

The Effects of Weather Variance on Local Beer Sales

Samuel Evans

Department of Economics
Metropolitan State University of Denver
Campus Box 77, P.O. Box 173362
Denver, CO 80217
svans49@msudenver.edu

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1. Introduction

In Colorado, and Denver specifically, local craft breweries have become an institution; during the Covid-19 stay at home orders, they were defined as “essential business.” On a sunny, warm Saturday afternoon, you would be very hard pressed to find an open seat on any brewery taproom’s patio. Colorado breweries know this, and intentionally release easy drinking light beers in the summer, hoping to you keep you there longer, and spending more. But how much are their taproom sales really affected by the nice weather? Can breweries look at a long term forecast and use it to accurately forecast sales? Does it only take a nice day to drive sales, or are there other, more nuanced defining factors?

Anecdotally, brewery managers believe that the weather has a significant impact on aggregate demand for craft beer, but also that there is more to it than that. We live in Colorado after all, and a significant portion of the state is an outdoor enthusiast’s playground. If the weather is *too nice*, many people will be out in the mountains hiking, biking, climbing, paddling, or camping, and not sitting on a patio drinking. If it is one of those summer holidays that we all associate with grilling, it can be difficult to entice beer drinking outside of one’s backyard. Or, maybe it is just a Tuesday and most just don’t feel like drinking.

The costs of a full brew are significant, as are the frustrations of seeing an empty taproom with a fully staffed bar. Inversely, one can empathize with the panic of a manager who planned incorrectly and cannot keep up with demand. So how can managers use their historical sales data to predict future demand, produce efficiently,

and staff appropriately? This paper addresses the quantifiable relationship between different measures of weather and taproom sales.

2. Empirical Strategy

Previous studies show that human behavior is significantly affected by the weather. Mood, decision making, and physical limitations have all been shown to act as demand deterrents or boosters (Parsons 2001). Expanding on this, I hypothesize that certain weather factors, particularly temperature, affect the sales of a local craft brewery.

2.1. Craft Beer Sales

2.1.1. Sales

Craft beer sales have been the subject of study recently, as their popularity has grown significantly. Malone and Lusk (2017) studied the various consumer groups in the U.S. beer market, but focused on the taste perceptions and customer segmentation of some of the largest beer producers in the country. Consumer preferences, based on demographic, have also been studied, but in Italy, and there was little focus on aggregate demand (Donadini and Poretta 2017).

In contrast, the effects of weather have been shown on retail demand (Parsons 2001), restaurant menu sales (Bujisic, Bogicevic and Parsa 2017), and guest feedback (Bujisic, Bogicevic, et al. 2019). The focus on restaurant sales was centered around the variances in specific menu items due to weather effects, but only addressed food items, and drew data from Florida, a rather homogeneous climate. Bujisic, Bogicevic,

and Parsa even conclude that further study should not only focus on varying climates, but also on more diverse establishments. They also suggest more granular data, up to hourly weather and sales measures.

2.1.2. The brewery taproom

An ideal data set would have included hourly sales for specific menu items of multiple craft breweries in the area, but unfortunately, I only have access to a single local craft brewery's sales data. I believe this is an adequate indicator of craft beer in the Denver metro area for several reasons: it is centrally located, on the borders of the urban center and more residential areas; has a large relative seating capacity, with indoor and outdoor seating; serves craft German style beer; and does not focus on special events to drive sales.

The location of the brewery is important for several reasons. In order to be accepted as an indicator for the entire craft beer industry in Denver, it is important to avoid taprooms that may have an exaggerated dependency on weather. A brewery taproom in Boulder or Golden, for example, may be far more impacted by local tourism driven by outdoor enthusiasts. Furthermore, the available demographics about craft beer drinkers signal that they are primarily educated millennials (Carvalho, et al. 2018), however there is a risk that certain neighborhoods capture *only* that demographic. The taproom's location in the lower highlands with accessible parking makes it more available to a more accurate representation of the Denver metro area's consumer base. Though they were not made available for this paper, social media demographics for the brewery support this assertion.

The size and layout of the brewery is important as to not be a significant limiting factor for daily sales. A small but popular brewery could suffer from the limits on their capacity during high sales days. Additionally, a lack of indoor or outdoor seating would lead to a poor representation of the metro area as a whole.

Hart (2018) finds that consumers' demand is driven primarily by price and style, in that order. The brewery studied serves primarily, but not exclusively, German style beers. This allows for a variety of styles comprising all of those studied by Hart, with the exception of ciders and Belgian beer. The brewery also uses a nearly flat pricing model based on volume of the pour, and this pricing is in line with bars and breweries in the surrounding area.

It is significant that the brewery does not promote large events regularly. A concern for would have been that planned events could negate the effects of weather on consumer preferences. The exceptions to this are large city wide events and holidays, like the Great American Beer Festival, and events spanning several days or weeks, like Oktoberfest.

2.2. Weather

First, I determined which common measures of weather are most associated with "nice weather." This includes mean temperature, precipitation, minutes of sunlight, cloud coverage, and humidity. Intuitively, we all believe that temperatures in the 70s and 80s, on sunny, dry days will lead to the highest sales totals. I believe it is most likely that there is a nonlinear relationship with temperature in particular: there is relative maximum of predicted sales in the 70s and 80s, and average

temperatures higher or lower than this lead to a decline in sales. Previous study on weather's effect on restaurant sales (Bujisic, Bogicevic and Parsa 2017) concluded that there is high multicollinearity between certain weather variables and excluded one of them from specific models.

I choose to focus on the minimum, maximum, and mean surface temperature in separate models in order to determine which might have the greatest effect on daily sales. Though all three measures were highly correlated, I expect that the minimum temperature has the least effect, considering that it would be reached late at night while the taproom is closed. Furthermore, I hypothesize that the greatest predictor of demand based on weather would be the maximum daily temperature.

2.3. Controls

2.3.1. Weekly variation

Perhaps more than any other variable, the day of the week had a profound effect on daily sales. Rather than use weekly averages for my two data sets, I used six dummy variables to control for the weekly effect on sales, setting appropriate intercepts for each day of the week. The coefficients on these time dummy variables are already very intuitive without regression and are not the focus of this paper.

These dummies also control for the weekly specials employed by the brewery. Any influence by these specials will be contained in the various intercepts.

2.3.2. Time trends

Because I am looking at a single business over almost two years, it is necessary to quantify any underlying growth in sales due to factors other than the weather. The brewery underwent a significant turnover in staff, renovations, a rebranding, and large off premises sales growth over the period.

3. Data

3.1. Sales data

The ideal data set for this paper would have been hourly beer sales from a collection of breweries throughout the Denver metro area. Obviously, privately owned breweries are loath to release any sales data at all, not to mention data that is so granular. As such, I am only able to model the detailed sales of a single local brewery, primarily because I already had access to this data. The sales data set consists of the daily gross sales totals from May 22, 2018 through March 15, 2020. May 22 was chosen because it was the day the brewery switched to a new point of sale system that tracked daily gross totals. March 15 is the end of that data set because it was the last day the brewery was allowed to serve regularly before social distancing measures were put in place to prevent the spread of covid-19.

Then, I excluded days that the brewery was closed. This included national holidays, as well as several instances of maintenance issues, and inclement weather. There were only 3 closures due to weather, specifically high snow totals, and they are excluded because they are large outliers that are not specifically indicative of consumer behavior. The closures were likely more reflective of staff preference than

consumer preference. Lastly, a single extremely large outlier was removed, as it was the result of a large private party hosted by a corporate partner. This left us with 653 observations, as follows:

3.2. Weather data

The weather data set was obtained from Meteoblue. Hourly data of thirty two different weather measures are available, however I chose daily measures to match the sales data set. Meteoblue is a company that provides simulated data with a spatial resolution of 4 to 30 kilometers. This was as detailed and complete of a data set as I could acquire. I chose to focus on minimum, maximum, and mean temperature (Fahrenheit); precipitation (millimeters); and sunshine (minutes). Humidity, cloud cover, and wind speed are all excluded in part due to the multicollinearity observed in previous studies, and due to the high variability associated with some specific measures. Cloud cover, for example, is measured as a percentage of the sky covered by clouds. This would be far more useful in an hourly data set, but the total minutes of sunshine per day is more reliable for this set. Wind speed in particular seems to be extremely variable throughout the day in the Denver area, and would be a poor indicator of consumer preferences.

The complete data summary is as follows:

Table 1	<u>Observations</u>	<u>Mean</u>	<u>Std. Deviation</u>	<u>Minimum</u>	<u>Maximum</u>
<u>Sales</u>	653	2500.85	1669.476	353.02	11688.90
<u>Min. Temperature</u>		35.37	15.54	-4.99	68.69
<u>Max Temperature</u>		64.22	20.91	16.90	98.98
<u>Mean Temperature</u>		50.95	19.14	10.56	85.24
<u>Precipitation</u>		0.75	1.88	0	15.9
<u>Sunshine</u>		464.94	227.45	0	781.25

4. Results

4.1. Effects of different weather factors

After controlling for the weekly variance and time trend, I modelled the regression considering all three measures of temperature, as well as precipitation and sunshine. This showed a predictably high r-squared, but all of the regressors failed the null-hypothesis test. I then excluded the precipitation variable, the mean temperature variable, and the minimum temperature variable. Each was eliminated by stepwise regression: the highest p-value was eliminated until all p-values were less than 0.05. This left me with a model that predicts higher beer sales as maximum temperatures and the amount of sunshine increases throughout the day. Given the concerns raised by Bujisic (2017) about multicollinearity between correlated measures of weather, I chose to separate these two variables in to separate models. This fits intuitively, because keeping these two regressors together would only confirm a seasonal increase in sales likely due to longer days and warmer weather in general.

The variance in daily sales was best explained by the maximum temperature, which had an adjusted R-squared of 0.64. Each degree increase in max temperature predicts an overall increase in sales of \$24.06, or about three and a half pints. The measures of mean and minimum temperature showed similar results and can be seen in Table 2. This is no surprising considering their correlation.

Sunshine has a similar effect, which is also not surprising given the correlation with temperature. Even in winter, more sun during the day leads to higher relative temperatures.

Precipitation failed to show statistical significance in all models. This was not surprising, given that those particular data points violate the third least squares assumption for causal interference. 442 of 653 observations of precipitation are 0mm. I have omitted the results regarding precipitation from Table 2.

4.2. Implications

The predicted increase in sales by higher temperatures should can lead to significant efficiency gains for taproom managers. Weekly forecasts can be used to predict sales, manage stock levels, and staff appropriately. These results also confirm the stated hypothesis that the weather has a statistically significant effect on brewery sales. It also shows that temperature is the greatest weather predictor of variations of sales.

The implication that precipitation is a poor indicator of beer sales is intuitively surprising, but this was also the case in previous research (Bujisic, Bogicevic and Parsa 2017). Further research could focus on the effects of precipitation on aggregate demand for craft beer in a less homogenous climate.

Future research can also expand by evaluating the relationship between forecasted weather and craft beer sales. Is the daily forecast or observed weather more influential on consumers' preferences? Access to more detailed sales data can be used to model preferences in different beer styles influenced by the weather.

Ultimately, these results are not terrible surprising, especially to an industry veteran. Intuition and anecdote already tell us these things are true. However, the particular quantification of the effect of incremental rises in temperature can be used to great effect in the craft beer industry. There is the potential to model long term consumption, and therefore produce far more efficiently.

Table 2

		<u>1</u>	<u>2</u>	<u>3</u>	<u>4</u>	<u>5</u>
Minimum Temperature	Coeff.	-16.78	-6.97			
	Robust Std. Error	(10.559)	(6.496)			
	p-value	0.113	0.284			
Maximum Temperature		14.53	27.03	22.07	24.06	
		(14.816)	(5.311)	(1.948)	(1.852)	
		0.327	0.000	0.000	0.000	
Mean Temperature		21.16				
		(21.668)				
		0.329				
Sun time		0.36	0.36	0.45		1.18
		(.2)	(.199)	(.184)		(.187)
		0.071	0.075	0.016		0.000
Date	Coeff.	1.29	1.28	1.31	1.33	0.54
	Sunday	-2735.80	-2735.07	-2740.29	-2744.04	-2754.42
	Monday	-3543.22	-3540.89	-3548.16	-3542.69	-3609.46
	Tuesday	-3649.61	-3643.09	-3649.97	-3654.73	-3673.69
	Wednesday	-3178.53	-3174.79	-3172.87	-3177.41	-3171.77
	Thursday	-3125.37	-3118.90	-3123.73	-3122.13	-3148.57
	Friday	-1541.88	-1542.70	-1541.90	-1539.09	-1547.19
	Intercept	3013.22	2944.06	2967.89	3040.77	4315.36
	R-sq		0.644	0.644	0.643	0.640

5. Bibliography

- [1] Bujisic, Milos, Vanja Bogicevic, and H. G. Parsa. 2017. "The effect of weather factors on restaurant sales." *Journal of Foodservice Business Research* 20 (3): 350-379.
- [2] Bujisic, Milos, Vanja Bogicevic, H. G. Parsa, Verka Jovanovic, and Snupama Sukhu. 2019. "It's raining complaints! How weather factors drive consumer comments and word-of-mouth." *Journal of Hospitality & Tourism Research* 43 (5): 656-681.
- [3] Carvalho, Naiara, Luis Minim, Moyses Nascimento, Gustavo Ferreira, and Valeria Minim. 2018. "Characterization of the consumer market and motivations for the consumption of craft beer." *British Food Journal* 120 (2): 378-391.
- [4] Donadini, Gianluca, and Sebastiano Poretta. 2017. "Uncovering patterns of consumers' interest for beer: A case study with craft beers." *Food Research International* 91: 183-198.
- [5] Hart, Jarrett. 2018. "Drink Beer for Science: An Experiment on Consumer Preferences for Local Craft Beer." *Journal of Wine Economics* 13 (4): 429-441.
- [6] Malone, Trey, and Jayson L. Lusk. 2017. "If you brew it, who will come? Market segments in the U.S. beer market." *Agribusiness* 34 (2): 204-221.
- [7] Parsons, Andrew G. 2001. "The Association Between Daily Weather and Daily Shopping Patterns." *Australasian Marketing Journal* 9 (2): 78-84.