

Revisiting the Leading Economic Indicators

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Abstract

Leading economic indicators have long been a tool of American economists, particularly those working in the business sector, for anticipating turning points in the business cycle. Armed with knowledge of likely peaks and troughs in the pace of aggregate economic activity, business economists can advise corporate leaders as to the probable path of the macroeconomy, thereby influencing if not improving the quality of strategic decision making within organizations. This chain of events is predicated on the assumed reliability of leading indicators to forecast correctly the future, an assumption put to the test in this paper via a novel application of statistical process control (SPC) to a well-known set of leading indicators that have been studied for the better part of half a century.

To give context to the overall discussion, the paper begins with a quick review of the historical development of leading indicator forecasting as it evolved in the United States. This is followed with an explanation of statistical process control, the singular methodology used in this paper, but one seldom employed in general economic analysis save for the area of production economics and its emphasis on manufacturing. Once explained, the SPC process is applied to a representative set of eleven leading indicators that have been tracked quarterly or more frequently for anywhere from 38 to 71 years.

The results of the SPC analysis of this data pool of some 7,000+ observations suggest that *collectively* leading indicators reliably forecast business-cycle turning points, with the caveat that *individually* the effectiveness with which specific indicators within a set predict the future of the macroeconomy is subject to wide variation.

Keywords: *Leading indicator forecasting; statistical process control; forecasting reliability.*

JEL Codes: C00; E32

Introduction

Leading economic indicators are an American institution, and as such, most economists, especially those in business, are apt to assume they are reliable signals of the near-future state of the macroeconomy. The purpose of this study is to test that conclusion using statistical process control analysis, an empirical technique seldom applied in economics, with the exception of production economics with its focus on manufacturing. The paper begins with a short history of indicator forecasting. This is followed with a description of statistical process control (SPC) and how it will be used to test the reliability of a publically-available set of leading economic indicators. The third section of the paper summarizes the result of applying SPC analysis to a data set of the leading indicators covering roughly the last 50 years of aggregate economic activity in the United States. The paper concludes with an assessment of leading indicators as a forecasting tool and some caveats about the results of this study.

1. The Development of Indicator Forecasting

In the United States, the desire to see “around economic corners” likely had its first formal expression in Wesley Clair Mitchell’s (1874-1948) 1913 publication *Business Cycles*, a massive treatise on the nature, causes and consequences of the periodic variations in the overall level of aggregate activity in the American economy over the previous 100 years [Burns, 1952]. Beginning in 1920 the statistical study of national income, business cycles, and economic forecasting became the primary focus of Mitchell’s scholarship when he became the director of research at the newly established National Bureau of Economic Research (NBER), a private, nonprofit economic think-tank dedicated to empirical studies particularly of the United States economy. Mitchell first demonstrated his inclination for forecasting in the article “The Outlook of 1921 as Seen by Bankers, Business Men and Economists,” published in the *New York Evening Post* in December 1920 [Mitchell]. Seven years later he published an enhanced and revised version of his classic work on business cycles under the new title *Business Cycles: The Problem and Its Setting*. During the 1930’s, Mitchell began working with Arthur F. Burns (1904-1987), a partnership that produced in 1938 *Statistical Indicators of Cyclical Revivals*. Working with approximately 500 monthly and quarterly time series, many covering more than half a century of data, Mitchell and Burns applied objective criteria to their impressive data set and selected 71 series as fairly reliable indicators of the 21 revivals studied [Mitchell and Burns, 1938]. Because of World War II, a full and definitive account of their collaborative effort was postponed until 1946 when they published *Measuring Business Cycles*, a book that became the foundation of the emerging field of indicator forecasting [Doody, 1965]. In 1939, Mitchell and Burns took on a protégé, Geoffrey H. Moore (1914-2000), who joined the NBER as a senior research staff. Building on the work of his mentors, Moore broadened and refined the efforts of Mitchell and Burns, publishing in 1950 *Statistical Indicators of Cyclical Revivals and Recessions*, a book that examined indicators of troughs as well as peaks [Klein, 1990]. Initial reaction to indicator

forecasting among academic economists was negative as the approach was seen as statistical empiricism without an underlying theoretical foundation [Koopmans, 1947]. Over the next five decades, Moore, working alone or with others such as Julius Shiskin (1913-1978) of the Bureau of Labor Statistics [Boschan and Banerji], published a number of professional articles and books that demonstrated (1) the robustness of leading indicator forecasting and (2) that this approach to forecasting was “rooted in sound economic theory...[Dua, 2004].” The cumulative body of work that Moore produced earned him the designation of “the father of leading indicators as we know them today [Hershey, 2000],” and, over the course of time, he made this method of forecasting as prominent as the construction and interpretation of econometric models [Klein, 1990].

2. SPC and Its Application to Indicator Forecasting

Unlike leading indicator forecasting, whose origins and development involved several individuals working in a non-linear fashion over a considerable period of time, statistical process control derives primarily from the efforts of one person, Walter A Shewhart (1891-1967), who in the 1930s published two books that established the principles of SPC, principles that others have tweaked over the years [Roberts, 2006]. Born in New Canton, IL, Shewart attended the University of Illinois and the University of California-Berkeley, earning a baccalaureate at the former institution and a doctorate in physics at the latter. In 1918 he went to work as an inspection engineer at Western Electric’s Hawthorne Works in Cicero, IL. Six years later Shewhart made use of a control chart in a short, in-house memo, and SPC was born. Over the next 15 years, he perfected and expanded his concepts of SPC, writing two seminal books on the topic: *Economic Control of Quality of Manufactured Product* (1931); and, *Statistical Method from the Viewpoint of Quality Control* (1939), a book that benefitted from the editorial assistance of W. Edwards Deming (1900-1993), Shewhart’s protégé, who went on to use SPC as an integral part of his system of total quality management developed in Japan in the 1950s [Wheeler and Chambers, 1992].

At the heart of SPC is the use of statistical analysis to determine if the performance of a specific process—say the filling of plastic bottles with a set amount of soft drink—is under control, that is, operating within a desired norm or range. In a manufacturing process the desired range is pre-set, while in an economic process such as monitoring the reliability of leading indicators, the norm is the long-term arithmetic mean of the variable in question. Over time, repeated samples randomly drawn from the process will generate a sampling distribution that adheres to the Empirical Rule, with two-thirds of the actual sample means falling within one sigma (standard deviation) of the mean of the sampling distribution, 95% of the sample means lying within two sigma’s of the sampling mean, and 99% within three sigma’s. Continuous performance within the six-sigma range indicates that the process is in control, with roughly half of the observed sample means falling above the sampling distribution mean and half below. The degree of variation that occurs when a process is in control is called chance or common causes of variation, that is, the variability inherent in the process over time. Such variation is always present in a time series, and re-engineering the

process is the only way to reduce common or chance variability, which by its nature cannot be eliminated.

Special or assignable causes of variation are large fluctuations in performance that lie outside the six-sigma range. They are not endemic to the process, making them correctable without re-engineering the process. In the soda example above, a defective bottle that causes the amount of soft drink dispensed to differ significantly from the desired or set quantity would be a special or assignable variation. A special or assignable cause of variation in economic forecasting would be the tragedy of September 11, 2001, which exacerbated the economic downturn associated with the dotcom bubble of 2000 [Frumkin, 2004]. Besides delineating special variation from chance ones, SPC also allows for the detection of unusual patterns or trends even when all sample means are within the range of control. This aspect of SPC is essentially a signaling mechanism that suggests an outcome or performance outside the control limits is in the offing [Oakland, 1986]. The identification of “performance drift” is crucial when using SPC to evaluate the reliability of leading indicators, which in this paper is defined as the probability that an indicator can anticipate a turning point in a time series, be it a peak or a trough.

Through various stages of trial-and-error, SPC practitioners have settled on several rules of thumb to detect when a process is drifting from the desired (mean) outcome. Whenever, for instance, eight or more consecutive points lie on one side of the mean, or eight or more consecutive points increase or decrease, the time series in question is likely shifting from its long-term mean [Wheeler, 2000]. Other heuristics for identifying an approaching turning point include two out of three consecutive outcomes lying beyond the two sigma limit, or four out of five consecutive values lying outside the one sigma range [Box, et al., 2009]. Applying SPC to leading indicator evaluation requires adapting the various signs of performance drift to time series where individual observations occur monthly or even less frequently.

In manufacturing, 50 observations from a production run of thousands may take only minutes to acquire, a time period short enough to make *ceteris paribus* a credible assumption. In indicator forecasting, it would often take more than four years to collect 50 data points, during which time the probability of “other things remaining equal” would approach zero. This means that identifying a possible turning point in an economic time series needs to happen using relatively few observations in order to mitigate the impact of assignable or special causes of variation. In this study, at least four consecutive increases or decreases in the value of an indicator or four successive data points above or below the mean are considered a sign that a peak or trough is imminent. This is in keeping with the philosophy that defines a recession as two successive quarters of a decline in real GDP, a time period some believe is too short for such a designation and others contend is too long to initiate timely and effective countercyclical economic policies.

3. SPC Analysis and the Reliability of Leading Indicators

To test the reliability of indicator forecasting, the SPC process described above was applied to the Conference Board's widely-used list of eleven leading indicators listed in Figure 1 (below). Founded in 1916 as the National Industrial Conference Board, the Conference Board (CB) is a world-wide nonprofit organization that provides business members a variety of educational experiences and conducts research of relevance to managers and executives. In America the CB is probably best known for its monthly registered trade-mark publication "The Conference Board Leading Economic Index (LEI) for the United States." The CB's list of eleven consists of ten publically-available leading indicators, and the organization's composite index, which is a weighted combination of the other ten indices. The Conference Board's set of leading indicators changes periodically, and the set of leading indicators investigated in this study may not match exactly the set that the CB is currently using.

Indicator	Description	From/To	Source	Frequency
		No. of Observ.		
Jobless Claims	A measure of the number of people filing first-time claims for state unemployment	1967-2010	Dept of Labor (BLS)	Weekly*
Average Workweek	The length of the average workweek in manufacturing	525* 1939-2010	Dept of Labor (BLS)	Monthly
New Orders Cons. Goods	Manufacturers' new orders for consumer goods	861 1958-2010	Census Bureau	Monthly
New Orders Capital Goods	Manufacturers' new orders for nondefense capital goods	739** 1968-2010	Census Bureau	Monthly
ISM Index (PMI)	A manufacturing index based on a survey of purchasing managers at roughly 300 industrial comp.	619*** 1948-2010	Institute For Supply Management	Monthly
Building Permits	New Housing Starts and Building Permits (privately owned)	752 1960-2010	Census Bureau	Monthly
S&P 500 Index	The Index of the prices of 500 large cap stocks traded in the US	607 1950-2010	Standard & Poor	Monthly
Money Supply M2	The inflation-adjusted measure of the M2	728 1959-2010	Federal Reserve	Monthly
Consumer Sentiment	Consumer confidence index (1966 = 100)	619 1978-2010	University of Michigan	Monthly
Interest rate spread	The interest-rate spread between the 10-year Treasury note and the fed funds rate	392**** 1954-2010	Federal Reserve	Daily, Weekly, Monthly*
Composite Index	The composite index of the 10 leading economic indicators	674 1959-2010	Conference Board	Monthly
		621		

Figure 1

(*)Bureau of Labor Statistics reports new unemployment claims weekly. It also reports the four-week moving average. For this study we calculated the simple monthly average.

(**), (***) The measurement method for new orders for consumer goods and nondefense capital goods changed recently. From 1958 to 2001 the Standard Industry Code (SIC) was used. In 1992 the North American Industry Classification System (NAICS) was introduced.

(****) Consumer Sentiment Index data goes back to 1952. However, only quarterly data is available for the 1952-1977 periods (in addition, data in 1950's were not collected consistently).

The data set for each of the indicators listed in Figure 1 was transferred into a control chart using the Minitab Release 14.20 Statistical Software package. A control chart (a sample portion for the indicator “Rate of Change of the Money Supply” is displayed in Figure 2) shows the variation in a time series relative to the mean of the series and the six-sigma range delineated by the UCL (upper control limit) and LCL (lower control limit). Some SPC practitioners believe that the data points of a reliable control chart must be normally distributed about the mean, and if not, the data should be massaged with the Box-Cox transformation. Other practitioners disagree, arguing that such a transformation does not alter materially the pattern of variation in a time series [Wheeler and Chambers, 1992]. Several data sets in this study were so transformed, and as expected, no appreciable differences in variability patterns emerged. In the spirit of Occam’s razor, untransformed or original data was used for a majority of the indicators in this analysis. However, five indicators – Money Supply, S&P 500 Index, New Orders for Capital Goods, the Composite Index, and New Orders for Consumer Goods – were moderately transformed. These time series are essentially monotonically increasing over time and do not displays the variability in raw form essential for SPC analysis. In these five cases control charts were developed using month-to-month percentage changes in the raw data. The resulting control charts had the customary chance or common variation patterns associated with time series processes.

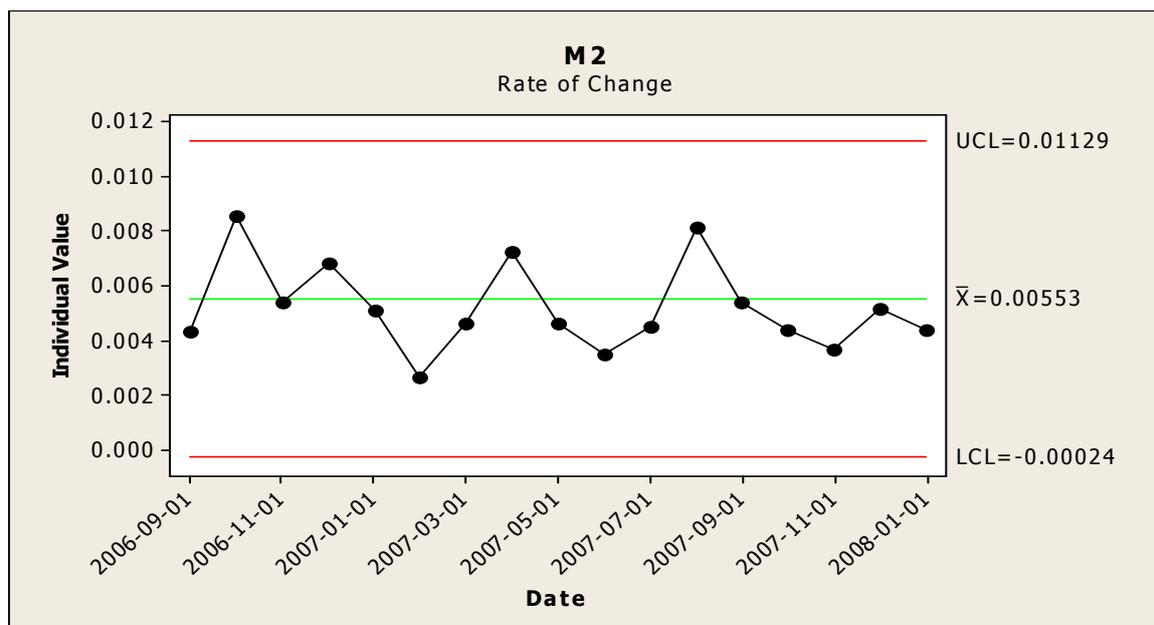


Figure 2

The next step in the evaluation of leading indicators involved overlaying the swings in the United States business cycle since World War II on the control chart of the eleven indicators examined in this study. The dating of the economic upturns and downturns as well as the marking of peaks and troughs is based on the NBER timing of the American business cycle as revealed in published information (nber.org/cycles). Although not government generated, the work of the NBER's Business Cycle Dating Committee is considered official [Frumkin, 2004]. The committee's dating of the beginning and end of expansions and recessions establishes the reference points for determining the reliability of leading, coincidence, and lagging indicators. Because the committee is a nongovernmental body, its designations of peaks, troughs, expansions, and contractions are considered apolitical, objective, and accurate, especially the revised versions, which benefit from the insights of hindsight [Frumkin, 2004].

With the booms and busts superimposed on the individual control charts, the reliability of the eleven leading indicators can be evaluated individually using the four consecutive data point criteria described above. That is, four successive increases or values about the mean presage a peak, while four successive decreases or values below the mean portend a trough. The results of this analysis (Figure 3) suggest that the indicators can be grouped into three distinct categories using the condition that a reliable indicator must have a "probability of forecasting" a turning point greater than 0.5 to at least beat the chance or guess factor [Cicarelli, 1982]. The first category is symmetrical indicators, which are indicators where the probability of forecasting a peak and the probability of forecasting a trough both exceed 0.5. Only one indicator—the Money Supply—falls into this classification with a .75 probability of forecasting peaks during the time period under review, and a .63 probability of forecasting troughs. The Money Supply averaged lead times of 5 months for peaks and 4.5 months for troughs. The high level of forecasting reliability of the Money Supply would explain why the CB places such an inordinate amount of weight on this particular indicator when creating its composite index [Conference Board, 2010].

Indicator	Symmetrical		Asymmetrical		Underperforming	
	Peak	Trough	Peak	Trough	Peak	Trough
Money Supply	.75	.63	-	-	-	-
PMI (ISM) Index	-	-	.73	.18	-	-
Average Workweek	-	-	.82	.18	-	-
New Bld. Permits	-	-	.88	.25	-	-
Cons. Conf. Index	-	-	.60	.20	-	-
Composite	-	-	.88	.12	-	-

Index						
Int. Rate	-	-	-	-	.33	.11
Spread						
S&P 500	-	-	-	-	.40	.30
Index						
Initial Un.	-	-	-	-	.29	.14
Claims						
New Orders	-	-	-	-	.38	.00
Cons. Goods						
New Orders	-	-	-	-	.00	.00
Nondefense						

Figure 3

The second class of leading indicators is asymmetrical indicators, specifically indicators with a probability of forecasting in excess of 0.5 for predicting peaks or troughs but not both. There are five indicators in this group—PMI, Consumer Confidence, Average Workweek, New Building Permits, and the Composite Index—all of which are reliable when forecasting peaks with an average lead time for the group of 5.2 months. No asymmetrical indicator had a probability of forecasting troughs in excess of .5, an outcome consistent with past research showing the poor performance of leading indicators in anticipating recessions [Popkin, 1990]. The third category of leading indicators is underperforming indicators; these are indicators that are not reliable in predicting either peaks or troughs.

4. Conclusions and Caveats

Given their simplicity and ease of interpretation, leading economic indicators perform reasonably well considering that they are predicting the future, an innately difficult task. Their previously recognized bias, confirmed in this analysis, of correctly predicting more peaks than troughs makes leading indicator forecasting decidedly asymmetrical, suggesting that maybe “separate sets of leading indicators are needed at troughs and peaks [Popkin, 1990].” Despite the overall positive results, some caveats are in order. First, for the entire set of eleven indicators, the four successive data-values criteria for predicting a turning point produced 124 false signals, that is, predicting a peak when the next turning point was a trough or vice versa. This works out to roughly eleven false signals per indicator or about one false signal every 4.5 years for each indicator. Increasing the number of successive data points needed to predict a pending turning point would reduce the likelihood of false signals, but the trade-off would be more missed turning points, a second type of error associated with leading indicator forecasting.

Missed turning points errors involve not predicting turning points—a peak or a trough – before they occur. The incidence of this kind of error is limited to the number of peaks and troughs, in this study 22, experienced during the time period being examined. For the set of leading indicators studied in this paper, there were 27 missed turning point errors, about 2.5 per indicator or roughly one every twenty years.

A second caveat involves the risks and rewards associated with the classification of indicators. The symmetrical/asymmetrical indicators as a group yield greater rewards predicting turning points than the underperforming indicators, but the quid pro quo is more false signals, proportionally speaking. A third proviso of indicator forecasting is more philosophical and less technical than the others. One of the attributes of a good leading indicator is a consistent, long-term relationship between the indicator and the ebbs and flows of the United States business cycle [Roth, 1992]. Implicit in this characteristic is the assumption of structural constancy of the American economy. Most of the leading indicators have been tracked for long periods of time, maybe too long. In the 1990s, Geoffrey Moore and his colleagues made a case for major changes in the economic indicator system to provide more coverage of the rapidly expanding service sector and less for the corresponding relative decline in manufacturing [Moore, 1990]. In this vein, a redesign of leading indicator forecasting may be overdue now that the digital age is in full bloom.

References

- Boschan, C., & Banerji, A. (1990). A Reassessment of Composite Indexes. *Analyzing Modern Business Cycles: Essays Honoring Geoffrey H. Moore*. (P. A. Klein, Editor). Armonk, NY. M. E. Sharpe. 206-225.
- Box, G. E. P., Alberto, L., & Paniague-Quinones, M. (2009). *Statistical Control by Monitoring and Adjustment*. (Second Edition). Hoboken, NJ. Wiley.
- Burns, A. F. (1938). *Statistical Indicators of Cyclical Revivals*, (Bulletin 69). New York, NY. National Bureau of Economic Research.
- Burns, A. F. (Editor). 1952. *Wesley Clair Mitchell, The Economic Scientist*. New York, NY. National Bureau of Economic Research.
- Cicarelli, J. (1982). A new method of evaluating the accuracy of economic forecasts. *Journal of Macroeconomics*, 4, 469-75.
- Conference Board. (2010). The Conference Board Leading Economic Index (LEI) For the United States. New York, NY. November 18.
- Doody, F. S. (1965). *Introduction to the Use of Economic Indicators*. New York, NY. Random House.
- Dua, P. (2004). Geoffrey H. Moore. *Business Cycles and Economic Growth*. (P. Dua, Editor). New York, NY. Oxford University Press: vii-xi.
- Federal Reserve Bank of St. Louis. M2 and Components: Historical Data: 1959-Present. Retrieved from: <http://research.stlouisfed.org>
- Frumkin, N. (2004). *Tracking America's Economy*. (Fourth Edition). Armonk, NY. M.E. Sharpe.

- Hendry, D. F. (2001). How Economists Forecast. *Understanding Economic Forecasts*. (D. F. Hendry and N. R. Ericsson, Editors). New York, NY. Cambridge University Press. 15-41.
- Hershey, Jr., R. D. (2000). Geoffrey H. Moore, 86, Dies: An Analyst of Business Cycles. *New York Times, March 11*: A-13.
- Institute for Supply Management. ISM Manufacturing Report on Business: PMI History, 1949-present. Retrieved from www.ism.ws/ISMReport
- Klein, P. A. (1990). Geoffrey H. Moore and His Impact on Modern Business Cycle Research. *Analyzing Modern Business Cycles: Essays Honoring Geoffrey H. Moore*, (P. A. Klein, Editor). Armonk, NY. M. E. Sharpe: 3-22.
- Koopmans, T. (1947). Measurement Without Theory. *Review of Economics and Statistics*, 29, 161-72.
- Mitchell, W. C. (1920). The Outlook of 1921 as Seen by Bankers, Business Men and Economists. *New York Evening Post*. December 31.
- Moore, G. H. (1950). *Statistical Indicators of Cyclical Revivals and Recessions*, (Occasional Paper 31). New York, NY. National Bureau of Economic Research.
- Moore, G. H. (1990). *Leading Indicators for the 1990's*. Homewood, IL. Dow Jones-Irwin.
- National Bureau of Economic Research. US Business Cycle Expansions and Contractions. Retrieved from www.nber.org/cycles
- Oakland, J. S. (1986). *Statistical Process Control: A Practical Guide*. Portsmouth, NH. Heinemann.
- Popin, J. (1990). Why Some of the Leading Indicators Lead. *Analyzing Modern Business Cycles: Essays Honoring Geoffrey H. Moore*. (P. A. Klein, Editor). Armonk, NY. M. E. Sharpe: 59-68.
- Roberts, L. (2006). *SPC for Right-Brain Thinkers*. Milwaukee, WI. ASQ Quality Press.
- Roth, H. L. (1992). Leading Indicators of Inflation. *Leading Economic Indicators: New Approaches and Forecasting Records*. (K. Lahiri and G. H. Moore, Editors). New York, NY. Cambridge University Press. 275-301.
- Standard & Poor's. Index Data. Retrieved from: www.standardandpoors.com/indices
- The Conference Board LEI for the United States: Historical Data, 1959-present. Retrieved from www.conference-board.org
- U.S. Census Bureau. (2010). Economic Indicators: Historic Time Series 1958-present. Retrieved from www.census.gov/cgi-bin/briefroom
- U.S. Department of Labor. Unemployment Insurance Weekly Claims Data, 1967-2010. Retrieved from: www.ows.doleta.gov/unemploy/claims.asp

University of Michigan. Consumer Confidence Index: Survey of Consumers. Historical Data 1978-Present. Retrieved from: www.sca.isr.umich.edu

Wheeler, D. J. (2000). *Understanding Variation: The Key to Managing Chaos*. (Second Edition). Knoxville, TN. SPC Press.

Wheeler, D. J., & Chambers, D. S. (1992). *Understanding Statistical Process Control* (Second Edition). Knoxville, TN. SPC Press.

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