditions to improve but this expectation has not been met, short winner stocks and buy the losers.* This result again supports our over-reaction interpretation; in other words, the winner stocks are those whose prices over-reacted to the good news and are now over-valued, and our strategy exploits this by shorting the winners and buying the losers.

Does Sentiment Predict the Business Cycle?

There is no evidence that sentiment is a reliable predictor of the business cycle. In fact, positive investor outlook is negatively correlated with future market movements. Our results show that business cycle indicators alone improve portfolio performance only marginally, while the addition of sentiment indicators has a much more dramatic effect. In other words, investor sentiment clearly contains information beyond simply that contained in commonly used business cycle variables.

4. Conclusions

Recent finance research that draws on behavioral psychology suggests that investors systematically make errors in forming expectations about asset returns, and thus that investor sentiment can have predictive power for asset returns. A number of empirical studies using both market and survey data as proxies for investor sentiment have found support for these theories. In this study we investigate whether investor sentiment as measured by a component of the University of Michigan survey can help improve dynamic asset allocation over and above the improvement achieved based on commonly used business cycle indicators.

We find that sentiment-based dynamic trading strategies, even out-of-sample, would not have incurred any significant losses during the October 1987 crash or the collapse of the dot.com bubble in late 2000. In contrast, standard business cycle indicators fail to predict these events, so investors relying on these variables alone would have incurred significant losses. The sentiment-based strategies appear to systematically exploit investor over-reaction to time the market or pick between winners and losers. They are active alpha strategies with low betas and high alpha. An in-sample test shows that these results are statistically significant and not just artifacts of the chosen sub-period.

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Appendix

A.1. Dynamically Efficient Strategies

To specify a dynamically managed trading strategy, we denote by $\theta_{t-1}^k = \theta^k(Z_{t-1})$ the fraction of portfolio wealth invested in the k -th risky asset at time $t-1$, given as a function of the vector Z_{t-1} of (lagged) predictive instruments. The return on this strategy is given by,

$$r_t(\theta) = r_{t-1}^f + \sum_{k=1}^n (r_t^k - r_{t-1}^f) \theta_{t-1}^k, \quad (2)$$

where r_t^k is the return on the k -th risky asset, and r_{t-1}^f denotes the return on the risk-free Treasury bill. The difference in time indexing indicates that, while the return r_{t-1}^f on the risk-free asset is known at the beginning of the period, the returns r_t^k on the risky assets are uncertain *ex-ante* and only realized at the end of the period. Note however that we do *not* assume r_{t-1}^f to be unconditionally constant. It can be shown¹⁰ that the weights of any unconditionally efficient managed strategy can be written as,

$$\theta_{t-1}^* = \frac{w - r_{t-1}^f}{1 + H_{t-1}^2} \cdot \Sigma_{t-1}^{-1} (\mu_{t-1} - r_{t-1}^f e). \quad (3)$$

Here, μ_{t-1} and Σ_{t-1} are the conditional (on Z_{t-1}) mean vector and variance-covariance matrix of the base asset returns, and $w \in \mathbb{R}$ is a constant. By choosing $w \in \mathbb{R}$ in (3) appropriately, we can construct efficient strategies that track a given target expected return or target volatility.

A.2. Measures of Statistical Significance

To measure the economic gain due to predictability, we measure the extent to which the optimal use of predictive information expands the unconditionally efficient frontier, i.e., the opportunity set available to the investor. In the absence of an unconditionally risk-free asset, the efficient frontier is described by three parameters, the location (mean and variance) of the GMV, and the asymptotic slope of the frontier (i.e., the maximum Sharpe ratio relative to the zero-beta rate corresponding to the mean of the GMV). Note however that because of the low volatility of T-bill returns, the location of the GMV will be virtually unaffected by the introduction of predictive instruments (see also Figure 3). Therefore, we focus here on the change in asymptotic slope of the frontier as a measure of predictability. Denote by λ_* the slope of the frontier *with* optimal use of predictability, and by λ_0 the slope in the fixed-weight case (without making use of predictive information). In a slight abuse of terminology, we often refer to λ_* and λ_0 simply as Sharpe ratios.

One can now show that up to a first-order approximation, the (squared) maximum slope of the dynamically managed frontier is given by,

$$\lambda_*^2 \approx E(H_{t-1}^2), \quad \text{where} \quad H_{t-1}^2 = (\mu_{t-1} - r_{t-1}^f e)' \Sigma_{t-1}^{-1} (\mu_{t-1} - r_{t-1}^f e).$$

Here, μ_{t-1} and Σ_{t-1} are the conditional mean vector and variance-covariance matrix of the base asset returns. The error in the above approximation is of the order $\text{var}(H_{t-1}^2)$. To obtain the corresponding expression for λ_0 , we simply replace μ_{t-1} and Σ_{t-1} by their unconditional counterparts.

Note that H_{t-1} is the *conditional* Sharpe ratio, once the realization of the conditioning instruments is known. From (3), it is clear that H_{t-1} plays a key role in the behavior of the optimal strategy. Moreover, the above result shows that the maximum unconditional Sharpe ratio is given by the unconditional second moment of the conditional Sharpe ratio.¹¹ Consequently, time-variation in the conditional Sharpe ratio improves the *ex-post* risk-return trade-off for the mean-variance investor, a point also noted by Cochrane (1999).

To measure the effect of predictability, we define the test statistic $\Omega = \lambda_*^2 - \lambda_0^2$. Our null hypothesis is that predictability does not matter, i.e. $\Omega = 0$. As the set of fixed-weight strategies is contained in the set of dynamically managed strategies, we always have $\Omega \geq 0$.

¹⁰ - See Ferson and Siegel (2001).

¹¹ - In the case of a single risky asset, this was shown by Jagannathan (1996).

In the linear predictive setting (1) used in our empirical analysis, one can show that under the null, the test statistic

$$\frac{T - K - 1}{K} \cdot \Omega \quad \text{is distributed as} \quad F_{K, T-K-1} \quad \text{in finite samples,}$$

and $T \cdot \Omega$ is distributed as χ^2_{NK} asymptotically. Here, N is the number of assets, K is the number of instruments in Z_{t-1} , and T is the number of time-series observations. This result allows us to assess the statistical significance of the economic gains due to predictability.

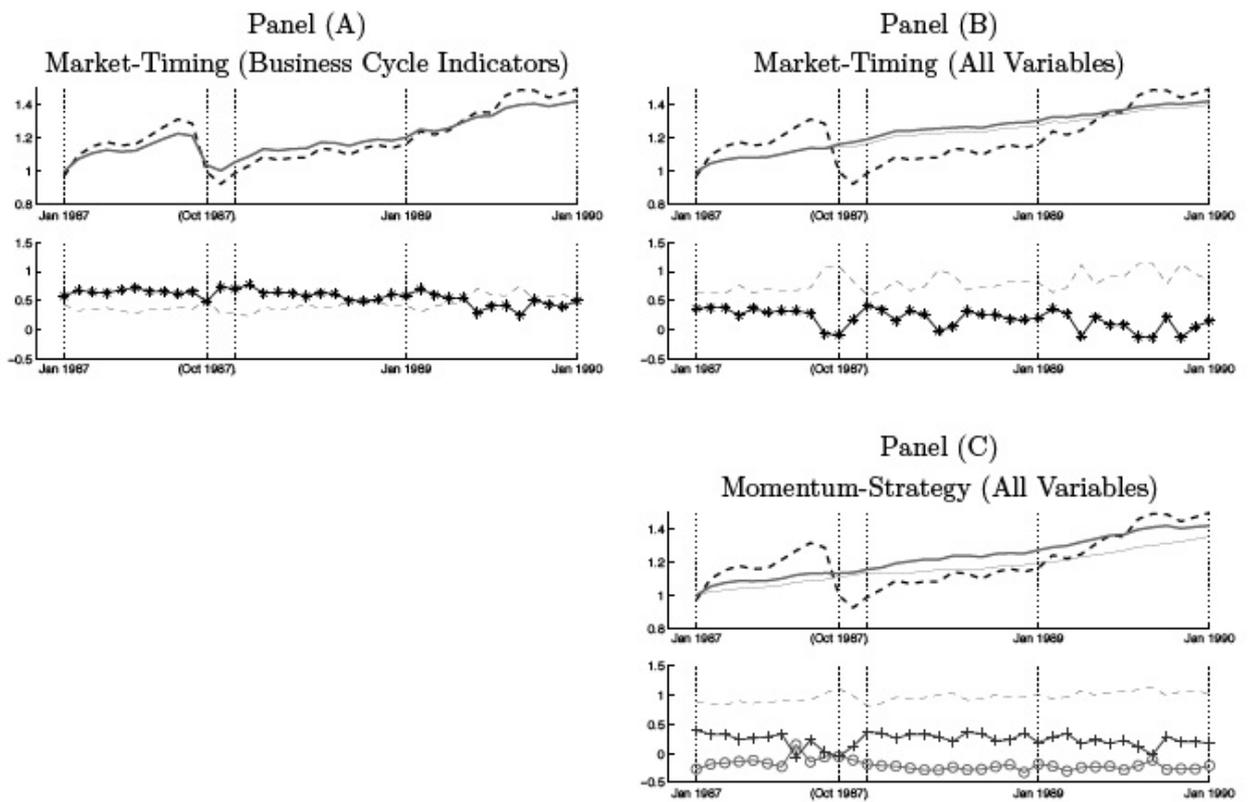


Figure 2: October 1987 Crash (Minimum-Variance Strategies)

These graphs show the performance and portfolio weights of three different minimum-variance strategies around the October 1987 market crash. In each panel, the top graph shows the cumulative return of the strategy (solid line) and the market index (dashed line), normalized to have unit value in December 1986. Also shown (light-weight line) is the return on the constrained (long-only) strategy. The bottom graph shows the portfolios, weights on the risk-free asset (dashed line), the market index (*), or the winner (+) or loser (o) portfolios respectively. Panels (A) and (B) focus on market-timing (allocating between the risk-free asset and the index), while panel (C) allows in addition allocation between the two momentum (winners and losers) portfolios. The strategy in panel (A) uses only business cycle indicators, while panels (B) and (C) use all (including sentiment) instruments.

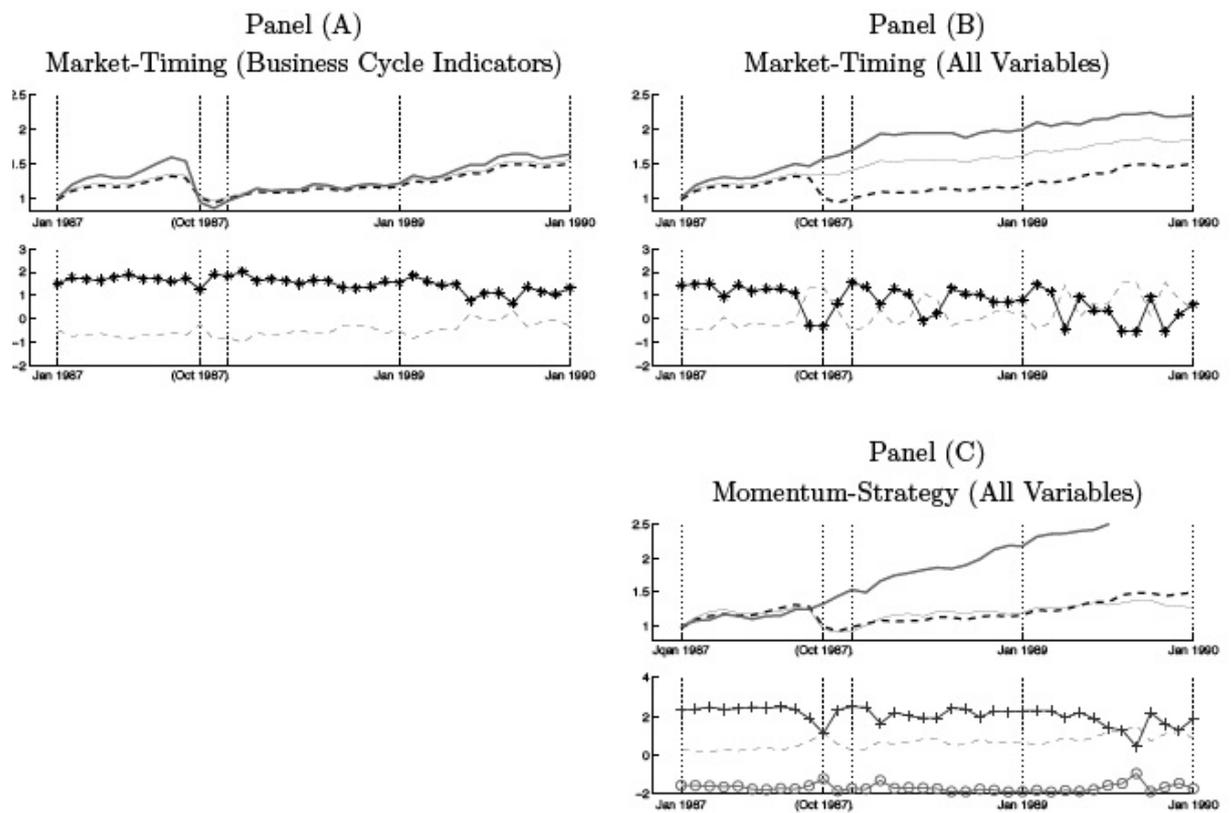


Figure 3: October 1987 Crash (Maximum-Return Strategies)

These graphs show the performance and portfolio weights of three different maximum-return strategies around the October 1987 market crash. In each panel, the top graph shows the cumulative return of the strategy (solid line) and the market index (dashed line), normalized to have unit value in December 1986. Also shown (light-weight line) is the return on the constrained (long-only) strategy. The bottom graph shows the portfolio weights on the risk-free asset (dashed line), the market index (*), or the winner (+) or loser (o) portfolios respectively. Panels (A) and (B) focus on market-timing (allocating between the risk-free asset and the index), while panel (C) allows in addition allocation between the two momentum (winners and losers) portfolios. The strategy in panel (A) uses only business cycle indicators, while panels (B) and (C) use all (including sentiment) instruments.

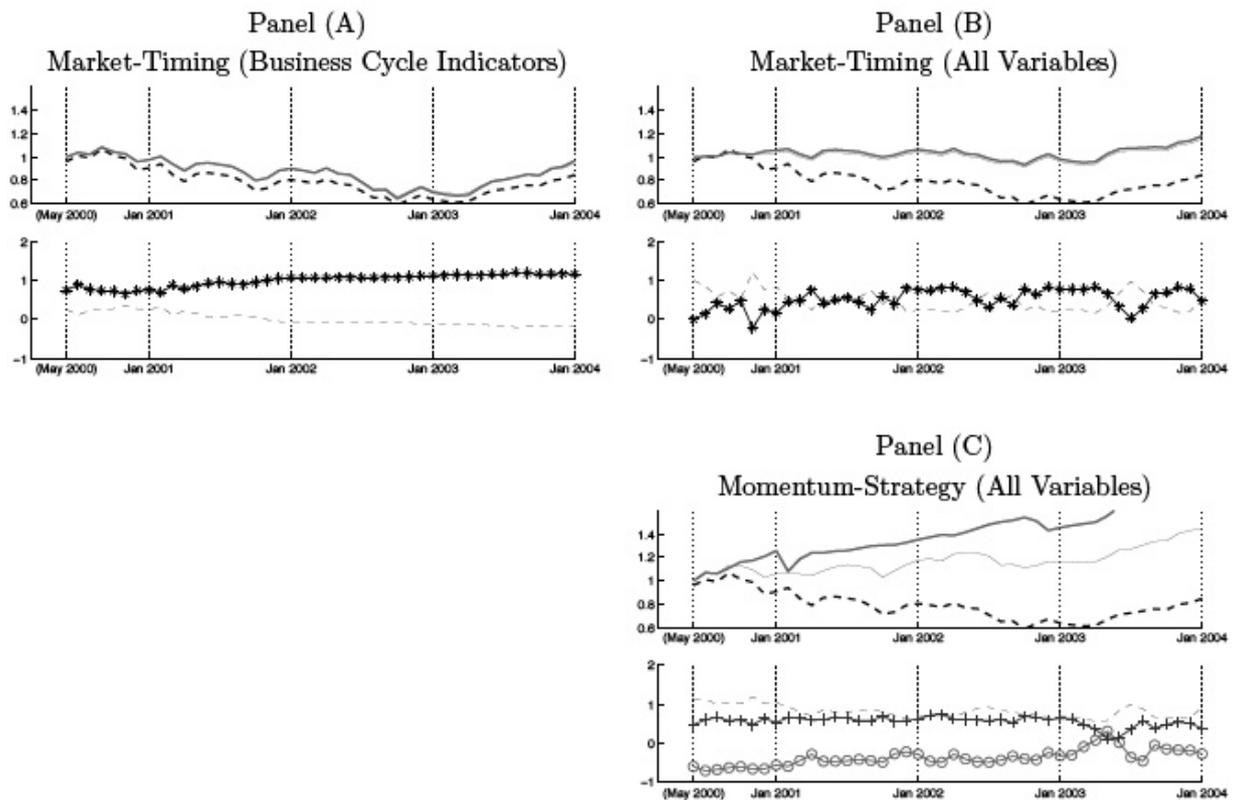


Figure 4: Collapse of the Internet Bubble (Minimum-Variance Strategies)

These graphs show the performance and portfolio weights of three different minimum-variance strategies around the collapse of the dot-com bubble that began in late 2000. In each panel, the top graph shows the cumulative return of the strategy (solid line) and the market index (dashed line), normalized to have unit value in April 2000. Also shown (light-weight line) is the return on the constrained (long-only) strategy. The bottom graph shows the portfolio weights on the risk-free asset (dashed line), the market index (*), or the winner (+) or loser (o) portfolios respectively. Panels (A) and (B) focus on market-timing (allocating between the risk-free asset and the index), while panel (C) allows in addition allocation between the two momentum (winners and losers) portfolios. The strategy in panel (A) uses only business cycle indicators, while panels (B) and (C) use all (including sentiment) instruments.

	Column (1)		Column (2)	
	RF	MKT	RF	MKT
<i>Panel (A) Summary Statistics</i>				
Average Return	6.3%	14.1%	6.3%	14.1%
Volatility	0.9%	15.9%	0.9%	15.9%
Sharpe Ratio		0.45		0.45
<i>Panel (B1) Regression Coefficients (Business Cycle Indicators)</i>				
TB1M		-2.75		-6.45
TSPR		0.75		1.55
CSPR		-0.85		-2.17
<i>Panel (B2) Regression Coefficients (Sentiment Indicators)</i>				
NG				-1.39
NB				-0.28
NG3L				0.63
NB3L				0.33
NG6L				0.48
NB6L				0.33
R^2		1.1%		5.8%
<i>Panel (C) Optimal Sharpe Ratio</i>				
Fixed-Weight		0.46		0.58
Dynamically Managed		0.46		0.98
(p -Value)		0.376		0.036

Table 1: Estimation Results (Market-Timing)

This table reports the summary of the full-sample estimates in the market-timing case. column (1) reports the results when only business cycle variables are used, while in column (2) all instruments (including sentiment indicators) are used. The table reports the mean-variance performance (panel A) of the assets themselves, the coefficients of the predictive regression (panel B), and the theoretically optimal Sharpe ratios (panel C). The p -values are obtained from the asymptotic χ^2 -distribution of the test statistic Ω (see appendix A.2).

	Column (1)			Column (2)		
	RF	M01	M03	RF	M01	M03
<i>Panel (A) Summary Statistics</i>						
Average Return	6.05%	9.01%	18.72%	6.05%	9.01%	18.72%
Volatility	0.91%	21.58%	19.84%	0.91%	21.58%	19.84%
Sharpe Ratio		0.13	0.57		0.13	0.57
<i>Panel (B1) Regression Coefficients (Business Cycle Indicators)</i>						
TB1M		-0.04	-0.61		-5.33	-5.60
TSPR		0.55	-0.31		1.08	0.85
CSPR		0.32	0.49		-1.50	-1.39
<i>Panel (B2) Regression Coefficients (Sentiment Indicators)</i>						
NG					-0.90	-1.22
NB					-1.52	-0.82
NG3L					-0.84	-1.14
NB3L					1.04	1.35
NG6L					1.26	2.04
NB6L					0.43	0.22
R^2		0.68%	0.91%		7.55%	6.96%
<i>Panel (C) Optimal Sharpe Ratio</i>						
Fixed-Weight		0.79			0.79	
Dynamically Managed		0.88			1.43	
(p-Value)		0.956			0.019	

Table 2: Estimation Results (Momentum-Strategies)

This table reports the summary of the full-sample estimates for the momentum portfolios. Column (1) reports the results when only business cycle variables are used, while in column (2) all instruments (including sentiment indicators) are used. The table reports the mean-variance performance (Panel A) of the assets themselves, the coefficients of the predictive regression (panel B), and the theoretically optimal Sharpe ratios (panel C). The p-values are obtained from the asymptotic χ^2 -distribution of the test statistic Ω (see appendix A.2).

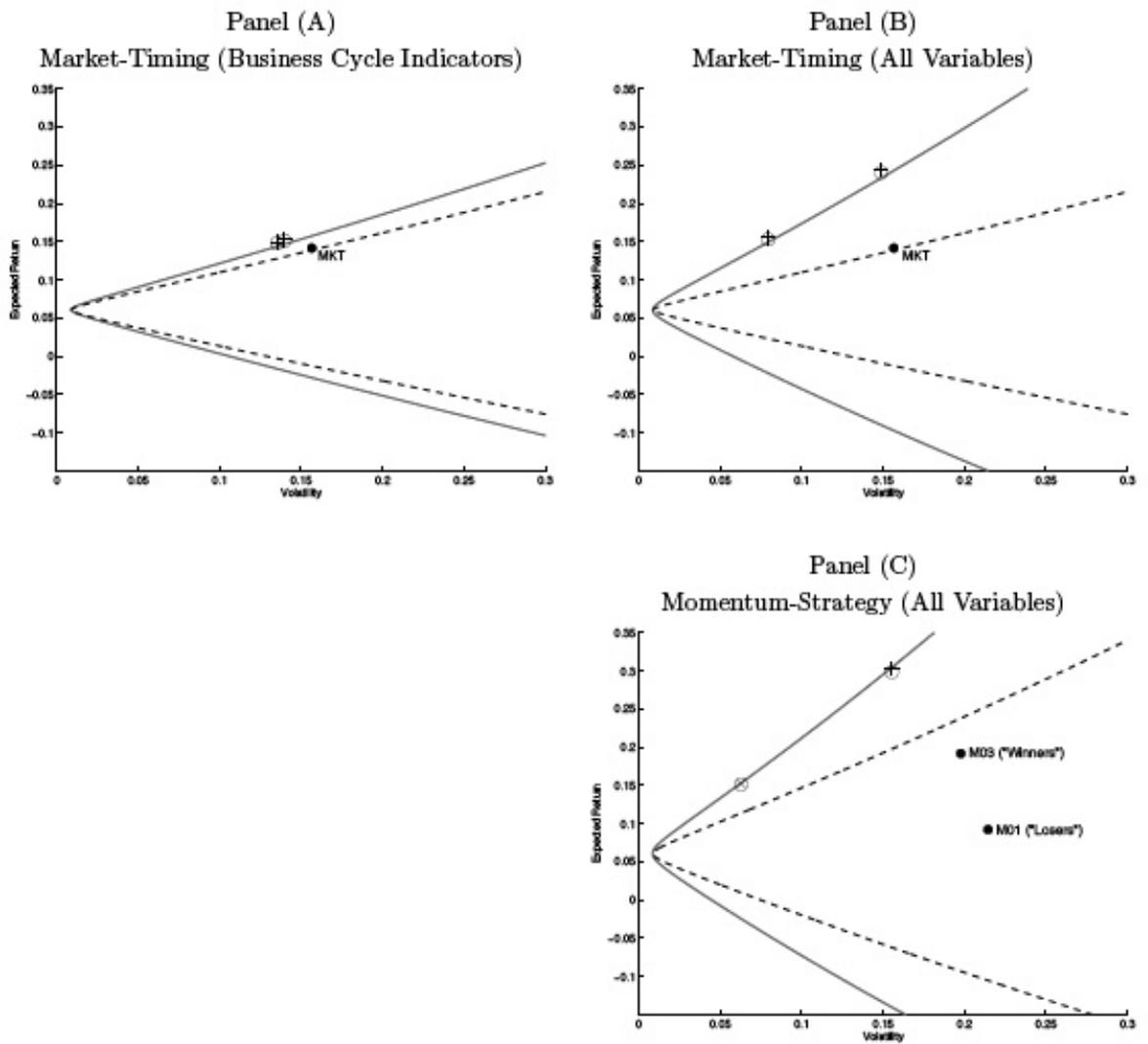


Figure 5: Efficient Frontiers

These graphs show the unconditionally efficient frontiers with (solid line) and without (dashed line) the optimal use of predictability. Panels (A) and (B) focus on market-timing (allocating between the risk-free asset and the index), while panel (C) allows in addition allocation between the two momentum portfolios (winners M03 and losers M01). The strategies in panel (A) uses only business cycle indicators, while panels (B) and (C) use all (including sentiment) instruments. Also shown are the *ex-post* mean and variance of the maximum-return (+) and minimum-variance (x) strategies. The circles indicate the performance of these strategies net of transaction costs.

	Column (1)	Column (2)	
	Fixed-Weight	Business Cycle Instruments	All Instruments (incl. Sentiment)
<i>Panel (A) 1987 Crash</i>			
Expected Return	9.15%	9.04%	9.90%
Volatility	9.39%	8.09%	3.57%
Sharpe Ratio	0.28	0.32	0.94
CAPM Beta	0.56	0.47	0.15
Jensen's Alpha	0.03%	0.32%	2.35%
Information Ratio		0.23	0.93
Four Factor Alpha	0.03%	-0.10%	3.07%
<i>Panel (B) Collapse of the 'dot.com' bubble</i>			
Expected Return	-0.14%	1.20%	4.86%
Volatility	13.81%	16.63%	9.13%
Sharpe Ratio	-0.19	-0.08	0.25
CAPM Beta	0.94	0.68	0.33
Jensen's Alpha	0.00%	1.92%	3.85%
Information Ratio		0.63	0.79
Four factor alpha	-5.43%	-14.29%	4.27%

Table 3: Out of Sample Portfolio Performance (Market-Timing)

This table reports the *out-of-sample* performance of minimum-variance market-timing strategies from January 1987 to December 1992 (panel A) and from May 2000 to the end of 2004 (panel B), respectively. The available assets are the risk-free asset and the market index only. Column (1) reports the results for fixed-weight strategies (that do not use any predictive information), while column (2) reports the results for optimally managed strategies using macro indicators or all predictive variables, respectively. The four factor alpha uses the Carhart (1997) model, that augments the market return with size, book-to-market and momentum factors. All figures are annualized.

	Column (1)	Column (2)	
	Fixed-Weight	Business Cycle Instruments	All Instruments (incl. Sentiment)
<i>Panel (A) 1987 Crash</i>			
Expected Return	9.92%	8.15%	10.37%
Volatility	6.48%	5.46%	2.78%
Sharpe Ratio	0.52	0.32	1.36
Information Ratio	0.48	0.16	1.41
CAPM Beta	0.86	0.50	0.06
Jensen's Alpha	2.07%	0.55%	3.55%
Four factor alpha	0.47%	-0.59%	4.01%
<i>Panel (B) Collapse of the 'dot.com' bubble</i>			
Expected Return	13.59%	14.95%	14.98%
Volatility	15.62%	13.44%	10.80%
Sharpe Ratio	0.66	0.85	1.07
Information Ratio	0.66	0.92	1.11
CAPM Beta	-0.31	0.09	-0.13
Jensen's Alpha	9.69%	12.49%	11.70%
Four factor alpha	3.60%	2.58%	5.22%

Table 4: Out of Sample Portfolio Performance (Momentum-Strategy)

This table reports the *out-of-sample* performance of minimum-variance momentum strategies from January 1987 to December 1992 (panel A) and from May 2000 to the end of 2004 (panel B), respectively. The available assets are the risk-free asset and the market index only. Column (1) reports the results for fixed-weight strategies (that do not use any predictive information), while column (2) reports the results for optimally managed strategies using macro indicators or all predictive variables, respectively. The four factor alpha uses the Carhart (1997) model, that augments the market return with size, book-to-market and momentum factors. All figures are annualized.