A Linguistic Examination of the CapitalCube™ Market Effect Variables

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Abstract

Introduction: Linguistic variables and the nuanced market information they afford are critical to the efficient and effective functioning of market trading platforms. In this research, we report on our investigation of the Linguistic Variables of the CapitalCube™ market navigation platform [CCMNP]. **Study Précis**: The focus of the study is to determine if there is directional meaning: {*Neutral*: *Unfavorable*: *Favorable*} implied by the unique Linguistic Qualifiers [LQ] attached to each set of Market Performance Variables [MPV] of the CCMNP. To this end, we collected these directional indications and linkages from a sample of Experts and also Informed & Trained Students. **Results**: We found that: (i) there was a high degree of agreement between the two rating groups respecting these directional indications for the LQ over the MPV, (ii) these directional rating results were differentiable from a random assignment, and (iii) there was general agreement relative to the directional indications respecting an *a priori* scoring given by two other experts. **Impact**: The LQ tested for the selected MPV of the CCMNP exhibited directional relevance, sensitivity, and specificity and therefore seem to be an intelligent set of linguistic descriptors enhancing the navigation acuity of the CapitalCube™ market navigation platform.

Keywords: Content Analysis, Directional Linguistic Acuity, Market Codex

1. Introduction: Setting the Analytic Context for the Linguistic Vetting of the CapitalCube™ Market Navigation Platform

1.1 Previous Research Summary [Lusk & Halperin (2015)]

In our first paper, for the S&P500 panel expressed in the CCMNP[http://www.capitalcube.com/] we examined the following eight variables which are principally involved in the CapitalCube platform:

Using the ***context variable*** pairings:

1. [Fifty-Two Week Low] & [Fifty-Two Week High];
2. [Capital Cube Price Range Min] & [Capital Cube Price Range Max],

we eliminated only 1% of the firms in the S&P500 Panel because they failed to exhibit rational measured-value patterns for these CapitalCube context parings. The fact that only 1% of the firms in the S&P500 Panel were screened as non-compliant outliers on the two CapitalCube context variable sets is strong evidence that these context variables are dynamically in-sync with the empirical profile as we know it for the tracking of the S&P500 over the accrual period.

Using the variables (Note 1):

V1: *Current Price Level Annual* [CPLA]

V2: *Scaled Earnings Score Average Latest* [SESAL]

V3: *Previous Day Closing Price Latest* [PDCPL]

V4: *CapitalCube Price Latest* [CCPL]

and hypothesis-driven factor screens, we examined the reasonability of these four variables as expressed through the S&P500 Panel. As we rejected the Nulls of the expectations formed for the three empirical validation hypotheses in support of the factor profiling hypotheses, there is strong evidence for support of the expected structural nature of {V1, V2, V3 & V4} in that they behave in an expected manner given the usual AR & Fixed-Effects character of a Panel of Traded Firms.

One may reject, with a high degree of assurance, the random or chance generating process as the driver of these eight variables in that they behave as one would expect for a Panel of Traded Firms. **Implication:** ***The CapitalCube variable set, herein examined, is structurally in-sync with the expected market generating process(es) and therefore, in this sense, the CapitalCube variable set represents variables from which longitudinal market performance information can likely be gleaned.***

With this research result as the basis, we will now consider the various market performance category variables and their related event descriptors offered in the navigation panoply of the CCMNP.

2. Linguistic Coding: The GPS for Effective Inference from the CCMNP

2.1 Linguistic Indexing

Cross-disciplinary studies focused on finance-related topics have become extremely popular in recent years. Using marketing models to study financial services industry (Riasi, 2015), applying data mining techniques to financial problems (Ansari & Riasi, 2016), and using behavioral concepts to study financial market trends are examples of cross-disciplinary studies focusing on finance-related topics. The current cross-disciplinary research uses linguistic variables and financial information.

A linguistic codex is a way that humans arrive at an action. Indeed, "branch-and-bound-linguistic platforms" are the processing facility that defines *Watson*™: the *IBM*™ computer that is the current reining *Jeopardy*™ champion defeating Ken Jennings and Brad Rutter in a "Men vs. Machine" two day face-off where the prize contested was one million dollars. According to McCord, Murdock & Boguraev (2012, *slightly paraphrased*) the central functionalities of *Watson* are:

> Two deep parsing components, an English Slot Grammar (ESG) parser and a predicate-argument structure (PAS) builder, that provide the core linguistic analyses of both the questions and the text content used by IBM Watson**™** to find and hypothesize answers. Specifically, these components are fundamental in question analysis, candidate generation, and analysis of passage evidence.

It is the case, that *Watson*, owing to the miraculous programmed linguistic codex, understands how to address the question:

"*I know what you said, but what did you mean?*"

The necessity of linguistic mapping derives from the need that we have, in communication, to *convert* ***data signals*** [*I know what you said.*] to ***inferential information*** [*I know what you mean!*]. Such linguistic inference is the way that decision-makers [DM] arrive at and rationalize an action plan. This is particularly critical in the Big Data market-trading world where terabytes of streaming data are readily click-able. In the Big Data milieu, Market Analytic platforms, such as the CapitalCube platform are intermediate interactive dynamic symbol or labeling "machines". They are parameterized by experts to serve as dynamic expert surrogates. Their linguistic codex becomes critical whenever the Expert Decision Support System [EDSS] is a decision-making enhancement or even a servo-decision-maker such as day-trading "real-time" stock trading models. Both domains employ linguistic conditioning. In the case of day trading models, the linguistic codes will work in the same manner as enablers of *Watson*. For example, Hufford (2015) notes that:

> Algorithms can help traders follow hundreds of stocks instead of just a handful. Strategies can be complex, taking into account breaking news and social media for instance, but they can also be pegged to more traditional price moves.

Most EDSS in the market-trading world are richly endowed with linguistic markers designed to inform the decision-making process. A simple illustrative example is the prevailing stock action linguistic codex for the eight inference categories for CAPM-regression β: {*Hedge-β*; *Market Detachment-β*, *Low Association-β*; *Suggestive Association-β*; *Ideal-β*, *Market-β*; *Volatility Growth-β*; & *Roller-Coaster-β*} offered by Lusk, Heilig & Halperin (2013). This β-lexicon is created from an analysis of β for a population-size sample of firms traded on the NYSE, NASDAQ & WorldScope™. For example, the β range starts at [-1 to -.025] and so traded securities in this β-range are given the linguistic-label of: *Hedge-β* as these firms move in the opposite direction to the benchmark market index. The *Market-β* is suggested as the linguistic code for firms whose β is in the range [0.95 to 1.05] where the Stock and the Index are moving in-sync. Therefore, rather than considering only a β-value the DM can also reference the β-linguistic codex for the range within which is the firm-β to form an action plan.

2.2 The Content Context

The theoretical basis for imputing reliable decision-making intel from a linguistic codex, such as the CAPM-regression β-codex, is offered by the paradigm of: *Content Analysis*. *Content Analysis* is a class of methods and protocols of abstracting *Meaning* from data-signals where the data-signals are *Words or Word-packages*. In the Market Trading milieu *Content Analytic* models have proven to be consistent and reliable in ferreting out *Meaning* from *Text* pertaining to the market traded firms. For example, analysts, using *Context Analytic* protocols, have been able to analyze specific linguistic descriptors found in: (i) the 10-k MD&A*[7 & 7a sections]*, (ii) press releases issued by management, (iii) the annual report, and (iv) CEO letters appended to the annual report to enrich their understanding of what the ***Words*** as signals ***Imply*** relative to the firm. Indeed, the linguistic codex of screening models such as Diction™ and LIWC™ have been used in forensic screening[fraud and/or accounting irregularities] to identify firms that would likely necessitate SEC re-filings and/or re-statements. For an excellent historical perspective on the versatile *Content Analysis* paradigm see: Sydserff & Weetman (2002) and Churyk, Lee & Clinton (2009) who report on *Content Analysis* from the early 1990s to just before the enactment of Sarbanse-Oxley:2002 [SOX] and Lee, Lusk & Halperin (2014) and Wisniewskia & Yekini (2015) for about ten years after SOX.

Relying on the power, logic, and reliability of linguistic coding we will introduce three directional Linguistic Qualifiers[LQ]: {*Neutral*: *Unfavorable*: *Favorable*} to examine the CapitalCube MPV and their LQ as they pertain to market traded organizations. This information will be offered as the logical vetting of the various market performance category variables [MPV] and their related linguistic-event descriptors [LQ] as nuanced by these directional indications: {*Neutral*: *Unfavorable*: *Favorable*}. As was the case in the vetting of the context and decision-making variables reported by Lusk & Halperin (2015), the inferential testing of the market performance variables and their unique codex is addressed to the inferential Null of no association. In this case, if we determine that the linguistic codex is relatively random, or linguistically inconstant, or is restricted to a small idiosyncratic linguistic "carve-out", then this will call into question the utility of the CapitalCube variable set and the related Linguistic Codex; i.e., we will not be able to reject the Null of no association.

2.3 Précis of the Research Report

We will now:

1.) ***Preview*** selected market performance variables [MPV] which are categorical in nature from the CCMNP and present their scripted linguistic qualifiers [LQ],

2.) Using the three LQ directional indicators: {*Neutral*: *Unfavorable*: *Favorable*} ***present and evaluate independent expert scoring*** of the various LQ relative to these directional indicators for the selected MPV set,

3.) ***Evaluate the consistency*** of the directional LQ-mapping profile of a sample of Experts compared to that of Informed & Trained Students.

4.) Test these LQ-directional indications compared to a ***Random assignment***.

5.) ***Compare*** the Expert and Student Group scoring to an *a priori* agreement-profile

3. The Selected Set of Market Performance Measures & Their Linguistic Qualifiers

We received from AnalytixInsight on 9April2015 a Panel-download of the CapitalCube variable set encoded in the S&P500 from 2005 to and including 2015. This Panel offered 20 Market Performance Variables [MPV] each of which has a unique set of Linguistic Qualifiers [LQ]. These LQ are meant to capture the inferential content of "most of the market action" for these MPVs without trying to be an exhaustive set which would likely create too many parsed-differentiations. The spirit of MPV[LQ] pairings seems to be one of reasoned parsimony; or the "*80/20 Rule*" in action: where 80 percent of the activity is captured by 20 percent of the possible linguistic event qualifiers. Some of these MPV were not sufficiently populated over the S&P500 Panel relative to their LQ to include them in the analysis. Specifically: we eliminated, for reasons of lack of inferential power, the following MPV: *Operating Model* [71%]; *Drivers of Margin* [75%]; *Dividend Quality Trend* [88%]; *Dividend Action I* [81%]; *Dividend Action II* [85%] & *Equity Action* [96%]: where, the percentages in brackets are the missing data percentages. The other 14 Performance categories had LQs that were sufficiently populated to form an inferential base to evaluate the sensitivity and specificity of the triage of the LQs relative to a random categorical assignment. To set the analytic context, consider the following comprehensive illustration.

3.1 Illustration of the nature of the decision context using the CCMNP

In Figure 1 is the scripting of the lattice screening system for the MPV: *Borrowing Capacity* & its unique LQ [**Constrained; Limited Flexibility; Quick & Able; Some Capacity**].

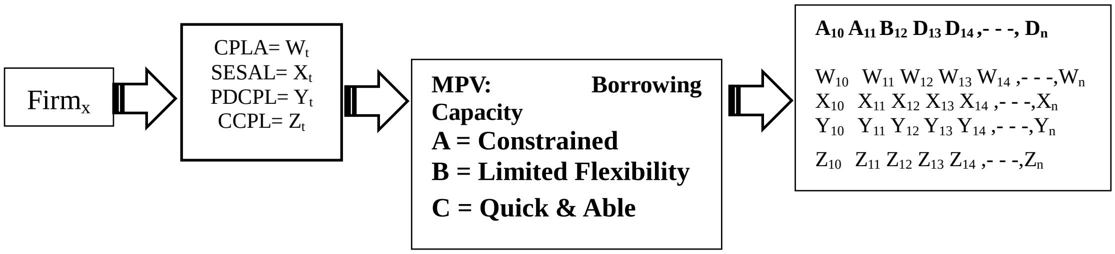

Figure 1. CapitalCube Screening Logistical Tracking Lattice

At time t_{10}, the CapitalCube heuristic fixed for the MPV: ***Borrowing Capacity*** a Linguistic Qualifier: **A=Constrained**; further, at t_{10} the four Decision-making variables expressed the following measured values:

{CPLA[W_{10}]; SESAL[X_{10}]; PDCPL[Y_{10}] & CCPL[Z_{10}]}

Then the $Firm_x$ is tracked over time; at time t_{12} the Linguistic Qualifier changes to **B=*Limited Flexibility*** for which the Decision-making variables had the following value set:

{CPLA[W_{12}]; SESAL[X_{12}]; PDCPL[Y_{12}] & CCPL[Z_{12}]}

The critical issue that we will address is: Whether there can be inferential directional meaning ***implied*** by the various CapitalCube LQ. For our research purposes, we have created three directional inference categories, detailed following:

{***Neutral***: Indicating that the LQ for the MPV for the Firm in question is ***by itself*** at ***this time*** not a positive or a negative sign for the market performance of the Firm at the time when CapitalCube fixed the particular LQ for the MPV.}

{***Unfavorable***: Indicating that the LQ for the MPV for the Firm in question is a negative sign for the market performance of the Firm at the time when CapitalCube fixed the particular LQ for the MPV.}

{***Favorable***: Indicating that the LQ for the MPV for the Firm in question is a positive sign for the market performance of the Firm at the time when CapitalCube fixed the particular LQ for the MPV.}

As an elaboration, *IF we knew* that at t_{10} the LQ: ***Constrained*** for the MPV: **Borrowing Capacity** generally is viewed by experts in evaluating the market performance of a Firm as a ***negative indication*** this would be valuable linguistic information. The DM could ***THEN*** form an interval scaling DSS for **Borrowing Capacity** using the DMV: {CPLA[W_{10}]; SESAL[X_{10}]; PDCPL[Y_{10}] & CCPL[Z_{10}]} to nuance the global linguistic nature of ***Constrained***. Clearly this would be an obvious direction to develop a market navigation Decision Support System [DSS] that used the CapitalCube streaming-feed and three directional indications to refine, in a content analysis sense, the DM understanding of the CapitalCube signal-set.

A critical pre-condition to the functioning of such a DSS is to form and validate the directional acuity of the linguistic context for the various LQ sets. Then one can further develop and so nuance the MPV profile. This is the focus of this research. ***Specifically, using our three directional inference categories, we will enhance the contextual content of the various LQ as nuanced temporal indications for the particular MPV under examination.*** To create this critical information, we have collected from two groups directional rating indications for the LQ for the selected MPV.

3.2 The Expert and Trained Student Rating Groups

As we are interested: (i) in the directional meaning of the CapitalCube Linguistic Qualifiers, (ii) if the meaning is shared, and (iii) if the scored meaning is different from a random assignment, we conducted the following experiment:

1. We created an Excel workbook with 13 MPV that were extensively populated in the CapitalCube download each of which had its unique LQ-set. We randomly ordered these MPV in the first worksheet. Additionally,

to avoid the conditioning-or anchoring-effect of the respondents respecting the LQ, we randomly presented the various intra-MPV LQ choices.

2. On the second page/Tab, we included the link to the CapitalCube glossary http://www.capitalcube.com/blog/index.php/glossary/. This enabled access to each of the 13 MPV.
3. The instructions, here paraphrased, were: *Highlight in **GREEN,** the choice that seems to indicate the **MOST Positive/Desirable/Strongest** indication of a Firm's stock performance relative to the Linguistic Qualifier for the particular MPV. In **RED,** highlight the choice that seems to indicate the **LEAST Positive/Desirable/Strongest** indication of a Firm's stock performance relative to the Linguistic Qualifier for the particular MPV. Also, IF you do not have an opinion **or** the particular Linguistic Qualifier for the particular MPV is not clear as a positive or a negative indication, then do not score/highlight that Linguistic Qualifier for the particular MPV and so leave it as it is—un-highlighted.*
4. The set of experts was selected from among our colleagues both in the USA and in Europe. Fourteen experts were invited and twelve completed the survey. [See acknowledgments for the list of respondents.]
5. The second was a group of students that we had in the terminal/Cap-stone course in the accounting program at SUNY:Plattsburgh. All the respondents were seniors. They were given a quiz grade credit for completing the exercise. [About 1% of the final grade]. About 50% of the students completed the exercise. All of the students were Accounting majors, all had statistical training, and all had training in Finance as it is a core requirement.

4. Selected CapitalCube Market Performance Variables for the Experimental Testing

4.1 Presentation Plan

Following, we will present, alphabetically, the 13 MPV that were given to the Expert, n_e=12 and Trained Student, n_s = 32 groups (Note 2). Each will be briefly detailed from information taken from the CapitalCube link mentioned above. Then we will present a table where the Experts' proportions for {*Neutral*: *Unfavorable*: *Favorable*} are noted as NE, UE, or FE. The same notation is given for the Trained Students [NS, US, or FS]. These percentages, of course, must add to 100% by respondent group. Also we have bolded these instances where there was a statistically significant separation between the two groups for a LQ respecting a particular MPV. In this regard, we used a two-tailed test for 95% confidence between the profile of the Experts and that of the Students. Additionally, we have shaded the cells which had on average the largest proportional weighting for the LQ. This is an indication of consensus as we are focusing on the average that both groups had for the particular variables under analysis. This shading will be a valuable indication of the strength of the linguistic coding. For example, if there were to be a high degree of confusion then one would expect that on average the scores would be equi-probable or a third for each. The shading will be an excellent indication of the ***concurrent or shared communication*** for the linguistic context. Finally, the corresponding author and a colleague scored for each of the variables the LQ that we felt "clearly" indicated a positive or negative signal. If there was any disagreement then we eliminated that scoring indication. The positive indications are noted in the profile tables as (+) affixed to the LQ; negative indications are noted as (–).

4.2 A Priori Expectations

To test inferentially:

H1: Shared Meaning Hypothesis: Dual-Conditioned

Condition A: We expect that there will be very few instances where the rating profile difference between the Experts & the Trained Student Groups will have a two-tailed test of proportion difference that will rationalize rejecting the Null of no difference at the 95% level of confidence. Specifically, we set this test expectation at 10%. This conditional inferential test is: ***If the percentage of time that the comparative profile Null is rejected is greater than the upper limit of the 95% CI for the 10% expectation, then the hypothesis of general agreement will be rejected.***

Condition B: We expect that the highest rated average scores for the LQ relative to the indications: {*Neutral*: *Unfavorable*: *Favorable*} ratings will be greater than 50%. Specifically, for this second conditional test ***we expect 50% to not be greater than the lower limit of the 95% Confidence interval for the highest average of the profiles of the Experts & the Trained Student Groups over the various LQ for all of the MPV.***

Discussion: It is necessary to offer a duel-conditioned inferential test as the profile of no-difference *while it does suggest general agreement* could also obtain if all the judgments were random. Therefore, it is needed to test Condition A and then, respecting Condition B, to examine the magnitude of the average comparative profiles. If the highest average profiles dominate the sample space then this will indicate that there is likely a lack of disagreement.

In this case then Condition A is the *sensitivity test* and Condition B is the *specificity test*. For example, Condition A: for the MPV: **Accounting Quality** for the LQ: ***Conservative Accounting*** [CA] there is NO inferential difference between the Experts who 92% of the time rated CA as a favorable indication compared to the students who 81% of the time rated this LQ as favorable. Condition B: the average rating was 86.5% different from 50% clearly indicating that both groups agreed on ***Conservative Accounting*** as a positive indication and which is also different from the *Neutral* or the *Unfavorable* option.

H2:The Agreement compared to a Random Assignment: If there were to be random assignment of the {*Neutral: Unfavorable: Favorable*} indications over the various LQ then the expectation would be thirds over the three groups. Interestingly, this would also be the aggregated expectation for the design that we have used. Therefore, a creative way to test for the difference between a Random assignment and the results of our design will be to test the parametric variance Null of a random assignment relative to our design. The rejection of this Null will reinforce the specificity result. In this case, we will use the usual two-sample tests of the Null for the variances: [O'Brien[.5](1979) a constructed variable approach using correlations; Brown-Forsythe(1974) a Median form test & Levene (1960) OLS:ANOVA form test (SASJMP, v.12). ***The operational hypothesis is that our experiential situation will have higher variance than a random assignment.*** This will be tested by using all of the group mean profiles over the 13 MPV for the particular LQs.

H3: The Agreement with the author Scored Positive and Negative Indications:

Based upon a dual agreement protocol, we have scored the particular LQs relative to the expected indications: *Favorable* and *Unfavorable*. For the 49 LQ possibilities over the 13 MPV, there were 19 indications from the corresponding author and 21 from the invited colleague rater. The overlap or agreement was for 18 LQ: Nine (9) *Favorable* and Nine (9) *Unfavorable* indications. These are noted with a superscript (+) or (–). We will mark a success if the largest average score is located in the *a-priori* identified category. ***The inference test will be the Bernoulli p-value for a test against random chance and also the Counting combinatorics ratio.***

5. The Scoring Profiles for the Market Performance Variables

Following we will present the various MPV as scored-profile tables. These are presented alphabetically and for each we will indicate the percentage profile for the Expert and the Trained Student Groups for the three directional research indications: {*Neutral*: *Unfavorable: Favorable*}. These are noted as: {EN & SN}; {EU & SU} and {EF & SF} over the various LQs for each of the MPV. Further, for each of the profiles where there is a statistically significant difference between the two rating groups for each of the directional research indications we will **bold** those profiles. Additionally, we will shade the cell's profile grouping for each LQ that has the highest average profile rating for the two scoring groups. Finally, at the left boarder of the Tables we will indicate if the LQ suggests a Positive (+) or Negative (–) indication.

MPV1: Accounting Quality [**AQ**][Assesses possible overstatement or understatement of Net Income]

Linguistic Codex: [L1:*AA,* L2*:CA,* L3*:PS &* L4*:N-CE*]

L1:A*ggressive* ***A****ccounting****[AA]***: [Company's net income margin is higher than peer median while the percentage of accruals is lower than peer median. Usually indicative of a company with an aggressive accounting policy.]

L2:C*onservative* ***A****ccounting****[CA]***: [Company's net income margin and percentage of accruals are both higher than peer median. Usually indicative of a company with 'understated' income because of a conservative accounting policy.]

L3:P*ossible* ***S****andbagging*:[***PS***] [Company's net income margin is lower than peer median while percentage of accruals is higher than the median. Usually indicative of a Company with 'understated' income because of a conservative accruals policy.]

L4:N*on-****C****ash* ***E****arnings****[N-CE]*** [Company's net income margin and percentage of accruals are both lower than peer median. Usually indicative of a company with an aggressive accruals policy that could have contributed to the declared net income number.]

Table 1. Scoring of **MPV1: Accounting Quality[AQ]**

AQ	NE	NS	UE	US	FE	FS
L1	42%	38%	58%	53%	0%	9%
L2[+]	8%	16%	0%	3%	92%	81%
L3	67%	50%	25%	34%	8%	16%
L4	75%	53%	17%	38%	8%	9%

Inferential Difference 0% [0/12]

To elaborate and so illustrate the important information that is encapsulated in these scoring group comparisons, we will detail the inferential basis of the comparisons. Consider, for L1 which is ***Aggressive Accounting***. For the Expert group there were 5 of the 12 experts that indicated that they believed this to be neither a positive or negative aspect ***in and of itself*** and so they rated this as Neutral. For the Trained Student Group there were 12 among the 32 that scored L1 as Neutral. The two-tailed p-value for this comparison Experts vs. Trained Student Group is:

$$z_{calc} = 0.2509 = Abs\left[\left(\frac{5}{12}\right) - (\frac{12}{32})\right] / [(0.007324 + 0.020255)\hat{}.5]$$

We have used the two-tailed 95% confidence level as the divergence indicator between the two comparison groups. As this L1 comparison is not greater than 1.96, the L1: Expert [42%] vs. Trained Students [38%] profile is <u>not</u> bolded. Also the shading indicates the cell grouping for each of the LQ with the highest average profile. Finally, L2: ***Conservative Accounting*** was agreed upon as a Positive indicator wherein a (+) is affixed to L2. We wish to note that in addition to this information there is a wealth of codex impact information in these Linguistic Comparison tables. For example, rarely did the Experts or the Trained Students feel that L1: ***Aggressive Accounting*** would be a favorable indication of the performance of a traded organization. Whereas L2: Conservative Accounting is overwhelmingly viewed as a positive indication of the firm's performance profile as indicated by the scoring: Experts [92%] and Trained Students [81%]. Finally, the consensus was that L3: Possible Sandbagging and L4: Non-Cash Earnings in and of themselves are mostly *Neutral* indications and so suggesting that these LQ are in need of additional context.

MPV2: Borrowing Capacity[BC] [Measures the company's financial and operating capacity to borrow by comparing its leverage (using Debt/Enterprise Value) and Liquidity (using EBIT/Interest Expense)]

Linguistic Codex [**L1:*Constrained*; L2:*Limited Flexibility***; L3:*SC* & L4;*Q&A*]

L3*:Some Capacity[**SC**]*: [Companies that have some debt capacity based on interest coverage greater than a 2.5x threshold, even though D/EV exceeds a 25 % threshold, suggesting there is some additional borrowing capacity available.]

L4*:Quick & Able[**Q&A**]*: [Companies that have significant debt capacity with D/EV less than a 25% threshold and interest coverage greater than a 2.5x threshold, suggests ability to increase debt leverage.]

Table 2. Scoring of **MPV2: Borrowing Capacity[BC]**

BC	NE	NS	UE	US	FE	FS
L1[−]	25%	9%	75%	91%	0%	0%
L2	83%	72%	17%	28%	0%	0%
L3	83%	69%	8%	3%	8%	28%
L4[+]	0%	9%	8%	0%	92%	91%

Inferential Difference 0% [0/12]

MPV3: Capital Investing Strategy[CIS] [Company's level of re-investment (3-year change in capital) into supporting its sustained operating returns (3-year ROIC), relative to peers.]

Linguistic Codex [L1:*BoF*; L2:*MM*; **L3:*Milking the Business*** & L4:*SG*]

L1*:Betting On Future[**BoF**]* [Companies where 3-year change in capital is above, but sustained operating returns (3-year average ROIC) is below the peers, suggesting they are possibly overinvesting for future returns.]

L2:*Maintenance Mode[**MM**]*: Companies where 3 year change in capital and sustained operating returns (3-year average ROIC) are both below the peer median, suggesting minimal reinvestment in a [glossary_exclude]problematic[/glossary_exclude] business.

L4:*Supporting Growth[**SG**]*: Companies where 3 year changes in capital and sustained operating returns (3-year average ROIC) are both above the peer median, suggesting that they are properly reinvesting in a strong performing business.

Table 3. Scoring of **MPV3: Capital Investing Strategy[CIS]**

CIS	NE	NS	UE	US	FE	FS
L1	75%	53%	17%	25%	8%	22%
L2	58%	47%	33%	50%	8%	3%
L3	50%	38%	42%	56%	8%	6%
L4$^+$	17%	19%	0%	6%	83%	75%

Inferential Difference 0% [0/12]

MPV4: Dividend Coverage[DC] [The extent to which the company's ending cash balance covers the dividend paid in the last twelve months.]

Linguistic Codex: [**L1:*Moderate*, L2:*Weak*** & L3:*S*]

L3:*Strong[**S**]* The ending cash is greater than or equal to 3x the cash dividend paid in the last twelve months.

Table 4. Scoring of **MPV4: Dividend Coverage[DC]**

DC	NE	NS	UE	US	FE	FS
L1	92%	91%	8%	0%	0%	9%
L2$^-$	25%	3%	75%	91%	0%	6%
L3$^+$	17%	3%	8%	6%	75%	91%

Inferential Difference 0% [0/9]

MPV5: Dividend Quality[DQ] [Dividend quality is assessed by the cash flow coverage of the dividend paid.]

Linguistic Codex: [L1:*MQ*, L2:*HQ* & L3:*LQ*]

L1:*Medium Quality[**MQ**]* [Dividends needs the support of: Net Issuance Cash InFlow & Net Share buyback]

L2:*High Quality[**HQ**]* [Dividend is covered by Operating Plus Investing Cash Flow less (Net debt repayment & Net decrease in deposits (for banks)],

L3:*Low Quality[**LQ**]* [Dividend also uses the Beginning Cash Balance + Net Share buyback.

Table 5. Scoring of **MPV5: Dividend Quality[DQ]**

DQ	NE	NS	UE	US	FE	FS
L1	75%	78%	8%	0%	17%	22%
L2$^+$	**0%**	**16%**	17%	6%	83%	78%
L3$^-$	17%	6%	83%	88%	0%	6%

Inferential Difference 11% [1/9]

MVP6: Earnings Leverage[EL] [Measures a company's revenue and net income growth performance over the past one year relative to peers.]

Linguistic Codex: [L1:*EF;* **L2*:Laggard;* L3*:Leader*;** L4:*RF*]

L1:*Earnings Focus[**EF**]*: Companies where the yearly revenue growth is below peer median while net income growth is above peer median suggesting that the company is focused on earnings.

L4:Revenue Focus[***RF***]: Companies where the yearly revenue growth is above peer median while net income growth is below peer median suggesting that the company is focused on revenues.

Table 6. Scoring of **MVP6: Earnings Leverage[EL]**

EL	NE	NS	UE	US	FE	FS
L1	58%	63%	8%	13%	33%	25%
L2⁻	25%	3%	75%	97%	0%	0%
L3	50%	28%	0%	0%	50%	72%
L4	67%	66%	8%	0%	25%	34%

Inferential Difference 0% [0/12]

MPV7: Growth Expectations[GE] [Company's relative earnings growth trend (3-year revenue growth) compared to Market expectations for long term growth (P/E).]

Linguistic Codex: [**L1*:Expected Decline;*** **L2*:Superior****;* L3*:SP &* **L4*:Substandard***]

L3*:Strategic Play[**SP**]*: [Companies that exhibit expected earnings growth (P/E) that is above peer median, but historical revenue growth (over 3 years) that is below peer median, indicative of a startup or anticipated strategic play.]

Table 7. Scoring of **MPV7: Growth Expectations[GE]**

GE	NE	NS	UE	US	FE	FS
L1	58%	38%	33%	50%	8%	13%
L2⁺	25%	19%	0%	3%	75%	78%
L3	75%	63%	8%	0%	17%	38%
L4	25%	31%	67%	63%	8%	6%

Inferential Difference 0% [0/12]

MPV8: M&A Action[M&A] [Possible Acquirer or Target based on comparative attributes.]

Linguistic Codex: [**L1:*Acquirer* & L2:*Target***]

Table 8. Scoring of **MPV8: M&A Action[M&A]**

M&A	NE	NS	UE	US	FE	FS
L1⁺	17%	19%	25%	13%	58%	69%
L2⁻	8%	16%	58%	66%	33%	19%

Inferential Difference 0% [0/6]

MPV9: Management of Reserves [MoR] [Impact of accruals on the buildup or draining of Reserves.]

Linguistic Codex [L1:*MBUp*; L2:*MD*; **L3:*Strong Drain* & L4:*Strong Buildup***]

L1*:*ModestBuild-Up* ***[MBUp[]***: Company's percentage of accruals is above zero but lower than peer median — usually indicative of a company building its reserves in a modest manner relative to peers.

L2*:ModestDrain [**MD**]*: Company's percentage of accruals is below zero but higher than peer median — usually indicative of a company draining its reserves in a modest manner relative to peers.

Table 9. Scoring of **MPV9: Management of Reserves [MoR]**

MoR	NE	NS	UE	US	FE	FS
L1	58%	69%	8%	0%	33%	31%
L2	67%	84%	8%	16%	**25%**	**0%**
L3	**42%**	**9%**	58%	88%	0%	3%
L4	33%	25%	25%	9%	42%	66%

Inferential Difference 17% [2/12]

MPV10: Relative Performance Evaluation [RPE] [Implied price is calculated using industry standard relative valuation metrics. These metrics are also available in the peer analysis tab. Based on this we can comment on whether a company is Undervalued or Overvalued relative to its peers. We look at price volatility along with standard deviations of the implied price to come with our bands around the implied price.]

Linguistic Codex [**L1:** ***P/B: Above Peers*** **& L2:** ***P/B Below Peers*** where: P/B: Previous day's closing market cap divided by shareholder equity.] Expected Positive Indications 50%.

Table 10. Scoring of **MPV10: Relative Performance Evaluation [RPE]**

RPE	NE	NS	UE	US	FE	FS
L1⁻	0%	0%	**25%**	**0%**	**75%**	**100%**
L2⁺	0%	3%	75%	97%	**25%**	**0%**

Inferential Difference 50% [3/6]

MPV11: **Share Price Performance [SPP]** [The share price return (%) over the previous 12 months vs. the share price return (%) over the previous 30 days.]

Linguistic Codex [L1:*F*; **L2:*Lagging*; L3:***L* **& L4:*Rising***]

L1:*Fading* Share***[F]*** price performance that outperformed the peer median over the previous 12 months but lagged the peer median over the last 30 days.

L3:*Leading[**L**]* Share price performance that outperformed the peer median on both the previous 12 months and latest 30-day timeframes.

Table 11. Scoring of **MPV11**: **Share Price Performance [SPP]**

SPP	NE	NS	UE	US	FE	FS
L1	42%	34%	58%	56%	0%	9%
L2	50%	31%	**25%**	**69%**	**25%**	**0%**
L3	42%	16%	17%	0%	**42%**	**84%**
L4	58%	53%	0%	6%	42%	41%

Inferential Difference 25% [3/12]

MPV12: **Sustainability of Returns** [**SoR**][Company's ability to sustain its return on assets relative to the peer median not only over the last year but also over the last 5 years (on average). For financials and insurance companies, we use return on equity.]

Linguistic Codex [**L1:Eroding; L2:Improving;** L3:S **& L4:Questionable**]

L3:*Sustainable* [***S***] Company's ability to sustain its return on assets relative to the peer median not only over the last year but also over the last 5 years (on average). For financials and insurance companies, we use return on equity.

Table 12. Scoring of **MPV12**: **Sustainability of Returns** [**SoR**]

SoR	NE	NS	UE	US	FE	FS
L1⁻	42%	19%	50%	78%	8%	3%
L2	**83%**	**53%**	8%	3%	**8%**	**44%**
L3⁺	8%	28%	0%	0%	92%	72%
L4	50%	53%	50%	47%	0%	0%

Inferential Difference 17% [2/12]

MPV13: **Valuation Characteristics** [**VC**] *Linguistic Codex* [L1:*C*; L2:*H*; L3:*T* & L4:*O*]

L1:*Challanged [C]* Companies with lower Operating Advantages (ROE) and lower Growth Advantages (P/E) usually suggests [glossary_exclude]problematic[/glossary_exclude] current operating results coupled with limited long-term opportunities, so they are "Challenged" in performance and growth.

L2:*Harvesting [H]* Companies with higher Operating Advantages (ROE) but lower Growth Advantages (P/E) usually suggests a focus on current operating results at the expense of long-term opportunities, so they are "Harvesting" out profits.

L3*:TurnAround* ***[T]*** Companies with lower operating advantage (ROE) coupled with [glossary_exclude]superior[/glossary_exclude] growth advantages (P/E), suggest that an upturn in performance is expected by the market. Companies in startup mode typically

L4*:Outperforming* ***[O]*** Companies with higher Operating Advantages (ROE) and higher Growth Advantages (P/E) than its peers. This is usually indicative of a company that can continue to "Outperform" its peers in terms of operating performance and expected growth.

Table 13. Scoring of **MPV13**: **Valuation Characteristics** [**VC**]

VC	NE	NS	UE	US	FE	FS
L1	33%	6%	67%	78%	**0%**	**16%**
L2^{-}	83%	66%	0%	9%	17%	25%
L3	83%	81%	8%	9%	8%	9%
L4	33%	13%	0%	9%	67%	78%

Inferential Difference 8% [1/12]

6. Summary of Hypotheses Tests

6.1 Inferential Results

Now that we have presented the various profiles for the MPV as scored by the Expert and Trained Student Groups, we will summarize these results for the three *a priori* hypotheses:

H1: Shared Meaning Hypothesis: Dual-Conditioned

Condition A: If the percentage of time that the profile Null is rejected is outside the upper limit of the 95% for the 10% expectation, then the hypothesis of general agreement will be rejected. Results: There were 12 instances where the Null of no difference was rejected; these are bolded in the profile tables.

Condition B: We expect 50% to not be greater than the lower limit of the 95% Confidence interval for the average of the highest profiles of the Experts & the Trained Student Groups over the various LQ for all of the MPV.

Results: For Condition A in the sensitivity direction there were 138 points of comparison between the Experts and the Trained Students: [9×12 + 2×9 + 2×6]. There were 12 instances, **or 8.7%** where the two-tailed z-calculated was > 1.96 rationalizing rejecting the Null of no difference in the profiles. The upper limit of the relevant 95% confidence interval was 14.2%; as 8.7% is lower than this upper-limit this provides support for the first conditional test that there is shared meaning. For Condition B, in the specificity direction, the 95% directional left hand side for the average of the profiles was 67.8%. Our test expectation was 50% which is excluded on the left hand side providing support for Condition B that there is general agreement of a large magnitude. In summary, there is support that the Expert and Trained student Groups focused their profiles suggesting that there was shared meaning in the sensitivity and specificity directions.

H2: The Agreement compared to a Random Assignment: The operational hypothesis is that our experimental situation will have higher profile variance than a random assignment. This will be tested by using all of the group-mean profiles over the 13 MPV for the particular LQs. *Results:* In this instance, for the experimental design [ED] the variance for the scored profiles relative to the average which is expected to be on the order of one third for the 276 profiles [138×2] was: Mean[0.33];varED[0.089]. For the un-constrained random assignment [RAN] for the set {*Neutral*: *Unfavorable*: *Favorable*} where the expectation for the average will be <u>also</u> one-third, the profile was: Mean[0.33]; varRAN[0.012]. The ratio varED/varRAN was: 7.4; using the three relatively different tests for testing variances relative to the Null: [O'Brien[.5]; Brown & Forsythe; and Levene all had p-values <0.0001 clearly supporting that there were non-random foci in the profiles.

H3: The Agreement with the Author/Colleague Scored Positive and Negative Indications:

The last inferential test is that of the agreement of the focus of the different profiles for the *Unfavorable* and *Favorable* scoring. *Results* In this counting test: for 17 of the 18 cases scored, as noted above, there was agreement. The Bernoulli combinatorial counting probability for this was <0.0001 [[18C0 + 18C1]/ $\sum_0^{18} 18Ci$] also the 95% one-sided CI for the results was 85.5% for the realization of 94.4% [17/18] exhibiting a very high degree of selected agreement.

6.2 Extended Presentation Summary

In summary, there is clear evidence that most often there was shared meaning between the Experts and the Trained Student Group demonstrating the quality of the acuity of the CapitalCube linguistic codex. Additionally, the scored profiles were focused and when tested for a spectral separation relative to an agreement scoring there was a high degree of focus in the differentiated linguistic space. This testing then rationalizes incorporating into a navigational DSS these directional profiles{*Neutral*: *Unfavorable*: *Favorable*} to nuance the market impact signals that may be gleaned from these 13 MPV profiles. For example, as the frame for a DSS consider that a DM is interested in a particular firm over the time periods: {t_{14}, t_{16}, t_{18} & t_{20}}. The DM collects from the CCMNP the following longitudinal indications for $Firm_y$:

Table 14. Longitudinal & Cross-sectional Informational Performance Profile: $Firm_y$

MPV	T_{14}	T_{16}	T_{18}	T_{20}	**Modal**	**Assessment Profile**	**Action**
13VC:	***L3:TurnArou***	*L3:TurnArou*	*L2:Harvestin*	*L3:TurnArou*	*L3:TurnArou*	Neutral	*H*
9MoR	***L2:StromgDr***	*L3:ModestDra*	*L3:ModestD*	*L3:ModestD*	*L3:ModestD*	Neutral	*H*
2BC:	***L1:Constrain***	*L2:SomeCapa*	*L1:Constrai*	*L1:Constrai*	*L1:Constrai*	Unfav	*WS*
1AQ:	***L1:AggAcctg***	***L3:PossS-Bag***	***L4:N-CashE***	***L4:N-CashE***	***L4:N-CashE***	Neutral	*H*
Modal	*UnFav*	*Neutral*	*Neutral*	*Neutral*	*Neutral*	**N&N**	**H**

For example, at T_{16} the CapitalCube navigation platform for the MPV; ***Accounting Quality*[*AQ*]** has selected from the LQ menu: [L1:***CA***; L2:*AA*; L3:*PSB* & L4:*N-CE*]→ L3:***Possible Sandbagging***. From our results we can NOW attach inferential meaning to L3:***Possible Sandbagging***; specifically in the OPINION of the ratings reported above: L3:***Possible Sandbagging*** is a *Neutral* indication—that is not *Unfavorable* or not *Favorable*. Therefore, our research results add inferential directional information to these longitudinal CapitalCube indications. Also, note should be taken that there is important information at each cross-section {t_{14}, t_{16}, t_{18} & t_{20}} for this Panel. In this regard, we recommend spacing out the measurement points to every two or three periods. Adjacent contiguous measurements may not allow sufficient time for structural changes in the economic context. Indeed, there is not high category volatility in the CapitalCube panel. This is consistent with the reality of most changes in the economic fortunes of organizations; it would be a questionable indication for a market trading platform if there were *too much* or *too little* category volatility. We recommend that both the cross-section indications as well as their longitudinal tracking be examined. In this instance, let us examine the various indications and their directional information. At t_{14} the CapitalCube indications, **bolded**, are: {[**VC**:*Turn Around*]; [**MoR**:*Strong Drain*]; [**BC**:*Constrained*] & [**AQ**:*Aggressive Accounting*]} from our research results we may now attach the following matched directional profile: {*Neutral*; *Unfavorable*, *Unfavorable*, & *Unfavorable*}. The Modal cross-sectional indication at t_{14} is: ***Unfavorable***. Also the DM can track $Firm_y$ for a particular LQ. If we select **AQ** then for the Panel we have, **bolded**: AQ: {t_{14}: Aggressive Accounting; t_{16}: Possible Sandbagging; t_{18}: Non-Cash Earnings; t_{20}:Non-Cash Earnings} for which our research results indicate: {*Unfavorable; Neutral*; *Neutral & Neutral*}. The Modal longitudinal indication for AQ is: ***Unfavorable***. If we summarize all of these Cross-sectional and longitudinal indications and take the overall Modal indication we arrive at Neutral & Neutral or **N&N**. Finally, we wish to introduce a summary linguistic measure called Stock Action Alert [SAA] which has the following ordered event space:

{*Strong Sell*[SS]; *Weak Sell*[WS]; *Hold/Wait&See*[H]; *Weak Buy*[WB] & *Strong Buy*[SB]}.

This proposed SAA codex can further be used to inform the decision-making process. One may suppose for $Firm_y$ as profiled by CapitalCube and ***according to the above scoring indications*** that $Firm_y$ profiles as: *Hold/Wait&See*[H]. We wish to draw attention to the fact that this SAA codex has not been formally vetted; the SAA, however, will be developed and tested in subsequent investigations of the CCMNP.

7. Summary, Conclusion, & Outlook

7.1 Summary

The three research hypotheses have been inferentially supported indicating that:

H1: The CapitalCube linguistic qualifiers [LQ] over the MPV seem to impart the same meaning over a range of expertise and experience as the Expert and the Trained Students Groups were in high agreement as to the directional inactions: {*Neutral*: *Unfavorable*: *Favorable*} of these LQ over the 13 selected MPV.

H2: These LQ profiles, in general, were differentiable from a random assignment indicating that not only was there general agreement but also focus.

H3: For the *Favorable* and *Unfavorable* labels given there was general agreement as 94% of the time the focus of the profiles were in agreement with the *a priori* context given.

These test results rationalize enhancing the linguistic context of the CapitalCube navigation platform to include these directional indications that we introduced in the experimental design.

7.2 Conclusion

With such an enhancement in the linguistic context it seems that there would be valuable inferential directional information from the cross-section and longitudinal tracking of the selected MPV for specific firms as was detailed in the discussion of Table 14: Longitudinal Informational Performance Profile.

7.3 Outlook

Given these directional category indications {*Neutral*: *Unfavorable*: *Favorable*}, we suggest that the next logical step in the development of inference intel to inform the decision-making process is to examine the relationship of the CapitalCube Decision-Making Variables [DMV] as they relate to the MPV and their unique LQ as now nuanced as to their directional impact. Specifically, a tracking DSS such as the Longitudinal Informational Performance Profile can also use the DMV:

$$\{CPLA[W_t];\ SESAL[X_t];\ PDCPL[Y_t]\ \&\ CCPL[Z_t];\ \mathbf{t = 1,- - -, n}\}$$

to create a summary linguistic marker set [SAA]. We will address this natural extension subsequently.

This will likely provide further differentiation or transitivity links for testing the projective acuity of the CapitalCube navigation platform relative to the SAA-set at least into the short run which seems to be the projection horizon of most forecasting models. See for example the recent work of Adya and Lusk (2016). Testing the projective validity of the CCMNP is, in fact, the final research initiative supported by these penultimate studies that are needed as the pre-condition vetting of the various properties of the CapitalCube platform to support the validity of the projective testing.

Another recommendation, certainly begged by the above results, is to form the results of this study into a Decision Support System that can be used to form a Longitudinal & Cross-sectional Informational Performance Profile. The idea is: The DM selects the MPVs that pertain to the engaged analysis; for each MPV there will be a unique set of LQ and their directional context that we have encapsulated in the various tables above. Given these linkages then using simple LOOKUP Excel links or VBA/Modular enhancement to create information sets as to the cross-section, longitudinal, and summary or Modal indications: {*Neutral*: *Unfavorable*: *Favorable*} & SAA.

Finally, there were a number of important CapitalCube MPV that we were not able to use due to a relative dearth of sample points. In the future, as more of these MPV are measured and reported by CapitalCube the linguistic space can be expanded using the modeling protocol that is reported in this paper.

7.4 Time Context: Short or Long-Term?

In continuing to research CCMNP testing of the projection horizon should be undertaken. There seems to be two contexts in the forecasting literature that are relevant: *The Short-Run* or *The Long-Run*. The Short-Run suggested by the "usual going concern concept" that is the prevailing AICPA[GAAS], SEC, and PCAOB context relative to the certification audit where *Going Concern* suggests that the projective time-frame is the next operating year. This is also consistent with the early forecasting studies of Makridakis et al. (1980) and Collopy & Armstrong (1992) and the recent work of Adya & Lusk (2016) all of whom reported accuracy measures for one period-ahead projections. An alternative perspective is the: "*Regression to the Mean*" context which is a longer run perspective where major changes can often be expected. For example, in the Short-Run MPV Positive indications seem to be correlated or enduring in the Short-Run as the economic context is usually driven by Fixed Effects, see Lusk & Halperin (2016) and ARIMA process dominated by AR factors. However, in the *Regression to the Mean* context often the MPV-directional profiles seem to change in a Polar sense or from *Worst* to *First* or vis-versa. This seems to be due to the rapidity of technological innovations where market leaders succumb to the "outmoded tech-syndrome" where new enterprises with the latest tech-profiles are able to gain relative advantages precipitating market leaders "slipping" over time. Recall the Take-Off of the Japanese Auto industry and the demise of the US-Auto Juggernaut in the late 1960s. Therefore in calibrating the linguistic meaning and related market performance impact of the information presented above one should investigate if there is a short-run profile change over the long-run for particular firms or classes of firms.

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Notes

Note 1. Lusk & Halperin (2015) detail these decision-making variables as:

1. *Current Price Level Annual* [CPLA]; This is a ratio formed as the bell-price on a particular day as benchmarked by the Range of previous trading-day values going back one year in time. As such, basically the range of CPLA is [0 to 1].
2. *Scaled Earnings Score Average Latest* [SESAL]: This starts with the reported earnings of the firm and uses 50 or so calibration variables such as *Working Capital*; *Earnings Growth* & *Revenue Growth* to create an aggregate rolling benchmark that scales the reported earnings most always in the Range [1 to 100].
3. *Previous Day Closing Price Latest* [PDCPL]: Is the bell-price as adjusted for Stock splits and any sort of Stock spin-offs going back a number of years. The distribution of PDCPL resembling a Poisson pdf starting in the positive quadrant to the right of zero and tailing off into the low thousands.
4. *CapitalCube Price Latest* [CCPL]: This is a projective rolling variable—i.e., longitudinal—adjusted for Split/Spins, and benchmarked by a large number of market performance measures. The CCPL is projective in nature and used, for example, to index the *Under-and Over-Priced* labeling. The CCPL index-labeling employs a sensitivity analysis using a range around the mid-point of measured values of CCPL extending out to Min and Max boundaries. The CCPL indexing seems to be in nature the same performance indexing as one finds for the Tukey Box-Plot in SAS™ for outlier identification. The CCPL resembles a Poisson pdf starting in the positive quadrant to the right of zero and tailing off into the low thousands.

Note 2. There were 14 MPV. We help back Share Price Performance which had three LQ: {Neutral; Overvalued; Undervalued}. In a subsequent study we will use this summary indication to create a DSS lattice with the {Strong Sell, Sell; Hold; But; Strong Buy} }one which we considered to be a summary measure that we will use in forming the GPS:DSS