5-2021

The Effect of High Elevation Weather Stations on the USDA's Pasture, Rangeland, and Forage Insurance Program

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THE EFFECT OF HIGH ELEVATION WEATHER STATIONS ON THE USDA'S

PASTURE, RANGELAND, AND FORAGE INSURANCE PROGRAM

By

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A thesis submitted in partial fulfillment
of the requirements for the degree

of

MASTER OF SCIENCE

in

Economics and Statistics

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2021

ABSTRACT

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(35 Pages)

PUBLIC ABSTRACT

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This paper examines the effect of high elevation weather stations on the rainfall index used by the Pasture, Rangeland, and Forage insurance program. Weather station data for the state of Utah is used to identify high elevation weather stations and their location. Utilizing the corresponding rainfall index data, the effect of the high elevation weather stations is determined. This paper finds when high elevation weather stations begin reporting there is a jump up of 19.01–27.88 percentage points on average in the rainfall index for the corresponding grid locations. This indicates the rainfall index may not accurately represent actual precipitation amounts in areas with large elevation changes. If the measurements recorded by the rainfall index for PRF do not match actual amounts of precipitation, then the rainfall index is potentially introducing more risk and undermines the ability of PRF to effectively mitigate risk for producers.

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The Effect of High Elevation Weather Stations on the USDA's Pasture, Rangeland, and Forage Insurance Program

The Pasture, Rangeland, and Forage Program (PRF) is an insurance program offered by the United States Department of Agriculture Risk Management Agency otherwise known as the USDA-RMA. The program is designed to help crop and livestock producers mitigate risk by protecting a producer's operation from risks of forage lost due to the lack of precipitation (USDA-RMA 2017a). PRF is an index-based insurance program that does not measure individual production, but rather bases indemnities off precipitation amounts reported by the index. This gives PRF the advantage of minimizing information asymmetry held by the insured (Westerhold et al. 2018). In general, index-based insurance is lower-cost than similar individual-based insurance due to this minimization of information asymmetry. One of the downsides to index-based insurance is the risk of differences between individual outcomes and what is reported by the index, also known as basis risk.

Since its introduction, the PRF program has used both a vegetation index and rainfall index to measure precipitation. The vegetation index used satellite imagery to measure vegetation in specific areas, however, this index is no longer used by PRF. The rainfall index uses precipitation data from the National Oceanic and Atmospheric Administration Climate Prediction Center (NOAA CPC).

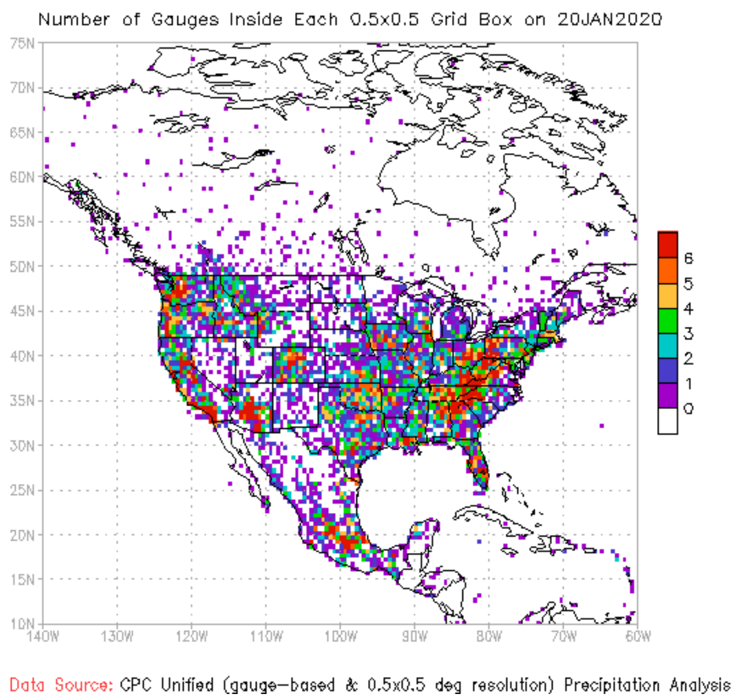
NOAA CPC uses a grid system to determine the rainfall index. Each grid is 0.25 latitude by 0.25 longitude, which is approximately 17 by 17 miles (USDA-RMA 2017a). NOAA CPC takes the rainfall measurements from at least the four closest weather stations to the centroid of each grid. The measurements are then weighted based on how close each station is to the centroid of the grid. Higher weights are assigned to the stations closer to the centroid. After taking the weighted rainfall measurements, the amount of precipitation for each grid is compared to a 70-year average. The rainfall index value for the grid is then determined as a percentage of the 70-year average. For instance, if the precipitation is the same as the 70-year average, the rainfall index value for the grid would be 100 percent. Rainfall index values are determined for each grid in overlapping two-month intervals. The intervals are Jan-Feb, Feb-Mar, Mar-Apr, Apr-May, May-Jun, Jun-Jul, Jul-Aug, Aug-Sept, Sept-Oct, Oct-Nov, Nov-Dec, for a total of 11 intervals.

For many areas, this is an effective and accurate system, however, in areas with fewer weather stations and high variations in elevation potential issues arise. Utah is a state that fits that description. It is a mountainous area with significant elevation changes and has fewer weather stations than most other states as seen in (figure 1). There are fewer stations within each grid, and in some cases, there are not any weather stations in the grid. As a result, the rainfall index for a grid is calculated using weather stations that are miles away from the grid itself. When a new weather station becomes active it can have a large effect on the grids it is closest to.

Figure 1

Density map of CPC Unified gauges,

https://www.cpc.ncep.noaa.gov/products/Precip_Monitoring/Figures/NAMS/NAMS_curr.p.gnum.gif



If the new station is at a similar elevation to the other weather stations close to the grids, then we wouldn't expect a significant change in the rainfall index. If the elevation of the new station is significantly different from the elevation of the other stations used, then we start to see changes in the rainfall index. Research by Daly et al. (2008) found that in mountainous regions the precipitation in low elevations can be significantly different than precipitation at the top of the mountains. Daly et al. (1994) found a linear relation between precipitation and elevation with precipitation increasing as elevation increases. Utah has some high variations in elevation. The lowest point in Utah being 2,179.8 ft above sea level and the highest point being 13,528 ft above sea level. The elevation within specific grids can sometimes change by thousands of feet. This combined with the low number of weather stations increases the likelihood of having new weather stations, at vastly different elevations, having significant effects on the rainfall index for the grids they are close to.

The research in this paper focuses on the impact to proximal grids of adding high elevation weather stations. High elevation stations were identified that became active in the last 20 years. A regression discontinuity design is then used to evaluate the effect these high elevation stations have on the rainfall indices for the grids they are closest to. This paper finds when high elevation weather stations began reporting there is a jump up of 19.01–27.88 percentage points on average in the rainfall index for the corresponding grids. With these jumps in the rainfall index, it may not accurately represent actual precipitation amounts in areas like Utah with large elevation changes.

Literature Review

Although still somewhat limited, research into the PRF insurance program has increased significantly in the last few years. Areas of focus include interval selection and participation patterns, basis risk, and the functionality of the PRF Program.

Papers by Westerhold et al. (2018), Belasco and Hungerford (2018), Goodrich, Yu, and Vandeever (2019), and Williams (2018) all address the participation patterns by producers in the PRF program.

To assess the risk-reducing effectiveness of the PRF program, Westerhold et al. (2018) examined historical data for two different locations in Nebraska to determine producer net income and risk based on interval selection. Risk was measured as the variance of net income. The authors found that both risk-increasing and risk-decreasing scenarios existed for both locations. Net income risk was reduced when insured intervals coincided with the growing season. They also found one scenario where net income risk increased but resulted in the highest net income suggesting a possible income maximizing strategy. The authors concluded that risk-averse producers should select insurance intervals during growing season months where there is high expected precipitation because PRF lowers net income risk. They also concluded that removing net income risk increasing intervals from the PRF program would result in a better allocation of government funds. Goodrich, Yu, and Vandeever (2019) agree with this conclusion, but express concern that restricting choices to the growing season would be met with pushback from participants and reduce the flexibility of the program.

Goodrich, Yu, and Vandeever (2019) came to similar conclusions after looking at PRF participant data for Nebraska and Kansas. Using cluster analyses the authors grouped participants with similar interval choice patterns. Depending on the intervals selected the groups were assigned a level of risk aversion. Groups that assigned more liability within the growing season on average were labeled as more risk-averse and groups that placed less liability within the growing season on average were labeled as less risk-averse. Goodrich, Yu, and Vandeever found that over time, the number of participants within groups considered less risk-averse increased and the number of participants in groups considered more risk-averse decreased. Based on these findings Goodrich, Yu, and Vandeever (2019) concluded there are two possible explanations for the increase in participants with low levels of risk aversion: 1) proportionally, more individuals with low levels of risk aversion have entered the program compared to individuals with high levels of risk aversion, or 2) participants have changed their choices over the years and become less risk-averse. Goodrich, Yu, and Vandeever (2019) point out it is possible participants have learned more about the payment distributions over time. If participants chose profit maximizing strategies in place of risk minimizing strategies it could explain this trend towards less risk-averse participants. This theory is supported by the findings of Westerhold et al. (2018) showing that higher risk profit maximizing strategies did exist. It is also supported by Williams (2018) who compared the PRF rainfall index to various drought indices.

Williams (2018) sets up several different theoretical models to evaluate how drought index-based insurance programs would function for the cattle ranchers. Specifying five different drought indices, the Palmer Drought Severity Index, Self-Calibrated Palmer Drought Severity Index, Palmer Z index, Standardized Precipitation index, and Standardized Precipitation-Evapotranspiration index, the author compares the theoretical payouts from these indices compared to the payouts of the PRF program rainfall index.

Williams (2018) finds the rainfall index can provide adequate protection through a drought if the right insurance intervals are chosen, but it would be very easy to choose low-paying intervals or miss needed payments altogether. Williams (2018) also finds there exists a general incentive under the rainfall index to strategize and insure the months with the highest chance of payout, and this incentive undermines the specificity required for an effective index-insurance plan. In contrast to the rainfall index. Williams (2018) observed PRF under the longer-term drought indices in place of the rainfall index would be very resilient against missed payouts during droughts and does not tend to pay at all during drought-free periods. Potentially eliminating the incentive to choose intervals outside of growing seasons and promoting risk aversion strategies by participants.

Another area of focus of research into the PRF program is the associated level of basis risk. The most notable studies being Yu et al. (2019) and Keeler and Saitone (2020).

Yu et al. (2019) investigated the basis risk of the PRF program using forage and rainfall data from three ranches in Nebraska and Kansas. Using a regression approach, they estimated false negative probabilities (FNPs) to determine basis risk. Calculating the FNPs, the authors found the overall basis risk of the PRF program was 26%. By using site-level rainfall data for each of the ranches they were also able to calculate basis risk for the rainfall index. They find that the basis risk for PRF coming from the rainfall index was 6-9%. Yu et al. (2019) conclude that most of the basis risk of the PRF program comes from non-precipitation factors.

Similar to Yu et al. (2019), Keeler and Saitone (2020) estimate the basis risk of PRF as the FNP associated with the program. In contrast to Yu et al (2019), Keeler and Saitone (2020) were able to utilize data from a much larger area in California by using the Normalized Difference Vegetative Index (NDVI). They found that the overall basis risk associated with the PRF program was 31-59%. A larger estimate than the estimate by Yu et al. (2019). They also found that the PRF rainfall index is poorly correlated with actual forage production in the state of California. Keeler and Saitone (2020) conclude that if climate predictions are correct, producers will face greater risk than in past decades and their findings suggest the PRF program will do little to mitigate that risk.

Cho and Brorsen (2020) also address basis risk of the PRF insurance along with evaluating the design of the product. Basis risk is addressed by quantifying how well the rainfall index matches actual precipitation. They compare the rainfall index to county-level weather stations in the State of Oklahoma. Cho and Brorsen (2020) find that the correlation between the rainfall index and actual precipitation averaged 0.94. They concluded the rainfall index was well designed. Looking at the productivity level the authors find that the minimum risk point occurs at a productivity factor of 45% which is lower than the current minimum of 60% that PRF offers. They suggest changing the productivity level to a range of 30% to 60%. On top of that, they suggest reducing the choice of coverage to only the 90% level. They find it is the most common choice among producers and it is preferred by both minimum risk and profit maximization strategies.

Contrary to the findings of Cho and Brorsen (2020) a study by Orden (2018) points out anomalies in the rainfall index pointing to potential design flaws. Orden (2018) looks at specific grids that display high rainfall index values after the implementation of new weather stations in the area close to the grids. He uses summary statistics, probability density functions, and analysis of variance to assess the increases in the rainfall indices for each of the grids.

Taking summary statistics on grids 26167 and 33663 Orden (2018) finds the overall average of the rainfall indexes increased by more than 50%. He also found that the variability in precipitation had increased in both grids after the new weather stations went into place. PDF's for the two grids exhibited similar results with grid 26167 seeing an increase of 60% in the mean index and grid 33663 seeing an increase of 50%. Orden (2018) concludes evidence points towards the presence of anomalies within the functionality of the PRF insurance program. He also concludes the placement of individual weather stations may in certain circumstances inadvertently skew rainfall indexes for the PRF insurance program at least in the Intermountain West region.

Both Yu et al. (2019) and Cho and Brorsen (2020) found a small percentage of basis risk was due to the rainfall index, however, their studies used data from great plain states with less variation in elevation. The research done by Orden (2018) hints the rainfall index may not function as well in more mountainous regions. This paper expands on the research done by Orden (2018) by obtaining a larger sample size. Gathering weather station data for the entire state of Utah we identify all high elevation stations that could potentially skew rainfall index measurements within the last 20 years. We then gather the rainfall index data for all the corresponding grids. With this larger set of data, we verify if high elevation stations positively skew the rainfall index on average or if the skewed measurements observed by Orden (2018) were isolated events. Our findings suggest high elevation weather stations raise rainfall index values initially, potentially degrading the effectiveness of the PRF program's ability to mitigate risk.

Data

To determine if the anomalies outlined in the paper by Orden were isolated events or part of a larger issue, the functionality of the rainfall index needed to be examined on a larger scale. Two different sources were used to compile data for the entire state of Utah. Weather station data was provided by the Utah Climate Center. Rainfall index data for each of the grids was obtained from the USDA-RMA's PRF support tool.

The Utah Climate Center gathers data from all reporting weather stations across the state of Utah. The data from the Utah Climate Center was provided in individual files for each weather station. The station name, identification number, elevation, longitude, latitude, date when the station started recording measurements, and date when it stopped recording measurements were gathered for each station and compiled into one dataset. The data was then trimmed down to only include the weather stations above 7000 feet that became active in the last twenty years.

Once these stations were identified, the USDA-RMA website was used to gather information on each of the grids in Utah. The location, as well as rainfall index observations for every interval for each grid, was obtained. Combining both the weather station data with the rainfall index grid data, the four closest weather stations to each of the grids were identified. Rainfall index observations were kept for grids where a high elevation weather station was part of the four closest weather stations. The observations for the other grids were dropped. A base rainfall index interval for the observations for each grid was designated when the high elevation weather station affecting that grid began reporting. The data was further trimmed down to five years of rainfall index observations before and five years after the base interval for each grid.

Summary Statistics

The resulting dataset has 69 grids and 111 observations for each grid for a total of 7659 observations. The 111 observations for each grid come from the five years of rainfall index intervals before the corresponding weather station begins reporting, the rainfall index interval the weather station begins reporting in, and the five years of rainfall index intervals after the weather station begins reporting. Means for each different interval for the full five years before and after the weather stations began reporting were collected and can be seen in tables 1 and 2. Note, the rainfall index reports values as a percentage. When data was collected for the rainfall index, the values were divided by 100 and are displayed as such in all following the figures and tables.

Table 1

Rainfall index averages five years before the new weather stations began reporting

Rainfall Index Averages Before												
	Jan-Feb	Feb-Mar	Mar-Apr	Apr-May	May-Jun	Jun-Jul	Jul-Aug	Aug-Sept	Sept-Oct	Oct-Nov	Nov-Dec	Over-all
5 Year Average	1.098	1.016	1.003	1.024	0.948	1.059	1.028	1.020	1.078	1.005	1.122	1.037
4 Year Average	0.972	0.948	1.009	1.035	0.928	1.036	0.993	0.979	1.039	1.005	1.113	1.005
3 Year Average	0.952	0.941	0.976	0.995	0.892	1.043	0.990	0.982	1.061	0.975	1.087	0.990
2 Year Average	0.827	0.897	1.014	1.022	0.867	1.097	1.025	1.030	1.030	0.953	1.158	0.993
1 Year Average	0.765	0.806	0.913	1.031	0.860	1.104	1.120	1.017	1.049	0.934	1.099	0.973

Table 2

Rainfall index averages five years after the new weather stations began reporting

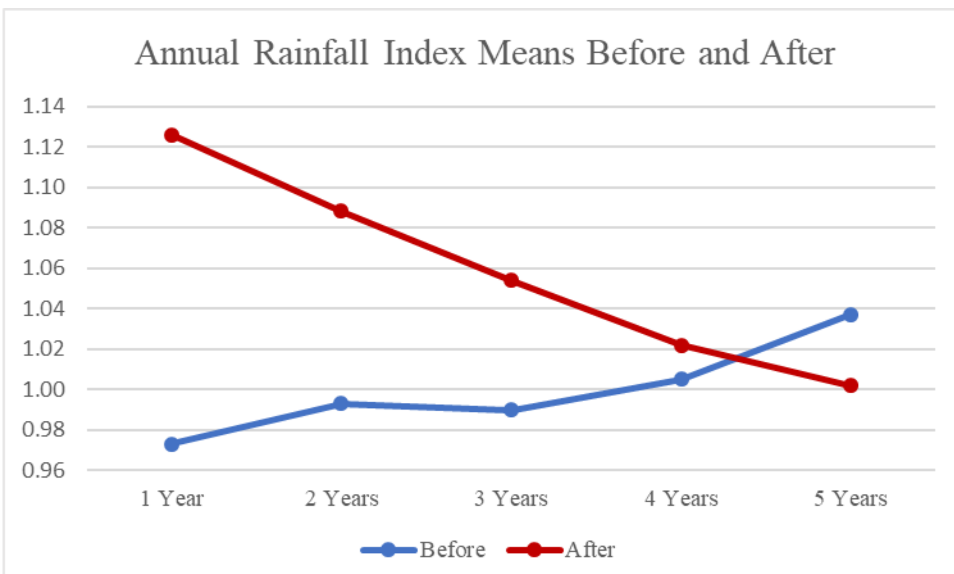
	Rainfall Index Averages After											
	Jan-Feb	Feb-Mar	Mar-Apr	Apr-May	May-Jun	Jun-Jul	Jul-Aug	Aug-Sept	Sept-Oct	Oct-Nov	Nov-Dec	Over-all
5 Year Average	0.979	0.917	0.937	1.040	0.954	1.005	1.091	1.087	1.080	0.938	0.999	1.002
4 Year Average	0.985	0.913	0.968	1.067	0.965	1.043	1.132	1.082	1.113	0.938	1.034	1.022
3 Year Average	1.047	0.929	0.997	1.129	1.003	1.106	1.157	1.081	1.084	0.983	1.075	1.054
2 Year Average	1.048	1.007	1.043	1.136	1.028	1.171	1.188	1.051	1.103	1.042	1.154	1.088
1 Year Average	1.120	1.120	1.120	1.226	1.260	1.313	1.225	0.923	1.019	0.894	1.165	1.126

For both tables 1 and 2, the averages for each yearly interval are the averages for that year combined with previous years. For instance, the five-year average is the average across all five years not just the fifth year. Comparing the overall five-year average in table 1 to table 2, it was higher before the new weather stations began reporting than after. Relying solely on this measurement would indicate there is no evidence that on average the new high elevation stations are causing increases in the rainfall index. However, further exploration of the data reveals that the averages closer to when the high elevation weather stations began reporting show evidence of the high elevation stations increasing rainfall index values.

Looking at the averages for all four years before and after the new stations began reporting (tables 1 and 2) there is a bit of a change with the overall average being higher after the new stations began reporting, but only by about 1.6%. When the interval is decreased to 3 years before and after (table 1 and 2) the overall average is 6.5% higher after the new stations began reporting. If the interval is decreased to two years before and after, the overall average is 9.9% higher after the high elevation weather stations began reporting. If the interval is decreased to one year before and after, the overall average is 15.7% higher after the high elevation weather stations began reporting. Figure 2 illustrates the pattern that the averages for the rainfall index intervals are higher initially after the high elevation stations began reporting and slowly return to the same level as the averages before the high elevation stations began reporting.

Figure 2

Rainfall index averages five years before and after the new weather stations began reporting



Methodology

Given the hypothesis high elevation weather stations could be increasing the rainfall index for corresponding grids, a regression discontinuity (RD) design analysis was carried out. RD is commonly used to determine the causal effects of policy or programs with a running variable (such as test score or income) that has a clear cutoff point. Subjects on one side of the cutoff point are not affected by the policy or accepted into the program while subjects on the other side are affected by the policy or accepted into the program. RD compares the outcomes of subjects close to the cutoff point on either side with the idea that they would all be very similar in all factors except for the effect of the policy or program. By comparing the outcomes of similar subjects, bias from outside factors is reduced and the causal effect of the policy is revealed.

The purpose of the RD design in the research of this paper is to evaluate the causal effect of high elevation weather stations on the rainfall index. The running variable is the two-month time intervals with the cutoff point being the base interval when the high elevation stations began reporting. The subjects of interest are the grids affected by the high elevation weather stations, and the variable of interest is the rainfall index measurements for the grids. Typically, in an RD design, each observation would be a unique subject. In the case of this research, the same set of grids are followed across time. Although the grids themselves do not change, the circumstances surrounding them do change over time. Weather patterns being the main circumstance changing over time. As a result of this, we can treat each observation as unique and we would still expect that the observations close to the cutoff would be the most similar.

A sharp RD design with a linear parametric model was used. With the high elevation weather stations entering in different years and different times of the year, any specific weather trends or patterns would be negated. As a result, there was no logical reason the data would not be linear in nature. The model is specified as:

$$Rainfall\ Index_{it} = \beta_0 + \beta_1(High\ Elevation\ Station)_{it} + \beta_2(Time\ From\ Station\ Install)_{it}$$
$$+\beta_3((High\ Elevation\ Station)_{it} \cdot (Time\ From\ Station\ Install)_{it}) + \varepsilon$$

Where

$$(High\ Elevation\ Station)_{it} = \begin{cases} 1 \text{ if } (Time\ From\ Station\ Install)_{it} \geq 0 \\ 0 \text{ if } (Time\ From\ Station\ Install)_{it} < 0 \end{cases}$$

Empirical Results

Estimating the model for the four closest weather stations to each of the grids resulted in the output in table 3.

Table 3

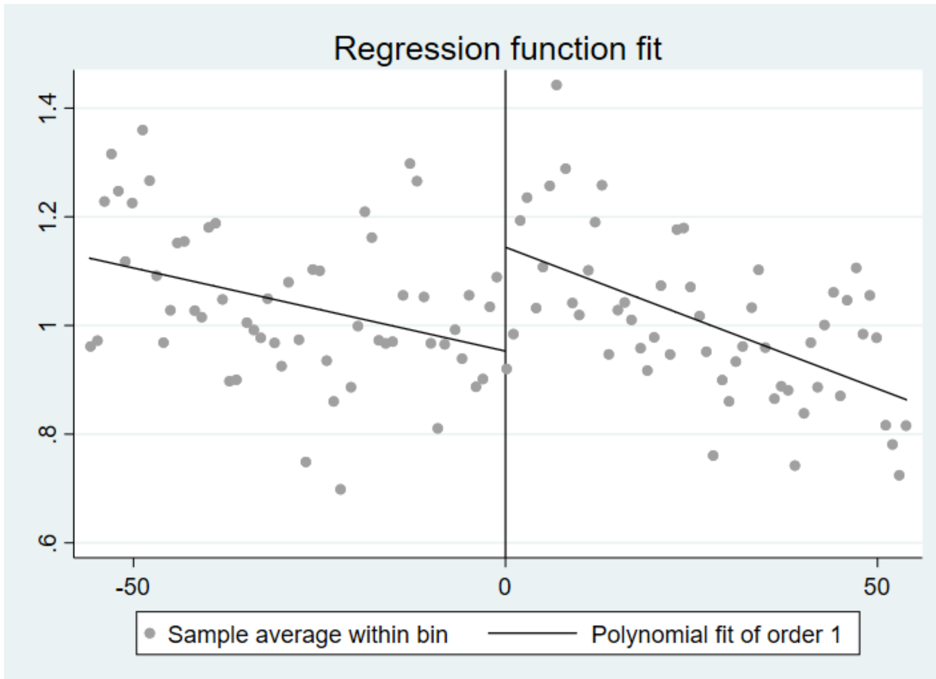
Regression output for the RD design for the four closest high elevation weather stations.

Regression Output						
Rainfall Index	Coefficient	Std. Error	t-value	P > |t|	[95% Conf. Interval]	
High Elevation Station	.1901323	.0269725	7.05	0.000	.1372588	.2430058
Time From Station Install	-.002993	.0005873	-5.10	0.000	-.0041444	-.0018417
High Elevation Station * Time From Station Install	-.0022349	.0008421	-2.65	0.008	-.0038856	-.0005842
Intercept	.9560073	.0192435	49.68	0.000	.9182848	.9937298

The discontinuity estimate is 0.1901 with a t-statistic of 7.05 and a p-value of 0. According to this model, the effect of the high elevation weather stations is an increase of about 19.01 percentage points in the rainfall index and is statistically significant. Visually that effect can be seen in figure 3.

Figure 3

RD design estimated regression function fit for the weather stations that are at least the fourth closest to the corresponding grids.



In figure 3 the vertical axis is the rainfall index level. The horizontal axis is the five years of rainfall index intervals before and after the high elevation stations began reporting with 0 on the axis being the base interval or cutoff point. It is clear looking at the estimated regression lines in figure 3 that there is a break in the line at the cutoff point. That is reflected in our estimated model. The regression line before and after the cutoff is negative sloping and rainfall index values drop back to where they previously were if not slightly lower. The negative slope after the cutoff point matches the findings in the summary statistics. It was observed within five years the rainfall index values had returned to previous levels before the new stations began reporting. The negative slope before the cutoff point was a little concerning, however, looking at the output in table 4 there exists a negative sloping trend in the rainfall index for all the grids in Utah over the last 25 years.

Table 4

Regression estimate for the rainfall index across all grids in Utah from 1995 – 2020.

Regression Output						
Rainfall Index	Coefficient	Std. Error	t-value	P > |t|	[95% Conf. Interval]	
Year & Interval	-.0007463	.0003367	-2.22	0.028	-.0014093	-.0000833
Intercept	1.469492	.1916353	7.67	0.000	1.09215	1.846833

Note. The Year & Interval variable is both the year and rainfall index intervals combined into one continuous variable of index intervals.

Reducing the data to the three closest weather stations to each grid resulted in the following estimated model in table 5:

Table 5

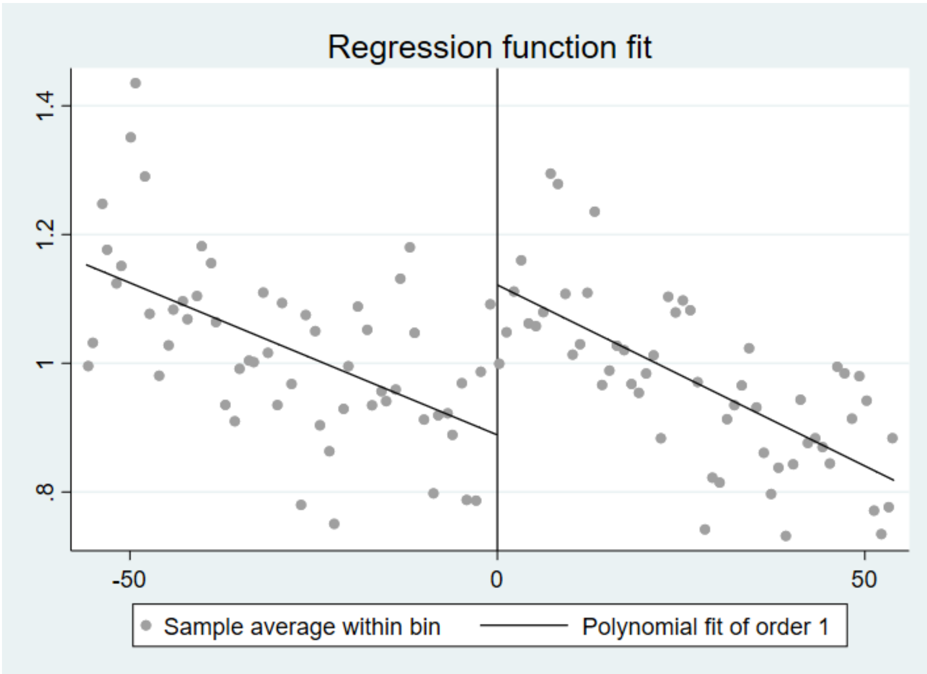
Regression output for the RD design for the three closest high elevation weather stations.

Regression Output						
Rainfall Index	Coefficient	Std. Error	t-value	P > |t|	[95% Conf. Interval]	
High Elevation Station	.2330106	.0324937	7.17	0.000	.169308	.2967132
Time From Station Install	-.004726	.0007076	-6.68	0.000	-.0061131	-.0033389
High Elevation Station * Time From Station Install	-.000898	.0010144	-.89	0.376	-.0028868	.0010908
Intercept	.8886671	.0231826	38.33	0.000	.8432185	.9341156

The discontinuity estimate, in this case, is 0.2330 with a t-statistic of 7.17 and a p-value of 0. Reducing the data to the three closest weather stations resulted in an increase of about 23.30 percentage points in the rainfall index and is statistically significant.

Figure 4

RD design estimated regression function fit for the weather stations that are at least the third closest to the corresponding grids



Further reducing the data to the two closest weather stations to each grid resulted in the following estimated model in table 6:

Table 6

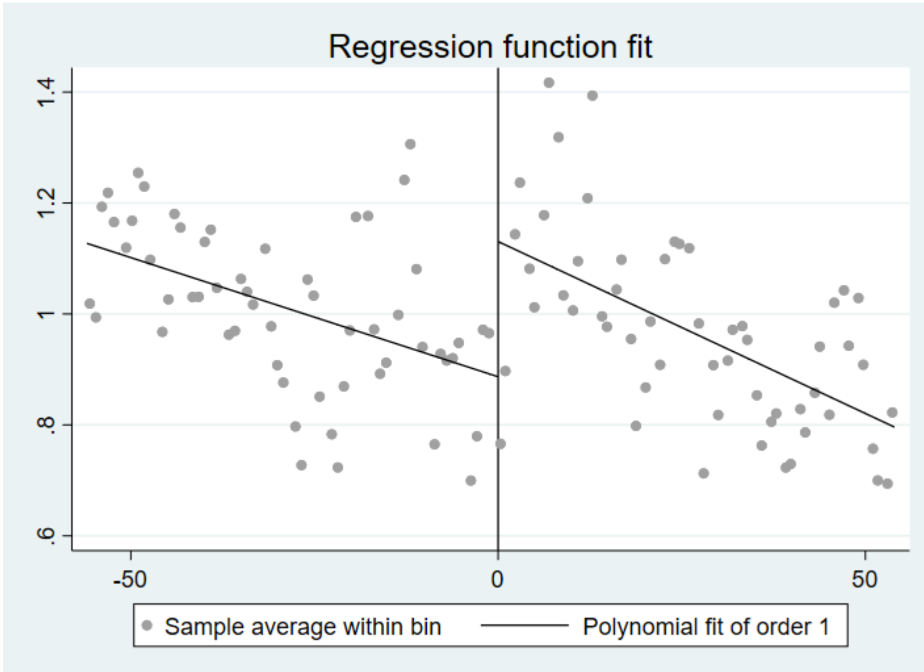
Regression output for the RD design for the two closest high elevation weather stations

Regression Discontinuity Output						
Rainfall Index	Coefficient	Std. Error	t-value	P > |t|	[95% Conf. Interval]	
High Elevation Station	.2438005	.0431961	5.64	0.000	.1591006	.3285004
Time From Station Install	-.0042962	.0009406	-4.57	0.000	-.0061406	-.0024518
High Elevation Station * Time From Station Install	-.0019036	.0013486	-1.41	0.158	-.0045478	.0007407
Intercept	.8867812	.0308182	28.77	0.000	.8263522	.9472102

The discontinuity estimate, in this case, is 0.2438 with a t-statistic of 5.64 and a p-value of 0. Reducing the data to the two closest weather stations to each grid resulted in an increase of about 24.38 percentage points in the rainfall index and is statistically significant.

Figure 5

RD design estimated regression function fit for the weather stations that are at least the second closest to the corresponding grids



Finally, reducing the data to the closest weather stations to each grid resulted in the following estimated model in table 7:

Table 7

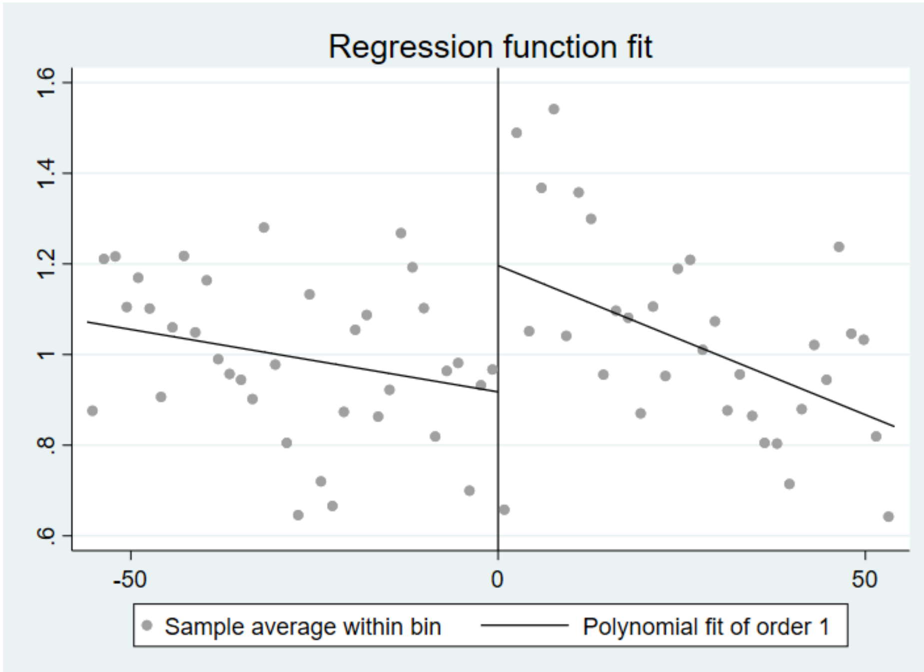
Regression output for the RD design for the closest high elevation weather stations

	Regression Discontinuity Output					
Rainfall Index	Coefficient	Std. Error	t-value	P > |t|	[95% Conf. Interval]	
High Elevation Station	.2788339	.0682596	4.08	0.000	0.1449254	.4127423
Time From Station Install	-.0027549	.0014864	-1.85	0.064	-.0056708	.0001609
High Elevation Station * Time From Station Install	-.0038306	.002131	-1.80	0.72	-.0080112	0.0003499
Intercept	0.9175673	0.486997	18.84	0.000	.8220305	1.013104

The discontinuity estimate, in this case, is 0.2788 with a t-statistic of 4.08 and a p-value of 0. Reducing the data to the first closest weather station to each grid resulted in an increase of about 27.88 percentage points in the rainfall index and is statistically significant.

Figure 6

RD design estimated regression function fit for the weather stations that are closest to the corresponding grids



Tightening the restrictions to only include closer and closer weather stations to each grid resulted in an increasing effect on the rainfall index for those grids. When using the weather stations that were at least the fourth closest stations to the grids there is on average an increase of 19.11 percent points in the rainfall index. Trimming the dataset down to the weather stations that are the closest to the grids, the increase in the rainfall index jumps up to an average of 27.88 percentage points. Intuitively this makes sense as weather stations that are closer to a grid would be expected to have a larger impact on the rainfall index for that grid. This is due to the fact that weather stations closer to a centroid of a grid would be weighted higher and have a greater effect on the rainfall index.

Conclusion

The purpose of the PRF program is to mitigate the risk of low precipitation for agriculture producers. To effectively do that as a single-peril insurance program, the payouts must be only dependent on precipitation amounts. The results from both the summary statistics and RD design analysis show that payouts are likely not solely influenced by precipitation, but also by weather station placement and activation. The results indicate that when a new weather station at a high elevation begins reporting, on average it has an immediate effect on the rainfall index for the grids it is close to. In the case where the new weather stations were the closest stations to the corresponding grids, the analysis shows a jump of 27.88 percentage points on average in the rainfall index for those grids.

The effect the high elevation stations have on raising the rainfall index of the grids they are close to appears to diminish over time. More research is needed to determine why the effect diminishes so quickly, but it could be due to corrections made by NOAA CPC. Even in the case of the closest weather stations to the grids, it appears on average that, the raising effect on the rainfall index disappears within four to five years after the stations began reporting. If it is the case that NOAA is making corrections, it may be possible for them to develop a way to correct for new high elevation weather stations as soon as they begin reporting to avoid the initial jump in the rainfall index.

It also needs to be noted that the data on the weather stations did not come from NOAA CPC, but instead came from the Utah Climate Center. It cannot be guaranteed that all the weather stations in our data set are used by NOAA in their calculations of the rainfall index. However, due to the direct correlation in our results between new weather stations reporting and increases in the rainfall index of the grids it can be reasonably assumed that most if not all of the weather stations in the dataset are being used by NOAA.

Utah is a unique state, having high variations in elevation along with relatively few reporting weather stations. These conditions made it ideal for this research and the results show that there are real widespread issues with the PRF program in Utah. Other states with high variations in elevation may also be experiencing similar issues. It is hypothesized that research into states similar to Utah would yield similar results.

Although the negative effects of new, high elevation weather stations seem to occur in a short time frame it is still an issue that may need to be addressed by USDA-RMA for the PRF program. The issues we found highlight increased risk for participants in the PRF program in the state of Utah and possibly in similar areas. There may be solutions to these issues through more coordination with NOAA and a proactive approach to making sure newly activated weather stations accurately reflect the grids they affect. Other possible solutions include a hybrid system between the rainfall index and vegetation index or changing the focus of the program to drought insurance and using a drought index as suggested by Williams (2018) in his research. As valuable as the PRF program is for agriculture producers, it is important that efforts are made to improve the program and reduce unnecessary risk for its participants.

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