Demolition in Detroit: The Effect of the Hardest Hit Fund in the Distressed Housing Market

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5/2/2018

Question

- What is the effect of rapid, targeted demolition on house sales prices in a distressed housing market?
  - Does getting rid of nearby “blight” improve a home’s property value?

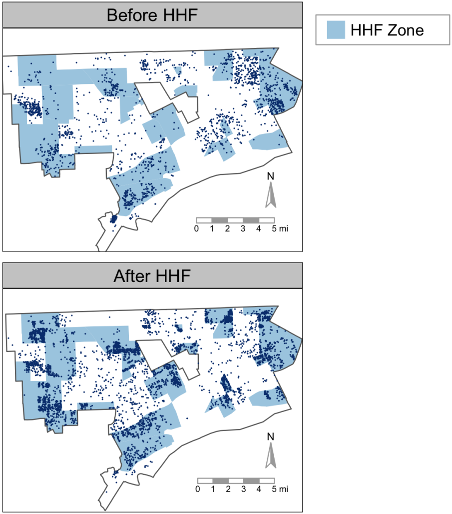
Background

- Depopulation of Detroit
  - 1.8 million in 1950 to 700,000 today
  - Accelerated by foreclosure crisis
  - Households leave, but houses left behind
- Distressed housing market
  - More supply than demand
  - Large number of aging structures
  - "Blight" is common

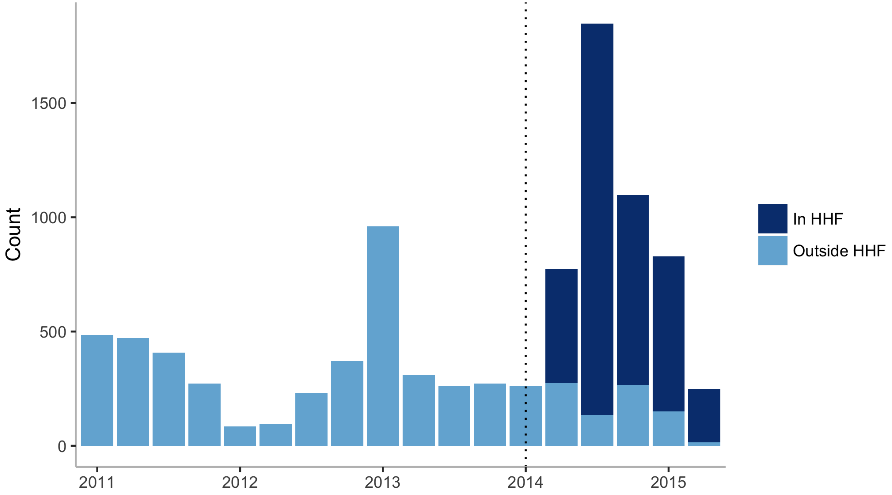
Policy Intervention

- Federal government allocates money to states for foreclosure prevention in 2010
  - Hardest Hit Fund distributed by US Treasury to 18 states, including Michigan
  - Goal: support homeowners with their mortgages
- Michigan funding reallocated in 2013
  - Hardest Hit Fund now can be used for demolition efforts
  - First HHF-funded demolition in Detroit, April 2014

Demolitions Before/After HHF



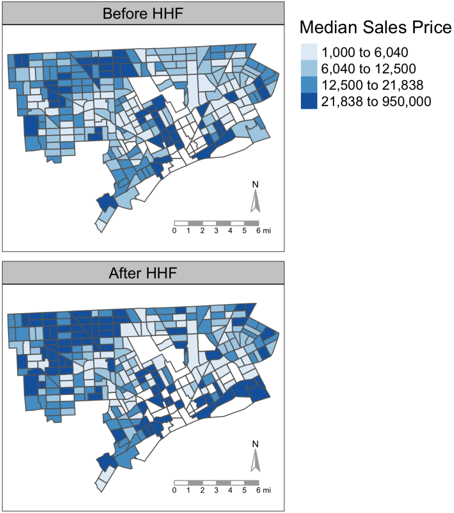
Demolitions Over Time



Motivation

- Take Hardest Hit Fund demolitions as a natural experiment
- What effect did they have on house sales prices, if any?
- Goals:
    - Assess impact of nearby distress conditions (blighted structures vs. vacant lots)
    - Assess impact of demolition program

Median Sales Price Before/After HHF



Literature Review

- Effect of property distress
  - Foreclosure: Kobie (2003), Immergluck (2006), Lin (2009), Harding (2009)
  - Tax delinquency, additional conditions: Mikelbank (2008), Whitaker (2013), Carroll (2016)
- Hedge effect
  - Griswold (2006), Griswold (2014), **Dynamo Metrics (2015)**

Data

- Detroit Space-Time Analytics Data System (D-STADS^{TM})
  - Compiled by Dynamo Metrics
  - ~400,000 city parcels with quarterly information
    - Sales, property characteristics
    - Demolition
    - Occupancy, vacancy
    - Tax foreclosure, delinquency
    - Crime
  - I use data from April 2013 - March 2015
- Detroit Open Data Portal
  - City record of all demolitions
  - Detroit boundary shapefiles

Summary Statistics

Table 1: Summary Statistics for Properties Sold, Q2 2013 - Q1 2015 (N = 8592)

Variable	Mean	Standard deviation	Min	Max
Sales price	$25,699.91	$39,264.22	$1,000*	$1,600,000.00
Log of sales price	9.563	1.126	6.900	14.400
Unoccupied tax foreclosable	5.722	4.560	0	34
Vacant lots	8.423	10.326	0	100
Occupied	73.959	23.232	4	312
Violent crime (500 ft)	0.158	0.507	0	8
Property crime (500 ft)	0.413	0.865	0	7
Res. sales (500 ft) >$25,000	0.291	0.710	0	24
Tax foreclosure eligible sale	0.124	0.330	0	1
Square footage	1,138	1,492	0	32,767
Number of bathrooms	1.220	0.473	0	9
Number of fireplaces	0.404	0.519	0	3
If brick	0.690	0.463	0	1
Porch area	104	78	0	948
If air conditioning	0.152	0.359	0	1
Age	74.4	13.6	0	135
Q1	0.217	0.412	0	1
Q2	0.273	0.446	0	1
Q3	0.264	0.441	0	1
Q4	0.245	0.430	0	1
Arms-length sale	0.047	0.212	0	1
Quit-claim sale	0.013	0.114	0	1
Warranty deed sale	0.038	0.191	0	1
Land contract sale	0.037	0.190	0	1
REO sale	0.159	0.366	0	1
Investor sale	0.158	0.365	0	1

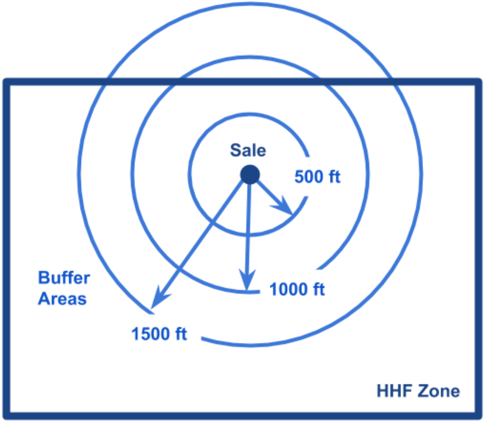
**Note: n = 8592; sales lower than $1000 were omitted from analysis.*

Hedonic Model Specification

$$log(salesprice_i) = \beta_0 + \beta_1 D_i^R + \beta_2 P_i^{HHF} + \beta_3 S_i + \beta_4 M_i + \beta_5 Q_i + \beta_6 T_i + u_i \quad (1)$$

- D_i^R, property counts
- P_i^{HHF}, policy variables,
- S_i, physical characteristics,
- M_i, housing submarket,
- Q_i, quarter sold,
- T_i, sale or deed type,
- u_i, error term (heteroskedastic)

Property Counts



Property Counts

Table 2: Average Number of Nearby Properties by Buffer Size

	Buffer Size		
Property Type	500 ft	1000 ft	1500 ft
Unoccupied and Tax Foreclosable	5.72	21.31	45.86
Vacant Lots	8.42	33.44	74.68

**Note: counts are for residentially-zoned properties.*

Spatial Hedonic Model Specification

- I first do OLS regressions:
  - Policy variables only
  - Policy variables with full controls
- I run spatial diagnostics on my regression results and find that spatial autocorrelation is likely present.
- I perform a spatial specification search and proceed with the following spatial regression models:
  - Spatial lag
  - Space-time lag, past quarter
  - Space-time lag, all previous periods

Spatial Lag Models

- Spatial lag model

$$lnP_{i,t} = \beta_0 + \beta X + \lambda \mathbf{W_t P_{i,t}} + u_i \tag{2}$$

- Space-time lag model

$$lnP_{i,t} = \beta_0 + \beta X + \lambda \mathbf{W_{t-1} P_{i,t-1}} + u_i \tag{3}$$

where X represents a matrix of the original hedonic variables.

Results

Table 3: Space-Time Lag Model, Past Quarter, All Controls

	Dependent variable:		
	Log of sales price		
	(1)	(2)	(3)
Buffer Size	500 ft	1000 ft	1500 ft
Spatial Lag ($W_{t-1}P_{t-1}$)	0.263***	0.239***	0.225***
	(0.021)	(0.022)	(0.022)
Spatial Variables			
Unoccupied Tax Foreclosable	−0.029***	−0.010***	−0.005***
	(0.003)	(0.001)	(0.000)
Vacant Lots	−0.008***	−0.002***	−0.001***
	(0.002)	(0.000)	(0.000)
Policy Variables			
In HHF Zone	0.100***	0.099***	0.097***
	(0.022)	(0.022)	(0.022)
After HHF Implementation	0.050	0.068*	0.082*
	(0.037)	(0.040)	(0.042)
Unoccupied Tax Foreclosable ∗ After HHF	−0.014***	−0.005***	−0.003***
	(0.005)	(0.002)	(0.001)
Vacant Lots ∗ After HHF	−0.002	−0.001	−0.0002
	(0.002)	(0.001)	(0.000)
Observations	8592	8592	8592
R^2	0.358	0.359	0.359
Adjusted R^2	0.356	0.356	0.357
Note:	*p<0.1; **p<0.05; ***p<0.01		

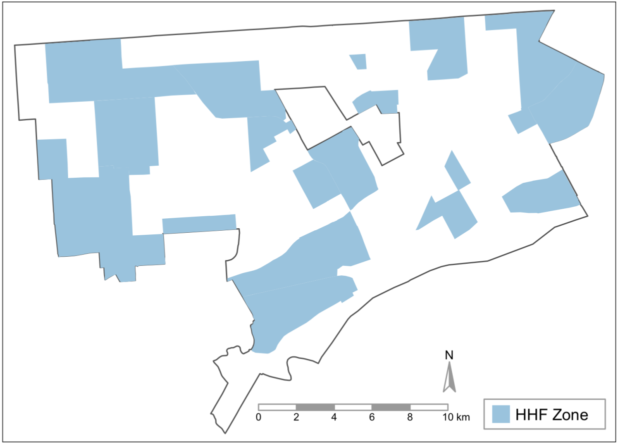
Results Summary

- For the baseline model, we find:
  - Blight decreases home values more than vacant lots
  - Blight has a larger negative impact after HHF implementation
  - Sales prices are higher within HHF zones
- This holds up across models

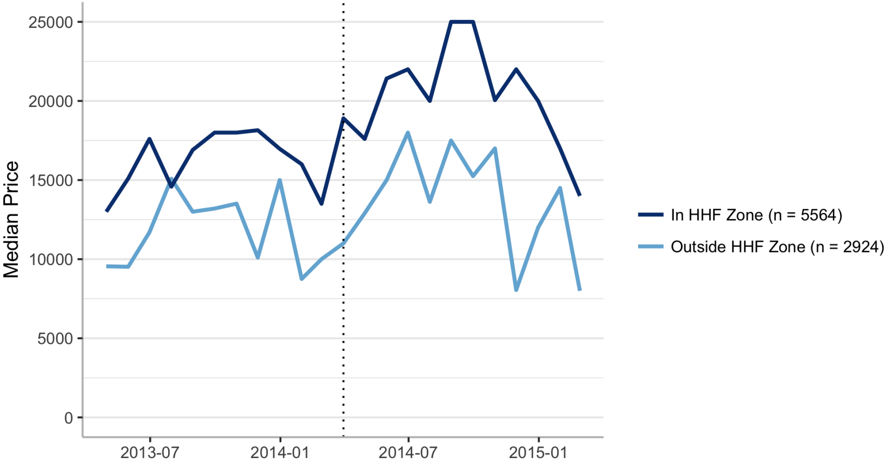
Policy Evaluation

- Treatment effect analysis
  - Before/after implementation
  - In/out of HHF zone
- Use spatial regimes specification
  - Identification strategy similar to difference-in-differences
  - Addresses *spatial* heterogeneity

Spatial Heterogeneity



Spatial Heterogeneity



Results

Table 4: Spatial Regimes Model by In/Out of HHF Zone, 500 ft Buffer

	Dependent variable:	
	Log of sales price	
	(1) In HHF Zone	(2) Out of HHF Zone
Spatial Variables		
Unoccupied Tax Foreclosable	−0.032***	−0.042***
	(0.003)	(0.006)
Vacant Lots	−0.005**	−0.014***
	(0.002)	(0.002)
Policy Variables		
In HHF Zone	—	—
After HHF Implementation	0.142***	−0.043
	(0.043)	(0.073)
Unoccupied Tax Foreclosable ∗ After HHF	−0.015**	−0.010
	(0.006)	(0.009)
Vacant Lots ∗ After HHF	−0.005*	0.002
	(0.003)	(0.004)
Observations	5626	2966
R^2	0.306	0.392
Adjusted R^2	0.302	0.386
Note:	*p<0.1; **p<0.05; ***p<0.01	

Results Summary

- For this spatial regimes model, we find:
  - Blight is worse than vacant lots in both zones
  - Blight only has an additional negative effect within HHF zones
  - HHF implementation is indeed a treatment

Results

Table 5: Spatial Regimes Model by Submarket, 500 ft Buffer

	Dependent variable:			
	Log of sales price			
Submarket	(1) Low	(2) Medium Low	(3) Medium High	(4) High
Spatial Variables				
Unoccupied Tax Foreclosable	-0.038^{***}	-0.031^{***}	-0.049^{***}	-0.092^{***}
	(0.006)	(0.004)	(0.007)	(0.020)
Vacant Lots	-0.009^{***}	-0.008^{***}	-0.005	-0.014^{*}
	(0.003)	(0.002)	(0.005)	(0.008)
Policy Variables				
In HHF Zone	0.167^{***}	0.174^{***}	0.095^{**}	-0.284^{*}
	(0.044)	(0.031)	(0.045)	(0.168)
After HHF Implementation	-0.061	0.104^{*}	0.071	0.306^{**}
	(0.089)	(0.060)	(0.068)	(0.128)
Unocc. Tax Forecl. $*$ After HHF	0.004	-0.021^{***}	-0.010	-0.018
	(0.009)	(0.008)	(0.013)	(0.034)
Vacant Lots $*$ After HHF	0.0002	-0.004	-0.008	0.010
	(0.004)	(0.004)	(0.008)	(0.011)
Observations	2327	3775	2093	397
R^2	0.288	0.270	0.338	0.536
Adjusted R^2	0.279	0.265	0.329	0.502
Note:				*p<0.1; **p<0.05; ***p<0.01

Results Summary

- For this spatial regimes model, we find:
  - Blight has worse effects in higher-price submarkets
  - Effects of vacant lots differ across submarkets
  - Interaction effect of blight and policy is only significant for the Medium Low submarket

Conclusion

We find that:

- Blight is worse than vacancy for house prices
- Effect of blight varies across spatial regimes
- Demolition appears to be effective

Further Work

- Refine defintion of submarkets
- Add accessibility measures
- Explore cost-benefit analysis