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Individual Final Report

One data related economic issue specifically for my chain, Jimmy John's, is regarding the effect of seasonal and holiday demand fluctuations. This specific issue regarding seasonal demand fluctuations was seen after taking a closer look at the average daily visits by year-month graph in project two. This graph depicting the average daily visits by year-month shows a pattern of peaks and troughs revolving around the time of year. Specifically, the graph shows how during the summer months the average number of daily visits reach their peak and as the year ends there seems to be a consistent drop in the average number of daily visits, making the winter months the lowest.. The reason this issue is relevant is because Jimmy John's profits and overall efficiency aren't being maximized. Being unable to alter key factors of a restaurant business will have you susceptible to fluctuating demands throughout the year. These specific key factors include staffing, inventory, and marketing, which without proper management can cause profits to be lost. Starting with staffing management, it would make no sense to schedule the same amount of staff during peak months and drought months. Improper planning of the employee schedule could lead to overstaffing or understaffing employees, which would ultimately decrease the total profits made by the company. Inventory management follows a similar pattern. During a drought month if there is too much inventory and not enough demand then it leads to a waste of food. Finally, the marketing team needs to tailor their strategies based on the demand each specific

month averages. Without proper management of staffing, inventory, and marketing strategies Jimmy John's could be missing out on profits.

Jimmy Johns experiences significantly higher average daily visits during the summer months(June, July, August, September) in comparison to the winter months(December, January, February) ranging from the years 2018-2022. This hypothesis is true because during the summer months, many people will be vacationing and enjoying the outdoors, which leads them to be more enthusiastic towards eating out too. On the other hand, during the winter months many people will be less enthusiastic to eat out as holiday distractions and colder weather are all in play. This hypothesis is supported by the graph in project 2, where the years 2019 2019-2020, 2020-2021, 2021-2022, and 2022-2023 all had a dip around December after reaching its peak a few months back. This hypothesis would make every single month a categorical independent variable and the average daily visits as the dependent variable. The control variables would include the year, region, and the day of the week. The year control variable would be responsible for variations such in the years 2018-2022, such as the impacts Covid-19 had. The region control variable would be responsible for adjusting any geographic differences. The day of week control variable would be used to adjust for any weekly patterns. We would start by performing this test by first preparing the data, specifically, by extracting the dailyvisits values for summer and winter months from the jj_long dataset. After this step, we must then create an indicator that corresponds to the specific season each month is in, in order to effectively extract the months under observation. Once the data is all prepared, the next step is to calculate the average dailyvisits per every season and then averaging that out per year. Once the data has been prepared and aggregated, in order to test the hypothesis we must conduct a two sample t-test. The t-test will compare the mean dailyvisits from both the summer and winter seasons, all at a 0.05

significance level. In order to interpret the results of the two sample t-tests, we must pay attention closely to the p-value. If the p-value is less than the statistical significance amount of 0.05, then the hypothesis would be rejected. A positive result of this hypothesis test would confirm the null hypothesis and would suggest that staffing, inventory, and marketing should all be tailored to the specific season. Ultimately, this would allow for Jimmy Johns to maximize profits during high demand seasons and avoid unnecessary losses in low demand seasons.

Throughout the years 2018-2022 the largest statistically significant percentage decrease in average daily visits to Jimmy Johns occurred in the 2 month period right before the winter months (December and January). The reason why this hypothesis holds is because during the winter transition period, the weather starts getting colder and there are more holidays around this time. Considering these factors makes individuals more inclined to a home cooked meal, rather than dining out. However this hypothesis is negligible in the months going from 2018-2019 because of outside variables, specifically Jimmy John's was bought by Inspire Brands. This pattern is also negligible from March 2020 to a couple months after as every single business was affected by Covid-19 and all its restrictions and safety protocols. We can see from the data that in the year 2022 the months September, October, and November all had daily visits around 21-23 and then all of a sudden in December the average daily visits reached 7 and then 3 in January, 2023. This same pattern is shown in years 2019-2020, 2020-2021, 2021-2022, and 2022-2023, where the most statistically significant drop in daily visits started its descent in December. The independent variables for this hypothesis would include the two specific periods in the year, October - November vs December - January . The dependent variables for this hypothesis include the average daily visits from the jj_long data set. The control variables include the year, region, and holiday indicators. We would perform the hypothesis test by first extracting the

dailyvisits from jj_long for October - November and December - January for all the years from 2018 - 2022, except 2020 and then create a period column. We then calculate the mean daillyvisits for October/November and from December/January for every single year. The percentage drop must be computed now using the formula (((October/November_mean - December/January_mean) / October/November_mean) * 100). Now we must calculate the percentage drop for all the months in order to see if the drop from November to December was the largest drop. Once this is completed we will perform a paired t test in order to compare the October/November months to the winter months for each year. We will focus on the p-value to determine the statistical significance, as well as the percentage drops. A positive result for my hypothesis would suggest that an immediate adjustment in staffing, inventory, and market strategy management must be tailored to overcome the obstacles the winter months bring. Ultimately, it could help them in planning the future on how to prepare for the obstacles and hurdles that the winter months bring with them.

For the first data exercise I would create a table that shows the average daily visits by season in the specific year, ranging from 2018-2022. The columns would include the specific year, the mean for the summer months, and the mean for the winter months. The rows would include each year ranging from 2018 to 2022. The reasoning behind this table is that it would serve the purpose of highlighting the differences in means for the two different seasons. I would include a bar chart that compares the two seasons for each specific year. The x-axis would have one summer bar and one winter bar for each specific year, while the y-axis would just be the mean daily visits. For the second data exercise I would create a table that has each two month period as one column and the next column would be the percentage drop. Each row would indicate the specific years that these percentage drops occurred. This would help highlight if the

transition period from November to December is the largest, as well as significant. I would also include a bar graph for every year of the percentage drops for each transition period. Every percentage drop would cause the bar to go upwards for any increases in percentages and downwards for any decreases. In order to accomplish this, I need a list of packages that will help me to create these tables and visualizations. First I would need pandas for all the manipulation and aggregation of Jimmy John's data. Secondly, numpy would be beneficial for calculating the percentage changes for every transition period. Third, in order to perform statistical tests the python package scipy.stats would help. Fourth, matplotlib would allow me to create the actual data visualizations and make them look presentable. Finally, I would need to use datetime to handle any sort of dates and period creation.