Causal Variation: Exploring the Non-Random in Stock Price, Stock Index, Sales, and Accounting Time Series

Keith I. Taylor[1] & Halil Kiymaz[2]

[1] Rollins College of Liberal Arts, Winter Park, FL, USA

[2] Crummer Graduate School of Business, Rollins College, Winter Park, FL, USA

Correspondence: Keith Taylor, Department of Business, Rollins College of Liberal Arts, Winter Park, FL, 32789, Tel: 1-407-748-1193. E-mail: kitaylor@rollins.edu

Received: March 10, 2023 Accepted: April 12, 2023 Online Published: April 20, 2023

doi:10.5430/jbar.v12n1p39 URL: https://doi.org/10.5430/jbar.v12n1p39

Abstract

We show two methods for measuring non-random observations using statistical control software, specifically SigmaXL, across diverse time series. First, we use an error counting method based on eight non-random rules of statistical control charts, and subsequently we assign a dollar value to each of those non-random observations to evaluate non-random to random rates. The computed error rates are also compared to a randomly generated sample of 100K and the corresponding probably of occurrence. Finally, these methods, coupled with a new indicator, the Taylor-Kiymaz multiple, allow for the comparison of stock prices, market indexes, sales metrics, chart of accounts across many time periods.

Keywords: time series; non-random sequences; statistical process control charts; accounting index, stock index

1. Introduction

1.1 Importance

People participate in various daily life and work processes around the world. Within an organization, management has developed those processes and hired workers who complement those processes necessary to achieve organizational goals. When adverse events occur, the first reaction is often attributed to employee behavior, an exception, or a non-random cause which is often sourced through financial statement review. The 85/15 rule, not to be confused with Pareto's 80/20 rule, suggests that employees, i.e. non-random interventions, are responsible for only about 15 percent of the process whilst 85 percent is related to the business process itself.

1.2 Contributions

This paper examines how statistical process control (SPC) chart software can separate random from non-random variation and test the 85/15 rule using multiple time-series categories such as stock prices or their respective indexes, and even sales and accounting metrics. Therefore, our research contributions are as follows: First, we propose two methods to examine time-series random and non-random variance: one method involves counting the non-random occurrences within a series, while another assigns a monetary value to those non-random events. Second, we compare both methods to an actual calculated probability of occurrence, and these probabilities are compared to an actual simulation. Third, we propose a new metric, the Taylor-Kiymaz ratio (T-K), that indicates the relative weight of a particular time series to its random occurrence. Lastly, both methods were tested with several distinct time series types, including accounting and sales metrics, a stock price, and a stock index over several different time periods.

The study offers the following structure. The literature review section provides the relevant historical works of SPC development, the practical use of control charts in various fields, the basics of its design, and caveats of application. The succeeding section outlines methodology and reports our analyses, findings, and insights. The final section provides concluding remarks and further research opportunities in this domain.

1.3 Scholarship Review

Clemmer (1992) summarized the 85/15 rule, which originated with Deming and Juran in similar yet different nuances. The author noted that in analyzing root cause, 85 percent of errors were systematic issues while only 15 percent were personnel-related. Deming (1982) estimated, based on his experience, that "94% belong to the system (responsibility of management) 6% special" (p. 315). He argues that common causes for systemic faults were among notes in conversations with Harry Alpert as early as the mid-1940s, which focused on prison riots and which Deming published in the mid-1950s. Deming observed that management believed that workers themselves caused most, if not all, production problems. Similarly, in writing about management myths, Juran (1989) suggested that information biases about the source of quality problems relayed to top management were often hidden, but that in his research, "80 to 90 percent of the damage done by poor quality is traceable to management actions" (p. 300).

Shewhart (1931) outlined three postulates for the scientific basis of control in manufacturing in his seminal work. These included all causes are not alike, chance causes exist in nature, and assignable causes can be discovered and removed. He divided variation into two distinct types. The first was the assignable cause (later named special cause), which equated to influences outside the current process (phenomenon) being studied, i.e., today termed non-random error. The second was termed "causes left to chance" (later named common cause), which were factors that could occur by chance, i.e., random error today. The author devoted a large part of his book to explaining the detection of deterministic observations and how to calculate process limits, which would be used to develop SPC charts. He concluded by stating that the purpose of a quality report was to differentiate common from special causes and clarifying the actions necessary to eliminate assignable variation.

While most individuals with general knowledge of SPC charts consider their use in manufacturing or sales environments (see Selden, 1996), the methodology also applies to service industries. Henderson, Mead, van Dijke, Ramsay, McDowall & Dennis (2008) reviewed patient stroke care of 2,962 patients in three U.K. hospitals by retroactively plotting SPC charts to assess common or special cause variation in four areas: brain imaging, prescribing aspirin after stroke, the proportion of patients receiving strong unit care, and the proportion of patients discharged on a statin. Findings included the confirmation of improvements in patient care and those expected improvements that did not occur. Moreover, the authors stated that several unexpected signals of special cases were investigated. Some specific causes were determined, while others were not.

Mohammed, Cheng, Rouse, and Marshall (2001) provided several examples of retrofitting SPC charts to determine both special and common causes in a hospital setting: mortality rates of children younger than one year from the UK Cardiac Surgical Register, mortality rates from the medical doctor and serial killer Harold Shipman, IVF treatment, prevalence of coronary heart disease among general practitioners, and neonatal deaths. The authors also cited several U.S. studies, including the study of mortality rates in hospital trauma cases, infection control, and monitoring and detecting outliers in public health reporting. The variety of types and domains analyzed points to the overall applicability of the tool and its ability to gain insight into diverse problems.

Wheeler and Chambers (1992) specified how to create an SPC chart manually. The chart itself is a graphical representation of time-series observations plotted along a center-line and where each event varies around that average. The basic center-line calculation uses the mean or average of the data points and a measure of dispersion, a moving range. They calculated control limits, both the upper and lower bounds (UCL, LCL), and numerical values demarcating the minimum and maximum boundaries that separate common and special variations (see also Mohammed, Cheng, Rouse, & Marshall, 2001).

A visual depiction of an SPC chart is shown in Figure 1 based on a Sigma XL software output. This time series varies around 0.0%, shown by the green center-line. One standard deviation from the average is +/- 5%, the purple line; two standard deviations are +/-10%, the blue line; and the upper and lower control limits are +/- 15% (brown line).

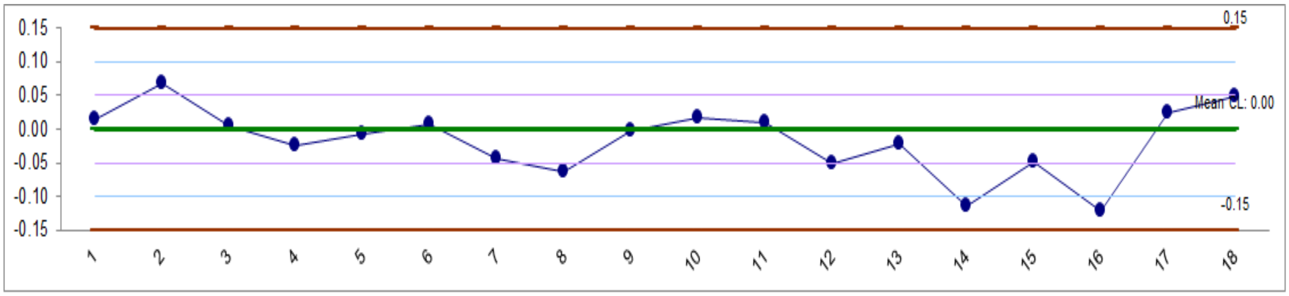

Figure 1. SPC Chart Randomness Diagram

Eighteen observations from the average or green centerline. Brown lines show control limits, while blue and purple lines represent one and two standard deviations.

Over time, the number of rules and definitions for determining non-random observations has changed. Noskievičová (2013) provided both a brief history and summary of chart rules (also known as Nelson's rules) over the history of quality improvement. Table 1 below represents a summary of the historical rules; years developed, and changes over time. Today, software packages such as Sigma XL and SPC Excel can calculate, draw, and test time series based on default or user-determined points of non-random variation.

Table 1. SPC Chart Rules Through Time

This table provides the SPC chart rules through time from Shewhart (1931) to Nelson's rule (2013) showing the different rule number conventions and associated default values. From left to right: SigmaXL rule defaults, Shewhart's original work, Western Electric, Nelson, SPC Excel defaults, and suggestions from Griffiths and Noskievičová.

Sigma XL Rule Definitions	**Shewhart (1931)**	**Western Electric (1958); Boeing, GE**	**Nelson (1984) & ISO 2589 (1991)**	**SPC Excel**	**Griffiths et al. (2010)**	**Noskievičová (2013)**
Test 1: 1 point more than 3 StDev from CL	**Test 1:** 1	**Test 1:** 1	**Test 1:** 1	**Test 1:** 1	**Test 1:** 1	**Test 1:** 1
Test 2: 7 points in a row on same side of CL			**Test 2:** 9	**Test 4:** 7	**Test 2:** 9	**Test 4:** 8
Test 3: 7 points in a row all increasing or all decreasing			**Test 3:** 6	**Test 5:** 7	**Test 3:** 6	**Test 5:** 6
Test 4: 14 points in a row alternating up and down			**Test 4:** 14	**Test 8:** 14	**Test 4:** 14	**Test 7:** 14
Test 5: 2 out of 3 points more than 2 StDev from CL (same side)		**Test 2:** 2 of 3	**Test 5:** 2 of 3	**Test 2:** 2 of 3	**Test 5:** 2 of 3	**Test 2:** 2 of 3
Test 6: 4 out of 5 points more than 1 StDev from CL (same side)		**Test 3:** 4 of 5	**Test 6:** 4 of 5	**Test 3:** 4 of 5	**Test 6:** 4 of 5	**Test 3:** 4 of 5
Test 7: 14 points in a row within 1 StDev from CL (either side)			**Test 7:** 15	**Test 7:** 15	**Test 7:** 15	**Test 6:** 15
Test 8: 8 points in a row more than 1 StDev from CL (either side)		**Test 4:** 8	**Test 8:** 8	**Test 6:** 8	**Test 8:** 8	**Test 8:** 8

Specifically, Table 1, column one, lists the rules found in the SigmaXL package, the software used to construct the measures for this test. Each rule is numbered from one to eight; however, each rule number varies over time and by software package. Similarly, each rule contains several observations, which establishes the division between special and common cause variation. These variations are also visible in the table. Shewhart (1931) only described rule one, the three-standard deviation rule, in his original work. By the late 1950s, Western Electric had expanded the rule list to four. With the quality of revolution that resulted from the success of Japanese companies in the U.S. beginning in the 1970s and 1980s, Nelson (1984) expanded the rule list to eight items while also providing a graphical representation of specific rules.

Furthermore, Nelson's rule two stated nine points in a row on the same side of the centerline. The two software packages use seven points, and Noskievičová (2013) used eight, corresponding to a different probability of occurrence. However, the default values in most software packages can be adjusted as necessary to the desired probability. While a general standard of the exact number of points does not seem to exist, Griffiths, Bunder, Gulati, and Onizawa (2010) calculated probabilities for selecting rules and proposed a fixed probability of occurrence with a convergence of ratios of 0.003. The authors also noted that the rules were not mutually exclusive and that one observation could be assigned multiple rule violations.

Moreover, they computed the probability of rule four, which described alternation sequences, and reviewed early alternation studies dating to Andre (1879, 1881, 1883). Given the tendency, previously noted, of non-random alternation rates, Griffiths et al. (2010) also created a table of probabilities based on alternation rates between three events (probability of 0.667) to 14 events (probability of 0.005). The probability calculation was based on the equation $p = 2.5592e^{-0.452x}$, where p is the probability, and x is the number of alterations (Griffiths et al., 2010, p. 5). Additionally, the authors calculated the probabilities of each of Nelson's eight rules adjusted based on the Sigma XL rules, as noted in Table 1. The second column of Table 2 shows these probabilities.

SPC chart calculations based on the underlying observations do have caveats. Taleb (2008) has argued many weaknesses of variable measurement in economics based on moments of probability, mean, standard deviation, skewness, and kurtosis. The author stated that most conventional methods fail to capture the "fat-tailed" distribution of unlikely events, i.e., being correct at 99%, which may be insufficient when consequences are large. And he observed that rare events will be infrequent or will not occur in most small samples (see Bye et al., 2011, for climate cycle composed of 30-year random walks, also Silver, 2012, for rare events). Therefore, this weakness also applies to the SPC chart, whose limits and moment calculations are based on small samples determined by the analyst (Sigma XL software does offer the possibility to use limits determined by the analyst). And even though the types of distributions are not limited, events that violate the rules, especially rule one, could include observations that are many standard deviations from the mean. For example, Figure 2 below shows two different distributions plotted on the chart. The top image, the SP500 graph, shows limits of approximately +/- 2% on its Y-axis, while the limits of the bottom graph are about +30% to -35%. The red numbers visible near the observations denote each non-random occurrence, and the number itself represents the rule which was violated.

Mandelbrot and Taleb (2010) described these rare events in the bottom graph of Figure 2 as wild randomness, defined as any single observation or event that inordinately affects the total. The authors gave examples of this type of concentration in certain winner-take-all markets. They cited best-selling authors by book volume or sales, internet traffic, and an outlier effect in the stock market: "10 trading days represented 63% of the returns for the past 50 years" (p. 50). In a table, the authors compared non-scalable versus scalable distributions. In the former, winners get small pieces of the total, while in the latter, winners-take-all or the vast majority of the total. Non-scalable distributions include human physical qualities such as height and weight, where deviations are easily estimated. Scalable distributions are difficult to predict even from historical information and are governed by the "tyranny of the accidental" (p. 54). De Vany (2004) studied this phenomenon in the film industry and showed how only a few movies garnered the majority of revenue or were profitable while most generated losses.

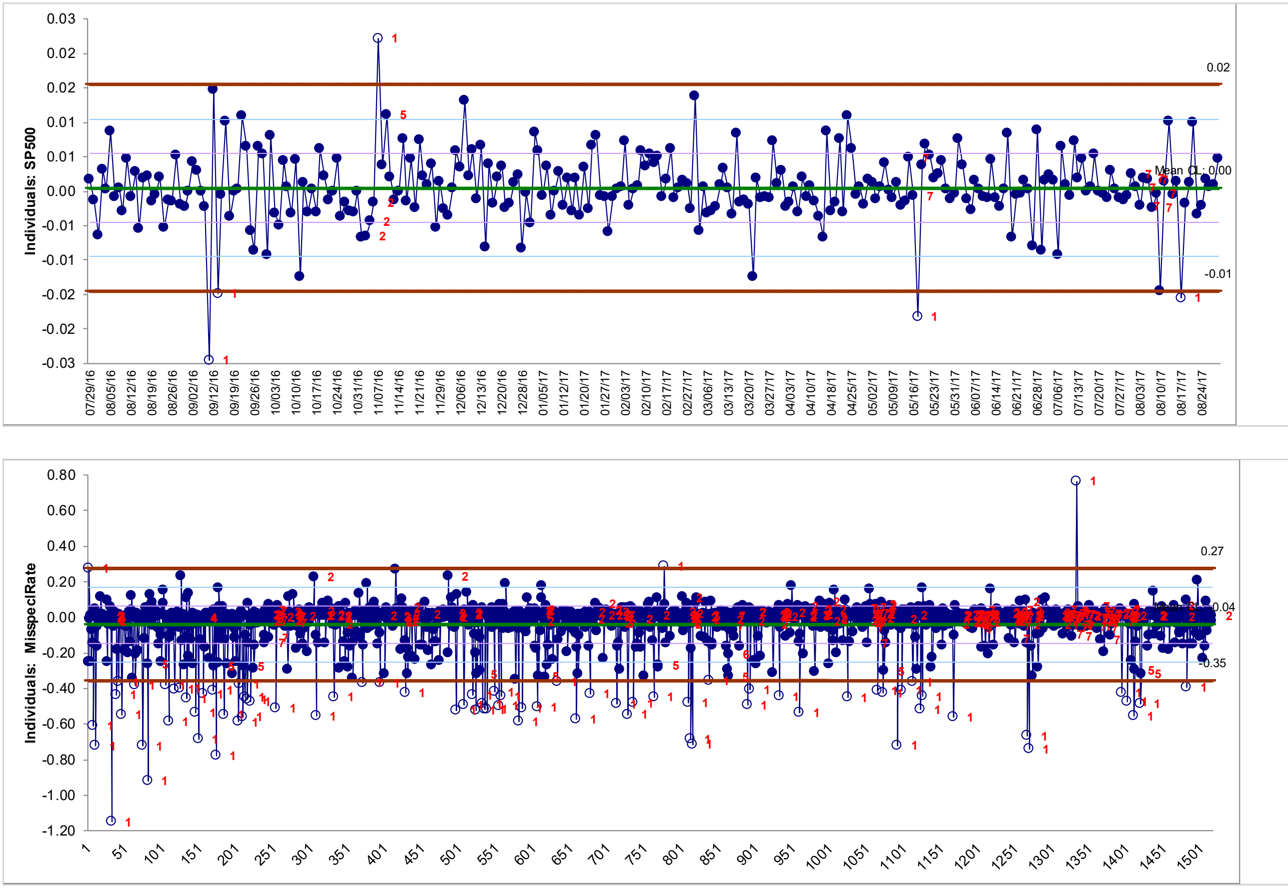

Figure 2. SPC returns for SP500 and a Sales Process Noting Scale Differences

Observations of two separate processes where the SP500 above indicates a plus or minus 0.02 upper and lower control limit with extreme values to -0.03. The sales process limits are 0.27 to -0.40, respectively, with extreme values of -1.20.

2. Methods & Analytics

Because of the law of large numbers, simulated random occurrences should approach the calculated probabilities in large samples. As an incidental test, the rand() function in MS Excel was used to produce 10 trials of 500 numbers from which an SPC chart was created. These results are in column three of Table 2. With a finite string, an overall non-random error rate can be calculated. This simulation was repeated with a string from the website random.org and is visible in column four. The final two simulations used 100,000 observations by norm.inv(rand()) and random.org. These results are in columns five and six of Table 2. For the base calculation of comparison to other time series, the random.org results were used. But, as visible in Table 2, appreciable differences are non-existent in both simulations. As an example, the difference between the overall rates of MS Excel and random.org were four basis points.

Table 2. Probabilities of Nelson's Rules and Simulation Results

From left to right, this table provides the calculated probabilities of the individual Nelson's rules, associated simulations of 5,000 and 100,000 trials using MS Excel and random.org.

Tests for Special Cause Variation	Probability of Occurrence Griffiths et al. (2010) adjusted	500 number strings MS Excel [Rand()] for 10 Trials (misconception of chance)	500 number strings Random.org for 10 Trials	10K number strings MS Excel [NORM.INV(RAND(), mean, standard dev)] for 10 Trials	Random10K (Random.org) for 10 Trials
Test 1	0.00270		0.00220	0.00252	0.00257
Test 2	0.01563	0.01400	0.01560	0.01559	0.01544
Test 3	0.00040		0.00040	0.00004	0.00010
Test 4	0.00457	0.00500	0.00180	0.00250	0.00204
Test 5	0.00306		0.00260	0.00161	0.00183
Test 6	0.00553	0.00680	0.00540	0.00440	0.00443
Test 7	0.00478		0.00140	0.00446	0.00507
Test 8	0.00010	0.00020		0.00012	0.00011
Total		0.02540	0.02800	0.03019	0.03059

We use two methods to assess non-random variation in the selected time series. The first method uses counting the error frequency for each of the eight rules and the overall rate. The second method employs isolating the actual observation associated with non-randomness and assigning a dollar value based on that observation. Using these methods, one can compare time series of any type with any other, e.g., a sales variance process, a service accounting metric, a stock price, or a stock index (data selected for availability and convenience). When the calculated non-random (special cause) variation exceeded random chance, special cause variation existed in that string.

3.1 Error Count Method

Using the error count method, Table 3 provides the results from several time series, including a one-year sales variance assessment, Mondelez and SP500 prices for 275 trading days, and a two-year service recovery period. Each series contains an associated rate of non-random variation by rule. Furthermore, the frequency rate from each rule has an associated *p-value* calculated to show significant differences from what would occur randomly in a simulation. Because the simulation method allows for a calculation of the overall error rate assessment, the associated *p-values* show whether the series error rate is significantly different from the simulation. In the examples, as shown in Table 3, a random simulation has a total 3% error rate versus 13% for a sales process, 9% for a Mondelez stock price, 7% for the SP500 index during that same period, and 4% for a two-year service recovery metric. Similarly, the error rates for each rule can be compared in each of the same time series. Moreover, the absence of occurrence of non-random rules could be an indication of non-randomness when sample sizes are large.

Table 3. Time Series Comparisons Using Nelson’s Rules and Error Counts

From left to right, this table provides error rates based on Nelson’s rules: random occurrence, fiscal year sales variance, Mondelez, SP500, and a 2-year service recovery metric with associated *p-values*.

Tests for Special Cause Variation	Random10K (Random.org) for 10 Trials	2017 Sales Variance Sample PB (n=12,432)	*p-value*	MDLZ Daily Returns 29 June 2016 to 30 August 2017 (n=275)	*p-value*	SP500 Daily Returns 29 June 2016 to 30 August 2017 (n=275)	*p-value*	Service Recovery 2016-2017 (n=24)	*p-value*
Test 1	0.00257	0.03081	0.000	0.03636	0.003	0.01818	0.053	0.04167	0.338
Test 2	0.01544	0.02960	0.000			0.01091	0.470		
Test 3	0.00010	0.00016	0.606						
Test 4	0.00204	0.00161	0.265						
Test 5	0.00183	0.00507	0.000	0.01091	0.147	0.00727	0.288		
Test 6	0.00443	0.00040	0.000						
Test 7	0.00507	0.03588	0.000	0.05091	0.001	0.03273	0.010		
Test 8	0.00011								
Total	**0.03059**	**0.09934**	0.000	**0.09091**	0.001	**0.06545**	0.019	**0.04167**	0.786
T-K Multiple Calculation	**1.00000**	**3.24748**		**2.97186**		**2.13974**		**1.36210**	

3.2 Taylor-Kiymaz Multiple

We propose the use of the T-K multiple which divides the rate of non-random occurrence by random occurrence or probability. Therefore, the T-K multiple, found on the last row of Table 3, measures the degree of non-randomness, variation, or volatility of each time series based on random occurrence. In a large sample simulation, if an event occurs randomly about 3 percent of the time, then the 2017 sales variance was 3.2 times random; Mondelez was 3.0 times; the SP500 was 2.1 times; the service metric was 1.4 times random for their respective time intervals. The T-K multiple could also be used to calculate non-randomness among each of the individual rules, comparing any time series to random occurrence. For example, a measure of cycle time might concentrate principally on observations violating rule 1. In this case, the random base divisor could be either random occurrence or a calculated probability of that random occurrence. Furthermore, the T-K multiple offers an advantage over typical volatility calculations because it employs random occurrences outside the measured system or time series. For example, typical volatility might use a stock index component in the system itself. Reviewing Mondelez versus the SP500 for the same time period in Table 3, Mondelez exhibits a 1.4 multiple, which is very different from the calculated T-K multiple. Moreover, comparisons can be made with time series which are better understood or more frequently occurring.

Table 4 shows the sales variance metric calculated over five fiscal years during decreasing revenue volume, as visible by the reductions in sample sizes. Interestingly, the T-K multiple varied from 3.0 times to 4.2 times random occurrence over those years.

Table 4. Sales Variance Time Series Comparisons Using Nelson's Rules and Error Counts

From left to right, this table provides error rates based on Nelson's rules: random occurrence and each of five-year sales variance with associated *p-values*.

Tests for Special Cause Variation	Random10K (Random.org) for 10 Trials	2017 Sales Variance Sample PB (n=12,432)	*p-value*	2018 Sales Variance Sample PB (n=10,656)	*p-value*	2019 Sales Variance Sample PB (n=7,400)	*p-value*	2020 Sales Variance Sample PB (n=5,504)	*p-value*	2021 Sales Variance Sample PB (n=4,256)	*p-value*
Test 1	0.00257	0.03081	0.000	0.03031	0.000	0.02721	0.000	0.02707	0.000	0.02820	0.000
Test 2	0.01544	0.02960	0.000	0.03613	0.000	0.04723	0.000	0.01326	0.171	0.02138	0.008
Test 3	0.00010	0.00016	0.606	0.00009	0.950			0.00036	0.309	0.00047	0.268
Test 4	0.00204	0.00161	0.265	0.00282	0.146	0.00282	0.216	0.00236	0.631	0.00117	0.112
Test 5	0.00183	0.00507	0.000	0.00432	0.000	0.00334	0.028	0.00672	0.000	0.00399	0.027
Test 6	0.00443	0.00040	0.000	0.00066	0.000	0.00026	0.000	0.00036	0.000	0.00352	0.331
Test 7	0.00507	0.03588	0.000	0.05349	0.000	0.05364	0.000	0.04669	0.000	0.02279	0.000
Test 8	0.00011										
Total	**0.03059**	**0.09934**	0.000	**0.12265**	0.000	**0.12782**	0.000	**0.09139**	0.000	**0.07777**	0.000
T-K Multiple Calculation	**1.00000**	**3.24748**		**4.00961**		**4.17860**		**2.98751**		**2.54242**	

When considering the 85/15 rule using the error-count method, non-random occurrence is about 3 percent when simulated but is between 4 and 9 percent in the yearly samples exhibited in Table 3. In Table 4, the range expands from 8 to 13 percent over the 13-year period, but both tables appropriately fulfill Deming's expectation for non-random occurrence.

3.3 Special Cause versus Random Variation Method of Rates

An additional method to examine, compare, or benchmark time series processes is through a ratio of special versus random variation. This calculation separates the total variation of a time series into its components by calculating the underlying dollar values related to special cause variation. When a specific non-random error occurs, for example, the dollar amount of sales variance or the daily change in a stock price or index, that amount represents non-random variation. Total variation in the time series would be the total amount of both random and non-random; therefore, subtracting non-random from total variation would be random variation. Table 5 details the similarities of non-random variation in the same sales process over a 13-year period. Non-random variation varied from a low of about 19 percent to a high of 31 percent. For the two stocks previously mentioned, the special cause variation for Mondelez and SP500 were 20% and 8%, respectively. Once again, the totality of this information gives additional credence to the 85/15 rule that postulates that 85% of the root causes of errors are attributable to "systems, processes, and structure while 15% can be traced to people" (Clemmer, 1992, p. 67).

Table 5. Sales Variance: Separation of Random and Non-random Variation

This table provides 10-year sales variation, which separates over/undersold and assigns associated non-random variation based on Nelson's rules.

Year	Oversold (Positive Variation)	Undersold (Negative Variation)	Total Variation	Non-Random Variation	Random Variation	% of Non-Random Variation	% of Random Variation
2009	$2,840,207	($5,508,677)	$8,348,883	$1,874,309	$6,474,574	22.4%	77.6%
2010	$3,260,460	($5,795,934)	$9,056,394	$2,335,479	$6,720,916	25.8%	74.2%
2011	$3,932,765	($5,540,532)	$9,473,297	$2,679,310	$6,793,987	28.3%	71.7%
2012	$3,037,403	($5,221,363)	$8,258,766	$2,396,269	$5,862,497	29.0%	71.0%
2013	$2,663,584	($8,553,638)	$11,217,222	$3,474,567	$7,742,654	31.0%	69.0%
2014	$1,743,874	($7,872,060)	$9,615,935	$2,182,877	$7,433,058	22.7%	77.3%
2015	$1,786,043	($8,335,417)	$10,121,460	$2,747,146	$7,374,314	27.1%	72.9%
2016	$2,533,672	($4,577,125)	$7,110,797	$1,314,652	$5,796,145	18.5%	81.5%
2017	$2,021,944	($1,979,637)	$4,001,581	$1,023,995	$2,977,587	25.6%	74.4%
2018	$1,688,443	($1,915,520)	$3,603,963	$1,008,100	$2,595,863	28.0%	72.0%
2019	$1,073,908	($1,143,089)	$2,216,997	$574,324	$1,642,672	25.9%	74.1%
2020	$826,749	($1,126,062)	$1,952,810	$417,755	$1,535,055	21.4%	78.6%
2021	$807,205	($1,383,084)	$2,190,289	$433,300	$1,756,990	19.8%	80.2%

3. Conclusion

Through two methods, we have shown that error counting or random rate methods can be used to understand deterministic variation in sales and accounting metrics as well as stock prices and their indexes. This fact was postulated by the 85/15 rule many years ago, but this innovative idea seems to have been ignored outside of the quality literature.

In our detailed sales example, the exact number of sales personnel changes over these 13 years of sales variance is unknown but were numerous considering C-suite, regional, area, and district changes. Yet, even through frequent management transformations, the best possible range of non-random rates was between 19 and 31 percent and suggested that process/systems variation far exceeded any changes caused by personnel. The human and monetary costs of this unending search were immense to hire the "ideal" individuals. Therefore, whether error counting or non-random rate methods were employed, system variation, not the human actors in the system, were causing the majority of variation. This knowledge also holds true for those other series.

Finally, the T-K multiple actually calculates a ratio of random occurrence using the error-counting method to obtain a standard metric to evaluate any time series. This metric not only shows the current state of a process, but also its changes, improvements, or degradations over time.

4. Limitations

There were several limitations to this study. At the time of chart creation, Sigma XL was limited to the calculation of 36K observations which was considerably less than the sample generated by the random number algorithm. Similarly, with the advancement of computer technology, perhaps other non-random rules will be discovered and published.

We performed test of differences and Taylor-Kimaz multiple calculations only from extant data in our datasets. Nonextant data were not used in any calculations to avoid confusing absence of evidence with evidence of absence. Moreover, we do not speculate on the possibility of the human ability to create a totally random string or the philosophical discussion concerning whether any event is in fact random.

5. Future Research

Future research could examine the cognitive reasons behind the business's focus on people while minimizing its emphasis on process. Many exogenous variables could be explored that may create this inclination of thought: from locus of control, loss of control, and illusion of control to hubristic ideas about the human belief to dictate events which might be thought of, in sum, as the Cassius complex: "The fault, dear Brutus, is not in our stars, but in ourselves, that we are underlings."

Additionally, many more time-series types could be tested over extended periods. Examples include charts of accounts or subcategories from any financial statements or metrics, industrial classification systems, stock market index comparisons, specific production and/or operational metrics, to name a few. However, we suspect it is much easier to look towards individuals than to analyze, understand, change, or improve organizational processes.

Acknowledgements

An unpublished version of this article was cited in Taylor and Kiymaz (2022).

References

Bye, J., Fraedrich, K., Kirk, E., Schubert, S., & Zhu, H. (2011). Random walk lengths of about 30 years in global climate. *Geophysical Research Letters, 38*(5), 1-3. https://doi.org/10.1029/2010GL046333

Clemmer, J. (1992). *Firing on all Cylinders. The Service/Quality System for High-Powered Corporate Performance*. Toronto, Canada: Macmillan Canada.

Deming, W. E. (1982). *Out of the Crisis*. Cambridge, MA: Massachusetts Institute of Technology.

De Vany, A. (2004). *Hollywood Economics: How Extreme Uncertainty Shapes the Film Industry*. New York, NY: Routledge. https://doi.org/10.4324/9780203489970

Griffiths, D., Bunder, M., Gulati, C., & Onizawa, T. (2010). *The Probability of an Out of Control Signal from Nelson's Supplementary Zig-Zag Test*. Centre for Statistical and Survey Methodology, University of Wollongong, Working Paper 11-10, 1-9. https://doi.org/10.1080/15598608.2010.10412007

Henderson, G. R., Mead, G. E., van Dijke, M. L., Ramsay, R., McDowall, M. A., & Dennis, M. (2008). Use of Statistical Process Control Charts in Stroke Medicine to Determine if Clinical Evidence and Changes in Service Delivery Were Associate with Improvements in the Quality of Care. *Quality Safety Health Care, 17*, 301-306. https://doi.org/10.1136/qshc.2006.020784

Juran, J. M. (1989). *Juran on Leadership for Quality: An Executive Handbook*. New York, NY: The Free Press.

Mandelbrot, B., & Taleb, N. N. (2010). Mild vs. Wild Randomness: Focusing on Those Risks that Matter. In F. Diebold, N. Doherty, & R. Herring. (Eds.), *The Known, the Unknown and the Unknowable in Financial Institutions*, 47-58. Princeton, NJ: Princeton University Press. https://doi.org/10.1515/9781400835287-004

Mohammed, M. A., Cheng, K. K., Rouse, A., & Marshall, T. (2001). Bristol, Shipman, and Clinical Governance: Shewhart's Forgotten Lessons. *The Lancet, 357*, 463-467. https://doi.org/10.1016/s0140-6736(00)04019-8

Nelson, L. S. (1984). The Shewhart Control Chart-Tests for Special Causes. *Journal of Quality Technology, 16*(4), 237-239. https://doi.org/10.1080/00224065.1984.11978921

Noskievičová, D. (2013). Complex Control Chart Interpretation. *International Journal of Engineering Business Management, 5*(13), 1-7. https://doi.org/10.5772/56441

Selden, P. H. (1996). *Sales Process Engineering: A Personal Workshop*. Milwaukee, WI: ASQC Quality Press.

Shewhart, W. E. (2015). *Economic Control of Quality of Manufactured Product*. Mansfield Center, CT: Martino Publishing. (Originally printed in 1931 by D. Van Nostrad Company, Inc.).

Silver, N. (2012). *The Signal and the Noise: Why so Many Predictions Fail - but Some Don't*. New York, NY: Penguin Books.

SPC Excel. (n.d.) *Control Chart Rules and Interpretation*. Retrieved from https://www.spcforexcel.com/knowledge/control-chart-basics/control-chart-rules-interpretation

Taleb, N. N. (2008). *Errors, Robustness, and The Fourth Quadrant*. https://doi.org/10.1016/j.ijforecast.2009.05.027

Taylor, K. I., & Kiymaz, H. (2022). Error Propensities Amongst Finance and Accounting Professionals: Can We Quantitatively Measure Illusion of Control or Chaos?. *Accounting and Finance Research*, *11*(3), 22-34. https://doi.org/10.5430/afr.v11n3p34

Wheeler, D. J., & Chambers. D. C. (1992). *Understanding Statistical Process Control* (2nd Ed.). Knoxville, TN: SPC Press.