What was the Effect of Leukemia Cases on Churchill County from 2000 to 2002? An Examination Using a Difference-in-Differences Model.

I. Abstract

The goal of this report is to examine the effect that the rise in leukemia cases, in Churchill County, had on real house sale values. To accomplish this, I used a difference-in-differences model. The model takes the difference between average house sale prices between Churchill and Lyon after the rise in cases and subtracts this from the difference between average house sale prices between the counties before the rise in cases. My report found that the rise in cases had a - 12.5% effect on average real sale prices in Churchill, but I cannot conclude a causal effect from my model. Further research and data collection is warranted to study the true causal effect of leukemia cases on real house sale prices.

II. Introduction

Churchill, a county in Nevada, experienced a surprising amount of leukemia cases within a short period of time. Statistics from the American Cancer Society suggest that Churchill County should only expect about one case of leukemia every 5 years, based on the population of the county. In 1997, the residents of Churchill experienced their first, and only, case of leukemia that year. This first case was not a cause for concern, but by 2000, Churchill had 8 cases of leukemia, far exceeding the number of cases a county like Churchill should see. This was followed by an additional 4 cases in 2001, and a total of 16 cases in 2002.

While the Nevada Health Department and the CDC were unable to determine the cause of the sudden spike in leukemia cases, there was no indication that Churchill was uniquely inhospitable. Still, house prices dropped as residents left the county in mass, seemingly in fear of the increased number of cases.

The question naturally arises, did house prices drop in Churchill due to the increase in leukemia cases, or would Churchill have experienced this drop in house value regardless of the sudden uptick in leukemia cases? To examine this question, I am using a pooled cross-sectional dataset of 10,204 house sales, from the years of 1990 to 2002. This data set includes house sales from a nearby county, Lyon, which will prove useful as Lyon County did not experience a single case of leukemia over the same period of time, and Lyon has similar characteristics to Churchill.

To answer the question of whether leukemia cases did affect house values in Churchill, I will use a difference in differences model with this data set. If the assumptions of the model hold, we should be able to observe the causal effect of leukemia cases on house prices in Churchill.

Additionally, I will give explanations of the model and examine whether we can infer a causal inference in further sections.

III. Data Summary

In this section, I will explain general trends in the data and give reasons why I created new variables or transformed variables.

To begin, it is important to establish the variables I used to create my model. These variables include the lot size of the house sold in acres, the interior size of the house in square feet, the age of the house sold, and the perceived condition of the home rated on a scale from

zero to five. These variables are regressed on the real house sale price. With that clarification, let us dive into the transformations and generation of variables.

The first variable I adjusted was the real sale prices of houses. Intuitively, a variable that measures house prices is prone to skewness. This is because we can observe very large house sale values, with theoretically no limitation, but the smallest sale value we can observe is a house that sells for zero dollars. This inherently leads to skewness.

Skewness makes it more difficult to fit a linear regression to the data, so a transformation on this variable can help us avoid this. To check if the real house sale variable is skewed, I made a histogram of the variable, which is shown below:

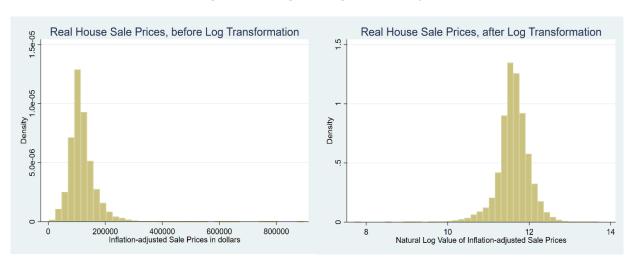


Figure 1 (on the right) and Figure 2 (on the left)

We can see that the right tail of the histogram in Figure 1 continues past \$800,000, which greatly contributes to right skewness. Specifically, the skewness value of the histogram in Figure 1 is about 3.67, which value of 0 would be perfectly normal. This means that the data is heavily right-skewed, and a transformation of this variable is justifiable. Taking the natural log of this variable will help to create a more normal distribution, which is shown in Figure 2.

The skewness value of this distribution in Figure 2 is only about -0.52. This is considered slightly left-skewed, but we can still reasonably consider this distribution normal with such a small skewness value. By utilizing this transformation, my model will more easily fit this data, and we will more consistently derive accurate estimators for our parameters of interest.

Next, I examined the variables used in the model that I constructed. There is worthy concern that these variables might not move in a linear fashion with the log of real sales prices of houses.

After checking each of the variables used in the model, a notable interaction involved the square footage of the home and the lot size of the home. Using scatter plots shows the non-linear relationship of these variables, shown below:

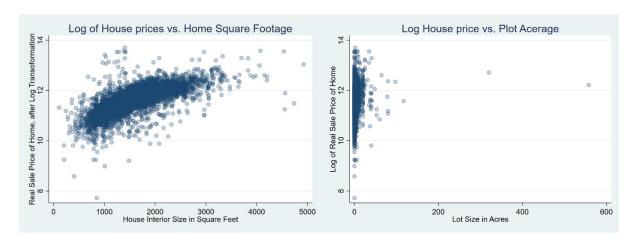


Figure 3 (shown on the right) and Figure 4 (shown on the left)

If we attempted to fit a linear line through this data, we would be missing several data points. If the factors did move linearly, a larger home or lot would always proportionally be more expensive than a smaller home. What is more likely, and what we are observing, is that a large home and a large lot tend to only be marginally more expensive, and that marginal increase in price decreases at the home and lot size increases. This is known as a diminishing marginal return.

The presence of diminishing marginal return justifies the addition of a term if our goal is to accurately fit the data. To achieve this goal, I will create a squared term for each of these variables. This means we will simply take the squared value of every observation of square footage and acreage in our data set and add them as new variables into the model. Doing this will allow the slope square footage and the acreage to decrease as the values increase and, as a result, capture the diminishing marginal return we observe.

My last variable to focus on is the "condition" variable. In this data set, the condition variable is missing values. A model that does not contain this variable will have 10,204 observations, but a model that includes this variable will only have 9,773 observations. This fact in itself could be a good reason to omit this variable, but I argue this would cause omitted variable bias, meaning that we could not infer a causal relationship from the model. The reason omitting this variable would cause omitted variable bias is because of the correlation between the square footage of a home and the rated condition of that home. It is fair to assume that homes that are larger are also going to be better quality, and as a result, will have a better condition rating.

To do this, I checked the correlation between the square footage of a home and the rated condition of the home. The correlation coefficient between these two variables is 0.5251. This can be considered a moderately high correlation and justifies the idea that the variables are indeed correlated. Therefore, we can conclude that omitting the condition variable would cause the omitted variable bias, and we would not be able to conclude a causal relationship from the difference-in-differences model.

Finally, to end this section, I want to examine the potential for heteroscedasticity in my model. Heteroscedasticity is an issue because when we run regression models in Stata, Stata assumes homoscedasticity in the data. Running a model with heteroskedasticity when assuming homoscedasticity will make our estimators less accurate, therefore we should avoid running this regression when possible (it should be noted that running a heteroskedastic model while assuming homoscedasticity will not make our estimators biased). A simple way to check for heteroskedasticity is with a graph off fitted values plotted against the residuals of the model. A plot of this is shown below:

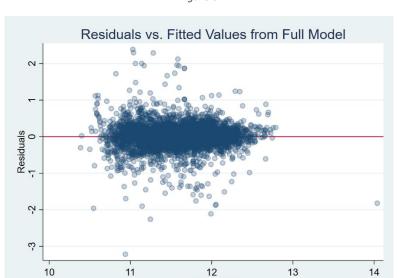


Figure 5

Our assumption of homoscedasticity is violated if we can observe a trend in the plotted residuals. We can see that the residuals grow larger in magnitude relative to the predicted values, as the predicted values approach 11.5, and they decrease in magnitude after that point. This shows a trend in the plotted residuals, and this justifies a method to adjust for this heteroscedasticity in the model. We do this by using the "robust" command in Stata when running the model.

IV. Regression Analysis

Now, let us examine the full model and its and implications. Here is the full model I constructed and an explanation of the variables:

$$Log \ House \ Price = \widehat{B}_0 + \widehat{B}_1 year 2000 + \widehat{B}_2 Churchill + \widehat{B}_3 year 2000 * Churchill$$

$$+ \widehat{B}_4 acres + \widehat{B}_5 acres 2 + \widehat{B}_6 sqft + \widehat{B}_7 sqft 2 + \widehat{B}_8 age + \widehat{B}_9 condition$$

The variables "acres," "sqft," and "condition" measure the lot size in acres of the house sold, the interior square footage of the house, and the rated condition of the home, respectively. Additionally, "acres2" and "sqft2" are the squared values of "acres" and "sqft" that I created, referenced earlier in this report. Along with continuous variables, there are two dummy variables in this model, which are "year2000" and "Churchill." These variables only take on the values of one or zero. In the context of the data set, "year2000" will equal one when the house was sold in or after the year, and "Churchill" will equal one if the house was sold in Churchill County.

The term of interest is the interaction between "year2000" and "Churchill." The slope coefficient of this term captures the difference-in-difference estimator, and, assuming our assumptions of the model hold, gives us the causal effect of the cases of leukemia on real house prices in Churchill County. Below is a table with the values of the slope coefficients for each term and the associated standard error.

Difference-in-Difference Models for The Effect of Cases on Average Real House Prices in Churchill

	(1)	(2)	(3)
	Simple Model, no	Model with Control	Robust model with
	Controls	Variables	Controls
Sale on or after 2000	0.0395	-0.0205	-0.0205
	(0.0101)	(0.00615)	(0.00537)
Sale Churchill	-0.0399	0.0840	0.0840
	(0.00951)	(0.00659)	(0.00733)

Interaction Term	-0.0774 (0.0187)	-0.125 (0.0114)	-0.125 (0.0117)
Lot Size in Acres		0.0139	0.0139
		(0.000670)	(0.00177)
Lot Size Squared		-0.0000236	-0.0000236
•		(0.00000150)	(0.00000345)
House Square Feet		0.000796	0.000796
		(0.0000241)	(0.0000467)
Square Feet Sqaured		-0.000000101	-0.000000101
1		(6.26e-09)	(1.33e-08)
Building Age in Years		-0.00421	-0.00421
		(0.000164)	(0.000248)
Condition of Home		0.193	0.193
		(0.00646)	(0.00767)
Constant	11.63	10.26	10.26
	(0.00596)	(0.0236)	(0.0432)
Observations	10204	9773	9773
Adjusted R ²	0.007	0.641	0.641

Standard errors in parentheses

All p < 0.001

In the third column of the table, the slope coefficient of the interaction term is -0.125. In the context of this model, this means leukemia cases decreased average house sale values by 12.5% in Churchill County, if the assumptions of the difference-in-differences model hold.

We can conclude a causal effect because of the implications of the difference-in-differences model. The model allows us to take the difference in average real sale prices between Churchill and Lyon after the spike in cases and subtract this difference from the difference between average real sale prices between Churchill and Lyon before the spike in cases. The difference between average sale prices after the spike in cases contains two types of information. First, it contains information that includes factors that do not vary with time. Second, it includes information that explains the difference in average sale prices caused by the rise in cases. To

extract the information that explains the effect of cases on average house sale prices, we can take the difference in house sale prices after the rise in cases and before the rise in house sale prices. This is because the difference between the counties before the rise in cases only contains information that explains the difference in average house sale prices from factors that do not vary with time. Therefore, the differences of these differences leave us with only the information that explains the change in average house prices that is explained by the rise in cases, which is the slope coefficient of the interaction term.

With this being said, I do not believe the assumptions of the difference-in-differences model holds, as zero conditional mean is violated by the omitted variable bias. A variable that was not included in this data set was the household income of the individuals who lived in the house when the house was sold, and therefore it could not be controlled for in this model. The issue being that household income would almost certainly correlate with the condition of the home. As a result, household income being omitted would cause omitted variable bias. One solution would be to omit the condition variable as well, but as stated earlier in this report, the condition of the home correlates with the size of the home, so this variable needs to be controlled for.

Considering this, I cannot conclude that the slope coefficient of the interaction term gives us the causal effect of leukemia cases on average home sale prices in Churchill County.

V. Conclusion

My model does give an association between leukemia cases in Churchill and average house sale prices but not a causal effect. To further study this causal effect, I recommend a new

data set be constructed that includes household income. A model that includes household income would more likely estimate the causal effect of cases on average house sale prices.

It is also important that we construct a new data set because we need the household income associated with each observed home sale for every observation. If we only used the average household income of Churchill residents for each year, our results would be inaccurate, and we would be no closer to determining the causal effect of leukemia cases on average house sale prices.

```
2
     cap log close
3
     log using Cesar_RM_Fall22_project, replace
4
5
     cap log close
     log using myproject, replace
6
8
     use "D:\1A.SchoolHW\2022 Fall\ECN 140\Emperical project\EPDATA F2022.dta", clear
9
10
     //installing package
     ssc install estout, replace
11
12
13
     //variables generated
     gen lnrealsales = log(realsales)
14
15
     gen sqft2 = sqft^2
     gen year2000 = year >= 2000
16
     gen y99 = year >= 1999
17
18
     gen casesPresent = 0
19
     replace casesPresent = 1 if cases > 0
20
     gen acres2 = acres^2
21
22
     sort year
23
24
     // Code for data summary
25
26
     // get a look at how the data is distributed
     histogram realsales, frequency title("Real House Sale Prices, before Log Transformation") // does
27
     appeare to be right skewed
28
     histogram lnrealsales, frequency title("Real House Sale Prices, after Log Transformation") xtitle(
     "Natural Log Value of Inflation-adjusted Sale Prices")
29
     //sactter plot of each variable, indiviually
30
     scatter Inrealsales sqft, title("Log House price vs. Home Square Footage") ytitle("Log of Real Sale
31
     Price of Home") mcolor(%25)
32
33
     scatter Inrealsales acres, title("Log House price vs. Plot Acerage") ytitle("Log of Real Sale Price
     of Home") mcolor(%25)
34
35
     scatter Inrealsales age, title("Log House price vs. Age of Home") ytitle("Log of Real Sale Price of
     Home") mcolor(%25)
36
     scatter Inrealsales condition, title("Log House price vs. Perceived condition of Home") ytitle("Log
37
     of Real Sale Price of Home") mcolor(%25)
38
     // get correlation coefficient of two variables
39
40
     correlate sqft condition
41
42
     //plot residuals to check for heteroskedasticity
43
     reg lnrealsales year2000##county acres sqft sqft2 age condition
     rvfplot, yline(0) title("Residuals vs. Fitted Values from Full Model") mcolor(%25)
44
45
46
     //
47
48
     // Code for Regression Analysis
49
50
     //full model
51
     reg lnrealsales year2000##county acres acres2 sqft sqft2 age condition, robust
52
53
     reg Inrealsales year##county acres sqft sqft2 age condition, robust
     margins, at(year=(1990(1)2002) county=(0(1)1))
54
55
     marginsplot, title("Average House Price per Year, by County") ytitle("Inflation-Adjusted Sale Price
     of House") xtitle("Year")
56
```

Emperical project code.do - Printed on 12/2/2022 9:08:45 PM

```
//create table for different models
58
     reg Inrealsales year2000##county
59
    est store m1
60
    reg lnrealsales year2000##county acres acres2 sqft sqft2 age condition
61
62
    est store m2
63
64
     reg Inrealsales year2000##county acres acres2 sqft sqft2 age condition, robust
65
    est store m3
66
67
68
    esttab m1 m2 m3 using "regTableDiD.rtf", se label ar2 replace ///
69
         title("Difference in Difference Models for effect of Cases on House Prices") ///
         mtitles("Simple DiD with no Controls" "DiD with Control Variables" "DiD with Robust SEs and
70
    Controls")
71
72
73
    log close
```

> e of Home") mcolor(%25)

```
county
         name: <unnamed>
         log: D:\1A.SchoolHW\2022 Fall\ECN 140\Emperical project\Cesar_RM_Fall22_project.smcl
    log type: smcl
    opened on: 2 Dec 2022, 21:17:45
 2 . use "D:\1A.SchoolHW\2022 Fall\ECN 140\Emperical project\EPDATA F2022.dta", clear
 3.
 4 . //installing package
 5 . ssc install estout, replace
  checking {\it estout} consistency and verifying not already installed...
   all files already exist and are up to date.
 7 . //variables generated
 8 . gen lnrealsales = log(realsales)
9 . gen sqft2 = sqft^2
10 . gen year2000 = year >= 2000
11 . gen y99 = year >= 1999
12 . gen casesPresent = 0
13 . replace casesPresent = 1 if cases > 0
   (1,582 real changes made)
14 . gen acres2 = acres^2
16 . sort year
18 . // Code for data summary
19 .
20 . // get a look at how the data is distributed
21 . histogram realsales, frequency title("Real House Sale Prices, before Log Transformation") // does
   > appeare to be right skewed
   (bin=40, start=2252.5337, width=22337.679)
22 . histogram lnrealsales, frequency title("Real House Sale Prices, after Log Transformation") xtitle(
   > "Natural Log Value of Inflation-adjusted Sale Prices")
   (bin=40, start=7.719811, width=.14964041)
24 . //sactter plot of each variable, indiviually
25 . scatter Inrealsales sqft, title("Log House price vs. Home Square Footage") ytitle("Log of Real Sal
  > e Price of Home") mcolor(%25)
```

27 . scatter Inrealsales acres, title("Log House price vs. Plot Acerage") ytitle("Log of Real Sale Pric

28 .

30 .

32

33 . // get correlation coefficient of two variables

34 . correlate sqft condition (obs=9,773)

	sqft	condit~n
sqft	1.0000	
condition	0.5251	1.0000

35 .

36 . //plot residuals to check for heteroskedasticity

37 . reg lnrealsales year2000##county acres sqft sqft2 age condition

Source	SS	df	MS		=	9,773
				F(8, 9764)	=	2094.10
Model	924.601583	8	115.575198	Prob > F	=	0.0000
Residual	538.883055	9,764	.055190809	R-squared	=	0.6318
 				Adj R-squared	=	0.6315
Total	1463.48464	9,772	.149763062	Root MSE	=	.23493

	,					
lnrealsales	Coefficient	Std. err.	t	P> t	[95% conf.	interval]
1.year2000	0222743	.0062275	-3.58	0.000	0344815	010067
county Churchill	.0833612	.0066713	12.50	0.000	.0702841	.0964382
year2000#county 1#Churchill	1210268	.0115758	-10.46	0.000	1437177	0983359
acres sqft sqft2 age condition _cons	.0046473 .0007923 -9.58e-08 0040411 .1882663 10.27468	.0003203 .0000244 6.33e-09 .0001656 .0065355	14.51 32.53 -15.14 -24.41 28.81 430.47	0.000 0.000 0.000 0.000 0.000	.0040196 .0007446 -1.08e-07 0043657 .1754554 10.22789	.0052751 .00084 -8.34e-08 0037166 .2010772 10.32147
	1					

38 . rvfplot, yline(0) title("Residuals vs. Fitted Values from Full Model") mcolor(%25)

39 . 40 . //

/11

42 . // Code for Regression Analysis

43 .

44 . //full model

45 . reg lnrealsales year2000##county acres acres2 sqft sqft2 age condition, robust

Linear regression

Number of obs = 9,773 F(9, 9763) = 1021.37 Prob > F = 0.0000 R-squared = 0.6409 Root MSE = .23202

-.0585781 -.0213101

-.0406669

11.63908

-.1140625

11.61571

lnrealsales	Coefficient	Robust std. err.	t	P> t	[95% conf.	interval]
1.year2000	0205192	.0053686	-3.82	0.000	0310427	0099958
county Churchill	.0840392	.0073315	11.46	0.000	.069668	.0984104
year2000#county 1#Churchill	1251008	.0117209	-10.67	0.000	1480761	1021254
acres	.0139477	.0017738	7.86	0.000	.0104707	.0174247
acres2	0000236	3.45e-06	-6.83	0.000	0000304	0000168
sqft	.0007962	.0000467	17.03	0.000	.0007045	.0008878
sqft2	-1.01e-07	1.33e-08	-7.60	0.000	-1.27e-07	-7.49e-08
age	0042133	.0002478	-17.01	0.000	004699	0037277
condition	.1928592	.0076735	25.13	0.000	.1778176	.2079008
_cons	10.26296	.0432453	237.32	0.000	10.17819	10.34773

⁴⁶

county Churchill

_cons

year2000#county 1#Churchill -.0399441

-.0773647

11.6274

Source	SS	df	MS	Number of obs	=	10,204 26.40
Model : Residual	12.1636567 1566.3638	_	4.05455225 .153565078	F(3, 10200) Prob > F R-squared Adj R-squared	= = =	0.0000 0.0077 0.0074
Total :	1578.52745	10,203	.15471209	Root MSE	=	.39187
lnrealsales	Coefficient	Std. er	r. t	P> t [95%	conf.	interval]
1.year2000	.0394579	.010135	5 3.89	0.000 .019	5903	.0593254

-4.20 0.000

-4.13

0.000

0.000

.0095062

.0187215

.0059601 1950.87

^{48 .} reg lnrealsales year2000##county

49 . est store m1

51 . reg lnrealsales year2000##county acres acres2 sqft sqft2 age condition

						F(9, 97	763)	=	1935.96
Model	9	937.932911	9	104	.214768	Prob >	,	=	0.0000
Residual		525.551727	9,763	.05	3830967	R-squar	red	=	0.6409
						Adj R-s	quared	=	0.6406
Total	:	1463.48464	9,772	.14	9763062	Root MS	SE	=	.23202
lnrealsale	25	Coefficient	Std. e	rr.	t	P> t	[95%	conf.	. interval]
1.year200	90	0205192	.00615	13	-3.34	0.001	032	5771	0084613
count Churchill	-	.0840392	.00658	87	12.76	0.000	.07	1124	.0969544
year2000#count 1#Churchill	-	1251008	.01143	52	-10.94	0.000	147	5161	1026854
acre	25	.0139477	.00067	03	20.81	0.000	.012	5337	.0152616
acres	2	0000236	1.50e-	06	-15.74	0.000	0000	3265	0000207
sqf	t	.0007962	.00002	41	33.10	0.000	.000	749	.0008433
sqft	:2	-1.01e-07	6.26e-	09	-16.13	0.000	-1.13	e-07	-8.86e-08
ag	ge	0042133	.00016	39	-25.71	0.000	004	5345	0038921
conditio	n	.1928592	.00646		29.85	0.000	.180		.2055242
_cor	ıs	10.26296	.02358	42	435.16	0.000	10.2	1673	10.30919

Source SS df MS Number of obs = 9,773

52 . est store m2

53 .

54 .
55 . reg lnrealsales year2000##county acres acres2 sqft sqft2 age condition, robust

Linear regression	Number of obs	=	9,773
	F(9, 9763)	=	1021.37
	Prob > F	=	0.0000
	R-squared	=	0.6409
	Root MSE	=	.23202

lnrealsales	Coefficient	Robust std. err.	t	P> t	[95% conf.	interval]
1.year2000	0205192	.0053686	-3.82	0.000	0310427	0099958
county Churchill	.0840392	.0073315	11.46	0.000	.069668	.0984104
year2000#county 1#Churchill	1251008	.0117209	-10.67	0.000	1480761	1021254
acres	.0139477	.0017738	7.86	0.000	.0104707	.0174247
acres2	0000236	3.45e-06	-6.83	0.000	0000304	0000168
sqft	.0007962	.0000467	17.03	0.000	.0007045	.0008878
sqft2	-1.01e-07	1.33e-08	-7.60	0.000	-1.27e-07	-7.49e-08
age	0042133	.0002478	-17.01	0.000	004699	0037277
condition	.1928592	.0076735	25.13	0.000	.1778176	.2079008
_cons	10.26296	.0432453	237.32	0.000	10.17819	10.34773