THE IMPACT OF COVID-19 ON FOOD ASSISTANCE

REQUESTS AT A FOOD PANTRY IN OKLAHOMA

By

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THE IMPACT OF COVID-19 ON FOOD ASSISTANCE REQUESTS AT A FOOD PANTRY IN OKLAHOMA

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Abstract:

In early 2020, the COVID-19 pandemic disrupted economies and food systems, raising concern for possible increases in food insecurity. This study investigates how COVID-19 affected the number of people served at a food pantry in Payne County, Oklahoma, an area affected by high levels of food insecurity. A statistical analysis was conducted to measure how the number of food assistance requests each week differed during the pandemic compared to before the pandemic began. The analysis finds no evidence for an increase in food assistance requests after the pandemic, and it is possible that requests even decreased.

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CHAPTER I

INTRODUCTION

In early 2020, the novel coronavirus (COVID-19) began to spread across the United States, disrupting economies and food systems, raising concern for possible increases in food insecurity. Food insecurity occurs due to a lack of consistent physical, social, or economic access to adequate and nutritious food (Niles et al. 2020). In the United States, food aid services such as food banks, community kitchens, soup kitchens, and subsidized community markets have been established to bridge the food insecurity gap (Radimer and Radimer 2002; Bazerghi, McKay and Dunn 2016). These services, frequently called "emergency food aid", are intended to be short-term solutions for those who are experiencing food insecurity due to economic, geographical, or social barriers. At the heart of emergency food aid efforts are food pantry programs, which are services that provide grocery items directly to the food insecure at no cost (Bazerghi et al. 2016).

As many Americans faced sudden economic hardship in early 2020, food pantries prepared to rise to the occasion. Food insecurity is closely related to unemployment, poverty, and food prices (Niles et al. 2020; Coleman-Jensen et al. 2014). In April 2020, at the height of the pandemic, the unemployment rate increased by 10.3 percentage points to a historically high rate of 14.7 percent, totaling 23.1 million unemployed persons (Bureau of Labor Statistics 2020). Not only did COVID-19 increase economic barriers to food access, but it also affected the physical availability and accessibility of food. COVID-19 threatened the accessibility of food through effects on food costs and shortages, due to changes in infrastructure, distribution, public access, food purchasing behaviors, and shutdowns (Niles et al. 2020; Norwood and Peel 2021). Feeding America, a nationwide network of food banks, projected the number of food insecure people to have increased by 17 million people in 2020, to a total of 45 million food insecure Americans (Feeding America 2021).

While it is intuitive that the pandemic should increase food insecurity, studies are ambiguous about whether this is the case. Despite the economic uncertainty caused by the COVID-19 pandemic in the United States, the USDA estimated the percentage of Americans in food-insecure households in 2020 held steady at 10.5% (Coleman-Jensen et al. 2021; Gundersen 2021), and Ahn and Norwood (2021) find likewise. The lack of any change to overall food insecurity despite the economic recession caused by COVID-19 may point to the effectiveness of government intervention and emergency food assistance, namely food pantries. However, other studies (Goetz, 2021; Yin, 2021) conclude that food insecurity did rise throughout the pandemic.

The aforementioned studies measure how the estimated percent of food insecure Americans changed during the pandemic, but another measure of COVID-19's effect is to evaluate changes in food assistance requests at the food pantry level. That is the objective of this study: to measure the impact of COVID-19 on demand for food assistance at one food pantry in Payne County, Oklahoma.

CHAPTER II

BACKGROUND

This section first describes the food insecurity concept, including what it refers to and how it is measured. It then discusses how the food pantry system works, which is essential to understanding how the data are collected. Then a timeline of the COVID-19 pandemic is provided to identify when the pandemic might impact the number of people seeking food assistance.

Food Insecurity

Food insecurity exists when households lack access to nutritionally adequate and safe foods or the ability to acquire acceptable food in s socially acceptable manner is limited or uncertain (Radimer and Radimer 2002; Anderson 1990). Some food insecurity is transient, meaning that households move in and out of food insecurity as their circumstances change, but the insecurity for others is chronic (Bazerghi et al. 2016). There are two levels of food insecurity: low food security and very low food insecurity. Both refer to involuntary changes in diet due to a lack of money and resources, but the former refers to a reduction in the quality and variety of foods while the latter pertains to reduced food intake (Radimer and Radimer 2002; Anderson 1990).

Food security is inversely related to income (Gundersen and Ribar 2011; Gundersen, Kreider and Pepper 2011; Coleman-Jensen et al. 2014). A household is more likely to be food insecure if they are below the federal poverty threshold, or the the head of the household is single with children, a minority, disabled, or has a low level of education (Gundersen et al. 2011; Coleman-Jensen et al. 2014; Bazerghi et al. 2016; Bhattacharya, Currie and Haider 2004; Ratcliffe, McKernan and Zhang 2011).

Oklahoma has a particularly high food insecurity rate compared to the rest of the US. From 2018 – 2020 approximately 14.6% of Oklahomans were food insecure, compared to 10.7% for the US. Only three states have a higher rate. Moreover, within the state of Oklahoma, Payne County's food insecurity rate is above average. In 2019 about 16.1% of Payne County residents were food insecure. Of the state's 77 counties, 46 had a lower food insecurity rate (Gundersen, et al., 2021). As such, using this county as a test for the pandemic's effects at the food pantry level should provide useful information on its impacts on food insecurity.

Feeding America Food Bank System

The food bank system in the United States functions through a hierarchical system of institutions that in some ways mimic the conventional food system. Just as the conventional food retail system consists of food retail corporations, distribution centers, and grocery stores, the "food bank" system is comprised of Feeding America, food banks, and food pantries.

Food pantries are the organizations directly providing food to people in need. Their success and popularity have led many of these to branch out into other charitable services, like providing free haircuts and financial education, and for this reason many refer to themselves as Food and Resource Centers. Our Daily Bread in Payne County, Oklahoma is one of these food pantries. The food at food pantries comes from two sources: food banks and retail recovery.

Retail recovery includes all the donations from local stores, while food banks are like distribution centers for food pantries in their region. Most food pantries are formally affiliated with a single food bank. Likewise, most food banks are affiliated with the nonprofit organization Feeding America, which coordinates the distribution of food donations across the food pantry system.

While there are many organizations that hand out food which might call themselves a food pantry, for this study we will be focusing on only a food pantry affiliated with the Feeding America system. The Feeding America food pantry system includes 200 food banks and about 60,000 food pantries. Each food bank and food pantry are an independent non-profit organization partnered together to distribute resources to the food insecure in the most equitable way. While they are not owned by Feeding America, all of the Feeding America affiliated food banks operate under a set of rules and regulations.

Feeding America acquires its food from the government, donations, and purchases food as well. It then distributes this food to the food banks using a market-based system with auctions and a virtual currency. Each food bank is given a certain amount of the virtual currency which they can then use to bid on food in an online auction. The amount of the currency it receives is based on need, measured by "goal factors", which is the number of food insecure people served by a food bank relative to the total number of people served nationwide. This ensures that amount of food distributed to each food bank is relative to the size of their goal factor, and thus relative to the number of food insecure people they serve. A food bank with a higher goal factor, or proportion of food insecure people served at that food bank, the greater amount of food the food bank will receive.

Before 2005, Feeding America operated under a system in which all food banks received roughly the same type of food in different proportions relative to their goal factor. This, however, created problems because most food banks only receive 25% of their food from Feeding America, with the rest coming from other food sources including private and retail donations. Food banks were receiving food that they may have already had in excess from other sources, leading to food waste. At the time Feeding America wasn't able to communicate with the food banks in order to achieve the most efficient allocation of food. So, they created a system that mimics a free market using virtual currency and an auction system.

The virtual currency used is named "shares", and each food bank can bid a certain number of shares for different truckloads of food. Each "truckload" is described by the amount and type of food it contains. Every day truckloads are updated on the system and on the same day food banks can place a sealed bid for each truckload. At the end of the day the total shares are redistributed to the food banks according to the aforementioned goal factors. Food banks can also sell some of its food that it may have in excess to other food banks to earn additional shares. This market-based system allows Feeding America and food banks to communicate needs in order to facilitate a more equitable flow of foods, decreasing waste and increasing the total amount of food available for food banks (Prendergast, 2017).

Food banks then distribute this food to food pantries using an online purchasing system. Each food type is listed at specific prices (always low, sometimes zero), and the food pantry manager then simply purchases whatever items they like. The food bank also offers no-cost product requests, which usually consists of large pallets of fruits and vegetables. Food pantries receive the rest of its food from retail recovery. This is acquired by volunteers going to grocery stores around the community accepting donations. The stores donate excess food and receive a tax break for the donations, while being able to help their community. Food donations are then sorted, expiration dates are checked, and then the food is made available to pantry guests.

The inventory tracking system at food pantries is much simpler than what a conventional grocery store might use. Because they do not charge for food there is no need for a checkout system, negating the need for precise inventories. Instead of keeping inventories of the precise foods received, in storage, and given away using barcodes and information technologies, food pantries simply measure food in pounds and in broad categories like cereals and canned fruit. (Norwood 2021).

Our Daily Bread

Our Daily Bread (ODB), a Feeding America affiliated food pantry located in Stillwater, Oklahoma, provides assistance to low-income households in Payne County through the distribution of food items and basic household needs at no cost. ODB is a client-choice food pantry, allowing clients to choose their own food items from several food categories. Clients visiting ODB for food assistance typically receive an array of goods including canned goods, cereal, pasta, bread, dairy products, meat and fresh produce. There are three to five full time workers at ODB at one time, and the rest of the workforce comes from volunteer hours, which total more than 1,000 hours each month (Norwood 2021).

Since their opening in September 2017, ODB has provided food assistance to over 49, 984 households, averaging 256 households a week (Table 1). ODB is typically open three days a week for 2-3 hours at a time.

Table 1. Visits to Our Daily Bread

Total Visits Over Life	49,984
Average visits per operational day	68.56
Average visits per week	256.32
Average visits per year	12,905.67

Source: Eytcheson (2021)

Most food pantries only measure the total lbs. of foods entering the food pantry, but Our Daily Bread is unique in that a study was conducted measuring the amount of calories and monetary savings its visits were given. Alwahabi, Ates, and Norwood (2020) report that on average one-person household makes 4.7 trips to Our Daily Bread each year, each trip provides them with 38,577 calories or 16 days of food, saving them $87 each month. The numbers for a household with 2 adults and three children are 3.9 trips, 59,577 calories or 6 days, and $130.81 in savings.

The Our Daily Bread food pantry has collected data on each visitation and visitor since its opening on September 6, 2017. When clients arrive at Our Daily Bread, they are given a number and asked to wait in the waiting room. A staff or volunteer person will then call their number and escort them into one of 4 offices to confidentially complete the intake process. On any given day there are about 3 or 4 intake offices running at a time. During intake, the client's identity is verified, and demographic information is either collected if they are new or verified for accuracy if they are a repeat client. Each client on their first visit is assigned an ID, which allows ODB to keep track of each visit a household makes to the food pantry and store their information for a more efficient intake process. The demographic information collected includes many items such as household size, income, ethnicity, ages of household members, education, disability, and employment status.

Volunteer/staff asks for photo verification of client and other household members, if new. If a person does not bring an ID, they will still be served, but a note will be put in their account to verify identity on the next visit. The intake staff will verify DOB with ID or verbally to confirm that it is the correct client. Current address is verified either through driver's license or utility bill in order to establish Payne County residence.

Demographic questions sometimes may be omitted during the intake process depending on client comfort, disability, language barriers or system accessibility. TEFAP certification happens once a year, which is a certification that the client's income is less than a certain threshold depending on household size. All that is required is a signature, no proof is necessary. In the system "number of bags/boxes" is filled out based on the number of household members served, not on the actual number of bags. The shopping center has a separate system for determining how much a household gets. Clients wait for a shopping assistant to call their name and help them through the process (Alwahabi, 2019; Eytcheson 2021).

Mobile Market is a new program at ODB in which a pop-up food pantry is set up at different locations across Payne County to make food more accessible to certain people groups. This program is specifically targeted at rural communities and young people. The locations include the rural towns of Yale, Ripley, Cushing and Glencoe, and the Oklahoma State University campus. Mobile Markets occur every Wednesday and work on a rotating schedule so that each location is visited once a month. The first week the Mobile Market travels to Yale, to Oklahoma State University on the second, Glencoe and Ripley on the third and Cushing on the fourth. The intake process is also completed at the mobile market location; however, due to certain barriers of communication or facilities, the process can be less thorough than in the food pantry. For example, during harsh weather conditions clients are not expected to answer all of the intake questions while waiting outdoors. Additionally, there can be uncooperative or disabled clients who are unable or unwilling to answer the questions. In these cases, the intake volunteer or staff member is allowed to use their best judgement on whether to ask all of the questions (Eytcheson 2021).

This is a weakness of the data in that it makes it more difficult to measure the actual number of people being provided assistance. As described above, households with more members receive a larger amount of food, but if household size data are incorrect the core variable of interest is flawed. Fortunately, this is the one variable that Our Daily Bread staff are keen to record accurately.

Coronavirus Pandemic and Relief Efforts

The Coronavirus pandemic (COVID-19) brought worldwide economic uncertainty to businesses and households. The pandemic caused problems in food supply chains ((Norwood and Peel 2021) and widespread unemployment due to business shutdowns (Bureau of Labor Statistics 2020). As many Americans faced sudden economic hardship in 2020, food and resource assistance programs prepared to rise to the occasion (Feeding America 2021).

As mentioned previously, studies provide different conclusions on the impact of the pandemic on food insecurity rates. While intuitively the economic hardships would seem to increase insecurity, at the same time government and non-profit organizations quickly provided monetary relief, which, if sufficient in size might have keep food insecurity unchanged.

The Trump administration and Congress funded economic relief and stimulus packages that supplemented the incomes of millions of Americans. For some households, these measures meant their income was higher than it was before the COVID-19 pandemic. Meanwhile, the U.S. Department of Agriculture provided the maximum Supplemental Nutrition Assistance Program (SNAP) benefit for all recipients on a temporary basis. This policy change represented a huge increase for many families, up to roughly $620 a month for a family of four. Food banks and food pantries responded nimbly to an unprecedented increase in demand and provided assistance to at least 60 million Americans in 2020. This was a 50% increase from 2019 (Gundersen 2021).

Government income assistance affects the food insecure's ability to purchase their own food, and as a result is expected to have some impact on the number of requests for food assistance at food pantries. The COVID-19 pandemic and the economic uncertainty it caused sparked many different government assistance policies and programs. The first federal government assistance was enacted into law on March 6, 2020, with the passage of $8.3 billion Coronavirus Preparedness and Response Supplemental Appropriations Act. In the same month, the $192 billion Families First Coronavirus Response Act was enacted on March 18, 2020, and the Coronavirus Aid, Relief and Economic Security (CARES) Act was signed into law on March 27, 2020. With the CARES Act, Congress and former president Donald Trump set into motion a $2.2 trillion economic rescue plan, the single largest spending bill in U.S. history, providing tax relief, grants and capital. An interim funding bill, the Paycheck Protection Program and Health Care Enhancement Act signed into law on April 24, 2020 added $483 billion of funding to increase amounts authorized for the Paycheck Protection Program and provided additional economic injury disaster loans and emergency grants under the CARES Act (St. Louis Fed 2021).

Table 2: COVID-19 Federal Relief Dates

1st Stimulus Check hits Direct Deposit	4/11/20
2nd Stimulus Check	12/29/20
3rd Stimulus Check	3/11/21

On December 27, 2020, the Coronavirus Response and Relief Supplemental Appropriations Act, part of the Consolidated Appropriations Act, 2021 was signed into law. This legislation renewed the Paycheck Protection Program, provided additional funding for schools, vaccine distribution, and provided another round of Economic Impact Payments to eligible individuals and families. President Joe Biden signed the American Rescue Plan on March 11 2021, providing an increase in unemployment benefits through September, expands child tax credit, rental payment assistance, funds for COVID-19 vaccine distribution and testing and provides funding to state local and tribal governments (St. Louis Fed 2021). Additionally, the legislature authorized a third round of Economic Impact Payments as an advance payment of the tax year 2021 Recovery Rebate Credit (IRS 2022). These government relief programs funded several stimulus checks, which were first received by Americans in the dates listed in Table 2.

Payne County COVID-19 Legislation Timeline

In order to understand how COVID-19 affected food assistance requests in Payne County, it is important to look at the timeline of shutdowns and other regional mandates that may have disrupted the normal economic activity within the county.

March 15:

First confirmed case of COVID-19 in Payne County is announced by health authorities. Stillwater Mayor Will Joyce issues an emergency declaration closing city-owned facilities, municipal court dockets, non-essential committee meetings and cancelling large events.

March 16:

Oklahoma Governor Kevin Stitt declares a state of emergency in all 77 counties due to the spread of COVID-19.

Stillwater mayor issues emergency declaration allowing the City Manager to temporarily modify rules and regulations regarding employment within the city.

March 23:

Stillwater mayor announces third emergency declaration closing businesses identified as non-essential such as gyms, spas, beauty parlors and nail salons. Retail establishments were allowed to remain open providing they require patrons to keep a distance of six feet at all times. Gatherings of more than 10 people were prohibited.

March 30:

Stillwater's mayor issues a fourth emergency declaration requiring Stillwater residents to shelter in place, only leaving their homes for essential activities or to operate an essential business.

May 15:

A new emergency declaration allows non-essential to reopen with stricter health safety standards for employees and customers. Limits on gatherings are relaxed to no more than 50 people and medically vulnerable residents and people over the age of 65 are required to continue sheltering in place unless engaging in an essential activity.

June 1:

Another emergency declaration is issued repealing the prohibition on gatherings and shelter in place for vulnerable residents and those over 65 years of age. Specific requirements for businesses are no longer required but still encouraged. City Hall and other municipal facilities reopen to the public.

August 18:

A new state of emergency is declared, and limitations are placed on bar operations, limiting capacity to 50%.

November 30:

Emergency declaration requires six feet of distancing and 50% capacity at bats and restaurants.

February 26:

A revised emergency declaration lifts all restrictions on businesses.

CHAPTER III

DATA

The Our Daily Bread food pantry has collected data on each visitation and visitor since its inception on September 6, 2017. The data collection began through Charity Tracker, an online database where nonprofits can collect client information and collaborate with other local charities. On February 1, 2020, Our Daily Bread switched over to the Link2Feed system, the preferred client data tracking system of the Oklahoma Regional Food Bank network. In the beginning stages of this change the agency was using a simple online form (Google Forms) to collect data during intake, then transcribing it over to Link2Feed. When the COVID-19 pandemic hit, the food pantry was forced to switch its distribution from in-store shopping to passing out food boxes in a drive through. Because of this shock to their daily operations, the data collection process faltered, and the food pantry began to collect only each visit with no additional demographic information of the visitor. This began on March 17, 2020, and within the following weeks the pantry slowly transitioned back to doing a traditional intake and collecting full demographic information on each household through the online form. In July 2020, the pantry was finally able to streamline their process and began adding intake information directly into the Link2Feed System (Pereira 2021).

Table 3: ODB Data Collection during COVID-19

9/7/17	Charity Tracker collection begins
2/1/20	Switch from Charity Tracker to Link2Feed
3/17/20	In store shopping ends
6/7/20	Reopen to partial shopping
7/1/20	Began adding all data into Link2Feed
8/27/21	Completely open to in-store shopping

The Charity Tracker and Link2Feed datasets were compiled in order to have a complete record of all visits to Our Daily Bread since their opening. Each dataset had their own visitor ID system to keep track of repeat visitors. In order to match up clients' old IDs with the new ones they assigned, a set of lookups and checks was designed in Excel. First, the "trim" and "concatenate" formulas were used in order to create columns in both datasets with combinations of information on each client's first name, last name, and date of birth. The combinations were "LastFirst", "LastDOB" and "Last". The lookup formula was used in order to search the old dataset for each person in the new dataset. The program looked for the cells that contained the combinations we created, and if found, entered their corresponding ID. The three combinations of lookups produced three different ID's. If all three or two out of three lookups came up with the same result, then it is assumed that they are correct. If all three lookups failed to find an ID, then it is assumed this is a new client that was not part of the old database. In all other cases, a manual searched was conducted to determine if the person was a new client or had a previous ID.

Then a unique ID system was created in order streamline our data analysis. Two datasets were created, one in which each unique visitor was listed, including all available demographic information on the household, and another dataset in which contains each individual visit over the life of Our Daily Bread. These two datasets were used in order to match each individual visit to the number of people in the household of the person requesting assistance. The average household size was 2.2. This provided information on how many *people* were served from one visit, rather than just accounting for the one household member who came into the pantry.

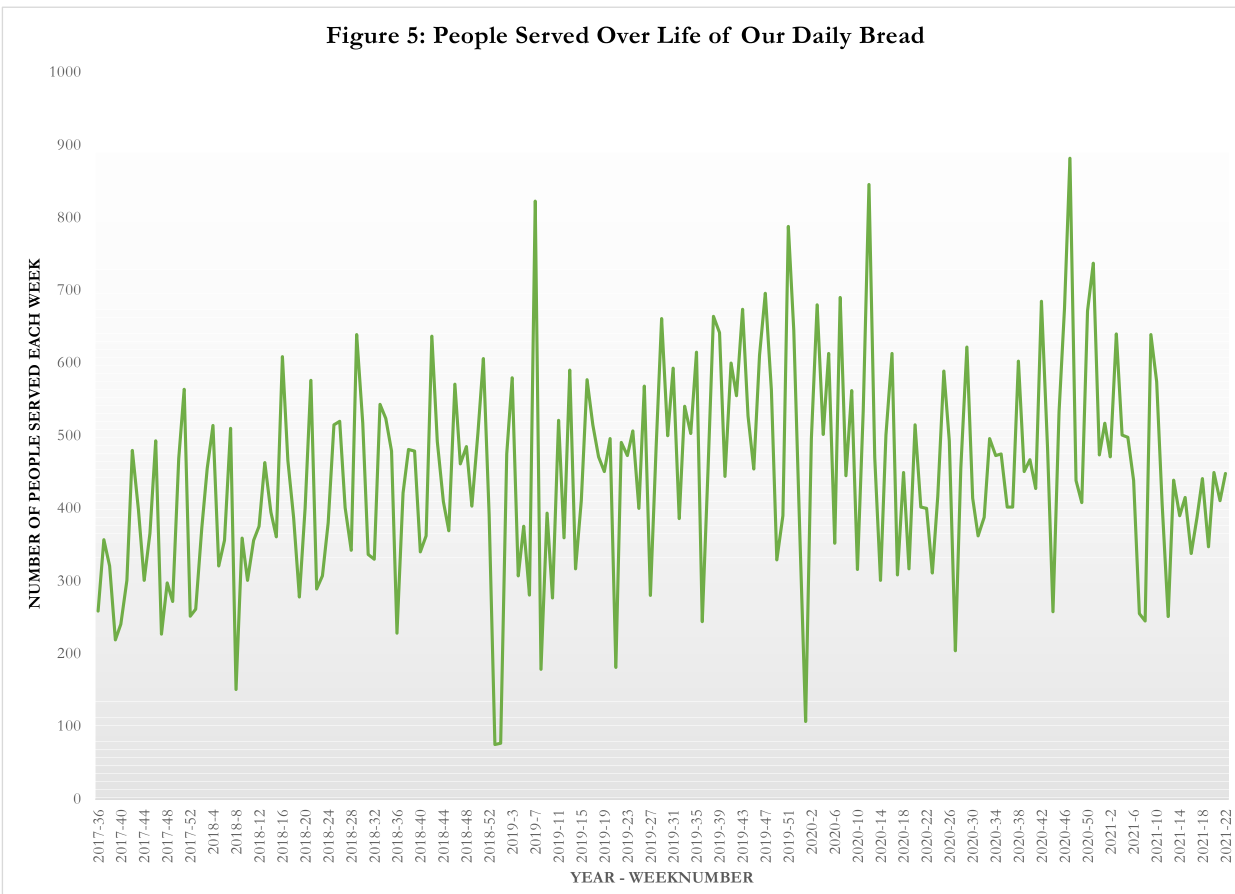
Mobile markets occur every Wednesday beginning on September 20, 2020. Because these are not actual visits to the pantry, they were omitted for the purposes of this study. This was done by assigning a value of 1 to every entry entered on a Wednesday. The data was then sorted and those entries with a 1 were deleted. However, it should be noted that the advent of the mobile pantry may have caused a reduction in the number of people visiting Our Daily Bread for assistance.

In order to measure the amount of people served in any given week, a code was created for each week of operation in the following format “YYYY-WW”. Each entry was assigned a code according to the year and week in which the visit was made. Then the household numbers for each week code were counted in order to obtain complete counts of number of people served per week.

Variables

The number of people provided food assistance at Our Daily Bread on week t, $Npeople_{t,}$, will be estimated using a COVID-19 indicator variable which equals 1 if COVID-19 was present and likely presenting obstacles to acquiring food, and 0 otherwise. Time, *t,* is an indicator variable measured in weeks since ODB's opening, equaling 1 on the first week, 2 on the second, and so on. Figure 1, which shows the people per week over the life of ODB, shows that ODB has generally experienced an upward trend in number of people served since its opening.

Figure 1:



The exact timeframe that is considered to be during COVID-19 can be ambiguous because there were many events surrounding the pandemic which may have presented obstacles to acquiring food. Obstacles to acquiring food include the virus itself, the business shutdowns, layoffs, and supply chain disruptions. Because this study focused on one food pantry located in Payne County, OK and a major contributor to the economic hardship during COVID-19 was businesses shutdowns, for this study, the precise timeframe for this variable is determined using the information on Payne County Legislation described previously. The COVID timeframe begins on March 23 when businesses in Stillwater, the largest metropolitan area in the county, declared a state of emergency in which all nonessential businesses were shut down.

Figure 2:

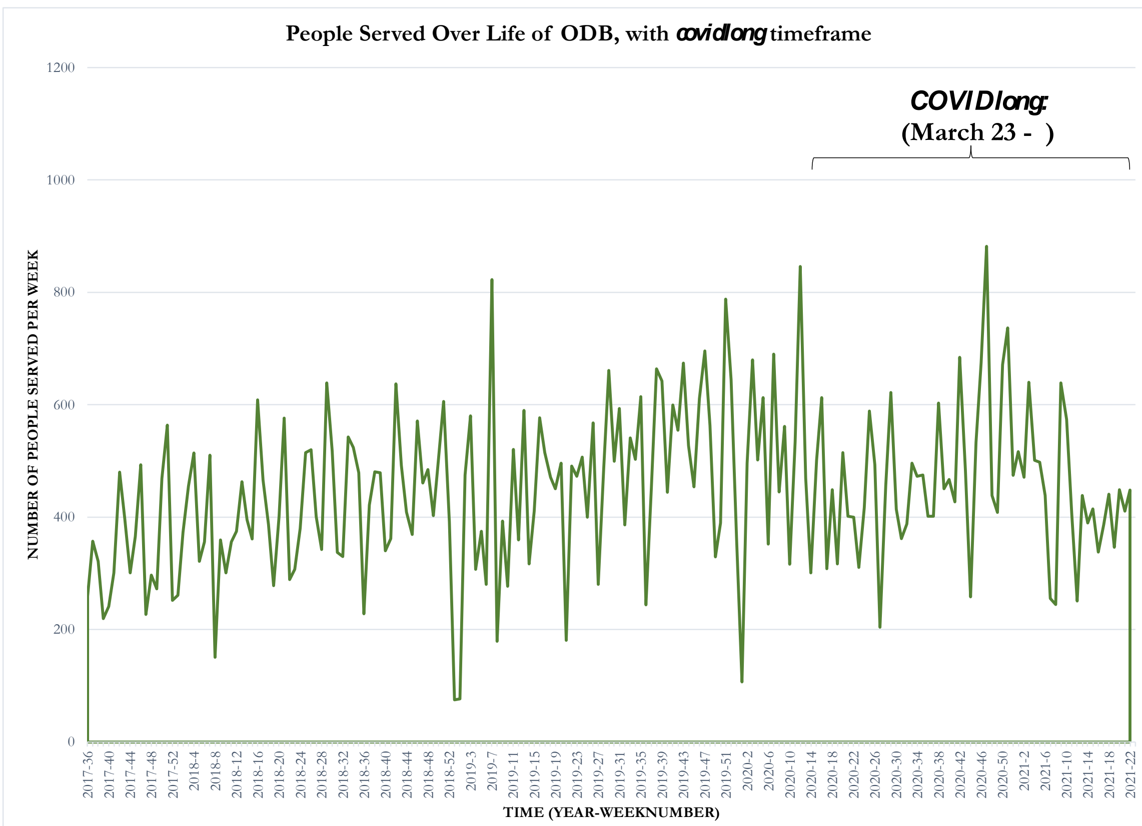
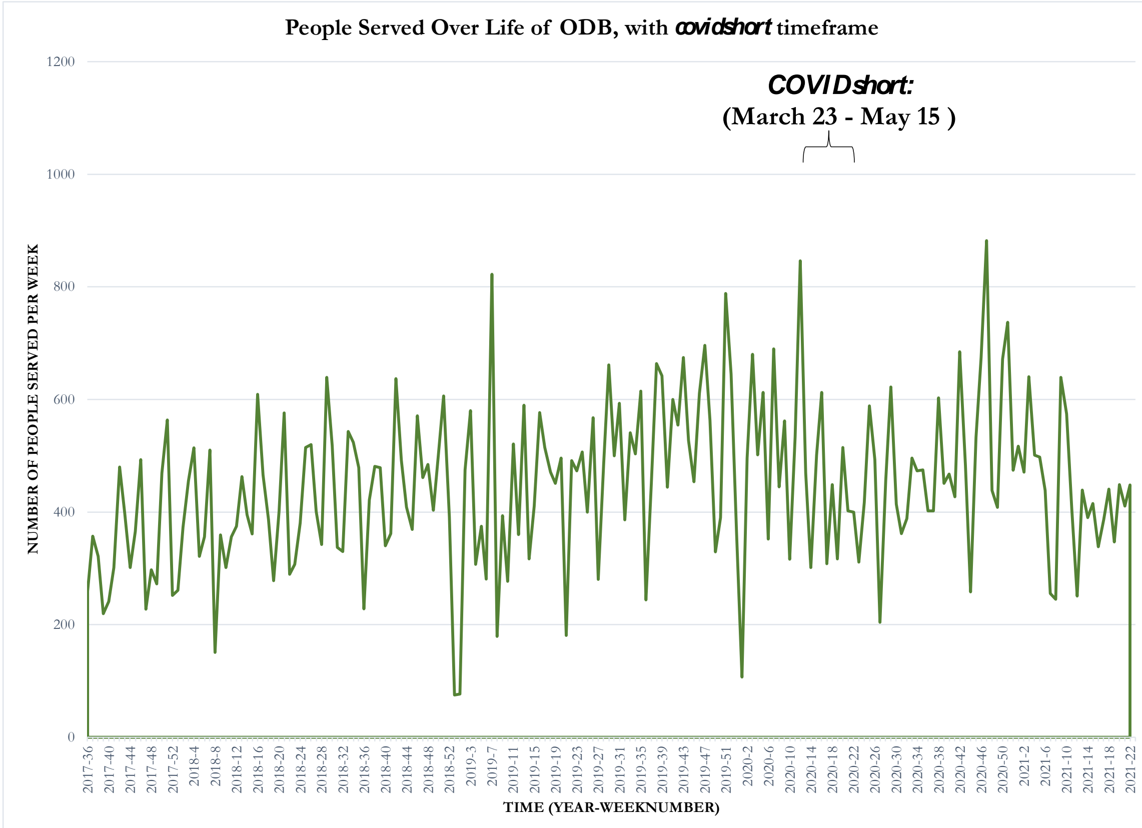


Figure 3:



The COVID timeframe was estimated in two ways. The first, *covidlong*, equals 1 in weeks which occurred after the initial Payne County shutdown, on March 23rd, 2020, and 0 otherwise. The other, *covidshort,* equals 1 in weeks during Payne County shutdown, from March 23-May 15, and 0 otherwise. These two separate variables are used in order to estimate both the long term effects of COVID on demand at ODB and the short term effects during the "worst" of the shutdown.

Table 4: Variables

Variable	Description	Mean	Standard Deviation
$Npeople_t$	number of people provided food assistance from Our Daily Bread on week t	446	140
$TIME_t$	indicator variable that equals 1 on the first week Our Daily Bread opened increases by 1 each week after	99	57
$COVIDlong_t$	indicator variable that equals 1 in weeks after March 23, 2020 *after* Payne County COVID-19 shutdown and 0 otherwise.	0.315	0.466
$COVIDshort_t$	indicator variable that equals 1 in weeks between March 23 and May 15, during Payne County COVID-19 shutdown and 0 otherwise	0.041	0.198

Number of Observations: 197

CHAPTER IV

METHODS

The purpose of this study is to test whether the COVID-19 pandemic caused an increase in food assistance requests at Our Daily Bread. The previous section described the data used to perform this test. It consists of information on the number of people provided food assistance each week since the opening of Our Daily Bread on September 6, 2017, until May 27, 2021. That section also described two indicator variables to represent the presence of the pandemic, and it demonstrated that since its opening Our Daily Bread has generally seen an upward trend in the weekly number of people assisted. Consequently, measuring the impact of COVID-19 requires accounting for that upward trend. It might be that food assistance requests did indeed increase during the pandemic, but that increase is consistent with previous trends. If this is the case that increase cannot be attributable to the pandemic.

This section describes the statistical models used to relate the time period of the pandemic to the number of people seeking food assistance (hereafter referred to as "visits" to the food pantry), while accounting for the upward trend in visits. Note that in the absence of an upward trend, and if a single indicator variable for the presence of the pandemic was used, the following regression model could be used

(1) $$N_t = \alpha_0 + \alpha_1\ (COVID) + \varepsilon_t$$

In (1), N_t is number of people provided food assistance in week t (visits), $COVID_t$ equals 1 during the COVID time period and 0 otherwise, and ε_t is an error term. Both α_0 and α_1 must be estimated. The parameter α_0 would be interpreted as the average number of visits absence the pandemic, and α_1 as the change in the number of visits due to the pandemic. If α_1 is positive and statistically significant this suggests COVID-19 increased the number of food assistance requests. It is assumed that ε_t has a zero mean and is identically and independently distributed (iid) according to the normal distribution, although this assumption will be questioned subsequently.

Recall that the *COVID* variable equals one when the pandemic may have posed obstacles for households acquiring food, largely through income and job losses. Though it is relatively easy to identify when the pandemic began, determining when its main effects on households' financial status should end is not. While there are certain dates when official government shutdowns ceased, demand for items like restaurant food did not just immediately return to its original level. In some ways the pandemic was still ongoing at the end of the data in May 2021, as people were still taking precautions to avoid contagion. Moreover, the pandemic may have initiated long-term changes in consumption that will require the economy to transform in more permanent ways, and this means job and income losses could persist for years.

As such, this study uses two indicator variables for the presence of the pandemic: both beginning with the shutdowns in March 23, but one ending when most of the official shutdowns ended, May 15 (*COVIDshort*), and the other continuing to the end of the data (*COVIDlong*).

The model in (1) is thus revised as

$$N_t = \alpha_0 + \alpha_1\ (COVIDlong_t) + \alpha_2\ (COVIDshort_t) + \varepsilon_t \qquad (2)$$

Where $COVIDlong_t$ is 1 if the observation occurred *after* the initial COVID-19 shutdown and 0 otherwise, $COVIDshort_t$ is 1 if the observation occurred *during* the COVID-19 shutdown period and 0 otherwise. Suppose both α_1 and α_2 are positive and statistically significant, but $\alpha_1 < \alpha_2$.

This would suggest that most of *COVID*'s impacts occurred during the official shutdowns, but that even after the shutdowns ended households continued to face food insecurity. Or, if α_1 is not statistically significant but α_2 is both statistically significant and positive, this testifies that the shutdowns increased food insecurity in Payne County, but that once the shutdowns ended food insecurity returned to its pre-pandemic level.

Our Daily Bread has not been open long, and a previous figure shows an upward trend in the number of people served. Assuming that the upward trend would have continued after March 2020 in the absence of the pandemic (an assumption which is impossible to verify or refute), the question is not whether the pandemic increased total visits compared to before the pandemic, but whether the visits are higher than expected visits given the trend. A time trend variable is thus included to ensure the COVID indicator variables captures increases in visits that might occur in addition to the increase expected from past trends. The model below specifies a linear time trend that increases by a value of one for each additional week.

$$N_t = \alpha_0 + \alpha_1\,(COVIDlong_t) + \alpha_2\,(COVIDshort_t) + \alpha_3\,(TIME_t) + \varepsilon_t \tag{3}$$

In (3), *TIME* equals 1 in the week beginning on Monday September 4, 2017, 2 in week beginning on September 11, 2017, and so on. If α_3 is statistically significant then a time trend indeed exists, and the estimate of α_1 and α_2 in (1) and (2) are biased because they capture effects of both the pandemic and the trend that started before the pandemic.

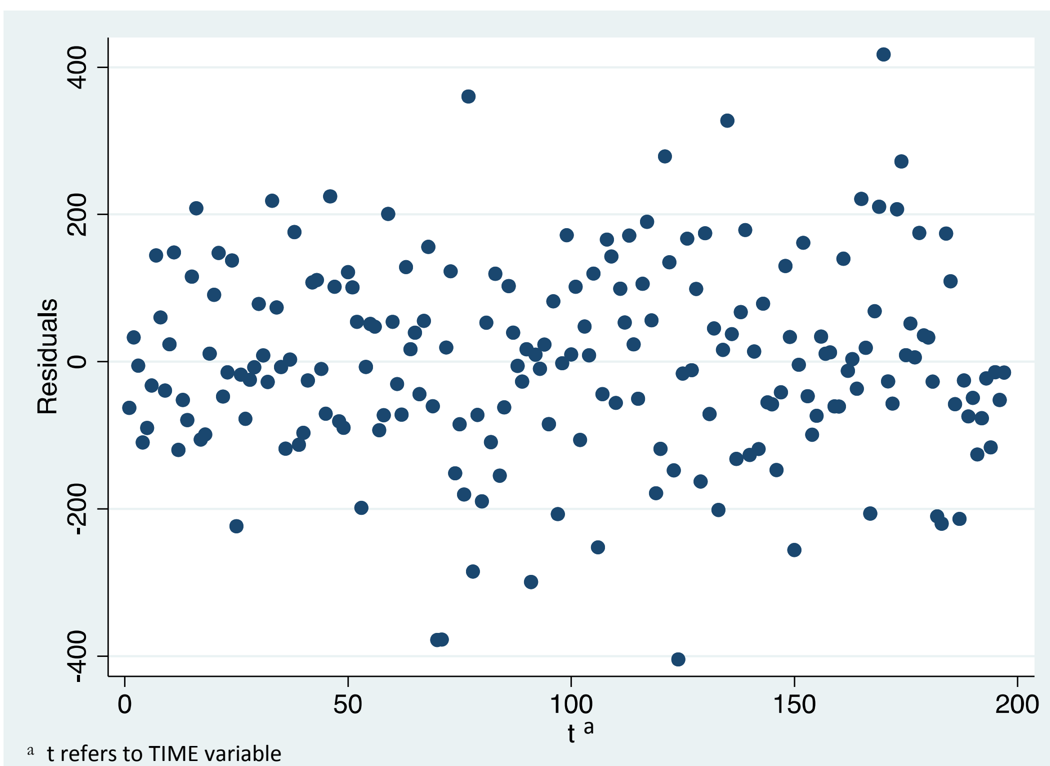
The actual trend may be non-linear in nature, so models are also estimated including a quadratic trend term to allow the change in number of visitors each time period to rise or fall over time. This leads to (4), shown below.

$$N_t = \alpha_0 + \alpha_1\,(COVIDlong_t) + \alpha_2\,(COVIDshort_t) + \alpha_3\,(TIME_t) + \alpha_4(TIME_t)^2 + \varepsilon_t \tag{4}$$

If both α_3 and α_4 are statistically significant, this suggests a non-linear trend. However, due to multicollinearity the individual t-tests may not be valid, so the adjusted R-square measure of model performance is used to determine the preferred specification.

The model in (4) is first estimated using Ordinary Least Squares (OLS), which assumes a constant variance: $\varepsilon_t \sim$iid N(0,σ^2). However, given this study uses time-series data, a nonconstant variance and autocorrelation in the error terms is a possibility. Figure 1 in a previous chapter showed a plot of visits over time and how visits between weeks displayed a negative correlation, where an unusually high number of visits one week tends to be followed by an unusually low number of visits the following week. This suggests that there may be autocorrelation in the error terms. A Durbin-Watson test is used to detect autocorrelation. A result of 1.892382 confirms that autocorrelation is not present, and the assumption of serial independence holds.

Figure 4: Residuals Plot over Time



One of the assumptions made in (4) is homoscedasticity of errors, meaning the variance of our error terms is constant across all observations. However, a plot of residuals over time shows what appears to be a pattern in the residuals in that the variance increases over time, meaning the model may be heteroskedastic. Heteroskedasticity is a systemic change in the spread of residuals over the range of observed values. As seen in Figure 4, it appears that as time goes on there is a larger variance in number of people served, meaning the errors in our model are increasing in magnitude as time t increases. Figure 4 suggests the error variance may be larger for larger values of the trend variable and perhaps for positive values of *covidshort* as well.

To test for heteroskedasticity, the squared residuals from (4) are regressed against *TIME*, *COVIDlong*, and *COVIDshort*. Results find the coefficients for *TIME* and *COVIDlong* variables are statistically significant, so heteroskedasticity is assumed and corrected for as follows. Because heteroskedasticity is present, the OLS estimators are still unbiased and consistent but no longer efficient, in that better estimates of the coefficients' standard errors are possible.

Ordinary Least Squares (OLS) minimizes the sum of squared errors, where each ε_t is weighted equally. In order to correct for heteroskedasticity, a weighted regression is used instead, in which each data point is assigned a weight based on the variance of the error at each observation. Specifically, the estimation technique gives small weights to observations associated with higher variances. Then the model minimizes the sum of weighted squared errors, presumably resulting in homoskedastic errors.

Consider how the estimate of the coefficients (4) is obtained. First, its coefficients are estimated using OLS. In step 2, an OLS regression of the squared residuals are regressed against the trend and two covid variables In Step 3, the models are estimated using weighted least squares as follows, using the predicted squared residuals as the inverse weight (Greene, 1997).

While (4) is considered the best functional form for achieving this paper's objective (hereafter referred to as (A)), different combinations of the explanatory variables are also estimated to test the robustness of the coefficient estimates. Specifically, the following combinations are estimated using WLS:

(B) $N_t = \alpha_0 + \alpha_1 \, (COVID1_t) + \alpha_2 \, (COVID2_t) + \alpha_3 \, (TIME_t) + \alpha_4 (TIME_t) + \varepsilon_t$

(C) $N_t = \alpha_0 + \alpha_1 \, (COVID1_t) + \alpha_3 \, (TIME_t) + \varepsilon_t$

(D) $N_t = \alpha_0 + \alpha_1 \, (COVID1_t) + \alpha_3 \, (TIME_t) + \alpha_4 (TIME_t)^{\,2} + \varepsilon_t$

(E) $N_t = \alpha_0 + \alpha_2 \, (COVID2_t) + \alpha_3 \, (TIME_t) + \varepsilon_t$

(F) $N_t = \alpha_0 + \alpha_2 \, (COVID2_t) + \alpha_3 \, (TIME_t) + \alpha_4 (TIME_t)^{\,2} + \varepsilon_t$

CHAPTER V

RESULTS

The previous section outlined a regression model for testing the impact of the COVID-19 pandemic on the number of people seeking food assistance at Our Daily Bread. This model, repeated in (5) below, states that the number of people assisted in week *t*, denoted N_t, is a function of a quadratic time trend variable, one indicator variable for when businesses where shutdown in Payne County (3/23 – 5 /15) and another indicator variable for time after the pandemic began on 3/23.

$$(5)\ N_t = \alpha_0 + \alpha_1\ (COVIDlong_t) + \alpha_2\ (COVIDshort_t) + \alpha_3\ (TIME_t) + \alpha_4(TIME_t)^{\ 2} + \varepsilon_t$$

As mentioned in the previous section, when (5) is estimated using OLS a Durbin-Watson test suggests autocorrelation is not present. The Durbin-Watson test statistic is 1.916, and given that Field (2009) indicates this is a normal level, the null hypothesis no autocorrelation is not rejected. Thus, no corrections for autocorrelation are made.

Next, the residuals in the OLS estimates of (5) are tested for heteroskedasticity using Breusch-Pagan and Cook-Weisberg test, using the estat hettest command on Stata. This method tests against the null hypothesis that error variance is homoscedastic against the alternative that heteroskedasticity exists. The test-statistic and p-value of the test is 7.12 and 0.0076, respectively. With such a low p-value the null hypothesis of homoskedasticity is rejected and the weighted least squares routine described in the previous section is used to correct for it, using the STATA command hetregress. The estimates of (5) using OLS and weighted least squares is as follows.

Table 5: Results of Ordinary Least Squares and Weighted Least Squares Model (N = 197)

Variable	Parameter	Ordinary Least Squares Estimates (p-value)	Weighted Least Squares Estimates (p-value)[a]
Intercept	α_0	319.191	322.669
		(0.000)	(0.000)
COVIDlong	α_1	-65.881	-63.859
		(0.211)	(0.235)
COVIDshort	α_2	-20.700	-20.529
		(0.716)	(0.672)
TIME	α_3	2.375	2.282
		(0.002)	(0.001)
$TIME^2$	α_4	-0.007	-0.006
		(0.165)	(0.165)

[a] The variable equation was estimated as $(\varepsilon_t)^2$= 9.113 + (.009)(*TIME*) – (0.925)(*COVIDlong*) (0.089)(*COVIDshort*), with p-values for each coefficient of 0.00, 0.01, 0.02, and 0.87, respectively.

The estimates above find virtually identical estimates using OLS or weighted least squares. The coefficient α_3 is positive and statistically significant, but the α_4 is not significant. This might suggest that the upward trend in the number of visits indicated in a previous figure is linear in nature, but then, due to multicollinearity between the *TIME* and *TIME*^{2} the standard errors might not be reliable. This will be revisited shortly.

Both coefficients α_1 and α_2 have p-values greater than 0.05 and are thus deemed statistically insignificant. This suggests that the average number of visits to Our Daily Bread during the pandemic is statistically indistinguishable from immediately prior to the pandemic. As such, Table 5 above suggests the pandemic did not cause an increase in food assistance requests at the food pantry.

Next, to better articulate the statistical relationship between time, the pandemic, and number of visits, the model in (5) is estimated using different combinations of explanatory variables. This can help determine the robustness of the results, an important question since all of the explanatory variables are correlated.

Table 6: Results of Weighted Least Squares Models (N = 197)

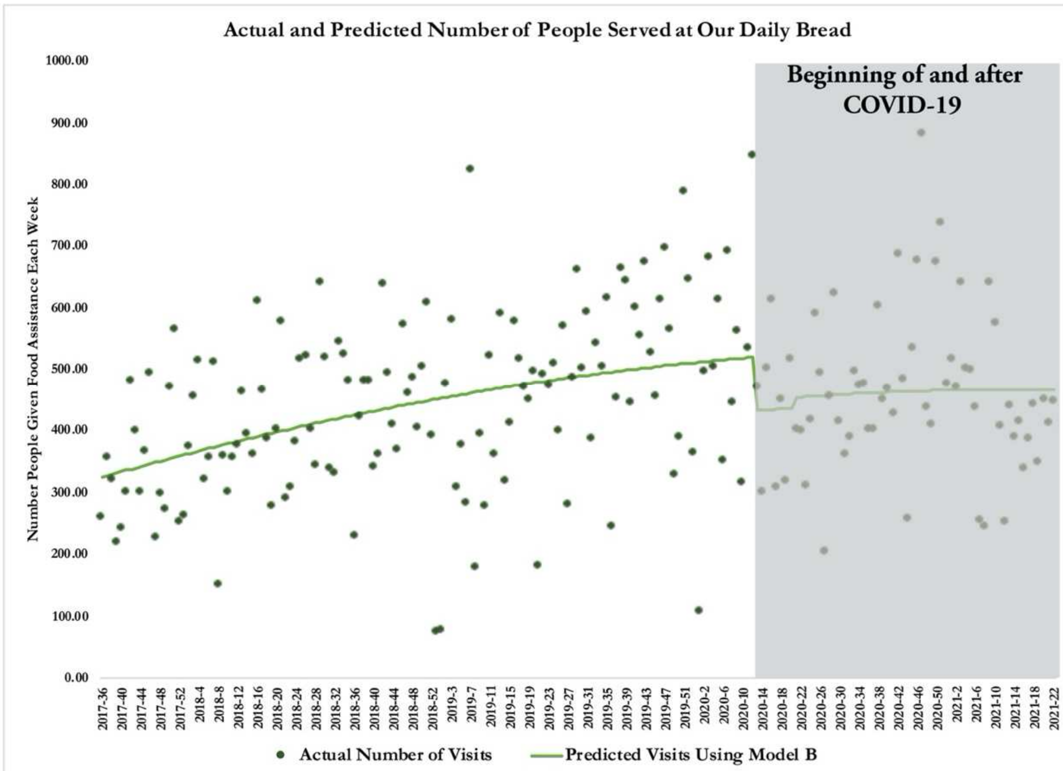
Variable	Parameter	Model A	Model B	Model C	Model D	Model E	Model F
AIC[a]		2489.01	2489.11	2487.09	2487.29	2496.32	2488.52
Intercept	α_0	342.2821 (0.000)	322.6693 (0.000)	343.0172 (0.000)	324.3917 (0.000)	375.6441 (0.000)	314.9806 (0.000)
covidlong	α_1	-117.4022 (0.002)	-63.85844 (0.235)	-113.923 (0.001)	-75.81763 (0.093)	-----	-----
covidshort	α_2	11.7881 (0.782)	-20.52922 (0.672)	-----	-----	-43.6551 (0.279)	-56.83083 (0.158)
Trend	α_3	1.417106 (0.000)	2.281512 (0.001)	1.403312 (0.000)	2.180208 (0.001)	.7332607 (0.000)	2.740645 (0.000)
$Trend^2$	α_4	-----	-.0062799 (0.165)	-----	-.0054131 (0.175)	-----	-.0105936 (0.001)

[a] AIC = Akaike Information Criterion, a model selection criterion where a lower value indicates a beter model. Calculated as AIC = 2K – 2ln(L) where K = number of estimated coefficients and L is the likelihood function of the model.

The estimate of (5) is given by Model B, above. First considers what happens to Model B when the squared trend variable is removed, resulting in a model that assumes a linear trend. The *COVIDlong* variable turns statistically significant and is negative, which would indicate that food assistance requests decreased due to the pandemic. This is quite possible if fear of the virus caused people to avoid visiting the food pantry, even if their food insecurity increased. Model C removes the *COVIDshort* variable in addition to the squared time trend variable, also finding that *COVIDlong* is negative and statistically significant.

In no model is the *COVIDshort* variable statistically significant, which suggests that no matter the model specification, the two months of shutdowns did not result in an increase in food assistance requests. Notice also that the only model where the squared trend variable is statistically significant is when the *COVIDlong* variable is excluded. What this suggests is that there was a likely a decrease in food assistance requests after June of 2020, and this decrease can be captured in either *COVIDlong* and/or $TIME^2$.

Figure 5:



Consider Figure 5 above, showing the actual number of visits to Our Daily Bread as well as the predicted number using Model B. Until 2020 there is a general increase in the number of people seeking food assistance, and the increase falls with each subsequent week. If the Model B is used to predict when the number of visits would peak in the absence of the pandemic we would first take the derivative of (5) with respect to *TIME*, insert the coefficient estimates, and then solve for the value of TIME where the derivative equals zero.

(6) $\frac{\partial N_t}{\partial TIME} = \alpha_3 + 2\alpha_4(TIME_t) = 2.282 - 2(0.006)(TIME_t)$

The value of (6) equals zero when *TIME* is 2.282/(2*0.006) = 190. This suggests that, based on the trend in visits prior to 2020, the number of visits would peak at week 190, which would be the fifteenth week of 2021. After that the equations suggests a reduction in food assistance requests, but there are only seven weeks of data after week 190. Note that this reduction in visits could be captured by both a quadratic time trend variable or a linear time trend variable and the *COVIDlong* variable. This multicollinearity suggests it is difficult to disentangle the effects of a quadratic time trend effect and the effects of the pandemic.

Notice also that the pandemic began when *TIME = 136*. The value of (6) at this level is 0.65, meaning at this time the increase in number of visits is less than one person. So between the advent of COVID and the end of the data the weekly increase in visits according to (6) is small. On top of this, the coefficients for the COVID variable suggest either no change or a decrease in the number of visits. Consequently, the data strongly testify that the pandemic did not increase the number of people seeking food assistance at Our Daily bread.

The AIC in Table 6 can be used to help discern which models fit the data best. A lower AIC indicates greater predictive performance, and the lowest AIC is found in Model C, which uses only a linear time trend and the *COVIDlong* variable. Relying on the AIC measure alone for model selection, this would conclude the pandemic did cause a decrease in the number of people seeking food assistance, relative to what would be expected given previous trends before the pandemic. However, there is not sufficient justification to conclude Model C is the best model, so this conclusion is not claimed.

Consider now the magnitude of the effects of *COVIDlong*. Estimates predict somewhere between 65 and 114 less people sought food assistance after the pandemic. Compared to the average number of visits of 446 in the data, this is a large effect—if the effect is real.

The overall lessons from the model estimates are as follows. It is unclear whether the growth in number of visits occurring in the first years of ODB is due to long term effects of COVID or the natural decrease due to a nonlinear timetrend. So, it is unclear if the decreasing growth in number of people is due to *covidlong* or just a natural slowing of the timetrend shown by the squared time variable. However, there is no indication that the number of people went up due to either of the two COVID-19 effects analyzed here.

CHAPTER VI

CONCLUSION

This study investigates how the COVID-19 pandemic affected the number of people served at Our Daily Bread food pantry. This question is posed as a way of inferring the impact of the pandemic on food insecurity. The question was answered by observing each visit at ODB and the household size of the visitor in order to determine the number of people served each week at ODB since its opening in September 2017. The timeframe used for COVID was determined by local and regional shutdown dates, and the effects were evaluated both *during* the shutdowns and *after* the shutdowns. Then an empirical analysis showed that the growth in number of people served at the food bank slowed during the COVID timeframe, but it is unclear whether that is due to actual changes caused by COVID-19 or due to a natural slowing of growth in visitation at the food pantry. However, there is no indication that number of people seeking food assistance grew during COVID.

The findings of this study are useful in understanding how the COVID-19 pandemic affected overall food insecurity. While some studies concluded that food insecurity increased due to the economic insecurity caused by COVID-19, other studies concluded otherwise. Food insecurity is addressed in part by charitable organizations such as Our Daily Bread. It is possible that food insecurity did not change due to an increase in service from charitable efforts, keeping families our of food insecurity during the pandemic. However, this was not the case at ODB. Either food insecurity did not increase in Payne County due to the pandemic, or fear of the virus prevented people from seeking extra food assistance.

This study simply looks at the change in visits during the COVID-19 timeframe. It does not address how food insecurity actually changed during COVID. There are many reasons a person experiencing food insecurity may not request assistance at ODB, such as other charitable organizations, income assistance, SNAP benefits, or lack of access to the food pantry. It is possible that ODB did not experience an increase in food service requests due to food insecure households seeking assistance elsewhere, such as local churches, SNAP benefits or even the mobile market. Additionally, the income assistance efforts, such as the stimulus checks, may have sufficiently offset the income effects of COVID shutdowns to keep household out of food insecurity. Food insecurity research would benefit from future research which includes government and charitable actions in their analysis in order to better understand how food insecurity was affected during the pandemic.

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