TOO COOL FOR DOORS: DO YOU THINK A GLASS DOOR WOULD PREVENT YOU FROM BUYING FRESH PRODUCE?

by

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LAND ACKNOWLEDGEMENT

We respectfully acknowledge the University of Arizona is on the land and territories of Indigenous peoples. Today, Arizona is home to 22 federally recognized tribes, with Tucson being home to the O’odham and the Yaqui.

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ABSTRACT:

Using data from Information Resources, Inc. (IRI), accessed through NORC (National Opinion Research Center), we utilize weekly sales data for eight supermarket stores in Northern California across the years 2016-2018. Four of these stores received retrofit doors on the produce section in various weeks of February of 2017 while the other four did not. We matched these four pairs of treatment and control stores by demographics such as annual total store sales values, annual total produce sales values, and geographic location. We control for factors such as weather, holidays, and extreme events such as an E. coli outbreak in 2018 and then run three Difference-in-Difference (DiD) models. As a result of installing retrofit doors, we find that produce sales increased by about $5,000 per week for the treatment store #3 and about $2,000 per week for treatment store #4. We also find that there was no statistically significant influence on produce sales after the installation of retrofit doors for treatment stores #1 and #2. Our multivariate econometric approach contributes to the literature by addressing how retrofit doors influence produce sales.

INTRODUCTION:

For many supermarkets in the United States, product displays in the produce section, which contains leafy greens and various other vegetables, are intentionally left exposed and accessible to the shopper. The logic behind the decision to leave the produce displays exposed is that if there were to be protective cases or doors, it would act as a barrier between the shopper and the fresh products, thereby decreasing the likelihood of purchasing these items. The assumption that doors would hinder sales, which is held by many managers and executives of supermarkets, is consequential for several reasons. There are many potential benefits of installing these retrofit doors. For example, the installation of doors in the produce section would help maintain temperature uniformity across all spatial dimensions of the refrigerated display case. Temperature uniformity in refrigeration systems is important because it would minimize the risk of harmful bacteria growing while on display (Brenes, et al., 2020A).

Installing doors in the produce section is not only a public health issue, but it is also an economic one. Another benefit is that enclosing these refrigerators with doors would significantly reduce energy consumption in a perceivably resource-intensive industry. Supermarket refrigeration accounts for about 2-3% of total energy consumption from commercial buildings in the United States (Klemick, et al., 2017). Also, many supermarkets in the United States do not pay industrial electricity rates. Therefore, supermarkets are subject to peak energy rates which further emphasizes the importance of saving energy. Apart from energy savings, the installation of retrofits increases the shelf life of the produce. Doors allow the refrigerators to consistently maintain the FDA's Food Code threshold of 5 °C (de Frias, et al., 2018). Keeping the produce cool minimizes food waste and maximizes the number of days to sell these products. Given these discernable public health and economic benefits, why are retrofit doors not already installed in more supermarkets in the United States?

While there are immediate, tangible benefits that could be obtained by the supermarket industry by simply installing doors, there are justified reservations about the investment. There is a lot of uncertainty clouding the decision to retrofit or install new display cases with doors. Although the supermarket executives and managers who make these financial decisions would save on energy bills, perhaps it is true that installing doors would decrease sales. Given the precariousness of how such decisions would affect sales, it is not difficult to rationalize why the supermarket executives and managers would be wary to invest in doors. Klemick et al. conducted interviews with numerous managers, owners, and supermarket executives to discern what causes the wariness associated with the investment. One common theme that the authors discovered was how concerned the respondents were with the payback period. In an industry with already low profit margins, it is imperative that supermarket executives have a firm idea of when they will receive a return on investment (ROI) (Klemick, et al., 2017). To complicate the issue, there are multiple components that contribute to a refrigeration system such as, display cases, compressor racks, and walk-in refrigerators and freezers (2017). According to the subjects from Klemick's survey, another concern is that stores experience significant renovations every 5-10 years further impeding a definitive ROI timeline for any given project (2017). Klemick et. al state that 63% of the participants in their survey claimed that at least some of their display cases are replaced during a store renovation (2017). Perhaps the uncertainty of how a store remodel will alter the display cases is yet another barrier to the installation. Without a transparent answer to how doors on the produce section affect sales, it is not surprising why managers and representatives do not rush to conduct the experiment with their own capital.

Retrofit doors have been found to alter shopper behavior according to a qualitative study by Lindberg et. al. who explains that shoppers value the ability to see, smell, and touch the items being purchased. Based on the research group studied in the experiment, they find that doors inhibit shoppers' ability to touch and smell the product. In fact, when produce goes bad and creates an unpleasant odor, doors can even concentrate this smell which is realized once the door is opened (Lindberg et al., 2018). The authors of the paper reason, however, that the effects of doors are not all negative. For example, for doors that were clean on brightly illuminated displays, shoppers may perceive freshness and cleanliness (2018). Supermarkets are installing LED lights to enhance the presentability of the produce which has a multitude of benefits for product appearance, energy efficiency, and decreased spoilage (Klemick, et al., 2017). Also, some shoppers enjoyed the warmer store temperatures, as the refrigerated air was contained behind the doors. The exact effect of how a shopper interacts with produce is circumstantial and depends upon a myriad of different variables. Perhaps the inherent complexity of the effect of doors is what complicates the issue and why there has yet to be a robust cost-benefit analysis in the literature.

Despite the uncertainty of the profitability of such financial decisions, we are going to narrow the scope of this research to one particular question: If doors are installed in the produce section, what effect does this have on produce sales? As alluded to in the preceding paragraphs, the answer to this question has significant implications for how supermarket managers and owners perceive the investment decision. While there is apprehension about the profitability of doors, the positive impacts that they can provide for the fight against climate change and public health issues are well established in the academic literature. Using data from 2016-2018, we will compare four stores where doors were retrofitted in the produce section with four stores without doors. Using a difference-in-difference (DiD) regression model, we will estimate the impact on sales quantitatively. To the best of our knowledge, a quantitative analysis of the impacts of doors has not been addressed in the literature.

LITERATURE REVIEW:

As mentioned in the introduction, many studies have analyzed the issue of implementing doors through an engineering or public health perspective. Klemick et al. is the only study in the literature that addresses the issue using economic concepts such as incentives, uncertainty, and opportunity costs. But, without substantial data, the authors of this paper were unable to perform a quantitative analysis. Apart from the economics intrinsically engrained in a potential answer, there are numerous studies that delve into how doors efficiently encapsulate the cool air, which significantly reduces energy costs. Likewise, the importance of maintaining this coolness is emphasized throughout various articles pointing to the many deadly pathogens that can proliferate when the refrigerate temperature exceeds the 5-degree Celsius threshold established by the U.S Food and Drug Administration (FDA). When produce cannot be kept properly cooled, there are serious public health repercussions. The literature review chapter will first summarize the papers that focus on the engineering and energy savings. Then, we will review the papers that focus on the public health implications. Lastly, we will address the papers that pertain the most to our research question, thereby acknowledging the gap we would like to fill.

Engineering Studies

Temperature profiles are better able to be kept at regulation standard and fluctuate less when retrofit doors are utilized. Brenes et. al (2020) conducted an experiment measuring temperatures in various sections of refrigerators for both open and closed display cases. The data from the study was collected over a 9-month period, and they found that doors improve ambient conditions, reduced case temperatures, increased relative humidity, and reduced the variation of temperatures throughout the different parts of the display cases. The finding by Brenes et al. is corroborated by de Frias et. al (2020) who conclude doors are effective at maintaining temperature uniformity even when the cases are opened with relatively high frequency.

It makes sense intuitively that if doors have a causal relationship with keeping the produce cool, then there must be some impact on energy consumption. De Frias et. al (2020) calculated that energy consumption was 66% lower than open-retail display cases when holding the model, mark, size, operating schedule, and thermostat setting constant. Relative to a display case without any doors, energy savings were 45% when 3 out of the 6 doors were opened for the duration of the experiment, 66% when 3 doors were opened every 10 minutes for 12 seconds, and 68% when the doors remained closed. A similar study calculated the energy savings that doors provide from an experiment in New Zealand. Doors were retrofitted on 10 refrigerated cases in total that were in service from June 2013 - October 2013 (Robertson and Plugge, 2015).

During the five-month span, the authors find that energy savings were 42% relative to the period observed before the installation of the doors.

Public-Health Studies

There are significant public health costs associated with leafy green vegetables in the United States. Leafy greens have a propensity to host pathogens such as norovirus*, E. coli, Salmonella,* and *Listeria monocytogenes* that can cause severe health problems. From 1973 to 2012, there were 606 leafy vegetable-associated outbreaks, with 20,003 associated illnesses, 1,030 hospitalizations, and 19 deaths in the United States (Herman et al., 2015). With more recent data associated with leafy green illnesses, Marshall et al. (2020) find that Shiga toxin-producing *Escherichia coli* alone accounted for 40 outbreaks, 1,212 illnesses, 77 cases of hemolytic uremic syndrome, and 8 deaths in the United States and Canada from the years 2009-2018. One particular reason why there is a risk for outbreaks associated with leafy greens is because there is no action that can effectively kill all harmful pathogens that can develop on the surface of the leaves of leafy greens (Herman et al., 2015). Also, many leafy greens in the United States are consumed raw which adds an additional layer of risk for a potential outbreak (Turner et al., 2019). Therefore, given the associated risks of consuming leafy green vegetables, Herman et. al argue that local, state, and federal agencies should invest more to reduce the likelihood of an outbreak. They believe that more precautionary measures should be implemented to safely handle leafy greens from the farm all the way to consumption at home (Herman et al., 2015).

Installing doors on the produce section in supermarkets certainly could be a precautionary measure to combat harmful pathogens. While keeping produce cool behind doors would not kill the harmful pathogens of concern, it could prevent them from multiplying. Maintaining product coolness thereby could minimize the public-health costs associated with outbreaks and lower their risk significantly. De Frias et. al inoculated bacteria and monitored the growth of *E. coli, S. enterica,* and *L. monocytogenes* on several produce items such as packaged baby spinach, chopped romaine, and lettuce mix. They found that after 3 days behind a display case there was no significant bacterial growth relative to the date of inoculation (de Frias, et al., 2018). The observed lack of proliferation was true for the baby spinach and mixed leaf salads while there was minimal bacterial growth on the chopped romaine lettuce. According to the literature we have reviewed, it is apparent that retrofit doors have the potential to significantly reduce energy consumption and mitigate the public health risks associated with leafy greens.

There have only been a handful of studies that considered consumer behavior as a result of installing doors. One such study is Lindberg et. al (2018). But the results are a qualitative study that draws conclusions from observations and focus group interviews. The only study that uses data to draw a conclusion about the quantitative effects of doors is a study Fricke and Becker (2010). They compare sales data before and after doors had been installed on refrigerated displays of alcoholic beverages, yogurt, prepackaged cheese, butter, and sour cream (Fricke and Becker, 2010). Fricke and Becker find that the store that installed the doors resulted in a 27% increase in weekly mean quantity of beer sold and a 2% decrease in weekly mean quantity sold for dairy products (2010). Fricke and Becker use sales data to reach this conclusion using descriptive statistics, but their study does not control for other variables that might influence sales. Also, their sample size is small- weekly sales data was used from January 4th, 2009 – June 6th, 2009, with the installation of doors on April 21st, 2009. Another limitation of this study is that only two stores were included in the analysis. Our paper will contribute to the literature with its econometric analysis and our multivariate approach. In the proceeding chapters, we will explain how our data were obtained, how we assembled the data and utilized to draw causal inferences with a DiD model.

DATA:

In this paper, we use data from Information Resources, Inc. (IRI), accessed through NORC (National Opinion Research Center), which is a research institution affiliated with the University of Chicago. The U.S. Department of Agriculture, Economic Research Service facilitates access to IRI's proprietary data through approved third-party agreements. We assembled weekly sales data from the years 2016-2018 for eight supermarket stores in Northern California which we are prohibited from identifying due to a data confidentiality agreement. As part of our data generating process, we then utilized this weekly sales data that included the eight stores of interest. Since there are 52 weeks in a year, across the three-year period, each store has 156 observations. Multiplying this number by the eight stores in the study results in 1,248 observations in the total sample. Of the eight stores in the sample, four of these stores received retrofit doors in the produce section while the other four did not. From these datasets that included total weekly store sales, we segmented these data into a subset consisting of produce sales which we were able to identify by Universal Product Codes (UPC). UPCs in our sample of weekly produce sales was identified by items purchased in the produce or vegetable aisles. These criteria were chosen as the best way of categorizing the items that could be purchased behind the newly installed retrofit doors.

After establishing our four pairs of treatment-control stores, we estimated a difference-in-difference (DiD) model. The data in our sample are from a natural experiment. We do not know with certainty why the four stores in the sample received retrofit doors and the other four did not.

Considering the types of available data, we attempted to match pairs of stores that resembled each other. Our method was to match each pair of stores by three important characteristics: annual total store sales values, annual total produce sales values, and geographic location. Tables 1 and 2 below contain each treatment-control pair of stores and their respective weekly mean produce sales and weekly mean total store sales for the years 2016, 2017, and 2018. As can be seen, both the weekly mean total store and produce sales are similar in magnitude across pairs of stores. We decided that proceeding with these pairs was the best approach in lieu of randomization. To further illustrate the relationship between each treatment-control pair and their produce sales over time, we display the following graph below in Figure 1 for each pair. In Figure 1, the y-axis consists of the average weekly produce sales and the x-axis is the time period which ranges from the beginning of January 2016 to the end of December 2018. The blue and red lines represent the treatment and control stores' produce sales respectively. The vertical green line during the first week of February 2017 signifies when retrofit doors were installed in the treatment store. The horizontal, straight blue line is simply a trend line capturing how the treatment and control store weekly produce sales change from 2016 to 2018. These graphs containing the weekly produce sales over time were also conducted for pairs 2, 3, and 4 which can be found in the appendix. In most cases, produce sales tend to move in parallel for each pair of stores, indicating their week-to-week produce sales should be suitable for analysis with a difference-in-difference approach.

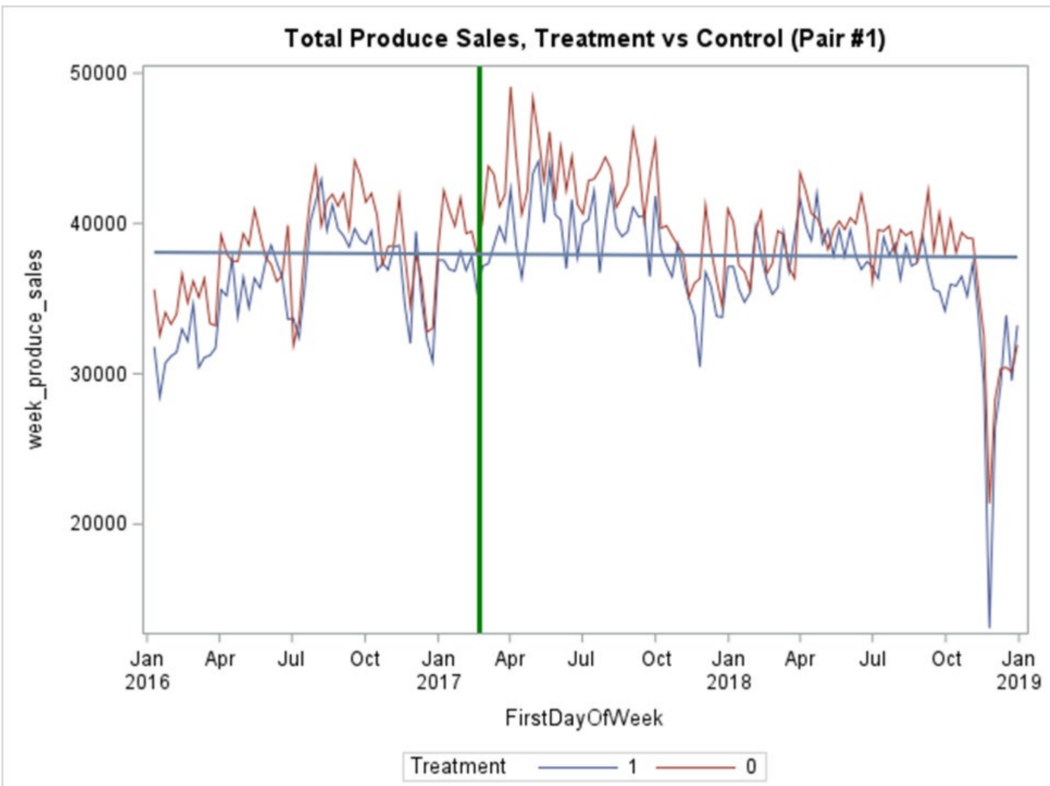
Table 1. Weekly mean produce sales values (nominal US $):

	Pair 1		Pair 2		Pair 3		Pair 4	
Time	Treatment	Control	Treatment	Control	Treatment	Control	Treatment	Control
2016	35,683	37,802	47,683	41,522	54,409	58,295	47,168	57,165
2017	38,451	41,526	54,040	46,298	61,834	63,479	52,930	63,471
2018	36,165	37,801	49,601	42,535	57,941	53,933	50,791	57,055

Table 2. Weekly mean total store sales values (nominal US $):

	Pair 1		Pair 2		Pair 3		Pair 4	
Time	Treatment	Control	Treatment	Control	Treatment	Control	Treatment	Control
2016	234,210	228,267	325,624	266,873	331,432	358,174	289,757	328,778
2017	236,441	228,279	336,679	271,981	358,262	361,047	307,716	338,107
2018	230,511	214,188	324,872	257,007	349,490	326,343	313,307	311,766

Figure 1. Produce weekly sales for store pair #1



Also, each pair of stores is in close proximity, and all eight stores are part of the same anonymized supermarket chain. The aerial distance in miles between each treatment-control pair can be seen in Table 3 below. These distances were calculated in Google Maps using the "measure distance" function. Given the relatively short distances between each pair, we figured that each pair would share similar climatic variations, which could have an effect on both total store sales and total produce sales. We gathered daily weather data from the National Oceanic and Atmospheric Administration (NOAA) from the three nearest weather stations to each store.

The NOAA provides daily minimum and maximum temperatures in degrees Fahrenheit. If there was a missing observation for a given day, we simply substituted the missing value from a nearby weather station. To compensate for fluctuations in daily weather temperature, we calculated daily midpoint temperatures using the minimum and maximum values provided. Daily midpoint temperatures were averaged into weekly observations corresponding to the exact dates of the weekly sales data. The oscillations in weekly midpoint temperatures for treatment-control pair #1 can be seen in Figure 2. These graphs containing weekly midpoint temperatures over time were also conducted for pairs 2, 3, and 4 which can be found in the appendix. Also, Table 4 delineates this relationship as the mean midpoint temperatures are displayed for the years 2016, 2017 and 2018 for each store in the sample.

Table 3. Aerial distance between pairs of stores (miles)

	Pair #1	Pair #2	Pair #3	Pair #4
Distances	5.4	21.1	17	12.6

Figure 2. Weekly midpoint temperature (Degrees Fahrenheit) for store pair #1

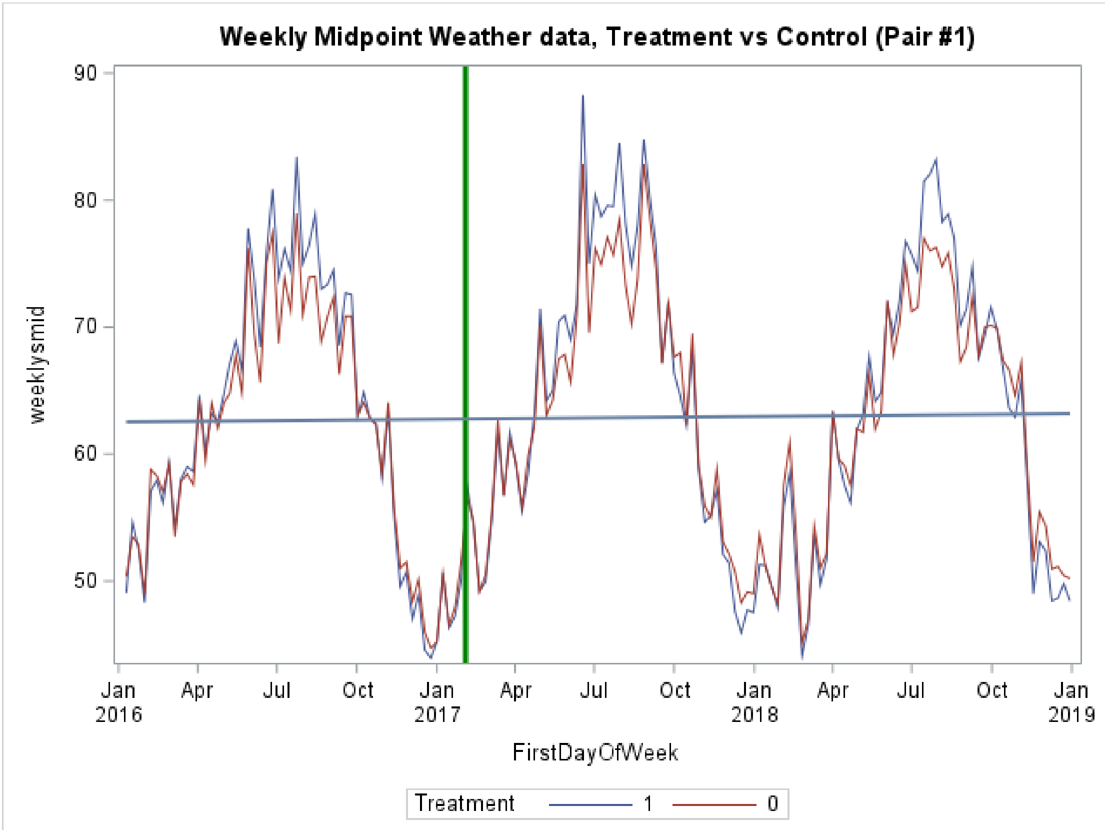


Table 4. Weekly mean midpoint temperatures (Degrees Fahrenheit)

	Pair 1		Pair 2		Pair 3		Pair 4	
Time	Treatment	Control	Treatment	Control	Treatment	Control	Treatment	Control
2016	63.7	62.7	59.2	61	58.1	62.7	58.4	60.4
2017	63.4	62.7	59.5	61.1	58.3	62.3	58.4	60.7
2018	62.5	62.2	59.1	60.9	57.6	61.7	57.5	60.3

Before delving into our DiD model, we report mean produce sales before and after retrofits across treatment and control stores. For each treatment-control pair, we calculated the weekly mean produce sales and weekly mean total store sales before and after the retrofit doors were installed. The installation of retrofit doors occurred in various weeks of February 2017 for each of the treatment stores. For example, Treatment store #1 received the retrofit on February 3rd, 2017, Treatment store #2 on February 22nd, 2017, Treatment store #3 on February 10th, 2017, and Treatment store # 4 on February 13th, 2017. Therefore, considering our sample from 2016 to 2018, there were significantly more observations after the installation than before, which perhaps would not accurately reflect the treatment effect. To control for any potential seasonality that may occur in a calendar year, we only included weekly mean sales 52 weeks before the installation, and weekly mean sales 52 weeks after the installation. To clarify, to calculate the standardized difference for treatment store #1, we only considered weekly mean sales 52 weeks before February 3rd, 2017, and 52 weeks after February 3rd, 2017. We applied this logic for each treatment store, considering the installation date of retrofit doors.

To measure whether average sales from before and after retrofits were statistically different, we used standardized differences (Austin, 2009). This method differs from t-tests for example because it does not consider the size of the sample or test for differences in variances. In Table 5, the weekly mean produce sales are displayed both before and after doors are installed across all four treatment stores in the sample. Austin uses a 0.2 threshold guideline for determining a statistically quantifiable difference. But, it is worth noting that there are varying levels of significance. For example, according to Cohen's Effect Size Index, 0.2, 0.5, and 0.8 can be used to indicate various magnitudes of effect between the treated and untreated groups (2009). For our purposes, we will proceed using a 0.2 threshold. For any value less than 0.2, we conclude there was not a statistically quantifiable difference between the two groups. However, Table 5 shows that the absolute standardized difference value is larger than 0.2 for each treatment store that installed retrofit doors. Therefore, it appears that there is a significant difference in weekly mean produce sales for the two-year period examined.

It is worth noting that weekly mean produce sales increased after the installation for each treatment store. Although there is an increase in sales after the installation of doors, the values were not adjusted for inflation. Therefore, the increase in weekly mean produce sales displayed in Table 5 and weekly mean total store sales in Table 6 is likely more pronounced than if the figures were adjusted for inflation. Using Consumer Price Index (CPI) data, we calculated that inflation from January 2016 to December 2018 was about 6%. Although inflation was relatively mild during our sample from 2016-2018, it is important to keep this in mind as we present our results from our descriptive statistics and from the DiD models in the subsequent chapters.

Table 5. Standardized differences using weekly mean produce sales (nominal US $)

	Weekly Mean Sales Before Installation	Weekly Mean Sales After Installation	ABS Std Diff
Treatment#1	36,349	38,399	0.698
Treatment#2	49,071	53,914	1.325
Treatment#3	55,132	62,088	1.923
Treatment#4	48,277	52,928	1.350

Furthermore, we calculated the standardized difference values for weekly mean of total store sales in Table 6. Treatment store #1 is the only store that has an absolute standardized difference value below the 0.2 threshold. So, these findings suggest that weekly mean total store sales did not significantly change after the retrofit doors were installed for Treatment store # 1. However, the weekly mean total store sales for Treatment stores #2, 3, and 4 were statistically different after the installation of the retrofit doors. Also, similarly to Table 5, the weekly mean total store sales all increased after the installation of doors.

Table 6. Standardized differences using weekly mean total store sales (nominal US $)

	Weekly Mean Sales Before Installation	Weekly Mean Sales After Installation	ABS Std Diff
Treatment#1	235,001	235,137	0.008
Treatment#2	327,332	334,859	0.338
Treatment#3	334,563	358,710	1.003
Treatment#4	292,234	307,725	0.716

From Tables 5 and 6, it appears that sales increase after the installation which is akin to the results presented by Fricke and Becker (2010). But, simply comparing weekly mean sales before and after the retrofit doors were installed can be misleading for several reasons. The results displayed in tables 5 and 6 do not account for the many factors that could potentially influence sales between the two different periods of interest. As we examine the results from our models in the proceeding chapter, we will take a deeper look and attempt to establish any sort of causal relationship between the installation of retrofit doors and sales. Our contribution to the literature will be estimation of multivariate econometric models that not only compare the differences between treatment and control over time, but also controls for seasonality and other yearly events that could induce a spike or drop in sales.

EMPIRICAL MODEL:

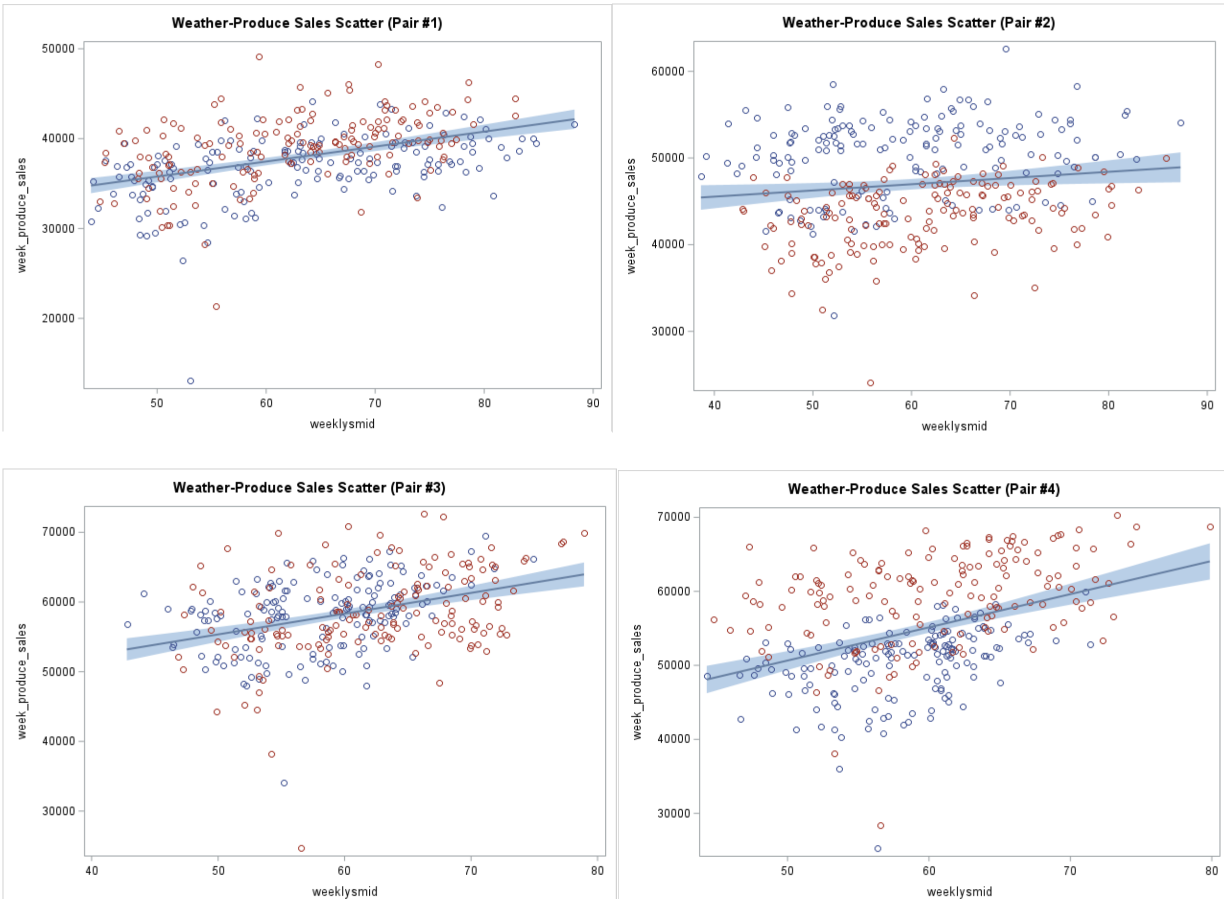
Given the nature of our data, we determined that a DiD was the most appropriate model to use in order to explain the causal relationship between produce sales and the installation of retrofit doors. While we used several variations of a DiD model, the essential components can be found in the equation below. Our dependent variable in this model is weekly produce sales which is an aggregation of weekly sales purchased in the aisles, “produce” or “vegetable”.

$$Y_{it} = \beta_0 + \beta_1 d\_after + \beta_2 d\_treatment_{it} + \beta_3 d\_interaction_{it} + \beta_4 weeklysmid_{it} + \beta_5 x_{5it} + \cdots + \beta_n x_{nit}$$

The i subscripts indicate observations by store pair and the t subscripts indicate the time series component, which in this model is weekly. d_after is a dummy variable for the period after the doors were installed, $d\_treatment$ is a dummy for the treatment store, $d\_interaction$ is the interaction term between the after dummy and treatment dummy, $weeklysmid$ is the weekly average of daily midpoint temperatures, x_5- x_n are dummy variables for holidays in the United States such as the Super Bowl, Easter, Memorial Day, July 4th, Labor Day, Thanksgiving, and Christmas. Before explaining the several variations of our DiD models, we are going to justify the importance of our explanatory variables and why they may aid in explaining variation in the data and therefore the credibility of our results.

Apart from the essential DiD components such as a dummy variable for the treatment store, a dummy for when the retrofit door was installed, and an interaction term between the two dummies, we included numerous independent variables, for example, average daily midpoint temperature in each given week denoted "weeklysmid". We believed that our weeklysmid variable not only serves as a proxy for seasonality, but also it could possess some explanatory power on how sales may fluctuate, especially for produce sales. For example, we posited that as temperatures increase, people may be more inclined to purchase leafy greens and other assortments of salads. In Figure 3, we graphed a binary relationship between weekly produce sales on the y-axis and weeklysmid temperatures on the x-axis for each pair of treatment and control stores. The blue dots are observations for the treatment store and the red dots are observations for the control store. Based upon the regression lines in each graph, it appears that weekly midpoint temperatures and weekly produce sales are positively correlated for each pair of stores in our sample.

<u>Figure 3. Relationship between weekly produce sales and weekly midpoint temperatures across store pairs</u>



Note: Vertical and horizontal scales are not uniform across graphs. Blue line is the simple regression line, and the shaded blue area is a 95% confidence interval about the regression line. Some observations between each treatment and control are separate. The separation is due to the difference in magnitude of produce sales.

Throughout the year, supermarket sales may fluctuate for many reasons. To capture some of this fluctuation, we decided to add dummy variables for holidays in the United States that would conceivably influence a jolt in sales. The seven holidays we identified were the National Football League's Super Bowl, Easter, Memorial Day, July 4th, Labor Day, Thanksgiving, and Christmas. So, for our seven holidays across the three-year sample, we have a total of 21 holidays in our data set.

We averaged total store sales for the 21 observations where a holiday occurred and compared it to the average of total store sales for the 135 observations where a holiday did not occur for each treatment and control store. We compared the mean weekly produce sales average for each treatment and control stores which can be found in Table 7. According to the percent difference column, only Treatment store #2 had an increase in mean weekly produce sales on holidays. The other seven stores in the sample experienced a decrease in produce sales on holidays. However, for mean weekly total store sales, weeks including a holiday were significantly larger than weeks where a holiday did not occur. In Table 8, the percent difference column indicates that the percentage spike was about 7-11% across all stores in the sample. The results displayed in Tables 7 and 8 foreshadow some regression results that we will discuss later on.

Table 7. Mean weekly produce sales for holidays vs. non-holiday across three-year sample (nominal US $)

	Mean weekly produce sales when holiday occurred	Mean weekly produce sales for when holiday did not occur	Percent difference
T #1	35,346	37,008	-4.59%
C #1	37,472	39,315	-4.80%
T #2	50,643	50,457	0.37%
C #2	41,973	43,717	-4.07%
T #3	56,817	58,310	-2.59%
C #3	55,502	59,084	-6.25%
T #4	49,602	50,447	-1.69%
C #4	57,537	59,540	-3.42%

Table 8. Mean weekly store sales for holidays vs. non-holiday across three-year sample (nominal US $)

	Mean weekly sales when holiday occurred	Mean weekly sales for when holiday did not occur	Percent difference
T #1	257,058	230,107	11.1 %
C #1	245,132	220,225	10.7 %
T #2	357,790	324,671	9.7 %
C #2	282,988	262,571	7.5 %
T #3	370,534	342,838	7.8 %
C #3	372,770	344,771	7.8 %
T #4	331,580	299,373	10.2 %
C #4	358,088	321,328	10.8 %

Not all drastic fluctuations in weekly sales were positive in the sample. Recalling Figure 1 which displays weekly produce sales for the three-year study period, we can see a steep decline in sales at the end of 2018. Considering this was around the same time as Thanksgiving and Christmas, in which we would expect sharp increases in sales, we found this result particularly peculiar. We calculated the same graph for each pair of stores which can be found in the appendix, and it is evident that every store in our sample experienced a similar decline in produce sales at the same time. After investigating foodborne illness outbreaks in the region during November and December of 2018, we found that there was an E. coli outbreak at the end of November in 2018 (FDA, 2018). According to the FDA, Adam Bros. Farming, Inc. in Santa Maria, CA, halted the shipment of any romaine after November 20, 2018, and recalled items such as red leaf lettuce, green leaf lettuce, and cauliflower (2018). The E. coli outbreak resulted in 62 illnesses and 25 hospitalizations which prompted hesitant produce buyers throughout Northern California. Accordingly, we created a dummy variable called "Ecoli_2018" which takes a value of 1 for two weeks at the end of November 2018 to account for the decline in sales.

Considering the variables that we included, we ran the following model for the four pairs of stores which has 312 observations each.

<u>Model 1. Four separate regressions for each store pair (N=312)</u>

$$\begin{aligned}
Y_{Pair\#1it} &= \beta_0 + \beta_1 d_after_{it} + \beta_2 d_treatment_{it} + \beta_3 d_interaction_{it} + \beta_4 weeklysmid_{it} \\
&\quad + \beta_5 x_{5it} + \cdots + \beta_n x_{nit} \\
Y_{Pair\#2it} &= \beta_0 + \beta_1 d_after_{it} + \beta_2 d_treatment_{it} + \beta_3 d_interaction_{it} + \beta_4 weeklysmid_{it} \\
&\quad + \beta_5 x_{5it} + \cdots + \beta_n x_{nit} \\
Y_{Pair\#3it} &= \beta_0 + \beta_1 d_after_{it} + \beta_2 d_treatment_{it} + \beta_3 d_interaction_{it} + \beta_4 weeklysmid_{it} \\
&\quad + \beta_5 x_{5it} + \cdots + \beta_n x_{nit} \\
Y_{Pair\#4it} &= \beta_0 + \beta_1 d_after_{it} + \beta_2 d_treatment_{it} + \beta_3 d_interaction_{it} + \beta_4 weeklysmid_{it} \\
&\quad + \beta_5 x_{5it} + \cdots + \beta_n x_{nit}
\end{aligned}$$

One concern with this model is that the sample size for each equation is relatively small to the total sample of 1,248 observations that we have access to. To test the robustness of our results from these models, we stacked all 1,248 observations in a single data set. For this model, we ran into an issue given the nature of ordinary least squares fitting the model with a single intercept. Since there are potentially systematic differences between each store, a single intercept may not account for variation in sales across stores of different sizes. Therefore, we created four intercept variables for each of the pairs. This model included dummy variables, intercept1, intercept2, intercept3, and intercept4. To clarify, intercept1 took a value of one if an observation included either the treatment or control store for pair #1. This logic holds for intercept variables 2-4. Additionally, to ensure that each intercept would be plotted efficiently, we created dummy variables for each treatment store, the time the store received a retrofit, and the interaction term for each pair. So, we had d_treament1-4, d_after1-4, and d_interaction1-4. The changes to this model can be found below in Model 2.

Model 2. DiD stacked regression (N = 1,248)

$$\begin{aligned} Y_{it} = {} & \beta_{1intercept1it} + \beta_{2intercept2it} + \beta_{3intercept3it} + \beta_{4intercept4it} \\ & + \beta_{5d\_after1it} + \beta_{6d\_after2it} + \beta_{7d\_after3it} + \beta_{8d\_after4it} + \beta_{9d\_treatment1it} \\ & + \beta_{10d\_treatment2it} + \beta_{11d\_treament3it} + \beta_{12d\_treatment4it} + \beta_{13d\_interaction1it} \\ & + \beta_{14d\_interaction2it} + \beta_{15d\_interaction3it} + \beta_{16d\_interaction4it} \\ & + \beta_{17} weeklysmid_{it} + \beta_{18} x_{5it} + \cdots + \beta_n x_{\ nit} \end{aligned}$$

Lastly, to account for some potential confounding effects between our dependent and independent variables, we utilized a seemingly unrelated regression (SUR) model. We postulated that perhaps the error terms from across pairs of equations could be correlated. There is substantial literature that suggests coefficients can be estimated more efficiently when there is potential correlation in error terms across equations (Carlson, 1978). Instead of estimating each equation separately, the SUR model accounts for this correlation and provides more efficient coefficients. For Model 3, we made four different dependent variables for each store pair. Then, similarly to Model 2, we made unique dummy variables for each pair to account for the treatment store, when the retrofit was installed, an interaction term, and a unique weeklysmid variable for each pair. The holiday dummies consisted of the same value for each equation in Model 3. The results from each model will be interpreted in the following chapter.

Model 3. DiD SUR (mT = (4 x 312) = 1,248)

$$\begin{aligned}
Y_{Pair\#1\,it} &= \beta_0 + \beta_1 d_after_{Pair\#1it} + \beta_2 d_treatment_{Pair\#1it} + \beta_3 d_interaction_{Pair\#1it} \\
&\quad + \beta_4 weeklysmid_{Pair\#1it} + \beta_5 x_{5it} + \cdots + \beta_n x_{nit} \\
Y_{Pair\#2\,it} &= \beta_0 + \beta_1 d_after_{Pair\#2it} + \beta_2 d_treatment_{Pair\#2it} + \beta_3 d_interaction_{Pair\#2it} \\
&\quad + \beta_4 weeklysmid_{Pair\#2it} + \beta_5 x_{5it} + \cdots + \beta_n x_{nit} \\
Y_{Pair\#3\,it} &= \beta_0 + \beta_1 d_after_{Pair\#3it} + \beta_2 d_treatment_{Pair\#3it} + \beta_3 d_interaction_{Pair\#3it} \\
&\quad + \beta_4 weeklysmid_{Pair\#3it} + \beta_5 x_{5it} + \cdots + \beta_n x_{nit} \\
Y_{Pair\#4\,it} &= \beta_0 + \beta_1 d_after_{Pair\#4it} + \beta_2 d_treatment_{Pair\#4it} + \beta_3 d_interaction_{Pair\#4it} \\
&\quad + \beta_4 weeklysmid_{Pair\#4it} + \beta_5 x_{5it} + \cdots + \beta_n x_{nit}
\end{aligned}$$

RESULTS:

Although we proceeded with several estimation procedures, there were consistent estimation results across the different procedures. While the estimates were consistent across models and store pairs, the interpretations would not be as pronounced if converted to real dollars. As mentioned in the data chapter, all results are in nominal U.S. $ and the inflation rate was about 6% during the period of our study from January 2016 to December 2018. The estimated increases in nominal produce sales are larger than if they were adjusted for inflation. But with a rate of inflation of only 6 percent over the three-year period, using nominal sales figures seems reasonable.

When estimating the effect that retrofit doors have on produce sales, it appears that doors positively influenced sales for the treatment stores from pairs 3 and 4 while the installation of doors did not significantly influence produce sales for the treatment stores from pairs 1 and 2. The positive influence that retrofit doors have on produce sales can be found by observing the coefficient values for variables "d_interact3" and "d_interact4" in Table 9. For treatment store #3, weekly produce sales increased about $5,000 after the installation of the retrofits which is about an 11% increase relative to the intercept3 value. Likewise, for treatment store #4, weekly produce sales increased about $2,000 after the installation which is about a 4% increase relative to the intercept4 value. Since the interaction terms for store pairs 1 and 2 are not statistically significant, we can conclude that the installation of doors for treatment stores 1 and 2 did not have a significant effect on weekly produce sales. The robustness of these results is illustrated from the estimations from each pair of stores estimated as separate DiD models (see Table 10). Estimation results for the segmented DiD models in Table 10 indicate that weekly produce sales increased about $5,000 for treatment store #3 and about $2,000 for treatment store #4 after the retrofit installation. The $5,000 and $2,000 increase were approximately a 13% and 5% boost relative to the respective intercept values. Also, in Table 10, it appears that the installation of doors did not have a statistically significant effect on weekly produce sales for treatment stores 1 and 2. Lastly, the SUR estimations from Model 3 can be found in Table 11 with similar results for the interaction variables for store pair 3 while being marginally significant at the 90% level for store pair 4.

Apart from the interaction terms, which are variables that indicate the retrofit doors' treatment effect, there were several common patterns found in each model's estimation results. For example, as postulated previously, as the average weekly midpoint temperature increases in proximity to each store location, so do weekly produce sales. The coefficient estimates for each model and store pair have relatively similar magnitude and are all highly statistically significant. A supermarket from our sample can typically expect weekly produce sales to increase about \$100-\$300 dollars for each incremental degree °F increase in weekly midpoint temperature. Future studies could perhaps look more closely at the seasonality relationship between leafy greens and produce sales.

For our models from Tables 9, 10, and 11, the holiday dummies do not appear to have a positive influence on weekly produce sales. In fact, many of the holidays either have no statistically quantifiable effect on produce sales, or negatively influence weekly produce sales. For example, a common result amongst the models suggests that weekly produce sales decrease on the 4th of July, Thanksgiving, and Christmas. Considering the results from Tables 7 and 8, it is possible that consumers are occupied purchasing an assortment of other items not in the vegetable or produce aisles. Lastly, a robust result for each model and each coefficient estimate, is the effect that the E. coli outbreak in November of 2018 had on produce sales. The sharp decline in sales in Figure 1 was no fluke in estimating the effect that it had on weekly produce sales. The E. coli dummy coefficient is negative and highly significant for each model and the coefficient estimate ranges from about -\$13,000 to -\$23,000. The supermarket in our sample endured a \$13,000 to \$23,000 decrease in weekly produce sales. Accounting for the results from our DiD SUR model in Table 11, we can conclude that weekly produce sales during the E. coli outbreak decreased 45% for store pair #1, 38% for store pair #2, 45% for store pair #3 and 51% for store pair #4 relative to each respective intercept value, holding all else equal. It is possible that these estimates can vary in magnitude, depending on the severity of the outbreak.

To accentuate the impact of the interaction terms and E. coli dummy, it is important to emphasize that sales increased by about $2,000 and $5,000 for treatment stores 3 and 4 after the installation *each* week after February 2017. If this result is constant across seasonal patterns, the returns from installing doors could potentially not only mitigate the economic losses of an E. coli outbreak, but also mitigate its severity and spread. For a supermarket chain with many stores, there are many augmented benefits that could result by simply installing doors. Foodborne illnesses pose a serious public health threat and a severe economic one as is present from the Ecoli_2018 variable across the models.

Table 9. Results from stacked DiD model in U.S. nominal $ (N = 1,248)

Variable	Parameter	Pr > |t|	Parameter	Pr > |t|	Parameter	Pr > |t|
Model A			Model B		Model C	
intercept1	38,052	<.0001	27,186	<.0001	29,448	<.0001
intercept2	41,912	<.0001	31,423	<.0001	33,617	<.0001
intercept3	58,770	<.0001	47,882	<.0001	50,159	<.0001
intercept4	57,727	<.0001	47,231	<.0001	49,429	<.0001
d_after1	1,584	0.044	1,272	0.088	1,713	0.008
d_after2	2,526	0.001	2,024	0.006	2,503	0.000
d_after3	-265	0.735	-466	0.530	-60	0.926
d_after4	2,458	0.002	2,131	0.004	2,569	<.0001
d_treatment1	-2,215	0.013	-2,370	0.005	-2,339	0.001
d_treatment2	6,373	<.0001	6,708	<.0001	6,642	<.0001
d_treatment3	-4,040	<.0001	-3,272	<.0001	-3,423	<.0001
d_treatment4	-10,174	<.0001	-9,856	<.0001	-9,919	<.0001
d_interact1	-106	0.924	-57	0.957	-66	0.942
d_interact2	1,009	0.359	970	0.351	978	0.280
d_interact3	5,588	<.0001	5,568	<.0001	5,572	<.0001
d_interact4	1,968	0.075	2,135	0.041	2,102	0.021
weeklysmid			177	<.0001	142	<.0001
_Jul4th					-2,830	0.001
_Thanksgiving					-1,683	0.054
_Christmas					-3,125	0.000
_Easter					-582	0.467
_SuperBowl					-750	0.350
_Memorial_Day					276	0.732
_Labor_Day					1,686	0.038
Ecoli_2018					-18,223	<.0001

Note: Coefficients significant at the 95% level are highlighted green or red, indicating positive or negative estimates respectively

Table 10. Results from individual pairs of estimates model in U.S. nominal $ (N = 312)

	Pair #1 (Produce Sales)		Pair #2 (Produce Sales)		Pair #3 (Produce Sales)		Pair #4 (Produce Sales)	
Variable	Parameter	Pr > |t|	Parameter	Pr > |t|	Parameter	Pr > |t|	Parameter	Pr > |t|
Model A								
Intercept	38,052	<.0001	41,912	<.0001	58,770	<.0001	57,727	<.0001
d_after	1,584	0.01	2,526	0.00	-265	0.77	2,458	0.01
d_treatment	-2,215	0.00	6,373	<.0001	-4,040	0.00	-10,174	<.0001
d_interact	-106	0.91	1,009	0.28	5,588	<.0001	1,968	0.11
Model B								
Intercept	27,863	<.0001	36,992	<.0001	40,213	<.0001	39,502	<.0001
d_after	1,291	0.02	2,290	0.00	-607	0.48	1,890	0.02
d_treatment	-2,360	0.00	6,530	<.0001	-2,731	0.01	-9,622	<.0001
d_interact	-60	0.94	991	0.28	5,553	<.0001	2,258	0.05
weeklysmid	166	<.0001	83	0.00	302	<.0001	307	<.0001
Model C								
Intercept	29,738	<.0001	38,444	<.0001	43,606	<.0001	41,935	<.0001
d_after	1,636	0.00	2,681	<.0001	-121	0.87	2,403	0.00
d_treatment	-2,336	<.0001	6,484	<.0001	-2,953	0.00	-9,692	<.0001
d_interact	-68	0.92	996	0.23	5,559	<.0001	2,221	0.02
weeklysmid	138	<.0001	59	0.00	250	<.0001	268	<.0001
_Jul4th	-2,863	0.02	-2,437	0.10	-4,338	0.02	-2,377	0.17
_Thanksgiving	-3,026	0.02	-345	0.83	-2,540	0.21	-815	0.66
_Christmas	-3,303	0.01	-2,398	0.10	-4,866	0.01	-593	0.74
_Easter	-135	0.91	211	0.88	-1,464	0.43	-762	0.66
_SuperBowl	-722	0.54	358	0.81	-976	0.60	-1,592	0.36
_Memorial_Day	-137	0.91	104	0.94	832	0.66	-23	0.99
_Labor_Day	1,246	0.30	2,585	0.08	494	0.79	1,545	0.38
Ecoli_2018	-13,795	<.0001	-14,847	<.0001	-20,825	<.0001	-23,005	<.0001

Note: Coefficients significant at the 95% level are highlighted green or red, indicating positive or negative estimates respectively

Table 11. Results from DiD SUR model in U.S. nominal \$ (N = 1,248)

	Pair #1 (Produce Sales)		Pair #2 (Produce Sales)		Pair #3 (Produce Sales)		Pair #4 (Produce Sales)	
Variable	Parameter	Pr > |t|	Parameter	Pr > |t|	Parameter	Pr > |t|	Parameter	Pr > |t|
Intercept	30,825	<.0001	39,178	<.0001	46,768	<.0001	44,596	<.0001
d_after	1,603	0.001	2,776	<.0001	-102	0.887	2,580	0.000
d_treatment	-2,090	<.0001	6,798	<.0001	-2,778	0.001	-9,372	<.0001
d_interact	-433	0.500	455	0.558	4,940	<.0001	1,536	0.099
weeklysmid	121	<.0001	46	0.008	199	<.0001	222	<.0001
_Jul4th	-2,662	0.026	-2,293	0.119	-3,978	0.035	-2,056	0.236
_Thanksgiving	-3,165	0.015	-396	0.803	-2,651	0.192	-865	0.644
_Christmas	-3,561	0.003	-2,518	0.087	-5,343	0.005	-1,020	0.559
_Easter	-173	0.884	169	0.908	-1,586	0.395	-841	0.624
_SuperBowl	-811	0.494	295	0.840	-1,098	0.557	-1,673	0.332
_Memorial_Day	39	0.974	224	0.878	1,094	0.559	182	0.916
_Labor_Day	1,468	0.220	2,756	0.062	964	0.609	1,911	0.272
Ecoli_2018	-13,802	<.0001	-14,863	<.0001	-20,946	<.0001	-23,112	<.0001

Note: Coefficients significant at the 95% level are highlighted green or red, indicating positive or negative estimates respectively

All our regression results from Tables 9, 10, and 11 include only weekly produce sales as the dependent variable. Clearly, this is the dependent variable of interest when trying to measure the effect that the installation of doors might have on supermarket produce sales. But the results we have presented so far have *only* accounted for impacts on produce sales. And taking into consideration the interaction terms for store pairs 3 and 4, it appears that produce sales increase as a result of installing doors while there was no effect on produce sales for store pairs 1 and 2. We observe these results even though the segmented produce sales contained items in the vegetable and produce aisles which are not refrigerated such as onions, potatoes, etc. Sales for vegetables that are not refrigerated were likely not affected as a result of installing retrofit doors. Therefore, given that non-refrigerated items were included in our calculation of produce sales, the positive interaction coefficient for store pairs 3 and 4 appear to be tenable.

However, supermarket managers and executives who might be considering installing retrofits in the produce section might observe these results and still have apprehensions about the doors. Many consumers have a fixed budget when they shop. If it is true that consumers are inclined to purchase more produce when the product is confined behind a door, then it is possible that their expenditure for other items in the supermarket may decrease. Perhaps shoppers just spend more in one section of the store, while spending less in another which could lower the return on investment. To address this concern, we ran the same models in Tables 9, 10, and 11 but had total store sales as the dependent variable.

Table 12 displays the regression results for our SUR model with total store sales as the dependent variable. The intercept values are much higher in this model than in the previous models as total store sales are significantly higher than the segmented produce sales. The interaction terms for pairs 1 and 2 are positive but not statistically significant at the 95 % threshold, implying that the installation of retrofit doors did not have a significant effect on total store sales. Interestingly, the interaction term for pair 1 is marginally significant at the 90% threshold. Also, analogous to Tables 9, 10, and 11, the interaction terms for pairs 3 and 4 are both positive and statistically significant. The interaction term for pairs 3 and 4 are also positive and statistically significant for both the total store sales stacked, and total store sales segmented DiD models which can be found in the Appendix. The consistency in the interaction term coefficient estimates suggest that the increase in produce sales after the retrofit doors were installed did not hinder shoppers from spending money in other sections of the store. If we adopt the assumption that shoppers have a fixed budget when they buy groceries, this result may seem counterintuitive. Perhaps there are some underlying characteristics about the socioeconomic status of the shoppers from treatment stores 3 and 4. Or, maybe when retrofit doors were installed in treatment stores 3 and 4, there were other renovations at the time that could make the store more appealing which in effect attracted more customers. The effect from higher spending customers or another factor could have spilled over into the produce section, and it is possible that the retrofits do not explain the boost in sales. Unfortunately, we were unable to control for these potential factors in our model, but they could provide some fruitful insights in future studies.

Table 12. Results from DiD SUR in U.S. nominal $ (N = 1,248)

	Pair #1 (Total Sales)		Pair #2 (Total Sales)		Pair #3 (Total Sales)		Pair #4 (Total Sales)	
Variable	**Parameter**	**Pr >|t|**	**Parameter**	**Pr >|t|**	**Parameter**	**Pr >|t|**	**Parameter**	**Pr >|t|**
Intercept	223,397	<.0001	264,593	<.0001	357,112	<.0001	312,794	<.0001
d_after	-5,994	0.001	-682	0.782	-13,254	<.0001	-2,852	0.344
d_treatment	7,269	0.001	60,760	<.0001	-24,036	<.0001	-36,930	<.0001
d_interact	4,495	0.085	4,803	0.164	34,375	<.0001	23,544	<.0001
weeklysmid	10	0.858	-36	0.612	-58	0.656	180	0.206
_Jul4th	22,102	<.0001	19,129	0.005	20,468	0.014	38,275	<.0001
_Thanksgiving	46,474	<.0001	65,846	<.0001	77,154	<.0001	82,021	<.0001
_Christmas	50,783	<.0001	41,352	<.0001	48,044	<.0001	65,314	<.0001
_Easter	17,688	0.000	21,303	0.002	10,824	0.188	17,380	0.033
_SuperBowl	20,352	<.0001	22,790	0.001	24,497	0.003	18,295	0.025
_Memorial_Day	17,112	0.001	11,817	0.079	15,859	0.055	14,520	0.075
_Labor_Day	11,557	0.021	15,797	0.020	10,704	0.197	14,208	0.083
Ecoli_2018	-13,519	0.040	-36,176	<.0001	-42,003	0.000	-31,602	0.004

Note: Coefficients significant at the 95% level are highlighted green or red, indicating positive or negative estimates respectively

The weeklysmid variable did not seem to significantly affect total store sales in any of the models. Since weekly mean midpoint temperatures influence produce sales but not total store sales, maybe the disparity of results elucidates the relative elasticities of each dependent variable. The holiday dummies in our total store sales models possess high explanatory power. Contrary to our previous results for produce sales, nearly every U.S. holiday that we included has a highly significant and substantial positive impact on total store sales. Of the holidays that we created dummy variables for, supermarkets in our sample can expect anywhere from about a $10,000 to $80,000 bump in weekly total store sales when there is a holiday during the given week. To put these values into perspective, the stores from Pair 4 can expect about a 26% increase in total store sales for the week that Thanksgiving occurs, 21% increase when Christmas occurs, and 12% increase when the 4th of July occurs. Another conclusion about the results is that the Ecoli_2018 variable was not only significant for produce sales. Considering the range of coefficients on the Ecoli_2018 variable, it appears that total store sales appreciably suffer when there is a foodborne illness being spread. For example, results from Table 12 indicate that because of the E. coli outbreak, total store sales decreased about 6% for store pair #1, 14% for store pair #2, 12% for store pair #3, and 10% for store pair #4 relative to each respective intercept value. Perhaps the hesitation to buy produce extends to other food items. The results from our models suggest some salient implications for public policy which will be discussed in the following chapter.

PUBLIC POLICY IMPLICATIONS AND CONCLUSION:

The installation of retrofit doors in the produce section of supermarkets has multi-faceted implications for public policy. Simply enclosing refrigerated displays with glass doors significantly reduces energy consumption and therefore can help reduce greenhouse gas emissions. From a public health perspective, installing doors also mitigates the likelihood of foodborne illness proliferation. Supermarket managers and executives do not necessarily reap the benefits for mitigating the effects of climate change or preventing a bacterial outbreak. So, when considering economic incentives, and the uncertainty of investing in such projects to install doors, it is evident why doors in the produce section are not widespread across the United States. However, from a governmental point of view, there is certainly an incentive to reduce energy consumption and improve public health. In this chapter, we will propose several policies in the context of our results that we found from the previous chapter. Then, we will identify existing gaps in the literature and suggest how future studies can improve upon what we have found in this paper.

Contrary to the concerns of supermarket managers and executives, we can conclude that the installation of doors on the produce section do not negatively affect produce sales. Based upon our sample and results, doors influenced an increase in produce sales for two out of the four treatment stores while doors did not have any influence on produce sales for the other two treatment stores. As mentioned in the literature review chapter, Herman et. al (2015) argue that governments should invest more in ensuring food safety at each step of the supply chain.

Assuming that our results are robust and would hold across other stores elsewhere in the United States, then it would seem logical for local, state, and federal agencies to invest in projects that could have profound implications for the climate and well-being of its citizens. Not only do doors minimize the risk of harmful bacteria to proliferate, but our results suggest that it is plausible for produce sales to increase after installing doors. Recall that we identified produce sales in our study to include only items purchased in the produce and vegetable aisles. If consumers eat more leafy greens and other fresh vegetables, then there must be additional positive externalities on public health not accounted for; there is substantial literature about the relationship between consumption of leafy greens and improving cardiovascular health (Blekkenhorst, et. al, 2018). Subsidizing the installation of doors for supermarkets would be a unique opportunity for governments to address multiple public-health issues: prevent foodborne illness and promote healthy eating.

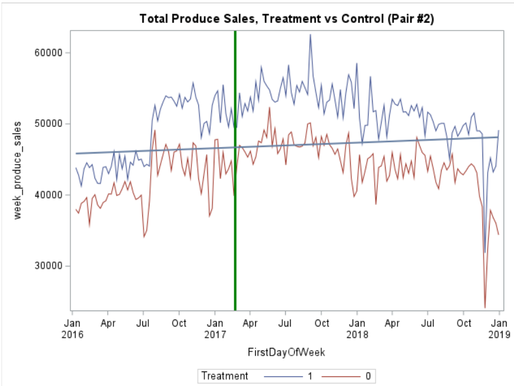
Governments and supermarkets likely have different incentives to install doors. While supermarkets might not necessarily be able to internalize the positive externalities from doors, it is conceivable that the investment to install doors is a financially sound decision. While our study focuses on the effect that doors have on produce sales, a comprehensive cost-benefit study needs to be conducted. As Klemick et. al (2017) propose, supermarket managers and executives are concerned with ROI as profit margins in the industry are low. Certainty is imperative when contemplating an investment. Future studies could look to provide a more concrete answer that considers variables such as initial costs, the installation process, energy savings, store size, store location, and doors' influence on sales to name a few.

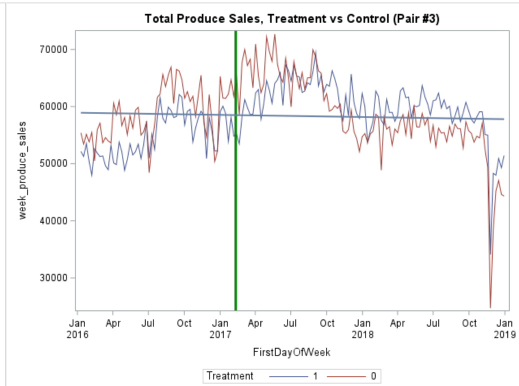
For a study to build upon ours, addressing the question about the influence that doors have on produce sales, a larger number of stores in different geographic areas would be desirable. Also, more pairs of stores would likely improve the robustness of the results. As mentioned earlier, our study was a natural experiment. Future studies on this subject can consider adding more controls and ensuring that the treatment-control attributes are truly random. In this study, we paired stores based on their weekly mean produce sales, weekly mean total store sales and geographic location. To reiterate, we are unaware of the exact reasons why some stores from the supermarket chain in our sample received doors and others did not. Understanding the rationale supermarket chain executives used to install the doors in particular stores would have provided valuable insight into our analysis.

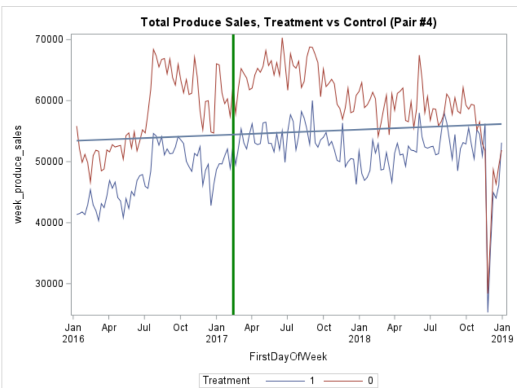
Having more data about the store characteristics would likely improve our model and possibly would elucidate why we did not have uniform results across store pairs. Studies by Lindberg et. al (2018) suggest that there are many factors after a door is installed that might influence consumer behavior. We did not have data on if the produce was illuminated with LED lights, aisle spacing width, ambient temperature, or how the doors were marketed. Considering the results from Lindberg's qualitative study, perhaps the discrepancy in results across store pairs lies within character variables about how the doors were installed. Despite further research needing to be conducted on the topic, this paper provides a viable starting point in examining how retrofit doors effect produce sales via econometrics. Do you think a glass door would prevent you from buying fresh produce?

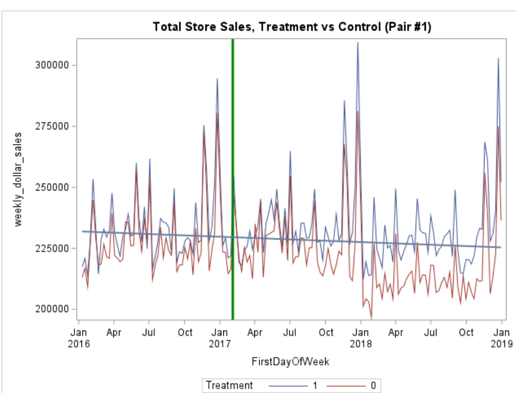
APPENDIX:

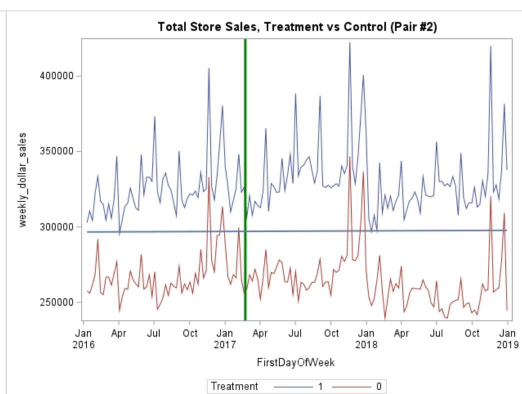
Appendix A. Sales over time with trend lines. For produce sales and total store sales

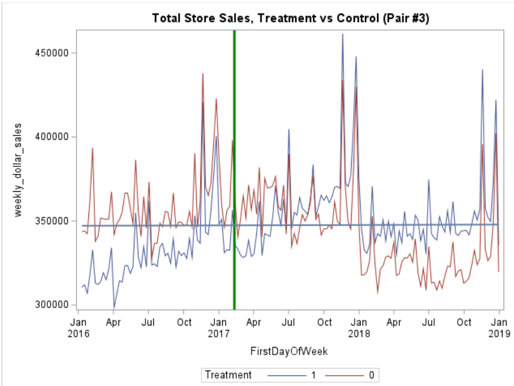


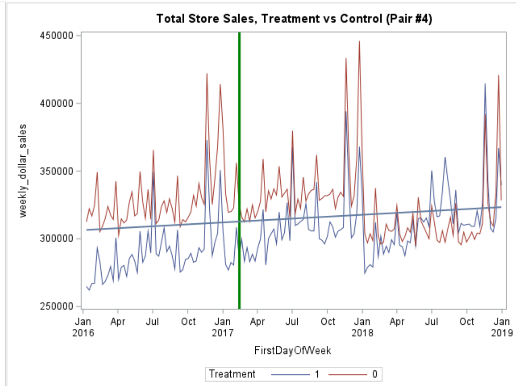




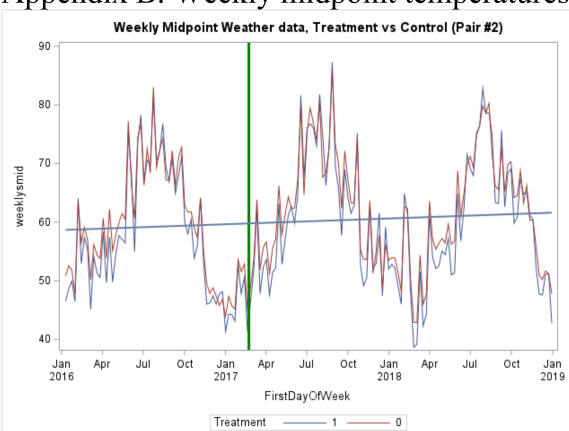


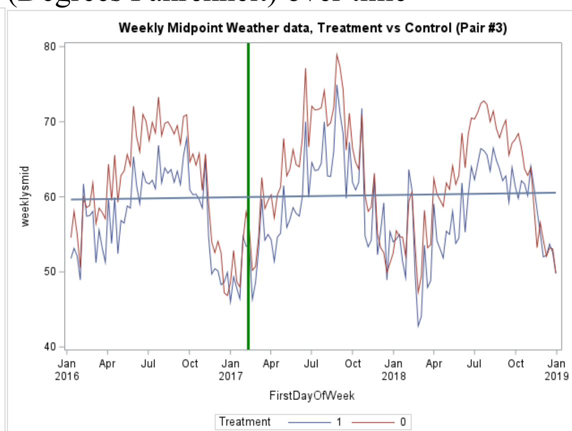


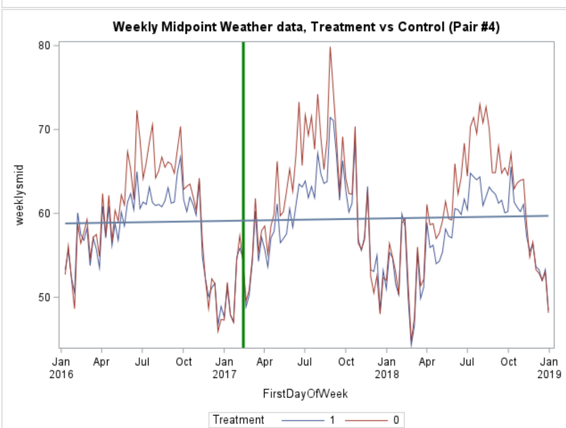




Appendix B. Weekly midpoint temperatures (Degrees Fahrenheit) over time







Appendix C. Regression results for Model 1 and Model 2 on total store sales

Regression results for Model 1 in U.S. nominal $ (Total Store Sales)

	Pair #1 (Total Sales)		Pair #2 (Total Sales)		Pair #3 (Total Sales)		Pair #4 (Total Sales)	
Variable	**Parameter**	**Pr > |t|**	**Parameter**	**Pr > |t|**	**Parameter**	**Pr > |t|**	**Parameter**	**Pr > |t|**
Intercept	229,506	<.0001	266,015	<.0001	370,609	<.0001	332,014	<.0001
d_after	-6,899	0.00	-2,804	0.30	-15,506	<.0001	-4,986	0.13
d_treatment	5,981	0.01	58,244	<.0001	-27,730	<.0001	-40,326	<.0001
d_interact	6,601	0.02	8,845	0.02	38,892	<.0001	27,825	<.0001
weeklysmid	-79	0.27	-38	0.69	-252	0.15	-116	0.54
_Jul4th	23,098	<.0001	19,151	0.00	21,802	0.01	40,303	<.0001
_Thanksgiving	45,890	<.0001	65,832	<.0001	76,850	<.0001	81,808	<.0001
_Christmas	49,407	<.0001	41,340	<.0001	46,193	<.0001	62,516	<.0001
_Easter	17,448	0.00	21,301	0.00	10,325	0.21	16,827	0.04
_SuperBowl	19,847	<.0001	22,759	0.00	24,366	0.00	18,086	0.03
_Memorial_Day	17,983	0.00	11,836	0.079	16,819	0.04	15,801	0.05
_Labor_Day	12,667	0.01	15,822	0.02	12,456	0.14	16,522	0.05
Ecoli_2018	-14,082	0.03	-36,145	<.0001	-42,927	0.00	-32,748	0.00

Regression results for Model 2 in U.S. nominal $ (Total Store Sales)

Variable	**Parameter**	**Pr > |t|**	**Parameter**	**Pr > |t|**	**Parameter**	**Pr > |t|**
Model A			Model B		Model C	
intercept1	228,014	<.0001	238,989	<.0001	229,741	<.0001
intercept2	267,527	<.0001	278,122	<.0001	268,896	<.0001
intercept3	359,187	<.0001	370,186	<.0001	360,620	<.0001
intercept4	329,775	<.0001	340,377	<.0001	331,079	<.0001
d_after1	-6,919	0.049	-6,605	0.059	-6,587	0.022
d_after2	-3,550	0.306	-3,042	0.380	-2,845	0.318
d_after3	-16,777	<.0001	-16,575	<.0001	-16,017	<.0001
d_after4	-5,568	0.110	-5,238	0.132	-4,848	0.090
d_treatment1	5,912	0.137	6,068	0.126	5,990	0.066
d_treatment2	58,315	<.0001	57,976	<.0001	58,145	<.0001
d_treatment3	-26,637	<.0001	-27,412	<.0001	-27,025	<.0001
d_treatment4	-40,117	<.0001	-40,438	<.0001	-40,278	<.0001
d_interact1	6,623	0.182	6,573	0.184	6,598	0.104
d_interact2	8,837	0.072	8,875	0.070	8,856	0.028
d_interact3	38,864	<.0001	38,884	<.0001	38,874	<.0001
d_interact4	27,934	<.0001	27,766	<.0001	27,850	<.0001
weeklysmid			-179	0.010	-90	0.138
_Jul4th					25,930	<.0001
_Thanksgiving					67,608	<.0001
_Christmas					50,145	<.0001
_Easter					16,535	<.0001
_SuperBowl					21,236	<.0001
_Memorial_Day					15,519	<.0001
_Labor_Day					14,145	<.0001
Ecoli_2018					-31,354	<.0001

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