Effect of Rent Control on Housing Quality: Evidence from New York

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Abstract

Using data from the 2014 New York City Housing and Vacancy Survey, this study employs two different methods to examine the effect of rent control on housing quality in New York City, including a logistic model and decision tree methods. While prior literature has not reach an agreement on how rent control affects housing maintenance and improvements, this study provides evidence that rent control has a negative impact on housing quality.

keywords: Rent control, housing quality, decision trees.

1 Data

For this study, we use the data from the 2014 New York City Housing and Vacancy Survey to study the effect of rent control on housing quality. Our motivation for choosing data from year 2014 comes from the Rent Act of 2011, which specifically changed how home improvements costs should be reflected in rent. This leads us to question if rent control has negative impact on housing quality in New York City.

The New York City Housing and Vacancy Survey (NYCHVS) is conducted every three year by the Department of Housing Preservation and Development (HPD) together with the U.S. Census Bureau. The first round of the survey was conducted in 1965. The survey asks questions about various features of apartments and houses in New York City. In terms of the quality of these dwellings, the survey asks about different aspects of housing quality, such as the condition of windows and floors and whether the kitchen supplies function well. The survey also asks about the rent control or rent regulatory status [1].

This data source has been used by many of the previous literature on housing in the specific context of New York City (e.g. Desalvo, 1971; Olsen, 1972; Gyourko & Linneman, 1990; Early, 2000; Glaeser & Luttmer, 2003). In particular, Gyourko and Linneman use this dataset to study the effect of rent control on housing quality in New York City, and they find that a rent controlled or regulated dwelling is more likely to be in unsound condition (Gyourko & Linneman, 1990).

This study makes use of the data on the occupied rental units in New York City from NYCHVS. The total sample size is 8791, with 4966 rent controlled units and 3825 uncontrolled units.

[1] In the specific case of New York City, rent control is implemented in two ways: rent control and rent regulation. In the rest of this paper, rent control units includes both rent controlled and rent regulated housing units.

2 Models and Estimation

2.1 Variables

To study the effect of rent control on housing quality, the key question we need to answer is how to categorize a housing unit as in good condition. Gyourko and Linneman use the condition of the building as a representation of the condition of the housing units within it (Gyourko & Linneman, 1990). In the NYCHVS data, condition of the building is documented for each housing unit as "Sound", "Dilapidated" or "Deteriorating", and the last two are considered to be "unsound".

Although there should be some connection between the condition of units and the condition of building, one may doubt that the condition of the building cannot fully reflects the condition of each unit within it. The efforts made on individual apartment improvements cannot be well captured by the condition of the building. Thus, we consider using more detailed information about each unit from the survey to measure the condition of individual units. The NYCHVS asks about various features of each housing unit. We make use of ten features of housing quality to compute a score for each unit. We first set a score of 0 for each of the housing units and then change this score by the quality of each feature. For example, the survey asks each unit if there have been any heating equipment breakdowns. If there have been heating equipment breakdowns, we deduct one point from the score. If no heating equipment breakdowns have occurred, we add one point to the score. Table 1 in Appendix provides details of these features and how the score is calculated. Thus, we obtain a housing quality score for each of the occupied units in our sample.

Although the score of an apartment can take more values than 1 and 0, we argue that the quality of housing is hardly a continuous variable in nature. It is difficult to find a way to construct a continuous variable of housing quality and how we weight each of the apartment features is a relatively subjective process. Therefore, we simplify this process by categorizing each of the housing units as "in good condition" or "in bad condition" based on their score. One way to do this is to compare the score of a unit with the mean score of all units. we categorize each housing unit as

”in good condition” if the score is higher or equal to the mean score.

Table 1 provides cross-tabulations of rent control status with the apartment condition that we computed.

Table 1: Housing Condition by Rent Control Status

Unit Condition	Rent Control Status: Controlled	Rent Control Status: Uncontrolled	Row Sums
In good condition	2942 (51.57%) (59.24%)	2763 (48.43%) (72.24%)	5705 (64.90%)
In bad condition	2024 (65.59%) (40.76%)	1062 (34.41%) (27.76%)	3086 (35.10%)
Column Sums	4966 (56.49%)	3825 (43.51%)	8791

In terms of the explanatory variables, we modified the variables used in Gyourko and Linneman's study. Gyourko and Linneman use location (borough), building age, rent control status, high-rise status (number of stories), and a subsidy variable that they compute (Gyourko & Linneman, 1990). In our model, we continue to use location (borough), rent control status and high-rise status as the explanatory variables. We change the high-rise status (number of stories) to the number of unit in building. There are two reasons behind this change: first, one can expect a strong connection between a building's number of stories and the number of units; second, the Rent Act of 2011 changed the criteria for rent increase due to home improvements: improvements made to units in buildings with more than 35 apartments allow landlords to increase the rent by 1/60th of the cost, while this rate used to be 1/40th. The rate is still 1/40th for buildings with less than 35 units. In other words, how rent increases due to home improvements differs by the number of units in the building rather than the height of the building. Thus, number of units in building is a more reasonable explanatory variable than number of stories. Gyourko and Linneman also computed a subsidy variable for the units, which is the difference between the rent controlled rent and a predicted rent if the unit was not rent controlled (Gyourko & Linneman, 1990). However, in their results, this variable has relatively weak impact on the condition of building ($\beta = 0.00003$). Moreover, there is no guarantee that the accuracy of the computation of this subsidy variable would not influence our estimation. Thus, we exclude the subsidy variable in our model. Table 2 provides more details on how we define the explanatory variables in our model.

Table 2: Explanatory Variables

Variable Name	Values
(I) Borough dummies	(a) Bronx (b) Brooklyn (c) Manhattan (d) Staten Island (e) Queens (the omitted category)
(II) Building age dummy - Old	(a) Old = 1 if built before 1947 (b) Old = 0 if built after 1947
(III) Rent control status dummy - Control	(a) Control = 1 if rent controlled (b) Control = 0 if uncontrolled
(IV) Number of Units in Building dummy - More_units	(a) More_units = 1 if building has at least 50 units (b) More_units = 0 if building has less than 50 units

2.2 Models

Because of the discrete nature of the housing quality variable, Gyourko and Linneman use a logistic model to estimate the effect of rent control (Gyourko & Linneman, 1990). This could be an effective model, but it should not be the only model that we can employ. More computationally enhanced methods enable us to construct other models, such as Decision Trees.

For the purpose of this study, we first consider a logistic model similar to the one used by Gyourko and Linneman in their study. We then use a decision tree model and compare their results.

The logistic model that we estimate takes the traditional form, where the variables are constructed as discussed above.

$$P(\text{In Good Condition} = 1) = \frac{e^{X'\beta}}{1 + e^{X'\beta}}$$

Here, $P(\text{In Good Condition} = 1)$ is the probability that the housing unit is in good condition.

3 Results

3.1 Logistic model

Table 3 provides the results of estimation. In this sample, housing units in Queens are more likely to be in good condition compared with Brooklyn, Manhattan, and the Bronx. With the largest coefficient in absolute value, we may infer that housing units in the Bronx are more likely to be in bad condition. Without surprise, older units are more likely to be in bad condition. Rent control has a significantly negative effect on the quality of housing unit. Although the positive coefficient suggests that apartments in buildings with more units are more likely to be in good condition, no evidence suggests that such effect is significant.

These findings are consistent with the findings of Gyourko and Linneman (Gyourko & Linneman, 1990). Our estimates again confirm that rent control has a negative impact on housing quality, which is not what the policy intends to achieve.

Table 3: Logistic Regression Results

Explanatory Variables	coef	std err	z	$P > \|z\|$	[0.025	0.975]
Const	1.4141	0.066	21.469	0.000	1.285	1.543
Brooklyn	-0.2572	0.066	-3.915	0.000	-0.386	-0.128
Manhattan	-0.2179	0.067	-3.229	0.001	-0.350	-0.086
Staten Island	0.2386	0.166	1.433	0.152	-0.088	0.565
Bronx	-0.5131	0.075	-6.811	0.000	-0.661	-0.365
Old	-0.4737	0.056	-8.432	0.000	-0.584	-0.364
Control	-0.4657	0.050	-9.401	0.000	-0.563	-0.369
More_units	0.0834	0.054	1.545	0.122	-0.022	0.189

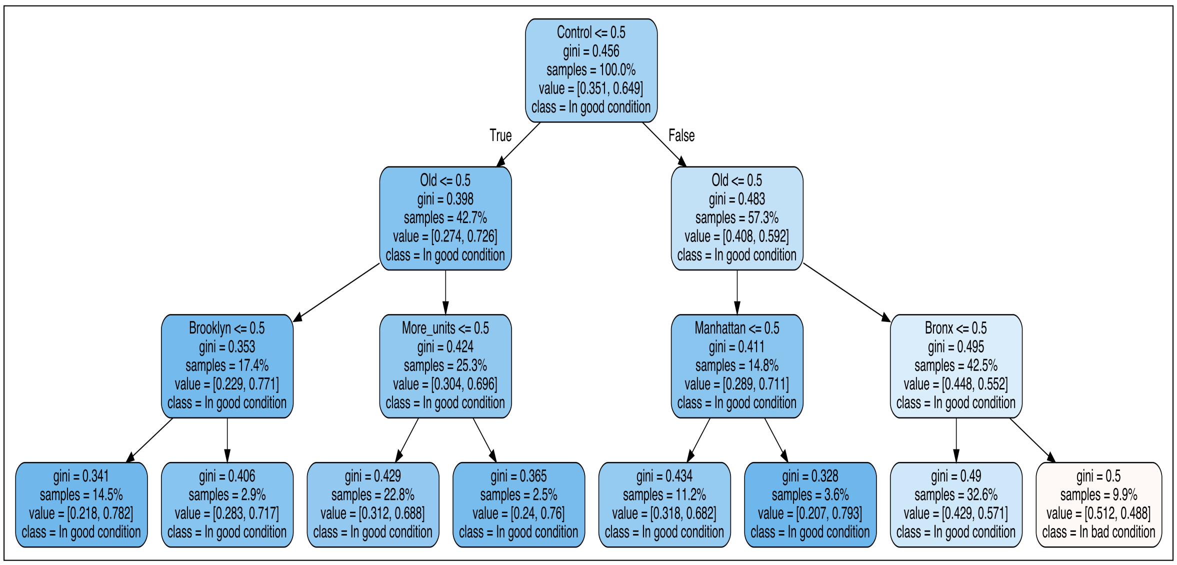
Pseudo R = 0.02984
n = 8791
Log-Likelihood = -5527.3

3.2 Random forest decision trees

Using the same sample and variables, we construct a random forest with the help of the Scikit-learn package in Python. Using the RandomizedSearchCV method, we find the optimal tuning parameters and construct the random forest accordingly. Figure 1 shows an example of the decision tree that we construct.

These results are consistent with the results of the logistic model. More specifically, a rent controlled housing unit built before 1947 and located in the Bronx is more likely to be in bad condition.

Figure 1: Decision Tree Example



Thus, both the logistic model and the decision tree model suggest that rent control has a negative effect on the housing quality in New York City.

To compare the performance of the two models, we fit the logistic model using k-fold cross validation with $k = 5$ folds and obtain the average MSE across the $k = 5$ test sets (MSE = 0.3486524365832536). The decision tree model with the optimal tuning parameters reports a slightly smaller MSE (MSE = 0.34796900193446867).

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Appendix

Table 1: Housing Features and Quality Score Calculation

Item Name	Description	Score (default= 0)
Condition of External Walls	Missing bricks, siding, or other outside wall material	-1
	Sloping or bulging outside walls	-1
	Major cracks in outside walls	-1
	Loose or hanging cornice, roofing, or other material	-1
	None of these problems with walls	+1
	Unable to observe walls	0
Condition of Windows	Broken or missing windows	-1
	Rotten/loose window frames/sashes	-1
	Boarded-up windows	-1
	None of these problems with windows	+1
	Unable to observe windows	0
Condition of Stairways	Loose, broken, or missing stair railings	-1
	Loose, broken, or missing steps	-1
	None of these problems with stairways	+1
	No interior steps or stairways	0
	No exterior steps or stairways	0
	Unable to observe stairways	0
Condition of Floors	Sagging or sloping floors	-1
	Slanted or shifted doorsills or door frames	-1
	Deep wear in floors causing depressions	-1
	Holes or missing flooring	-1
	None of these problems with floors	+1
	Unable to observe floors	0
Toilet Breakdowns	Yes	-1
	No	+1
	No toilet in this apartment	0
	Not reported	0
	Not applicable (no plumbing facilities)	0
Kitchen Facilities Functioning	Yes, all functioning	+1
	No, one or more is not working at all	-1
	Not reported	0
	Not applicable (no kitchen facilities in unit)	0
Heating Equipment Breakdown	Yes	-1
	No	+1
	Not reported	0
Cracks or Holes in Interior Walls or Ceiling	Yes	-1
	No	+1
	Not reported	0
Broken Plaster or Peeling Paint on Ceiling or Inside Walls	Yes	-1
	No	+1
	Not reported	0
Water Leakage Inside Apartment	Yes	-1
	No	+1
	Not reported	0

†These features and their descriptions are from the 2014 NYCHVS Survey.