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Surfing the *Index of Consumer Sentiment*: Identifying Statistically Significant Monthly and Yearly Changes

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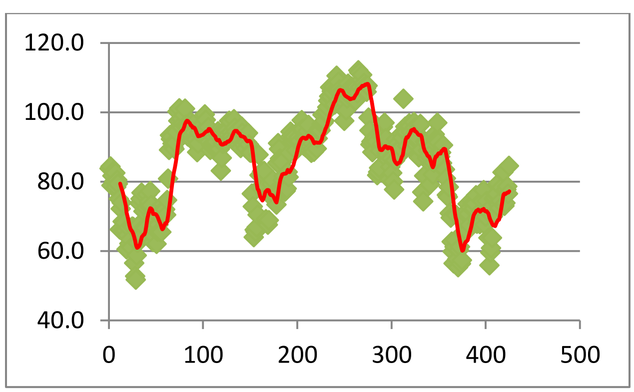
Published monthly by the Survey Research Center of the University of Michigan, the Index of Consumer Sentiment (ICS) is widely followed, and one of its factors (the Index of Consumer Expectations) is used in the Leading Indicator Composite Index published by the US Department of Commerce, Bureau of Economic Analysis.[1] Using household telephone interviews the ICS provides an empirical measure of near-term consumer attitudes on business climate, and personal finance and spending.[2] Variation in ICS influences price and volume in currency, bond, and equity markets in the US and in markets globally.[3] The practice of releasing monthly ICS values five minutes to two seconds earlier for elite customers via high-speed communication channels was recently suspended because it provided unfair trading advantages. This article investigates the trajectory of the ICS over the most recent three-years, evaluating the statistical significance of month-over-month and year-over-year changes. These analyses define a longitudinal series of class variables which may be modeled temporally using time-lagged single- (UniODA) and multiple- (CTA) attribute ODA methods.

Figure 1 is an illustration of the raw ICS series since inception January 1, 1978, through May 1, 2013 (a total of 425 sequential months). The one-year moving average, shown in red, has been beneath the index value—set to equal 100 in 1966, over most of the series. An index value is used to initiate the series (the starting value is arbitrary), but does not address variability in the series. In Figure 1 (and Figure 2) the 100th ICS value occurs on April 1, 1986; the 200th on August 1, 1994; the 300th on December 1, 2002; and the 400th on April 1, 2011.

Figure 1: ICS Since Inception (425 Months)



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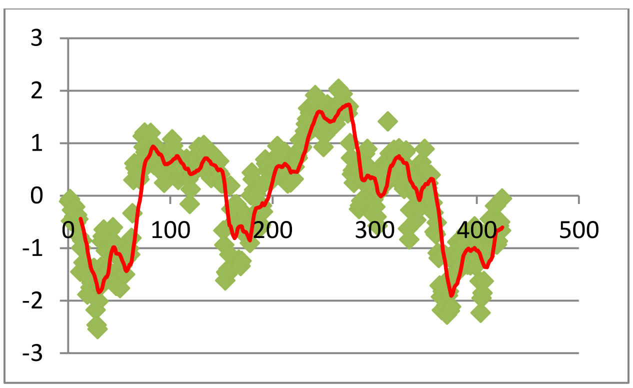
Because this is a longitudinal series the data are ipsatively standardized.[4,5] The formula for ipsative and normative standardization is: $z_i=(X_i$ – Mean)/SD, where z_i is the z-score for the i^{th} observation in the series, and X_i is the raw score for the i^{th} observation. In normative standardization Mean and SD are computed based on a sample of observations assessed at a single point in time, whereas in ipsative standardization Mean and SD are computed based on a single observation assessed on multiple points in time.[6,7] The ipsative z-score indicates the magnitude of the i^{th} observation (score) relative to all of the observations (scores) in the series. For the ICS series, Mean=85.2 and SD=13.2. Figure 2 presents the ipsatively standardized ICS series and 12-month moving average, which as seen closely resembles the raw data ICS series viewed across time (Figure 1).

Figure 2: Ipsatively Standardized ICS Since Inception (425 Months)



Despite their similar appearances, the ipsative series is more informative than the raw data series, because the former takes the variance between observations into consideration, whereas the latter does not account for variability. For example, Figure 2 reveals that the moving average has been above the mean value of the ICS assessed twice since inception, once between days 65 and 150 of the series, and again between days 200 and 360 of the series.

While a historical analysis of the entire series is of course interesting, the present study focuses on more recent trajectory—the past three years are considered. For the 36-month ICS series, Mean=72.6 and SD=6.5. Figure 3 presents a scatter plot of the ipsative ICS series over the most recent 36 months, and Figure 4 presents the same information with a line plot: both illustrate the 12-month moving average.

Figure 3: Scatter Plot of Ipsative ICS Score: Most Recent 36 Months

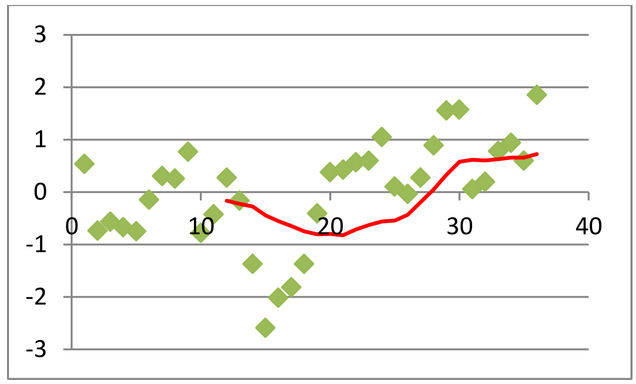


Figure 4: Line Plot of Ipsative ICS Score: Most Recent 36 Months

Evaluating Year-Over-Year Changes

In the first exploration of the recent ipsative ICS series, UniODA[8] is used to assess each of 13 year-over-year comparisons that exist for data in Figure 3. The analysis is called a forward-stepping little jiffy with a bin width of

24 months: the first half (more dated) of the ipsative ICS scores in each analysis are statistically compared with the second (more recent) ipsative ICS values.[9] The results of these analyses are summarized in Table 1: changes indicated as UP were statistically significant at the generalized criterion; changes indicated in red were significant at the experimentwise criterion.

Table 1: Summary of UniODA Analysis of 13 Year-Over-Year Changes in Ipsative ICS Score

Year Ending	Change in Annual z_{ICS}	ESS	ESP
May 2013	Up	58.3	70.6
April 2013	Up	58.3	70.6
March 2013	Up	66.7	75.0
February 2013	Up	75.0	80.0
January 2013	Up	75.0	80.0
December 2012	Up	75.0	80.0
November 2012	Up	58.3	70.6
October 2012	None	50.0	51.1
September 2012	None	41.7	42.0
August 2012	None	33.3	33.3
July 2012	None	33.3	44.4
June 2012	None	41.7	63.2
May 2012	None	41.7	63.2

As seen the ipsative ICS series did not have a statistically significant (p<0.05) year-over-year change from May through October of 2012, and during this period the accuracy of the UniODA model (indexed by ESS) was in the moderate range with the exception of October—which exactly met the criterion for a relatively strong effect.[8] In November of 2012 the first year-over-year increase in ipsative ICS score in the series occurred (a relatively strong effect), but it was statistically significant only at the generalized criterion. In the following three months, December of 2012 through February of 2013, statistically significant increases occurred (p<0.05, experimentwise criterion), and all three models exactly met the criterion for a very strong effect.[8] Finally, the most recent three months continue to show sustained, relatively strong, statistically significant year-over-year increases in ipsative ICS score, but only when considered at the generalized criterion.

The little jiffy analysis just performed treated all of the year-over-year comparisons as being of equal importance, in the sense that the Sidak Bonderroni-type multiple comparisons criterion that was used to assess experimentwise statistical significance[8] was not a sequentially-rejective procedure, but instead was computed based on all the tests of statistical hypotheses conducted. However, it is also possible to focus the analysis on the *earliest* part of the series (and use a forward-stepping little jiffy), on the *most recent* part of the series (and use a backward-stepping little jiffy), or on *any specific location* within the series (and use a forward-and/or backward-stepping little jiffy), by selecting the theoretical perspective and corresponding little-jiffy analytic approach that focuses statistical power on the specific comparisons which are of primary interest to the researcher.[9,10]

Professional traders are more interested in recent trajectory than historical trends, so the second exploration of the recent ipsative ICS series examines successive year-over-year comparisons for data in Figure 3, starting by using UniODA to compare the most recent 12-month period with the preceding 12-month period, stepping backwards in time one month at a time.[10] When this is done presently the first, most current analysis—comparing the year ending May 2013 versus the prior year—was statistically significant at p< 0.05 (estimated p<0.028): ESS=58.3, ESP=70.6. The second analysis, for the next-most-recent comparison involving year ending April 2013 versus the prior year, achieved exactly the same performance and thus was not significant at the experimentwise criterion. Using this approach, focusing on the most recent changes, only the most recent change had experimentwise p<0.05.

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Evaluating Month-Over-Month Changes

While the year-over-year changes in the ipsative CSI series are of interest to longer-term investors, short-term traders focus on more recent and more granular time horizons. For example, were the CSI updated every hour using a different random set of respondents, then hourly changes in the index would be of greatest interest to short-term traders (if the present study had been an analysis of the temporal trajectory of an individual investment instrument which is traded in real-time—such as a common stock, bond, or commodity, then a variety of time- and/or volume-based binning strategies could be used to define series for analyses conceptually consistent with series presented herein).

UniODA has been successfully used to analyze data for small samples, but comparing one month versus another month statistically is not possible using ODA methods.[11] Instead, statistical methods have been developed on the basis of classical test theory[7] which are used for analyzing data from a single-case "*N*-of-1" series involving a relatively small number of observations. Designs which may be analyzed via this method involve a single observation (series or subject) assessed on multiple variables at a single point in time; measured on a single variable that is assessed at multiple points in time; or measured on multiple attributes assessed at multiple points in time.[12-14]

In the *N*-of-1 classical test theory-based methodology, the ipsative *z*-score for the i^{th} observation (i.e., time, testing or measurement period) is subtracted from the ipsative *z*-score for the following $i+1^{th}$ observation: if the difference is positive then the more recent ($i+1^{th}$) measurement was greater than the less recent (i^{th}) measurement; if the difference is negative then the opposite is true; and if the difference is zero then the two measurements were identical. The absolute value of the difference between the two ipsative *z*-scores is compared against a *critical difference* (CD) score, which is a function of the lag-1 autocorrelation coefficient[7,14] [ACF(1)] for the data in the series; the number of inter-score comparisons which are being conducted (J); and the *z*-score corresponding to the desired experimentwise Type I error (p) level, taking into consideration if analyses are one- or two-tailed (for one-tailed $p<0.05$, $z= 1.64$; for two-tailed $p<0.05$, $z=1.96$).[15] CD is computed as $CD=z(J[1-ACF(1)])^{½}$.

In the present application ACF(1)=0.742 ($p<0.0001$), and a total of 35 month-over-month two-tailed comparisons are to be evaluated. Thus $CD=1.96*(35*(1-0.742))^{½}=5.89$. The CD score is massive due to the large number of tests of statistical hypotheses which are conducted (35). None of the month-to-month absolute differences in ipsative CSI score were as large as the CD score, indicating the absence of any statistically significant effects at the experimentwise criterion.

If one instead used the generalized "per-comparison" criterion, the value 1 is used in the formula for CD rather than 35 (indicating one test of a statistical hypothesis), and $CD=1.96*(1*(1-0.742))^{½}=0.996$. Presently, six of the month-over-month differences were as large or were larger than this CD score, indicating the presence of a statistically reliable month-over-month change at the generalized criterion. The six significant month-over-month changes which occurred are given in Table 2.

Table 2: Month-Over-Month Differences in Ipsative ICS Score with Generalized $p<0.05$

Month i	Month i+1	$z_{i+1} - z_i$
1 (6/1/2010)	2 (7/1/2010)	-1.27
9 (2/1/2011)	10 (3/1/2011)	-1.55
13 (6/1/2011)	14 (7/1/2011)	-1.21
14 (7/1/2011)	15 (8/1/2011)	-1.22
30 (11/1/2012)	31 (12/1/2012)	-1.52
35 (4/1/2013)	36 (5/1/2013)	1.25

As seen, five of the six statistically significant changes involved a precipitous decline in the ipsative ICS value. In Figure 4 the six

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significant month-over-month changes are readily seen. The five significant monthly declines occurred after months 1, 9, 13, 14 and 29. And, the only statistically significant rise in the ipsative ICS score over this series occurred in the most recent measurement, after week 35.

Conducting Inferential Statistical Analysis of Factors Affecting Statistically Reliable Temporal Changes in the Series

Findings of analyses conducted within series as done herein are of paramount interest to some people, yet in a sense these findings reflect the beginning of the analytic enterprise. If the subject of the investigation—here the ICS score—never changed across time then it would be a constant and statistical analysis would be impossible. However sometimes the series moves significantly up or down over time, whether compared in longer (year-over-year) or shorter (month-over-month) time perspective. In Table 1, for example, when the series increases it may be dummy-coded as 1, and when the series does not change it may be dummy-coded as a 0. In this manner, any sequential analysis such as reported herein defines a serial class variable. Factors (attributes) may be used to discriminate between these 0's and 1's, using UniODA[8] or it's BIG DATA software equivalent MegaODA[16,17] to analyze univariate relationships, and CTA[18] to analyze multivariate relationships. For example, potential attributes which could be evaluated as possible predictors of ipsative ICS scores at time *i* might include the most recent ipsative scores at time *i* or time *i*-1 for unemployment rate, political turmoil affecting financial matters, threat of war, Federal Reserve Board activity, 30-year interest rates, and so forth.

References

[1]http://research.stlouisfed.org/fred2/series/UMCSENT/

[2]Howrey EP (2001). The predictive power of the Index of Consumer Sentiment. *Brookings Papers on Economic Activity*, *1*, 175-216.

[3]Golinelli R, Parigi G (2004). Consumer sentiment and economic activity: A cross country comparison. *Journal of Business Cycle Measurement and Analysis, 1*, 147-172.

[4]Yarnold PR, Soltysik RC (2013). Ipsative transformations are *essential* in the analysis of serial data. *Optimal Data Analysis*, 2, 94-97.

[5]Yarnold PR (2013). Ascertaining an individual patient's *symptom dominance hierarchy*: Analysis of raw longitudinal data induces Simpson's Paradox. *Optimal Data Analysis*, 2, 159-171.

[6]Yarnold PR, Feinglass J, Martin GJ, McCarthy WJ (1999). Comparing three pre-processing strategies for longitudinal data for individual patients: An example in functional outcomes research. *Evaluation in the Health Professions*, *22*, 254-277.

[7]Yarnold PR. Statistical analysis for single-case designs. In: FB Bryant, L Heath, E Posavac, J Edwards, E Henderson, Y Suarez-Balcazar, S Tindale (Eds.), *Social Psychological Applications to Social Issues, Volume 2: Methodological Issues in Applied Social Research*. New York, NY: Plenum, 1992, 177-197.

[8]Yarnold PR, Soltysik RC (2005). *Optimal data analysis: Guidebook with software for Windows*. Washington, D.C.: APA Books.

[9]Yarnold PR (2013). Statistically significant increases in crude mortality rate of North Dakota counties occurring after massive environmental usage of toxic chemicals and biocides began there in1998: An optimal *static* statistical map. *Optimal Data Analysis*, 2, 98-105.

[10]Yarnold PR (2013). The most recent, earliest, and *K*th significant changes in an ordered series: Traveling backwards in time to assess when an-

2155-0182/10/$3.00

nual crude mortality rate most recently began increasing in McLean County, North Dakota. *Optimal Data Analysis*, 2, 143-147.

[11]Yarnold PR (2013). UniODA and small samples. *Optimal Data Analysis*, *2*, 71.

[12]Yarnold PR (1982). On comparing interscale difference scores within a profile. *Educational and Psychological Measurement*, *42*, 1037-1045.

[13]Yarnold PR (1988). Classical test theory methods for repeated-measures *N*=1 research designs. *Educational and Psychological Measurement*, *48*, 913-919.

[14]Mueser KT, Yarnold PR, Foy DW (1991). Statistical analysis for single-case designs: Evaluating outcomes of imaginal exposure treatment of chronic PTSD. *Behavior Modification*, *15*, 134-155.

[15]An excellent z-score calculator is available at: http://www.measuringusability.com/pcalcz.php

[16]Soltysik RC, Yarnold PR (2013). MegaODA large sample and BIG DATA time trials: Separating the chaff. *Optimal Data Analysis*, 2, 194-197.

[17]Soltysik RC, Yarnold PR (2013). MegaODA large sample and BIG DATA time trials: Harvesting the Wheat. *Optimal Data Analysis*, 2, 202-205.

[18]Soltysik RC, Yarnold PR (2010). Automated CTA software: Fundamental concepts and control commands. *Optimal Data Analysis*, *1*, 144-160.

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