Evaluation of the Predictive Validity of the CapitalCube™ Market Navigation Platform

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Abstract

Introduction This is the fourth research report where various aspects of the CapitalCube™ Market Navigation Platform [CCMNP] of AnalytixInsight™ have been examined. ***Previous Results*** In our previous three studies, we have tested many of the CCMNP-variables as expressed through the S&P500; we have rejected the Nulls of their inter-and intra-group association in favor of the likelihood that the variables that constitute the CCMNP are not produced by random generating processes. This suggests that the CCMNP is capable of creating market relevant information that may inform the investment decision. ***Current Study*** The previous results beg the question that is the focus of this report: *Given the Non-Random character of the various CCMNP panel variables, does this panel of information enable the identification of a particular stock that will, in the near future, experience a turning-point?* ***Results***: We find no evidence that the CCMNP aids in detecting turning-points for the S&P500 Panel of data tested. Various caveats to this study are detailed in the summary section of this research report. Finally, we offer that the methodology used in investigating the CCMNP is a simple, transparent, and useful model for evaluating the acuity of a MNP in detecting turning-points.

Keywords: stock market, turning-point, linguistic codex

1. Introduction: The Testing Landscape for Market Navigation Platforms [MNP]

1.1 Context of this Research Report

The focus of this research report is to follow-up on the research reports of Lusk & Halperin (2015, 2016 & 2017) which addressed the nature of the associational analysis of the variables of the CapitalCube™ Market Navigation Platform [CCMNP: [<http://www.capitalcube.com/>]] a commercial product of AnalytixInsight™ [<http://www.analytixinsight.com/>]. Considering the variables of the CCMNP, they report that the Nulls of their inter- and intra-group associations may be rejected in favor of the likelihood that these CCMNP variables are not produced by random generating processes. Given this as context in, we: (1) suggest a methodology for assessing the predictive acuity of a MNP, and (2) then apply this methodology to the analysis of the CCMNP.

1.2 Groups of MNPs

To focus this report in the vast domain of MNPs, we give the performance context within which we will form the testing of the CCMNP. In this regard, we classify MNPs into four groups:

Data Capture MNPs provide only a systematic collection of reported market data focusing on individual trading units [usually listed stocks] presented in a consistent standardized format for re-reporting the longitudinal tracking of this data: e.g., CRSP™ or COMPUSTAT™.

Screen Oriented MNPs collect market data that is filtered and reported using idiosyncratic functionalities so as to form a Linguistic, usually ordinal, scale or context over the Panel reporting time frame: e.g., the CCMNP has a Screen called Accounting Quality expressed using four Linguistic Qualifiers [LQ]: *Aggressive Accounting, Conservative Accounting, Non-Cash Earnings, & Possible Sandbagging*.

Suggestive MNPs summarize various data reporting screens using idiosyncratic functionalities so as to arrive, often tactically, at a suggestive recommendation: e.g., Stock Investor Pro™ of the AAII forms many screen oriented portfolios that are rated against many benchmarks including trading indices and relative returns. In this benchmark profiling, the ordinal ranking is the tacit preference ordering. Also, as an extension of the tacit nuance offered by the codex of the screens of the suggestive MNPs almost all of the major market "brokerage" houses have final summary recommendations, the most basic of which are: Buy, Hold, or Sell. These are variously called "analyst reports", "sell-side reports", or "equity research reports" and are often available, usually by subscription, from such sources as Thomson One (<http://www.thomsonone.com>). Also many market tracking platforms offer summary indications of analysts. For example, Bloomberg MNP[<https://www.bloomberg.com/>] IBM[*ANR*]], searched on 7April2018, reported 33 analyst recommendations ranging from Buy to Sell with intermediate codings as: Neutral, Hold and Overweight from houses such as: Goldman Sachs, J.P. Morgan, & Morgan Stanley.

Algorithmic MNPs offer trading e-programs that evaluate various suggestive screens and based upon frontier-benchmarks execute market-actions usually: Buy, Hold, or Sell as the market information is reported. An excellent summary of this class of MNP is found in Moldovan, Moca & Nitchi (2011). Interestingly, algorithmic trading is regulated by most exchanges as it can destabilize the market as many of these e-functionalities can be hyper-sensitive to directional volume changes and so create their own self-fulfilling prediction. An excellent document, that is a must read in any Market Trading Course, is offered by the NYSE:

> *Algos offered by third-party providers may provide a greater menu of trading strategies, provided that the provider enters into a connectivity agreement with the NYSE that includes an agreement to comply with NYSE rules and restrictions on specified trading activity. The third-party provider connectivity agreement is available here (Note 1).*

Our focus is NOT to test or collect information on the inter-class question: *Which of these four MNP-classes seems to be the best choice for engaging a comparatively high return?* Nor are we addressing an intra-class question: *For a given class of MNP which MNP or Grouping of MNPs are "best of the rest of their class"?* To be sure these are critically important questions and interestingly have not been comprehensively addressed to date—probably due to the enormous commitment of time to effect such a study! We are interested, as we have been in our other studies of the CCMNP, on the *per se* performance of the CCMNP and not in the relatively effectiveness of the CCMNP in comparison to the plethora of MNP currently commercially available.

2. Question of Interest: The Conceptual Setting of Our Investigation

What is a unifying variable that one may use to form an analysis of any of the types of MNPs? After we address this core question, we will offer a testing MNP methodology and then apply it to the CCMNP. Initially, however, it is important to address the *per se* utility of a MNP.

2.1 Are MNP Useful vis-a-vis Unaided Individual Prowess?

As a benchmark rationalization, an important question is:

> *What is the return performance of independent traders—that is, individuals acting without the aid of professional advisors or membership links to organizations that offer suggestive MNPs that justify traders eschewing other "safe" investments such as: (i) the wide range of T-Bills offered by the US Department of the Treasury, (ii) speculation in the precious metals markets, or (iii) highly-rated Bond offerings, usually AAA[S&P] or Aaa[Moodys].*

This question pre-conditions the analysis of MNPs because if independent traders are able to secure a "satisficing" return, then MNPs may not present an attractive economic choice and are more in the mode of "interesting market video-games". The research that addresses this question suggests that individuals, viewed in the aggregate, do not seem to outperform the vast array of MNP-alternatives. Specifically, Barber & Odean (2000) found that individuals were net-trading-return-losers on their Buy–Sell profile—to wit they were not skilled in detecting turning points or trajectory changes in the market profiles, target stocks, or portfolios. They seem to Sell on the eve of upturns and Buy on the eve of downturns; this is exactly the opposite of the Golden-Rule of Trading: *Buy Low & Sell High*! Following on this study, Korniotis & Kumera (2013) found for a relatively limited time period and at a time where market rationality was at issue, 1991 to 1996—i.e., the gestation of the dot.coms—that individuals who held trading accounts with |discount brokers were outperformed by the "wholesalers" holding trading accounts. They argue that this difference may be due to a differential in intelligent use of information relative to the future comparative market price trajectories. This is also implied by the Barber & Odean study. A final reference that focus on market sophistication and intelligent use of information screens and other variables is offered by Barber, Huang & Odean (2016) who find, not surprisingly, that intelligent use of market information is a key variable in successful investing.

In our study, therefore we will take it as given that MNP access is capable of providing intel, the nature of which, improves investment return decisions against an un/under informed individual.

2.2 Measures of Predicative Acuity

Accepting that MNPs justify their cost of engagement, we turn our attention to selecting a measure that has a logical rapport with the predicative acuity of a MNP. To recommend such a measure, we offer that the Screen Oriented & Suggestive MNPs, which we have classed above, provide a relevant insight. Both Screen Oriented and Suggestive MNPs create information that is profiled in the codex of their Market Screens to indicate or at least suggest that there is an "impending" change in the price-trajectory of the tracked stock. Using this common-sense measure, we offer that the most relevant, reliable, and independent—non-conditioned on the MNP Screen profiles—***is the trajectory of the stock as traded on the market***—i.e., valued at the bell-price.

This longitudinal tracking change is termed, in the relevant literature, as a ***Turning Point*** [TP]. The research on anticipating TPs in trading markets has occupied researchers since the inception of trading where value in exchange is one of the variable of interest. For example, the statistical modeling protocol developed by Bry & Boschan (1971) is one of the progenitors models focused on screening market activity to identity TPs and as such laid the statistical foundation for many of the subsequent programmed elaborations.

The theoretical—albeit logical—justification for using the TP in benchmarking the utility of a MNP is expressed succinctly by Nyberg (2013, p. 3352) who notes:

> *In general, the idea of classifying the state of the stock market into bear and bull markets is similar to identifying recession and expansion periods of real economic activity - - -. Measuring the state of the economy and understanding the transition between recessions and expansions has been a major topic in business cycle research for a long time. In principle, the methods that are used to determine the business cycle turning points can also be employed to find the stock market turning points.*

2.3 TP-Summary

The logical extension of Nyberg's advice is evident; if there is no functional or ordinal directional association between the MNP-Screen guidance information and the related market activity, then an inferential test for randomness will not be able to reject the Null—i.e., the MNP-Screens are able to provide Market-intel that outperformed random chance. In this context, we offer that a universally useful measure of a MNP is the prediction of [or sensitivity to] a ***turning point [TP] in the trajectory of a traded security.*** To the point:

If one finds after testing that there is NO relationship between the logical directional information of the MNP-Screens and the reality of the TPs in the market, then one may assume that the Screening information is not in-sync with the reality of the Market.

This will form the basis of our inferential test of the CCMNP. In the following sections of this research report, we will provide the context and, to be sure, the details needed to adequately evaluate the logic of our testing of the CCMNP all of which will provide the transparency needed to replicate the approach that we used and recommend.

3. The Evaluation of the CCMNP: Addressing the Detection of Turning Points

3.1 The CCMNP Context

We received the CapitalCube [CC] Market Navigation Platform [CCMNP] as a download from AnalytixInsight, Inc. [AI]. This CCMNP download included all the firms listed on the S&P500 as of 9 April 2015. The CCMNP longitudinal Panel starts on 2 Jan 2005; the last point was 20 March 2015; the data from inception to and including 2013 are monthly time series; starting in 2014 to the last data point in 2015 the time series is S&P500 values on trading days. For most of the firms there are 371 data Panel data points. We, the authors, together with Ms. Marjorie Churgin, Director of Development and Mr. Gautam Pasupuleti COO, both of AI & CC discussed over a few months questions of clarification regarding some of the variables of the CCMNP. This was a time to collect elaborations on the definitions offered by CC at: http://www.capitalcube.com/blog/index.php/glossary

The agreement with AI&CC was that we would not share this data with any others and there were to be no reporting restrictions placed upon us. CapitalCube was not given pre-draft publications and elected to not participate with us in any of the analyses. This is to say that this work is not conditioned by the reactions, opinions, advice, council, or feedback by AI or CC. In this sense this is our work as independent researchers. This was an academic analysis of the CCMNP—to wit: there are no monetary, in-kind, or *quid-pro-quo* compensation arrangements between us and AI&CC, nor do we have any financial interest of any type that would be a conflict of interest to our reporting of the analysis of the CCMNP. ***Caveat:*** As full disclosure, the authors do have free access to the WRDS™ platform of the

Wharton School of the University of Pennsylvania and to all of the resources that are part of the Lippincott Library of the Wharton School; some may view this as a conflict of interest.

3.2 Nexus of the research addressed to the CCMNP

Following we will:

1.) Discuss the context of this research report and our previous studies of the CCMNP,
2.) Propose and detail the TP-measure that we will use as the test of the CCMNP,
3.) Offer the protocols that we will use to test the market projections that we drew from the CCMNP,
4.) Summarize the results of the vetting of the CCMNP, offer caveats to our study, and
5.) Offer conjectures as to follow-up studies of MNPs.

4. Our Previous Studies and the Principal Variables of the CCMNP

4.1 Variables of the CCMNP

There are a number of variables that are part of the CCMNP that were used in our previous testing of the CCNMP. All of these variables are detailed on http://www.capitalcube.com/blog/index.php/glossary. For this reason, in the interest in the space constraints of the journal, we will only mention these variables and provide an overall summary of the results presented in our previous three studies.

4.1.1 Variables in the Real Domain Lusk & Halperin (2015) tested associational profiles of four of the major Market Navigation Interval Scaled Variables [MNISV]: *Current Price Level Annual [CPLA]*; *Scaled Earnings Score Average Latest [SESAL]*; *Previous Day Closing Price Latest [PDCPL]* & *CapitalCube Price Latest [CCPL]*. Also tested were context or possible benchmarking variable sets: [Fifty-Two Week Low]; [Fifty-Two Week High]; [Capital Cube Price Range Min] & [Capital Cube Price Range Max].

4.1.2 Market Performance Variables [MPV] and their Linguistic Qualifier[LQ] Screens Lusk & Halperin (2016) tested the associational profiles of the MPV with their LQs using information provided by experts who gave their assessment of the directional indications for the LQs. For example, one of the 12 MPVs is *Accounting Quality* for which there are four Linguistic variables: {*Aggressive Accounting[AA]*; *Conservative Accounting[CA]*; *Non-Cash Earnings[NCE]; Possible Sandbagging[PS]}*. The experts used by Lusk & Halperin (2016) judged that these four LQs suggest that *CA* & *PS* are indications of increases in the stock's future value; and *AA* & *NCE* would be indications of decreases in the stock's future value. Testing showed that there was non-random association in the expected direction for the 12 MPVs tested using the expert judgements of the LQs for each of the MPVs.

4.1.3 Integrated testing of the MPV[LQ]s over the MNISV. Lusk & Halperin (2017) tested the ensemble of the variables of the CCMNP and determined that there was non-random association of the profiles of the MPV[LQ] sets relative to the MNISV.

4.2 Overall Summary

For the Lusk & Halperin studies noted above, the overall take-away is that variables of the CCMNP tested are not produced individually or in conditioned composition by random generation processes. We offer that studies of this genre are necessary in any careful examination of the vetting of the predictive integrity.

4.3 Focus of the Research

In this paper, we take up the evaluation of the *reason d'être* of a MNP—to wit, the question of interest that will guide our research protocol is:

Does the past information set of the MNP panel provide specific insights into the future stock performance?

This is termed predictive validity. Although this seems a relatively clear evaluation criterion, there are many testing conditions that need to be considered to operationalize the testing of the predictive validity of a MNP. We will take up these operational issues following.

5. Market Navigation Platforms: An Enterprise of Magnitude

One is impressed with the variety of possibilities for collecting, forming screens and taking an action in the market trading world afforded by MNPs. Given the vast number of testing configurations of a MNP, we will endeavor to provide a simple but detailed protocol for testing the predictive acuity of the CCMNP. Following, we will articulate three principal components of the protocol that we will use to test the predictive validity of the CCMNP:

5.1 Component A the Essential Measure

Above we have arrived at the following nexus variable—The Turning Point of the Stock Trajectory[TP]. By this we mean:

> *The [TP] is a temporal-point in the historical market tracking of a particular stock where the tracking of the stock will dramatically change direction for a reasonable period of time.* Most simply stated:

A Turning Point is: The *Dramatic Change* in *Direction* of a *Time Series*.

5.2 Component B Dramatic Change in Direction

Next we need to operationalize the measure of: *Dramatic* relative to the tracking of a stock. In this regard, we need to have a variable that is NOT part of CCMNP but that is related to its predictive context. The actual values of the S&P500 are a perfect fit for this Benchmark. In this regard, we prefer the Chen and Chen (2016) modeling approach which is a coding protocol based upon pattern recognition that uses simple Excel functionalities in the VBA class as filters to create Screening profiles. Their innovative and intuitive approach seems, to us, preferable as such Intuitive-Screens are transparent and are formed along the cognitive plane of Human Information Processing [HIP] rather than "steeped in obscure assumptions which are often untested for applicability".

In this regard, referencing the work of Chen & Chen (2016) who focus on important turning points that they term: *Bullish turning points*, i.e., "enduring" upturns for some reasonable Panel segment in the longitude trajectory, we have selected a slightly simpler, but nonetheless programmable HIP-measure of a ***Dramatic Change***:

$$\text{Signed Relative Change [SRC]} = \frac{\left[\frac{\sum Y_{t+i}}{n} - Y_t\right]}{Y_t} \qquad \text{EQ1}$$

where: Y_t is the monthly average for the S&P500 at month (Note 2) t; the index of i ranges in units to 4, that is—four points in the Panel just ahead of the value at point: t & n=4.

To identify a *Dramatic Change* using the SRC of EQ1, we flag any monthly values for the S&P500 for which Abs[SRC] > 25%. We call these points: Reference Points [RP]; they are possible candidate TPs.

5.3 Component C The Focus of the Testing

As discussed above one may test individual stocks, size or value partitions of the Market, or portfolios of stocks as recommended by analysts. Further, one may identify stocks rated by a particular Screen, one may select sub-set of Screens for individual testing, or test select stocks for specific individual Screens. The testing possibilities are large, indeed vast.

In this regard, considering the nature of the variable sets previously tested from the CCMNP, we have made the following testing election. Our guiding principle, being attentive to the transparency of the Chen & Chen modeling perspective is: Keep It Simple [KIS]; not to the exclusion of logical market and trading relationships and certainly not eschewing the theoretical context established as background, but rather to most simply address the question: *How does the MNP fare in advising and informing investors on TP*? Specifically, for our HIP protocol there are seven phases in moving from the SRC information to a TP:

i.) *Component C1* Select individual stocks as the evaluation unit rather than a portfolio of stocks; this avoids selection bias in forming a representative portfolio over the entire Panel. See Hall (2014) & Mo & Qiao (2015).

ii.) *Component C2* Test simply the statistical separation of the market values around the proposed TP [See Chen & Chen (2016)],

iii.) *Component C3* Select all of the CCMNP screens for which there is previous vetting information reported over the Lusk & Halperin studies to avoid selection bias in the screening measures. See [North & Stevens (2015) who extended the work by Schadler & Cotton (2008)] ,

iv.) *Component C4* Select the entire S&P500-Panel as the temporal frame for the study to avoid selection bias in the accrual frame. See[Hall (2016)],

v.) *Component C5* Select a random sample of S&P500 stocks traded over the full Panel to avoid problems with survivor and selection bias as noted above. To be clear we will not attempt to select stratified samples from one of the many possible derivative partitions formed from the studies of Banz (1981) and Fama & French (1993), such as Small or Micro-CAP groupings.

vi.) *Component C6* Create a simple ordinal scoring measure for the selected set of MPV[LQ] using the results of Lusk & Halperin (2016). Also See Chen & Chen (2016), and

vii.) *Component C7* Benchmark the scoring measure of Component C6 to make the decision as to what is a likely final evaluation of the selected stock respecting the LQ-Codex compared to the reality of the actual S&P500-TP. In this case, we will use only three events for the comparisons: CCMNP suggested: Increasing Value, or Decreasing Value or No Expected Change compared to the S&P500 reality: Increasing Value, or Decreasing Value or No Expected Change in Value. This will create a 3×3 Fisher-Exact test classification tableau which will form our simple statistical testing frame.

In the following sections we will take this set of seven general aspects of the CCMNP testing protocol and provide the details needed to replicate our testing for most of the MNPs that are currently in the public domain; the simplest way to effect this communication is to form this information as part of an comprehensive illustration.

6. Integrated Illustrative Discussion of the Various Components

6.1 Illustrative Context

The screen for the SCR [EQ1] is a simple Smoothing filter in the Mean-Class. In this case, given the expected stochastic variation it is likely that the longer the filter the more flags will be created. This is just the reality of a smoothing filter. The question is: What is a reasonable value for n, the index value for i. To make a reasoned determination without biasing the selection by using the values of the CCMNP or those of the S&P500 Panel, we used the download of time-series values of the IIF[<https://forecasters.org/>] for the 181 series used in the groundbreaking forecasting study of Makridakis [1982]. We took a developmental sample of 37 series and employed the SCR screen for RP-values for n=: {2, 3, 4 & 5}. The greatest number of RP values identified, as expected, was for n=5 and the least was for n=2. We then took a holdback sample of 23 and found not different relative frequency results. Thus we aggregated the samples and using n=2 as the ratio-benchmark, the SRC filter ratio results flagged RP averages as follows: n=3 [The Standard Quarterly Sieve] gave as the Mean: [1.5]; n=4 [A Trimester Partition] gave as the Mean:[1.8]; and n=5 [An Asymmetric CY-Annual Sieve] gave as the Mean: [2.5]. As the smoothing screen results for n=3[Quarterly] and n=4[Trimester] are about the same, we used a blending criterion to decide between the two. Specifically, as there may be a Quarterly 10Q reporting and Market effect as documented by Hollie, Livnat & Segal (2005) that may be an artifact that acts to bias the creation of the flags, we prefer the trimester, n=4, that will, to some extent, blend-out this Quarterly-market effect.

Given this SCR calibration the best way to effectively communicate and elucidate the number of decision points that lead to the CCMNP testing profile is to illustrate them using an actual firm selected randomly from the CCMNP.

6.2 Illustration For Honeywell, Inc [Ticker:HON]

We downloaded the monthly S&P500 bell-closing prices from the WRDS™ dataset of CRSP prices from 1Feb2005 to 1Dec2013. For this stream of nine values, we applied the SRC as noted in EQ1:

59.62	**50.28**	**50.84**	**50.17**	**41.55**	**30.45**	**27.86**	**32.81**	**26.83**

Table 1 S&P500 values for HON: Point[41.55: Sept2008]

If we apply the SRC to this section starting at point 59.62 the following 9 SRC points are produced:

-0.1914*	**-0.1398**	**-0.2622**	**-0.3389**	**-0.2903**
-0.0529	0.0652	-0.0928	0.1520	

Table 2 S&P500 values for HON: SRC-Points from Table 1

*For example, -0.1914 = [Average[50.28, 50.84, 50.17, 41.55] − 59.62] / 59.62]

When the SRC-index moves to point 50.84 the SRC first flags a TP candidate and records as value of -0.2622; then as it moves along the Panel the points -0.3389 and -0.2903 are produced.

As these are the only TP candidate points identified in the S&P500 and they are contiguous, we selected the last RP in the series as the reference point [RP] which occurs at 41.55 that has an SRC of -0.2903. This selection was guided by a simple point selection rule: We selected the latest [most recent] RP in the contiguous turning point candidate stream as this would provide the least variance [most stable or robust] case in a back-cast; also, this point is most consistent with the HIP context as there are two RP flags that proceed the RP of 41.55 and thus act as reinforcement to the selected RP, 41.55 which then is the HIP-anchor value. This is the first screening phase where a RP has been identified. Before we label this RP as a TP we will test the statistical separation of the RP; this is the second phase of the testing of quality of the RP before we label it as a TP.

6.2.1 Testing the Separation Statistically The next test is to assess the quality of this RP of 41.55; bolded and shaded in Table 1. Before we examine the statistical separation around the RP we will verify the temporal quality of the association of the S&P500 with the CCMNP. The logic of this verification is simple: If there is an indication that the CCMNP is not temporally in sync with the S&P500 benchmark. Then we will not use this benchmark in evaluating the CCMNP. Recall that we [Lusk & Halperin (2015)] have previous tested overall temporal & intra-temporal association. This is now a further test of this temporal association. In this phase, we used the Pearson Correlation [PC] for the Panel segments to first determine the association of the S&P500 Panel segment with the PDCPL variable. Even though the PDCLP and the Month average of the S&P500 are not exactly the same [i.e., there is no isomorphic transformation that we could determine between the two], if they are not related there would be a logical jeopardy in using the related TP in the evaluation of the CCMNP. Specifically, we selected the time orientation of the RP and then indexed back nine (9) points and so select this time segment, n =10, of the S&P500 and the time matched time segment of the PDCPL. If the PC, n=10: [S&P500 w. PDCPL] is < 90% we will not use that RP as a candidate TP as there could likely be a miss-cue of the downloads as the S&P500 should logically be highly associated with the PDCPL. In the case of HON, the PC [S&P500 w. PDCPL] = 99.5% note that this is a strong test for allocation as it is > than 0.71 [(.5)^.5] the usual Harman[1960**]** eigenvalue frontier for factor group selection.

6.2.2 Statistical Separation Around the TP The next reasonability test is to examine the magnitude of the separation around the RP. In this regard, as argued above, we took the Trimester bland of four, n=4, monthly points around the RP and used the Excel Two-Sample test assuming unequal variance (Note 3) to determine significance of the Mean separation. If there were no evidence at a p-value < 0.05 that the Null could be rejected for this Mean separation then we rejected that RP as a possible turning point. Simply said this test is an indication of the mean separation around the RP of the two sub-Panel segments. If the Mean of the four observation pairs are relatively close this two-tailed p-value will be relatively higher than 0.05, and we would reject that RP as a “fair” test of a turning point. This testing protocol tactically gives a NO-Effect zone for the TP. This is an important zone as it separates positive TPs from negative TPs.

In the case of HON the two sets of four points around the RP of 41.55 tested to have a p-value of 0.0002 clearly rejecting the Null and suggesting likely important separation around the RP; further, as the points above 41.55 had a mean of 52.73 and the segment after the RP has a value of 29.49, the RP is a negative TP or consist with a Down-Turn in the tracking of the Panel values for HON. Note, if the positional orientation were to have been reversed the TP would have been positive in nature.

6.2.3 Summary: The Selection of the TP as a Benchmark

1.) We used EQ1 to screen the longitudinal panel to identify a SRC point that would qualify as a RP.
2.) Then we tested the PC association of a sub-panel of ten points [the last point being the RP]. Specifically, the PC of the matched CCMNP & S&P500 sub-panels is tested.
3.) Finally, we tested the magnitude of the Mean differential around the RP. If there was a Mean differential for which the two-tailed p-value, was > 0.05, we rejected this as a TP.

This then is the overview of the protocol for identifying a point in the S&P500 panel that we will use as a TP. Consider now the details of the full testing protocol that will use the CCMNP information variable set to evaluate this S&P500 benchmark TP as: {Positive, Negative or No-Decision}. In this section we will offer in detail, as did Chen & Chen (2016), the calibrations that are needed to form a simple and transparent evaluation protocol.

7. The CCMNP Testing Protocol Using the S&P500 Turning Point

To be very clear, the RP and related TP, *per se*, have derived association with a MNP. These are analytic creations, as detailed above, using the reported bell-prices reported by the S&P500 and summarized by WRDS[CRSP]. This is precisely why the S&P500 TP is an excellent benchmark for a MNP, as it is an independent measure of economic activity. Given that we now have this S&P500 TP-benchmark, the begged question is:

*Does the CCMNP provide information that permits the analyst to anticipate the change in the trajectory of the Market[*S&P500*] at the time point of the TP?*

To address this question, we examined the variables that are part of the CCMNP and make a selection of the variables to form a protocol to test the CCMNP’s acuity in identifying a TP.

7.1 Screens

The Linguistic Qualifier [LQ] Codex of the CCMNP Most all of the MNP that we have examined have linguistic labels that are generated as a summary communication measure. The reason for this is clear; the DM often needs to have a signal that is a communication rather than raw transformed data. If the MNP produces a mass of data with no related algorithmic or heuristic linguistic codex this is merely a data-capture data-base such as CRSP or COMPUSTAT. For the CCMNP Lusk & Halperin (2016, 2017) report that the linguistic codex of the CCMNP is a rich set of meaningful ordinal measures that are produced by the generating function or engine of the CCMNP. Its functionality, i.e., filtering data to form the linguistic codex, is the intellectual property of the CCMNP. For our purposes, rather than selecting a sub-set of the screens that were used by Lusk & Halperin (2016), we selected all 12 of their linguistic codes. These were tested by experts in Accounting and Finance and were found to be sensitive, specific and overall reasonable action codes. The rational for using all of the codes rather than a selected sub-set follows on the research of North & Stevens (2015) that reports that 30% of the Screens in that temporal environment were not individually effective; further Hall (2016) notes in an evaluation of 35 screens taken from DataStream™ that:

> *Unfortunately, it seems I was on to something, because as resources stocks have rebounded extremely strongly, many of the screens have indeed struggled to keep up with the indices from which they are compiled. The table includes all regular annually updated screens and excludes one-off thematic screens, the quarterly blue-chip momentum screen and five-year income screens.*

Let us now consider an elaboration of the relationship between the MPV and their particular unique LQ: MPV[LQ]. This illustrative discussion will aid in rationalizing the selection of our final inferential measure of the CCMNP's detection of a TP.

7.1.1 Accounting Quality As we will demonstrate, the CCMNP [LQ] of the MPVs are not constructed to offer directional queuing to guide the user to a {Buy, Hold or Sell} action. These CCMNP MPV[LQ]-codes are rather a suggestive context for a particular stock individually for that variable. That is to say there is NO "Super Summary" code that advises: {Buy, Hold, or Sell} or any of the intermediate nuance: such as Strong Buy. Given this, we elected to use the study results of Lusk & Halperin (2016) where a series of experts gave their reaction to the *directional implications of the linguistic codex*. For example, for the [MPV] *Accounting Quality*: There are four LQ variables: {*Aggressive Accounting*; *Conservative Accounting*; *Non-Cash Earnings; Possible Sandbagging*. The assignment of the normalized weights using the expert directional guidance reported by Lusk & Halperin (2016) was:

Aggressive Accounting was given (-1) as the 33.3% of the time the Expert Raters indicated that that Aggressive Accounting suggested a likely deterioration in the performance of the price of the stock.

Conservative Accounting was given (-1) as the 38.1% of the time the Expert Raters indicated that that Conservative Accounting suggested a likely enhancement in the performance of the price of the stock;

Non-Cash Earnings was given (-0.5) as the 16.7% of the time the Expert Raters indicated that that Non-Cash Earnings suggested a likely deterioration in the performance of the price of the stock,

Possible Sandbagging was given (+0.5) as the 11.9% of the time the Expert Raters indicated that that Possible Sandbagging suggested a likely enhancement in the performance of the price of the stock.

7.1.2 The CCMNP MPV[LQ] Codex The research report of Lusk & Halperin (2016) was used for all of the 12 MPV and their unique LQ; this resulted in the following scoring profile as presented in Table 3:

Linguistic Coding[LQ]	**Selected Market Performance Variables**
Strong Build-up[1.0]; Strong Drain[-1.0]; Modest Build-up[0.5]; Modest Drain[-0.5]	Management of Reserves
Conservative Accounting[1.0]; Aggressive Accounting[-1.0]; Non-Cash Earnings[-0.5]; Possible Sandbagging[0.5]	Accounting Quality
Leading[1.0]; Lagging[-1.0]; Rising[0.5]; Fading[-1.0]	Share Price Performance
Outperforming[1.0]; Challenged[-1.0]; [Harvesting[0.5]; [Turnaround[0.5]	Valuation Characteristics
Sustainable[1.0]; Eroding[-1.0]; Improving[0.5]; Questionable[-0.5]	Sustainability of Returns
Quick&Able[1.0]; Constrained[-1.0]; Some Capacity[0.5]; Limited Flexibility[-0.5]	Borrowing Capacity
Superior[1.0]; Substandard[-1.0]; Expected Decline[-0.5]; Strategic Play[0.5]	Growth Expectation
Leader[1.0]; Laggard[-1.0]; Earnings Focus[0.5]; Revenue Focus[-0.5]	Earnings Coverage
Supporting[1.0]; Milking the Business[-1.0]; Maintenance[0.5]; Betting on the Future[-0.5]	Capital Investment Strategy
Undervalued[1.0]; Overvalued[-1.0]; Neutral[0.5]	CCPL Upside Downside
Strong[1.0]; Weak[-1.0]; Moderate[0.5]	Dividend Coverage
P/B Above[1.0] P/B Below[-1.0]	Relative Evaluation

Table 3 Ordinal Coding of the 12 Linguistic dimensions of the MPV Selected for the Evaluation of the CCMNP

7.1.3 TP Measure Definition Using the coding schema scripted in Table 3 we then could compute a numeric value for each stock reported in the CCMNP. Specifically, the sample Panel segment as was used for the PC test, we selected for all of the 12 MPV, noted above, the ten (10) CCMNP LQ-codes recorded <u>from</u> the TP and indexed back nine months—i.e., ten (10) scripted realizations in total the last point of which being the TP. This created a data-capture for the 12 MPV and their LQ codex for the selected ten months that was a matrix of [10 ×12] [TenMonths x 12MPVs]. This matrix of 120 assigned values as parameterized from Table 3 is used to create the TP score for the selected stock.

7.2 HON Details

For example, for HON using SRC[EQ1] a RP at Sept 2008 was identified, which upon further testing (Note 4), was judged as a TP. Indexing back for 10 months, we arrived at Dec 2007. Next we used Table 3 to value this stock. As an illustration, consider the MPV:Share Price Performance. The CCMNP recorded occurrences for the ten months sub-Panel[Dec2007:Sept2008] as: *Leading* was noted twice: [Scored as 2], *Lagging* was noted once:[Scored as -1]; *Rising* was not recorded: [Scored as 0]; *Fading* was reported thrice: [Scored as -3]. The value thus given to the MPV: Share Price Performance: was: -2 = ([2] + [-1] + [0] + [-3]). This was done for all 12 MPVs and the final total using all of the 12 MPVs was: +31.5 as demonstrated in the following table:

For example, for HON the counts of the Linguistic that were formed by the CCMNP were:

Linguistic Coding	Market Performance Variables
Strong Build-up[5]; Strong Drain[0]; Modest Build-up[0]; Modest Drain[0]	**Management of Reserves** Score= 5
Conservative Accounting[0]; Aggressive Accounting[0]; Non-Cash Earnings[0]; Possible Sandbagging[0]	Accounting Quality Score= 0
Leading[2]; **Lagging[1]**; Rising[0]; **Fading[3]**	**Share Price Performance** Score= -2
Outperforming[0]; Challenged[0]; [Harvesting[0]; [Turnaround[0]	Valuation Characteristics Score= 0
Sustainable[0]; Eroding[0]; Improving[0]; Questionable[0]	Sustainability of Returns Score= 0
Quick&Able[9]; Constrained[0]; Some Capacity[0]; Limited Flexibility[0]	**Borrowing Capacity** Score= 9
Superior[0]; Substandard[0]; Expected Decline[0]; Strategic Play[0]	Growth Expectation Score= 0
Leader[0]; Laggard[0]; Earnings Focus[0]; Revenue Focus[0]	Earnings Coverage Score= 0
Supporting[0]; Milking the Business[0]; Maintenance[0]; Betting on the Future[0]	Capital Investment Strategy Score=0
Undervalued[1]; Overvalued[0]; **Neutral[9]**	**CCPL Upside Downside** Score=5.5
Strong[0]; Weak[0]; **Moderate[10]**	**Dividend Coverage** Score=5
P/B Above[9] P/B Below[0]	**Relative Evaluation** Score=9

Table 4 Ordinal Coding of the 12 Linguistic Dimensions as Parameterized

Note that not all the months were coded with a LQ. This is a very positive aspect of the CCMNP as there appears to be a frontier boundary to qualify recording a MPV[LQ] as opposed to always affixing a LQ to each MPV. This discretion gives more weight or meaning to the set of LQs.

7.3 Statistical Context

To give this signed accumulated numeric score a statistical framework, we decided to convert the accumulated total to a percentage on the possible highest score on a TP-analysis basis. As there are 12 MPVs this would then be 120 as the maximum score. In the case for HON, the percentage is: +26.25% [31.5/120]. To give a context to this percentage, we created a 95%CI to benchmark the accumulated percentage as different from the Null of No Effect; we constructed a Benchmarking interval around 5% as this seems a logical No-Effect zone and has a slightly greater precision than one closer to zero. Recall this is why we formed a Null space using the S&P500 for the two-sets of four points around the RP using the Mean test. This linguistic Null zone is: [1.1% to 8.9%]; as we are taking the absolute value of the score, we then are only interested if the score is outside the benchmark on the Right Hand Side [RHS]. We used this as the Null screen—to wit: If the ABS of the score for the firm at: Sept2008: TP is not outside the test CI on the RHS then there is NO signaled directional evidence of the TP and thus we record this as NO Effect—i.e., no evidence of a change in trajectory. If the value is larger than the RHS then we reject the Null of No-Effect as there is evidence that the score is an indication of the directional projection of the linguistic codex. In this case, for HON as the sign of the summed total is > 0 the CCMNP is signaling an Increase in the market price of the stock or a positive change in trajectory. If on the other hand, the sign of the sum where to have been negative, then the CCMNP signals a decrease in the stock price.

7.4 Summary

Therefore, using the CCMNP for HON the score is the sum of these 12MPV[LQ] scores: +31.5 [(5)-(2)+(9)+(5.5)+(5)+(9)]. This converted value +26.25% [31.5/120] is > than 8.9% and so the CCMNP suggests a Positive TP for HON after the TP. This is to say, overall the CCMNP linguistic codes were consistent with a positive or stock price growth scenario. ***However,*** the actual track of the HON as reported by the S&P500 using the bell-price was in fact to lose market value on a share basis. Specifically, referencing the numbers in Table 4 the Average of the four

S&P500 prices for HON above the RP was 52.7 and the Average of the four after the RP was 29.5 and this difference had a two-tailed p-value of <0.0002 suggesting a strong rejection of the Null of no difference. Therefore, for HON relative to this S&P500 TP at Sept:2008 the CCMNP offers incorrect information if one looks at the LQ-profile which suggests the stock price likely to increase in value which is contrary to the S&P500 benchmark reality. This is then the CCMNP TP acuity protocol as elucidated by the analysis of HON. With these calibration decisions and, restricting our analysis to the monthly reporting of the stock-trading valuations where there is a high degree of correspondence between the reported value of the S&P500 and the values reported by the CCMNP for the PDCPL, we now take up the evaluation of the CCMNP respecting the focus of this research report: The acuity of the prediction of the directional change as compared to the S&P500 benchmark using the TP as the benchmark

8. Evaluation of the CCMNP: Testing the Acuity of the Predictive Protocol

8.1 Sample Frame

As detailed above, as there is no clear or definitive classification of firms that may suggest a usual partition of the firm-set so as to have a cluster-sample profile or portfolio, we have decided to taken a random sample of 47 firms from the CCMNP. We arrived at a random sample of 47 as follows: We selected 47, as in a preliminary study of the average number of TPs per organization was 2.27. We intended to accrue about 100 sample points. Assuming that there would be two firms that would not provide useful data this would suggest that 45 [47-2] would provide about 100 sample points. This sample size was deemed to be adequate for a binary analysis which is the basic profiler for this vetting analysis. For example, a test-against for two events with a non-directional difference of 40% pegged at 50% with a Null benchmark of 10% gives Power of 93.1% for a sample split of 50%. Further, the FPE precision of a 95% confidence interval test for an expectation of chance is 9.8%. Both, the Power and the Precision, are consistent with a test that does not invite the FPE or incorrect rejection of the Null of NO-Effect and so is conservative in nature. The reality was that there was only one firm that dropped out of the accrual: Southwest Airlines [LUV]; for the 46 firms there were 103 sample points. Three of these firm sample points did not have a Pearson correlation of the [S&P500 w. PDCPL] and so were not used in the study. Overall for the 100 turning points the profile of the Correlation[S&P500 w. PDCPL] was: Range[93.0% to 99.9%]. This seems therefore a reasonable sample accrual profile.

8.2 Results Profile

The classification of the S&P500 as the state-of-nature-benchmark cross evaluated with the CCMNP scoring protocol as discussed above is presented in Table 5.

State of Nature	**CCScore: Increase**	**CCScore: Decrease**	**CCScore: No Decision+**
TP: S&P Up-Turn Track	Correct [30]	Error [1]	Error [9]
TP: S&P Down-Turn Track	Error [22]	Correct [2]	Error [10]
TP: S&P No Decision*	Error [22]	Error [0]	Correct [4]

Table 5 Profile of the CCMNP v. S&P500 Turning-Points, n =100

*****We recorded No Decision for the SRC if the p-value for the Mean-test of the two groups of the four points around the RP was not <0.25. +We recorded No Decision for the CC Linguistic analysis if the ABS of the LQ-Total was not greater than the Upper Limit of the 95% confidence interval for the Null-Zone.

8.3 Discussion

As an overall indication of the classification results consider the meaning of the cells in Table 5. The cell is the intersection of The S&P500 as the benchmark using the SCR [EQ1] and eventually coding the RP as a TP. Recall, after the PC screening, to further avoid any spurious flagging of RP as TP we used a Mean test of the SCR partitioning. In this context, anytime the Mean test had a p-value not <0.25, we coded this as a No Decision or No Effect. This is the ROW classification rationale where we have recorded the S&P500 indication as the *State of Nature*—this is our benchmark for the CCMNP. For example, there were 40 instances where the S&P500 protocol indicated that there would be an Up-turn. The Column coding then takes the LQ-profile of the 12 MPVs as presented in the CCMNP and applied the coding measures discussed above. The Column classification also make three decisions: The stock price is likely: To be Increasing, To be Decreasing, or There is No Decision. The intersection of a cell is the joint of the Row[S&P500] & Column[CCMNP] coding and so indicates the frequency [counts] of the number of times the

S&P500 TP coded benchmark & the CCMNP coding are in agreement. Only the main diagonal [Shaded] are where there is correct information of the CCMNP respecting the S&P500 benchmark. In this case, a simple overall measure is offered by the Pearson Chi2 inference statistic and the related Chi2 Cell classification value. For Table 5, the overall Chi2 has a Pearson p-value 0.47 [Fisher's Exact Test]; further there are no cells where the Chi2 cell contribution is >1.0 which is a usual boundary cut-point for important cells profiles that do not follow the marginals. See: Tamhane & Dunlop (2000, p.324). In this case, the overall analysis suggests that there is no relationship between the two classifications models that is divergent from the marginal expectations. This means that S&P500 TP-Benchmarks are not detected by the CCMNP when one accounts for the probability projections given the Row & Column marginals.

This statistical analysis mirrors the common sense of the information in the Classification Table 5. For example, consider the number of times that the TPs indicated a downturn in the S&P500 price tracking of a stock. There were 34 instances where the S&P500 analysis identified an impending downturn after the TP. Given this benchmark, the CCMNP profile was:

Correctly detected the Impending Downturn: 5.9% [2/34]

Failed to Correctly Classify the Impending Downturn: 94.1% [32/34]

Both 5.9% & 94.1% are outside the 95% test Confidence Interval around chance indicating that the CCMNP classifications did not calibrate to be in sync with S&P500 TPs.

Further, if we take the incidence as the S&P500 distribution of Increases, Decreases and No Decision, we have:

Increase 40% [40/100], Decrease 34% [34/100], and No Decision 26% [26/100].

For the CCMNP the classification we find:

Increase 74%[74/100], Decrease 3%,[3/100] and No Decision 23% [23/100].

The z-calculated values for the individual percentage comparisons are:

Classification of Increasing: S&P500 [40%] v. CCMNP [74%]; z-cal = 6.8

Classification of Decreasing: S&P500 [34%] v. CCMNP [3%]; z-cal = 6.2

Classification of No Directional indications: S&P500 [26%] v. CCMNP [23%]; z-cal = 0.6

If we compare this to the 95% standard cut-off of 1.96 there is clear evidence that there is a difference in the two classification systems [S&P500 & CCMNP] regarding the tracking of either an Increasing trajectory or a Decreasing trajectory after the TP. This is another way of profiling the information in the classification Table 5 where we found that the Pearson Chi2 was > than 0.05. The only case where they are In-sync is regarding the No Decision category.

8.4 Summary of Results

The CCMNP has a bias in making a classification—more often than not, the CCMNP suggests an ***Increase*** or ***Up-Turn*** in the S&P500 trajectory after the TP. Usually~~,~~ this is an error. Relative to the actual percentage of time, according to the S&P500 protocol there were 40 instances of an increasing trajectory after the TP, however, the CCMNP makes an increasing classification of 74 instances. This is a relative error compared to the benchmark of: 85% [[74 – 40] / 40]. This means that ***if the* S&P500 *was the correct or the actual state of nature***, then individuals using the CCMNP calibrated, as we suggested, will incorrectly assume 85% of the time that an increase is in the offing. If they were to act on this—i.e., ***Buy*** the stock—then the economic impact would likely to be a loss in portfolio market capitalization. This is opposed to the other case where investors fail to take advantage of a possible ***Buy*** indication due to an erroneous decrease indication. This is rarely the case as only in one case was the CCMNP indication a Decrease when the S&P500 indicated an Increase. *Overall summary: There is more than a reasonable possibility that the CCMNP is not likely to inform the stock selection decision.* This study and these results offer some directions for future research addressed to the evaluation of MNPs. Following, we provide a set of caveats that are needed as context of our results; further, we will offer a discussion of future studies that are begged by our results.

9. Summary, Caveats, & Outlook

9.1 Summary

The analysis that we conducted used the Market Navigation Platform that we received from the CapitalCube, LLP. [CCMNP]. The focus of our analysis was to evaluate the predictive acuity of the CCMNP. In this regard, we elected to use the conceptual framework offered by Chen & Chen (2016) that used a simple and transparent montage focused on the Turning Point [TP]; in our case, TPs of the monthly S&P500 time series were used. The idea is simple: If the codex used to scale the linguistic qualifiers that are part of the CCMNP *just before the TP* suggests an up-turn [or a downturn] in the S&P500, then there is predictive value in the information base of the CCMNP. In testing a random sample of firms traded over the S&P500 panel, we found that there is no statistically significant evidence that the CCMNP, as configured around the TPs, allows the detection of TPs. Rather, there is evidence that the linguistic codex produced by the CCMNP is biased to suggest up-turns.

9.2 Caveats

Does this mean that the CCMNP is wrong or misinforms investors? No, not necessarily! Recall, the S&P500-TP benchmark is based upon a series of calculations. The benchmark derived from the S&P500—i.e., the TP—is profiled effectively as a change in trajectory over two four-month time segments in the panel on either side of the TP. Only when these two averages are very different does the RP achieve the label of TP. Possibly, this is too short a sub-panel partition comparison. Maybe after the fourth point of the TP, the S&P500 re-tracks in the direction suggested by the sub-set above the TP. In this case, had we used this longer panel-segment there likely would not have been a RP/TP flag. *We did not investigate this possibility*. Also, perhaps using a parametric statistical measure to compute the p-value vetting is overly sensitive—i.e., too powerful. If we used a longer sub-panel and a non-parametric or a distribution free statistical test, usually less powerful, then possibly there would have been fewer RP/TP-flags generated. *This also was not tested.* Further, the directional designation ascribed to the CCMNP is formed by a ten-month Panel back-indexing from the TP. *Perhaps this is too long or too short*. Further, the scoring derived from Lusk & Halperin (2016) is very basic almost binary—i.e., perhaps naïve; possibly there needs to be a more sophisticated calibration that creates more ordinal differentiations and/or calibrations of the scoring metric. *This was not done.* Such a recalibration is likely to be needed, as over the Panel tested, the four MPV: {*CPLA: SESAL: PDCPL* & *CCPL*} exhibit high R^2 association with the S&P500 and also are sometimes highly co-associated in a Pearson sense and so often do not form a fully differentiated factor space. Finally, the Panel used was the monthly reported S&P500 values and so the values captured by the CCMNP are effectively a smoothed dataset relative to the dynamic movement of the stock clock-traded values, or day closing-bell prices or, for that matter, weekly values. Therefore, perhaps important detection information was lost due to using monthly smoothed values of the S&P500 data stream. Over a long Panel stream of trading reported by: minutes, days or weeks there may have been more detection acuity. However, for our study the concern with using a finer-mesh than monthly in the time series context is that: *The error to signal ratio is relative high and so there needs to be a very long data steam to ferret out the functional-signal which will likely traverse many Event spaces.* An alternative to this is to use error detection models [in the error to signal context] and employ error corrections filters that may not require such long time series as they are using designed error filters. In this regard, we recommend the research report of Guo (2017). This Error-Filtering direction could be a promising approach as our report has identified a possible error-filter that could be employed in that the TPs are directionally biased and so using this as a Bayes Qualifier may offer a design enablement. *We did not create this information in our study.* Our results ONLY mean that if one accepts all the many decisions made relative to the calibration of the S&P500 TP-benchmark, and the directional implications drawn from the CCMNP, then these results are possibly meaningful.

9.3 Outlook

In the CCMNP protocol that we used for testing, we selected ALL of the Screens and formed a scoring model, that while it was based upon expert guidance regarding to the linguistic nature of the screen, was, nonetheless, a derived coding modality. Further, we used all the stocks to form the random sample. Alternative testing protocols, to further investigate the CCMNP, are to: (1) use the MPVs to create projection or forecasts that may be used to condition the directional profiles, (2) test the acuity of individual Screens focused on Event Screens, such as before or after an Event such as the Lehman Bros Sub-Price debacle. See McDonald & Robinson (2009) , (3) test partitions of the firm-set: a logical choice being a comparison between the Large Cap, Small Cap & Micro Cap as was done and is reported on the AAII Investor Stock Pro platform, or (4) to opt for another modeling approach such as suggested by Guo (2017). These studies are needed to form a more comprehensive assessment of the CCMNP.

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Appendix

Table A Selected Firms from the CCMNP, n=47

AME	**BA**	**CAT**	**CHRW**	**CMI**	**CSX**	**CTAS**	**DNB**	**DOV**	**EFX**
ETN	EXPD	FDX	FLR	FLS	GD	GE	GWW	HON	IR
ITW	KSU	LLL	**LUV***	MAS	MCO	MMM	NOC	NSC	PBI
PCAR	PH	PWR	R	RHI	ROP	RSG	RTN	SNA	SRC
SWK	TXT	UNP	UPS	URI	UTX	WM			

*LUV [Southwest Airlines] was not used in the analysis of the CCMNP due to the failure of the Correlation screening check.

Notes

Note 1. https://www.nyse.com/publicdocs/nyse/markets/nyse/NYSEM_Algo_Routing_Access_Agreement_Form.pdf

Note 2. We took our measures from the WRDS™ platform referencing the CRSP™ Dataset.

Note 3. We used this test as from time to time there seemed to be an indication of unequal variance identified using the Welsh test as programmed in JMP™v.13 of the SAS™ Institute.

Note 4. Specifically, the p-value of statistical separation around the RP was <0.0002 and the qualifying correlation [S&P500 w. PDCPL] was: 0.995 which, was then the test information that was needed to label the RP a TP at Sept[2008].