FORECLOSURE EFFECTS ON NEIGHBORHOOD PROPERTY VALUES IN DURHAM COUNTY

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Introduction

Foreclosures have negative significant spillover effects on neighborhood property values in Durham. There is a distance effect that can be observed using a modified hedonic pricing model. Regression results from the model indicate that Durham home values can decrease by as much as 26% if a foreclosure is nearby. The effect is strongest within the first 0.2 km of a foreclosure and declines as distance away from a foreclosure increases. The distance effect is significant all the way out to 1.8 km away. Another modified hedonic model attempted to find a time effect of foreclosures but found no significant link between time since foreclosure and property value changes in Durham. The data used are very recent, from 2009 and 2010, in order to see if previously researched foreclosure effects, such as those of Lin et al. (2009), are stronger today due to the aftermath of the subprime mortgage meltdown.

Background

Subprime Mortgage Crisis Influences

The subprime mortgage crisis of 2007 led to the financial crisis at hand today. Its ramifications reach far around the globe and have caused a major recession – the likes of which have not been seen since the Great Depression. Homeowners are particularly troubled in this mess, their property value having fallen significantly, and available credit for refinancing having dried up. Many people are forced to default on their mortgages and enter foreclosure, a fact that I saw firsthand in my Durham overview assignment. I was curious to see how these foreclosures affect surrounding neighborhoods, and overall how they will affect a city like Durham in the next couple of years. I selected an outstanding paper by Lin et al. to learn more about the specifics of the subprime induced foreclosure crisis. I wanted to see existing data on how foreclosures affect the property values of homes nearby.

Lin et al. worked with mortgage data from the Chicago PMSA (Primary Metropolitan Statistical Area) from 1990-2006 in their study of spillover effects of foreclosures on neighborhood property values. Data on non-foreclosed home sales were gathered for two specific years – 2003 and 2006 – in order to account for the intensity of spillover effects during boom housing cycles like in 2003 and bust housing cycles like 2006. They used very large sample sizes, with 11,000 observations for the 2003 group and 14,427 for the 2006 group. The authors note that although Chicago PMSA prime loans performed at the national average, their subprime loans were consistently more delinquent than the average subprime loans around the country.

Lin et al. use four regression models to adjust for time and distance effects. Model 1 controls for the time effect only, Model 2 controls for the distance effect only, and Model 3 controls for the interaction between time and distance. Running the regression, the authors found that Model 3 best estimates the sales price change of a home near a foreclosure, accounting for 69% of the variance in sales price (Model 1 explained 48% and Model 2 explained 57% of the variance). An additional model, Model 4, was constructed to account for potential selection bias in Model 3. This model uses a two-stage Heckman method to correct for possible selection bias and improves the accuracy of the model to account for 73% of the sales price variance. They found that the distance effect is strongest within 0.9km (or 10 blocks) of foreclosure. The most drastic price change occurs if a foreclosure is within 0.1km, where the average home declines 9.7% in value. The distance effect is statistically significant at 5% within a 0.9km radius. The effect weakens, however, if a foreclosure is farther than 0.9km away, resulting in a loss of statistical significance beyond that point.

Effects on Durham

The negative consequences of foreclosures are not limited to defaulting homeowners. Foreclosed properties have a significant effect on surrounding neighborhoods, often leading to vandalism, disinvestment, and other undesirable results. As foreclosures continue during today's subprime mortgage fallout, it is important that Durham's government and policy-makers be properly informed about the impact that these foreclosures have on Durham neighborhoods. One major concern for lawmakers is whether the presence of a foreclosed home will decrease the value of surrounding homes. This paper looks to validate that hypothesis and to quantify the decrease in property values caused by nearby foreclosures. I suspect that the devaluation depends on two factors: the distance from foreclosures and the time discrepancy between the home-sale date and the entrance of a foreclosure. The devaluation effects should diminish as the distance from foreclosure increases and as the time discrepancy between home-sale and foreclosure increases.

Durham's foreclosure rate is much less than the national average, with 0.06% of all housing units foreclosed compared to 0.28% nationally (RealtyTrac.com). While this suggests that Durham is doing relatively better than the rest of the nation, the rate of houses being foreclosed in nearly double that of the national average. One out of every 1,649 housing units in Durham received a foreclosure filing in March 2010, which is roughly 50% above the current national average[1]. Also, according to RealtyTrac.com the foreclosure trend has been rising over the last six months.

Almost all of Durham's foreclosures are bank owned. They are slow to clear the market, with only 256 being sold in the past 12 months – which is small compared to the 798 outstanding foreclosures today. The average foreclosed home sells for $103,443 in Durham, which is 45% less than the Durham's average homesale value (RealtyTrac.com)[2].

Data and Model

The foreclosure data were collected from RealtyTrac.com's foreclosure database through signing up for a 7-day free trial. The earliest collected foreclosure date was from January 25, 2008, which was the latest record on the website that can be seen with the free trial. In total, I collected 643 foreclosures within Durham County. The homesale data were collected from Zillow.com, which I used because it had the largest publicly available listing of recently sold homes. As of April 24, 2010 (the date of data collection), Zillow.com reported 500 recent property sales on its site starting at March 11, 2010 and going back to June 2009.

I cleaned up the results of the 643 foreclosures and 500 homesales in Excel and then imported them into ArcMap for geolocation. Using a 70% confidence threshold, I matched 88% of RealtyTrac's foreclosures into ArcMap, resulting in 567 usable foreclosures. Zillow's homesales were geolocated with also a 70% threshold and matched 84% of the addresses, leaving 420 usable for analysis. These addresses were later subdivided into "buckets" based on their distances from one another and their time discrepancy as described in the Models (Figure 1).

[1] According to the March 2010 Foreclosure Rate Heat Map from RealtyTrac. http://www.realtytrac.com/trendcenter/default.aspx?address=Durham%20county%2C%20NC&parsed=1&cn=durham county&stc=nc

[2] Granted, the average foreclosed home is likely of lower quality than the average non-foreclosed home, so this probably attributes to some of the 45% difference in price.

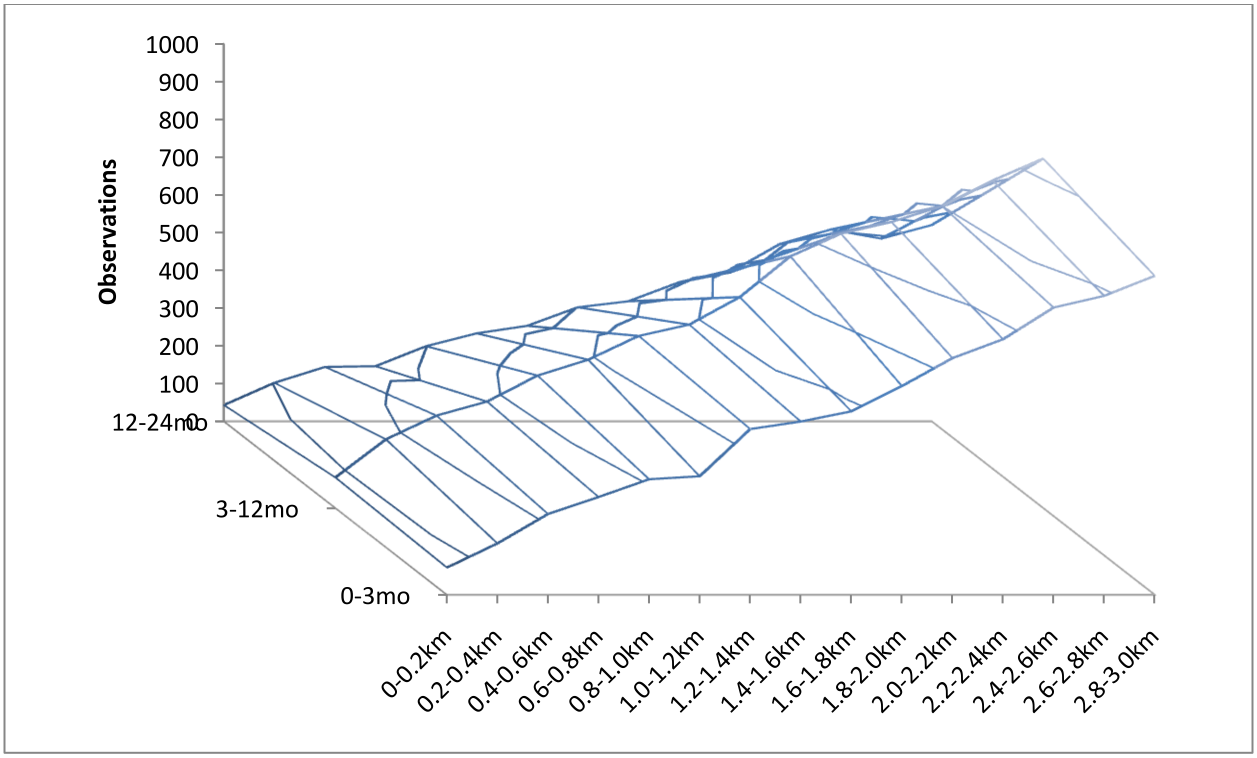

Figure 1: A visual representation of the number of observations collected for each time-distance interval.

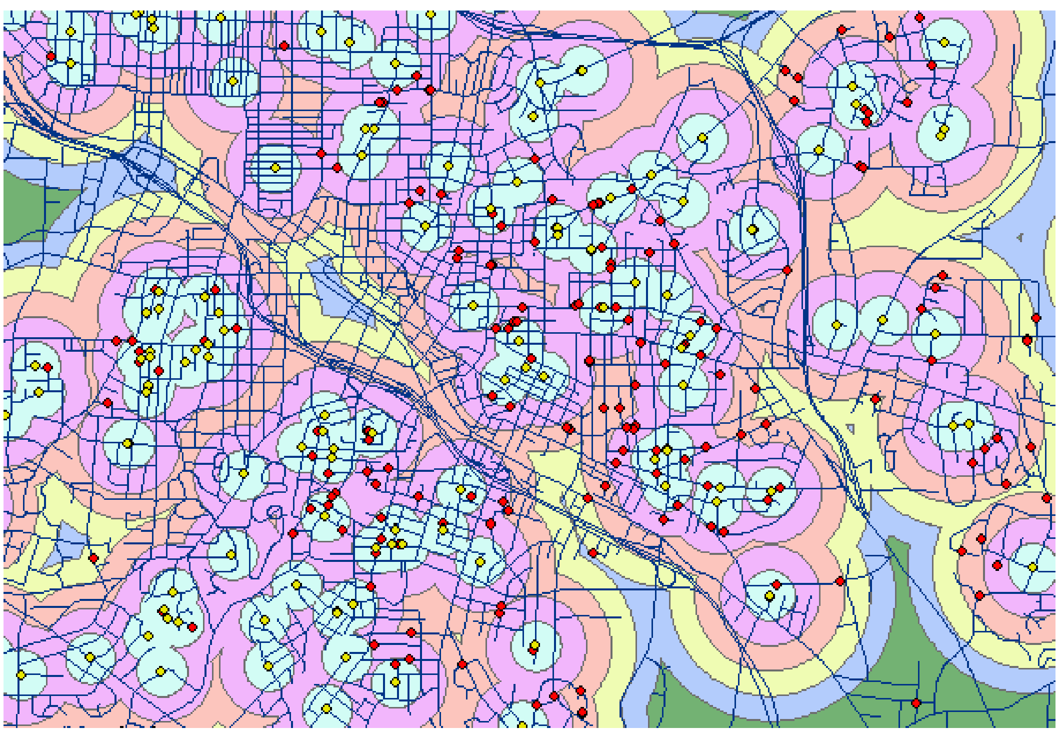

Figure 2: An area of downtown Durham showing some of the distance intervals around homesales (yellow dots). Foreclosures (red) are lumped into these intervals for analysis. The colored intervals are: light blue

(0.2km), purple (0.2-0.4km), magenta (0.4-0.6km), beige (0.6-0.8km), and blue (0.8-1km). Generated in ArcMap using *Multiple Ring Buffer* function.

Model

I develop my models from Lin et al.'s 2009 paper on foreclosure spillover effects in Chicago. They used a modified hedonic pricing model with housing characteristics such as square feet, lot size, number of bathrooms, and age of the house. Then they added in their unique foreclosure component to assess how a nearby and recent foreclosure affects pricing[3].

To assess a foreclosure's impact, I constructed four models: a simple OLS model, a distance effect model, a time effect model, and a time-distance interaction model, based on those of Lin et al. The differences lie in the number of distance intervals, the number of time intervals, and the omission of a County and Quarter dummy variables. I did not include a County dummy because unlike Lin et al.'s Chicago Metropolitan area study, all of my data were from Durham county. I left out a Quarter dummy variable because my dataset was restricted to very recent homesales that occurred almost exclusively in winter of 2009-2010[4].

Model A: Simple OLS

The basis of all four models is derived from Model A, which looks at the foreclosures within a time-distance interval. I chose 15 distance intervals ranging from 0-0.2km to 2.8-3.0km with increasing increments of 0.2km. I chose this measurement size because it was the minimum range in which I could derive enough observations to yield statistical significance. Also, I left out foreclosures outside of 3km of a homesale because Lin et al. found that the spillover effect at such a distance is negligible and insignificant. I also left out foreclosures that occurred exactly 0 km away from a homesale because, assuming the geolocation is accurate, this indicates they are the same house.

I chose three time intervals for my analysis: 0 – 3 months, 3 – 12 months, and 12 – 24 months between a homesale and the start of a foreclosure. I only bucketed foreclosures that occurred *before* a homesale, because otherwise there would be no foreclosure effect. The intervals were large and

[3] This foreclosure component is derived in Appendix II and is based on Lin et al. (2009).
[4] To be accurate, there were about 20 data observations where the sale data were slightly before of winter 2009. However, because they were miniscule compared to my 25,000 other observations, I chose not to include a quarter dummy.

uneven so that I could obtain roughly the same number of observations in each bucket. I could not pick narrower ranges for risk of losing statistical significance due to low sample sizes (see Figure 1).

Combined, the 15 distance intervals and 3 time intervals produced 45 distance-time buckets which I used as regressors in Model A (Eqn. 1). For example, $d_1 t_1$ is the time-distance interval of 0-3 months, 0-0.2 km away.

$$Lnprice = \beta_0 + \beta_1 * Sqft + \beta_2 * Lot + \beta_3 * Bath + \beta_4 * Age + \beta_5 * Age^2 + \beta_6 * Zip + \sum_{d=1,t=1}^{d=15,t=3} \beta_{d,t} * Foreclosures_{d,t} + \varepsilon \quad (1)$$

To prevent multicollinearity, the last time-distance interval, $d_{15}t_3$, was omitted from the regression.

Model B: Distance Effect

A second model (Eqn. 2) looks at solely the distance effect of a foreclosure on a neighboring property. The same 15 distance intervals from Model A are used here as regressors.

$$Lnprice = \beta_0 + \beta_1 * Sqft + \beta_2 * Lot + \beta_3 * Bath + \beta_4 * Age + \beta_5 * Age^2 + \beta_6 * Zip + \sum_{d=1}^{d=15} \beta_d * Foreclosures_d + \varepsilon \quad (2)$$

To avoid multicollinearity, the last distance interval, d_{15}(foreclosures within 2.8-3.0km), was left out of the regression.

Model C: Time Effect

A third model (Eqn. 3) was constructed to measure solely the time effect a foreclosure has on a nearby property. The three intervals were again 0 – 3 months, 3 – 12 months, and 12 – 24 months.

$$Lnprice = \beta_0 + \beta_1 * Sqft + \beta_2 * Lot + \beta_3 * Bath + \beta_4 * Age + \beta_5 * Age^2 + \beta_6 * Zip + \sum_{t=1}^{t=3} \beta_t * Foreclosures_t + \varepsilon \quad (3)$$

Like above, I left out the third time interval, t_3 (foreclosures occurring between 12-24 months before the homesale), to avoid multicollinearity.

Model D: Time and Distance combined

The fourth and last model (Eqn. 4) looked at the combination of time and distance effects of foreclosures on neighboring property values. It is constructed by adding together the basic hedonic model with the foreclosure components of Model B and Model C.

$$Lnprice = \beta_0 + \beta_1 * Sqft + \beta_2 * Lot + \beta_3 * Bath + \beta_4 * Age + \beta_5 * Age^2 + \beta_6 * Zip + \sum_{t=1}^{t=3} \beta_t * Foreclosures_t + \sum_{d=1}^{d=15} \beta_d * Foreclosures_d + \varepsilon \quad (4)$$

Again, the final observations, t_3 and d_{15}, were omitted to avoid multicollinearity.

I used the log of sale price like Lin et al. in order avoid heteroskedasticity. However, I surprisingly got slightly higher R^2 values with a linear sale price dependent variable than with the logged one. Nevertheless, I stuck with the log-linear model for comparison.

<u>Results and Interpretations</u>

I ran multivariate regressions of the four models in Stata and recorded their results in summary tables. The results showed a significant trend of foreclosures depressing nearby property values that was strongest at short distances. The effect diminished as distance from foreclosure grew and lost statistical significance. However, I did not find a significant pattern relating to time since foreclosure.

OLS (Model A) Regression Results

The standard OLS regression confirmed a strong fit to modeling housing prices near foreclosures with a R^2 value of 0.325 (Figure 4). The familiar hedonic variables used – square feet of house, lot size, number of baths, age of house, age squared of house, and zip code – were all significant at the 99% level. The square footage and lot size beta coefficients were both nearly zero, which is alarming at first glance. However, when considering that they are both are reported in feet, this result is not surprising because a one foot increase in home size will not have a measurable impact on a home price. A 100 sq foot increase, however, will have an impact, and it does increase home value by 6.9% according to Model A. The negative result for baths is puzzling, as an increase in baths leads to a 4.2% decrease in home value, but perhaps this finding will change if more hedonic characteristics are accounted for (such as Beds). According to the model, every additional year of age to a house decreases the sale price by 0.66% and does so at an increasing rate, as indicated by the negative coefficient of the age^2 variable. Lastly, being in the same zipcode as a foreclosure increases home values by 0.50%, which is interesting yet small and could disappear if the model were strengthened by added regressors.

As for the foreclosure variables, only about one-third of the time-distance intervals were statistically significant. This is likely due to lower sample sizes when breaking data up into small chunks and also because of the insignificant time effect found. The statistical significance appears to be randomly distributed across the time intervals, except that there are fewer significant distances at t_3. The lack of significance also appears randomly distributed across distances, and only buckets at intervals 1 (0-0.2km) and 12 (2.2-2.4km) are significant across all time periods.

Nonetheless, the trend is precise for all three time ranges – indicating that foreclosures have a strong negative effect on property values when nearby. After around 1km (5d on Figure 4), the effect begins to wane. The beginning observation for the 12-24 month line of Figure 3 is interesting and statistically significant – a foreclosure within 0.2 km that went on the market 1-2 years ago causes a 41.2% decrease in housing value!

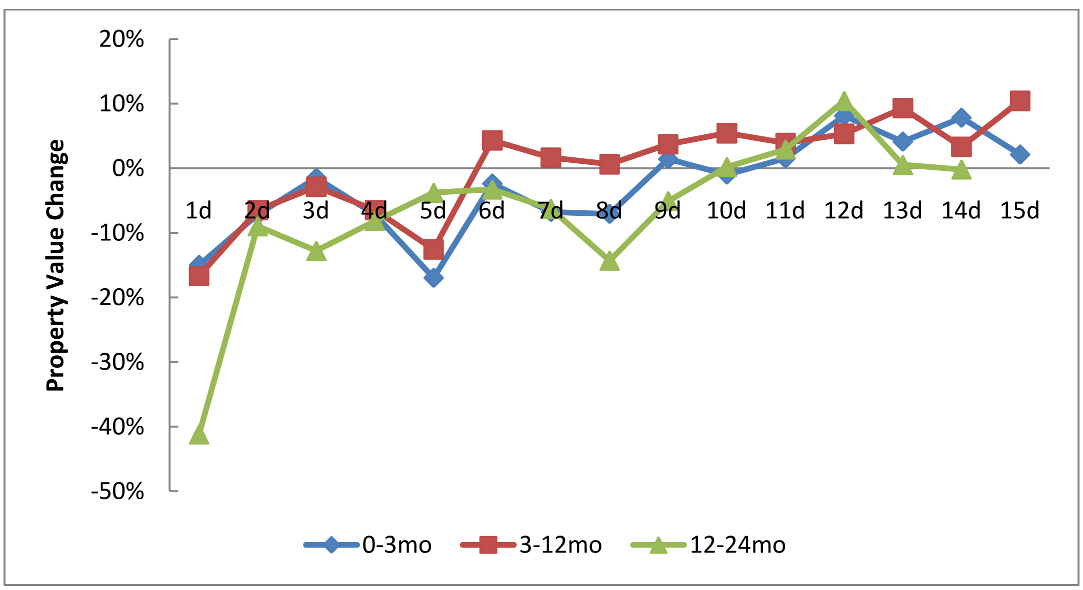

Figure 3: Model A's estimates of foreclosures effects based on distances and time since foreclosure. However, only 1/3 of these time-distance observations were statistically significant.

Source	SS	df	MS		
Model	6347.7175	50	126.95435	Number of obs =	24676
Residual	13190.5858	24625	.535658308	F(50, 24625) =	237.01
Total	19538.3033	24675	.791825869	Prob > F =	0.0000
				R-squared =	0.3249
				Adj R-squared =	0.3235
				Root MSE =	.73189

lnprice	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
sqft_1	.0006882	.0000106	65.13	0.000	.0006675	.000709
lot	2.89e-10	6.65e-11	4.35	0.000	1.59e-10	4.19e-10
baths	-.0417424	.0094946	-4.40	0.000	-.0603524	-.0231323
age	-.0065508	.0005933	-11.04	0.000	-.0077136	-.0053879
age_2	-.0000188	5.46e-06	-3.44	0.001	-.0000295	-8.09e-06
zip	.0049827	.0005653	8.81	0.000	.0038747	.0060907
d1t1	-.1497411	.0873192	-1.71	0.086	-.320892	.0214099
d1t2	-.1669897	.0861323	-1.94	0.053	-.3358142	.0018347
d1t3	-.4120342	.1146602	-3.59	0.000	-.6367752	-.1872932
d2t1	-.0720748	.0647999	-1.11	0.266	-.1990866	.054937
d2t2	-.065246	.0558875	-1.17	0.243	-.1747888	.0442969
d2t3	-.0897322	.0748687	-1.20	0.231	-.2364794	.057015
d3t1	-.014939	.0521401	-0.29	0.774	-.1171368	.0872588
d3t2	-.0289366	.0484782	-0.60	0.551	-.1239569	.0660836
d3t3	-.1281473	.0627158	-2.04	0.041	-.2510741	-.0052205
d4t1	-.0722988	.0466053	-1.55	0.121	-.1636479	.0190503
d4t2	-.0654432	.0449639	-1.46	0.146	-.1535752	.0226887
d4t3	-.0820062	.0618839	-1.33	0.185	-.2033024	.03929
d5t1	-.1703227	.0436926	-3.90	0.000	-.2559628	-.0846826
d5t2	-.1263172	.0411377	-3.07	0.002	-.2069496	-.0456848
d5t3	-.0377	.053711	-0.70	0.483	-.1429769	.0675769
d6t1	-.0241023	.0429099	-0.56	0.574	-.1082084	.0600037
d6t2	.0433715	.0389235	1.11	0.265	-.032921	.1196639
d6t3	-.0332131	.0497135	-0.67	0.504	-.1306545	.0642284
d7t1	-.0683858	.0367201	-1.86	0.063	-.1403595	.0035879
d7t2	.0164834	.0361328	0.46	0.648	-.0543392	.0873059
d7t3	-.0626272	.0482681	-1.30	0.194	-.1572357	.0319813
d8t1	-.0714223	.0360958	-1.98	0.048	-.1421722	-.0006725
d8t2	.0058224	.0353698	0.16	0.869	-.0635046	.0751493
d8t3	-.1430086	.0447923	-3.19	0.001	-.2308042	-.055213
d9t1	.0143636	.0351366	0.41	0.683	-.0545062	.0832335
d9t2	.0370424	.0330955	1.12	0.263	-.0278268	.1019116
d9t3	-.0507619	.0431307	-1.18	0.239	-.1353006	.0337769
d10t1	-.0097115	.0328637	-0.30	0.768	-.0741263	.0547033
d10t2	.0539604	.030201	1.79	0.074	-.0052355	.1131562
d10t3	.0015248	.0402961	0.04	0.970	-.0774579	.0805075
d11t1	.014833	.031149	0.48	0.634	-.0462209	.0758868
d11t2	.0391501	.0290137	1.35	0.177	-.0177186	.0960188
d11t3	.0294822	.03868	0.76	0.446	-.0463329	.1052973
d12t1	.0809034	.0302482	2.67	0.007	.021615	.1401917
d12t2	.0528558	.0285752	1.85	0.064	-.0031534	.108865
d12t3	.1040634	.0358132	2.91	0.004	.0338675	.1742594
d13t1	.0405328	.0286449	1.42	0.157	-.0156129	.0966784
d13t2	.0926999	.0278296	3.33	0.001	.0381523	.1472475
d13t3	.0049276	.0344094	0.14	0.886	-.0625168	.0723721
d14t1	.0779667	.0282213	2.76	0.006	.0226512	.1332822
d14t2	.0331099	.0268062	1.24	0.217	-.0194318	.0856516
d14t3	-.0016679	.0352067	-0.05	0.962	-.0706752	.0673395
d15t1	.0213944	.0273513	0.78	0.434	-.0322158	.0750047
d15t2	.104026	.0261598	3.98	0.000	.0527511	.1553008
_cons	-127.391	15.66135	-8.13	0.000	-158.0882	-96.69379

Figure 4: Results for the OLS regression (Model A). Values are significant to 5 digits.

Distance Effect (Model B) Results

The regression results of the distance effect model, Model B, show that there is a significant trend between homesale prices and distances away from foreclosures. Foreclosures within 0.2km of a home reduce its homesale value by 26.0% with 99% confidence. The spillover magnitude drops sharply in the subsequent distance ranges, with a 10.8% drop between 0.2 km and 0.4 km and 11.8% drop between 0.4 km and 0.6 km at 99% confidence (Figure 6). The property values begin to start dropping off after 1.3 km, where the magnitude drops to 6.4%. Unlike the OLS model results, the distance effect model had a pattern in which foreclosure terms were significant. Distances up to d_8, 1.6-1.8km, are all significant with 95% confidence (and all are significant with 99% confidence except for d_6). Distances after 1.8 km, however, begin to lose statistical significance and completely lose significance after 2.4 km – which coincides with where the effect approaches zero (Figure 5).

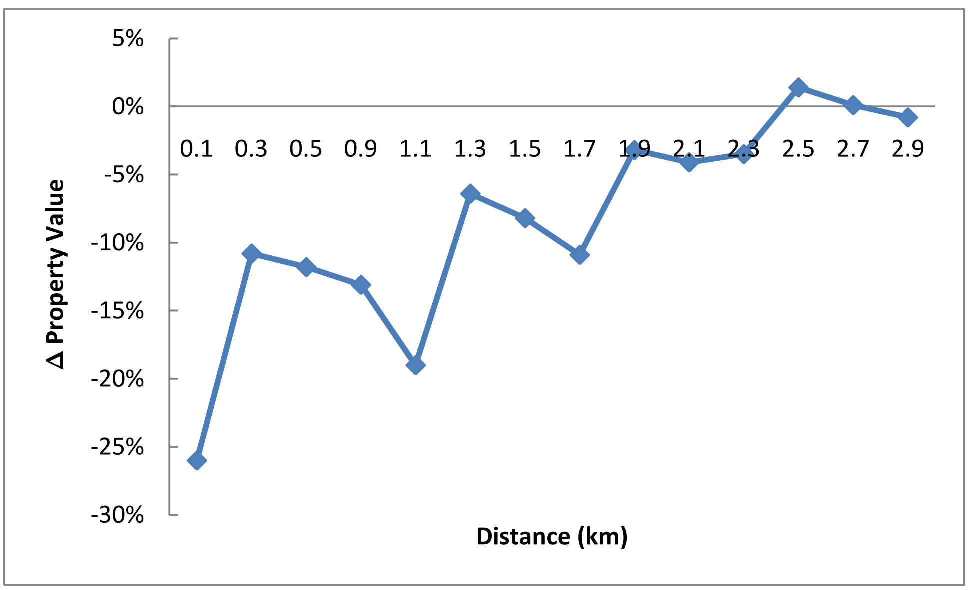

Figure 5: The effect of distance from foreclosure on the change in property value of a nearby home, according to Model B. Statistical significance begins to drop off after 1.8 km and completely disappears after 2.4 km.

Source	SS	df	MS
Model	6344.96951	20	317.248476
Residual	13193.3338	24655	.535117981
Total	19538.3033	24675	.791825869

Number of obs	=	24676
F(20, 24655)	=	592.86
Prob > F	=	0.0000
R-squared	=	0.3247
Adj R-squared	=	0.3242
Root MSE	=	.73152

lnprice	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
sqft_1	.0006884	.0000106	65.23	0.000	.0006677	.0007091
lot	2.88e-10	6.63e-11	4.34	0.000	1.58e-10	4.18e-10
baths	-.0411305	.0094841	-4.34	0.000	-.0597199	-.0225411
age	-.0064667	.0005925	-10.91	0.000	-.0076281	-.0053053
age_2	-.0000197	5.45e-06	-3.62	0.000	-.0000304	-9.03e-06
zip	.0049585	.000564	8.79	0.000	.003853	.0060641
d1	-.2597292	.0492007	-5.28	0.000	-.3561655	-.1632929
d2	-.1079669	.033871	-3.19	0.001	-.174356	-.0415777
d3	-.1179126	.0292178	-4.04	0.000	-.1751813	-.0606439
d4	-.1307483	.0276008	-4.74	0.000	-.1848476	-.076649
d5	-.1898454	.0258767	-7.34	0.000	-.2405652	-.1391255
d6	-.0641056	.0250519	-2.56	0.011	-.1132087	-.0150025
d7	-.0819578	.0233742	-3.51	0.000	-.1277725	-.036143
d8	-.1087741	.0228481	-4.76	0.000	-.1535578	-.0639905
d9	-.0318082	.0221433	-1.44	0.151	-.0752104	.0115939
d10	-.0407151	.0210198	-1.94	0.053	-.0819153	.0004851
d11	-.0353689	.0204457	-1.73	0.084	-.0754437	.004706
d12	.0140584	.0200151	0.70	0.482	-.0251723	.0532892
d13	.0009659	.0195915	0.05	0.961	-.0374346	.0393663
d14	-.00842	.0193454	-0.44	0.663	-.0463381	.0294981
_cons	-126.6702	15.62664	-8.11	0.000	-157.2994	-96.04105

Figure 6: Results for the distance effect regression (Model B).

Time Effect (Model C) Results

The regression results for the time effect model, Model C, show an inconclusive relationship between time since foreclosure and sale prices of nearby homes. Figure 8 indicates that foreclosures within 0 – 3 months increase nearby property values by 0.7%. However, this is very insignificant with a t value of 0.65. The results also state that foreclosures occurring within 3 to 12 months, in t_2, increase property values by 3.9% with 99% significance. This is shocking and leads one to believe that the data are somehow inaccurate – either I made an error somewhere or the date ranges were too large. Perhaps this lack of relationship is due to the maximum date range being only two years between a foreclosure and property. The most plausible explanation is that the data were affected by the macroeconomic time trends of the subprime mortgage crisis. Because all of this data took place during the subprime mortgage crisis, we cannot rule out there being a relationship between time and property values in Durham under normal market conditions.

Source	SS	df	MS	Number of obs =	24676
				F(8, 24667) =	1457.70
Model	6271.86642	8	783.983303	Prob > F =	0.0000
Residual	13266.4369	24667	.537821255	R-squared =	0.3210
				Adj R-squared =	0.3208
Total	19538.3033	24675	.791825869	Root MSE =	.73336

lnprice	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
sqft_1	.0006919	.0000106	65.43	0.000	.0006712	.0007127
lot	2.88e-10	6.65e-11	4.33	0.000	1.57e-10	4.18e-10
baths	-.0442721	.0094991	-4.66	0.000	-.0628908	-.0256533
age	-.0065558	.0005932	-11.05	0.000	-.0077185	-.005393
age_2	-.0000189	5.46e-06	-3.46	0.001	-.0000296	-8.18e-06
zip	.00499	.0005657	8.82	0.000	.0038812	.0060987
t1	.0074368	.0114962	0.65	0.518	-.0150965	.02997
t2	.0392854	.0110982	3.54	0.000	.0175323	.0610384
_cons	-127.5991	15.67194	-8.14	0.000	-158.3171	-96.88116

Figure 7: Results for the time effect regression (Model C).

Time Distance Combination (Model D) Results

Source	SS	df	MS	Number of obs =	24676
				F(22, 24653) =	539.82
Model	6352.17184	22	288.735084	Prob > F =	0.0000
Residual	13186.1315	24653	.534869244	R-squared =	0.3251
				Adj R-squared =	0.3245
Total	19538.3033	24675	.791825869	Root MSE =	.73135

lnprice	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
sqft_1	.0006879	.0000106	65.17	0.000	.0006672	.0007085
lot	2.83e-10	6.63e-11	4.27	0.000	1.53e-10	4.13e-10
baths	-.041242	.0094821	-4.35	0.000	-.0598275	-.0226566
age	-.0064934	.0005925	-10.96	0.000	-.0076548	-.005332
age_2	-.0000196	5.45e-06	-3.59	0.000	-.0000303	-8.88e-06
zip	.0050033	.0005643	8.87	0.000	.0038974	.0061093
t1	.0077351	.0114671	0.67	0.500	-.0147412	.0302114
t2	.0395746	.0110688	3.58	0.000	.0178791	.0612701
d1	-.2600472	.04919	-5.29	0.000	-.3564626	-.1636318
d2	-.1082665	.0338656	-3.20	0.001	-.1746452	-.0418879
d3	-.1175792	.0292122	-4.03	0.000	-.1748368	-.0603215
d4	-.1305886	.0275945	-4.73	0.000	-.1846754	-.0765017
d5	-.1898019	.0258708	-7.34	0.000	-.2405102	-.1390936
d6	-.0642915	.0250469	-2.57	0.010	-.113385	-.015198
d7	-.0818854	.0233692	-3.50	0.000	-.1276904	-.0360804
d8	-.1083494	.0228431	-4.74	0.000	-.1531232	-.0635755
d9	-.0318127	.0221382	-1.44	0.151	-.0752049	.0115796
d10	-.0410464	.0210155	-1.95	0.051	-.082238	.0001452
d11	-.0356273	.0204412	-1.74	0.081	-.0756933	.0044386
d12	.0143293	.020011	0.72	0.474	-.0248935	.053552
d13	.0014395	.0195874	0.07	0.941	-.0369528	.0398319
d14	-.008349	.0193409	-0.43	0.666	-.0462585	.0295604
_cons	-127.9237	15.63276	-8.18	0.000	-158.5648	-97.28249

Figure 8: Regression results for time-distance combined model (Model D).

The time-distance combination model confirms the general findings of Model B and Model D – that distance effects from foreclosure is significant while time since foreclosure is not. The beta coefficients are very similar to those of Model B and C, as are the significance values (Figure 9). The R^2 term is the highest of the four models.

Comparing the Four Models

Variable	Dist_B	Time_C	TimeDist_D
sqft_1	0.001***	0.001***	0.001***
lot	0.000***	0.000***	0.000***
baths	-0.041***	-0.044***	-0.041***
age	-0.006***	-0.007***	-0.006***
age_2	-0.000***	-0.000***	-0.000***
zip	0.005***	0.005***	0.005***
d1	-0.260***		-0.260***
d2	-0.108***		-0.108***
d3	-0.118***		-0.118***
d4	-0.131***		-0.131***
d5	-0.190***		-0.190***
d6	-0.064**		-0.064**
d7	-0.082***		-0.082***
d8	-0.109***		-0.108***
d9	-0.032		-0.032
d10	-0.041*		-0.041*
d11	-0.035*		-0.036*
d12	0.014		0.014
d13	0.001		0.001
d14	-0.008		-0.008
t1		0.007	0.008
t2		0.039***	0.040***
_cons	-126.670***	-127.599***	-127.924***
N	24676	24676	24676
r2	0.325	0.321	0.325
r2_a	0.324	0.321	0.325
legend: * p<.1; ** p<.05; *** p<.01			

Figure 9: Beta coefficients from regressions of models B, C, and D and their statistical significance. * indicates 90% confidence, ** indicates 95% confidence, and * indicates 99% confidence. Model A results are in Appendix III.**

Viewing just the beta coefficients and their significance levels in Figure 10, one can easily see the magnitude and direction of these variables on housing prices. All three models have strong R^2 values, with Model D having the largest. The beta coefficients of the hedonic variables, such as square feet and lot size, are the same across all the models, indicating a stable and reliable relationship. The significance levels of the foreclosure variables match in all three models and the beta values are nearly all identical.

Conclusions and Extensions

It was confirmed that foreclosures do have significant effects on nearby property values in Durham. A foreclosure can decrease a neighborhood property value by up to 26% if within the first 0.2 km. The effect diminishes in magnitude as the distance between foreclosure and neighborhood property increases. The distance effect is significant up to a 1.8 km radius away – the distance at which the effect approaches zero. The OLS model (Model A), Distance Effect model (Model B), and Time-Distance Combination Model (Model D) all supported this general trend of property values declining the closer they are to foreclosures.

It is important, however, not to overextend the conclusions. While the models validated that foreclosures have negative spillover effects on Durham property values, they also found an inconclusive relationship between time since foreclosure and property values. This suggests there were limitations to the process that should be addressed upon further analysis. The date range was too restricted and should be expanded in the search for validation of the time effect. The numerous geocoding errors from ArcMap when determining distance from foreclosures could have altered the results. Sample selection bias and was also not accounted for and should be considered when looking to strengthen the model.

I hope this analysis serves as background in a discussion on Durham's governmental policy on foreclosures. While foreclosures may be less frequent in Durham than elsewhere in the nation, those that do appear cause severe drops in home values, which lead to lower property tax revenue. Durham's strongest decline in property value at 26% was more than twice as strong as any decline in the Lin et al.'s Chicago analysis, which suggests that either the subprime crisis has exacerbated these effects or that Durham's housing market is more prone to these spillover effects (or both). It is through addressing questions like these that we may begin to draft legislation to address the significant burdens that these foreclosures put on nearby homeowners and communities.

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Appendix I: Stata .do file

```
//AAbraham, 4/30/10, update 9/8/10

set mem 500m
insheet using "E:\patrondata\AAbraham-durham\AAbraham-
finalpaper\BigTable_mod_formatted_csv.csv"

generate lnprice = ln(saleprice)
generate age_2 = age*age
generate sqft_100 = (sqft_1)/100

foreach x of numlist 1/15 {
     foreach y of numlist 1/3 {
          generate d`x't`y'=0
     }
}

foreach x of numlist 1/15 {
     generate d`x'=0
}

foreach y of numlist 1/3 {
     generate t`y'=0
}

rename v5 km1
rename v6 km2
rename v7 km3
rename v8 km4
rename v9 km5
rename v10 km6
rename v11 km7
rename v12 km8
rename v13 km9
rename v14 km10
rename v15 km11
rename v16 km12
rename v17 km13
rename v18 km14
rename v19 km15

rename mo_03 mo1
rename mo_312 mo2
rename mo_12241825365 mo3


foreach x of numlist 1/15 {
     replace d`x'=1 if km`x'==1
}

foreach y of numlist 1/3 {
     replace t`y'=1 if mo`y'==1
}

foreach x of numlist 1/15 {
     foreach y of numlist 1/3 {
          replace d`x't`y'=1 if mo`y'==1 & km`x'==1
     }
}
```

```
/*OLS*/
regress  lnprice  sqft_100 lot baths age age_2 zip d1t1-d15t2
estimates store OLS_A

/*Distance effect*/
regress  lnprice  sqft_100 lot baths age age_2 zip d1-d14
estimates store Dist_B

/*Time effect*/
regress  lnprice  sqft_100 lot baths age age_2 zip t1-t2
estimates store Time_C

/*Time-distance interaction*/
regress  lnprice  sqft_100 lot baths age age_2 zip t1-t2 d1-d15
estimates store TimeDist_D

estimates table OLS_A, b(%12.3f) star stats(N r2 r2_a)
estimates table Dist_B Time_C TimeDist_D, b(%12.3f) star stats(N r2 r2_a)

estout Dist_B Time_C TimeDist_D, cells(b(star fmt(3)) se(par fmt(2))) legend
label varlabels(_cons constant) stats(r2 df_r bic, fmt(3 0 1) label(R-sqr
dfres BIC))
```

Appendix II: Derivation of Foreclosure Component of Regression Models

Let's say $\hat{P}_{i,subject}$ is the price of a comparable home that is not involved in foreclosure. Then,

$$\hat{P}_{i,subject} = P_i + \sum_{j=1}^{m} a_j \Delta_{subject,i}^{Characteristic\ j} + f\left(\Delta_{subject,i}^{location}\right) + g\left(\Delta_{subject,i}^{timesale}\right) \tag{a1}$$

where P_i is the observed sale price of comparable house i, a_j is the adjustment factor for property characteristic j, $\Delta_{subject,i}^{Characteristic\ j}$ is the difference of property characteristic j between the subject property and comparable i, $f\left(\Delta_{subject,i}^{location}\right)$ is the adjustment for location difference between the subject property and comparable i, and $g\left(\Delta_{subject,i}^{timesale}\right)$ is the adjustment for time difference of sales between the subject and comparable property i.

Once you have price estimates for N comparable homes, you can estimate the value of the subject property being appraised. It is simply the weighted average of the sales prices for each comparable home i. That is,

$$\hat{P}_{subject} = \sum_{i=1}^{N} W_i \hat{P}_{i,subject} \tag{a2}$$

where W_i is a weight found by optimizing the minimum variance of valuation (Lin 390).

Now consider a foreclosed home as a comparable in the valuation process. Lin et al. state that a foreclosed comparable home, represented by k, is usually sold at a discount rate of approximately 23% to compensate for the moral risk, amenity deterioration, and other negative features from foreclosure (Lin 390). If $\bar{\theta}$ is the expected discount rate on the foreclosed comparable, then the price of a foreclosed comparable k is:

$$\hat{P}_{k,subject} = (1-\bar{\theta})P_k + \sum_{j=1}^{m} a_j \Delta_{subject,k}^{Characteristic\ j} + f\left(\Delta_{subject,k}^{location}\right) + g\left(\Delta_{subject,k}^{timesale}\right) \tag{a3}$$

If foreclosed homes are included in the set of N comparable homes, then the price of the subject home near foreclosure, $\hat{P}_{subject}(F)$, becomes:

$$\hat{P}_{subject}(F) = \sum_{i=1}^{N} W_i \hat{P}_{i,subject} - W_k \, \bar{\theta} P_k \tag{a4}$$

Therefore, to calculate the effect of a foreclosure on property value, you simply subtract Eqs. a2 and a4 to get:

$$\Delta = \hat{P}_{subject} - \hat{P}_{subject}(F) = W_k * \bar{\theta} * P_k \tag{a5}$$

In summary, Eqn. a5 shows that the two factors affecting neighboring property values are the discount rate of the foreclosure, $\bar{\theta}$, and the weight among comparables in the valuation, W_k. As discussed, the extent of the price drop varies based on the time since foreclosure, t, and the distance away from the foreclosure, d. These two factors can be reflected in our model as parameters of W_k, so Δ becomes:

$$\Delta = W_k(d, t) * \bar{\theta} * P_k \tag{a6}$$

Lin et al. hypothesize that the farther away a foreclosure is, the smaller the price drop of a neighboring property. Likewise, the longer it has been since foreclosure, the less severe the price drop. That is, $\frac{\partial \Delta}{\partial \mathrm{d}} < 0$ and $\frac{\partial \Delta}{\partial \mathrm{t}} < 0$[5].

Finally, if there are multiple foreclosures in the neighborhood, then the cumulative negative effect on the price of the subject home will be

$$\Delta = \sum_{l} W_l(d, t) * \bar{\theta}(s) * P_l \tag{a7}$$

[5] This hypothesis is more tediously derived in the appendix of Lin et al.'s paper

Andrew Abraham
Econ 145 – Professor Becker
05.03.10

Appendix III: Additional Figures

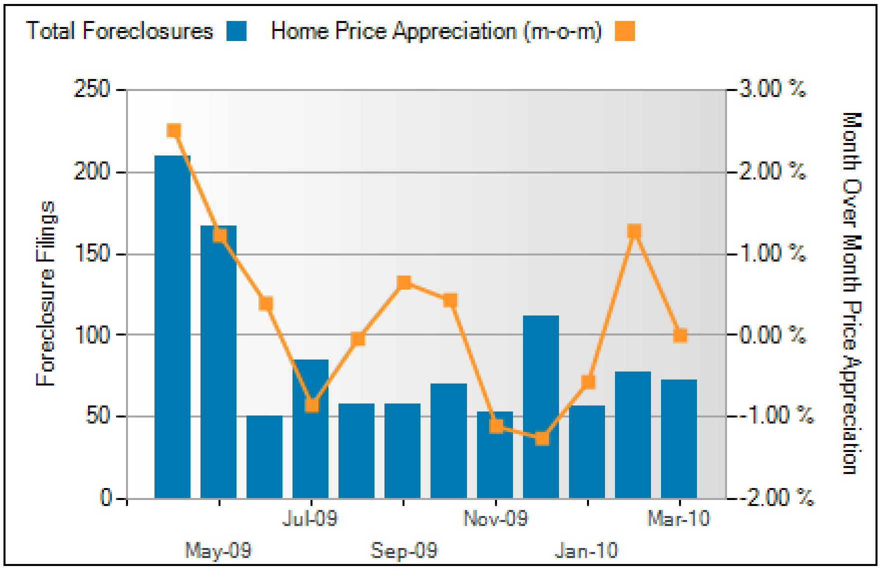

Figure 10: Trends between foreclosure occurrences and housing price appreciation in Durham, taken from RealtyTrac.com.

Variable	OLS_A
sqft_1	0.001***
lot	0.000***
baths	-0.042***
age	-0.007***
age_2	-0.000***
zip	0.005***
d1t1	-0.150*
d1t2	-0.167*
d1t3	-0.412***
d2t1	-0.072
d2t2	-0.065
d2t3	-0.090
d3t1	-0.015
d3t2	-0.029
d3t3	-0.128**
d4t1	-0.072
d4t2	-0.065
d4t3	-0.082
d5t1	-0.170***
d5t2	-0.126***
d5t3	-0.038
d6t1	-0.024
d6t2	0.043
d6t3	-0.033
d7t1	-0.068*
d7t2	0.016
d7t3	-0.063
d8t1	-0.071**
d8t2	0.006
d8t3	-0.143***
d9t1	0.014
d9t2	0.037
d9t3	-0.051
d10t1	-0.010
d10t2	0.054*
d10t3	0.002
d11t1	0.015
d11t2	0.039
d11t3	0.029
d12t1	0.081***
d12t2	0.053*
d12t3	0.104***
d13t1	0.041
d13t2	0.093***
d13t3	0.005
d14t1	0.078***
d14t2	0.033
d14t3	-0.002
d15t1	0.021
d15t2	0.104***
_cons	-127.391***
N	24676
r2	0.325
r2_a	0.324

legend: * p<.1; ** p<.05; *** p<.01

Figure 11: Model A's beta coefficients