How to Prepare for the Next Pandemic – Investigation of Correlation Between Food Prices and COVID-19 From Global and Local Perspectives

CHAO HUANG* and YUFEI ZHAO*, Department of Computer Science, University of Rochester, USA

The coronavirus disease (COVID-19) has caused enormous disruptions to not only the United States, but also the global economy. Due to the pandemic, issues in the supply chain and concerns about food shortage drove up the food prices. According to the U.S. Bureau of Labor Statistics, the prices for food increased 4.1% and 3.7% over the year ended in August 2020 and August 2021, respectively, while the amount of annual increase in the food prices prior to the COVID-19 is less than 2.0%. Previous studies show that such kinds of exogenous disasters, including the 2011 Tohoku Earthquake, 9/11 terrorist attacks, and infectious disease, and resulted unusual food prices often led to subsequent changes in people's consumption behaviors. We hypothesize that unforeseen food price changes are due to the COVID-19 pandemic and the price changes alter people's grocery shopping behaviors as well. To thoroughly explore this, we formulate our analysis from two different perspectives, by collecting data both globally, including *China*, *Japan*, *UK*, and *the US*, and locally from different groups of people inside *the US*. Concretely, we analyze the trends between food price and COVID-19 as well as food price and spending, aiming to find out their correlations.

Additional Key Words and Phrases: analysis, time series, food prices, COVID-19

1 INTRODUCTION

In the past two years, the outbreak of Covid-19 has severely impacted people's lives, in the ways of how people work, social and eat. As a necessity to living, the price of food fluctuated more drastically than before, which gradually changed people's shopping behavior and thus the spending on food. For example, rising beef prices may force people to choose other alternatives, such as pork and chicken. Hence, it is interesting and worth investigating the correlation between food price changes and the trend of Covid-19, helping us better understand how people's lives are affected.

To study the problem above, we first take a look at the price changes for different food categories, which can be broadly organized into specific subcategories, including meat, fruits, vegetables, dairy products, oil, cereals, sweets, and seafood. Secondly, there are also many factors that may impact consumer purchasing on both food at home (FAH) and food away from home (FAFH), e.g., income [19], region, age [34], education, neighborhood severity level measured by the number of local Covid-19 cases, and household size and composition [15, 28]. These factors all account for expenditure behaviors. Among those, we use four specific attributes which are income, region, number of children, and household size for further analysis.

Since the Covid-19 is a global pandemic rather than a local event, the *food price-Covid-19* relationship may vary in different counties, states, and even countries. To more thoroughly analyze this problem, we propose to perform data collection and analysis into two aspects, both *globally* and *locally*. To facilitate our research, we collect data of different attributes of consumers, group them based on these attributes, and compare their expenditure behaviors of different groups before and after the Covid-19 pandemic. This kind of data mainly focuses on the *local* perspective. Besides, we also collect data from consumers in different countries other than the United States and find out the trend and changes of their expenditure behaviors for different consumer attributes and for different food subcategories. The food prices in countries like China [33], U.K., and Japan all increased during the Covid-19 pandemic. We want to examine the price rises under the different political policy and security level throughout the Covid-19 and identify the countries with similar food price change trend together. We categorize this analysis into a *global* manner.

*Both authors contributed equally to this research.

To summarize, in this project, we are answering the questions as follows:

- How does the food price of each food subcategories change before and during the Covid-19 pandemic?
- How do consumers/households with different attributes change their shopping behaviors on food?
- What are differences and similarities of the change in food price in countries with different political policies and security level?

2 RELATED WORKS

As described in Section 1, the Covid-19 pandemic has drastically affected people's lives. Recent works on food supply chains suggested that some problems caused by Covid-19, such as labor shortage [26, 29] and reduced shipments [25] have led to higher food prices. As a result, people's lifestyles suddenly changed. A series of studies on shopping habits [7, 17, 21, 22] also show that the Covid-19 also change the way of buying, as consumers tend to stock up on groceries during the pandemic.

To further figure out the relationship between food price and consumers' spending behavior, we conduct studies on consumers' spending from different household groups. Prior works show that sudden exogenous events often resulted in temporal shopping behavior changes, including the 2003 SARS pandemic [32], the 2011 Tohoku Earthquake [14], the 9/11 terrorist attacks [6], and Fukushima Nuclear Accident [9]. The lesson learned from these events is that the spending pattern changes depending on multiple factors, including consumer income, consumer experience, education levels and etc. Thus, how the food price change affects consumers' spending behavior during the Covid-19 still needs to be explored. A most recent work [15] shows analysis on household purchasing trends after the economy had partially reopened. Compared to this work, we not only study how consumers' spending behavior changes on food, but also analyze the correlation between food price and spending pattern changes.

3 DATASETS

We need data related to the overall food price, FAH price, and food price for subcategories (meat, fruits, vegetables, dairy products, oil, cereals, and seafood) before and during the Covid-19. We also need data related to consumers' expenditure on food with their income, location, age, education, neighborhood severity level, and household size and composition.

We apply Consumer Price Index (CPI) to investigate the food price changes. By definition, The Consumer Price Index [23] is a measure of the average change over time in the prices paid by consumers for a market basket of consumer goods and services, such as transportation, food, and medical care. The basic formula is shown below:

$$CPI_t = \frac{C_t}{C_0} \times 100 \tag{1}$$

where: CPI_t is the Consumer Price Index in the current period, C_t is the cost of the market basket in the current period, C_0 is the cost of the market basket in the base period.

CPI is one of the most frequently used statistics for dealing with price change problems. However, there are many ways to use CPI for price change in reality. Take the publications and reports released by the U.S. Bureau of Labor Statistics as an example. They have unadjusted 12-month percent change of CPI, unadjusted 1-month percent change in CPI, seasonally adjusted 12-month percent change in CPI, and seasonally adjusted 1-month percent change in CPI. An example can be found in Figure 1. We use an unadjusted 1-month percent change in CPI to measure the price change in our study.

The following websites are the sources of our data. We then consolidate the data into our unified formats.

- U.S. Bureau of Labor Statistics: https://www.bls.gov/ We get data of food price change in the United States from this website.

	A	B	C	D	E	F	G	H
1		Table 2. Consumer Price Index for All Urban Consumers (CPI-U): U.S. city average, by detailed expenditure category, January 2021						
2		[1982-84=100, unless otherwise noted]						
3								
4				Unadjusted percent change		Seasonally adjusted percent change		
5	Indent Level	Expenditure category	Relative importance Dec. 2020	Jan. 2020- Jan. 2021	Dec. 2020- Jan. 2021	Oct. 2020- Nov. 2020	Nov. 2020- Dec. 2020	Dec. 2020- Jan. 2021
6								
7	0	All items	100.000	1.4	0.4	0.2	0.2	0.3
8	1	Food	14.119	3.8	0.3	0.0	0.3	0.1
9	2	Food at home	7.772	3.7	0.3	-0.2	0.3	-0.1
10	3	Cereals and bakery products	1.001	2.5	-0.3	-0.3	0.3	-0.8
11	4	Cereals and cereal products	0.308	2.6	-0.1	0.0	0.4	-0.5
12	5	Flour and prepared flour mixes	0.041	1.7	2.9	0.6	0.0	-1.6
13	5	Breakfast cereal(1)	0.142	3.2	-0.7	-0.6	1.0	-0.7
14	5	Rice, pasta, cornmeal	0.124	2.4	-0.5	-0.1	0.9	-0.8
15	6	Rice(1)(2)(3)		4.4	-0.4	1.2	0.0	-0.4
16	5	Bakery products(1)	0.693	2.5	-0.4	-0.8	0.1	-0.4
17	6	Bread(1)(2)	0.200	3.5	-0.8	-0.5	0.2	-0.8
18	7	White bread(1)(3)		2.3	-1.3	-0.6	0.0	-1.3
19	7	Bread other than white(1)(3)		4.8	-0.5	-0.6	0.7	-0.5
20	6	Fresh biscuits, rolls, muffins(2)	0.101	4.1	0.4	-0.5	0.2	0.1
21	6	Cakes, cupcakes, and cookies(1)	0.178	1.5	0.2	-0.5	0.3	0.2
22	7	Cookies(1)(3)		2.1	-0.9	-1.7	0.7	-0.9
23	7	Fresh cakes and cupcakes(1)(3)		0.0	2.0	0.1	0.1	2.0
24	6	Other bakery products	0.214	1.6	-0.8	0.4	0.0	-2.5
25	7	Fresh sweetrolls, coffeecakes, doughnuts(1)(3)		4.2	-1.4	1.0	0.1	-1.4
26	7	Crackers, bread, and cracker products(3)		3.2	1.3	2.1	-2.0	-1.3
27	7	Frozen and refrigerated bakery products, pies, tarts, turnovers(1)(3)		-0.7	-1.7	-3.4	1.3	-1.7
28	3	Meats, poultry, fish, and eggs	1.736	5.1	0.5	0.1	-0.2	0.5
29	4	Meats, poultry, and fish	1.637	5.4	0.6	0.1	0.0	0.5
30	5	Meats	1.026	5.5	0.7	0.1	0.2	0.6
31	6	Beef and veal	0.471	6.4	0.9	0.3	-0.1	1.1
32	7	Uncooked ground beef(1)	0.173	4.4	-0.2	0.4	-1.0	-0.2
33	7	Uncooked beef roasts(1)(2)	0.073	8.4	0.8	0.6	-0.4	0.8
34	7	Uncooked beef steaks(2)	0.180	6.6	2.1	-0.1	0.0	2.6
35	7	Uncooked other beef and veal(1)(2)	0.044	9.7	0.7	0.5	0.8	0.7

Fig. 1. An example of our dataset about CPI for subcategories in United States from the U.S. Bureau of Labor Statistics.

- U.S. Census Bureau: https://www.census.gov/en.html We get data of food spending for United States consumers with different income, household size, number of children, and location from this website.
- National Bureau of Statistics of China: http://www.stats.gov.cn/english/. We get data of the food price change in China from this website.
- Office for National Statistics: https://www.ons.gov.uk/. We get data of the food price change in the United Kingdom from this website.
- e-State/Statistics Bureau of Japan: https://www.stat.go.jp/english/. We get data of the food price change in Japan from this website.

4 METHODOLOGY

Pearson product-moment correlation: For the global perspective part, we want to catch the relationship between each pair of different food sub-categories and their importance in the overall food category for different countries. The formula is shown below:

- Pearson product-moment correlation
  For the global perspective part, we want to catch the relationship between each pair of different food sub-categories and their importance in the overall food category for different countries. The formula [11] is shown below:

$$\rho_{xy} = \frac{Cov_{xy}}{\sigma_x \sigma_y} \tag{2}$$

where: ρ_{xy} is the Pearson product-moment correlation coefficient, $Cov(x, y)$ is the covariance of two food sub-categories x and y, ρ_x and ρ_y are the standard deviation of x and y.
With a higher Pearson product coefficient, we claim that the two food sub-categories have a stronger association strength. With a higher Pearson product coefficient with the overall food category, we claim that the food sub-category has a stronger association strength or greater importance in the food category.

- Trend and Difference Stationary
In general, it is necessary for time series data to be stationary to satisfy the assumption of time series analysis models. A stationary time series is a time series whose properties do not depend on the time at which the series is observed. Time series with trend and seasonality are not stationary. In our case, there is no seasonality. Our Covid-19 data and food price data during Covid-19 do not experience regular and predictable changes over year for every calendar year, because the Covid-19 pandemic is an unpredictable and temporal disease in the recent two years. However, we need to consider the trend. There are some common ways to remove trends from time-series data, such as log transformation, power transformation, and difference transformation. We apply the difference transformation [16], which works by computing the differences between consecutive observations. The formula is shown below:
$$y'_t = y_t - y_{t-1} \tag{3}$$
The differenced series will have only t-1 values, since it is not possible to calculate a difference y1y1 for the first observation.
For the country whose time series still do not appear to be stationary after the first differencing, we perform a secondary-order differencing and a general detrend function to obtain a nearly stationary time series. The formula for the secondary-order differencing and detrend function are shown below:
secondary-order differencing:
$$y''_t = y'_t - y'_{t-1} = y_t - 2 \times y_{t-1} + y_{t-2} \tag{4}$$
detrend function:
$$y = detrend(x) \tag{5}$$
In this case, the time series will have t-2 values.
- Augmented Dickey-Fuller (ADF) Test and Kwiatkowski-Phillips-Schmidt-Shin (KPSS) test
The ADF test [4] and KPSS test [18] are the most commonly used statistical tests to analyze and check the stationary of a series. They make hypotheses about data and inform the degree to which a null hypothesis can be rejected or fail to be rejected.
ADF test is conducted with the following assumptions:
Null Hypothesis (H0): Series is non-stationary. Alternate Hypothesis (HA): Series is stationary. If test statistic < critical value or p-value<0.05, we reject the Null Hypothesis (H0) and state that time series is stationary. If the null hypothesis is failed to be rejected, this test may provide evidence that the series is non-stationary.
KPSS test is conducted with the following assumptions:
Null Hypothesis (H0): Series is stationary. Alternate Hypothesis (HA): Series is non-stationary. Special Note Here: Hypothesis is reversed in the KPSS test compared to the ADF Test. If test statistic < critical value or p-value< 0.05, we reject the Null Hypothesis (H0) and state that time series is non-stationary. If the null hypothesis is failed to be rejected, this test may provide evidence that the series is stationary.
- Granger Causality
The Granger causality test [12] is a statistical hypothesis test for determining whether one variable in the time series is useful for forecasting another in the multivariate time series with a particular lag. Our study chooses lag equals 1. A prerequisite for performing the Granger Causality test is that the input

time series should be stationary [1]. Granger Causality Test is conducted with the following assumptions: Null Hypothesis (H0): time series x do not explain the variations in time series y. (Or we say, x_t does not Granger-cause y_t.) Alternate Hypothesis (HA): time series x explains the variations in time series y. (Or we say, x_t Granger-causes y_t.) This test produces an F test statistic with a corresponding p-value. If p-value<0.05, we reject the Null Hypothesis (H0) and state that x_t Granger-causes y_t. If the null hypothesis is failed to be rejected, this test may provide evidence that x_t does not Granger-cause y_t.

5 EXPERIMENT

5.1 Global Perspective

Our global perspective part contains analysis for China, Japan, the United Kingdom, and the United States and is carried out in two steps.

In the first step, the CPI datasets of the eight food sub-categories (*exception: seven food sub-categories for China) and the Covid-19 statistics about confirmed cases and confirmed deaths of all the four countries are overviewed and explored using the Pearson product-moment correlation. The results of the Pearson product-moment correlation are displayed with heatmaps Fig 2 3 4 5.

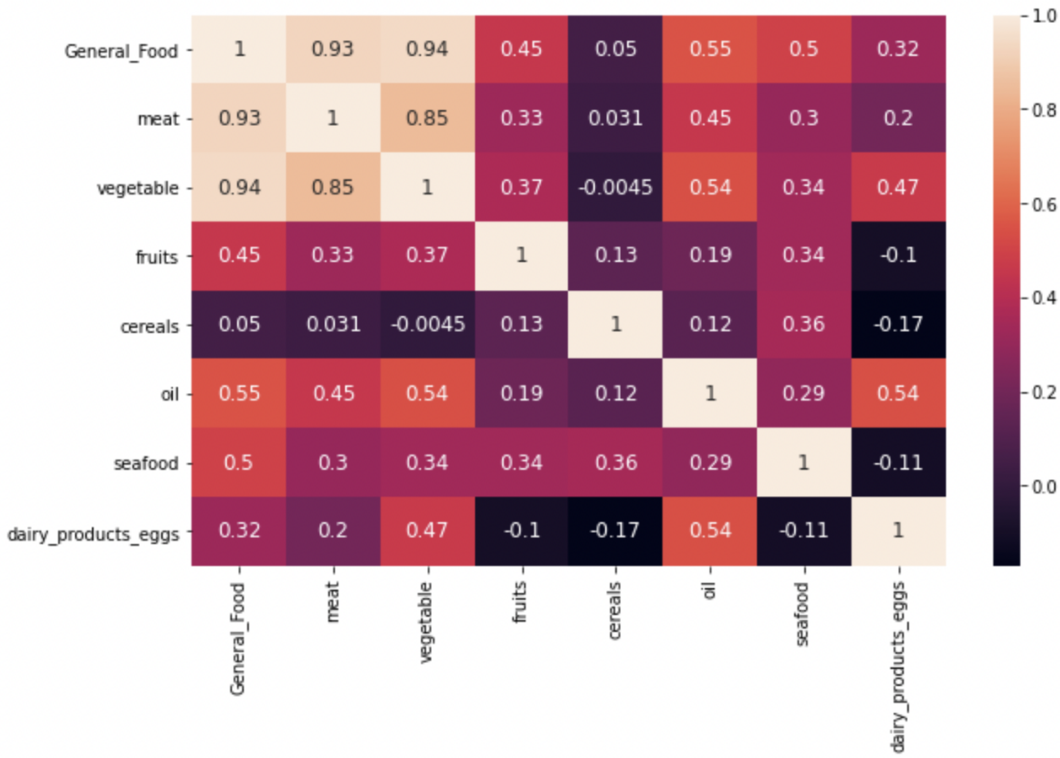


Fig. 2. China food CPI Heatmap

From the resulted heatmaps, we can get information about the importance of each food sub-categories. Ordinarily, the food sub-categories with a higher positive correlation with the general food tend to be relatively more important. The reason is that these food sub-categories are more likely to have their prices moving in

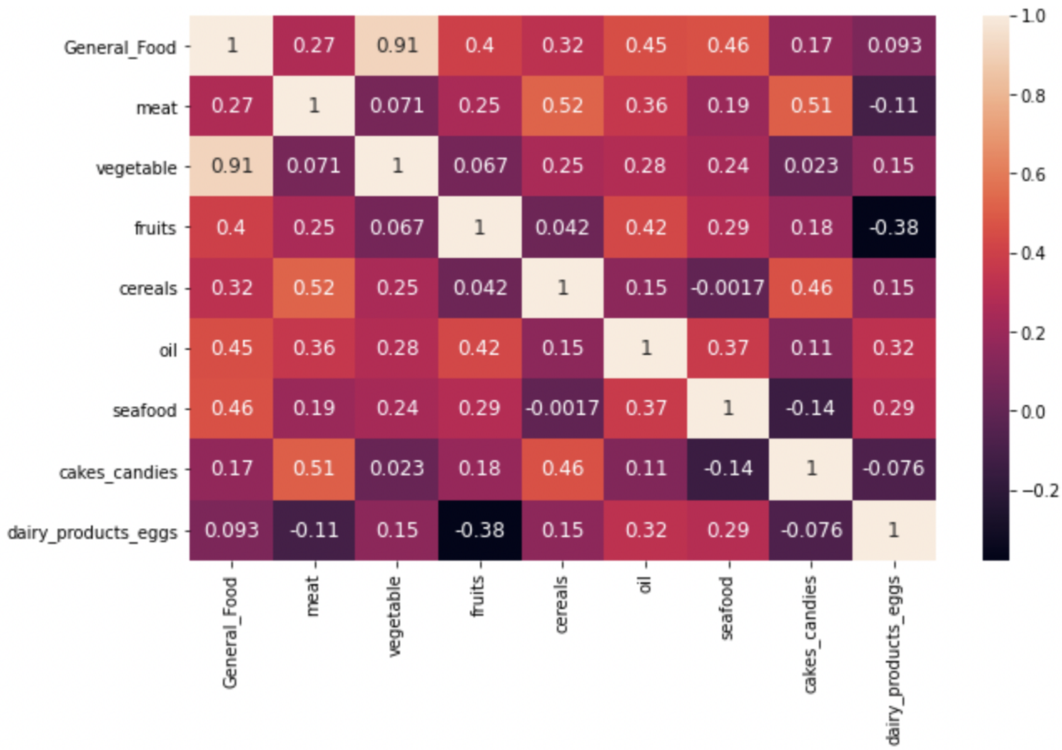


Fig. 3. Japan food CPI Heatmap

the same direction with the general food category, say increasing or decreasing together. In other words, when the price of these food sub-categories increases or decreases, the price of the general food category has a high probability to increase or decrease, respectively. For the assisted and less bought food, however, their price index does not affect the general food category a lot and thus perhaps does not this kind of synchronous price change. Hence, this strong association suggests a higher greater importance.

For China (Fig 2), meat and vegetables are particularly important, with a correlation above 0.90, which are much higher than other food sub-categories in China. These high correlations are also rare in other countries. However, it may be a little surprising that the cereals, which include the Chinese staple food rice, have a relatively low correlation with the general food category. This may be explained by the stable price level of cereals during the Covid-19 pandemic in China as shown in Fig 6.

For Japan (Fig 3), vegetables take an important place in their diet, due to a 0.91 correlation with the general food category. The seafood, fruits, oil, and cereals are in the following places. As an irreplaceable traditional Japanese food, seafood (sushi) does not have a correlation above 0.50, perhaps due to the relatively stable price level similar to Chinese cereals (Fig 7).

For the United Kingdom (Fig 4) and the United States (Fig 5), there are no particular food sub-categories that have a very high correlation and strong association with the general food category. Relatively, vegetables and dairy products are important diet sources for United Kingdom citizens, while meat, cereals, and seafood are important for Americans. Generally, these results accord with our expectations. The relatively low correlations

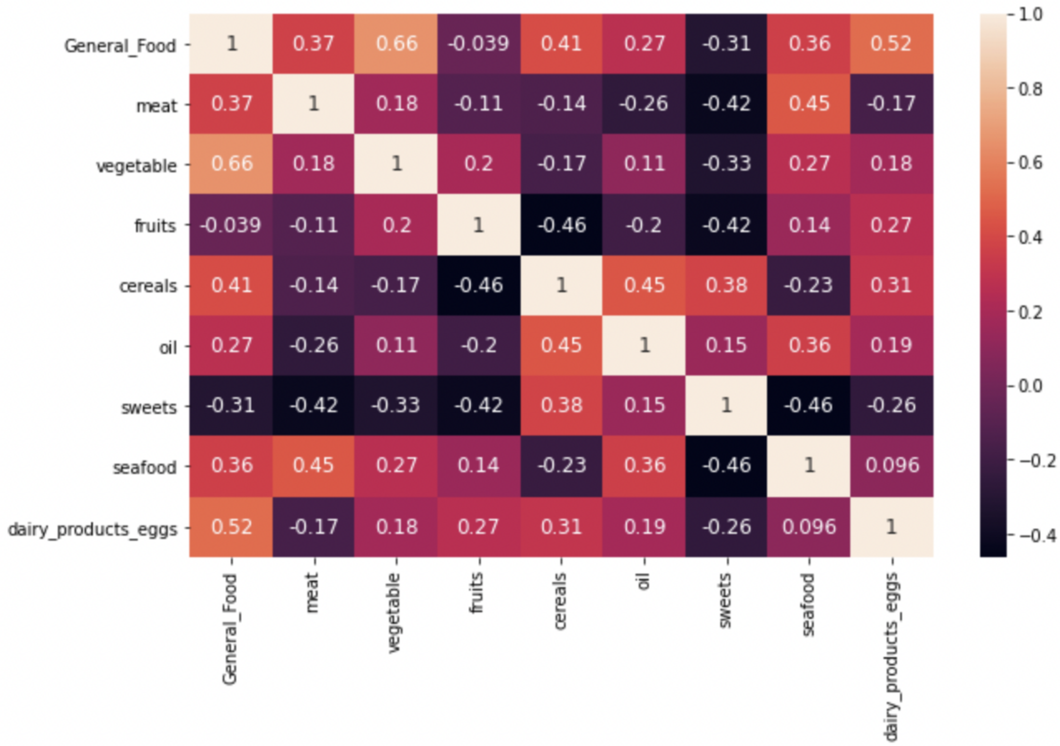


Fig. 4. United Kingdom food CPI Heatmap

among food sub-categories compared to China and Japan may be due to their rather small fluctuations as shown from the axes in Fig 8 9; thus, there is no strong evidence about the price change correlations.

Among the four countries, China has a special high correlation and association strength for a pair of food sub-categories, which are vegetables and meat. This means that the price of vegetables and the price of meat often change concurrently. As the price of food is heavily driven by the demand for food, we can infer that Chinese consumers often increase or decrease their demand for vegetables and meat together, and the vegetables and meat possibly are complementary food and both valuable in the Chinese diet.

In the second step, we create time series for all the food-related variables and Covid-19 related variables in our datasets and perform the Granger Causality Test on the time series to determine whether the Covid-19 conditions predict and influence the food prices.

According to the Methodology Section, we detrend the time series to make them stationary before the Granger Causality Test. The key variable we choose to represent the Covid-19 conditions and apply as a predictor is the monthly confirmed cases, although the total confirmed cases, total confirmed deaths, and monthly confirmed deaths can explain some temporal Covid-19 conditions as well.

According to the Granger Causality Test, if the p-value is less than 0.05, we have strong evidence that the Covid-19 condition influences that specific food price. The results for the Granger Causality Test for all the four countries are shown in tables 1 2 3 4:

From the results, we can say that the Covid-19 conditions have an influence on food price, since China, Japan, and United Kingdom all have a p-value less than 0.05 for their general food category. This result somewhat

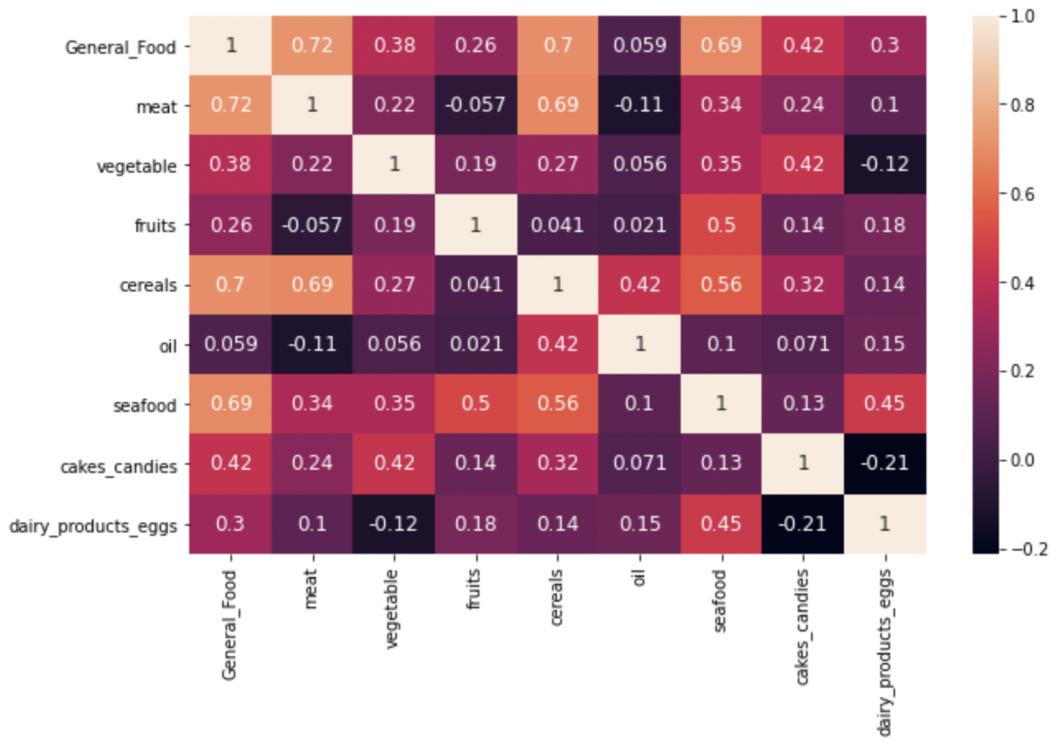


Fig. 5. United States food CPI Heatmap

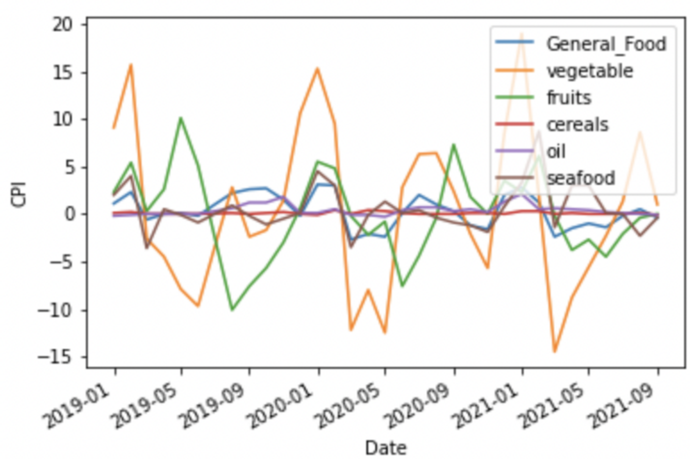


Fig. 6. Food Price Trend in China

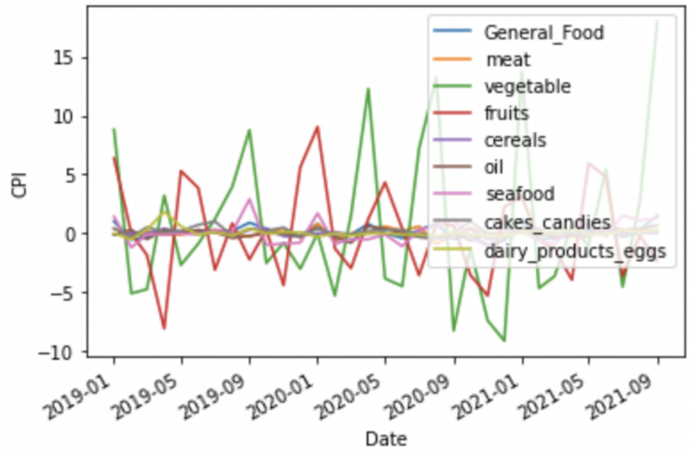


Fig. 7. Food Price Trend in Japan

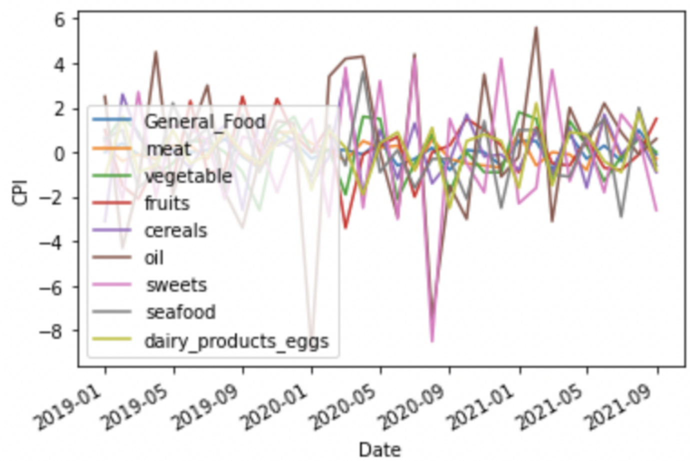


Fig. 8. Food Price Trend in United Kingdom

food type	food	vegetables	fruits	meat	cereals	dairy	seafood	oil
p-value	**0.0027**	**0.0239**	**0.0005**	**0.0248**	**0.0105**	0.4348	**0.0000**	**0.0002**

Table 1. p-values for China

epitomizes the food industry conditions during the Covid-19 pandemic. The panic buying and hoarding behaviors have been seen globally, many supermarket shelves with key food such as rice, pasta, canned goods, and sanitation supplies are emptied [5]. For Western countries, the major food retailing sectors are large, concentrated supermarkets chain, which has a significantly large buying power and relatively low stocks. The sudden change in the demand supply due to the Covid-19 pandemic disorganized the system and leads to a shortage. Moreover,

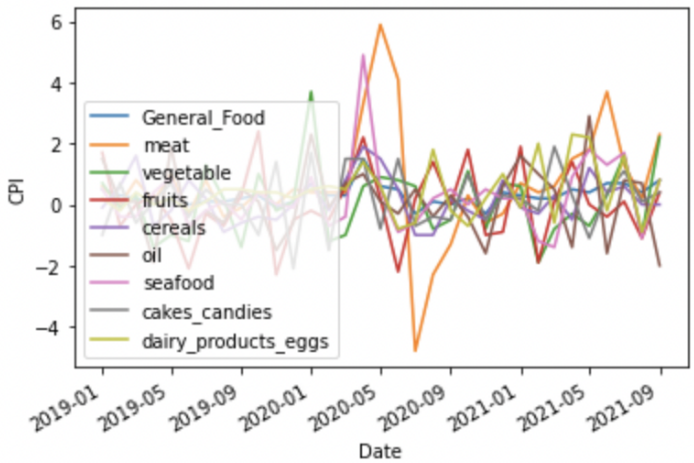


Fig. 9. Food Price Trend in United States

	food	vegetables	fruits	meat	cereals	dairy	seafood	cakes	oil
p-value	**0.0015**	**0.0107**	0.6827	0.4050	0.5074	**0.0000**	*0.0618*	0.4318	**0.0048**

Table 2. p-values for Japan

	food	vegetables	fruits	meat	cereals	dairy	seafood	cakes	oil
p-value	**0.0001**	**0.0189**	~~0.1033~~	0.4886	~~0.4764~~	**0.0468**	*0.0764*	0.2118	0.1122

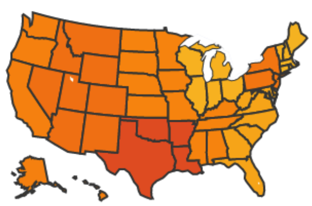
Table 3. p-values for United Kingdom (fruits and cereals not pass the stationary tests)

	food	vegetables	fruits	meat	cereals	dairy	seafood	cakes	oil
p-value	~~0.4067~~	0.4905	0.2921	0.5434	**0.0406**	~~**0.0148**~~	0.3209	~~**0.0012**~~	**0.0000**

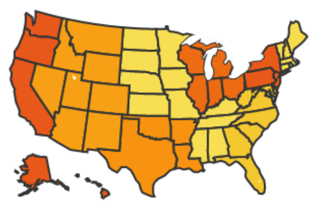
Table 4. p-values for United States (food, cakes, and dairy not pass the stationary tests)

many restaurants, bars, and cafes have closed due to the global stay-at-home policies and reduced outside mobility; this brings even more pressure to the food supply chain [13]. The joint impacts on the supply chain and demand chain drive the food price up.

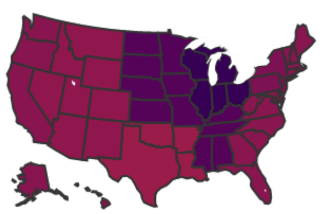
We can also see the differences in the degree to which the Covid-19 conditions influence the food price and the similarities of the influenced food sub-categories among the four countries from the tables. The food prices in the Chinese market are mostly struck, with almost all the food sub-categories being Granger-caused by the Covid-19 conditions. Part of the price changes is due to government suggestions. When the number of confirmed cases or deaths in some local areas, the central government will urge the local authorities to encourage families to stockpile food and other daily necessary goods. This authority encouragement even induces panic buying and intensifies the food price fluctuations with Covid-19 conditions [20]. Similar to other countries, the perception of threats and anxiety about the uncertainty also plays important role in the Chinese market [27]. On the contrary, the Covid-19 conditions in the United States do not have a clear impact on food price. This situation may be explained by the restricted transportation issues and US's role in the global food trade. In order to control the spread of the Covid-19 pandemic, both air and ground transportation become inconvenient and costly. Therefore, the countries that previously relied on food imports to some extent will get into trouble and experience some food shortage, including China, Japan, and the United Kingdom, while the countries that export food [24] primarily meet fewer food troubles. An important similarity among the results of the four countries is that the price of vegetables overall is influenced by the Covid-conditions, while the price of meat, another vital and necessary food intake, is almost not influenced. This situation may be referable to the difference in production mode [3]. Vegetables are much more labor-intensive and season-dependent than meat, which means that the limitations on the mobility and stay-at-home policy reduced the availability of seasonal workers and disrupted the timeline for planting and harvesting vegetables, but not affected meat production that much. Furthermore, the cut-off of air transportation makes it difficult for seed and fertilizer supply, the decisive factors, for vegetable production.



(a) Food CPI change in Jan 2018.



(b) Food CPI change in March 2019.



(c) Food CPI change in March 2020.

(d) Food CPI change in March 2021.

Fig. 10. An Overview of the Food CPI Change in Different Stages.

5.2 Local Perspective

In this section, we divide the analysis of the correlation between food prices and *local* consumer spending patterns into two parts: 1) the food CPI change before and during pandemic across different regions in the US; 2) the correlation between food price changes and certain US household, that is, whether food price fluctuation has affected the spending on food for the given household type.

Food CPI changes in different census divisions. We collect the food CPI data of different regions in the US from Jan 2018 to Oct 2021. Given the data, we can show how the food price changed before and during the Covid-19, indicating the impact that Covid-19 had on the food price.

Concretely, the data is collected from different Census Bureau regions [31], including *{New England, Mid-Atlantic, East North Central, West North Central, South Atlantic, East South Central, West South Central, Mountain, Pacific}*. Note that these census regions are widely used for data collection and analysis.

In Fig 10, we select four different timestamps before and during the pandemic, that is *Jan 2018*, *March 2019*, *March 2020* and *March 2021*, to provide an overview of how the food price change in different stages. For the range of CPI change, we normalize it to [-1, 1], using gradient color to represent the change. Before the pandemic, the food CPI changes were slight Fig 10 (a,b). However, due to the outbreak of Covid-19, the CPI changed drastically (Fig 10 (c)). In Fig 10 (d), we observe a similar change pattern as before the pandemic, partially caused by the reopening and people's accustomed attitude towards the Covid-19.

Visualization of food spending trends of different households. Other than only looking at the food price change, it is more interesting to explore the correlation between people's spending behavior and food prices. The data collected from U.S. Census Bureau provides us four different angles to investigate the problem, that is, *household size*, *number of children*, *income*, and *region*. Note that, although the data we use do not contain more specific subcategories like the age of people in the household with different sizes and whether there are people retired or under 18, it still can provide a meaningful study on how different groups of people are affected by the Covid-19. In the following, we will analyze the correlation between the change of food at home spending and the given household types.

- **Household size.** We study the monthly spending on food at home for households of different sizes, starting from 2 people in the household. In Fig 11, we can find that all the candidates are affected by the Covid-19, as they perform similar change points as the Covid-19. Since the blue curves represent spending on food at home, the similar pattern as Covid-19 indicates that when the monthly newly confirmed Covid-19 cases increase, people tend to stay at home and avoid eating-out at food-away-from-home establishments, such as restaurants, school cafeterias, sports venues, and other eating-out establishments [30]. Thus, food at home spending goes higher along with the newly confirmed cases. Interestingly, it is shown that with more persons inside the household, the spending trend is smoother before the first change point. The previous survey on household size and the demand for food [2] suggested that the larger households are better off food control since they have the option of decomposing themselves into smaller units. There will also be substitution effects toward the shared foods, which are effectively cheaper for members of the larger household. In this case, even the food price went changed at the beginning of the pandemic, larger households can still control their spending on food. The larger the household is, the better they can do in sharing food, which corresponds to the observation in Fig 11.
- **Number of children.** Similarly, we study the monthly spending on food at home for households with different numbers of children. Most of the spending patterns are similar to the trend of Covid-19. In other words, the spending on food at home went higher when the case of Covid-19 continuously increased. However, there are two types of households that perform differently. For households with four or more children, the spending on food at home increased at the beginning of outbreak. There are generally two reasons: 1) Most children attended school or received care at home, increasing the need for child care and home cooking; 2)Eat at home was perceived as safer especially for children, increasing the food at home spending [8].
- **Income.** In Fig 13, the spending behavior of households with different levels of income are similar. As previous studies [10] shown, higher income households spent significantly more money on both at home and away from home food compared with lower income households, especially on fruits/vegetables. But

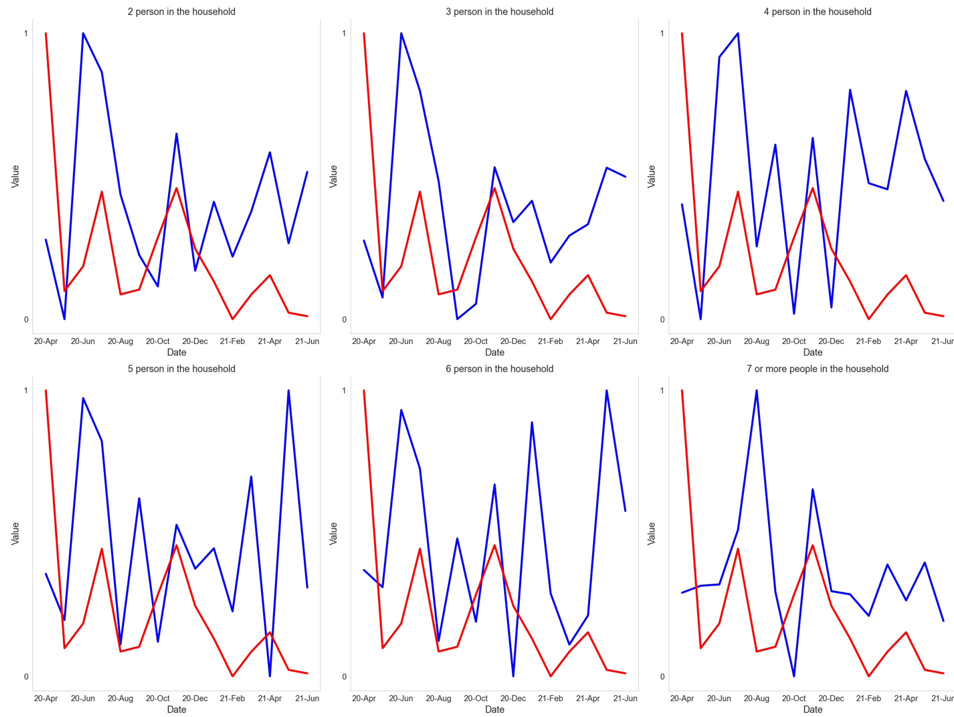


Fig. 11. Curve of Food Spending for Different Household Size (blue) and COVID-19 Trend (red).

in Fig 13, the curves denote the percentage change. Thus the spending patterns between high and low income households still need to be explored.

- Regions. In Fig 14, we visualize the at home food spending trend of different regions, including *Northeast*, *Midwest*, *South*, and *West*. Interestingly, the spending patterns are generally categorized into two groups: {Northeast, South} and {Midwest, West}. The change in the former group is sharper than the second one, which shows the difference between policies across different regions.

household size	1 person	2 person	3 person	4 person	5 person	6 person	7 or more people
p-value	0.3067	0.0767	0.1566	**0.0022**	**0.0017**	**0.0034**	**0.0007**

Table 5. p-values for Household Size

number of children	No children	1 child	2 children	3 children	4 children	5 or more children
p-value	**0.0000**	**0.0000**	0.0653	**~~0.0069~~**	~~0.7414~~	**0.0282**

Table 6. p-values for Households with Different Number of Children. Strikethrough denotes the time series is not stationary.

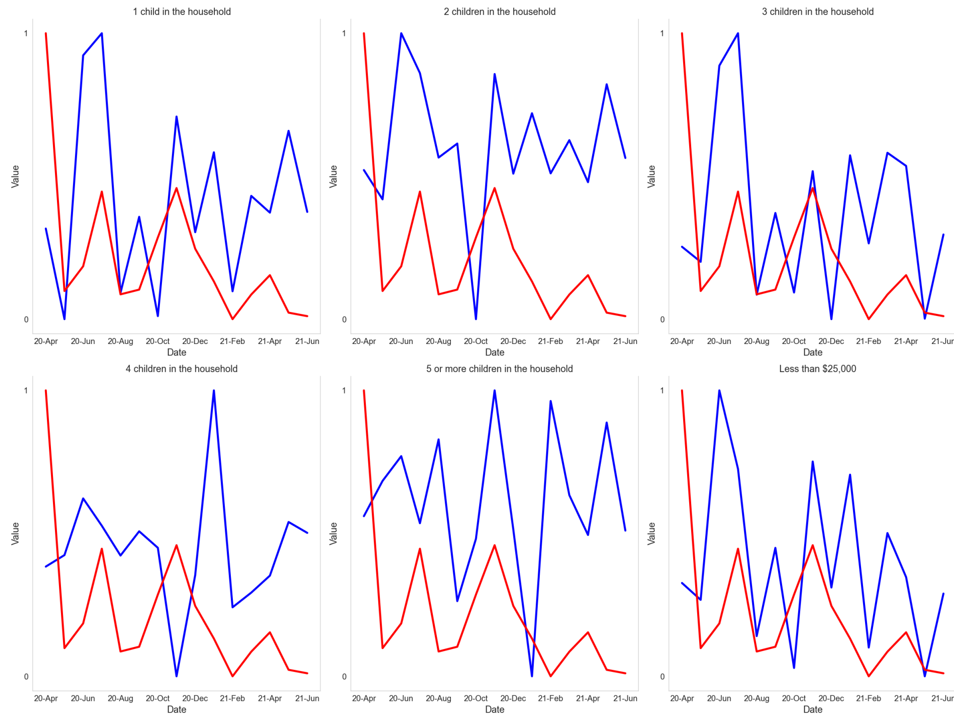


Fig. 12. Curve of Food Spending for Different Number of Children in the Household (blue) and COVID-19 Trend (red).

income	Less than $25,000	$25,000 to 34,999	$35,000 to 49,999	$50,000 to 74,999
p-value	**0.0006**	**~~0.0085~~**	**0.0004**	**0.0069**
income	Less than $75,000 to 99,999	$100,000 to 149,999	$150,000 to 199,999	$200,000 and above
p-value	**0.0000**	**0.0001**	0.3482	~~0.1555~~

Table 7. p-values for Households with Different Levels of Income.Strikethrough denotes the time series is not stationay.

region	Northeast	South	Midwest	West
p-value	**0.0078**	**0.010**	**0.000**	**0.0000**

Table 8. p-values for Households of Different Regions.

Statistical analysis between the food spending of different households and the food prices. In addition to the qualitative visualization, we also perform a statistical time series analysis for household spending and food price changes. Specifically, we follow the previous section and use the Granger Causality Test on the time series to determine whether the food price changes had impacted the food at home spending of different households. According to the Methodology Section 4, we differencing the time series to make them stationary before the Granger Causality Test. According to the Granger Causality Test, if the p-value is less than 0.05, we have strong

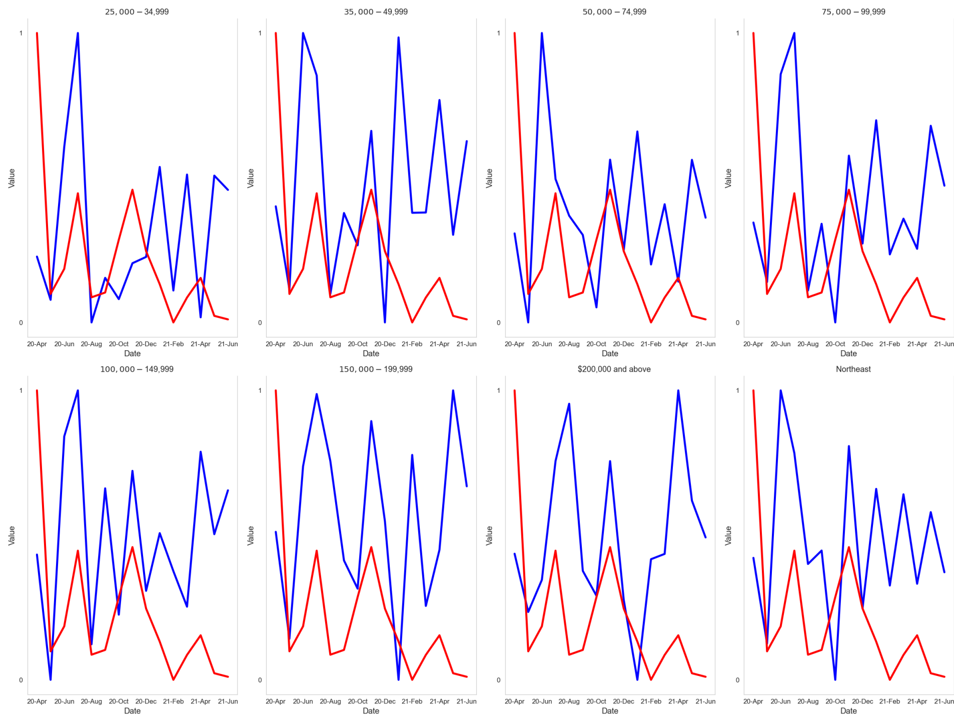


Fig. 13. Curve of Food Spending for Household with Different Income (blue) and COVID-19 Trend (red).

evidence that the food price change influences the spending of that specific household. The results for Granger Causality Test for all the households are shown in Tables 5 6 7 8.

In Table 5, we found that the food at home spending of households with 4, 5, 6, 7 or more people are more likely to be affected by the food price changes. We hypothesize the reason behind this phenomenon is that the consumer unit with less than four people is usually couples or single, and they are more like to order food away from home. Thus the spending on food at home for them is less affected by the Covid-19 and the food price change.

In Table 6, we compute the correlation between households with different numbers of children and food prices and found that the spending of households with 2 children is less likely to be affected by the food price changes, as the *p-value* > 0.05.

p-value shown in Table 7 illustrates that higher income households, e.g., with annual income from $150,000 to 199,999, has a lower correlation with the food price changes. A hypothesis is that higher income households tend to spend more on both at home and away from home food, especially on fruits and vegetables. However, due to the pandemic, there is reduced shipments [25] in the US, causing unstable fruits and vegetable price in different regions since they need careful storage and shipment. In this case, the correlation between food spending of this particular group and the food price changes is harder to analyze. It needs to take a closer look at other factors that may jointly affect the food price and spending, e.g., regions.

Results in Table 8 indicate that the food price change influences the spending patterns for households in all of the four regions. Specifically, {Northeast, South} group has a much higher *p-value* around 0.01 than the {Midwest,

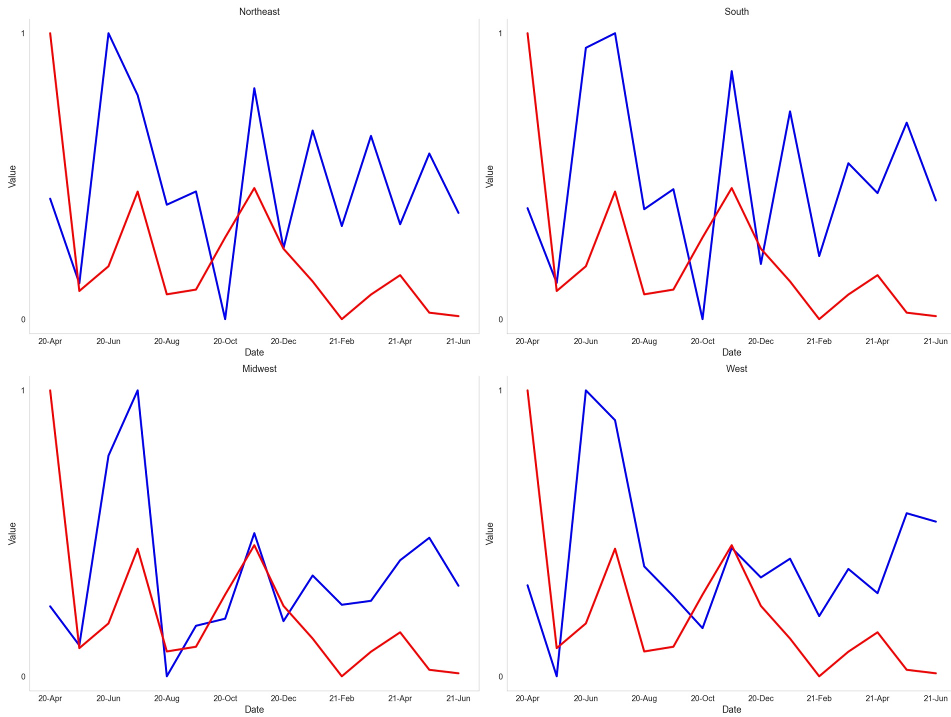


Fig. 14. Curve of Food Spending for Different Regions (blue) and COVID-19 Trend (red).

West} group, which is close to 0. This demonstrates that people in Midwest and West region shopping similarly, while people in the Northeast and South tend to share similar shopping habits.

6 CONCLUSION

From this study, we found that the Covid-19 severely affects people's living, subsequently changing people's shopping behaviors. By analyzing the data from both local and global perspectives, we draw several conclusions: 1) most countries have their food prices influenced by the Covid-19; 2) vegetables are the most vulnerable food sub-category to the pandemic and serve as one of the most important food intakes during Covid-19, while another important food meat is one of the most resistant food to the pandemic; 3) the spending on at-home food for larger households is more likely to be affected by the food price changes; 4) higher-income households perform different shopping habits with the lower-income households, showing that they are less likely to be affected by Covid-19; 5) People in the Midwest and West regions share similar spending patterns, while people in the Northeast and South regions perform similarly in buying;

In all, the changes in food price may have resulted in serious implications for household purchasing, requiring further attention from policymakers.

REFERENCES

[1] Han-Sheng Chen, Zhengbing Yan, Yuan Yao, Tsai-Bang Huang, and Yi-Sern Wong. 2018. Systematic procedure for Granger-causality-based root cause diagnosis of chemical process faults. Industrial & Engineering Chemistry Research 57, 29 (2018), 9500–9512.

[2] Angus Deaton and Christina Paxson. 1998. Economies of scale, household size, and the demand for food. Journal of political economy 106, 5 (1998), 897–930.

[3] Koen Deconinck, Ellie Avery, and Lee Ann Jackson. 2020. Food Supply Chains and Covid-19: Impacts and Policy Lessons. EuroChoices 19, 3 (2020), 34–39.

[4] David A Dickey and Wayne A Fuller. 1979. Distribution of the estimators for autoregressive time series with a unit root. Journal of the American statistical association 74, 366a (1979), 427–431.

[5] Aileen Donnelly. 2020. Coronavirus fears: Empty shelves as Canadians heed health minister's advice to stock up. https://nationalpost.com/news/canada/coronavirus-canada-stockpiling

[6] Leon F Dube and Gregory S Black. 2010. Impact of national traumatic events on consumer purchasing. International journal of consumer studies 34, 3 (2010), 333–338.

[7] Brenna Ellison, Brandon McFadden, Bradley J Rickard, and Norbert LW Wilson. 2021. Examining food purchase behavior and food values during the COVID-19 pandemic. Applied Economic Perspectives and Policy 43, 1 (2021), 58–72.

[8] Mackenzie J Ferrante, Juliana Goldsmith, Sara Tauriello, Leonard H Epstein, Lucia A Leone, and Stephanie Anzman-Frasca. 2021. Food Acquisition and Daily Life for US Families with 4-to 8-Year-Old Children during COVID-19: Findings from a Nationally Representative Survey. International Journal of Environmental Research and Public Health 18, 4 (2021), 1734.

[9] Björn Frank and Shane J Schvaneveldt. 2014. Self-preservation vs. collective resilience as consumer responses to national disasters: A study on radioactive product contamination. Journal of Contingencies and Crisis Management 22, 4 (2014), 197–208.

[10] Simone A French, Melanie Wall, and Nathan R Mitchell. 2010. Household income differences in food sources and food items purchased. International Journal of Behavioral Nutrition and Physical Activity 7, 1 (2010), 1–8.

[11] Stephanie Glen. 2021. Correlation Coefficient: Simple Definition, Formula, Easy Steps. https://www.statisticshowto.com/probability-and-statistics/correlation-coefficient-formula/

[12] Clive WJ Granger. 1969. Investigating causal relations by econometric models and cross-spectral methods. Econometrica: journal of the Econometric Society (1969), 424–438.

[13] Jill E Hobbs. 2020. Food supply chains during the COVID-19 pandemic. Canadian Journal of Agricultural Economics/Revue canadienne d'agroeconomie 68, 2 (2020), 171–176.

[14] Masahiro Hori and Koichiro Iwamoto. 2014. The run on daily foods and goods after the 2011 Tohoku earthquake: a fact finding analysis based on homescan data. The Japanese Political Economy 40, 1 (2014), 69–113.

[15] Kuan-Ming Huang, Ana Claudia Sant'Anna, and Xiaoli Etienne. 2021. How did Covid-19 impact US household foods? an analysis six months in. PloS one 16, 9 (2021), e0256921.

[16] Rob J Hyndman and George Athanasopoulos. 2018. Forecasting: principles and practice. OTexts.

[17] Edward S Knotek II, Raphael Schoenle, Alexander Dietrich, Keith Kuester, Gernot Müller, Kristian Ove R Myrseth, and Michael Weber. 2020. Consumers and COVID-19: A real-time survey. Economic Commentary 2020-08 (2020).

[18] Denis Kwiatkowski, Peter CB Phillips, Peter Schmidt, and Yongcheol Shin. 1992. Testing the null hypothesis of stationarity against the alternative of a unit root: How sure are we that economic time series have a unit root? Journal of econometrics 54, 1-3 (1992), 159–178.

[19] Jayson L Lusk. 2019. Income and (Ir) rational food choice. Journal of Economic Behavior & Organization 166 (2019), 630–645.

[20] Valerie McNamara. 2021. China's Warnings Spark Panic Buying: The Reasons and Consequences. https://globaledge.msu.edu/blog/post/57060/china's-warnings-spark-panic-buying--the-reasons-and-consequences

[21] Dave Mead, Karen Ransom, Stephen B Reed, and Scott Sager. 2020. The impact of the COVID-19 pandemic on food price indexes and data collection. Monthly Lab. Rev. 143 (2020), 1.

[22] Grace Melo. 2020. The Path Forward: US Consumer and Food Retail Responses to COVID-19. Choices 35, 3 (2020).

[23] U.S. Bureau of Labor Statistics. 2021. Consumer Price Index. https://www.bls.gov/cpi/

[24] Elisa Oteros-Rozas, Adriana Ruiz-Almeida, Mateo Aguado, José A González, and Marta G Rivera-Ferre. 2019. A social–ecological analysis of the global agrifood system. Proceedings of the National Academy of Sciences 116, 52 (2019), 26465–26473.

[25] Luis Peña-Lévano, Shaheer Burney, Grace Melo, and Cesar Escalante. 2020. COVID-19: Effects on US Labor, Supply Chains and Consumption Imagery Article. Choices 35, 3 (2020).

[26] Timothy J Richards and Bradley Rickard. 2020. COVID-19 impact on fruit and vegetable markets. Canadian Journal of Agricultural Economics/Revue canadienne d'agroeconomie 68, 2 (2020), 189–194.

[27] Sukanya Roy and Chinmay Chakraborty. 2021. Panic Buying Situation during COVID-19 Global Pandemic. Journal of Information Technology Management 13, 2 (2021), 231–244.

[28] Statista. 2020. Household grocery expenditure. https://www.statista.com/statistics/240595/weekly-us-household-grocery-expenditure-by-household-type/

[29] Dawn Thilmany, Elizabeth Canales, Sarah A Low, and Kathryn Boys. 2021. Local Food Supply Chain Dynamics and Resilience during COVID-19. Applied Economic Perspectives and Policy 43, 1 (2021), 86–104.

[30] USDA. 2021. Food and Consumers. https://www.ers.usda.gov/covid-19/food-and-consumers/

[31] Wikipedia. 2020. Census regions and divisions. https://en.wikipedia.org/wiki/United_States_Census_Bureau#Census_regions_and_divisions

[32] Yongshi Yang, Fujun Peng, Runsheng Wang, Kai Guan, Taijiao Jiang, Guogang Xu, Jinlyu Sun, and Christopher Chang. 2020. The deadly coronaviruses: The 2003 SARS pandemic and the 2020 novel coronavirus epidemic in China. Journal of autoimmunity 109 (2020), 102434.

[33] Xiaohua Yu, Chang Liu, Hanjie Wang, and Jan-Henning Feil. 2020. The impact of COVID-19 on food prices in China: evidence of four major food products from Beijing, Shandong and Hubei Provinces. China Agricultural Economic Review (2020).

[34] James P Ziliak. 2021. Food hardship during the COVID-19 pandemic and Great Recession. Applied Economic Perspectives and Policy 43, 1 (2021), 132–152.