Frozen Frugality: Winter Weather's Effects on Economic Growth

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1 Introduction

Effectively since the conception of state economies, economic actors have reckoned with the uncontrollable variable of weather; even the earliest agriculturally-derived economies were dependent upon meteorological phenomena for their primary productivity. As economies have grown increasingly complex, so, too, have the ways in which the whims of the weather seemingly affect economic growth.

Our study seeks to examine one particular aspect of the weather and its effects on the national economy: the winter. Utilizing domestic data collected by meteorological researchers meant to measure the intensity of the winter, we are able to examine the precise, year-to-year relative effects of a harsher winter. We find significant correlation between more intense winters and decreased first quarter economic growth. Interestingly, we see little change in economic activity in winters that are only slightly more intense than average, but then observe a noticeable effect as winters become increasingly harsh.

The remainder of our study begins with an examination of existing economic literature related to weather events in Section 2. We then summarize our data collection in Section 3, our econometric methodologies in Section 4, and present our results in Section 5. We suggest potential future avenues of research in Section 6. Section 7 concludes.

2 Literature Review

The topic of weather's effect on the economy is one that has caught the interest of researchers for a considerable amount of time. In particular, the potential climate change-related implications of such an effect make the field of study worthy of exploration. Given the topic's prevalence, there have multiple analyses using a variety of mechanisms and weather-related events [5, 7].

The ways in which weather can impact an economy are wide-ranging. Economists and psychologists have already established that weather has an effect on consumer behavior, suggesting one possible mechanism by which weather has an effect [4]. On the side of producers, harsh weather conditions have most obviously been shown to take effect on agricultural production [6].

Most prominently, researchers noted economic effects occurring during extreme temperature shocks [2]. Particular heat-wave events and notably harsh winters were used as natural interventions in experimentation, both of which demonstrated noticeable negative economic effects [3, 8].

Our research expands upon existing research into the effects of extreme weather events, particularly in relation to winter. We use a dataset of yearly winter extremity to test the effect of varying degrees of winter intensity upon economic productivity in the United States. Our work provides a comprehensive way of examining the effects of adverse weather on a year-to-year basis, as opposed to looking at individual effects of a single, isolated incident.

3 Data

3.1 Time Horizon

We choose 2001-2019 as the time horizon since such data is relatively new, relevant, and reflect the properties of a 21st century economy. 2020-2023 data are not covered in order to isolate our data from the impact of the COVID-19 pandemic.

3.2 Measurement of Winter Weather Severity

Our main dependent variable is the continuous variable Accumulated Winter Weather Severity Index compiled by Purdue University[1], which is a well-rounded measure of winter weather severity. We scraped the annual AWSSI data for all stations nationalwide from AWSSI's website. We also calculate the adjusted winter weather severity index for cities using

$$\frac{AWSSI_{y,c}}{\max[AWSSI_{y,c}|y \in \mathcal{Y}]}$$

Where $\mathcal{Y}$ is the set of years, 2001-2019. Note that both AWSSI and Adjusted AWSSI are useful since cities with higher AWSSI are more likely to be impacted more by winter weather. However, it is also true that cities with relatively cold climate are better prepared for winter weather, so the adjusted AWSSI is also a good measure of winter weather severity.

In order to present winter weather severity at a national scale, we use the following two ways to aggregate adjusted AWSSI (Citywide) data: 1) A simple average of AWSSI/ Adjusted AWSSI , which is useful since the stations are quite evenly distributed across the nation. 2) A population-weighted national

AWSSI/ Adjusted AWSSI, which is computed by

$$\sum_{c \in \mathcal{C}} \frac{(Adj)\_AWSSI_c \ \cdot \ Population_c}{\sum_{c \in \mathcal{C}} Population_c}$$

Where $\mathcal{C}$ is the set of cities included in the AWSSI. We also assume that this population-weighted AWSSI represents the national overall winter weather severity well since the population of cities correlate well with the population in their surrounding regions.

3.3 Dependent Variables

We use the seasonally adjusted annual rate of GDP growth as the dependent variable. If we have more time, we could utilize more dependent variables such as ISM PMI, the industrial production index, or nonfarm payrolls.

4 Econometric Method

4.1 OLS

Our dependent variable is first quarter GDP. In order to accurately gauge the impact of winter weather, we need to add additional controls (economic background) since, for instance, economic performance might just be bad when the economy is in a recession. To avoid the curse of dimensionality, we use economic output in the previous quarters as the controls. We run the Ljung-Box test for serial auto-correlation to determine how many previous quarters' GDP data we should use. (Plot 1) The null in this test is :

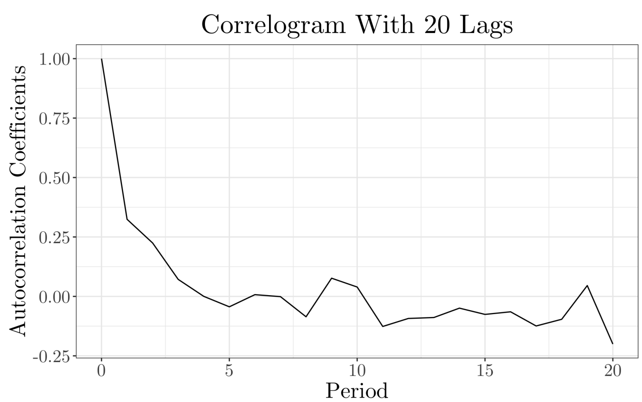
H_0 The data are independently distributed.

The test statistic (for p legs) is given as

$$Q = n(n+2)\sum_{k=1}^{p}\frac{\hat{\rho_k^2}}{n-k} \xrightarrow{d} \mathcal{X}^2(p)$$

where $\hat{\rho}_k$ is the estimated k-th order auto-correlation coefficient.

The following table (on next page) shows that autocorrelation is statistically significant for our GDP growth rate series, especially for the first few legs. To avoid the curse of dimensionality, we choose GDP growth in the past two quarters as controls. The correlogram is shown below.



Hence, our model is

$$Y = \beta X + \gamma_1 Q4gdp + \gamma_2 Q3gdp + \epsilon$$

Where

Variable	Explanation
Y	GDP Growth in Q1
X	A measurement of Winter Weather Severity
Q3gdp	Q3 GDP Growth in The Previous Year
Q4gdp	Q4 GDP Growth in The Previous Year

Legs	$\hat{\rho}$	Ljung-Box Statistic	P-value
1	0.32	81.04	0.00
2	0.22	89.67	0.00
3	0.07	93.87	0.00
4	0.00	94.30	0.01
5	-0.04	94.30	0.02
6	0.01	94.46	0.04
7	-0.00	94.47	0.07
8	-0.09	94.47	0.08
9	0.08	95.13	0.11
10	0.04	95.67	0.15
11	-0.13	95.82	0.14
12	-0.09	97.33	0.15
13	-0.09	98.15	0.17
14	-0.05	98.92	0.21
15	-0.08	99.16	0.24
16	-0.06	99.74	0.28
17	-0.12	100.17	0.25
18	-0.10	101.78	0.26
19	0.05	102.76	0.30
20	-0.20	102.98	0.17

We don't need to worry about endogenity since weather is obviously exogenous.

4.2 Local Linear Regression Using Gaussian Kernel

It is not sound to assume that first quarter economic performance linearly correlates with winter weather severity. For instance, a mild winter and a very mild winter might not be too different for the economy since most people have some preparedness for winter weather. However, an above-average winter might have some more severe effects on the economy since they could disrupt supply chains, hamper industrial production and deter consumers from consumption and travelling. Therefore, we perform two kinds of non-parametric regressions - kernel regression using the Gaussian kernel and B-spline estimation. We use the Gaussian kernel, which is

$$K(x) = \frac{1}{\sqrt{2\pi}}\exp(-\frac{x^2}{2})$$

We try to find the sequence of α and β

$$\text{argmin}\frac{1}{n}\sum_{i=0}^{n}(Y_i-\alpha_i-\beta_(X_i-x))^2K(\frac{X_i-x}{h})$$

Where h is bandwidth. Denote

$$w_i=\begin{pmatrix}1\\ X_i-x\end{pmatrix}\qquad k_i=K(\frac{X_i-x}{h})$$

Let

$$W=\begin{bmatrix}w_1^T\\ \vdots\\ w_n^T\end{bmatrix}\qquad K=\text{diag}(k_1\cdots k_n)$$

We have

$$\begin{bmatrix}\hat{m}_{n,h}\\ \nabla\hat{m}_{n,h}\end{bmatrix}=(W^TKW)^{-1}W^TKY$$

Its asymptotic variance is

$$\sqrt{nh}(\hat{m}_{n,h}-m(x)-h^2\sigma_k^2(\frac{1}{2}f_X(x)m''(x))\xrightarrow{d}\mathcal{N}(0,\frac{(\int K(u)^2du)\sigma^2(x)}{f_X(x)})$$

in our regressions, we note that $m(x)$ is quite smooth, which implies $m''(x)$ is quite small. This is consistent with reality since, usually, the worse the weather, the worse the economic outcome. Hence $m(x)$ should be monotonically decreasing and, barring extreme weather, $m''(x)$ should be quite small. Therefore, if we also note that h is aurally small, we can conclude that the impact of the bias term should be relatively small. We approximate it using

$$\sqrt{nh}(\hat{m}_{n,h}-m(x))\approx d\quad\mathcal{N}(0,\frac{(\int K(u)^2du)\hat{\sigma}^2(x)}{\hat{f}_X(x)})$$

Where

$$\hat{\sigma} = \frac{\sum_{i=1}^{n} K(\frac{X_i - x}{h}) e_i^2}{\sum_{i=1}^{n} K(\frac{X_i - x}{h})}$$

$$\hat{f}_X(x) = \frac{1}{nh} \sum_{i=1}^{n} K(\frac{X_i - x}{h})$$

and that e_i is prediction error. In the plots below, the ribbon shows the 95% CI.

Our bandwidth, h, is fine tuned by using leave-one-out cross validation.

4.3 B-Spline Estimation

Another nonparametric method we used is B-splines. In our work we used cubic spline, one of the most popular ones. The data and confidence intervals are generated by functions in R's spline package. We also fine-tune the number of knots in order to achieve maximum performance.

5 Results

5.1 OLS Results

All four regressions show a strongly negative and statistically significant relationship between winter weather severity and Q1 economic growth. The p-values for our winter weather severity variable is

Test	t-stat	p-value
Average AWSSI	-4.075	0.00100
Average Adjusted AWSSI	-4.198	0.00076
Average AWSSI, Population Adjusted	-3.211	0.00583
Average Adjusted AWSSI, Population Adjusted	-2.638	0.01860

Note that simple averages works better than population-adjusted averages in general. This could attributed to sub-optimal weighting, which could be caused by mismatch between weather stations and cities. (For instance, a weather station may bear the name of a small town yet serve for a major city). Another explanation is that larger cities may be more resilient to severe winter weather due to superior infrastructure and better medical facilities. In this is true, then simply weighting by population might not be the best weighting procedure.

In addition, both the raw AWSSI and the adjusted AWSSI are useful gauge of national winter weather severity as the both produce very significant results, regardless of whether its population-weighted or not.

Table 1: OLS Results (Not Population Adjusted)

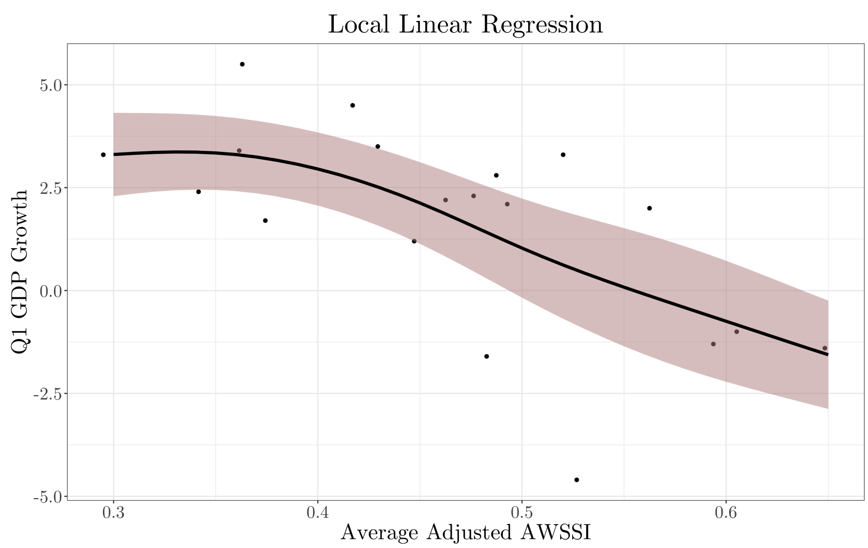
	Dependent variable:	
	Q1 GDP Growth	
	(1)	(2)
Average Adjusted AWSSI	-17.184^{***}	
	(4.093)	
Average AWSSI		-7.609^{***}
		(1.867)
Q4 GDP Growth	0.281^{*}	0.248
	(0.157)	(0.162)
Q3 GDP Growth	0.307	0.339
	(0.217)	(0.223)
Constant	8.483^{***}	44.745^{***}
	(1.924)	(10.824)
Observations	19	19
R^2	0.667	0.656
Adjusted R^2	0.600	0.588
Residual Std. Error (df = 15)	1.581	1.606
F Statistic (df = 3; 15)	10.017^{***}	9.546^{***}
Note:	*p<0.1; **p<0.05; ***p<0.01	

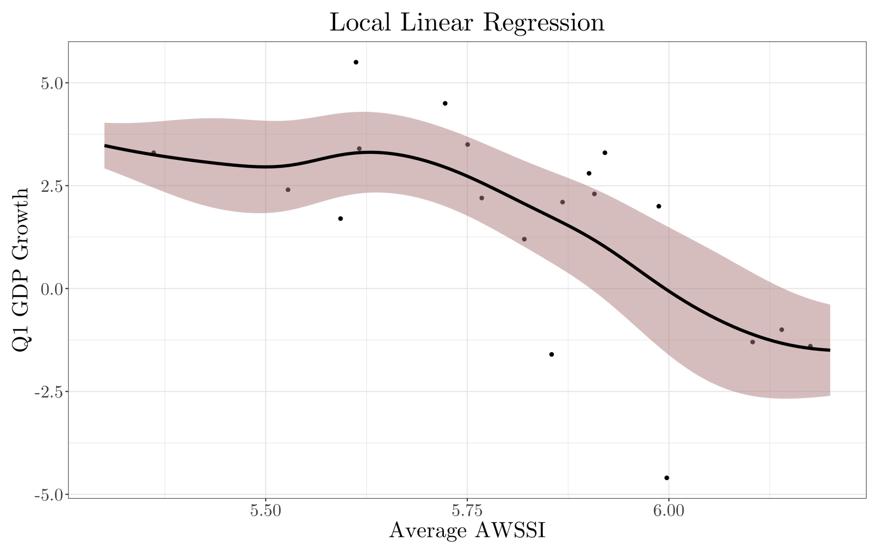
Table 2: OLS Results (Population adjusted)

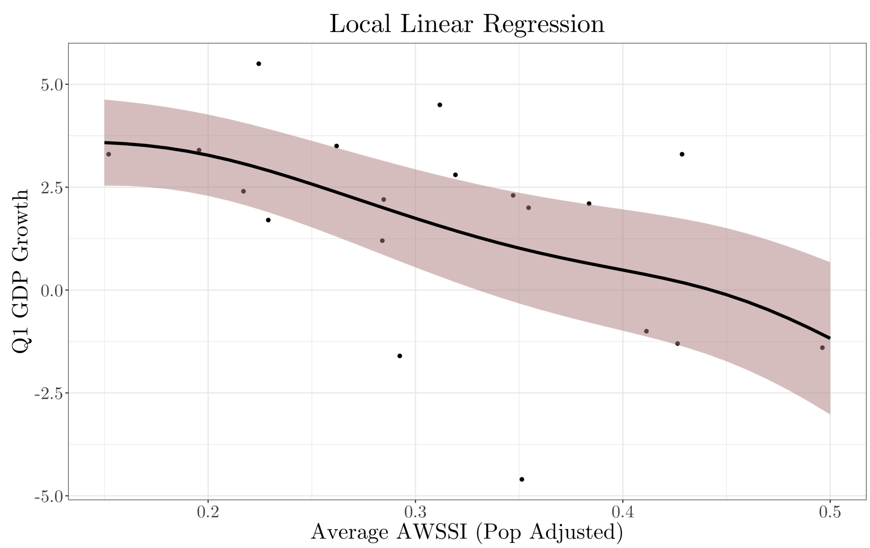
	Dependent variable:	
	Q1 GDP Growth	
	(1)	(2)
Population-Adjusted AWSSI Average	-16.782^{***}	
	(5.226)	
Population-Adjusted Adjusted AWSSI Average		-9.853^{**}
		(3.735)
Q4 GDP Growth	0.262	0.317
	(0.182)	(0.192)
Q3 GDP Growth	0.408	0.364
	(0.262)	(0.282)
Constant	5.553^{***}	4.339^{**}
	(1.620)	(1.515)
Observations	19	19
R^2	0.571	0.505
Adjusted R^2	0.485	0.406
Residual Std. Error (df = 15)	1.795	1.927
F Statistic (df = 3; 15)	6.651^{***}	5.107^{**}
Note:	*p<0.1; **p<0.05; ***p<0.01	

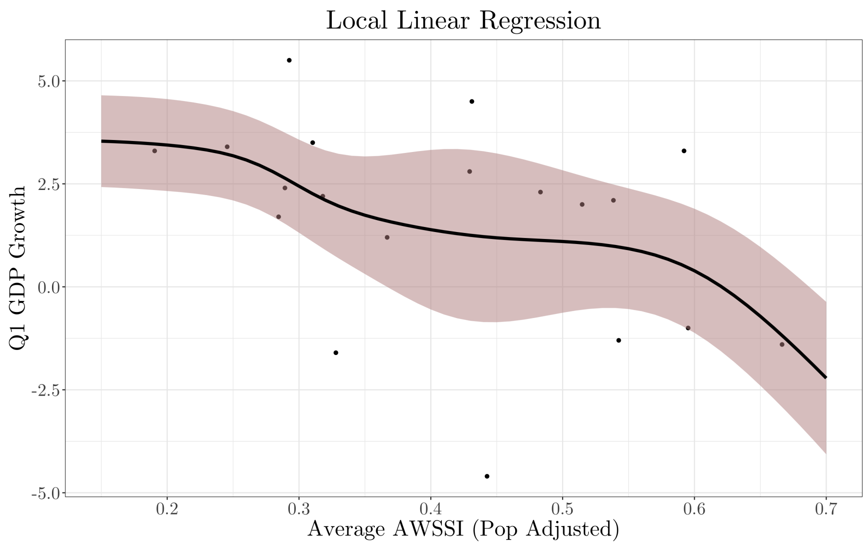
5.2 Local Linear Regression Using Gaussian Kernel

Our local linear regression yields interesting results. The better-performing non-weighted average AWSSI and adjusted AWSSI, in this analysis, both show that when the winter is relatively mild, additional winter severity has limited impact on output in Q1. Yet, when winter is severe, it is clear that additional severity has a negative effect on economic performance. This makes sense since economic activity only starts to be severely affected when the weather becomes very cold. When it is a bit cold or quite warm (for a winter), most economic activities won't be impacted. The other two show a more linear trend.



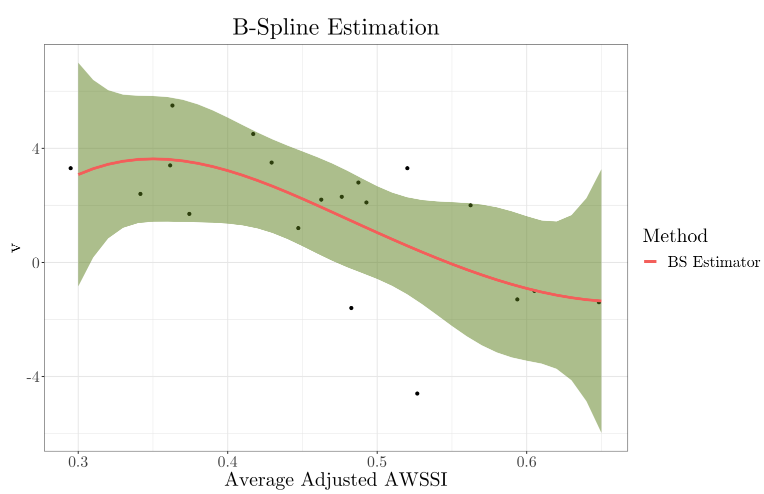

Local Linear Regression
Q1 GDP Growth
5.0
2.5
0.0
-2.5
-5.0
5.50
5.75
6.00
Average AWSSI

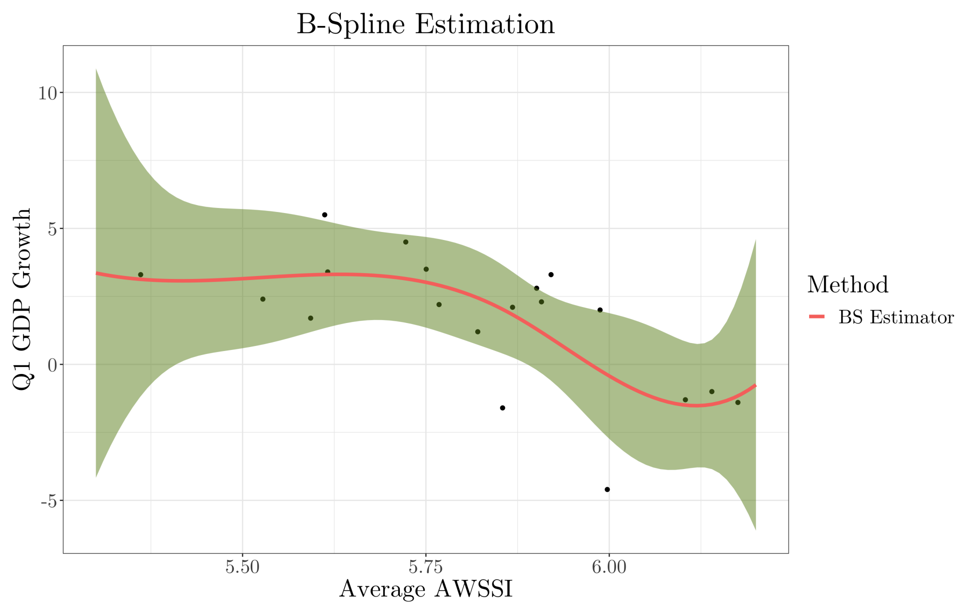

Local Linear Regression
Q1 GDP Growth
5.0
2.5
0.0
-2.5
-5.0
0.2
0.3
0.4
0.5
Average AWSSI (Pop Adjusted)

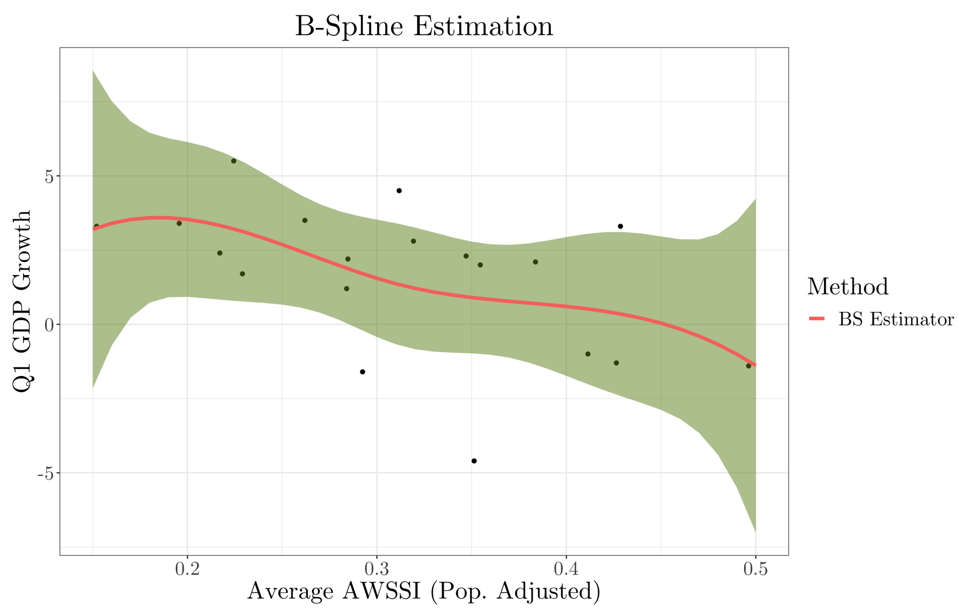


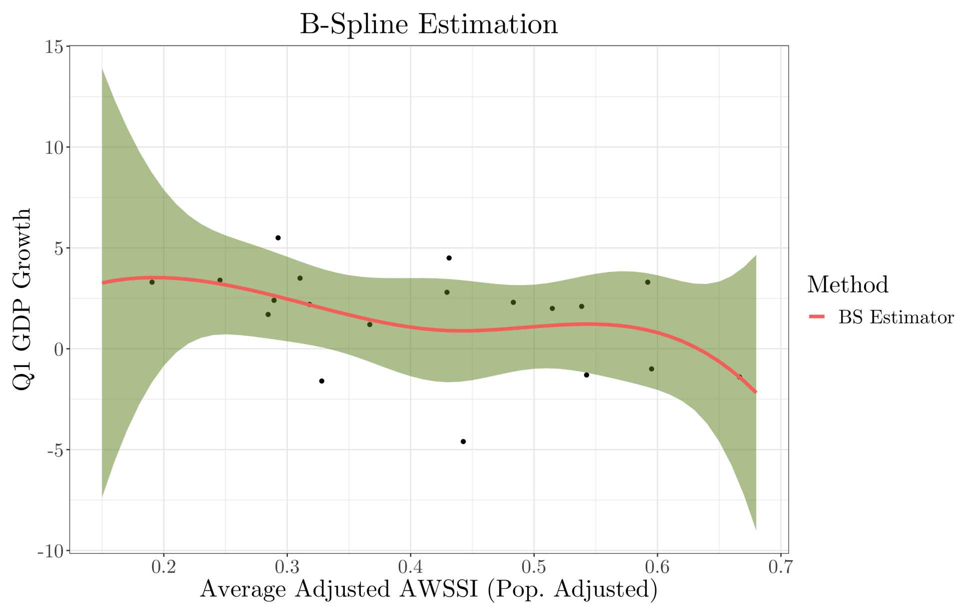
5.3 B-Spline Estimation

B-spline estimation offers similar results compared to their local linear regression counterparts. There are still some new findings: for instance, for average AWSSI, when winter is already severe, additional severeness has little impact on overall Q1 economic performance.




B-Spline Estimation
10
5
0
-5
Q1 GDP Growth
5.50
5.75
6.00
Average AWSSI
Method
BS Estimator


B-Spline Estimation
5
0
-5
Q1 GDP Growth
0.2
0.3
0.4
0.5
Average AWSSI (Pop. Adjusted)
Method
BS Estimator



6 Experiment Proposal

Given the unique nature of our experimentation, if we were to propose an experiment investigating the same research question, we would advocate for more ideal conditions for data collection. Ideally, we'd run yet another natural field experiment with some sort of large-scale winter weather event, like a super-storm. Again, since we're experimenting with weather as our intervention, we can't necessarily make this happen ourselves. However, we *can* control the amount of, and types of, economic data we collect, and where we collect it from.

We would survey local businesses to obtain a gauge of production, orders, and employment, in a manner similar to the Purchasing Managers' Index surveys. This would provide an accurate gauge of economic activities in the areas surveyed as compared to our current use of GDP numbers since national-wide data does not always reflect local economic activities. With this pinpoint data, we would have a more clear understanding of the minutia of economic effects caused by the winter-storm event.

Also important to this ideal experiment would be that we survey areas that are geographically near each other, but receive a range of the intensity of the winter-storm. This would best be achieved by collecting data near the relative borders of where the weather event was observed. Though meteorology can be a geographically imprecise science, we can utilize our already-existing methods of tracking winter intensity to ensure we operate on the borders of affected areas. This way, we can create a clear gradient of winter weather's effects and its exact economic impact with a more precise economic measure as well.

This experiment would allow us to normalize out geographic differences and other similar factors by testing relatively nearby locations, while also testing entirely different levels of treatment. Furthermore, by utilizing a specific weather-event, we can further corroborate our current results, proving that the weather specifically was a major cause of the economic effects we observed.0

Now we conduct a power analysis of the experiment. Suppose we have two adjacent counties A and B, who are neighbors and have a similar structure (For instance, two adjacent suburban counties), and that a winter storm strongly affects one but not the other. We will hand out business surveys. Due to the CLT, the distribution of average response will converge in distribution to the normal distribution. Let's set the critical value to two standard deviations.

From our previous analysis we know that good-bad weather could mean a growth difference of as much as 3-5 percent. However, it in unlikely that two adjacent counties will receive drastically different AWSSI scores. therefore, we should be expecting a growth difference of around 2 percent and around 5-10 percent difference in our PMI like index, for example 50 and 54. Hence, to reach a 0.95 power, a standard deviation should be about 1 on our PMI-like index. A usual sample of (0,50,100), assuming most are 50, usually do not have standard deviation above 30. Therefore, we need about 1000 small businesses per area.

7 Conclusion

Our research has shown that winter weather severity has a significant impact on economic growth in the first quarter. Non-parametric estimations further show that the effect of severe winter weather on Q1 GDP is more pronounced when the winters are harsh. We hope that this effect can be further examined with more precised research employing measures like the ones highlighted in our experimental proposal.

This investigation also specifically underscores the imperative for strategic weather-related risk management in economic planning and policy-making. As climatic unpredictability becomes increasingly pronounced due to global warming, understanding these seasonal effects on GDP growth is important. It is hoped that the insights drawn from this study will prompt further research in this domain, promoting proactive and adaptive strategies to build more resilient cities.

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