Causal Control Charts: Application to Assessing Impact of Trump's Election on Insurance Stock Prices

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Abstract - At its core, performance improvement requires a causal inference. The alternative causes of poor performance needs to be identified and statistically controlled so that the effect of the new intervention on performance can be assessed. Unfortunately, current control charts are not based on principles of causal inference. Objective: To provide a method of assessing causal impact of an intervention while controlling for alternative explanations. Methods: The impact of the intervention (cases) is compared to a counterfactual, simulated, control. The data are stratified by combination of alternative causes. Within each stratum cases after the intervention are compared to weighted controls, where weights are chosen so that the frequency of alternative explanations among cases and controls are the same. The methodology is applied to changes in stock prices after election of President Trump, with general trend in the economy and general trend in the healthcare stock prices being the alternative explanation. The impact of the election is examined after removing the effects of alternative explanations. Results: Impact of election on stock prices differs after we control for alternative explanations for rise of stock prices. Conclusions: Causal control charts may be useful in situations where several competing causes exists for changes in performance.

Keywords - Causal analysis, Causal control charts, Counterfactuals, Stratification.

1 Introduction

At its core, performance improvement requires a causal inference. The alternative causes of poor performance need to be identified and statistically controlled so that the effect of the new intervention on performance can be assessed. Control charts were designed to help improvement teams focus on causes of adverse outcomes. The purpose of control charts is to detect special "causes" that have led to changes in the underlying observed process. A claim is made that a special cause exists, if the observed event is outside of three standard deviations of historical or risk adjusted patterns (Amin 2001). All other events are attributed to random variation in the underlying processes. Despite clear causal interpretation of control chart, these methods do not use causal analysis and therefore could be misleading. In this paper we show how causal control charts can be constructed.

Note: Dr. Farrokh Alemi was receiving research funding from the Center from Disease Control during the writing of this paper.

A. Assumptions of causal claims

Several assumptions are necessary for making a causal claim (Pearl 2009). The first and obvious assumption is that the cause should lead to the effect. This is often referred to there being an association between cause and effect. The expectation is that one would see a change in the process after an intervention. The second assumption is that causes must occur before effects. Since a control chart is based on change in time, it is relatively easy to see that the effect of intervention follows and does not precede the intervention. The third assumption is that there should be a clear mechanism that connects causes to effects. In most control charts, the mechanism is not shown, but implied. The fourth assumption emphasizes that the causal impact of an intervention is calculated by comparing the effect when the cause is present to the effect when the cause is absent. In observation data used typically for constructing control charts, one can never be sure what would have happened if a particular intervention was not made. The post-intervention effects most always reflect the effect of the cause, and it is difficult to assess what would have happened if the intervention had not been made.Because these situations cannot be observed directly they are referred to as counterfactual and investigators have used pre-intervention data to estimate the likely effect if the cause was absent in the post intervention period. This fourth assumption is known as the *counterfactual assumption*. Finally, fifth an assumption must be made that all relevant causes are measured and available. Existing approaches to control charts verify the association, sequence and perhaps the mechanism assumptions but not the counterfactual assumption. The causal control chart directly tests the appropriateness of three of the assumptions: association, sequence, and counterfactual. The mechanism assumption is left to the imagination of the reader and the assumption that all relevant causes are measured and available is not tested but it is assumed that over time as more information about the factors that affect the process become available, causal control charts become increasingly more accurate.

Five Features of Causality

1. **Association:** Causes are associated with effects
2. **Sequence:** Causes must precede effects
3. **Mechanism:** Causes must have a mechanism that leads to the effect
4. **Counterfactual:** Effects should not happen causes are not present
5. **Comprehensiveness:** All relevant causes must be examined

In any causal analysis, an assumption is made that relevant variables are measured. We assume that all relevant differences among cases and controls are measured as covariates. This is an important assumption which is not testable within the data. We can never be sure that all relevant variables have been measured and are available. Yet, the assumption that all relevant variables are measured and available is the nature of scientific investigations and improvement efforts. Each investigator adds a new set of variables and tests their own hypotheses and insights. In these situations, every analysis is suspect. No analysis is complete, and some future investigator could do a better job of including all relevant variables. Similarly, causal analysis are suspect until additional variables that could change the findings are specified. This lack of completeness should not be reason for avoiding causal analysis. The fact that some future analyst may find other more relevant causes should not be reason for paralysis at current period. Improvement is a cumulative and iterative effort and over time, we will get better at adding and including all relevant variables. Future improvement teams can do more thorough analyses, but for now we need to focus on what we know and can measure—the current set of measures.

B. Construction of counterfactuals

The key difference between a causal and traditional control chart is the construction of the counterfactual group. A counterfactual group is an artificially constructed group of patients who have the same features as the observed cases except for the presence of the special cause. These cases are not observed. We are making a scenario of what we might have observed if the alternative causes were not present. This certainly is speculative, but it is an organized speculation where in the effect of alternative causes are removed. If a risk, severity, or prognosis index is available that aggregates the effects of various features of the patient, then the index is used to create the scenarios. In recent years, a number of authors, including us, have proposed new ways to risk adjust control charts, and therefore in principle create counterfactual groups (Hart et al. 2004; Cook et al. 2008; Cook et al. 2001; Alemi and Oliver 2001; Alemi and Sullivan 2001; Cockings, Cook and Iqbal 2006). These methods focus on balancing the data so that intervention (cases) and non-intervention group (controls) do not differ in having alternative causes/explanations (also referred to as covariates). The balancing of the data could occur through propensity scoring (where the intervention is predicted from various covariates) or through stratification (where the impact of intervention is examined within strata of covariates). If patients are stratified based on the covariates, then stratification controls for the alternative explanations and data within stratified groups provides estimates for the impact of the intervention. In short, stratification can be used to remove the effects of alternative causes and speculate what would have occurred if it were not for these alternative causes. In this paper, we focus on stratification methods for balancing data.

The counterfactual model for causal analysis of observational data can be traced to a series of articles by Rubin (1974, 1978, 1977, 2005). It has also roots in econometric models (Heckman, 1979, 2008), probability models (Pearl 2009), and philosophy (Collins and Paul 2004). The core concept behind this method is to artificially construct a control group that would resemble the intervention cases in all aspects but the intervention. Then, the comparison of the cases and the counterfactual control group can provide an estimate of the causal effect of the intervention. In causal control charts the same principals are followed. In these charts, cases are the observations that have the intervention, these data points are used to describe the process. Controls, also referred to as counterfactual group, are the same observations if they did not have the intervention. Control limits are derived by identifying the 95% or 99% values in the counterfactual group. In this fashion, a causal control chart contrast cases with the intervention to controls without the intervention. Except for the intervention, the controls are like cases in other measured aspects.

Suppose that we are interested in impact of intervention X on outcome Y. For simplicity assume that we have two outcomes: Y=1 or Y=0. Any time, the intervention is present we call it a case (X=1); and any time the intervention is absent we call it a control (X=0). Both the outcomes and the intervention are made over time: typically controls precede cases. The data are divided into k strata and each stratum represents combination of alternative causes of the outcome, which we will refer to as covariates. These causes co-occur with the intervention (X) and thus their impact on outcome is confounded. The purpose of the analysis is to remove the confounding through balancing the data across cases and controls; display the relationship between X and Y visually; and calculate the unconfounded impact of X on Y.

where t = 1, … , n and at time t either $c_{it} = d_{it} = 0$ *or* $a_{it} = b_{it} = 0$

Strata	Outcome Y=1		Outcome Y=0	
	Cases X=1	Controls X=0	Cases X=1	Controls X=0
1	a_{1t}	c_{1t}	b_{1t}	d_{1t}
2	a_{2t}	c_{2t}	b_{2t}	d_{2t}
…	…	…	…	…
i	a_{it}	c_{it}	b_{it}	d_{it}
…	…	…	…	…
k	a_{kt}	c_{kt}	b_{kt}	d_{kt}

Table 1 Observations of Cases and Controls over Time

To balance the data, Alemi, ElRafey and Avramovic (2016) recommends weighing controls so that the rate of occurrences of alternative causes among the intervention and non-intervention group are the same at any post-intervention period. Weights are chosen so that the effects of co-occurring causes *A*,…, *R* are removed. Let w_{it1} and w_{it0} indicate weights for strata i, period t, for cases (X=1) and controls (X=0). These weights are chosen so that there are no differences in probability of co-occurrence of alternative causes:

$$p(A, \dots, R|X = 1) = p(A, \dots, R|X = 0) \ \forall \text{ combinations of } A, \dots, R \qquad Eq1$$

A set of weights that guarantees equation 1 holds for time period t, is given as follows:

$$w_{it1} = \begin{cases} 0 & a_{it} + b_{it} = 0 \\ 1 & Otherwise \end{cases}$$

$$w_{it0} = \frac{a_{it} + b_{it}}{(\sum_t c_{it} + \sum_t d_{it})/n}$$

These weights ensure that the intervention and non-intervention group do not differ in rate of observing alternative causes. Thus, these weights provide a way of removing the effect of the alternative causes. The only variation that remains is the difference in the intervention and non-intervention group. Once the weighted controls are estimated, then the upper and lower control limits are estimated as:

$$Control\ Limit = \bar{p} \pm 3\sqrt{\frac{\bar{p}(1-\bar{p})}{n}}$$

Where the $\bar{p}$ is the average probability of the outcome among the weighted controls.

A simpler method of balancing alternative explanations is to switch the frequency of the explanations (i.e. alternative causes) among the controls and cases. This method was first reported in benchmarking clinical care by Alemi and Gustafson (2006), where one physicians' outcomes are calculated on distribution of patients of other physicians. This method bypasses the calculation of weights and directly equates the distribution of alternative explanations among control and cases.

First, the alternative explanations are arranged into mutually exclusive and exhaustive combination set. Second, the frequency of the occurrences of alternative explanations before (control) and after (cases) is calculated. Third, the frequencies of the cases after are switched with the frequency of controls before the intervention. Note that the frequency of occurrence of alternative explanations varies considerably, in essence showing that these

explanations are confounded with the causal impact of the intervention. By switch these frequencies, we are simulating the situation where alternative explanations are equally likely before and after the intervention, de facto creating the counterfactuals. Weighting would have done the same but switching the probabilities by passes the need to estimate the weights.

2 Application to Real Data

To test the procedures on real data, we examined the impact of 2016 election of president Trump on stock prices for Humana insurance company. Humana was one of the participants in President Obama's health care reform. During the election, candidate Trump had promised to repeal and replace the reforms. Therefore, his election should have led to changes in evaluation of the stock. Unfortunately, stock prices are affected by a host of variables and we would need to remove the confounding that occurs when multiple variables affect the value of Humana stock prices. We begin the analysis without removing the confounding and then repeat the analysis after removing the confounding to contrast how the conclusions radically change. In removing the confounding, we will use the switch method

Date	AET	AET UP	IXIC	IXIC UP	S&P 500 Health Care (Sector)	S&P UP
5/20/2016	110.64	1	4769.56	1	803.65	1
5/23/2016	110.09	0	4765.78	0	799.96	0
5/24/2016	111.63	1	4861.06	1	811.76	1
5/25/2016	113.69	1	4894.89	1	816.98	1
5/26/2016	113.07	0	4901.77	1	817.04	1
5/27/2016	113.25	1	4933.50	1	821.20	1
5/31/2016	113.23	0	4948.05	1	822.36	1
6/1/2016	115.29	1	4952.25	1	825.49	1
6/2/2016	120.03	1	4971.36	1	836.28	1
6/3/2016	120.04	1	4942.52	0	833.58	0
6/6/2016	122.29	1	4968.71	1	838.21	1
6/7/2016	121.60	0	4961.75	0	832.57	0
6/8/2016	122.72	1	4974.64	1	836.56	1
6/9/2016	121.27	0	4958.62	0	834.58	0
6/10/2016	120.52	0	4894.55	0	827.01	0
6/13/2016	119.18	0	4848.44	0	820.92	0
6/14/2016	119.56	1	4843.55	0	821.68	1
6/15/2016	119.92	1	4834.93	0	815.98	0
6/16/2016	121.64	1	4844.92	1	818.80	1
6/17/2016	121.10	0	4800.34	0	809.83	0
Date	AET	AET UP	IXIC	IXIC UP	S&P 500 Health Care (Sector)	S&P UP
11/9/2016	118.02	1	5251.07	1	816.53	1
11/10/2016	119.90	1	5208.80	0	826.26	1
11/11/2016	119.28	0	5237.11	1	813.91	0
11/14/2016	123.98	1	5218.40	0	811.25	0
11/15/2016	123.59	0	5275.62	1	813.51	1
11/16/2016	123.30	0	5294.58	1	809.63	0
11/17/2016	126.20	1	5333.97	1	813.19	1
11/18/2016	124.88	0	5321.51	0	803.93	0
11/21/2016	126.86	1	5368.86	1	806.32	1
11/22/2016	128.42	1	5386.35	1	795.04	0
11/23/2016	129.33	1	5380.68	0	798.08	1
11/25/2016	129.57	1	5398.92	1	801.37	1
11/28/2016	128.39	0	5368.81	0	794.52	0
11/29/2016	132.03	1	5379.92	1	799.72	1
11/30/2016	130.84	0	5323.68	0	792.13	0
12/1/2016	134.90	1	5251.11	0	786.12	0
12/2/2016	133.49	0	5255.65	1	788.57	1
12/5/2016	129.45	0	5308.89	1	787.30	0
12/6/2016	128.54	0	5333.00	1	789.21	1

Table 2. sample of pre- and post-election data

We will use a dataset obtained from Yahoo Finance containing data for 60 days from before the election (the controls) and 60 days after the election (the cases) for a total of 120 days into 6 periods of 20 days each. A sample of these data is provided in Table 2. Notice that we will analyze the probability of Healthcare Insurance Companies (HIC) price going up, thus these calculations are not done directly on the price of the stock but on whether the stock value increased from the previous day. Also notice the difference between pre and post-elections. The seven columns on the left provide the data for pre-election and the second columns to the right are for post-election. The basic idea of the chart is to calculate the control limits from pre-election period and compare post-election values to these calculated limits. If the post-election data fall outside the control limits of pre-election period, then we know that the election has had an impact.

Control charts are used to detect variations in systems and processes. Traditional control charts detect two types of variations. The first type of variation is due to random variation. Natural variation that is internal to the process or system is considered Random variation. The second type of variation is called special or assignable cause. Variances in outcomes of the system or process that can be traced back to a source that is not part of the process are considered special or assignable causes. [1]. Figure 1. below shows the trends of the raw data and the daily variation.

In this paper, we are interested in the determining the special or assignable causes of the increase in healthcare stocks. We introduce Causal Control Charts (CCC) and apply the technique to analyze the impact of Trump presidency on healthcare stocks. We utilize CCC to estimate the unconfounded impact of an intervention on the process by removing the effects of alternative explanations using Stratified Covariate balancing and swapping. The analysis controls for (1) changes in an index of funds that measures changes in general economy, and (2) an index of funds that measure price changes in health insurance industry. With this methodology, we can address the impact of Trump's presidency on fluctuations in individual insurance stocks

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2.1 Assumptions of causal claims

According to Pearl, causal claims must meet several criteria [2]. Initially, the cause should lead to the effect. Often, we refer to this as an association between cause and effect. If an association exists, one would see a change in the process after the intervention. Should the first assumption prove true, next a mechanism should exist that leads from the cause to the effect. Control Charts make it easy to see that the effect of intervention follows and does not precede the intervention because they are temporal. Third, there should be a clear mechanism that connects causes to effects. Mechanism are implied in most control charts. The fourth criterion is that the causal impact of an intervention is calculated by comparing the effect when the cause is present to when the cause is absent. [2] One can never be sure what would have happened if a specific intervention was not made utilizing typical observation data for control charts. The post-intervention effects always reflect the effect of the cause and it is difficult to assess the counterfactual argument of what would have happened if the intervention had not been made. Because these situations cannot be observed directly they are referred to as counterfactual and investigators have used pre-intervention data to estimate the likely effect if the cause was absent in the post intervention period. This fourth assumption is known as the counterfactual assumption [3]. The final criteria that is all relevant causes are measured and available. [2] Existing approaches to control charts verify the association, sequence and perhaps the mechanism assumptions but not the counterfactual assumption. The causal control chart directly tests the appropriateness of three of the assumptions: association, sequence and counterfactual. The mechanism assumption is left to the imagination of the reader and the assumption that all relevant causes are

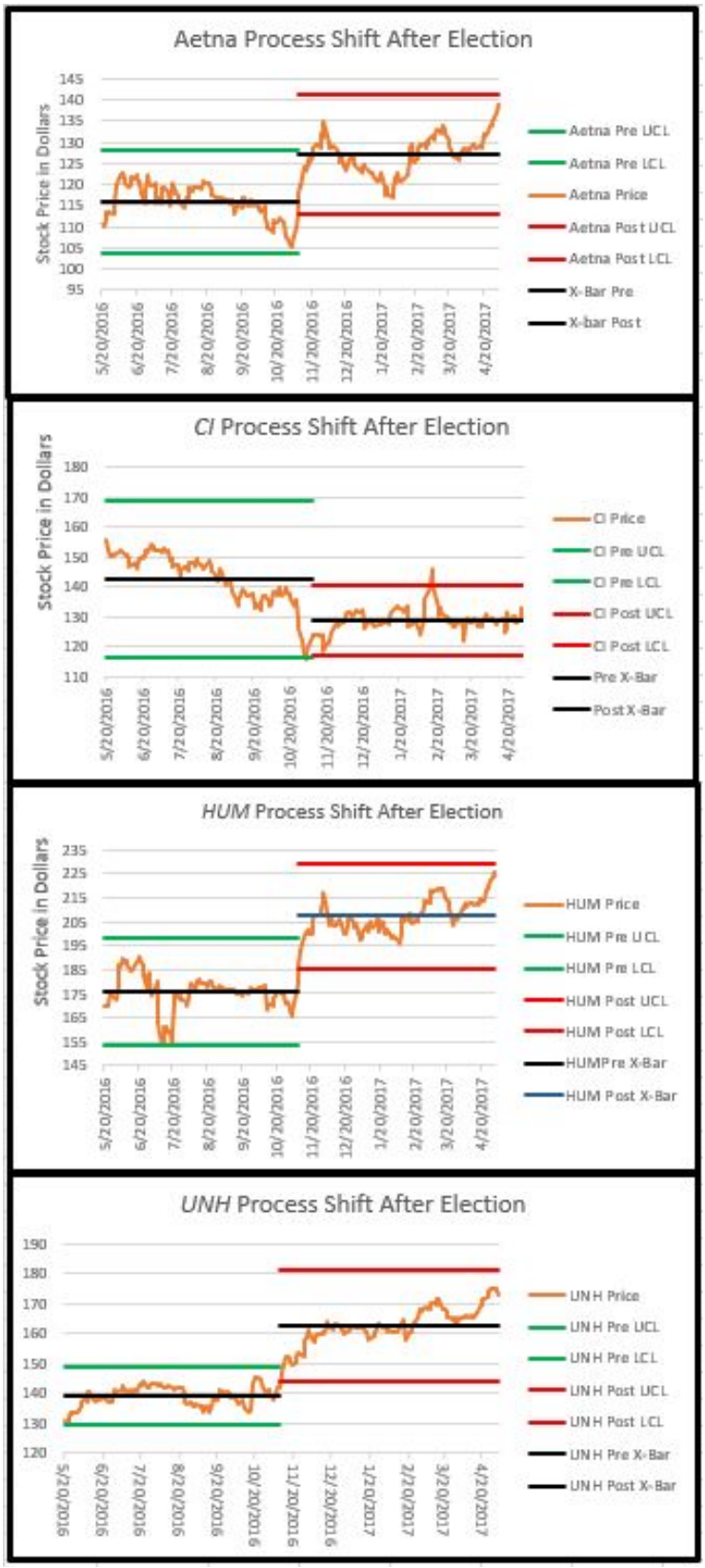

Figure 1. Four HIC stocks six months before and after the election

measured and available is not tested but it is assumed that over time as more information about the factors that affect the process become available, causal control charts become increasingly more accurate. In any causal analysis, it is assumed that relevant variables are measured. Additionally, we assume covariates include all relevant differences among cases and controls. This important assumption is not testable within the data. We can never be sure that all relevant variables have been measured and are available. Yet, that is the nature of scientific investigations and improvement efforts. Each investigator adds a new set of variables and tests their own hypotheses and insights. In these situations, every analysis is suspect. No analysis is complete. Some future investigator could do a better job of including all relevant variables. Similarly, causal analysis is suspect until additional variables that could change the findings are specified. This lack of completeness should not be reason for avoiding causal analysis. The fact that some future analyst may find other more relevant causes should not be reason for paralysis at the current time. Improvement is a cumulative effort and over time; we will get better at including all relevant variables. Future improvement teams can do better analysis but for now we need to focus on as complete a set of measures as possible.

2.2 Causal control charts

Causal Control Charts (CCC) utilize a counterfactual group that is an artificially constructed group that have the same features as the observed cases except for the presence of the special cause. In recent years, several authors, including the authors of this paper, have proposed new ways to risk adjust control charts, and therefore counterfactual groupings. [4]–[8] These methods focus on balancing the data so that intervention (cases) and non-intervention group (controls) do not differ in alternative causes/explanations (also referred to as covariates). Rubin provides the basis for a counterfactual model for causal analysis of observational data. This can be traced back to a series of articles by Rubin. [9]–[13] The counterfactual model also has roots in econometric models, [14], [15], probability models [2], and philosophy. [16].

Data are divided into six strata; each stratum represents combination of alternative causes of the outcome or covariates. We do this to remove the confounding through balancing the data across cases and controls; display the relationship; and calculate the unconfounded impact. The only variation that remains is the difference in the intervention and non-intervention group. Once the weighted controls are estimated, then the upper and lower control limits are estimated as:

$$Control\ Limit = \bar{p} \pm 3\sqrt{\frac{\bar{p}(1-\bar{p})}{n}}$$

Where the $\bar{p}$ is the average probability of the outcome among the weighted controls. We utilized the switch method to remove the confounding that occurs when multiple variables affect the Health Insurance stock prices. The switch method is a simplified method of balancing alternative explanations by switching the frequency of the explanations among the control and cases. The was first reported as a method for benchmarking clinical care alternatives by Alemi and Gustafson, where one's physician's outcomes are calculated and applied to the distribution of patients of other physicians. [17].

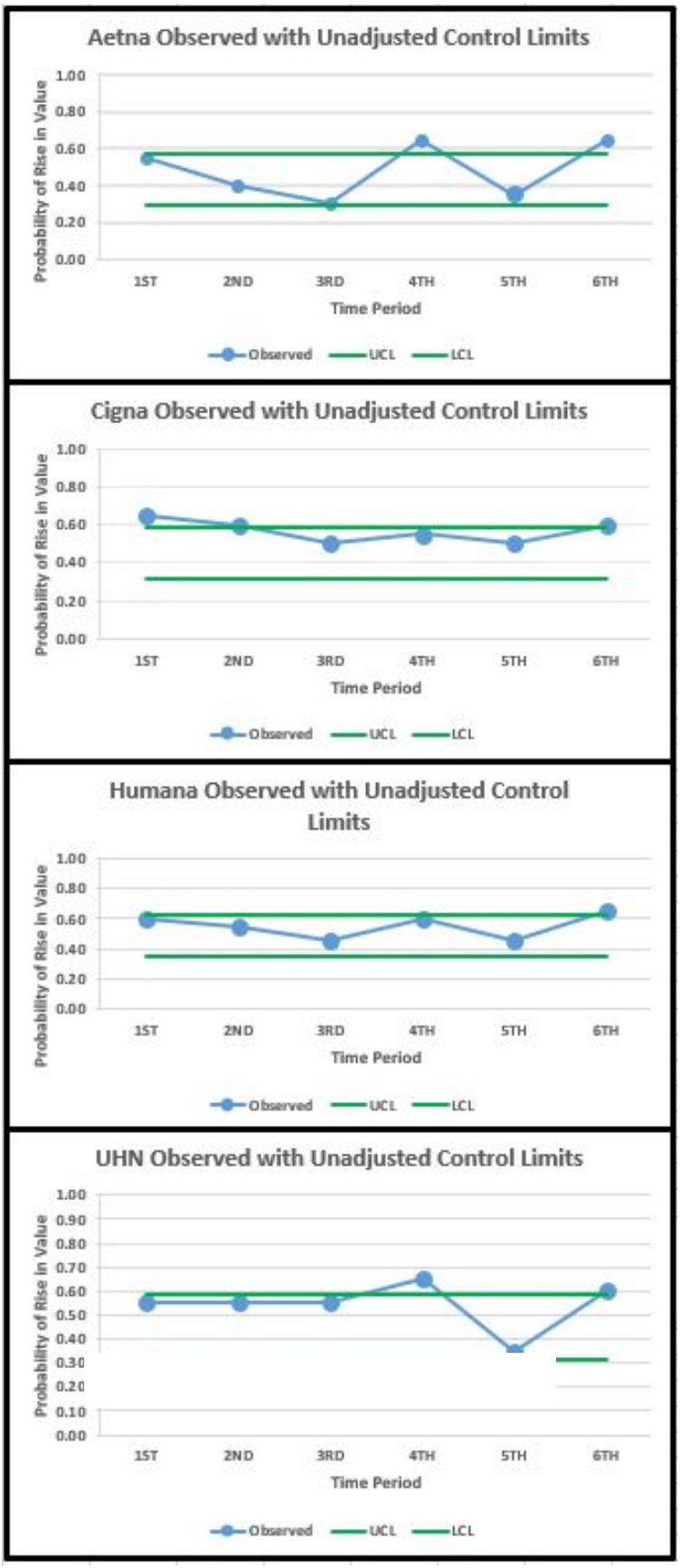

Fig.2 Unadjusted Observed and Control Limits

3 Data

We are interested in whether Humana stock went up if we remove the effect of general economy, as measured by Nasdaq, and health care sector's economy, as measured by S&P Health stock. There could be other factors that are known to affect the value of Humana's stock; but for purposes of this exercise we are assuming that these two factors is all that matters. We refer to Nasdaq and S&P as alternative explanations for why Humana's stock goes up or down. These two stocks provide us with four possible combinations of events, which we call strata. These combinations are provided in the first two columns of Table 6 and are the situations where neither, one but not the other, or each stock goes up. For the adjusted calculation, all analysis is done within these 4 strata.

A. Step 1: Control Limits without Adjustment

Let us first do the analysis without adjusting for the impact of Nasdaq and Standard and Poor Healthcare. We can do this by calculating the average number of days in which Humana's stock goes up in the pre-election period.

Humana prices going up in the pre-election period. Note that the number six in

$$\bar{p} = \frac{\#\text{ times stock up in pre} - \text{election days}}{\text{Number of pre} - \text{election days}} = 0.43$$

$$\text{Humana Control Limit} = \bar{p} \pm 3\sqrt{\frac{\bar{p}(1-\bar{p})}{n}}$$
$$= 0.4917 \pm 3\sqrt{\frac{0.4917(1-0.4917)}{120}}$$

The upper and lower control limits are calculated from the average probability of calculation of control limits comes from the fact that each post-election rate is calculated from six observations.

The chart for the post-election time periods is provided in Figure 2. Note that the variation in stock prices has produced control limits that are narrow. In this chart, the control limits show pre-election situation and the post-election stock changes are outside these limits. It appears as if the election did have an impact on Humana as well as the stock values of the other companies. However, this conclusion is premature as much of the variation in the stock could be due to other causes. We need to remove the alternative explanations of rises in Humana stock and re-examine the impact of the 2016 election.

B. Step 2: Organize Data within the Strata

We are interested in whether Humana stock went up if we remove the effect of general economy, as measured by Nasdaq, and health care sector's economy, as measured by S&P Health stock. There could be other factors that are known to affect the value of Humana's stock; but for purposes of this exercise we are assuming that these two factors are all that matters. We refer to Nasdaq and S&P as alternative explanations for why Humana's stock goes up or down. These two stocks provide us with four possible combinations of events, which we call strata. These combinations are provided in the first two columns of Table 3 and are the situations where neither, one but not the other, or both stocks go up. For the adjusted calculation, all analysis is done within these 4 strata.

Aetna Inc (AET)										
In Controls					Frequency in Post-Election Periods					
IXIC	S5HLTH	Count	Freq	Aetna Up	1ST	2ND	3RD	4TH	5TH	6TH
-	-	42	0.35	0.1190	0.25	0.20	0.30	0.30	0.20	0.30
-	+	12	0.10	0.5833	0.10	0.20	0.10	0.05	0.05	0.20
+	-	17	0.14	0.3529	0.25	0.10	0.20	0.05	0.40	0.05
+	+	49	0.41	0.6939	0.40	0.50	0.40	0.60	0.35	0.45
Adjusted Rate in Controls				**0.4333**	**0.4539**	**0.5227**	**0.4422**	**0.4989**	**0.4370**	**0.4823**
Cigna Corporation (CI)										
In Controls					Frequency in Post-Election Periods					
IXIC	S5HLTH	Count	Freq	Cigna Up	1ST	2ND	3RD	4TH	5TH	6TH
-	-	42	0.35	0.4524	0.25	0.20	0.30	0.30	0.20	0.30
-	+	12	0.10	0.5833	0.10	0.20	0.10	0.05	0.05	0.20
+	-	17	0.14	0.2941	0.25	0.10	0.20	0.05	0.40	0.05
+	+	49	0.41	0.4694	0.40	0.50	0.40	0.60	0.35	0.45
Adjusted Rate in Controls				**0.4500**	**0.4327**	**0.4712**	**0.4406**	**0.4612**	**0.4016**	**0.4783**
Humana, Inc (HUM)										
In Controls					Frequency in Post-Election Periods					
IXIC	S5HLTH	Count	Freq	HUM Up	1ST	2ND	3RD	4TH	5TH	6TH
-	-	42	0.35	0.2143	0.25	0.20	0.30	0.30	0.20	0.30
-	+	12	0.10	0.7500	0.10	0.20	0.10	0.05	0.05	0.20
+	-	17	0.14	0.6471	0.25	0.10	0.20	0.05	0.40	0.05
+	+	49	0.41	0.6122	0.40	0.50	0.40	0.60	0.35	0.45
Adjusted Rate in Controls				**0.4917**	**0.5352**	**0.5637**	**0.5136**	**0.5015**	**0.5535**	**0.5221**
UnitedHealth Group Uncorporated (UNH)										
In Controls					Frequency in Post-Election Periods					
IXIC	S5HLTH	Count	Freq	UNH Up	1ST	2ND	3RD	4TH	5TH	6TH
-	-	42	0.35	0.2143	0.25	0.20	0.30	0.30	0.20	0.30
-	+	12	0.10	0.5000	0.10	0.20	0.10	0.05	0.05	0.20
+	-	17	0.14	0.2353	0.25	0.10	0.20	0.05	0.40	0.05
+	+	49	0.41	0.7143	0.40	0.50	0.40	0.60	0.35	0.45
Adjusted Rate in Controls				**0.4500**	**0.4481**	**0.5235**	**0.4471**	**0.5296**	**0.4120**	**0.4975**

Table 3 Adjusted Rate of Rise in Insurance Stock Prices

C. Step 3: Switch Frequency & Simulate Rate of Rise in HIC's Stock in Pre-Election

The purpose of the adjustment is to make sure that Nasdaq (N) and Standard & Poor Healthcare (S&PH) are up or down at same rates in the pre- and post-election periods. This means that we must simulate a situation where pre- and post-election rates of each of these four strata are equal. One way to do so is to use frequencies of the strata in post-election time periods as a replacement for the pre-election frequency. This switch, as discussed earlier, guarantees that the strata occur at the same rate across the two periods. Note that for each post-election period, we have a different set of frequencies. For all of the pre-election time period we have one time period. Table 3 shows the pre- and post-election

frequencies. To simulate the situation where the controls have the same distribution as 1st period in post-election, the two frequencies are switched and the unadjusted rate of days in which Humana's stock price is rising is calculated as:

$$Humana\ \bar{p} = \sum_{\text{strata}} f_{\text{time 1}}\, p_{\text{rise in strata}}$$

$$= .35 * .25 + .10 * .10 + .14 * .25 + .41 * .4 = 0.5352$$

In above equation, $f_{\text{time 1}}$ is the frequency of the strata in 1st post-election time-period, $p_{\text{rise in strata}}$ is the rate of days with rise in the HIC's stock price. This simulates the rate of rise for the HIC pre-election, if it had the same strata distribution as the 1st time-period post-election.

D. Step 4: Calculate Adjusted Control Limits

The control limits are calculated from adjusted rates of rise in HIC's stock in the pre-election period. These rates are given in grey at bottom of each section in Table 2.

Control Limits for Humana 1st Post Election Pe

$$= \bar{p} \pm 3\sqrt{\frac{\bar{p}(1-\bar{p})}{n}} = 0.5232 \pm 3\sqrt{\frac{0.5232\,(1-0.5232)}{20}}$$

N=20 because the sample size of each period is 20 observations. Figure 3 below details the calculated adjusted control limits superimposed over the unadjusted control limits for all four insurers. If the UCL less than 0, the UCL is set to 0.

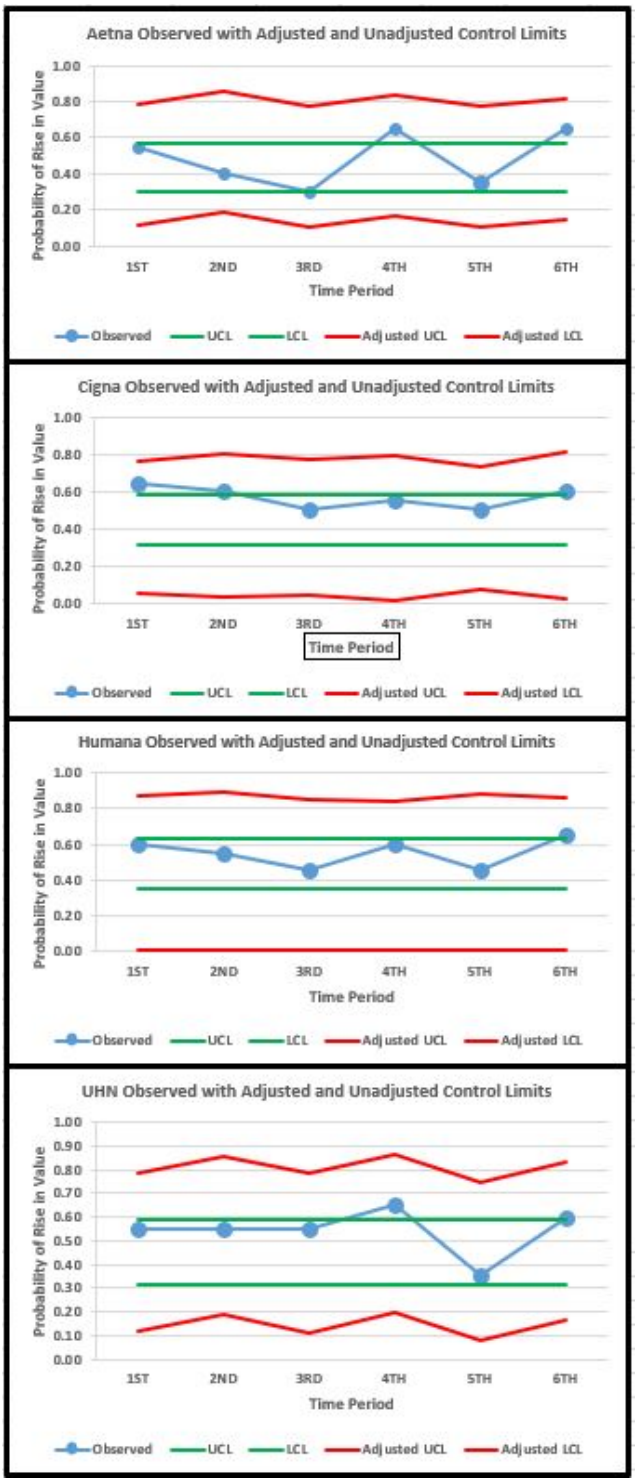

Figure 2 Adjusted and Unadjusted Control Limits

Utilizing stratification and switching of frequencies has allowed us to adjust the rate of rise in the HIC's stock price. As seen in

4 Results and Analysis

Table 2 above, the rate for the 1st time-period for Humana's has adjusted from 0.45 to 0.53. Or to restate this, if the controls had the same distribution of Nasdaq and Standard & Poor Healthcare rising as the 1st time-period, then the rate of Humana's rising among the controls will increase from 0.49 to 0.53. Table 2 shows the calculations for all time-periods. Notice that in all these time-periods the rate of Humana's stock rising has increase above 0.49, in part because the influence of alternative causes of increase on this rate have been removed.

With the unadjusted controls, all stocks had at least one point outside the control limits. In the case of Aetna, Cigna, and UHN, Figure 3 indicates that the rates were out of control for at least two periods of the strata in pre-election time-period. Removing confounding modified and increased the upper and lower control limits. In contrast to Figures 1 and 2, the adjusted analysis shows that the 2016 presidential election did not have an influence on the individual healthcare company stock prices. Because we removed the effect of the general economy (as measured by Nasdaq prices) and health industry (as measured by Standard and Poor Healthcare prices), the variation in the stock was increased and the control limits were further apart. This has allowed us to detect the effect of 2016 election separate from alternative explanations.

5 Conclusions

This paper has laid out how competing causes can be statistically controlled for so the effect of intervention on outcome of care can be separated out. We have shown by way of example the kind of intuitions that could emerge from causal analysis of improvement efforts.

ACKNOWLEDGEMENTS

This paper was edited by Nancy Freeborne, DrPH

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