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Predicting Returns Using Behavioral Market Barometers

By C. Thomas Howard, PhD

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ABSTRACT

This paper introduces market barometers that are based on measurable and persistent investor behavior. I test the ability of U.S. market, international market, and capitalization barometers to predict S&P 500, MSCI EAFE, and Russell 2000 returns, respectively. The empirical results for January 1981–December 2020 are statistically and economically significant and cannot be explained by trailing equity returns or the Institute of Supply Management Purchasing Managers' Index,[1] one of the best measures of economic activity. Barometers are used to develop a set of trading rules that show evidence of superior performance when compared with relevant benchmarks over the period evaluated.

INTRODUCTION

This paper builds on a long line of research, extending back at least to the 1950s, that attempts to identify factors driving individual stock as well as market-wide returns. Previous studies have identified numerous factor proxies, ranging from economic to fundamental to risk to behavioral. Gabaix and Koijen (2021) provides an analysis of money flows as a proxy for investor behavior, and along the way, the authors propose the innovative inelastic market hypothesis.

I present a unique approach for capturing investor behavior by focusing on the relative active equity mutual fund returns, in contrast to the Gabaix and Koijen (2021) flows approach. I make no assumption with respect to the drivers of investor behavior; rather, I am solely interested in the predictive ability of market barometers, the investor behavior proxy I introduce in this paper.

This study also contributes to a newly emerging line of research that explores the value of the principal investment strategies sections of active equity mutual fund prospectuses. Abis and Lines (2020) introduce prospectus-based strategy peer groups using an approach similar to the one presented in this paper. Applying a text-based algorithm to a large sample of active equity fund prospectuses, they identify fund strategy peer groups. They find rich variety in funds' self-described strategies that cannot be fully accounted for by differences in risk-adjusted returns. Peer groups, though, display significant and interpretable differences in characteristics of stocks held. Funds in different peer groups have a different likelihood of targeting retail, institutional, or retirement investors who, in turn, self-allocate differently across peer groups.

Abis et al. (2021) employs these same peer groups to explore the usefulness of prospectus information. The authors ask whether active equity mutual funds differentiate their product offerings to match preferences of heterogeneous investors. They find evidence for this using a comprehensive dataset of fund prospectuses: Funds with more informative descriptions are larger and more specialized, exhibit lower flow-performance sensitivity, and show higher correlation between size and flow volatility.

This study addresses a different issue. I am interested in whether prospectus-based strategy peer groups provide a stable framework for organizing the numerous factors driving equity returns that can be used to capture current investor behavior. Further, I explore whether this approach can provide an estimate of expected market returns and, in turn, can be used successfully in a simple set of trading rules.

CURRENT RETURN FACTOR MIX

Aggregate stock market returns are driven by the collective buy and sell decisions of individual and institutional investors. Many considerations enter investor decisions, with their relative importance ever-evolving. At times investors will emphasize economy-wide considerations, at other times stock market activity, and at other times relative attractiveness of industry sectors or even specific stock information.

These investor decisions are the manifestations of the otherwise unobservable mix of return factors currently driving market-wide stock returns. Sometimes this mix is favorable and thus expected returns are higher. At other times, it is less favorable, resulting in lower expected returns. When estimating overall market expected returns, it is important to have a measurable and persistent proxy that captures the current factor mix.

In this paper, I present an approach for predicting market returns based on "put your money where your mouth is" investor behavior that provides a window into the current state of the market. Three market barometers are used to generate return predictions. Two of these barometers are based on the investment strategy being pursued by active equity mutual fund managers in U.S. and international equity markets, respectively; they are referred to here respectively as the U.S. market barometer (USMB) and the international market barometer (IntlMB). Howard (2012) is the only other research I am aware of that uses mutual fund equity strategies to capture the current factor mix for the purpose of predicting future market returns. Thus, these two strategy-based barometers, USMB and IntlMB, represent new behavioral return predictors. The third is the capitalization barometer (CB), which is based on the sentiment index (SI) of Baker and Wurgler (2006; 2007).

I present empirical evidence, using data from 1981–2020, that these three barometers produce statistically and economically significant return predictions for the S&P 500, MSCI EAFE, and Russell 2000, respectively. In addition, the barometers reveal that, during the four decades covered by my data, the state of the market varied dramatically. Finally, I discuss how barometer predictions can be used in a simple set of trading rules.

In developing a strategy, a manager identifies key company and market characteristics upon which to focus, which differ from manager to manager. The manager then develops a strategy around the identified characteristics and fashions a methodology for implementing a strategy.

MAPPING RETURN FACTORS USING STRATEGIES

Equity managers in a particular strategy peer group pursue a specific approach for making money that differs from the approach followed by managers in other peer groups. For example, there are managers who focus on finding the best companies in each industry, as measured by management quality, ability to innovate, defensible market position, and strong company fundamentals. On the other hand, there are managers who attempt to buy undervalued stocks regardless of the quality of the company.

More specifically, strategy is the way an active equity mutual fund manager goes about analyzing, buying, and selling stocks. Put more succinctly, it is the way a manager goes about trying to earn excess returns. In developing a strategy, a manager identifies key company and market characteristics upon which to focus, which differ from manager to manager. The manager then develops a strategy around the identified characteristics and fashions a methodology for implementing a strategy.

For example, a manager pursing a competitive position strategy (explained in more detail below) will develop a methodology for gauging the quality of a company's management team, the defensibility of the market position of the company's product, and the level of company adaptability. The fund company for which the manager works assembles the resources needed to execute this methodology. The resulting equity strategy is at the core of the investment process and shapes the business and investment decisions of the fund company.

From a conceptual standpoint, the collective skill of active equity managers, as captured by the strategies being pursued, provides an intelligent mapping of return factors. A strategy's return performance rank relative to other strategies varies over time because investors collectively focus on a changing mix of strategies and, in turn, market factors. However, most of the time investment managers continue to pursue an investment strategy regardless of whether it is in favor with investors or not. The largely consistent pursuit of a strategy by equity managers provides a stable prism for viewing what is, or is not, being favored by investors. In other words, managers keep doing the same thing but investors constantly change focus.

Market barometers capture the factor mix that investors are currently rewarding. A high barometer reading means that market participants favor a high return factor mix, and a low reading means participants favor a low return factor mix. Consequently, a high reading is predictive of high future market returns, and a low reading is predictive of low future returns.

To be clear, market barometers differ from technical concepts such as momentum and mean reversion, which often are used for predicting future market returns. Instead, barometers focus on longer-term relative strategy performance, rather than on whether returns are positive or negative. It is possible to observe a high or low reading regardless of overall market performance. The empirical tests that follow reveal barometer readings are independent of trailing market returns, thus they capture something other than short-term momentum and mean reversion.

Barometers are based on actual investor behavior. Strategy ranks are the result of collective investment activity, so they reflect what investors do and not just what they say about current market conditions. Thus, barometers are a "put your money where your mouth is" type of measure.

Individual strategy performance varies as investors favor one strategy over another through time. Consequently, I find relative strategy performance to be indicative of the current market state. For example, the combination of Future Growth (explained in more detail below) as the best-performing strategy with Risk as the worst-performing strategy is indicative of a strong market state and, in turn, high expected returns. The reverse rankings—when Risk is the best-performing strategy and Future Growth is the worst-performing strategy—signal a weak market state and lower expected returns. Thus, current strategy performance ranks are a proxy for the return factor mix currently underpinning the market. The question I address in this paper is whether current strategy performance ranks are predictive of subsequent equity returns. The empirical tests presented in this paper provide support for an affirmative answer to this question.

CALCULATING MARKET BAROMETERS

Thousands of U.S. and international active equity open-end mutual funds domiciled in the United States have been strategy-identified. This is accomplished by gathering tens of thousands of pieces of strategy information from fund prospectuses, organizing it among forty strategy elements (the specific things a manager does to implement a strategy, such as determining the quality of the company's management team), then assigning each element to one of ten equity strategies.

Each active equity fund is then identified as pursuing a primary strategy and becomes a member of a single strategy peer group. Designating elements and strategies was accomplished over the two-year period 2005–2007 with a series of iterations involving professional manager input, data gathering, and trial element/strategy combinations. Once the element/strategy framework was settled, the data gathering and identification algorithm was built as a computer application.[2] The strategy-identification algorithm was finalized in early 2007, and since then the strategy data base has been updated monthly.

For data from 1980–2006, funds were assigned a strategy based on their 2007 strategy. Thus the 1980–2006 sample does not include all properly strategy-identified funds in existence during that period. This could possibly introduce a survivor bias during this period, a concern addressed in the analysis that follows.

The ten equity strategies are described in table 1 and the mapping of elements to each strategy is shown in table 2.

Table 1

ACTIVE EQUITY MUTUAL FUND STRATEGIES

Future Growth	Focuses on companies poised to grow rapidly relative to others. The future growth and valuation strategies are not mutually exclusive and both can be deemed important in the investment process.
Competitive Position	Based on business principles, including quality of management, market power, product reputation, and competitive advantage. Considers the sustainability of the business model and history of adapting to market changes.
Opportunity	Unique opportunities may exist for a small number of stocks or at different points in time. These may involve combining stocks and derivatives and may involve use of considerable leverage. Many hedge fund managers follow this strategy, but a mutual fund manager also may be so classified.
Profitability	Focuses on company profitability metrics such as gross margin, operating margin, net margin, and return on equity.
Quantitative	Emphasizes use of mathematical and statistical inefficiencies in market and individual stock pricing; involves mathematical and statistical modeling with little or no regard to company and market fundamentals.
Valuation	These are stocks selling cheaply compared with peer stocks based on accounting ratios and valuation techniques.
Market Conditions	Considers a stock's recent price and volume history relative to the market and similar stocks as well as the overall stock market conditions.
Economic Conditions	Top-down approach based on economic fundamentals; can include employment, productivity, inflation, and industrial output. Gauges where overall economy is in the business cycle, the resulting supply and demand situations in various industries, and the best stocks to purchase as a result.
Social Considerations	Companies' ethical, environmental, and business practices are top concerns, as are evaluations of company business lines in light of current social and political climate. A manager can look for these criteria or the lack of in selecting a stock.
Risk	Aims to control overall risk, with increasing returns a secondary consideration. Risk measures considered may include beta, volatility, company financials, industry and sector exposures, country exposures, and economic and market risk factors.

The resulting peer groups are based on self-declared strategy. Some question the reliability and usefulness of such information. To address this issue, a series of statistical reliability strategy peer group tests were conducted, and the results are reported in Howard (2010) and recently updated in Detzel and Howard (2021). The three main conclusions are the following:

- Based on cross-fund correlation analysis, funds within a strategy peer group are more alike, on average, than those across strategies. Table 3 reports the fund cross-correlation results from Detzel and Howard (2021). The final row in table 3 reveals that the ratio of within strategy (i.e., diagonal) fund cross-correlation to across strategy (i.e., off diagonal) cross-correlations ranges from a low of 1.32 to a high of 4.60. Thus, for each of the ten strategies, funds within are more similar than funds across strategies.[3]
- Based on cross-fund correlation cluster analysis, forming fund peer groups based on strategy is statistically superior to forming groups randomly or forming them based on style boxes (Howard 2010).
- Each strategy peer group pursues a statistically different set of return factors (Howard 2010).

Table 2

ELEMENTS MAPPED TO EACH STRATEGY

Strategy	Element
Future Growth	Overall company growth
	Strong earnings growth
	Sustainable growth
	Accelerated growth
Competitive Position	Strong fundamentals
	Defensible market position
	Management quality
	Strong innovation
Opportunity	Behavioral considerations
	Arbitrage
	Earnings surprise
	Absolute return
Profitability	Dividend yield
	Strong financials
	Return on equity
	Return on invested capital
Quantitative	Quantitative modeling
	Expected return modeling
	Stochastic modeling
	Time sensitive anomalies

Strategy	Element
Valuation	Intrinsic valuation
	Cash-flow valuation
	Price ratios (e.g., P/E, P/S, P/B)
	Contrarian
Market Conditions	Overall market conditions
	Momentum
	Technical analysis/charting
	Relative strength
Economic Conditions	Economic output
	Themes
	Interest rates
	Inflation
Social Considerations	Political issues
	Social responsibility
	International issues
	Religious issues
Risk	Excess volatility
	Country risk
	Downside risk
	Business risk

Table 3

AVERAGE THIRTY-SIX-MONTH ROLLING CORRELATIONS OF MARKET-ADJUSTED MUTUAL FUND RETURNS WITHIN AND ACROSS STRATEGY GROUPS

For each fund i and month t, we estimate rolling thirty-six-month market-adjusted returns, $\hat{\epsilon}_{i,\tau,t}$, $\tau = t - 35, \ldots, t$, as the residuals from a regression of the form: $rx_{i\tau} = \alpha_{i\tau} + \beta_{i\tau} MKT_{\tau} + \epsilon_{i,\tau,t}$ $(\tau = t - 35, \ldots, t)$, where $rx_{i\tau}$ denotes i's return in excess of the one-month Treasury bill in month τ and MKT_{τ} denotes the corresponding excess return on the CRSP value-weighted index. For every pair of funds i, j in month t with at least twelve observations we estimate the correlation coefficient between the returns, $\hat{\rho}_{i,j,t} = \text{corr}(\hat{\epsilon}_{i,\tau,t}, \hat{\epsilon}_{j,\tau,t})$, $\tau = t - 35, \ldots, t$. For each pair of fund strategies, we then form equal-weighted averages of the correlations within the strategy pair each month t. The array consisting of the first ten rows of this table present the time-series average of the resulting average correlations for each strategy pair, defined by the row and column headings, over all months in the sample. The untabulated average of all these cells is 0.055. The row beneath the array of average correlations contains the average of the off-diagonal entries from the column above and the bottom row contains the ratio of the diagonal entry to the corresponding off-diagonal average.

	Competitive Position	Economic Conditions	Future Growth	Market Conditions	Opportunity	Profitability	Quantitative	Risk	Social Considerations	Valuation
Future Growth	0.126	0.098	0.249	0.138	0.021	−0.049	0.067	−0.003	0.094	−0.003
Competitive Position	0.083	0.068	0.126	0.089	0.042	0.000	0.052	0.004	0.073	0.048
Opportunity	0.042	0.043	0.021	0.051	0.070	0.024	0.054	0.003	0.047	0.085
Profitability	0.000	0.023	−0.049	0.003	0.024	0.111	0.038	0.061	0.045	0.074
Quantitative	0.052	0.057	0.067	0.106	0.054	0.038	0.092	0.037	0.058	0.061
Valuation	0.048	0.044	−0.003	0.060	0.085	0.074	0.061	0.015	0.081	0.142
Market Conditions	0.089	0.069	0.138	0.161	0.051	0.003	0.106	0.023	0.074	0.060
Economic Conditions	0.068	0.071	0.098	0.069	0.043	0.023	0.057	0.020	0.064	0.044
Social Considerations	0.073	0.064	0.094	0.074	0.047	0.045	0.058	0.022	0.096	0.081
Risk	0.004	0.020	−0.003	0.023	0.003	0.061	0.037	0.060	0.022	0.015
Average off diagonal	0.056	0.054	0.054	0.068	0.041	0.024	0.059	0.020	0.062	0.052
On/off diagonal	1.482	1.317	4.598	2.370	1.695	4.576	1.563	2.992	1.548	2.750

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U.S.-domiciled U.S. and international active equity mutual fund data was gathered from Morningstar in recent years and from Thomson Reuters and Lipper in earlier years. Prospectuses were gathered from Morningstar, SEC EDGAR (Securities and Exchange Commission Electronic Data Gathering, Analysis, and Retrieval system), and other sources. Fund universe data are updated monthly. Fund strategy is updated whenever the fund issues a new prospectus, if necessary, which is typically on an annual basis. Funds changing strategies from year to year are rare. The number of strategy-identified funds included in the sample grows from 137 at the beginning of 1980 to 1,840 at the beginning of 2007 to 3,107 by the end of 2020.

Figure 1 shows the long-term demand for each strategy, with the darker arrows toward the top signifying larger returns. Strategies are arranged (from the top of figure 1 clockwise) in their long-term performance rank (based on 1988–2007 returns).[4] That is, Future Growth is the top performing long-term strategy, Competitive Position is the next, and so forth on around to Risk, which is the worst long-term performer. Table 4 provides summary statistics by strategy.

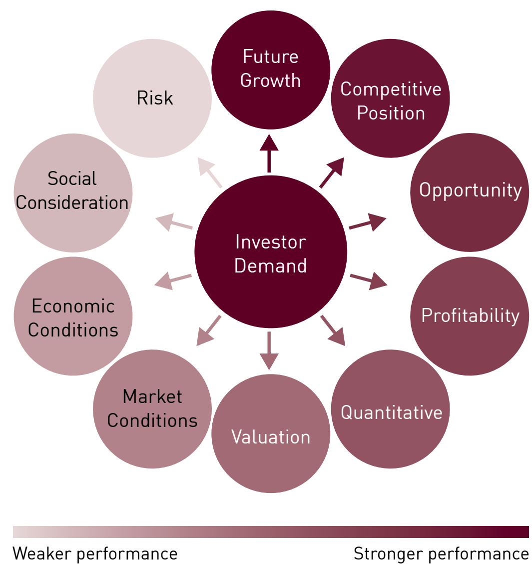
Relative strategy performance varies over time, resulting in periods in which strategies in the lower left of figure 1 are favored by investors. The empirical question addressed in this paper is whether the ever-changing strategy performance ranks are predictive of equity returns.

Several relationships must hold for this to be the case. First, the set of strategies must span the set of factors driving individual and overall market returns. Second, each factor should be associated, to the greatest extent possible, with a specific strategy, with as few multiple strategy associations as possible. Finally, managers should pursue the same strategy and not change strategies over time.[5] If these relationships hold, strategy performance ranks will be reliably associated with the current return factor mix.

Figure 1

STRATEGY RELATIVE PERFORMANCE: 1988–2007

Strategy returns are calculated as a simple average return across all funds. Individual fund returns are averages across all share classes, in that strategy, for that month. Monthly individual fund returns are net of automatically deducted management, trading, 12B-1, and other fees. The return rankings are based on monthly compounded annual returns during 1988–2007. The strategies are organized with the top return, Future Growth, at the top, with ever lower returns clockwise around the circle to Risk at the top left of the circle.



Sources: AthenaInvest, Morningstar, Thomson Reuters, and Lipper

Table 4

SUMMARY STATISTICS BY STRATEGY: 1988–2007

This table presents time-series averages of the number of funds within each strategy and strategy-level month-by-month averages of fund-level statistics: assets under management (AUM, $millions), the number of different stocks held by a given fund (#Stocks), annualized return (Ret), and expense ratio (Exp ratio). The final row, (All), presents corresponding statistics for all funds in the sample.

Strategy	#Funds	AUM	#Stocks	Ret (%)	Exp ratio (%)
Future Growth	304	1,772.9	122	13.18	1.30
Competitive Position	563	2,601.8	113	12.83	1.29
Opportunity	68	751.8	135	12.72	1.60
Profitability	40	1,544.9	105	12.52	1.24
Quantitative	83	736.3	202	12.21	1.20
Valuation	555	1,491.8	130	12.07	1.27
Market Conditions	14	307.6	252	11.14	1.43
Economic Conditions	58	826.7	118	10.97	1.41
Social Considerations	53	526.2	168	10.50	1.27
Risk	35	684.9	153	9.68	1.51
All	1773	1,756.4	128	11.78	1.30

Sources: AthenaInvest, Morningstar, Thomson Reuters, and Lipper

In order to capture investors' overall response to the ten equity strategies, separate U.S. market (USMB) and international market (IntlMB) barometers are calculated using the sum of the absolute difference of each strategy's trailing one-year return rank from its long-term (i.e., 1988–2007) return rank.[6] Each sum is then scaled to have a long-term mean of around 10 percent and an approximate range of ±10 percent.

Table 5

CONVERTING STRATEGY RETURN RANKS INTO EXPECTED RETURNS

Strategy Ranks (1988–2007)		Current Strategy Ranks	Expected Returns
1	Future Growth	Aligned	High
2	Competitive Position		
3	Opportunity	Mixed	Medium
4	Profitability		
5	Quantitative		
6	Valuation		
7	Market Conditions	Inverted	Low
8	Economic Conditions		
9	Social Considerations		
10	Risk		

Table 6

U.S. MARKET BAROMETER SAMPLE CALCULATIONS

The second column is the sum of the ten absolute differences of monthly strategy return ranks relative to the 1988–2007 strategy return ranks (reported in table 5). The third column is the trailing twelve-month average of the absolute sums in column 2. The final column is the end-of-the-month USMB, which is equal to 70 – (2 × the 12-month average), rounded to the nearest whole number. Scaling values of 70 and 2 were chosen to produce a long-term average USMB of 10, with an approximate range of 0–20.

Month	Sum Absolute Rank Differences	12-month Average	Month End USMB
1	27		
2	21		
3	31		
4	20		
5	34		
6	34		
7	22		
8	21		
9	36		
10	19		
11	36		
12	26	27.25	16
13	16	26.33	17
14	44	28.25	14
15	40	29.00	12

Barometers capture the extent to which the current strategy return ranks differ from long-term ranks. The process for converting long-term versus current ranks into expected returns is represented in table 5. The more closely current ranks align with long-term ranks (that is, the smaller the sum of the absolute rank differences), the larger the barometer and the higher the expected market return.

Table 6 provides an example of how the USMB is calculated.

CAPITALIZATION BAROMETER

The capitalization barometer (CB) measures the attractiveness of U.S. small-cap stocks relative to U.S. large-cap stocks and is generated using a different methodology than that for calculating the USMB and IntlMB. Instead, it is based on the sentiment index (SI), which was first proposed by Baker and Wurgler (2006) and further elaborated upon in Baker and Wurgler (2007). Rather than estimate the pricing impact of specific investor behaviors, such as the disposition effect, Baker and Wurgler (2006; 2007) (hereafter BW) take a top-down approach built on two critical assumptions of behavioral finance: (1) time-varying investor sentiment and (2) limits to arbitrage. BW use these two assumptions to explain which stocks are likely to be most affected by investor sentiment.

They view investor sentiment as simply optimism or pessimism about stocks in general, and they allow the limits to arbitrage to vary across stocks. As a first step in constructing SI, they consider a range of possible sentiment measures, from surveys to market-wide variables, that are thought to be affected by changing market sentiment. Many of these possible measures were discarded, some because they were believed to be unreliable, such as survey data, and some because of data unavailability over the entire period they wished to test their concepts (1963–2001).

BW settled on six measures for constructing SI (see Baker and Wurgler 2006 for more details):

1. Closed-end fund discount
2. Detrended log of share turnover
3. Number of initial public offering (IPOs)
4. First-day return on IPOs
5. Dividend premium
6. Equity share in new issues

Each of these six measures is standardized, with the effect of macroeconomic conditions removed. The resulting SI is a weighted, principal component combination of the six proxies. BW hypothesize that a low (high) SI implies weak (strong) investor sentiment, which leads to stock undervaluation (overvaluation) and in turn is predictive of higher (lower) returns going forward. BW's empirical tests focus on those companies most susceptible to sentiment mispricing (i.e., younger, smaller, more volatile,

Table 7

BASIC STATISTICS FOR BAROMETERS AND RETURNS: 1981–2020

USMB and IntlMB are scaled sums of the absolute difference of trailing twelve-month strategy ranks versus 1988–2007 long-term strategy ranks. CB is a weighted, scaled sum of the six BW sentiment components: closed-end fund discount, detrended log of share turnover, number of IPOs, first-day return on IPOs, dividend premium, and equity share in new issues. The Russell 2000 Index was launched in January 1995. During January 1981–December 1994, the monthly return on the JP Morgan Small Cap Core fund + 0.18 percent was used to represent small-cap returns.

	USMB	IntlMB	CB	S&P 500	MSCI EAFE	Russell 2000
Annual Return	10.70	10.31	11.19	11.50	8.30	11.54
Annual Standard Deviation	5.21	3.04	3.90	15.04	17.14	18.55
Monthly 1st Serial Correlation	0.93	0.93	0.96	0.03	0.09	0.09

Sources: AthenaInvest, Morningstar, Thomson Reuters, and Lipper

unprofitable, non-dividend paying, distressed, or extreme growth potential companies). They postulate a "sentiment seesaw" in which the companies opposite from the above (i.e., "bond-like" companies) underperform when SI is high and outperform when SI is low. BW present empirical evidence supporting the sentiment seesaw.

BW also provide limited evidence that SI is predictive of overall market returns. I build on this result and present evidence that CB is indeed predictive of small-caps outperforming large-caps. CB is based on a multiple regression involving the six BW lagged variables. It was introduced in 2011 and has gone through several revisions, the most recent in 2020, due to changing reliability and availability of the six BW variables. The regression results are scaled so that the full-period CB mean and volatility roughly match the respective annual statistics of the Russell 2000: a mean of around 10 percent and a volatility of about ±10 percent.

EMPIRICAL TESTS: STATISTICAL SIGNIFICANCE

I have just described three barometers, USMB, IntlMB, and CB, that are intended to forecast U.S. large-cap stock returns (S&P 500), international developed market returns (MSCI EAFE), and U.S. small-cap returns (Russell 2000), respectively. Table 7 reports basic statistics for each of these time series.

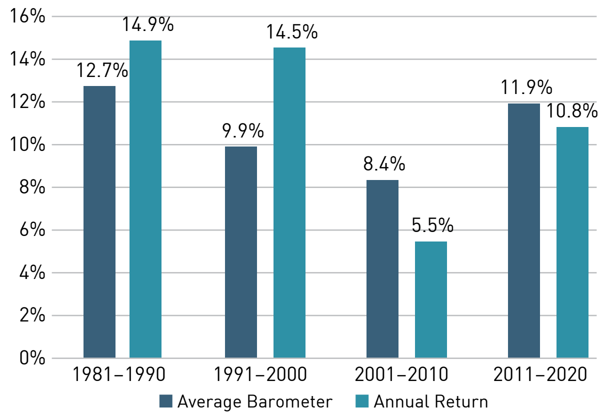
Howard (2012) presents a comprehensive set of empirical tests of barometer predictive power, albeit over the shorter period 1981–2011. The paper concluded that barometers are both statistically and economically significant predictors. An important question is whether the tests in the current paper, based on a longer period, produce similar conclusions. The answer is yes, because the newer 1981–2021 tests reported in this paper yield significant results as well.

To obtain a general feel for the relationship between barometers and market returns, figure 2 presents average barometer readings along with the corresponding average annual market returns for each of the four decades 1981–2020. The barometer value is a simple average over the three barometer readings, USMB, IntlMB, and CB, in each month during each decade.

Figure 2

AVERAGE BAROMETER READINGS VS. AVERAGE ANNUAL RETURNS 1981–2020

USMB and IntlMB are scaled sums of the absolute difference of trailing twelve-month strategy ranks versus 1988–2007 long-term strategy ranks. CB is a weighted, scaled sum of the six BW sentiment components: closed-end fund discount, detrended log of share turnover, number of IPOs, first-day return on IPOs, dividend premium, and equity share in new issues. Reported results are simple averages across all three barometers and all three indexes, respectively, for each of the four decades. The Russell 2000 Index was launched in January 1995. From January 1981–December 1994, the monthly return on the JP Morgan Small Cap Core fund + 0.18 percent was used to represent small-cap returns.



Sources: AthenaInvest, Morningstar, Thomson Reuters, and Lipper

The annual return is a simple average of the three annual, ten-year monthly compounded market returns: S&P 500, MSCI EAFE, and Russell 2000.

As can be seen in figure 2, barometers decline from the 1980s through the 2000s and then rebound in the 2010s to a value close to that seen in the 1980s. Market returns follow a similar pattern, declining into the 2000s then rebounding in the 2010s. Figure 2 presents intriguing visual evidence that the drivers captured by barometers are the same as those driving market-wide returns. In addition, the state of the market is quite different from decade to decade.

REGRESSION TESTS

To test the predictive power of barometers, I run a series of regressions that explore the collective relationship between barometers and the corresponding subsequent market returns, between each barometer and its matching return, and finally between barometers augmented by economic and lagged market returns. Table 8 presents results for the ten regressions for predicting subsequent-month returns. The top half reports results for the entire period 1981–2020, and the bottom half reports results for 2007–2020. As mentioned above, there is a potential for survivor bias impact in the data before 2007; the 2007–2020 results are broken out separately in table 8 to gauge this potential bias.

The first regression listed in table 8, labeled "regression 1," includes all three barometers from 1981–2020, appended one to another, to form a single independent variable with the corresponding subsequent-month market return (S&P 500 returns for USMB, MSCI EAFE returns for IntlMB, and Russell 2000 returns for CB) appended to form a single dependent variable. The slope coefficient reveals that a 1-percent barometer increase (e.g., an increase from 10 percent to 11 percent) on average indicates a 1.23-percent annualized increase in the subsequent-month annual market return. This relationship is highly significant as revealed by the 3.31 t-value for this coefficient, shown in bold in table 8. As to be expected, the regression sports a highly significant F-statistic value as well. Collectively, then, barometers provide useful information regarding future returns.[7]

In untabulated results, I find that serially correlated residuals are not an issue in regression 1 because the Durbin-Watson

Table 8

SUBSEQUENT-MONTH MARKET RETURN REGRESSION COEFFICIENTS*

Independent variables are listed as columns. USMB and IntlMB are scaled sums of the absolute difference of trailing twelve-month strategy ranks versus 1988–2007 long-term strategy ranks and are matched with the S&P 500 and MSCI EAFE index returns, respectively. CB is a weighted, scaled sum of the six BW sentiment components: closed-end fund discount, detrended log of share turnover, number of IPOs, first-day return on IPOs, dividend premium, and equity share in new issues and is matched with Russell 2000 Index returns. ISM PMI is the Institute of Supply Management monthly survey of U.S. manufacturing activity. Trailing returns are compound returns for the respective index over the trailing period. # of observations is the number of month-barometer observations for the specified time period. Coefficients are annualized. The Russell 2000 Index was launched in January 1995. During January 1981–December 1994, the monthly return on the JP Morgan Small Cap Core fund + 0.18 percent was used to represent small-cap returns.

Regression	All Barometers	USMB	IntlMB	CB	ISM PMI	Trailing Market Returns			#Obs.	F Sig
					−1 month	3 months	6 months	12 months		
1981–2020										
1	1.23								1440	**0.001**
	(3.31)									
2		0.92							480	**0.043**
		(2.03)								
3			1.07							0.231
			(1.20)							
4				1.81						**0.016**
				(2.41)						
5	1.33				0.00	0.09	−0.15	0.03		**0.031**
	(3.37)				(0.00)	(0.38)	(−0.74)	(0.28)		
2007–2020										
6	2.55								504	**0.000**
	(3.52)									
7		1.80							168	**0.043**
		(2.04)								
8			1.92						168	0.246
			(1.17)							
9				5.81					168	**0.001**
				(3.31)						
10	2.77				2.08	0.38	−0.46	−0.61	504	**0.000**
	(3.60)				**(2.71)**	(0.88)	(−1.34)	**(−2.66)**		

**Coefficients are annualized, t-value in parentheses, bold numbers are statistically significant at the 5-percent level.*
Sources: AthenaInvest, Morningstar, Thomson Reuters, and Lipper. The 2007-2020 results reported in the bottom half of the table are free from survivor bias.

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statistic is about 2.0. I also estimate regression 1 using dependent and independent variables that are adjusted for heteroskedastic residuals and find that the resulting barometer coefficient remains highly significant.

Regressions 2, 3, and 4 in table 8 separately test the subsequent-month predictive ability of each barometer. A similar picture emerges, with two of the three slope coefficients statistically significant at the 5-percent level and the other positive but insignificant. Based on t-values, CB is the strongest predictor of the Russell 2000 return, USMB is next strongest as a predictor of the S&P 500 return, and IntlMB is the weakest as a predictor of MSCI EAFE. On their own, each barometer provides useful information regarding market returns.

Economic data and technical analysis are frequently used for market timing. An interesting question is whether some of the predictive ability of barometers is the result of these two information sources. Regression 5 in table 8 tests this proposition by including the previous month's Institute of Supply Management (ISM) Purchasing Managers' Index (PMI), one of the best indicators of current economic conditions, along with three-, six-, and twelve-month trailing market returns, which are common technical analysis inputs. All variables are on the same footing because they are available at the beginning of each month.

For regression 5 in table 8, the barometer coefficient changes little and remains highly significant. On the other hand, the economic and trailing return variables are insignificant. In untabulated results, each of these independent variables remains insignificant when included one at a time in the market return regression. It appears that current as well as trailing returns do not provide useful information regarding future returns. Moreover, the barometers are capturing drivers that are not subsumed in the ISM PMI, as well as trailing returns, and thus barometers are independent of these commonly used market timing tools.

The strategy-identification algorithm was finalized in early 2007 and since then, the strategy database has been updated monthly. For data from 1981–2006, funds were assigned a strategy based on their 2007 strategy. Thus the 1981–2006 sample does not include all properly strategy-identified funds in existence during that period and might lead to a survivor bias.

To see if this incomplete sample biased the estimate of barometer performance, regressions 6–10 are a repeat of regressions 1–5 over the shorter 2007–2020 period. The resulting regression 6–10 slope coefficients are all positive and significant, with the exception of the IntlMB regression, thus revealing a pattern similar to the full sample regression 1–5 results. This indicates that survivor bias in the earlier period is not driving barometer predictive ability.

The overall conclusion drawn from table 8 is that barometers provide useful information regarding future market returns.

The overall conclusion drawn from table 8 is that barometers provide useful information regarding future market returns. This relationship is robust to each barometer regressed separately and to adding certain economic and trailing return variables. Across the ten regressions in table 8, barometer slope coefficients are all positive, fall in a narrow range, and are significant in all but the two IntlMB regressions 3 and 8.

The regressions discussed so far are based on predicting market returns one month in the future. I now examine the barometer's ability to predict returns further out. Table 9 reports the slopes and t-values for one-month ahead to twelve-months ahead. These regressions are on single monthly returns, not on cumulative returns, in order to avoid the well-known standard error bias inherent in overlapping variable regressions (see Britten-Jones et al. 2011).

Table 9 presents results revealing that barometers are strong predictors of future market returns, with the 1–9 months-ahead slopes statistically significant. Although not significant,

Table 9

ANNUAL SLOPE COEFFICIENTS FOR FUTURE RETURNS: 1981–2020

Months ahead are shown as columns. All barometers and matching indexes are appended one to another for estimating slope coefficients. USMB and IntlMB are scaled sums of the absolute difference of trailing twelve-month strategy ranks versus 1988–2007 long-term strategy ranks and are matched with the S&P 500 and MSCI EAFE index returns, respectively. CB is a weighted, scaled sum of the six BW sentiment components: closed-end fund discount, detrended log of share turnover, number of IPOs, first-day return on IPOs, dividend premium, and equity share in new issues and is matched with Russell 2000 Index returns. Returns are cropped at the end of each of the three series so that barometers are matched only with associated monthly lead. Coefficients are annualized and bold t-values are statistically significant at the 5-percent level. Sample period is 1981–2020.

Month Lead	1	2	3	4	5	6	7	8	9	10	11	12
Slope	1.23	1.27	1.25	1.34	1.35	1.19	1.15	0.95	0.80	0.58	0.64	0.58
t-value	**3.30**	**3.41**	**3.35**	**3.61**	**3.64**	**3.20**	**3.10**	**2.56**	**2.14**	**1.55**	**1.73**	**1.55**

Sources: AthenaInvest, Morningstar, Thomson Reuters, and Lipper.

Table 10

SUBSEQUENT-MONTH MARKET ANNUAL RETURNS BY BAROMETER READING: 1981–2020

The three barometer readings are separately partitioned into the lowest 1/6 over the full period, the middle 2/3, and the highest 1/6. USMB and IntlMB are scaled sums of the absolute difference of trailing twelve-month strategy ranks versus 1988–2007 long-term strategy ranks and are matched with the S&P 500 and MSCI EAFE index returns, respectively. CB is a weighted, scaled sum of the six BW sentiment components: closed-end fund discount, detrended log of share turnover, number of IPOs, first-day return on IPOs, dividend premium, and equity share in new issues and is matched with Russell 2000 Index returns. Returns are annualized, not compounded. The Russell 2000 Index was launched in January 1995. During January 1981–December 1994, the monthly return on the JP Morgan Small Cap Core fund + 0.18 percent was used to represent small-cap returns.

Barometer Reading		Annualized Returns			
Range	Level	S&P 500 (USMB)	MSCI EAFE (IntlMB)	Russell 2000 (CB)	Overall
Lowest 1/6	Low	4.63	9.62	9.64	7.96
Middle 2/3	Normal	12.11	7.03	9.58	9.57
Highest 1/6	High	19.58	22.60	26.86	23.01
	Overall	**11.50**	**8.30**	**11.54**	**10.45**

Sources: AthenaInvest, Morningstar, Thomson Reuters, and Lipper

Table 11

BEST MARKETS 1981–2020

Market	% Months	Unlevered	Levered
S&P 500	35%	20%	15%
MSCI EAFE	13%	7%	6%
Russell 2000	35%	21%	13%
T-bill	17%	17%	0%
Overall	100%	65%	35%

months 10–12 slopes are relatively large and positive. These results provide further evidence that behavioral market barometers provide useful information regarding market returns for up to twelve months into the future.

EMPIRICAL TESTS: ECONOMIC SIGNIFICANCE

Can barometer forecasting ability be used to manage a portfolio's market exposure to be capable of earning superior returns? To answer this question, I construct a simple trading rule involving the three markets S&P 500, MSCI EAFE, and Russell 2000, along with Treasury bills (T-bills). Table 10 presents barometer readings upon which the trading rules are based.

The low, normal, and high readings are based on the lowest 1/6, middle 2/3, and highest 1/6 barometer values, respectively. Table 10 shows that the corresponding market returns increase as barometer values increase, with MSCI EAFE from low to normal the only important exception to this upward movement. Overall annual returns increase by 1.61 percent from low to normal and a whopping 13.44 percent from normal to high. The barometers are particularly effective at signaling high return markets.

The "best markets" trading rules are the following:

- Invest 100 percent in the market with the highest beginning-of-the-month reading across the three barometers.
- The one exception to this rule is to invest in T-bills when USMB is low.
- Lever 2x when the best market barometer reading is high.

The best market investments signaled by the simple trading rules are presented in table 11.

The beginning-of-the-month barometers signal investing 100 percent exclusively in U.S. large-cap stocks (S&P 500) or U.S. small-cap stocks (Russell 2000) during 35 percent of each of the months during 1981–2020. The next most frequent investment was 17 percent of months in T-bills, which are those months with low USMB readings. The least invested market was international developed (MSCI EAFE) at 13 percent of months. Overall, the barometers signaled an investment in equity markets 83 percent of the 480 months during 1981–2020. The average time the investment is held is 3.4 months for these trading rules, a longer holding period than the typical market timing strategy. Investing 100 percent in the best market (levered or not) also differs from the typical timer.

As observed above, barometers are particularly good at signaling strong equity markets. To take advantage of this feature, table 10 shows that the barometers indicated taking a levered 2x position in the current strongest market 35 percent of months. Mirroring the unlevered results, U.S. large- and small-cap markets were the most frequently levered investments.

Table 12 presents the performance comparisons for the equal-weighted benchmark, trading rules without leverage, and trading rules with leverage. The equal-weighted portfolio (25-percent invested in each of the four markets S&P 500, MSCI EAFE, Russell 2000, and T-bills) is designated the benchmark. Because a best market investing strategy is being tested, an equal-weighted benchmark is logical. It generates a compound return of 9.26 percent, accompanied by a 42.4-percent maximum drawdown.[8] I focus on maximum

Table 12

TRADING RULES PERFORMANCE STATISTICS: 1981–2020

	Equal Weight Benchmark				Trading Rules w/o Leverage				Trading Rules with Leverage			
Period	Ret	Max DD	Stan Dev	Sharpe	Ret	Max DD	Stan Dev	Sharpe	Ret	Max DD	Stan Dev	Sharpe
1981–2020	9.26	42.40	11.40	0.47	10.44	32.20	14.55	0.45	18.01	32.90	21.79	0.64
2007–2020	5.71	42.40	12.90	0.38	9.46	32.20	14.56	0.59	16.99	32.90	21.81	0.74
1981–2011	9.36	42.40	11.57	0.39	10.83	31.80	14.57	0.42	17.82	32.80	21.83	0.59
2012–2020	8.73	22.10	10.84	0.75	8.82	32.20	14.58	0.56	18.54	32.90	21.85	0.82

Performance statistics based on monthly trading using the barometer trading rules described above. Returns are monthly compounded annual gross returns. Max DD is the largest percent drop in compounded returns from the most recent high to the lowest value before a new high is reached. Also reported are annualized standard deviation and Sharpe ratio. Over the full period, each 100-percent position is held an average of 3.4 months. The trading rule benchmark R-square is 0.60 (unlevered) and 0.52 (levered) with beta of 0.99 (unlevered) and 1.39 (levered).
Sources: AthenaInvest, Morningstar, Thomson Reuters, and Lipper

drawdown as the risk measure in the following discussion because it best captures the emotions and risk of investing using the trading rules strategy.

The first row in table 12 reports the annual compound potential returns for the full period 1981–2020. The trading rules without leverage portfolio generates an annual compound return that is 1.18-percent higher (10.44 percent versus 9.26 percent for the benchmark), along with a maximum drawdown that is about one-quarter less than the benchmark (32.2 percent versus 42.4 percent). Being in the best market each month, in particular investing in T-bills when USMB is low, leads to a very attractive return-to-risk portfolio.

The ability of barometers to identify when markets are particularly strong presents an opportunity to lever when such a decision is most likely to succeed. The trading rules with leverage results reported in table 12 for the entire period confirm this to be the case. The average return jumps by 7.56 percent (18.01 percent versus 10.44 percent unlevered), and the maximum drawdown changes little. Comparing with the benchmark reveals that the trading rules with leverage nearly double the benchmark return (18.01 percent versus 9.26 percent) and reduce max drawdown by nearly one-quarter (32.9 percent versus 42.4 per-cent). There is a significant benefit to knowing when future market returns will be strong, as signaled by the barometers.

As mentioned above, the strategy-identification algorithm was finalized in 2007 and has been used to strategy-identify active equity funds monthly since then. For data from 1981–2006, funds were assigned a strategy based on their 2007 strategy. Thus the 1981–2006 sample does not include all properly strategy-identified funds in existence during that period and may introduce survivor bias. To see if this incomplete sample biases trading-rule performance, the second row in table 12 reports the results for 2007–2020. The important observation is that the 2007–2020 performance differs little from the full period's levered and unlevered results. Thus, the earlier 1981–2006 period results are essentially the same as the longer period, strengthening the overall performance results.

Howard (2012) was based on a 1981–2011 period. In essence an out-of-sample test can be conducted by examining the earlier period 1982–2011 and the follow-up period 2012–2020. To test this, row 3 in table 12 reports performance results for 1981–2011 and row 4 reports 2012–2020 results. The unlevered return is slightly lower in the 2012–2020 period (8.82 percent versus 10.83 percent), and the levered return is slightly higher (18.54 percent versus 17.82 percent). Max drawdowns are virtually unchanged. However, for 2012-2020, trading-rule drawdowns were 50-percent larger than the benchmark's; and for the other periods, drawdowns were 25-percent smaller than their benchmarks' drawdowns. So, barometer trading rules perform out-of-sample as well in 2012–2020 as they did in 1981–2011.

Implementing the trading rules during this period would have resulted in trading and exchange-traded fund management fees of about 120 basis points for the levered version. Thus, net investor returns would have been very attractive.

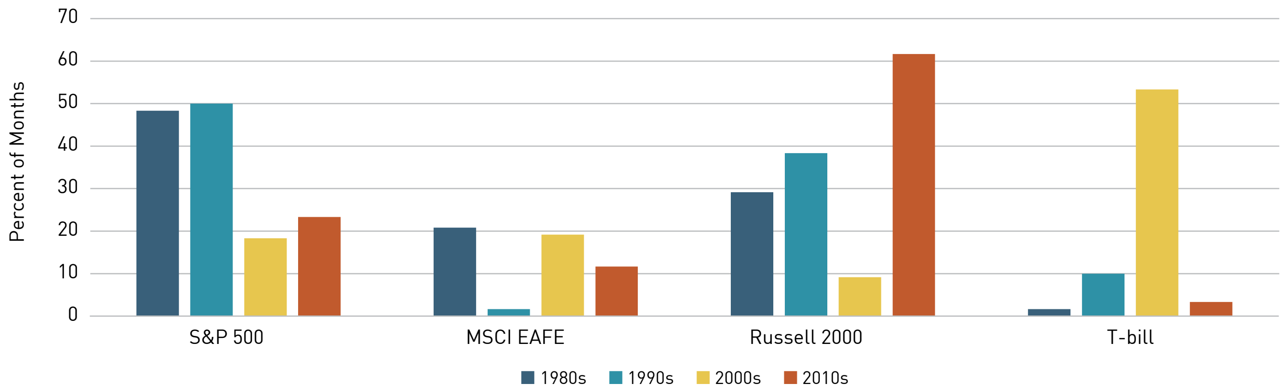
Because MBs were not created until 2011, the 2012–2020 results reported in the bottom row of table 12 provide the cleanest indication of investor returns. Implementing the trading rules during this period would have resulted in trading and exchange-traded fund management fees of about 120 basis points for the levered version. Thus, net investor returns would have been very attractive.

Finally, the Sharpe ratios reported in table 12 reveal that unlevered return success in beating the benchmark returns

Figure 3

BEST MARKETS BY DECADE 1981–2020

Best markets by decade as selected by the barometer trading rules described earlier.

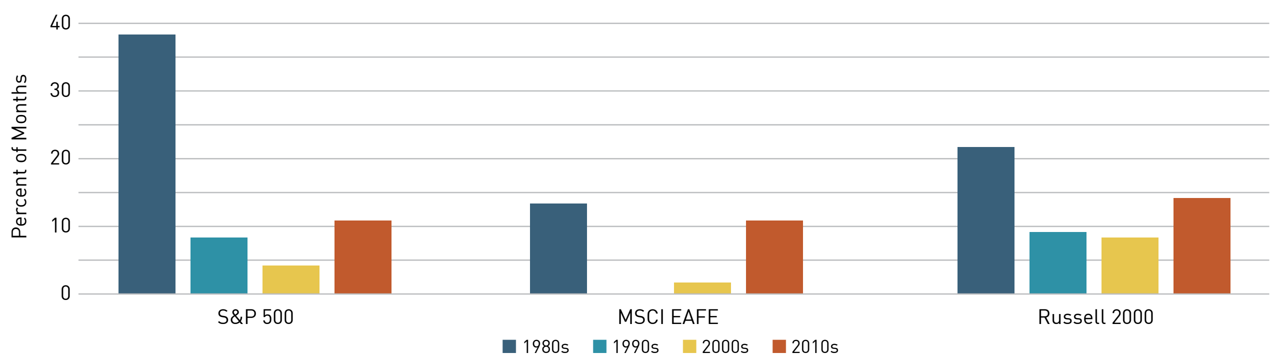


Sources: AthenaInvest, Morningstar, Thomson Reuters, and Lipper

Figure 4

LEVERAGE (2X) BY DECADE 1981–2020

Leverage by decade as determined by the barometer trading rules described earlier.



Sources: AthenaInvest, Morningstar, Thomson Reuters, and Lipper

Table 13

LEVERED TRADING RULES ANNUAL RETURNS BY DECADE

Decade	Benchmark	Trading Rules
1980s	13.35	31.06
1990s	12.24	18.39
2000s	3.80	7.48
2010s	7.90	16.28

varied from period to period, and the levered returns outperform their benchmark in every period.

BEST MARKETS AND LEVERAGE

Figure 2 showed that barometer averages declined from the 1980s through the 2000s and then bounced back in the 2010s. Actual returns displayed a similar pattern. Figure 3 shows that the best markets selected by the barometer trading rules vary significantly by decade. The S&P 500 dominates in both the 1980s and 1990s. T-bills are the most invested in the 2000s, a decade racked by the dot-com bust and the Great Financial Crisis. The Russell 2000 was heavily favored in the 2010s and in fact had the largest allocation of any market in any decade.

Leverage also varied across decades as shown in figure 4. The greatest leveraging occurred in the 1980s with the S&P 500 levered nearly 40 percent of the time. The next most levered market was the Russell 2000 in the 1980s and 2010s.

Thus, barometers signaled different market conditions across decades and as a result, the trading rules led to decade-to-decade variation in market exposure and the use of leverage.

Table 13 presents returns by decade. The trading-rule portfolio (with leverage) performs well, besting the benchmark by a wide margin in each decade, doubling or more the benchmark returns in all but the 1990s, in which the trading-rule return was half again larger. The ability of the trading rules to navigate these four decades, with their very different market states, provides further evidence that barometer readings capture the ever-changing drivers of equity returns.

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CONCLUDING REMARKS

Market barometers are statistically and economically significant predictors of market returns. U.S. large-cap (USMB) and international developed (IntlMB) market barometers are based on investor response to active equity strategies in the form of recent strategy performance ranks relative to historical performance ranks. If recent ranks align with historical ranks, barometers are signaling high expected market returns; if they are not aligned, they are signaling lower returns. The capitalization barometer is based on various objective behavioral proxies and is used to indicate when U.S. small-caps will outperform U.S. large-caps.

Statistical tests of the barometers show them to be good predictors of market returns for up to twelve months in advance, with the slope coefficients for 1–9 months ahead significant at the 5-percent level during 1981–2020. Including trailing market returns and one of the best measures of current economic conditions, the Institute for Supply Management Production Managers' Index results in insignificant slope coefficients for these variables and little or no change in the barometer coefficient that remains highly significant.

A simple set of barometer-based rules are created for trading among U.S. large-caps (represented by the S&P 500), international developed markets (MSCI EAFE), U.S. small-caps (Russell 2000), and cash (T-bills). These trading rules generate gross returns that are double the return of the benchmark (equal-weighted across the four markets) and result in a max drawdown that is about one-quarter less than the benchmark for the entire period. Performance is robust to the period being considered, across the four very different market states of the decades 1981–2020, and out-of-sample.

As a final out-of-sample empirical test, an investment product was launched in 2010, based on research presented in Howard (2012), using trading rules much like those tested in this paper. Performance of this portfolio in the 11-plus years since inception beats that reported on row 4 in table 13. Thus, barometers are statistically and economically significant predictors of market returns and, more importantly, have shown their mettle in real-time markets for more than ten years.

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C. Thomas Howard, PhD, is professor emeritus at the Reiman School of Finance, Daniels College of Business, University of Denver and chief executive officer and chief investment officer at AthenaInvest, Inc. Contact him at tom.howard@athenainvest.com.

ENDNOTES

1. The ISM manufacturing index, also known as the purchasing managers' index (PMI), is a monthly indicator of U.S. economic activity based on a survey of purchasing managers at more than 300 manufacturing firms. It is considered to be a key indicator of the state of the U.S. economy.
2. In 2010 the computer-based strategy identification algorithm was granted a U.S. patent and in 2011 it was granted a Singaporean patent. See Howard (2010) for more details.
3. Abis and Lines (2020) run a multivariate fund characteristic test and also conclude funds are more alike within strategy peer groups than across peer groups.
4. Strategy returns are calculated as the simple average net-of-fees return across all funds, with individual fund returns averaged across all share classes, in that strategy that month. Unlike many proprietary measures described in the literature, Athena's strategy returns, along with other strategy information, are available at no cost to researchers who are willing to sign a non-disclosure agreement.
5. Note that it is not necessary to assume active equity managers are superior stock pickers. It is only important that they consistently pursue the same strategy over time, successful or not.
6. An obvious alternative to ranking strategies based on recent returns is to rank them based on recent fund flows. But because flows tend to follow returns it is likely that returns provide a more up-to-date estimate of investor strategy demand.
7. Because barometers are estimated using 1988–2007 strategy return ranks, there is a potential look-ahead bias in the reported 1981–2020 results. The strong 2007–2020 results reported in regressions 6–10 in table 8 indicate that this bias seems not to be a problem because this later period is mostly free of this bias.
8. A benchmark equally weighted across the three equity markets (S&P 500, Russell 2000, and MSCI EAFE), leaving out cash returns, generated a 10.76-percent compounded return with a 53.1-percent maximum drawdown of 53.1 during 1981–2020. This means that the unlevered best markets strategy would have slightly underperformed over the full period but with a much lower drawdown than this all-equity benchmark. On the other hand, the levered best markets would have outperformed on both return and drawdown.

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5619 DTC Parkway, Suite 600
Greenwood Village, CO 80111
Phone: +1 303-770-3377
www.investmentsandwealth.org