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Effect of Foreclosures on Nearby Property Values

Abstract

The effect of real estate foreclosures on nearby property values is well studied by economists. In fact, this effect has its own name, the contagion effect. With the recent financial crisis and the recession that followed it, it has become even more important to be able to accurately measure the contagion effect. Also, recent policies being proposed in Oregon for treatment of vacant foreclosed properties make this local research even more relevant. This study will use data of property transactions between 2008 and 2010 from the Lane County housing records. The aim of this study is to estimate the contagion effect in Lane County within this period. The effect will be measured on a census tract level using data from the U.S. Housing and Urban Development website.

Michael Kuhn – Faculty Advisor

Introduction

With the financial crisis in the recent past, Americans have experienced significant decreases in their home equity resulting from the nearby foreclosures. "This year alone, it says, foreclosures will cause an estimated 69.5 million nearby homes to suffer price declines averaging $7,200 per home. The loss in property value could total $500 billion." (Tedeschi, 2009). These estimates are for the year 2009, when this article was written. With such a high number of homes affected by the foreclosures in 2009, the issue of understanding and accurately measuring the relationship becomes even more important.

Leading up to the financial crisis, housing prices were increasing at a dangerously fast rate. This was a result of the banks reducing loan requirements for owning a home, causing a housing bubble. "Traditionally, lenders required that monthly payments on a house could be no more than 25 percent to 33 percent of the borrower's gross income. But in the boom mortgage years some brokers made loans with payments that took as much as 70 percent of the borrower's monthly income." (Dietz, 2009). It was these types of subprime loans that resulted in the millions of foreclosures. These foreclosures were different as well because so many of the families were middle class families that under previous loan requirements would not have been approved.

John P. Harding, professor at the University of Connecticut's Center for Real Estate and Urban Economic Studies explains this relationship in terms of the neglect the house and the property in the months leading up to the foreclosure. He states that "The worst time for immediate neighbors to sell their homes, refinance or cash out some of their home equity, is just before the bank takes title to the property, because that is the point of greatest neglect." (Tedeschi, 2009) Harding suggests that the neglect a house receives during the foreclosure process may be as impactful on housing prices as the foreclosures itself. The distinction that is

being made is that when a bank forecloses on a property it will then sell the property below what is market price, thus forcing nearby properties to lower their own prices. Harding offers that the drop in price may not be because of the competition but instead the neglect that a house receives during a foreclosure.

Legislators in Oregon have proposed a Good Neighbor Bill that if passed would give local governments the ability to secure a property or mow a lawn, while attached the costs to the property as a lien. The bill itself exemplifies how the contagion effect can matter for local government policy: taking care of vacant, foreclosed houses could mitigate the effect on the value of nearby properties. There are similar programs already established in Hillsboro, Oregon and there has also been an increase in spending by the city of Portland to hire a fulltime housing inspector to "intervene at properties that show up most frequently at complaints." (Njus, 2013) When it is the local government that is spending money to fix up these properties, economists naturally question the program's spending and ask "Is it cost effective?" Are the community members receiving more value from benefits of the program than the costs of the program? The aim of this research paper is to be able to help monetize these benefits within a local context and give an answer to this question.

Literature Review

The leading economic paper on this subject is *The Contagion Effect of Foreclosed Properties (2009)* by Harding, Rosenblatt, and Yao. This paper was written in response the financial crisis and the rapid increase in foreclosures it led to. The paper wanted to differentiate "whether the lower prices are the result of a general decline in neighborhood values or whether foreclosures reduce the prices of nearby non-distressed sales through a contagion effect"

(Harding Rosenblatt Yao, 1). They are able to estimate that a neighboring property that is in the foreclosure process can discount market property value up to 1% per nearby foreclosure. This effect decrease as the distance from the foreclosure increases. This paper also recognizes the competition effect on sales prices. When foreclosed properties are sold by the loan holder, they are commonly sold below the market price and thus have a competition effect on nearby properties values that is less tied to the distance away from the foreclosure.

In Ioannide's *Residential Neighborhood Effects* (2002), the relationship between social interactions and household maintenance decisions are explored. Ioannide was addressing the issues This paper is able to estimate the effect of social interactions within residential neighborhoods on maintenance decisions. This paper relates to the work I am doing because it explains how the neglect of one home in a neighborhood can discourage the other residents to maintain their own properties or communal property. Some of the effect that I am capturing in my research can be linked to residential maintenance attitudes when there are nearby foreclosures.

Another study *The External Costs of Foreclosure (2006)*, was run by Immergluck and Smith looking at the effect of foreclosures on nearby housing values in Chicago. Immergluck and Smith looked at the ten nearest neighbors to see the effect, while this paper separates them by census tracts. Immergluck and Smith estimated that each foreclosure resulted in a decline of 0.9 percent in value of a single-family home.

Methodology

Although other economists have studied the contagion effect in broad context, I want to look at the local effect within Lane County. To do so, this paper uses multiple data sources to

construct a mapping between home sales and census-tract level foreclosure statistics. The home sales data consists of all Lane County housing transactions from 1987 to 2012 (henceforth LCHR for Lane County Housing Records). The dataset has extensive characteristics on each house transaction. However this dataset did not indicate which sales were foreclosures.

To get around this, I am able to use census tract data from the Neighborhood Stabilization Program (henceforth NSP). The NSP data provides information on foreclosures, vacancy rates, mortgages, and other local economic indicators for each census tract in the years 2007 through 2010. Each of the NSP datasets are slightly different in terms of the statistics they provide for each census tract. The NSP dataset for the year 2008 provided the foreclosure rate as the estimated percent of mortgages to start foreclosure process or be seriously delinquent in the past two years. This was an issue because I want the foreclosure rate for the single year of 2008. I can calculate the actual rate of each census tract by taking the 2007 foreclosure rate and deriving the true foreclosure rate for 2008 using simple algebra. This is an example of the types of modifications that I had to make to the dataset, these modifications make reproducing this data a bit more complicated. After organizing the data so that it was uniform for all three years I combine the three NSP datasets into one.

Finally, I merge this data with the LCHR. I do this by taking the addresses from the housing records and submit them through a U.S. census geocoder, http://geocoding.geo.census.gov/geocoder. The geocoder gives back the census tract for each address. Addresses of home transactions are merged to their tract-level foreclosure statistics in this manner. I use the data analysis software, Stata for my statistical analysis of the constructed dataset.

Results

In Table 1, the first regression is a baseline regression that estimates the effect of a one percent increase in foreclosure rate on the sale price while holding only the time trend variable constant. We find that a one percent increase in the foreclosure rate correlates with an 11.13% decrease in the sales price within a census tract. The second regression was the same regression with a small group of housing characteristics added as controls. With the addition of the control variables the effect diminished to 7.45% decrease in sales price. The third regression added a large group of housing characteristics as controls and further decreased the effect to a 6.55% decrease. The fourth regression in Table 1 looked at the fixed effects with time trend as a control as well. With the addition of dummy variables for each census tract to create the fixed effect, we found that the estimated effect of 2.41% decrease was statistically significant at the one percent significance level. This regression is important it shows that effect of a one percent increase in foreclosures rate still had a statistically significant negative effect even while holding all the census tract variation constant. The fifth and sixth regressions look at the fixed effects with the addition of a small group and a large group, respectively, of housing characteristics controls. We see that the effect shrinks to 0.7% decrease with the small group of controls and a 1.3% increase with the large group of controls.

Table 2 is the same set of regressions ran in Table 1 but using the effect of the previous year's foreclosure rate on this year's sale price. The previous year's foreclosure rate is important because it will better explain the competition effect. There is a delay between when a house is foreclosed and when it is eventually sold by the loaner, commonly at a lower than market price. The sale theoretically results it a more price competitive market, and will eventually result in lower prices for the whole neighborhood. Also if we assume that the contagion effect comes from negligence of the foreclosed property, this effect may take time for the property to become

neglected and an eye sore for the neighborhood. The first regression in the table, which is a baseline regression with the time trend as a control shows that the estimated effect was a 15.34% decrease in this year's sales price resulting from a one percent increase in last year's foreclosure rate. Although this is only a baseline regression, it is still worth noting that the effect is larger than when the same regression without lagging the foreclosure rate. The fourth regression, a fixed effects regression with the time trend as a control, estimated the effect as 0.93% increase in sales price, with a large standard error. In conjunction with the results from Table 1, this indicates that when fixed effects and full set of controls are used simultaneously, little meaningful variation remains.

Table 3 focuses on the vacancy rate and what impact it has on the contagion effect. I used the vacancy rate to incorporate the effect of neglect into the regression. With policies like the Oregon Good Neighbor Bill, it is important to understand how these vacant homes can decrease the surrounding property values. Being able to estimate the effect will help policy makers and local governments justify spending money to fix up vacant homes. There is a potential net positive if local governments can spend less money fixing up the homes than the increase in value from the surrounding homes. The first regression was a baseline regression with the vacancy rate and the foreclosure rate with the time trend as the control. The foreclosure rate coefficient indicates 11.7% decrease and the vacancy rate coefficient indicates a 6.8% decrease with respect to a 1% increase in each respective rate. The foreclosure rate did not change much with the addition of the vacancy variable compared to the first regression in Table 1. The vacancy rate does capture a large amount of variance and is statistically significant at the 10% significance level. The second regression in this table adds an interaction term between the vacancy rate and the foreclosure rate. This interaction term is in the table under VFrate. The

estimate for the VFrate variable is a 0.6% increase in the sales price when increasing the foreclosure and the vacancy rate together. This estimate is significant at the 5% significance level. This very small increase tells us that the effect of increasing the foreclosure and vacancy rate together is smaller than summing the effect of increasing the foreclosure and vacancy rate separately. The third regression is a fixed effects regression with the vacancy rate and the foreclosure rate. The estimate on the vacancy rate is 0.8% increase. This very diminished effect is common for the vacancy rate for all of the regressions with a large amount of control variables. The effect becomes ambiguous and it becomes clearer that the effect of vacancy rate on the nearby property sales price is not as significant as the foreclosure rate.

TABLE 1

	(1)	(2)	(3)	(4)Fixed Effect	(5)Fixed Effect	(6)Fixed Effect
VARIABLES	ln_price	ln_price	ln_price	ln_price	ln_price	ln_price
f_rate	-0.1113***	-0.0745***	-0.0655***	-0.0241**	-0.0073	0.0128
	(0.0110)	(0.0097)	(0.0073)	(0.0100)	(0.0077)	(0.0151)
y2	0.1466	-0.0062	-0.0343	0.0498**	-0.0608***	-0.0907***
	(0.1088)	(0.0327)	(0.0445)	(0.0211)	(0.0162)	(0.0315)
y3	0.2568***	0.1473***	0.1180***	-0.0470	-0.0834***	-0.1685***
	(0.0364)	(0.0307)	(0.0408)	(0.0392)	(0.0301)	(0.0631)
y4	0.2288***	0.0882**	0.1079***	-0.0230	-0.1054***	-0.1830***
	(0.0349)	(0.0405)	(0.0281)	(0.0388)	(0.0297)	(0.0627)
total_acres		0.0057	-0.1005		0.0215	-0.0624
		(0.0938)	(0.1197)		(0.0266)	(0.0743)
total_finish_sq ft		0.0004***	0.0003***		0.0003***	0.0003***
		(0.0000)	(0.0000)		(0.0000)	(0.0000)
no_bedrooms			-0.0017			-0.0066
			(0.0065)			(0.0090)
no_fullbaths			0.0429			0.0415
			(0.0271)			(0.0270)
no_halfbaths			0.0359*			0.0408

			(0.0206)			(0.0272)
attached_garsf			0.0000			0.0001
			(0.0001)			(0.0001)
Grade			-0.0008			0.0003
			(0.0025)			(0.0034)
driveway_sf			0.0000			0.0000
			(0.0000)			(0.0000)
Fireplace			-0.0110			-0.0166
			(0.0259)			(0.0251)
heat_forcedair			-0.0209			-0.0279
			(0.0343)			(0.0310)
heat_hpump			-0.0589			-0.0619
			(0.0408)			(0.0382)
heat_base			-0.1515*			-0.1584***
			(0.0813)			(0.0486)
roof_gable			-0.0153			0.0052
			(0.0347)			(0.0288)
roof_shingle			-0.0288			-0.0238
			(0.0301)			(0.0393)
roof_cedar_wood			0.0606**			0.0443
Constant	12.6378***	11.9709***	11.9965***	12.5630***	11.9199***	12.1581***
	(0.0459)	(0.0655)	(0.1044)	(0.2170)	(0.1803)	(0.5454)
Observations	6,412	6,217	2,354	6,412	6,217	2,354
R-squared	0.075	0.300	0.226	0.182	0.338	0.253

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

1. Baseline
2. Baseline small control
3. Baseline large control
4. FE
5. FE small control
6. FE large control

TABLE 2

	(1)	(2)	(3)	(4)Fixed Effect	(5)Fixed Effect	(6)Fixed Effect
VARIABLES	ln_price	ln_price	ln_price	ln_price	ln_price	ln_price

rate_lag	-0.1534***	-0.1010***	-0.0423	0.0093	0.0398	0.0786
	(0.0343)	(0.0225)	(0.0385)	(0.0516)	(0.0468)	(0.0926)
y2	-0.3239**	-0.2551**	-0.0367	0.1209	0.1399	0.1441
	(0.1472)	(0.1181)	(0.1981)	(0.1900)	(0.1723)	(0.3561)
y3	-0.2789*	-0.1739	-0.0523	0.0370	0.0882	0.3225
	(0.1470)	(0.1204)	(0.1763)	(0.1539)	(0.1393)	(0.3015)
total_acres		0.2505	0.0745		0.2801*	0.2146
		(0.1856)	(0.3278)		(0.1558)	(0.3319)
total_finish_sqft		0.0003***	0.0002		0.0002***	0.0000
		(0.0001)	(0.0001)		(0.0001)	(0.0002)
no_bedrooms			0.0319			0.0791
			(0.1010)			(0.1025)
no_fullbaths			0.0838			0.0704
			(0.1123)			(0.1239)
no_halfbaths			0.1951*			0.1962
			(0.1154)			(0.1254)
attached_garsf			0.0002			-0.0002
			(0.0004)			(0.0005)
Grade			0.0298**			0.0370**
			(0.0142)			(0.0145)
driveway_sf			0.0001			0.0002
			(0.0002)			(0.0002)
Fireplace			0.0249			-0.0257
			(0.1415)			(0.1740)
heat_forcedair			-0.0769			-0.0184
			(0.1346)			(0.1577)
heat_hpump			-0.0846			-0.0907
			(0.1575)			(0.2012)
heat_base			-0.0210			0.3778
			(0.1992)			(0.2350)
roof_gable			-0.1938			-0.1008
			(0.1370)			(0.1471)
roof_shingle			0.0827			-0.1984
			(0.1968)			(0.2731)
roof_cedar_wood			0.2168			-0.3463
			(0.2464)			(0.3149)
Constant	13.1033***	12.2486***	11.6479***	12.1942***	12.0592***	11.0378***
	(0.2304)	(0.2096)	(0.4864)	(0.4914)	(0.3716)	(0.5971)
Observations	152	149	69	152	149	69
R-squared	0.161	0.489	0.629	0.581	0.678	0.856

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

1. Baseline
2. Baseline small control

3. Baseline large control
4. FE
5. FE small control
6. FE large control

TABLE 3

VARIABLES	(1) ln_price	(2) ln_price	(3)Fixed Effect ln_price	(4)Fixed Effect ln_price	(5) ln_price	(6) ln_price
f_rate	-0.1165***	-0.1264***	-0.0243**	-0.0515***	-0.0640***	-0.0569***
	(0.0101)	(0.0213)	(0.0100)	(0.0133)	(0.0080)	(0.0129)
vrate	-0.0683	-0.0900	0.0080	-0.0365*	0.0258	0.0429
	(0.0605)	(0.0933)	(0.0142)	(0.0202)	(0.0167)	(0.0296)
y2	0.3192	0.3437	0.0298	0.0744*	-0.0946*	-0.1137**
	(0.2518)	(0.2874)	(0.0413)	(0.0437)	(0.0493)	(0.0564)
y3	0.4380***	0.4513**	-0.0656	-0.0350	0.0530	0.0412
	(0.1590)	(0.1776)	(0.0513)	(0.0522)	(0.0599)	(0.0623)
y4	0.3457***	0.3670**	-0.0334	0.0220	0.0678	0.0499
	(0.1063)	(0.1351)	(0.0430)	(0.0466)	(0.0496)	(0.0558)
VFrate		0.0062		0.0144***		-0.0043
		(0.0106)		(0.0046)		(0.0062)
total_acres					-0.1017	-0.1004
					(0.0725)	(0.0726)
total_finish_sqft					0.0003***	0.0003***
					(0.0000)	(0.0000)
no_bedrooms					-0.0016	-0.0016
					(0.0083)	(0.0083)
no_fullbaths					0.0458*	0.0457*
					(0.0265)	(0.0265)
no_halfbaths					0.0375	0.0379
					(0.0269)	(0.0269)
attached_garsf					0.0001	0.0001
					(0.0001)	(0.0001)
grade					-0.0008	-0.0007
					(0.0034)	(0.0034)
driveway_sf					0.0000	0.0000
					(0.0000)	(0.0000)
fireplace					-0.0117	-0.0117
					(0.0247)	(0.0247)
heat_forcedair					-0.0219	-0.0211
					(0.0304)	(0.0304)

heat_hpump					-0.0599	-0.0609
					(0.0381)	(0.0382)
heat_base					-0.1540***	-0.1543***
					(0.0476)	(0.0476)
roof_gable					-0.0127	-0.0133
					(0.0284)	(0.0284)
roof_shingle					-0.0228	-0.0235
					(0.0384)	(0.0384)
roof_cedar_wood					0.0648	0.0647
					(0.0495)	(0.0495)
Constant	12.6461***	12.6623***	12.5720***	12.5936***	11.9814***	11.9702***
	(0.0425)	(0.0495)	(0.2176)	(0.2176)	(0.0741)	(0.0758)
Observations	6,412	6,412	6,412	6,412	2,354	2,354
R-squared	0.081	0.081	0.182	0.183	0.227	0.227

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

1. Baseline + vacancy rate
2. Baseline + vacancy rate + interaction term
3. FE + vacancy rate
4. FE + vacancy rate + interaction term
5. Vacancy Rate + large control
6. Vacancy Rate + interaction term + large control

Conclusion

One of the important figures to know that is not in the tables is what is the total cost of a single foreclosure on the nearby properties. This is important to know so that policies similar to the Oregon's Good Neighbor Bill can be cost effective. In order to calculate this take a conservative estimate of the effect of one percent increase in foreclosures will have on the housing prices, I use 2.4%. Then multiple the effect by the average house price, in Lane County in 2010 this was $349,645.60. This yields a decrease of $8391.49 per house in the tract. Then divide 8391.49 by 1% of the average number of houses in a tract, which is 1% of 2089.3. This will yield $401.64. Take this value and multiply by the average number of homes sold in a tract

in a year, which is 72.71. This gives the cost per foreclosure of $29,203.33 in a tract. This calculation can be used to motivate policies that support the maintenance of foreclosures.

The data shows that even in a fixed effect regression, the effect of foreclosures on nearby housing prices was still significant and estimated at a decrease of 2.4%. Even though the value of the estimate decrease when using fixed effects compared to the baseline regression, this is expected with the addition of the census tracts as controls. When using the vacancy rate variable, the estimate of its effect was less than expected. With the addition of more control variables the effect became more ambiguous and the effect was not significant at the 5% significance level for the first two baseline regressions. The data shows that the effect of the vacancy rate and the effect of the foreclosure rate are stronger together than the effect of them cumulatively, as expressed through the interaction term. The lagged foreclosure rate was estimated to have more of an effect than the current year's foreclosure rate for the first the first three baseline regression. This can be explained by the delay it takes the market to react to a foreclosure and also explained by the time it takes for a foreclosed home to become neglected.

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