A Measure of Market Incertitude

Introduction

A trending market leads to inevitable questions: *Is the trend exhausting? Is a market correction looming?* Technical analysts seek to answer these questions with internal strength measures based on characteristics of constituent price movement. These techniques are intended to detect a change in market character by revealing transitions from robust strength to potential deterioration.

Internal strength techniques fall primarily into two areas. First, internal market breadth measures, which quantify the extent to which constituents are going along with the overall trend – often via a count of declining issues and advancing issues. Second, diffusion measures, which quantify breadth via a count of the number of issues meeting a given criteria such as those above a 40-day moving average. This paper explores a third area of strength measurement emanating from the question: *Does today look like yesterday?*

This paper begins by examining the nature of advance/decline (A/D) counting and then introducing and exploring a more granular measure. The measure will then be extended into an indicator and, in turn, extended into an oscillator. Signal cases will be presented and their usefulness assessed for judging trend strength and detecting changes in market character.

Background and Literature Review

Market breadth analysis is an approach to understanding overall market conditions associated with market movement. A succinct description is provided by Martin Pring (1985): "Market breadth measures the degree to which a market index is supported by a wide range of its components." Pring further states two beneficial purposes. "First, it indicates whether the environment for most items in a universe (normally equities) is positive or negative. Second, market breadth indicators signal major turning points through positive and negative divergences."

Numerous technical analysis reference works cover the subject of breadth analysis. Notable is the comprehensive survey of breadth methods provided by Gregory Morris (2015). Many of these methods are internal market breadth measures built upon advances, declines, up and down volume, new highs and new lows. These are "used in almost every conceivable method and mathematical combination, by themselves, or in combination with other breadth components. After they are mathematically arranged, they are then again smoother, averages, summed, and normalized." The number of A/D techniques abound yet their calculations depend upon only a few direct measures.

Breadth indicators are prevalent in contemporary technical analysis literature. Recent *Technically Speaking* articles (Deemer 2023 and Wells 2022) and recent Dow award papers (Diodato 2019 and Whaley 2010) directly address or touch upon market breadth topics. The tempo of research and publications attest to the enduring relevance of breadth studies.

Framing Advance-Decline Counting as Data Binning

In data science, data binning is a pre-processing method for data smoothing whereby a large set of original data is segregated into intervals called bins, and the discrete values in every bin are treated to derive a representative value. Data binning categorizes continuous data to decrease noise but it does so at the risk of information loss. The advance-decline count in technical analysis is a type of data binning as it divides an entire range of daily price change values into three subranges and applies the subrange labels of advancers, decliners, and unchanged as substitutes for the actual values.

In other fields, many situations lend themselves to proper data treatment by binning. Even so, researchers in those fields often lament that information is lost by doing so. For example, biomedical researchers Bennett and Vickers (2012) have noted cautions regarding binning namely “it requires an unrealistic step-function … that assumes homogeneity … within groups”. In the field of behavioral research Kim and Frisby (2018) state “discretization is considered to be a downgrading of measurement, because it transforms ratio or interval scale data into ordinal scale data” and “(continuous) scale data include more numeric information than do ordinal scale data.” Data mining and analytics expert Dorian Pyle (1999) states “Binning itself discards information in the variables for a practical gain in usability.” The potential consequence is information loss, over-smoothing, or under-smoothing, which can further result in misinterpretation and inaccurate outcomes.

Should technical analysis discard information in order to gain expedient usability? Given the many widely-used variants of A/D the first blush answer is yes. And given the many tested and demonstrated uses of those techniques, this paper does not discourage their use. Even so, exploring the use of all the data remains enticing. Examining the full complete distributions is a new way of examining trend strength and trend exhaustion. Can treating all the data lead to a useful measure of strength?

Daily Price Changes as Bins

Consider the advance-decline count of the S&P 500 on Monday, September 25, 2023 and its visual representation in Figure 1. Each trading day stocks experience a daily price change which is expressed as a one-bar rate of change (ROC(1)). A/D puts the entire continuum of index constituents’ daily price change into a mere three bins: 300 Advancers, 200 decliners, and 3 unchanged[1]. Here data has been categorized and binned into three discrete buckets. The horizontal axis is comprised of categories rather than values.

[1] Note there are 503 symbols in the S&P500 index due to dual class shares.

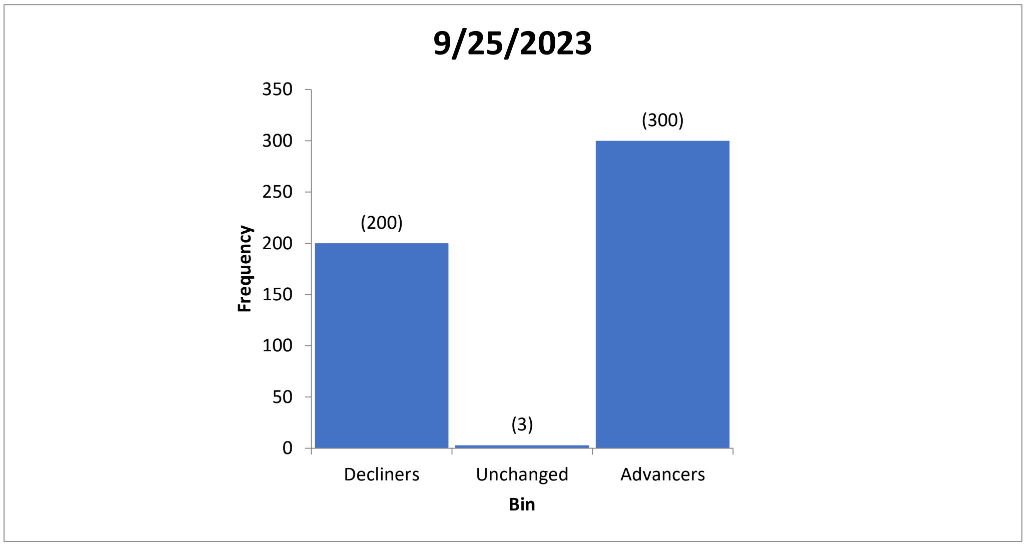

Figure 1. ROC as a Categorical Distribution

To illustrate the loss of information from discretization, five stocks from the index are shown on Table 1. First consider three stocks at the center of the distribution (RSG has an ROC of -0.00683, TRV has an ROC of zero, and COST has an ROC of +0.005371). In this binning rubric these three datapoints, though nearly indistinguishable, are placed into three separate buckets. Using zero as the bin boundary is perhaps an unrealistic step function. Consider now the minimum stock WBD with an ROC of -3.96. It is placed into the same bin of decliners as is near-zero RSG despite their considerable difference being ~4 apart. Consider as well that the maximum stock SEE with an ROC of +3.57 is placed into the same bucket of advancers as near-zero COST even though they are ~3.5 apart. Too much homogeny is imputed into both the advancers bin and the decliners bin. In short, this approach *lacks granularity*.

Table 1. Five Example Stocks

Date	Symbol	Security Name	Open	High	Low	Close	ROC(1)	Bin
Friday, September 22, 2023	WBD	Warner Bros Discovery Inc	11.51	11.605	11.01	11.1		
Monday, September 25, 2023	WBD	Warner Bros Discovery Inc	11.15	11.18	10.62	10.66	-3.96396	Decline
Friday, September 22, 2023	RSG	Republic Services Inc	146.69	147.86	146.18	146.36		
Monday, September 25, 2023	RSG	Republic Services Inc	146.16	147.03	145.865	146.35	-0.00683	Decline
Friday, September 22, 2023	TRV	Travelers Companies Inc	168.77	169.38	167.74	167.84		
Monday, September 25, 2023	TRV	Travelers Companies Inc	166.39	168.03	166.38	167.84	0.00000	Unchanged
Friday, September 22, 2023	COST	Costco Wholesale Corp	555.16	562.97	554.78	558.59		
Monday, September 25, 2023	COST	Costco Wholesale Corp	559.49	561.27	554.735	558.62	0.00537	Advance
Friday, September 22, 2023	SEE	Sealed Air Corp	31.9	31.925	31.255	31.41		
Monday, September 25, 2023	SEE	Sealed Air Corp	32.36	32.95	32.16	32.53	3.56574	Advance

Daily Price Change as Distribution

Looking again at the S&P 500 for 9/25/2023, the daily price change of a group of stocks can be shown as a frequency distribution as depicted in Figure 2 which, when smoothed, is a probability density function that ranges from -4.0% to +3.6%. The distribution is continuous and has observable features of shape and has characteristics of location. Shape is quantified by descriptive statistics such as variance and skew. Location is quantified by descriptive statistics such as median and mean. The horizontal axis, instead of discrete categories, is a continuum of values. That is, any unique value of ROC has a given probability. A large body of inferential statistics can be garnered from this including distribution tests. In short, this approach *has granularity*.

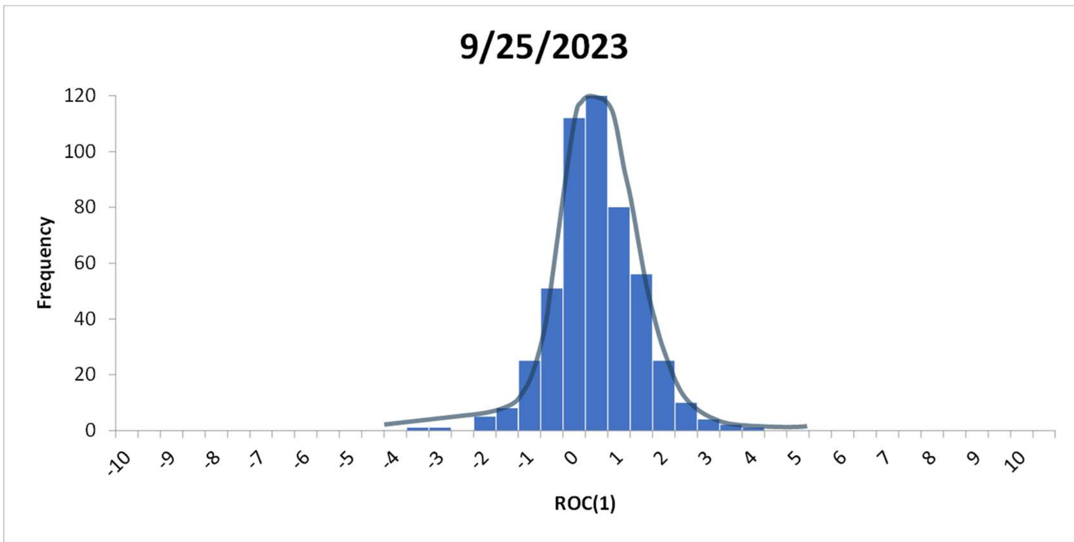

Figure 2. Daily Rate of Change as a Probability Density Function

To illustrate further the distinction between granular continuous distributions and less-granular categorical distributions, consider for example the data for 8/20/2010 shown in the upper panel of Figure 3 and compare it to the data from 3/19/2009 in the lower panel. Both have the same advance-decline ratio but clearly have different distributions – one narrow and one wide. Similarly, in Figure 4, both 2/13/2020 and 4/4/2022 have the same A/D but again clearly different distributions - one skewed left and one skewed right.

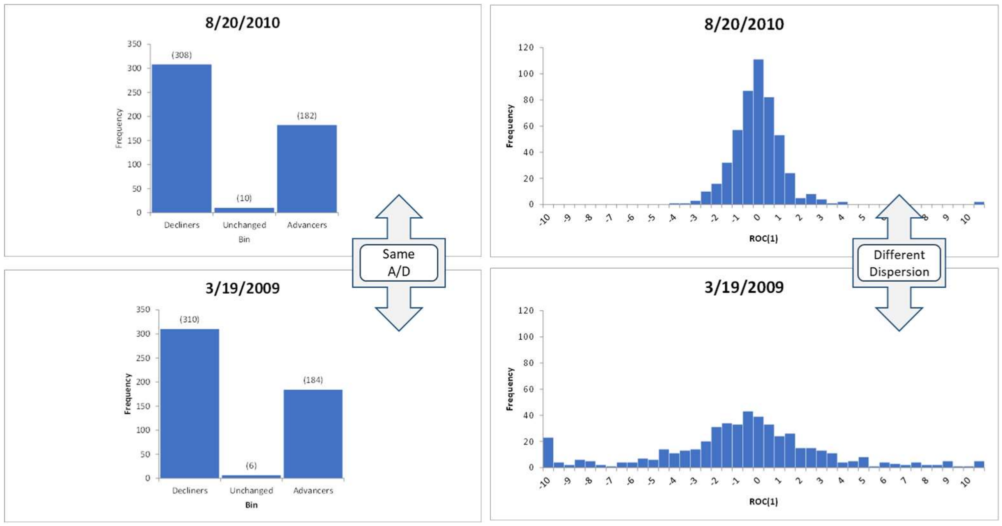

Figure 3. Days with Same A/D But Differing Dispersion: Narrow and Wide

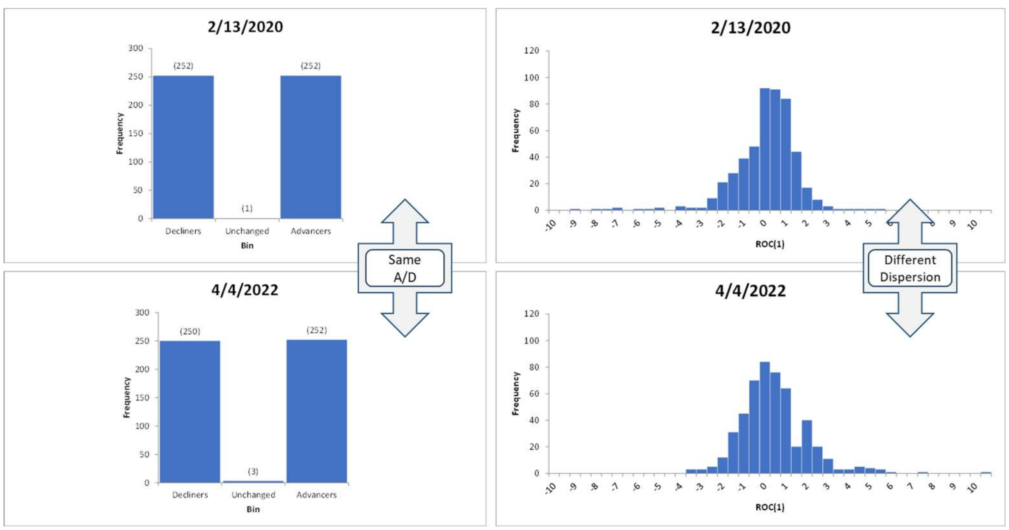

Figure 4. Days with Same A/D But Differing Dispersion: Skewed Left and Skewed Right

Distribution Tests

It stands to reason then that if the A/D count has indeed discarded information, then every downstream use of it (e.g., McClellan Oscillator, ARMS Index, breadth thrusts, and many others) will likewise carry information loss. So, with motivation to not discard information, let's turn to statistical ways to use all the data.

Statistics is a field replete with methods to compare distributions. The first published statistical test was centuries ago by Arbuthnot (1710). The idea of testing was further codified and elaborated early in the twentieth century, mainly by R. A. Fisher (1925). The basic steps outlined in his work continue to be the framework in use today. The first step is formulating a null hypothesis as an assertion regarding a characteristic of this data. By starting with the proposition that this characteristic exists, statistical tests can estimate the probability that an observed characteristic could be due to chance. A test statistic T as a function of the data, "is used to indicate the degree to which the data *deviate* from the null hypothesis.

And the significance of the given outcome of the test statistic is calculated as the probability, if the null hypothesis is true, to obtain a value of T which is at least as high as the given outcome." (Snijders 2015). This empirical rote is familiar to students of sophomore statistics (form null hypothesis; compute a statistic; compare statistic to table value; reject the null hypothesis or not). The process results in a binary outcome which is certainly an appropriate use case in many settings but not this one. Rather here the interest is in a measure of how different today is compared to yesterday.

If we were to perform a full test around our thesis (*Does today look like yesterday?*), we would phrase the null hypothesis in the form of "*today <u>is</u> the same as yesterday*", compute a measure of the difference between today and yesterday, obtain an appropriate reference value at a stated level of confidence, and compare the two. If the computed measure is larger than the reference value, the hypothesis is rejected. That is, the difference is so great we cannot say that they are equal days. But the dichotomous outcome, concluding today is different from yesterday, is not useful here. After all, what would we do with that outcome? An indicator of binaries is unappealing. So, moving forward we refine the thesis question to: *How different is today than yesterday?* And by asking "how different?" we need to measure the degree to which they differ.

<u>The Measure</u>

The statistic used in this paper was devised by Yves Lepage (1971). The Lepage test statistic is a combination of two nonparametric rank-ordering tests: the Wilcoxon Rank-Sum[2] test for location (1945) and the Ansari–Bradley test for scale (1960). The Wilcoxon Rank Sum test is used to test the equality of medians from two samples and its calculation involves replacing observations of the combined samples with their ascending ranks. The Ansari-Bradley test is used to test the equality of scale from two samples and its calculation involves replacing the observations of the combined sample less than or equal to the median with their ranks in increasing order and those larger than the median with their ranks in decreasing order. The ranks of the second sample in each case are summed to form the respective statistic of each. Each of the cited references provides details on these tests but for the purposes of this paper an illustrative calculation example is provided in four steps.

To illustrate calculation of the Lepage statistic, consider the fictional closing price data for twelve stocks on three consecutive days in the left-hand portion of Figure 5. Closing prices are shown for Monday, Tuesday, and Wednesday followed by the rate of change for Tuesday and Wednesday. Rate of change is the one-day price movement computed as: ROC(1)=((Today's Close-Yesterday's Close))/(Yesterday's Close)*100.

Lepage step 1: The rank-ordering process begins with combining Tuesday's 12 ROCs and Wednesday's 12 ROCs into one 24-member superset in ascending sort. Two sets of ranks are assigned as shown in the right-hand portion of Figure 5. First, assign ordered ranks 1 through 24 to each member. Second, assign ranks from the top and from the bottom toward the middle. Both the Wilcoxon and Ansari-Bradley statistics will be computed from the sum of these ranks. For example, AAPL Wednesday ROC of 1.1765 is assigned a rank of 19 in the second column and a rank of 6 in the third column. Note that the remaining calculations do not use closing prices or ROCs but use only these ranks.

[2] The Wilcoxon Rank-Sum test is also known as the Mann-Whitney U test (Mann and Whitney 1947).

	Close Monday	Close Tuesday	Close Wednesday
AAPL	173	170	172
MSFT	326	331	330
GOOGL	136	135	136
AMZN	125	126	124
NVDA	413	404	415
META	308	309	306
TSLA	335	330	336
LLY	212	216	210
UNH	585	591	595
V	233	232	227
XOM	111	109	111
WMT	154	155	154

ROC(1) Tuesday	ROC(1) Wednesday
-1.7341	1.1765
1.5337	-0.3021
-0.7353	0.7407
0.8000	-1.5873
-2.1792	2.7228
0.3247	-0.9709
-1.4925	1.8182
1.8868	-2.7778
1.0256	0.6768
-0.4292	-2.1552
-1.8018	1.8349
0.6494	-0.6452

Tuesday and Wednesday ROC Superset Ascending	Ordered Ranks	Ranks From Each End Towards The Middle
-2.7778	1	1
-2.1792	2	2
-2.1552	3	3
-1.8018	4	4
-1.7341	5	5
-1.5873	6	6
-1.4925	7	7
-0.9709	8	8
-0.7353	9	9
-0.6452	10	10
-0.4292	11	11
-0.3021	12	12
0.3247	13	12
0.6494	14	11
0.6768	15	10
0.7407	16	9
0.8000	17	8
1.0256	18	7
1.1765	19	6
1.5337	20	5
1.8182	21	4
1.8349	22	3
1.8868	23	2
2.7228	24	1

Figure 5. Illustrative Example Rank Ordering

Lepage step 2: The Wilcoxon uses the rank order of the combined Tuesday and Wednesday's ROCs and sums the ranks of only the Wednesday values. From the sum, W, the standardized Wilcoxon statistic is computed by subtracting the expected values and dividing by the square root of the expected variance:

$$W_* = \frac{W - E(W)}{\sqrt{V(W)}} = \frac{W - n(N+1)/2}{\sqrt{mn(N+1)/12}}$$

$$W_* = \frac{73 - 12 * (24+1)/2}{\sqrt{12 * 12 * (24+1)/12}} = 0.40415$$

The resulting value of 0.404145 is illustrated in Figure 6.

Tuesday and Wednesday ROC Superset Ascending	Ordered Ranks
-2.7778	1
-2.1792	2
-2.1552	3
-1.8018	4
-1.7341	5
-1.5873	6
-1.4925	7
-0.9709	8
-0.7353	9
-0.6452	10
-0.4292	11
-0.3021	12
0.3247	13
0.6494	14
0.6768	15
0.7407	16
0.8000	17
1.0256	18
1.1765	19
1.5337	20
1.8182	21
1.8349	22
1.8868	23
2.7228	24

ROC(1) Wednesday	Rank Within Tues&Wed Superset
1.1765	19
-0.3021	12
0.7407	16
-1.5873	6
2.7228	24
-0.9709	8
1.8182	21
-2.7778	1
0.6768	15
-2.1552	3
1.8349	22
-0.6452	10
Sum (W)	157
m	12
n	12
N	24
W*	0.40415

$$W_* = \frac{W - E(W)}{\sqrt{V(W)}} = \frac{W - n\,(N+1)/2}{\sqrt{mn\,(N+1)/12}}$$

Figure 6. Illustrative Example Wilcoxon Rank-Sum

Lepage step 3: The Ansari-Bradley uses the ranks ordered from each end of the combined Tuesday and Wednesday's ROCs and sums the ranks of only the Wednesday values. From the sum, C, the standardized Ansari-Bradley statistic is computed by subtracting the expected values and dividing by the square root of the expected variance:

$$C_* = \frac{C - E(C)}{\sqrt{V(C)}} = \frac{C - n(N+1)^2/(4N)}{\sqrt{mn(N+1)(3+N^2)/(48N^2)}}$$

$$C_* = \frac{73 - 12 * (24+1)^2/(4 * 24)}{\sqrt{12 * 12 * (24+1)(3+24^2)/(48 * 24^2)}} = -0.59025$$

The resulting value of -0.590248 is illustrated in Figure 7.

Tuesday and Wednesday ROC Superset Ascending	Ranks From Each End Towards The Middle
-2.7778	1
-2.1792	2
-2.1552	3
-1.8018	4
-1.7341	5
-1.5873	6
-1.4925	7
-0.9709	8
-0.7353	9
-0.6452	10
-0.4292	11
-0.3021	12
0.3247	12
0.6494	11
0.6768	10
0.7407	9
0.8000	8
1.0256	7
1.1765	6
1.5337	5
1.8182	4
1.8349	3
1.8868	2
2.7228	1

ROC(1) Wednesday	Rank From Each End Within Tues&Wed Superset
1.1765	6
-0.3021	12
0.7407	9
-1.5873	6
2.7228	1
-0.9709	8
1.8182	4
-2.7778	1
0.6768	10
-2.1552	3
1.8349	3
-0.6452	10
Sum (C)	73
m	12
n	12
N	24
C_*	-0.59025

$$C_* = \frac{C - E(C)}{\sqrt{V(C)}} = \frac{C - n(N+1)^2/(4N)}{\sqrt{mn(N+1)(3+N^2)/(48N^2)}}$$

Figure 7. Illustrative Example Ansari-Bradley

Lepage step 4: The Lepage statistic, D, is the sum of the squares of the standardized Wilcoxon and Ansari-Bradley statistics:

$$D = {W_*}^2 + {C_*}^2$$

$$D = 0.404145^2 + (-0.590248)^2 = 0.511727$$

The resulting value of 0.511727 quantifies the difference between Wednesday's ROC distribution and Tuesday's ROC distribution. This is the degree to which Wednesday deviated from Tuesday.

A pair of similar days with a small degree of deviation from one another will result in a small Lepage value. Two similar examples are shown in Figure 8 with low values. A pair of dissimilar days with a large degree of deviation from one another will result in a large value. Two dissimilar examples are shown in Figure 9 with large values.

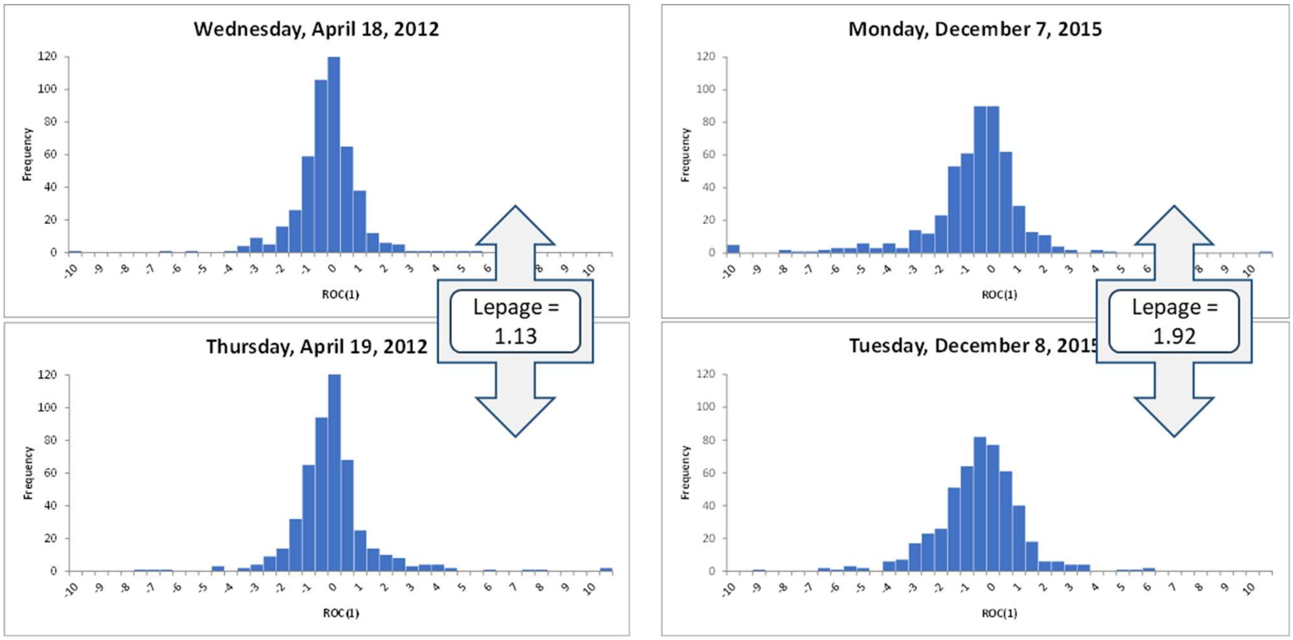

Figure 8. Similar Days Have Low Lepage Values

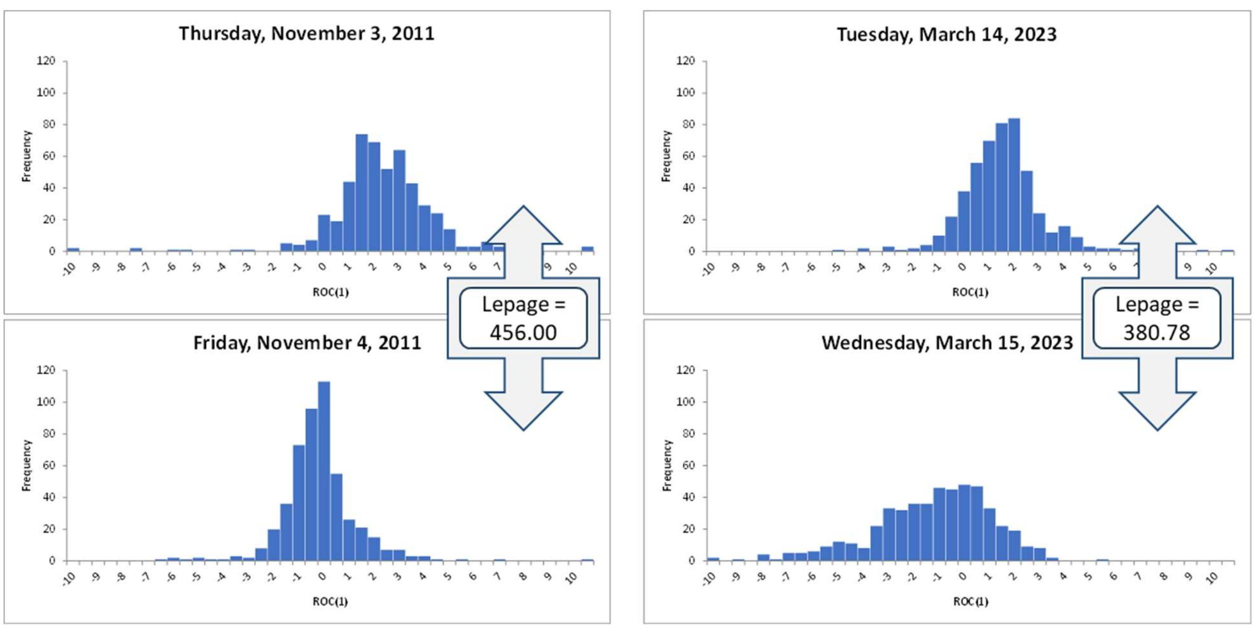

Figure 9. Dissimilar Days Have High Lepage Values

Construct the Incertitude Approach

Thus far, we have presented characteristics of a continuous ROC distribution contrasted with the discretized A/D. In addition, we have presented a statistical measure of the difference between the distributions of two consecutive days' ROCs. Now we introduce a new breadth measure in the form of an indicator and in the form of an oscillator.

The ***Incertitude Indicator*** is the three-day simple moving average of each day's Lepage statistic. This indicator represents the extent to which days are behaving unlike their previous days. When the indicator value is high it indicates a degree of *chaos* in the market; When the indicator is low it indicates a degree of *sameness* in the market.

The ***Incertitude Oscillator*** is the difference between two exponential moving averages of the Incertitude Indicator in the same manner as the McClellan Oscillator is constructed. Subtracting the 39-day exponential moving average of Incertitude Indicator from the 19-day exponential moving average of Incertitude Indicator forms the Incertitude Oscillator. Oscillators typically support interpretations of *overbought* at their highs and *oversold* at their lows. But these terms are not applicable here rather, the interpretation here is *overchaos* at its highs and *oversameness* at its lows.

The incertitude approach posits that either high degrees of sameness or high degrees of chaos may portend a change in market character. On the one hand, repeated days of sameness occur at the end of a trend with a dearth of new ideas. On the other hand, repeated days of chaos occur at the end of a trend with an abundance of new, but weak, ideas. Either extreme coincides with trend exhaustion.

A case of sameness could occur when most market participants believe the last blowout has taken place, have acted on the macro factors in play, and are awaiting new information to launch new sector leadership for the next counter wave. The lack of new information in either sector price movements or in market-moving news leads to complacent resignation to the move. With market directional movement as the primary reinforcing factor, the trend continues as the market overshoots fundamentals.

A case of chaos could occur when most market participants trade on each day's news as though it is genuine informational signal but they experience no confirmational price action follow-through. "Noise traders are investors who buy and sell based on signals that they think are informative but that are not" (Aronson 2011). Moves are made with more psychologically-driven factors than fundamental ones as the market overshoots fundamentals.

Candidate Incertitude Signals

The incertitude approach, built upon the Lepage measure of daily price change distribution differences, provides a measure on the scale of sameness to chaos. Figure 10 presents a notional depiction of the incertitude scale. The center of this scale represents the norm of a market behaving healthily as market participants with varying information insights, goals, and time horizons provide liquidity to one another in orderly fashion. An over-extended market with characteristics of extreme chaos or extreme sameness are conditions ripe for a trend reversal. It is from these extremes that we will seek signal. This section presents a discussion of candidate counter-trend signals observed in assessing the viability of the incertitude approach. The section that then follows will quantitatively assess each candidate signal.

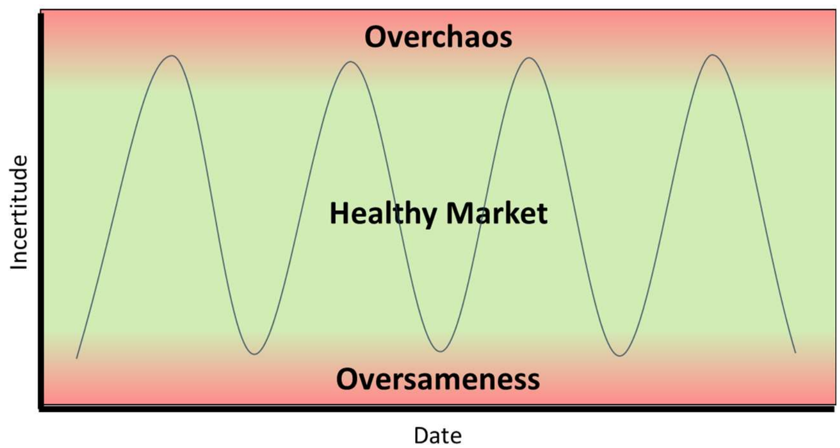

Figure 10. The Incertitude Scale

Each of these candidate signals is presented as a chart with accompanying text. The signal type is described in prose followed by a formulaic set of signal logic. In the signal logic formulas “II” represents Incertitude Indicator and “IO” represents Incertitude Oscillator. Observed anecdotal episodes of signal are discussed. Before jumping into the signal descriptions, a template is offered to define the content of the charts.

Candidate Signal Template

Each figure in this section is comprised of six panels as depicted in the template definition of Figure 11. Panel 1 at the top presents the II or IO with overlays that highlight the pertinent patterns of that signal. The signal is noted with a red circle and a vertical dashed line anchoring the signal date across all six panels. Panel 2 is the SPX in candlestick format with the trend prior to the signal noted with a highlighted line and three simple moving averages. Panel 2 also notes the post-signal counter-trend with a highlighted line.

Panels 3 and 4 present two internal breadth measures: The AD Line and the percentage of index members above their 50-day moving averages. A highlighted line on each will note post-signal conditions of deteriorating (or strengthening) breadth.

Panels 5 and 6 present two momentum indicators on the SPX itself: The Relative Strength Index (RSI) and the Moving Average Convergence/Divergence (MACD) oscillator. RSI is shown with a 14-day parameter and the MACD is shown with a 12-day and 26-day configuration with no signal line. A highlighted line on each will note post-signal increasing or decreasing momentum.

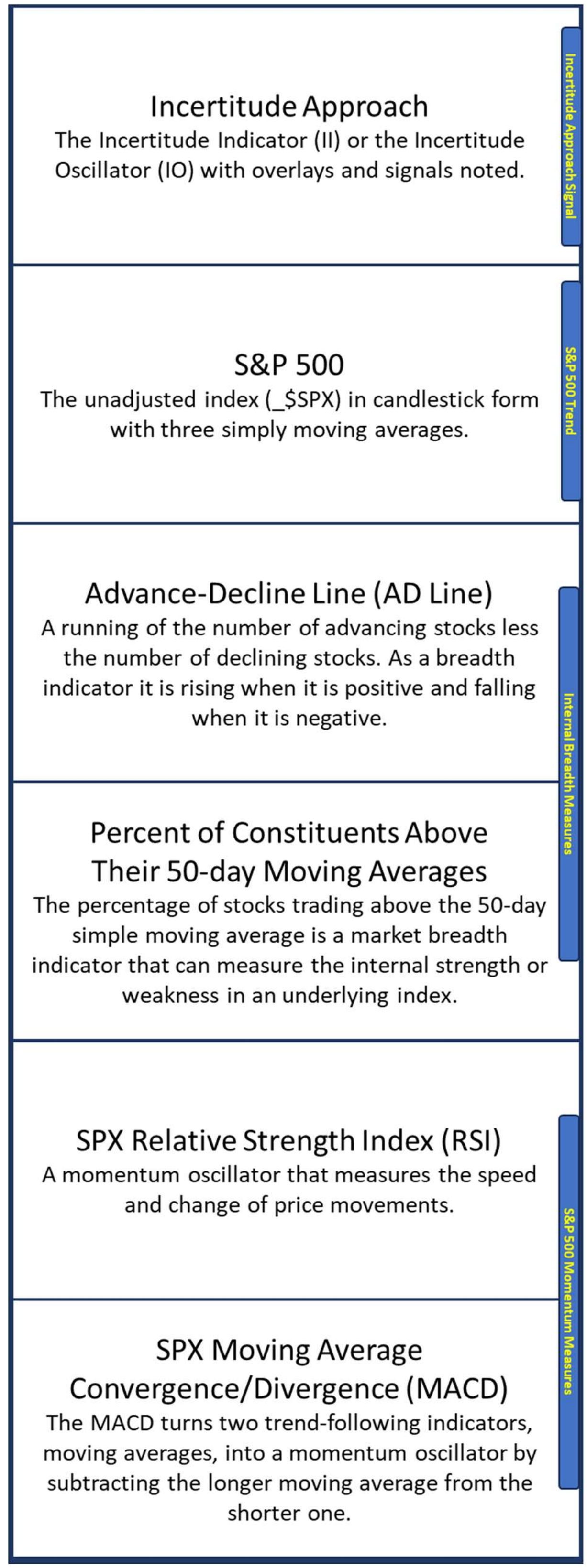

Figure 11. Template for Signal Charts

Signal Type 1: Incertitude Indicator Cross Up from Sameness

The top panel of Figure 12 depicts the Incertitude Indicator with channels and a fast pair of EMAs. A signal is triggered when the smoothed indicator is below the channel and the 4-day EMA crosses up over the 9-day EMA.

Signal Type 1 is defined as:

- Today’s 4-day EMA of the II > Today’s 9-day EMA of the II; and
- Yesterday’s 4-day EMA of the II <= Yesterday’s 9-day EMA of the II; and
- Yesterday’s 9-day EMA of the II < (Yesterday’s 20 Day Minimum Channel of the II + 50).

The idea captured here is when the indicator is reading sameness, a change in market character is pending. When it begins to abandon sameness and churn begins, the character is indeed changing. New emergent leaders are beginning to move in the countertrend direction.

On 7/28/2023 a signal is triggered (top panel) when the index trend is upward (second panel) and afterward market breadth deteriorates (panels three and four), momentum declines (the bottom two panels), and index reverses direction (second panel).

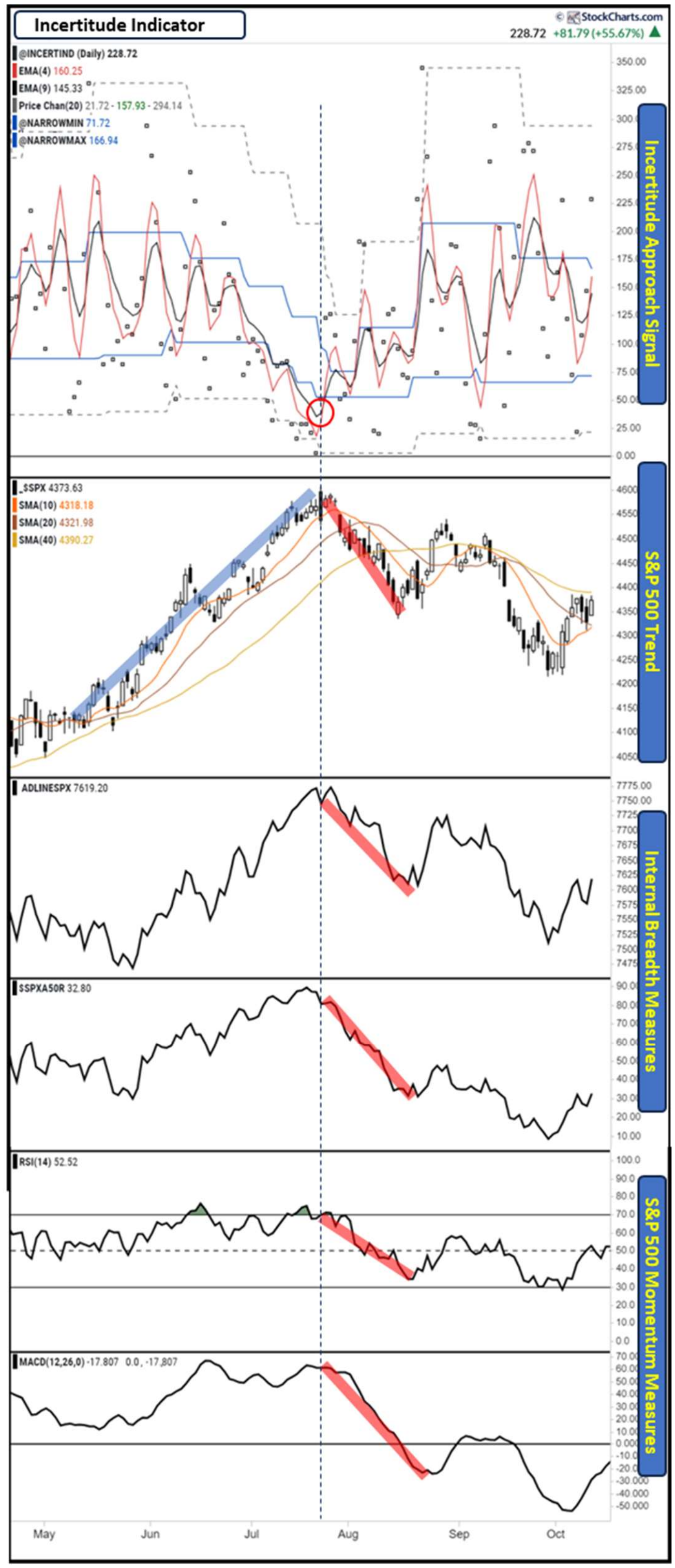

Figure 12. Incertitude Indicator Cross Up from Sameness

Signal Type 2: Incertitude Indicator Cross Down from Chaos

The top panel of Figure 13 depicts the Incertitude Indicator with channels and a fast pair of EMAs. This signal type pertains to the opposite side of the scale from signal type 1. A signal is triggered when the smooth indicator is *above* the channel and the 4-day EMA *crosses down* over the 9-day EMA.

Signal Type 2 is defined as:

- Today's 4-day EMA of the II > Today's 9-day EMA of the II; and
- Yesterday's 4-day EMA of the II <= Yesterday's 9-day EMA of the II; and
- Yesterday's 9-day EMA of the II > (Yesterday's 20-Day Minimum Channel of the II * 0.6).

The idea captured here is when the indicator is reading chaos a change in market character is pending. When it begins to abandon chaos and exhibits a more routine churn, the character is indeed changing. New emergent leaders are beginning to move in the countertrend direction.

On 1/5/2023 a signal is triggered (top panel) when the index trend is downward (second panel) and afterward market breadth strengthens (panels three and four), momentum advances (bottom two panels), and the index reverses direction (second panel).

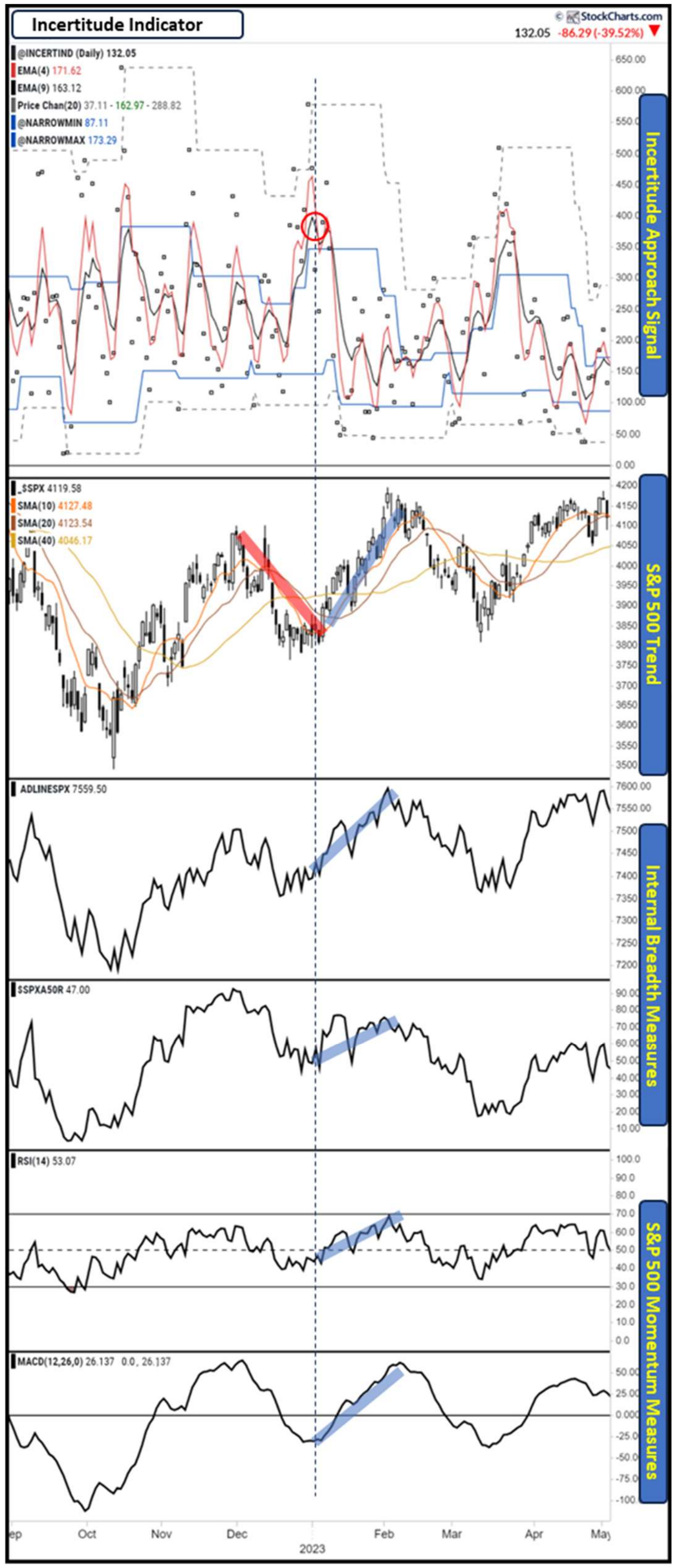

Figure 13. Incertitude Indicator Cross Down from Chaos

Signal Types 3 and 4: Smoothed Incertitude Indicator Extremes

In the interest of attaining a fast responsive signal, the ConnorsRSI (Connors and Radtke 2014) is applied to smooth the Incertitude Indicator. The top panel of Figure 14 depicts the smoothed Incertitude Indicator with horizontal values 10 and 90 drawn. A chaos signal is triggered when the smoothed indicator is above 90 and a sameness signal is triggered when the smoothed indicator crosses below 10.

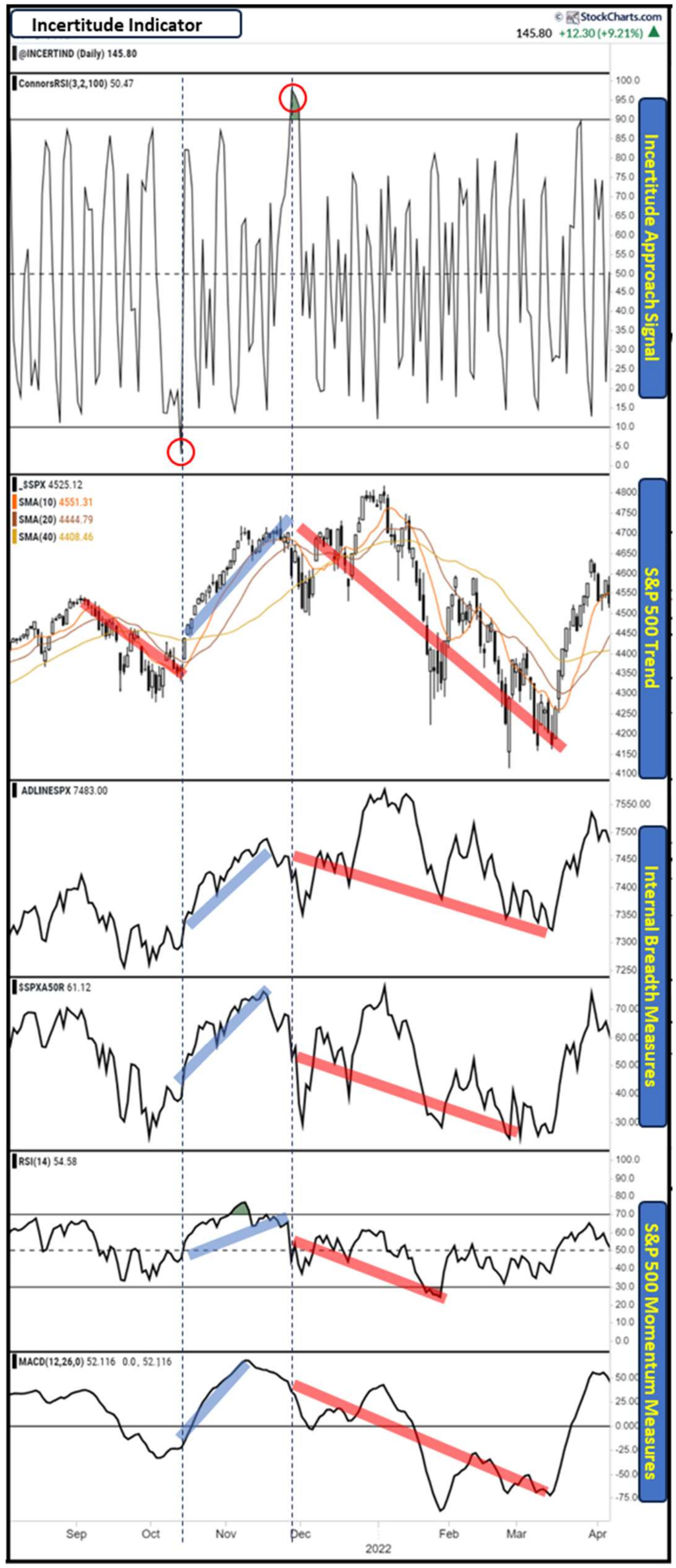

Figure 14. Smoothed Incertitude Indicator Extremes

Signal Type 3 is defined as:

- Today's ConnorsRSI of the II > 10; and
- Yesterday's ConnorsRSI of the II <= 10.

Signal Type 4 is defined as:

- Today's ConnorsRSI of the II > 90; and
- Yesterday's ConnorsRSI of the II >= 90.

The idea captured here is when the indicator is reading chaos a change in market character is pending. The smoothed indicator does not tend to stay at the extreme very long so this signal is not formulated with a prerequisite (e.g. expressed as a pending range from which a signal is then noted as the prior signal types were). When it signals the counter trend direction may have already begun.

On 10/13/2021 a sameness signal is triggered (the first red circle in the top panel) when the index trend is downward (second panel) and afterward market breadth strengthens (panels three and four), momentum advances (bottom two panels), and index reverses direction (second panel). On 11/26/2021 a chaos signal is triggered (second red circle in top panel) when the index trend is upward and afterward market breadth deteriorates, momentum declines, and the index reverses direction.

Signal Type 5: Incertitude Oscillator Signal Line Cross Up

The top panel of Figure 15 depicts the Incertitude Oscillator with a 9-day EMA signal line. A signal is triggered when the oscillator crosses above the signal line when the oscillator is less than 10.

Signal Type 5 is defined as:

- Today's IO > Today's 9-day EMA of the IO; and
- Yesterday's IO <= Yesterday's 9-day EMA of the IO; and
- Yesterday's IO < -10.

The idea captured here is when the oscillator is reading relative sameness and then reverses away from continued sameness, the character is indeed changing. Normal liquidity is being restored. New emergent leaders are moving in the counter-trend direction.

On 7/28/2023 a signal is triggered (top panel) when the index trend is upward (second panel) and afterward market breadth deteriorates (panels three and four), momentum declines (bottom two panels), and the index reverses direction (second panel).

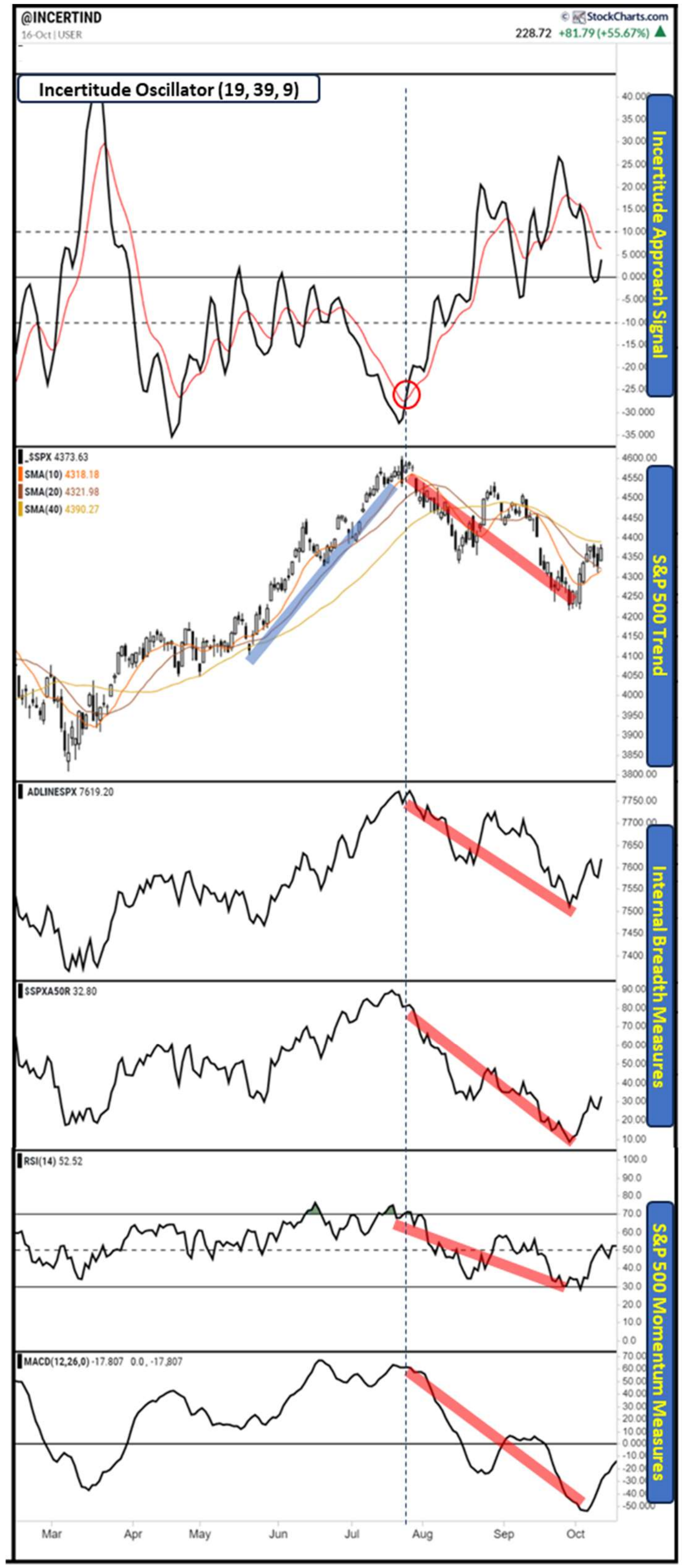

Figure 15. Incertitude Oscillator Signal Line Cross Up

Signal Type 6: Incertitude Oscillator Signal Line Cross Down

The top panel of Figure 16 depicts the Incertitude Oscillator with a 9-day EMA signal line. This signal type pertains to the opposite side of the scale from signal type 5. A signal is triggered when the oscillator crosses *below* the signal line when the oscillator is *greater than* 10.

Signal Type 6 is defined as:

- Today's IO < Today's 9-day EMA of the IO; and
- Yesterday's IO >= Yesterday's 9-day EMA of the IO; and
- Yesterday's IO > 10.

The idea captured here is when the oscillator is reading relative chaos and then reverses away from continued chaos, the character is indeed changing. New emergent leaders are moving in the counter-trend direction.

On 3/23/2020 a signal is triggered (top panel) when the index trend is downward (second panel) and afterward market breadth strengthens (panels three and four), momentum advances (bottom two panels), and the index reverses direction (second panel).

Figure 16. Incertitude Oscillator Signal Line Cross Down

Empirical Assessment

The six candidate signal types were tested using data from January 3, 1990 to October 17, 2023. The data set is daily unadjusted closing prices for the S&P500 index SPX and its constituents as they were comprised on each day. Unadjusted data, that is data not altered to accommodate splits or dividends, represents the prices available to traders on that day. The data source for index value, constituent prices, and daily index constituents was Norgate Data. The internal measures were obtained from StockCharts.com. The incertitude formula and tests were coded in Python.

Given the goal of this paper is assessing changes in market strength, for testing purposes we choose other strength metrics as the objective measures for signal outcomes. Since the goal is not a trading system for the index, framing the assessment as trading profits, drawdowns, percent profitable trades, etc. is not applicable. The assessment here is the counter-trend change in the selected strength metrics for 20, 40, and 60 days after each signal is triggered.

Each signal type is neutral as to the trend direction. No matter if the trend is up or down, the signal portends a reversal in trend strength. Their utility though is based on the presence of a trend so the test design must also define what constitutes a trend. For the purposes of this paper, the selected trend definition is three simple moving averages in directional order defined as:

- Downtrend: Index 10-day SMA < Index 20-day SMA < Index 40-day SMA.
- Uptrend: Index 10-day SMA > Index 20-day SMA > Index 40-day SMA.

Table 2 presents the downtrend reversal results. Table 3 presents the uptrend reversal results. For each table the columns are the signals. The rows are grouped into internal strength metrics. Percent of constituents above their 50-day simple moving average expressed as the mean arithmetic change and the A/D Line expressed as mean percent change. The second set of rows are the momentum measures of the SPX index itself (RSI and MACD) both expressed as mean arithmetic change. The positive cells are shaded green in the downtrend table and the negative values shaded red in the uptrend table. Most of the cells support the conclusion that incertitude signals lead to reversals in strength. In each case, a t-test was made to determine if the mean change to each metric is different from zero. The idea is that if the signal does not influence the outcome, then the outcomes would be random in which case the collective results would converge to zero. Cells not passing this test are noted with shading. 92% of the cells passed the test.

Table 2. Average Metrics Following Incertitude Signals in a Downtrend

	Incertitude Indicator Sameness Cross Up	Incertitude Indicator Chaos Cross Down	Incertitude Indicator ConnorsRSI Over Sameness	Incertitude Indicator ConnorsRSI Over Chaos	Incertitude Oscillator Signal Line Cross Up	Incertitude Oscillator Signal Line Cross Down
Number of Signals	33	103	30	18	15	73
PercentAbove50DMA change in 20 days	16.13	16.72	17.90	15.74	15.57	15.07
PercentAbove50DMA change in 40 days	37.87	23.99	22.53	49.37	32.36	22.51
PercentAbove50DMA change in 60 days	36.80	22.73	22.52	53.54	20.23	27.85
ADLine %-change in 20 days	9.34	12.85	4.91	-7.95	-13.07	6.44
ADLine %-change in 40 days	7.24	14.87	0.28	-46.79	-8.10	11.15
ADLine %-change in 60 days	-2.56	13.92	5.43	-55.26	17.61	6.75
RSI change in 20 days	12.31	8.16	9.80	13.33	11.54	8.16
RSI change in 40 days	9.76	8.17	10.26	16.62	14.78	9.07
RSI change in 60 days	12.41	8.77	8.38	19.11	9.67	11.82
MACD change in 20 days	6.00	21.81	23.00	2.88	10.27	21.45
MACD change in 40 days	8.29	23.83	23.21	33.06	24.49	24.09
MACD change in 60 days	5.78	24.47	23.74	29.39	10.08	31.52

Table 3. Average Metrics Following Incertitude Signals in an Uptrend

	Incertitude Indicator Sameness Cross Up	Incertitude Indicator Chaos Cross Down	Incertitude Indicator ConnorsRSI Over Sameness	Incertitude Indicator ConnorsRSI Over Chaos	Incertitude Oscillator Signal Line Cross Up	Incertitude Oscillator Signal Line Cross Down
Number of Signals	140	95	75	57	126	27
PercentAbove50DMA change in 20 days	-7.03	-11.09	-9.84	-6.86	-9.33	-3.43
PercentAbove50DMA change in 40 days	-12.10	-15.10	-15.46	-10.76	-15.83	-14.63
PercentAbove50DMA change in 60 days	-9.76	-15.98	-16.46	-9.78	-14.07	-6.99
ADLine %-change in 20 days	-0.34	15.35	9.94	0.28	-0.48	73.86
ADLine %-change in 40 days	-1.20	5.83	14.51	9.91	0.46	84.28
ADLine %-change in 60 days	-5.85	20.53	38.24	10.44	2.32	118.84
RSI change in 20 days	-6.19	-7.31	-7.78	-2.35	-5.32	-3.55
RSI change in 40 days	-6.76	-6.98	-8.91	-2.21	-6.14	-8.72
RSI change in 60 days	-7.20	-7.45	-10.10	-2.53	-5.84	-4.24
MACD change in 20 days	-8.48	-7.21	-6.52	-10.67	-11.03	-5.16
MACD change in 40 days	-8.14	-7.90	-11.06	-9.57	-12.55	-12.21
MACD change in 60 days	-7.22	-11.83	-14.73	-9.35	-12.92	-9.69

The candidate that produced the most signals in a downtrend was the Incertitude Indicator Cross Down from Chaos. This column is noted in Table 2 with a thicker border. Note that all cells in that column are positive and passed the t-test. This intuitively resonates as when a market is chaotically down, the trend ends with the emergence of order as evidenced by strengthening breadth and momentum.

The candidate that produced the most signals in an uptrend was the Incertitude Indicator Cross Up from Sameness. This column is noted in Table 3 with a thicker border. Note that all cells in that column are negative and most passed the t-test. This intuitively resonates as when a market is up with no new emerging sectors, the trend ends with the emergence of disorder as evidenced by deteriorating breadth and momentum.

Conclusions and Further Considerations

This paper introduced a new approach for examining market strength that benefits from the granular inclusion of all the applicable constituent data. A statistic was fully described to measure the difference in the structure of each day's price change with its prior day's structure. The interpretations of the statistic were placed into the context of a range from extreme chaos to extreme sameness.

The statistic was then fully developed into an indicator and an oscillator from which candidate signal cases were developed, quantitatively assessed, and shown to be statistically significant in signaling counter-trend changes. The incertitude approach has merit as a granular measure of the market environment and is a recommended addition to the technical analysis community's tool set. The benefit of incertitude techniques to practitioners is that they will augment existing count-based market breadth and market strength techniques by providing a more granular approach to detecting trend change.

Although developed and tested using the S&P 500, the incertitude approach is broadly applicable to any market, sector, or index (e.g. NASDAQ market, Technology sector, or S&P 100 index) that contains a sufficient number of constituents from which to make the calculations described herein. Note also the fixed values such as moving average durations chosen for testing purposes are not permanent fixtures of the incertitude approach. Parameters stated in the description of candidate signals are malleable in practice and recalibration to each market of interest is recommended.

This topic is fertile ground for further research. The signal types discussed herein were crossovers at the extremes but additional signal types and alternative oscillator interpretations are worthy of further study. Devising methods to incorporate incertitude into other technical analysis indicators would also be a potentially beneficial pursuit. Although the research presented in this paper is anchored on the Lepage statistic as the measure of today's difference from yesterday, it is not the sole measure available. The discipline of distribution comparison has many alternate statistical tests other than Lepage that merit exploration.

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