Effects of Food Safety Events on U.S. Romaine Lettuce Prices

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(ABSTRACT)

Romaine lettuce and leafy greens have been at the center of food safety concerns over the last several years. More specifically, romaine lettuce has been directly linked to seven(7) foodborne illness outbreaks and resulted in five(5) recalls over the eight(8) years period of January 1, 2012, to December 31, 2019. This paper estimates the effects that these food safety events have had on the price returns of romaine lettuce utilizing a series of Generalized Autoregressive Conditional Heteroskedasticity (GARCH) models. Importantly, the GARCH models allowed us to capture the effects of the recall and illness outbreaks on both the returns and volatility of the romaine price series. We find that three (3) of the seven (7) illness outbreaks resulted in marked increases in the price returns– between 4.1% and 9.6%. Conversely, three (3) of the five(5) recalls reduced price returns– between 30% and 57%. However, the volatility is not found to be significantly nor to affect the price volatility significantly. We conclude that recalls serve as a market correction in the romaine lettuce market. Consequently, a continued focus on increasing traceability within the romaine lettuce market will help to reduce price fluctuation and limit the number of illnesses resulting from outbreaks.

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(GENERAL AUDIENCE ABSTRACT)

Romaine lettuce and leafy greens have been at the center of food safety concerns over the last several years. More specifically, romaine lettuce has been directly linked to 7 foodborne illness outbreaks resulting in 5 recalls over the previous eight years, January 1, 2012, to December 31, 2019. This paper estimates the effects these food safety events have on the price returns of romaine lettuce.It was found that 3 of the seven illness outbreaks lead to increase price returns between 4.1% and 9.6%, while 3 of the 5 recalls reduced price returns between 30% and 57%. However, the volatility is not found to significantly affect the price returns nor are these events found to affect the price volatility significantly. It is concluded that recalls serve as a market correction in this market. A continued focus on increasing the traceability within the romaine lettuce market will help to reduce price fluctuation and limit the number of illnesses resulting from outbreaks.

Dedication

I would like to dedicate this thesis to my father, the late, Steve Adams and my mother Diane Adams for all of their love and support. Additionally, I dedicate this to my brother Deuce Adams.

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Thank you, Shamar Stewart and Clint Neil, for your patience, support, and guidance on completing this thesis. Without the countless hours you spend working with me, this thesis would not have been possible. Thank you, Matt Holt, for serving on my committee and allowing me to pursue a Master's degree while working in the department. Additionally, I Thank the faculty and staff of the Agricultural and Applied Economics department for their support over the last several years. Finally, Thank you, Toby Akers, for your support and encouragement throughout this process. It was good having someone to bounce ideas off and vent to (on most occasions).

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Chapter 1

Introduction

Over the past several years, food safety concerns continue to make headlines in the United States. One of the main vectors of foodborne disease is leafy greens - specifically, romaine lettuce. Headlines such as "Do Not Eat Romaine Lettuce, Health Officials Warn" from the New York Times November 2018 (Jacobs, 2018) and "U.S. Officials Say Don't Buy or Eat Romaine Lettuce From Salinas, California" from CBS News November 2019 (CBS News, 2018) are just two of the national headlines resulting from these foodborne illness outbreaks. Romaine lettuce accounted for 30 percent of the lettuce consumed in the United States after an increase in consumption from 1.2 pounds per capita in 1990 to 7.7 pounds per person in 2009 (FSI, 2019).Thus, making numerous foodborne illness outbreaks with in this market even more concerning.

In the last eight years, romaine lettuce has been directly linked to seven(7) foodborne illness outbreaks resulting in 549 cases, 254 hospitalizations, and seven(7) deaths as shown in table2 (CDC, 2020). The Center for Disease Control and Prevention (CDC) suspects that romaine lettuce is also responsible for other outbreaks related to mixed-greens products. When asked about the numerous foodborne illness outbreaks in romaine lettuce, Laura Whitlock, Communications Lead for foodborne outbreaks at the CDC, stated that foodborne illnesses from contaminated fresh produce has been increasing. This increase is consistent around the world as well given increased consumption, changes in production and distribution channels, and a growing ability to detect the problem (Healio, 2019). Leafy vegetables, including lettuces (romaine, baby leaf, iceberg), cabbage, chard, kale, and spinach, are more prone to contamination throughout the supply chain due to the lack of a rind or shell.

Underlying the severity and number of outbreaks linked to leafy greens, the United States Food and Drug Administration(FDA) has issued a specific action plan for 2020 (FDA, 2020). The plan titled *2020 Leafy Greens STEC Action Plan* focuses on a three-prong approach: (1) how to prevent future foodborne illness outbreaks within the leafy greens market, (2) ways to better respond to outbreaks when they occur, and (3) ways to reduce knowledge gaps such as potential sources of foodborne outbreaks. In sum, this plan adds to the Food Safety Modernization Act by including a focus on animal intrusion and worker hygiene. Further, the importance of the plan is highlighted by the 40 foodborne outbreaks of Shiga toxin-producing E. coli (STEC) linked to leafy greens between 2008 and 2018. STEC is known to cause potentially life-threatening conditions such as anemia, blood-clotting issues, and kidney failure (FDA, 2020). One of the common sources of these outbreaks is romaine lettuce(FDA, 2020).

Increases in food safety events, like those in the romaine lettuce markets, extend beyond household consumption, In fact, such food safety events have been shown to increase the volatility in stock prices (Wang et al., 2002) as well as in futures prices in cattle markets (Schroeder and Lusk, 2002). Similarly we expect food safety events to increase the volatility in romaine price returns. This study examines the effect of foodborne illnesses and recalls on the percentage price change of romaine lettuce in the retail market. Using a Generalize Autoregressive (GARCH) approach to better understand the degree of price volatility consumers experience in the face of these recalls and foodborne illness outbreaks. We find three(3) of seven(7) illness outbreaks in our study increase average price returns and three(3) of five(5) recalls reduced average price returns meaning consumers are likely seeing significant fluctuations in romaine prices. However, food safety events were found to be insignificant in effecting the overall volatility in the market.

The remainder of this thesis is organized as follows. Chapter 2 highlights the food safety legislation and existing literature. Chapters 3 and 4 describe our data and empirical approach. Chapters 5 and 6 present our model results and concluding remarks.

Chapter 2

Background

2.1 Food Safety Legislation

Specialty crops, defined by law as ”fruits and vegetables, tree nuts, dried fruits, and horticulture and nursery crops” by the USDA, make up a significant portion of U.S. Crop production (USDA, 2018). The 2017 Census of Agriculture valued specialty crops at 64.4 billion dollars, with approximately 48% of production taking place in California (NASS, 2019). Within the specialty crop sector, the lettuce market had an estimated value of 1.5 billions, making lettuce the leading vegetable crop in terms of value (AGMCR, 2018). Moreover, the total value of crop production for the U.S. was 193.5 billion dollars, meaning specialty crops made up approximately 33% of the total value of crop production in the United States in 2017 (NASS, 2019). In a sector where a large percentage of the products are consumed raw, food safety is a high priority for the FDA. Therefore, lettuce is an important market to study to potentially better understand the effects of food safety events in specialty crop markets.

Since the early 1900’s fruits and vegetables have been inspected for safety at the federal level. Inspection of fresh produce began in 1917, while processed produce inspection started in 1931 under a different federal division (Blue Book Service, 2015). In 2012, these two inspection divisions merged to create The Specialty Crops Inspection Division (SCI) of the United States Department of Agriculture, Agricultural Marketing Services. SCI is designed to provide quality assurance and food safety services to the specialty crop industry, including romaine lettuce, from farm to fork.

In 2000, the Global Food Safety Initiative (GFSI) was created to collaboratively drive improvements to reduce food safety risks and increase consumer confidence in a safe food supply chain (GFSI, 2020). To align U.S. food safety standards with the global initiative, the Food Safety Modernization Act (FSMA) was signed into law on January 4, 2011, (FDA, 2018). This bill gives the Food and Drug Administration (FDA) the ability to better protect public health. FSMA is focused on providing the FDA with preventative tools rather than simply reacting to food safety events. Among other regulatory controls, FSMA allows the FDA to enact mandatory food recalls when companies fail to voluntarily recall unsafe food (FDA, 2018). These mandatory recalls can be very impactful on both consumers and producers of products such as romaine lettuce.

More recently, the FDA has announced the New Era for Smarter Food Safety Blueprint (FDA, 2020).This announcement outlines the approach FDA will take over the next decade to enhance traceability, improve predictive analytics, and foster the development of stronger food safety cultures (FDA, 2020). This new blueprint shows the FDA's continued commitment to the prevention of foodborne illness outbreaks and supply disruptions in leafy greens.

2.2 Background Research

Most of the existing literature on the effects of recalls and foodborne illnesses has focused on meat, poultry, and eggs, due to data availability. Several studies examine the consumer demand impacts based on food scares for meat products, but these studies have shown inconsistencies in price effects and the duration of those effects. Schroeder and Lusk (2002) studied the impact of beef and pork recalls on nearby live animal daily futures prices. Using futures markets to estimate demand changes, their study suggests systematic changes in cattle and hog demand due to recalls are likely to occur over an extended amount of time. Thomsen, Shiptsova, and Hamm (2006) examined the effects of foodborne pathogen recalls in branded ready-to-eat frankfurter products and found that sales declined 22% in the four weeks around the recall. Moreover, they find that brand recovery began two to three months after the recall, and sales approached pre-recall levels after four(4) to five(5) months. Caap and Joelsson Heurlin (2016) found the average reduction in a firms value fell approximentely $304 million twenty days after a foodborne illness outbreak in U.S. meat and poultry markets. Houser and Dorfman (2019) studied the longterm effects of beef recalls on furture prices; finding recalls overall adversely impacting prices and decreasing farm-level revenue although a relatively economically small decrease.

To the best of knowledge, there is a paucity of literature focusing on the effect of recalls in specialty crops. In fact, the only study, known to us, is by Arnade, Calvin, and Kuchler (2008) related to the major spinach recall of 2006. This study used an Almost Ideal Demand System (AIDS) model of six closely related leafy green products by utilizing scanner data. The research showed sales of bagged spinach fell 49% compared to the same time window of the previous year. Additionally, bulk spinach fell 44%, bagged spring mix fell 14%, and bulk spring mix fell 15%. Due to the size and magnitude of this event, the leafy greens industry also reacted. Growers plowed under current crops, stopped planting new fields of spinach, and planted more alternatives. Underpinned by falling sales, marketers cut back the production of products containing spinach and diverted lettuces to products without spinach (Arnade, Calvin, and Kuchler, 2008). On the retail front, outlets decided to stop selling certain products. For example, Costco did not sell spinach in its store for four(4) months after the outbreak was announced (Schmit, 2007). Specialty crop producers and consumers are negatively affected when supply chain partners stop carrying certain products as a result of a food recall. Thus, acts like FSMA, are essential and impactful.

One way to measure the effect foodborne illness outbreaks have on price returns is by utilizing the times series framework. In line with our model approach, Wang et al. (2002) used the GARCH framework to examine how foodborne recalls affected the stock price of two publicly traded companies. The GARCH model allowed researchers to determine the initial food recall resulted in reductions in the average price returns and increased volatility. These results are important because they show these events not only affect the price returns but also increase the observed variances over time. Increased volatility leads to greater uncertainty in markets. Abstracting the GARCH model approach to our retail market data, we are able to comment on the potential impacts on consumers of leafy green products– romaine lettuce to be exact.

Chapter 3

Data

To analyze the effects of recalls and illness events on price, data on retail romaine prices is needed. In addition, information on recalls and food borne illnesses is also obtained. Within the following sections the sources of data and any transformations are discussed in detail. In addition, descriptive statistics on variables employed in the corresponding analyses are presented. This chapter concludes with a discussion of the illness and recall periods as per the FDA and CDC reports.

3.1 Price Data

The USDA Agricultural Marketing Services (AMS) reports weekly specialty crop retail prices to provide a succinct overview of price movements across the country's retailers. The AMS surveys more than 500 retailers, comprising over 29,000 individual stores which have online weekly advertised features. Prices are recorded for each region, which are then combined to form the weighted national average price per pound. For our purpose of analyzing the effects of recalls and food borne illnesses, the weekly national-weighted average price per pound for romaine lettuce between January 1, 2012 through December 31, 2019 is used. The top panel of Figure 1 reports the average observed price per pound.

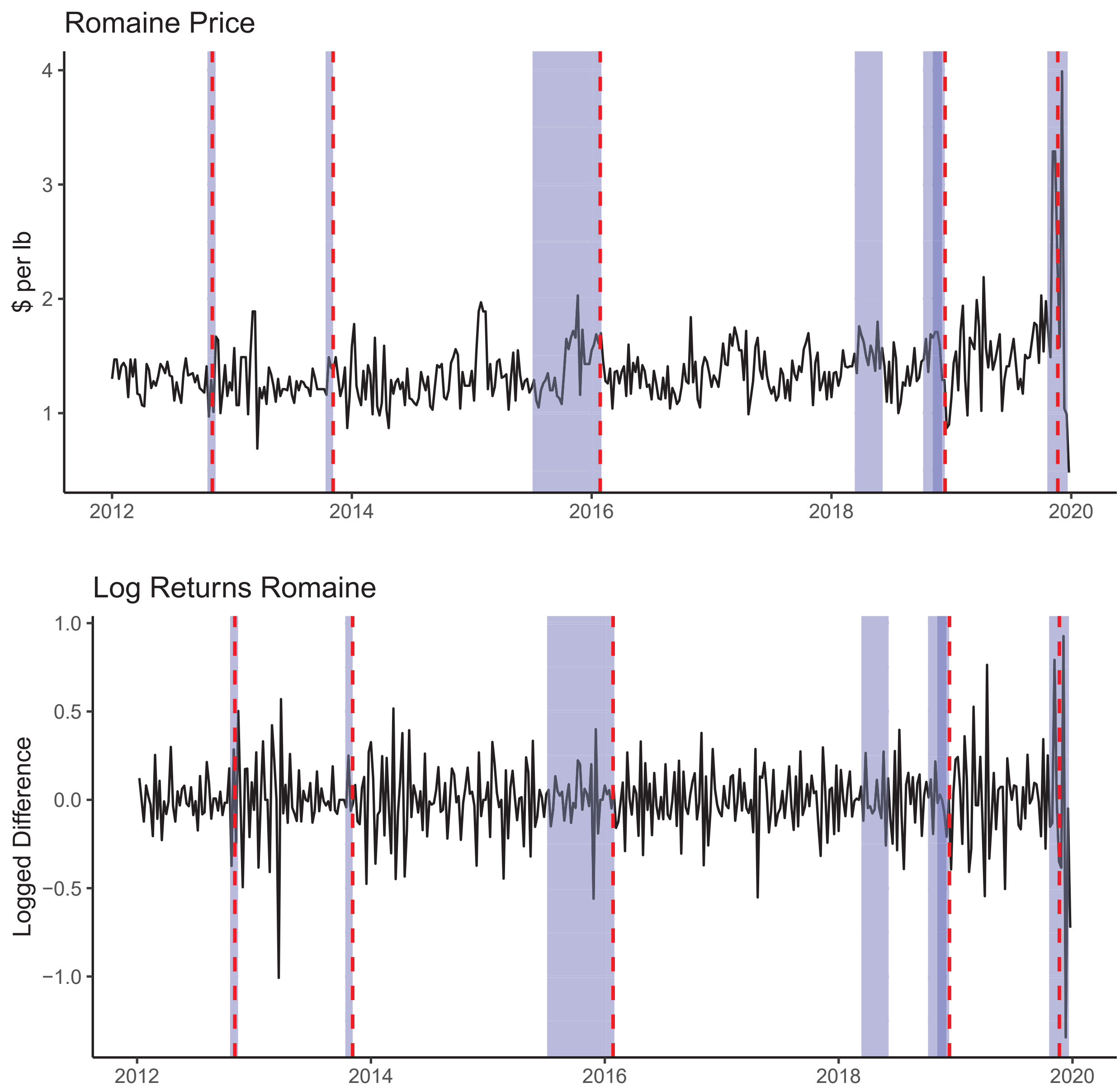
The romaine prices returns, calculated as the logged difference, are used instead of levels. Strong (1992) conjectured that "there are both theoretical and empirical reasons for preferring logarithmic returns. Theoretically, logarithmic returns are analytically more tractable when linking together sub-period returns to form returns over long intervals. Empirically, logarithmic returns are more likely to be normally distributed and so conform to the assumptions of the standard statistical techniques." Returns are, therefore, calculated as

$$R_t = \ln\left(\frac{p_t}{p_{t-1}}\right) \tag{1}$$

where R_t represents the week-on-week return of romaine prices, p_t is the retail price of the current week, and p_{t-1} is the retail price one week prior. The plot in the lower panel of Figure 1 is consistent with the transformation noted in Equation (1). The shaded regions represent illness outbreaks and dotted lines represent recalls. Future discussion of these events is reserved for Section 3.3.

The price series of romaine lettuce shown in Figure 1 appears to have a near-zero mean throughout. Periods of increased volatility are seen either after a recall or during the illness outbreaks. These observations suggest a need to test the effects of the events on the prices and price volatility.

Figure 1: Romaine Prices – Level and Returns



Note: Blue shaded areas correspond to the illness outbreak range while dotted red lines indicate the recall dates.

3.2 Descriptive Statistics

The descriptive statistics for the level romaine prices and associated returns are presented in Table 1. Across the sample period, the average price reported by retailers was $1.36 per pound. This translated to an average percentage return of -0.2% week-over-week. Additionally, over the sample period, consumers were faced with prices ranging from $0.48 to $3.99 per lb. The kurtosis value of 5.92 for romaine return prices indicates that the sample distribution of the returns exhibits a fatter tail than a normal distribution. This implies a greater probability that prices are seen at the extremes as compared to a normally distributed sample. This causes consumers to face increased volatility when purchasing romaine lettuce. Food safety events may explain this level of volatility, which would increase the level of uncertainty consumers have about the price of romaine. This will lead consumers to move away from regularly consuming romaine to a less nutritious, price-stable product. Additionally, romaine returns have a skewness value of -0.58 slightly left of standard normal distribution of 0.

Table 1: Descriptive Statistics of Romaine Prices Data

	Levels	Returns
Mean	1.367	-0.002
Sample Variance	0.088	0.046
Kurtosis	22.266	5.924
Skewness	3.17	-0.586
Range	3.51	2.271
Minimum	0.48	-1.345
Maximum	3.99	0.926
Count	416	415

3.3 Illness and Recall Data

In the United States, the FDA and the CDC report and publish information surrounding food safety. The FDA reports any voluntary recall resulting from a single random sample testing positive for a pathogen such as E. coli, Salmonella, and Listeria. The CDC reports events that cause human illnesses related to foodborne illness. Between January 2012 and December 2019, there were seven bacteria foodborne illness outbreaks, and five recalls linked to romaine lettuce.

Figure 1 provides a visual representation of the illness ranges represented by the highlighted regions and recalls denoted by dotted line. As shown in Table 2, the outbreaks vary significantly in impact and duration. Column 4 is the number of weeks a new case linked to that outbreak was recognized by the CDC. Outbreak length ranges from three(3) weeks for the sixth outbreak, in 2013, to 30 weeks in the fifth outbreak in 2015-2016. The number of cases linked to each outbreak ranges from 19 to 210 cases. A case is recorded when someone becomes ill and the CDC is able to link it to a particular foodborne illness outbreak. The sixth and seventh outbreaks only caused illness in a few states, while the first and third outbreaks are more widespread causing illness in more than 25 states. The largest outbreak was the third outbreak in 2018, resulting in 210 cases in 36 states, with 36 hospitalizations and 5 deaths. The smallest outbreak in terms of the number of severe cases is the sixth outbreak in 2013. This outbreak resulted in 33 cases in 4 states with 7 hospitalizations. A hospitalization is the result of one of the ill individuals requiring in-patient medical attention due to the symptoms resulting from the foodborne illness. The last column details the recall information for each associated illness event. A recall only occurs if the CDC can link the outbreak to a specific product or location. Therefore, not all outbreaks result in product recalls.

Within our estimations, we include both recalls and illness outbreak ranges since not all outbreaks have an associated recall. Moreover, we are also interested in the distinct effects a recall might have compared to an illness outbreak, as recalls only occur during one week while illness events cover multiple weeks of the time series. By including both types of events we are able to obtain a clear picture of how food safety events affect consumer prices in romaine markets.

Table 2: Illness and Recall Overview (January 1, 2012 - December 31, 2019)

Outbreak	Illness						Deaths	Associated
No.	Start	End	Weeks	Cases	States	Hospitalizations		Recall
1	20-Oct-19	21-Dec-19	9	167	27	85	0	21-Nov-19
2	7-Oct-18	4-Dec-18	5	62	16	25	0	13-Dec-18
3	13-Mar-18	6-Jun-18	8	210	36	96	5	No Recall
4	5-Nov-17	12-Dec-17	12	25	15	9	1	No Recall
5	5-Jul-15	31-Jan-16	30	19	9	19	1	27-Jan-16
6	13-Oct-13	5-Nov-13	3	33	4	7	0	10-Nov-13
7	18-Oct-12	12-Nov-12	4	33	5	13	0	2-Nov-12

Note: Cases refers to an individual becoming ill after consuming romaine. A hospitalization occurs when one of the individuals needs inpatient medical attention.

Chapter 4

Methods

To understand the effects of food safety events on romaine prices, several variables need to be created to include in the models. In this section we explain the creation of these food safety event variables before discussing Ordinary Least Squares (OLS) Models and the limitation of that model in this case. Finally, we develop a framework to examine food safety events that relaxes the assumptions of the OLS model and examine the effects these events on price returns and volatility.

4.1 Ordinary Least Squares

As a starting point to analyzing the effects of recalls and reported illnesses on the romaine returns, various specification of the traditional Ordinary Least Squares (OLS) method are utilized. The basic model structure for this analysis is as follows:

$$R_t = \mathbf{x}_t'\mathbf{b} + \varepsilon_t \tag{2}$$

where $\mathbf{x}$ is a matrix of food safety event variable– illness and recall variables. $\mathbf{b}$ is the vector of coefficient values, including a constant and ε is the normally distributed regression error.

In order to analyse the effect of recall and reported illnesses, a series of variables were created. Five (5) individual recall variables, *Recall*, were created (one for each of the recall events noted in Table 2).[1] Here, $Recall_k$ is a dichotomous variable that takes a value of 1 for the week that that recall event was announced and a 0 otherwise. That is:

$$\text{Recall}_k = \begin{cases} 1 & \text{if recall} = \text{True} \\ 0 & \text{otherwise} \end{cases} \qquad k = 1, 2, \ldots, 5$$

Also, to account for the cumulative effect of all recalls, a $\text{Recall}_{\text{Total}}$ variable is created. In short, this is a horizontal (weekly) summation of the individual recalls noted above. That is

$$\text{Recall}_{\text{Total}} = \sum_{k=1}^{K} Recall_{kt}$$

where t represents the weekly index.

Additionally, a series of variables, Illness_m, was created for each of the seven (7) illness outbreaks. $Illness_m$ takes a value of 1 for each week a new case was reported within an outbreak event and a 0 in weeks no new cases were reported.

$$\text{Illness}_m = \begin{cases} 1 & \text{if cases} \geq 1 \\ 0 & \text{otherwise} \end{cases} \qquad m = 1, 2, \ldots, 7$$

Likewise, our $\text{Illness}_{\text{Total}}$ dummy captures the horizontal summation of the individual Illness dummies noted above. This will also allow for the effect illness outbreaks overall have on price variance to be examined. That is:

$$\text{Illness}_{\text{Total}} = \sum_{m=1}^{M} Illness_{mt}$$

again, t represents the weekly index. Our empirical models will use a combination of these four (4) variable representations.

4.1.1 OLS Specification Issues

Predicated on the implicit assumptions of the OLS model, we perceive several limitations. Chiefly, the efficiency of the OLS estimates is underpinned by the assumption of homoskedasticity and no serial correlation.

[1] Our variables are created in reversed chronological order, as per their event numbering in Table 2

Mathematically, the homoskedasticity assumption assures that

$$Var\left(\varepsilon|X\right) = \sigma^2$$

If this variance is not constant (i.e. dependent on X), then the linear regression model has heteroskedastic errors and likely to affect hypothesis testing. The OLS assumption of no autocorrelation implies that the error terms of different observations should be contemporaneously uncorrelated. That is,

$$Cov\left(\varepsilon_i, \varepsilon_j|X\right) = 0 \quad \forall\, i \neq j$$

The romaine price returns plots, in the lower panel of Figure 1, provides visual evidence of possible clustering at and around the recall and illness windows. Moreover, this could suggest possible changes in the variance observed over time. That is, the homoskedasticity assumption may be violated. A formal test of these assumptions are performed before proceeding with our alternative model specifications. This is discussed in more detail within the results chapter. If the serial correlation assumption is violated, an Autoregressive Conditional Heteroskedasticity (ARCH) models will be used to model the effects of recalls and food borne illness on retail prices.

4.2 (Generalized) Autoregressive Conditional Heteroskedasticity – (G)ARCH

As mentioned in the previous section, if the assumption of no serial correlation (a relationship between a variable and its lagged-value over a time period) is violated then traditional statistical analysis cannot be performed as it causes inaccurate relationships to be assumed. This section explains how (G)ARCH models are formulated and account for serial correlation to produce more accurate results. Moreover, these models are able to address possible heteroskedasticity– which often induce serial correlations– and clustering of volatility at and around observed events.

4.2.1 Autoregressive Conditional Heteroskedasticity (ARCH)

One way to model the variance in a series would be to explicitly introduce an independent variable that will help estimate the volatility (Enders, 2008). Engle (1982) demonstrates how the ARCH model estimates the mean and variance simultaneously where the variance is dependent on previous squared errors (Panait and Slavescu, 2012). The ARCH processes assume zero mean, serially uncorrelated with non-constant variances conditional on the past, while having constant unconditional variance. Therefore, the ARCH process incorporates the variance of the time series in the past when estimating variance in the current period.

The ARCH(q) process is characterized by a mean and conditional variance equation. The mean equation is defined as:

$$R_t = \alpha_0 + \sum_{q=1}^{Q} \vartheta_q R_{t-q} + \mathbf{z}_t'\mathbf{b} + \varepsilon_t; \quad \varepsilon \sim \; N(0, \sigma_t^2) \tag{3}$$

where $\mathbf{z}$ is a matrix of food safety event variables and intercept, and $\mathbf{b}$ is a vector of parameters. R_{t-q} captures lags of the return that might be important to remove serial correlation from our model.

Now suppose that, unlike the OLS model assumption, the conditional variance is not constant. In such a case, the conditional variance equation can be defined as Equation (4) where σ_t^2 represents the time-varying conditional variance. Moreover, the conditional variance is expressed as an AR(q) process using squares of the estimated residuals and α is a vector of parameters. This allows for the estimation of how influential the conditional variance is on the current period price returns.

$$\sigma_t^2 = \omega_0 + \sum_{q=1}^{Q} \alpha_q \varepsilon_{t-q}^2 \tag{4}$$

There are many possible applications for ARCH models since the residuals in Equation (4) can come from an autoregressive, an autoregressive moving average (ARMA), or a standard regression model.

4.2.2 Generalized Autoregressive Conditional Heteroskedasticity (GARCH)

The ARCH model was modified by Bollerslev (1986, 1987) to include past conditional variances in the current conditional variance equation (Equation (4)). This addition is shown in Equation (5) as $\sum_{p=1}^{P} \lambda\sigma_{t-p}^2$.

$$\sigma_t^2 = \omega_0 + \sum_{q=1}^{Q} \alpha_q \varepsilon_{t-q}^2 + \sum_{p=1}^{P} \lambda\sigma_{t-p}^2 \tag{5}$$

The conditional mean equation remains the same as Equation (3). Furthermore this extension allows for all historical shocks to influence the conditional variance. Along this line, one of the major benefits of the GARCH framework is that it allows for the modeling of both the level of the returns and allows for time-varying volatility (Wang et al., 2002).

4.2.3 GARCH-in-Mean

Engle, Lilien, and Robins (1987) extended the basic ARCH framework to allow the mean of a sequence to depend on its own conditional variance. This class of model, called the ARCH in mean (ARCH-M) model, will allow for the estimation of the uncertainty in the romaine market at the retail level. Where a positive coefficient would indicate an increase in the volatility would increase price returns and a negative coefficient would indicate and increase in volatility would reduce price returns. In order words, a positive coefficient would mean during periods of increased volatility consumers would likely be met with higher prices at the grocery store. Likewise a negative coefficient would indicated consumers would see a reduction in prices during periods of increased volatility in the market.

In short, the (G)ARCH-in-mean model goes one step further and includes the conditional variance equation in the conditional mean equation, Equation (6) as σ_t^2. Consistent with our earlier specification, the recall and illness variables are included as external regressors in the following variance equation, Equation (7):

$$R_t = \alpha_0 + \sum_{q=1}^{Q} \vartheta_q R_{t-q} + \mathbf{Z}_t'\mathbf{b} + \theta\sigma_t^2 + \varepsilon_t \tag{6}$$

$$\sigma_t^2 = \omega_0 + \sum_{q=1}^{Q} \alpha_q \varepsilon_{t-q}^2 + \sum_{p=1}^{P} \lambda\sigma_{t-p}^2 + \mathbf{X}_t'\mathbf{b} \tag{7}$$

where $\mathbf{Z}$ and $\mathbf{X}$ are matrices of external regressors.

In general, θ is referred to as the risk premium. A positive value on θ would indicate that the observed return series is positively related to its volatility. That is, higher volatility increases the mean returns of romaine prices. Furthermore, the GARCH-M model implies that there are serial correlations in the data series itself which were introduced by those in the volatility, σ_t^2, process.

Chapter 5

Results

In order to understand the general effect(s) of food recalls and illness outbreak events on romaine price returns, our preliminary investigation begins with estimating five variants of the OLS model.

5.1 OLS Results

Table 3 presents the results of each OLS model. In general, we observe consistent results across our 5 model specifications. Specifically, we note that the first, fifth and sixth recalls reduced the observed romaine price returns with coefficients ranging from -52% to -6% while the second and third recalls are shown to increase the price returns with coefficients ranging from 0.01% to 4.6%. Similar effects were seen with the illness outbreaks. The first and second illness outbreak reduce price returns with between 4$ and 10.5% the other five resulting in increased price returns with estimates ranging from 0.1% to 15%. However, across all models the only variable to be statistically significant was the fifth recall. When aggregated, the combined recalls effect reduces the price returns while the illness combined outbreaks variable increases the price returns but neither estimate is statistically significant.

Table 3: OLS Model Results for Romaine Returns

Model	(1)	(2)	(3)	(4)	(5)
Ind. Variable: Romaine Returns					
α	-0.002 [0.012]	-0.001 [0.011]	-0.003 [0.012]	-0.002 [0.012]	-0.002 [0.011]
Recall_1	-0.306 [0.228]	-0.349 [0.215]			-0.354 [0.216]
Recall_2	0.002 [0.216]	0.001 [0.215]			0.002 [0.215]
Recall_3	0.046 [0.219]	0.055 [0.215]			0.050 [0.216]
Recall_4	-0.060 [0.216]	-0.062 [0.215]			-0.061 [0.215]
Recall_5	-0.523^{*} [0.249]	-0.373^{**} [0.215]			-0.379^{**} [0.216]
$\text{Recall}_{\text{Total}}$				-0.148 [0.101]	
Illness_1	-0.041 [0.077]		-0.075 [0.073]	-0.059 [0.073]	
Illness_2	-0.105 [0.124]		-0.100 [0.125]	-0.105 [0.124]	
Illness_3	0.066 [0.099]		0.066 [0.099]	0.066 [0.099]	
Illness_4	0.001 [0.063]		0.001 [0.063]	0.001 [0.063]	
Illness_5	0.011 [0.042]		0.013 [0.041]	0.017 [0.041]	
Illness_6	0.072 [0.125]		0.072 [0.125]	0.071 [0.125]	
Illness_7	0.151 [0.125]		0.021 [0.108]	0.057 [0.111]	
$\text{Illness}_{\text{Total}}$					0.007 [0.027]
R^2	0.021	0.014	0.005	0.011	0.014

Note: Values in brackets represent the standard errors of parameters. *, **, and *** denote statistical significance at the 10%, 5% and 1% level, respectively.

Figure 2, a plot of the squared residuals from the 5 simple OLS model, shows a clustering pattern in the data confirming the assumption of homoskedasticity is violated. Therefore, a variant of the Autoregressive Conditional Heteroskedasticity (ARCH) is necessary.

5.2 GARCH Model Selection

5.2.1 ARIMA Model Selection

The optimal number of lags to include in the GARCH model was determined from an Autoregressive Integrated Moving Average (ARIMA) model using the Box-Jenkins procedure (see Box and Jenkins, 1976, for further details of the algorithm). The general algorithm is detailed in Figure 4 and discussed below.

Test for Stationarity

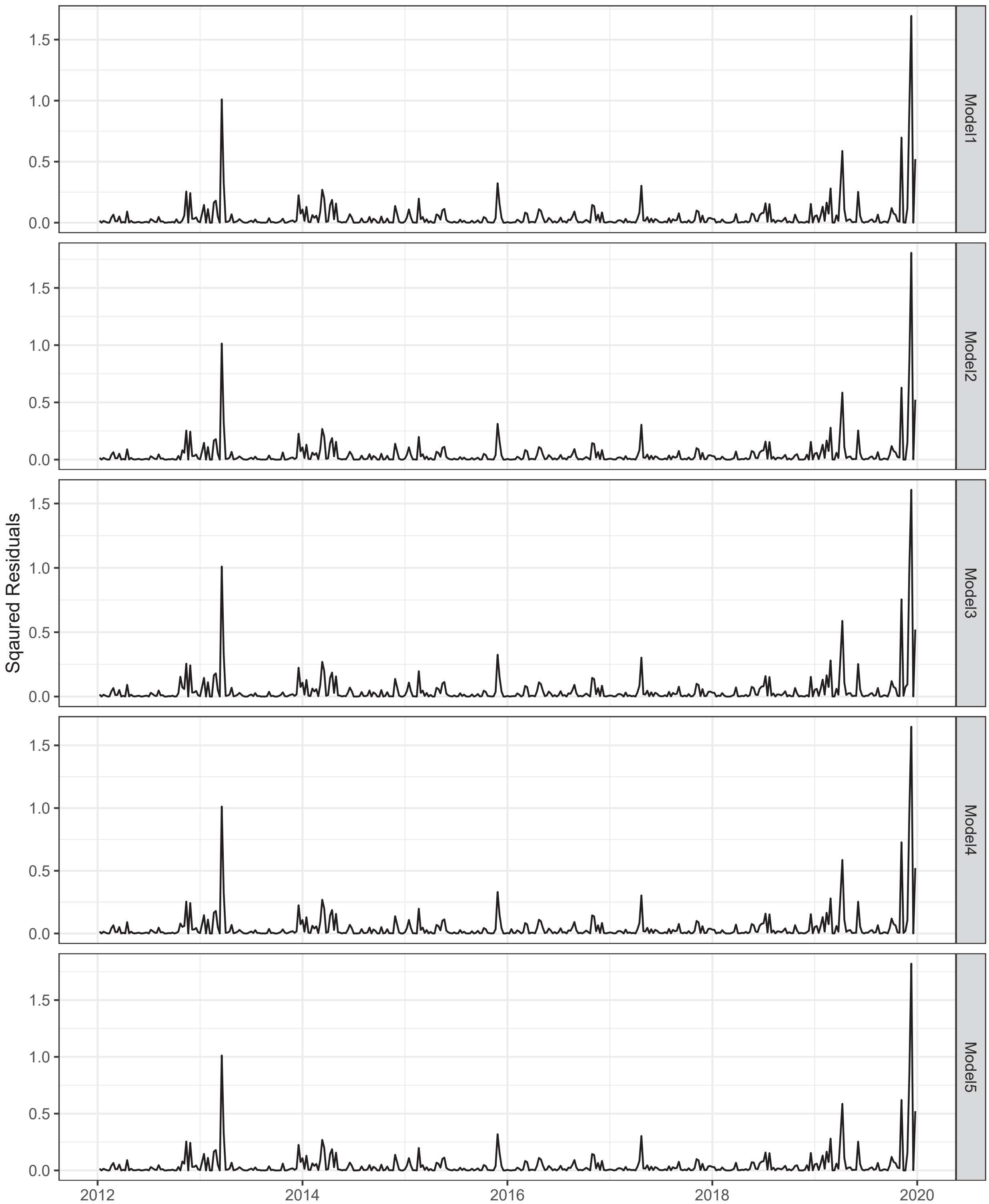
One of the main requirements for standard statistical testing is the assumption of stationarity. A stationary process is one where the statistical properties do not vary with time (Nason, 2006). That is, the series exhibits a constant mean, variance and autocorrelation over time. If a time-series is non-stationary, the results of traditional econometric techniques such as OLS and ARMA are misleading and invalid Chang (2003). This can cause inaccurate interpretations of results potentially leading to invalid conclusions about a price series.

Another standard reason for requiring stationarity in the time series variables is to be able to obtain meaningful sample statistics such as means, variances, and correlations with other variables. If the series is stationary, this provides a accurate base for predicting the future path of the data. Instead, if sample statistics such as the variance are persistently increasing over time, the model will consistently underestimate the mean and variance in future periods. The same holds true for the correlation of the series as well.

The Augmented Dickey-Fuller (ADF) and Kwiatkowski-Phillips-Schmidt-Shin (KPSS) test for stationarity are utilized. The ADF test examines whether $\rho_1 = 1$ in Equation (8).

$$R_t = \alpha + \beta t + \rho_1 R_{t-1} + \rho_2 \Delta R_{t-1} + \rho_3 \Delta R_{t-2} + \ldots + \epsilon_t \tag{8}$$

Figure 2: Squared Residuals of OLS models



The null hypothesis for the ADF is that the data is non-stationary. We reject the null hypothesis with a test statistic of -10.32 and p-value of 0.01 for romaine returns. Therefore, we conclude the returns series is stationary at levels, that is integrated of order 0, 1(0), above the 1% significance level.

Similarly, the KPSS is another unit root test using a linear regression. Where the series is broken into three parts shown in Equation (9):

$$R_t = r_t + \beta t + \epsilon_t \tag{9}$$

where βt is a deterministic trend, r_t is a random walk, and ϵ_t is a stationary error. The null hypothesis assumes that the series is stationary. We were unable to reject the null hypothesis of stationarity in the KPSS given a test statistic of 0.072 and critical value of 0.347 at the 90% confidence level. This allows for us to conclude the romaine returns are stationary at all conventional levels of significant.

Model Selection

After verifying the stationarity of the return series, we proceeded with obtaining the Autocorrelation function (ACF) and Partial Autocorrelation function (PACF) as shown in Figure 3. The ACF helps determine the Moving Average (MA) component. For this data an MA(0) appears most appropriate since all lags, zero excluded, fall within the 90% confidence interval. Simultaneously, the PACF is used to determine the Autoregressive (AR) component. The bottom right panel of Figure 3 points to the possibility of the first two lags of the PACF being statistically different from zero. This, coupled with the quickly decaying ACF, suggests having two possible model candidates, an AR(1) and an AR(2).

Figure 3: Price Plot of Romaine Returns

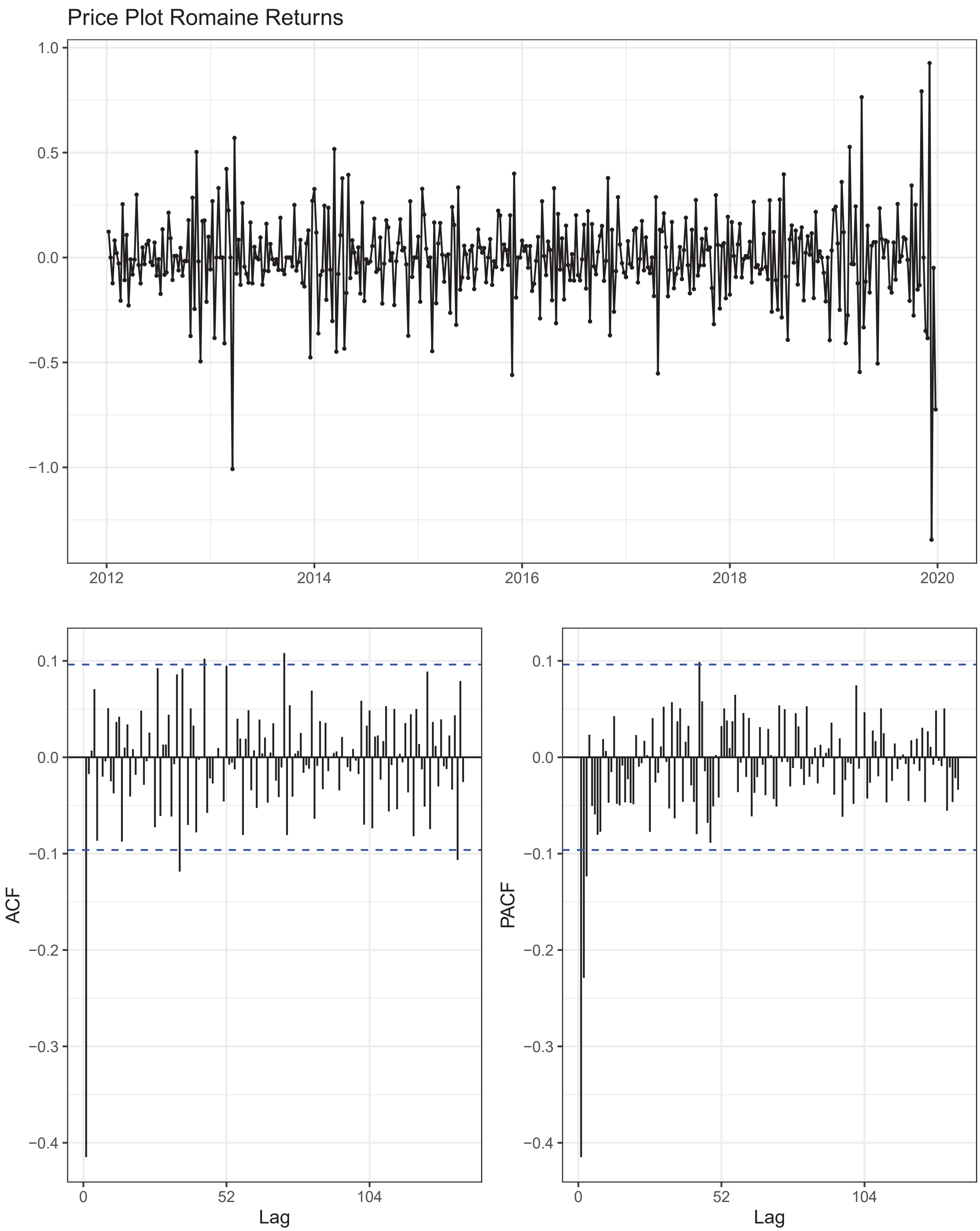
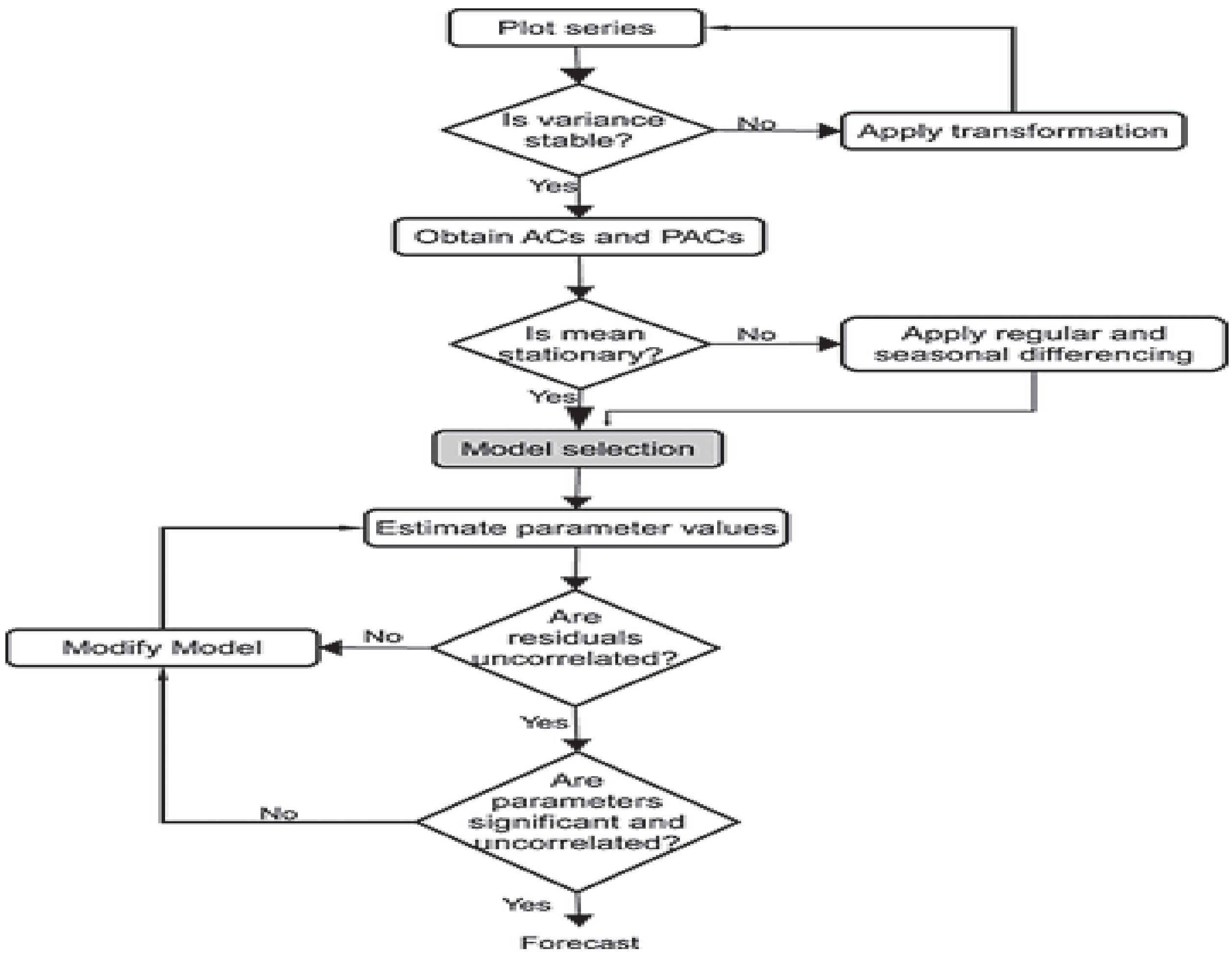


Figure 4: Basic Concept of the Box-Jenkins Algorithm



Continuing through the Box-Jenkins procedure we preformed several diagnostic checks, starting with the most parsimonious model, the ARIMA(1,0,0) model. The model estimates are presented below:

$$R_t = \underset{[0.007]}{-0.002} - \underset{[0.0451]}{0.4259} \cdot R_{t-1} \tag{10}$$

$$\sigma^2 = 0.038, \ \text{log likelihood} = 90.87, \ AIC = -175.73$$

where the standard errors are represented in square brackets.

The estimates of the ARIMA(1,0,0) model indicate that the intercept was insignificant and could possibly be excluded from the model. However, we decided to include an intercept term in our specification given that a non-zero mean was observed on the returns in Table 1. The AR(1) value was statistically significant at all conventional levels of significance.

Our plot of the model residuals, shown in the upper pane of Figure 5, reveals no obvious outliers or discernible pattern that would suggest any specific omitted variable or model misspecification. The residuals, in the bottom right panel, for example, seem to be largely normally distributed. However, based on the ACF, the lower left panel, several lags appear to fall outside or near the 90% confidence interval indicating serial correlation may still exist. A joint test of significance of these lags, as per the Ljung-Box test, supports this hypothesis of possible serial correlation. In fact, we reject the null hypothesis of no serial correlation at all conventional levels of significance given a Q^*= 121.87 and P-value of 0.002.

Due to the presence of serial correlation in the AR(1) model above, we proceeded to check the second possible model, the ARIMA(2,0,0). The model estimates are

$$R_t = \underset{[0.005]}{-0.002} - \underset{[0.049]}{0.531} \cdot R_{t-1} - \underset{[0.048]}{0.245} \cdot R_{t-2} \tag{11}$$

$$\sigma^2 = 0.036, \text{ log likelihood} = 103.31, \ AIC = -198.62$$

Following the same approach as detailed above, we plotted the diagnostics of the ARIMA(2,0,0) in Figure 6. Unlike the ARIMA(1,0,0), the ACF, in the lower left suggests that most of the lags fall within the 90% confidence interval. This suggests that the serial correlation issue identified earlier has been removed with the additional lag of the returns. The Ljung-Box test, again confirms this assumption, with a maximum lag at 83 and we fail to reject the null hypothesis of no serial correlation in the model. The Ljung-Box test reported a Q^*= 90.04 and a p-value of 0.21. To this extent, we were able to conclude that there was no explanatory power remaining in the residuals and therefore it was not distinguishable from a white noise process. Again, the residuals appear to be normally distributed, allowing us to conduct standard hypothesis testing and create reliable confidence intervals.

Figure 5: Residual Plot ARIMA (1,0,0)

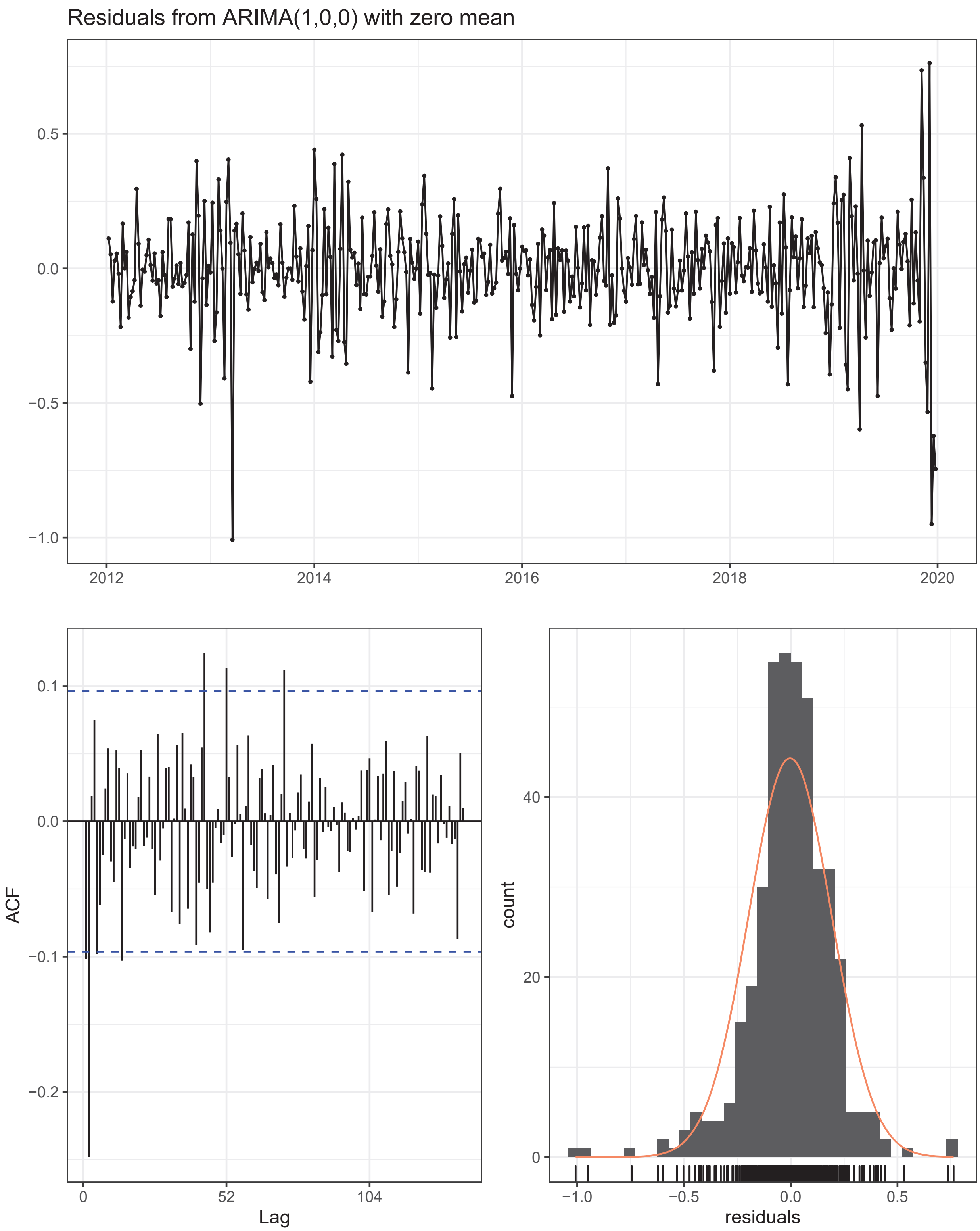
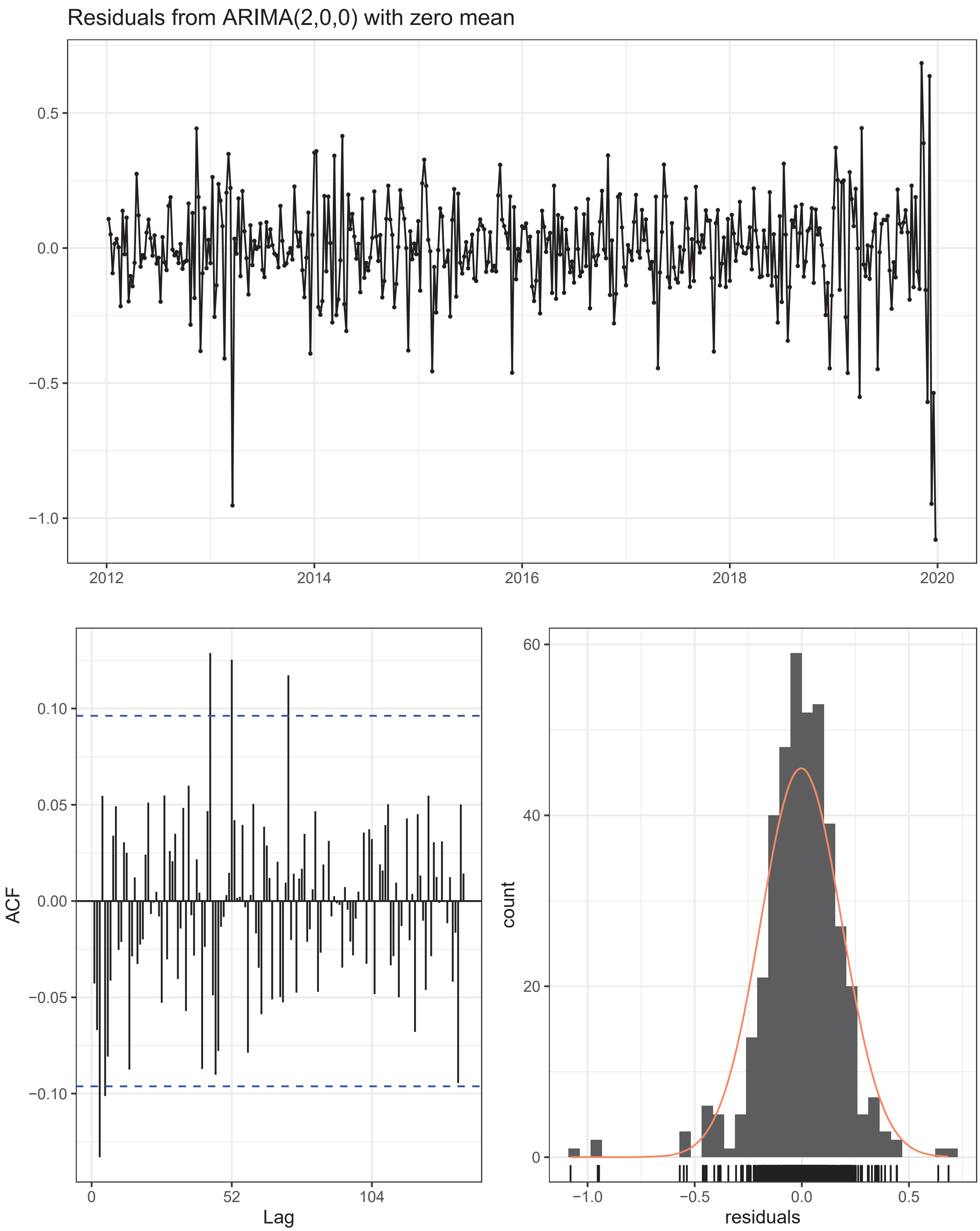


Figure 6: Residual Plot ARIMA (2,0,0)



5.2.2 Testing for an ARCH effect

In order to test for the presence of an ARCH effect, we employed a Lagrange multiplier (LM) test. For this purpose, we will use the squared residuals from our chosen ARIMA model – ARIMA(2,0,0). Without loss of generality, we can use an auxiliary equation framework to test for first-order ARCH effect using the form:

$$\hat{e}_t^2 = \delta_0 + \delta_1 \hat{e}_{t-1}^2 + \zeta_t \tag{12}$$

where ζ_t is a random error term. The null and alternative Hypothesis of the LM test are:

$$H_0 : \delta_1 = 0$$
$$H_1 : \delta_1 \neq 0$$

If there are no ARCH effects, then $\delta_1 = 0$ and the fit, R^2 of Equation (12), will be poor. If an ARCH effect exists however, we can expect that current values of the squared residuals will depend on its lagged values, and therefore the R^2 value will be relatively high.

The standard LM test statistic is $(T{-}q)R^2$ where T is the sample size, q is the number of e_{t-q}^2 terms included in Equation (12). Finally, the LM statistic is distributed $\chi^2(q)$, where q is again the order of lag. If $(T{-}q)R^2 \geq \chi^2_{(1-\alpha,q)}$, then we can reject the null hypothesis that $\delta_1 = 0$

To formally test for an ARCH effect, we employed the Ljung-Box test on the squared residuals of the ARIMA(2,0,0) as per Equation (12). Our auxiliary equation produced a χ^2 statistic of 32.041 and P-Value of <0.001. Therefore, at all conventional levels of statistical significance, we reject the null hypothesis and conclude that an ARCH processes is present.

In the ARCH(q) model the mean equation, Equation 13, is determined using the best ARIMA process which was found to be ARIMA(2,0,0) as detailed above.

$$R_t = \alpha_0 + \vartheta_1 R_{t-1} + \vartheta_2 R_{t-2} + \mathbf{z}_t'\mathbf{b} + \eta_t;\ \eta \sim iid\ N(0,1) \tag{13}$$

After determining the best fitting ARIMA model, where there is no additional explanatory power remaining in the residuals, we then apply the various (G)ARCH processes to the model. Specifically, we employ three (G)ARCH(1,1) and two (G)ARCH in Mean models. Model specifications for each models can be found in

Table 4.

Table 4: GARCH Model Specifications

Model	(1) GARCH(1,1)	(2) GARCH(1,1)	(3) GARCH(1,1)	(4) GARCH-M(1,1)	(5) GARCH-M(1,1)
Ind. Variable: Romaine Returns					
Conditional Mean Equation					
α_0	✓	✓	✓	✓	✓
R_{t-1}	✓	✓	✓	✓	✓
R_{t-2}	✓	✓	✓	✓	✓
Archm				✓	✓
Recall_1	✓	✓			✓
Recall_2	✓	✓			✓
Recall_3	✓	✓			✓
Recall_4	✓	✓			✓
Recall_5	✓	✓			✓
Illness_1	✓		✓	✓	
Illness_2	✓		✓	✓	
Illness_3	✓		✓	✓	
Illness_4	✓		✓	✓	
Illness_5	✓		✓	✓	
Illness_6	✓		✓	✓	
Illness_7	✓		✓	✓	
Conditional Variance Equation					
ω	✓	✓	✓	✓	✓
ε^2_{t-1}	✓	✓	✓	✓	✓
σ^2_{t-1}	✓	✓	✓	✓	✓
$\text{Illness}_{\text{Total}}$					✓
$\text{Recall}_{\text{Total}}$				✓	

Note: A ✓indicates the inclusion of the terms in each model

5.2.3 Model Selection Criteria

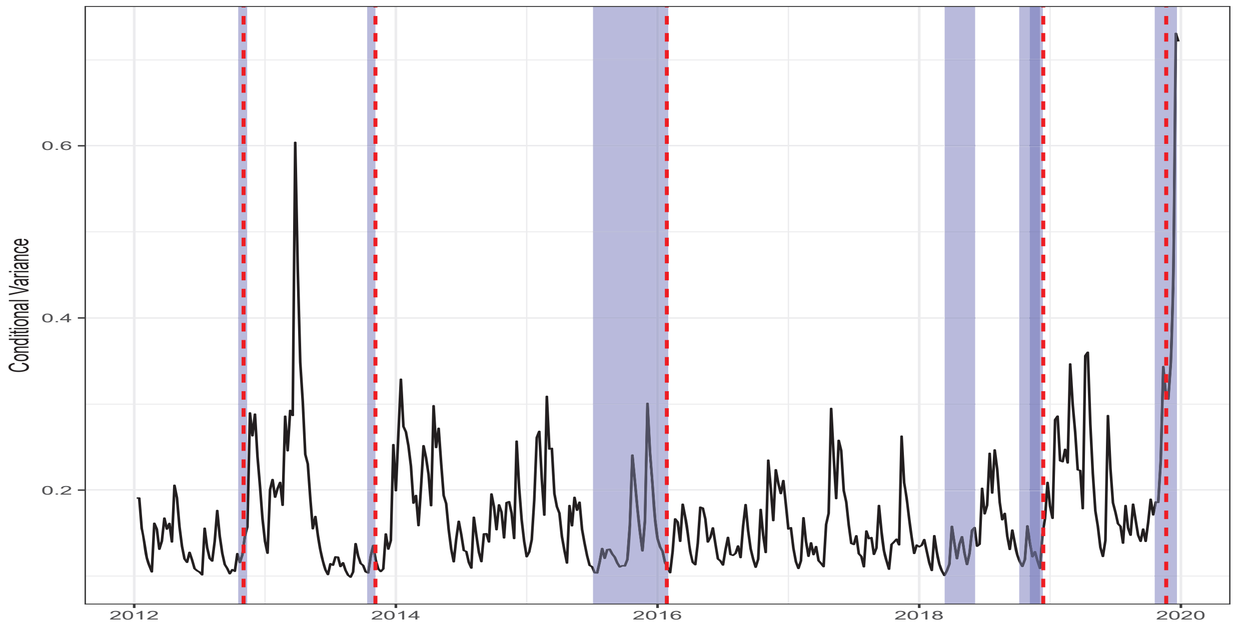
The best-fitting GARCH model is determined using the Akaike Information Criterion (AIC). The AIC is an estimate of the relative distance between the unknown true likelihood function of the data and the estimated likelihood function. Therefore a lower/more negative AIC is considered superior. The AIC and BIC value for each of the five GARCH models are shown at the bottom of Table 5. Model 1 and Model 5 have the same AIC score of -0.746. However, the ARCH-in-mean (Archm) coefficient associated with the variance term in the mean equation is insignificant in both GARCH-in-mean models.

In other words, during our sample period January 1, 2012 through December 31, 2019 our GARCH-M model fails to show a statistically significant relationship between price volatility and romaine price returns. In effect, this indicates that the volatility was not correlated with the average return prices observed over the period. This invalidates our assumption that there is correlation between the volatility and price returns in the romaine market. Therefore, we conclude the GARCH-M model is not appropriate and we focus on Model 1 as the model of choice. The remaining results section focuses on the Model 1 estimates.

5.3 GARCH Results

figure 7 presents the unconditional variance of the selected model, GARCH(1,1) model, model 1. We observe several periods of high volatility and volatility clustering across the sample period. Several of the upticks seem to be related with the illness and recall events. This pattern holds true especially for events one(1), two(2), five(5) and six(6) albeit not perfectly. It is of importance to note the two spikes in volatility followed first and sixth events in the series.

Figure 7: Conditional Variance GARCH Model 1



Of the 5 GARCH models estimated, three of them are GARCH(1,1) models. Results for these three models are shown in Table 5. The standard errors for these estimates are presented in the parenthesis. Across all three models, the autoregressive (AR) terms for both lags are significant at the 1% level. These results show variable effects across the seven foodborne illness outbreaks. As mentioned in the model selection section, the following results will focus on model 1 estimates although statistical significance and estimated coefficients are similar across all three (3) GARCH(1,1) models. The majority of the illness outbreaks, six of the seven, are found to increase the price returns of romaine lettuce shown. Of those six with an increased effect, three of them were found to be statistically significant - the first, third, and sixth illness events. The most deadly illness outbreak of this time series, the third outbreak, appears to have caused an increase in the price returns by 4.1% and is found to be statistically significant at the 5% significance level. This outbreak is also the largest studied in terms of the number of cases but does not have an associated recall. Also, the first illness outbreak occurring in late 2019 is shown to be statistically significant at the 10% level and appears to increase price returns by 9.6%, the largest effect seen within the illness outbreak variables. The sixth illness range, the smallest in terms of the number of cases, is found to be statistically significant and increases price returns in romaine lettuce by 5.2% in late 2013. Illness outbreaks 4, 5, and 6 were also found to increase the price returns by 1.5%, .02%, and 7.8%, respectively, but were not found to be statistically different from zero at all of the standard confidence levels. Finally, the second illness range occurring in 2012, which resulted in 62 cases, is estimated to reduce price returns by negative 5.6%, though this event was not statistically significant.

Similarly to the illness outbreaks, we find the effects of recalls on price returns vary across recalls. The first, second, and third recalls are found to reduce price returns and are shown to be statistically significant. The first recall occurring in November of 2019 is shown to have the largest effects on price returns with an estimate of -0.579, meaning price returns fell by 57.9% following this particular recall. This recall is associated with the first illness event in our series, which was found to increase price returns by 9.6% initially. To better understand this event, it is the second largest in terms of a number of cases, states, and hospitalizations but the largest illness outbreak with an associated recall. The fifth recall, which occurred in November of 2012 and is associated with the seventh illness outbreak, causes the second-largest decrease of 30.5%. Likewise, the second recall occurring in 2018 is shown to have an estimate of -0.0287, implying there was a 28.7% drop in returns following this event. Although found to be statistically insignificant, the third and fourth recalls were found to increase the price returns by 7.5% and 4.1%, respectively. This means consumers experienced an increase in retail prices following the recall. The third recall occurred in January of 2016 and is associated with illness outbreak 5, which was the smallest in terms of the number of cases but the longest in terms of the number of weeks new cases were reported. This recall is found to increase the average price returns by 7.9% although not statically significant. Similarly, the fourth recall occurred in November of 2013 was associated with the sixth illness outbreak that only affected people in 4 states. This recall is reported to increase price returns by 4.1% however not statistically significant.

The GARCH coefficients in the variance equation are found to be statistically significant. This suggests that the conditional variance of romaine price returns in the current period is only 56% dependant on the week prior's conditional variance estimate. Similarly, the prior week's residuals has an influence of 36.7% on the current periods observed residuals.

Similar results are found with the two GARCH-M(1,1) models noted as Model 4 and Model 5 in Table 5. The AR coefficients are also found to be significant in these two models. Model 4, which includes all illness outbreak dummies in the mean equation, contains similar estimates as those reported from model 1. However, this model shows the second illness outbreak reduced romaine returns by 6.8% at the 10% significance level while the GARCH(1,1) models shows this outbreak as not statistically significant. Model 5, which includes all five recall dummies in the mean equation, shows similar results as those in Model 1. All signs remain consistent across the two models, only the second recall was found to be significant in Model 5. The GARCH-M(1,1) models allow for estimation of the effects of total recalls and total illness on the volility of price returns. This is shown as the coefficents presented for the $\text{Recall}_{\text{Total}}$ and $\text{Illness}_{\text{Total}}$. Both values are reported as positive meaning recalls and illness outbreaks increase the variance in the romaine market by 5.4% and .2% respectively. However, neither value is statistically significant. As mentioned in section 5.2, the correlation between volatility in the series and price returns was found to be statistically insignificant. Therefore a GARCH−M model is not appropriate in this case.

Table 5: GARCH Model Estimates

Model	(1) GARCH(1,1)	(2) GARCH(1,1)	(3) GARCH(1,1)	(4) GARCH-M(1,1)	(5) GARCH-M(1,1)
Ind. Variable: Romaine Returns					
Conditional Mean Equation					
α_0	-0.004 [0.003]	-0.001 [0.003]	-0.003 [0.004]	0.004 [0.457]	0.006 [0.007]
R_{t-1}	-0.629^{***} [0.052]	-0.623^{***} [0.052]	-0.622^{***} [0.053]	-0.061^{***} [0.051]	-0.622^{***} [0.052]
R_{t-2}	-0.332^{***} [0.049]	-0.329^{***} [0.050]	-0.320^{***} [0.050]	-0.357^{***} [0.049]	-0.326^{***} [0.050]
Archm				-0.357 [0.246]	-0.287 [0.251]
Recall_1	-0.579^{***} [0.227]	-0.232 [0.314]			-0.103 [0.377]
Recall_2	-0.287^{***} [0.094]	-0.337^{***} [0.117]			-0.337^{***} [0.124]
Recall_3	0.079 [0.091]	0.075 [0.096]			0.077 [0.116]
Recall_4	0.041 [0.090]	0.072 [0.107]			0.070 [0.116]
Recall_5	-0.305^{*} [0.172]	-0.130 [0.109]			-0.142 [0.122]
Illness_1	0.096^{**} [0.040]		0.075^{**} [0.039]	0.098^{**} [0.045]	
Illness_2	-0.056 [0.037]		-0.032 [0.042]	-0.068^{*} [0.037]	
Illness_3	0.041^{*} [0.025]		0.038 [0.025]	0.040 [0.017]	
Illness_4	0.015 [0.016]		0.015 [0.016]	0.011 [0.017]	
Illness_5	0.002 [0.011]		0.004 [0.011]	< 0.001 [0.011]	
Illness_6	0.052^{*} [0.030]		0.055^{*} [0.031]	0.046 [0.032]	
Illness_7	0.078 [0.063]		-0.001 [0.029]	0.035 [0.043]	
Conditional Variance Equation					
ω	0.004^{***} [0.002]	0.004^{***} [0.001]	0.004^{***} [0.001]	0.002^{**} [0.001]	0.002^{**} [0.001]
ε^2_{t-1}	0.367^{***} [0.087]	0.307^{***} [0.077]	0.357^{***} [0.086]	0.265^{***} [0.072]	0.279^{***} [0.070]
σ^2_{t-1}	0.560^{***} [0.094]	0.618 [0.086]	0.579^{***} [0.087]	0.662^{***} [0.078]	0.657^{***} [0.002]

Continued on Next Page

Table 5: GARCH Model Estimates

Model	(1)	(2)	(3)	(4)	(5)
	GARCH(1,1)	GARCH(1,1)	GARCH(1,1)	GARCH-M(1,1)	GARCH-M(1,1)
$Illness_{Total}$					0.002 [0.002]
$Recall_{Total}$				0.054 [0.039]	
Akaike	-0.746	-0.743	-0.742	-0.746	-0.740
Bayes	-0.571	-0.636	-0.616	-0.600	-0.614
Ljung-Box†	1.138 (.286)	0.910 (.340)	0.438 (.508)	0.652 (.420)	0.743 (.389)
LogLikelihood	172.746	165.076	166.943	169.71	166.49

Note: Values in brackets represent the Standard errors of parameters. *, **, and *** denote statistical significance at the 10%, 5% and 1% level, respectively. † : P-value presented in parentheses.

Chapter 6

Conclusion

This study estimates the effects of all foodborne illness outbreaks and recalls directly linked to romaine lettuce from January 1, 2012 to December 31, 2019. The analyses utilized an event method approach where each illness outbreak and recall associated with romaine lettuce was treated as separate and cumulative events affecting the average romaine price returns. A series of GARCH(1,1) and GARCH-M(1,1) models were employed to model the data.

Our results show that the effects of illness outbreaks and recalls vary across our sample of events. However, within the class of illness outbreaks, we know that their effects on romaine price returns were consistent,if found to be statistically significant. Three (3) out of seven (7) illness outbreaks, are shown to increase the romaine price returns between 4.1% and 9.6%. It appears that the larger, likely more publicized foodborne illness outbreaks, such as the outbreaks in 2013, 2018 and 2019 are more likely to affect romaine lettuce returns. This conforms to the *a priori* expectation that the bigger an event, the more news coverage there is, and the more aware are customers of the potential risk when grocery shopping.

A similar trend was observed in the effects recalls have on romaine price returns. The three largest foodborne illness outbreak that resulted in a recall, three (3) of five (5) recalls studied, were found to be statistically significant. These recalls were found to have a large and negative effect on average romaine price returns ranging between 30% and 57%. This highlights the fact that the price returns dropped substantially in weeks following the announcement of the recall. Therefore, it is shown that a single event like the first illness outbreak in our study, between January 1, 2012 through December 31 2019, is found to increase the returns during the initial illness outbreak but then cause a drastic reduction in returns following the announcement of the recall. It is also important to note that most of the recalls occur at the end of an outbreak. Therefore, the effects seen could be a combination of the recall but also the increased consumer knowledge of a foodborne illness outbreak. Overall, the romaine market is negatively effected by recalls, a result of current food safety policy. Ultimately, a continued focus on prevention and tracebility is needed to limit human illness and market disruptions resulting from recalls resulting in foodborne illness outbreaks.

Although our results suggest that food safety events do not significantly increase the volatility, nor does the volatility have a statistically significant effect on the mean price returns, these events still affect both consumers and producers of romaine lettuce. These recalls and outbreaks likely affect the availability of the products on grocery store shelves creating scarcity and increasing the uncertainty in the minds of consumers which could cause a shift away from nutritious romaine lettuce. Likewise, the volatility of price returns negatively affects producers of romaine lettuce, particularly due to the short shelf life of leafy greens producers are unable to store this produces and wait for better prices in the market. Ultimately, it is in the best interest of consumers, retailers, producers, and policy makers to continue to increase food safety standards and traceability within the romaine market. Along this line, new focus at the federal level, such as the *2020 Leafy Green STEC Action Plan* are a step in the right direction.

6.1 Policy Considerations

Food safety and associated policy, especially in the leafy greens industry, continues to be a focus of the FDA as indicated by recent initiatives. The current policy intervention to ensure a safe food supply is to use recalls to inform consumers about food borne illnesses within the supply chain. This type of policy ensures consumers are less likely to contract food borne illnesses and ensure lower/more consistent food prices for consumers. However, recalls are sometimes issued after the shelf life of products has passed or not issued at all due to an inability to link an outbreak to a particular product. Continuing efforts to increase traceability within the lettuce markets will allow for recalls to be issued earlier in the outbreak window and increase prices stability for consumers. In addition, traceability through technologies like blockchain can limit future consumer exposure to food borne pathogens. Traceability addresses the additional food safety challenge of blended products such as salad mixes. Romaine has been suspected to be the vector of disease that prompts recalls on salad mixes, but this is difficult to confirm given the blending of several products from potentially different growing regions. Based on the results of this research, if we can increase traceability, then we can identify the source of the issue sooner and issue recalls sooner. This will help reduce illness and provide less price fluctuations to consumers.

6.2 Limitations and Avenues for Future Research

To more precisely understand the effects of foodborne illness outbreaks in romaine lettuce and other specialty crop markets, further research is needed. One of the biggest limitations found with our study is the lack of readily available data in specialty markets. Further, research should focus on consumer response to foodborne illness outbreaks.

While conducting this research, two interesting and policy relevant questions arose. We postulate that future research could therefore focus on assessing questions such as whether

- consumers react the same to foodborne outbreaks in specialty crop markets as they do to outbreaks in meat markets, for example?
- consumers become less responsive with recall frequency, and how quickly consumers substitute away from specialty crops once foodborne outbreaks occur?

These questions and others could be adequately answered with research and data focused on the demand and consumer choice within the specialty crop markets.

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