Court-ordered Busing and Housing Prices: The Case of Pasadena and San Marino

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Abstract

In 1970, the Federal District Court ordered that no school in the Pasadena School District would be allowed to open with a "majority minority population." To comply with this order, Pasadena began busing many of its minority students to other within-district schools with smaller minority populations. This article will examine the effect of this integration policy on housing prices, using home sales data gathered from within the Pasadena and San Marino Unified School Districts (busing was not implemented in the latter district). The results indicate that the busing policy does not have a significant effect on the house prices.

1 Introduction

The hedonic price framework of Rosen (1974) has been widely applied to determine the impact of the characteristics of a durable good on its price. This paper uses the hedonic price method to determine the change in the value of a house when that house is affected by a school integration policy; in this case, busing. The hypothesis that busing has no significant contribution to the price of housing is tested using two estimation methods: difference-indifference and repeat-sales. Analysis of various specifications under both methods shows that school integration by busing does not significantly contribute to the already existing price difference between treatment and control groups that exists in the sample.

General hedonic price studies of the housing market are abundant. Similarly, measuring the effect of neighborhood school quality on housing prices is a topic that has been of great interest (Jud and Watts (1981), Colwell and Guntermann (1984), Walden (1990), Evans and Rayburn (1991), Bogart and Cromwell (1997), Black (1999), Brasington (1999), Clapp and Ross (2004)). The general consensus in the literature is that school quality, particularly when measured by student achievement, has a significant impact on the price of housing, with housing in high achieving school districts being more expensive than other housing. Studies examining the impact of educational integration, however, are relatively scarce in the literature. Clotfelter (1975) studied desegregation in Atlanta and its impact on housing prices. He used aggregated census data differenced over the decade 1960-1970, with the dependent variable equal the change in median house price in a census tract and independent variables being the decade changes in racial composition of the tract and changes in median housing characteristics (i.e., median number of rooms). He also included decade changes in minority enrollment for schools in the sample tracts. With this data, Clotfelter concluded that an increase in the minority enrollment percentage for a school will lead to a decrease in the median housing price for the tract in which the school is located.

An explicit busing policy is one way of acutely changing the racial composition of schools in a district, and opponents argued that integrating students would reduce educational quality and student achievement of non-minority students (Gray (1995)). Angrist and Lang (2004), however, provide empirical evidence to the contrary. Their study shows that an integration program has no spill-over effects on non-minority students in the receiving schools. That is, once the integration program is introduced, the tests scores of local non-minority students are unaffected. These results give support to the idea that an integration policy may not be a "bad" neighborhood amenity. If that is the case, then the integration policy would not be capitalized into the local housing prices.

The present study explores the apparent conflict in the results of Clotfelter (1975) and Angrist and Lang (2004) by measuring the amenity value of integration through a busing policy. If busing is detrimental to school quality, then busing should produce a negative price effect in the hedonic model. If, however, busing does not hinder the academic performance of local white children, then busing should have no significant effect on housing prices.

The article proceeds as follows: A brief background on major court cases that influenced integration policies in the U.S. since the 19th century is provided. The estimation techniques used to properly measure the effect of busing on housing prices are described. The empirical results are reported and discussion concludes the article.

2 Brief Background on Integration

Prior to the civil rights era of the 1960's, racial segregation was commonplace throughout the United States. Minorities were segregated from whites in many aspects of life. The justification for segregation came from the 1896 landmark case *Plessy vs. Ferguson*[1], in which the Supreme Court ruled that segregation was constitutional if the facilities into which racial groups were segregated were "separate but equal." Therefore, anything from rail cars to drinking fountains could be segregated, as long as equal quality was maintained. Though the decision of *Plessy vs. Ferguson* was continually challenged before the Court, it held for 55 years, making it a litmus test for further segregation decisions.

In 1951, however, a new case came before the courts. *Brown vs. Board of Education*[2] argued that although segregated schools were "equal" in physical facilities, minority children suffered by not having the same educational opportunities as white children. The case went through the appeals process prior to coming before the Supreme Court, and, in 1954, the Court ruled that the idea of "separate but equal" had no place in public schools. The effects of this decision were felt around the nation as other lawsuits against school districts were brought before various courts alleging segregation, one of which involved the Pasadena Unified School District as a defendant.

Pasadena Unified was the first school district in California (and outside of Southern United States) ordered to integrate its schools. The order came on January 20th, 1970 from

District Federal Court Judge Manuel Real, who ordered the Pasadena Unified School District to formulate a plan to integrate the schools in the district within 27 days[3]. The district proposed the busing plan, which was approved by the courts. The plan was to be initiated in September of 1970 at the start of the new school year.

3 Estimating the Impact of Busing

In general, a busing policy can be thought of as an experimental treatment to part of the housing stock. In this experimental setting, observations should be gathered from the treatment section of the stock as well as a section of the housing stock that did not receive the treatment (control section). While Pasadena Unified School District (hereafter PUSD) was ordered to integrate, the San Marino Unified School District (hereafter SMUSD) was not. Since Pasadena and San Marino are in close proximity, houses along the shared border between the two cities (and thus school districts) provide the desired data for the experiment.

Each house-sale observation was chosen through an examination of maps in Los Angeles County Assessor's Office. The properties were chosen along the border between the school districts in order to minimize unobserved heterogeneity between the treatment group of the sample and the control group. Physical characteristics were gathered from the Assessor's Office[4], and sales prices were gathered from the County Recorder's Office. Sales price was computed from the stamp tax shown on each deed. Sales were excluded if the deed conveyed that the stamp tax was not based on the full value of the sales price[5]. Any time a sample property was sold in the ten-year period of 1965-1975, it was counted in the data. In total, 104 transactions for both communities are used in the data set. Also, since this paper uses a repeat-sales analysis, it is worth mentioning that there are 27 pairs in the sample that had sale dates both before and after

1970, which are used in the repeat-sales analysis. Table 1 describes the data, showing variable means for the entire sample as well as means by district.

Table 1: Table of descriptive statistics for the entire sample and for each school district.

Variable	Total Sample			PUSD			SMUSD		
	Min	Max	Mean	Min	Max	Mean	Min	Max	Mean
Lot Size (sqf)	5310	70263	16241	6250	69286	14012	5310	70263	19164
House Size (sqf)	1312	12762	2885	1312	5920	2283	1615	12762	3674
Stories	1	2	1.18	1	2	1.07	1	2	1.33
Bedrooms	2	15	3.99	2	10	3.68	2	15	4.4
Bathrooms	1	10	3.13	1	5	2.59	2	10	3.84
Exterior Type*	0	1	0.91	0	1	0.86	0	1	0.98
Age	11	51	28.51	14	51	29.64	11	50	27.02
District	0	1	0.57						
Nominal Price	4000	215000	53131	4000	120000	37278	10000	215000	73917

The raw data suggest that there is a significant gap in sales price between the two districts as well as differences in the physical characteristics of the properties. In order to determine the driving force of the difference in price, however, the data need to be analyzed in a regression framework.

The standard way to estimate a natural or "quasi-natural" experiment as described above is to employ difference-in-difference estimation. However, because the data contain repeat sales of properties, a repeat-sales analysis is more appropriate[6]. Both methods are employed to estimate the effect of busing on housing prices, similar to the empirical methods of Bogart and Cromwell (2000).

3.1 Difference-in-Difference Hedonic Model

The hedonic model derives implicit prices of characteristics for some durable good. In this case, the characteristic in question is the busing policy. As previously discussed, Clotfelter's research suggests that the busing policy as a mode of student integration may have a negative effect on housing prices. But Angrist and Lang show that it is possible that busing is not a "bad" amenity. This subsection will cover the standard implementation of difference-in-difference estimation and how it relates to the data.

To carry out the difference-in-difference estimation, properties in the PUSD are considered as the "treatment" group that received the busing "treatment" starting in 1970 when the busing order was given. Properties in the SMUSD are considered the control group, since the amenity of interest does not change for this district. The estimation equation takes the form,

$$\ln(P) = C + \ln(Z)\beta_1 + D\beta_2 + \beta_3 dist + \beta_4 d_{1970} + \beta_5 b + \varepsilon \tag{1}$$

where P is the nominal sales price[7] , C is a constant term, Z is a matrix of continuously measured variables (lot and building square footage), D is a matrix of discretely measured variables (number of bedrooms, bathrooms, stories, exterior type, etc.), dist is the district dummy identifying the school district in which the house is located, x_{1970} is a dummy variable indicating if the house was sold after 1970, and b is an interaction term of dist and x_{1970}. b is at the heart of the difference-in-difference estimation and its coefficient is the focus of this study.

3.2 Hybrid Repeat-Sales Model

Because the sample contains a number of properties that were sold multiple times throughout the time period, the estimates in equation (1) are rendered inefficient. Multiple sales cause correlation in the error terms, a correlation not taken into account in the standard difference-in-difference approach. To address this problem, a method which combines elements from the both the hedonic approach and full repeat-sales approach proposed in Case and Quigley (1991) is applied.

Suppose that house i with constant physical characteristics sells twice, once at time τ_i and once at time t_i. Assume also, for the moment, that house prices exhibit a linear time trend with coefficient γ_1 (generalizing the post-1970 dummy in equation (1)). The hedonic equation for the first sale can be written as

$$\ln(P_{i\tau}) = C + \ln(Z_i)\beta_1 + D_i\beta_2 + \beta_3 b_{i\tau} + \gamma_1 \tau_i \tag{2}$$

where the $i\tau$ subscript denotes the sale of house i in time τ. In equation (2), $b_{i\tau} = 1$ if house i is in the PUSD and sells at a time τ after 1970 and zero otherwise. Isolating constant terms that do not vary with τ, equation (2) can be expressed as

$$\ln(P_{i\tau}) - \beta_3 b_{i\tau} - \gamma_1 \tau_i = C + \ln(Z_i)\beta_1 + D_i\beta_2 \tag{3}$$

Similarly, the hedonic equation for the second sale can be expressed as

$$\ln(P_{it}) = C + \ln(Z_i)\beta_1 + D_i\beta_2 + \beta_3 b_{it} + \gamma_1 t_i \tag{4}$$

The left hand side terms in equation (3) can be substituted into equation (4) since the sum $C + \ln(Z_i)\beta_1 + D\beta_2$ is constant for both equations. This yields an expression for the difference in the sales price based on the change in time between sales and the change in the busing variable:

$$\ln(P_{it}) - \ln(P_{i\tau}) = \beta_3 (b_{it} - b_{i\tau}) + \gamma_1 (t_i - \tau_i) \tag{5}$$

If t_i and τ_i are both observed before or after 1970, then $b_{it} - b_{i\tau} = 0$, yielding

$$\ln(P_{it}) - \ln(P_{i\tau}) = \gamma_1 (t_i - \tau_i) \tag{6}$$

Recognizing that equation (2) can also be used for the sale of properties *j* that only sell once, the relevant equations for the single and repeat-sale properties can then be written in the following stacked fashion:

$$\begin{bmatrix} \ln(P_\tau) \\ \ln(\frac{P_t}{P_\tau}) \end{bmatrix} = \begin{bmatrix} 1 \ \ln(Z)\, D & b_\tau & \tau \\ 0 \quad 0 \quad 0 & (b_t - b_\tau) & (t-\tau) \end{bmatrix} \begin{bmatrix} C \\ \beta_1 \\ \beta_2 \\ \beta_3 \\ \gamma \end{bmatrix} \tag{7}$$

This system, which can be estimated efficiently by generalized least squares, captures the implicit prices of the fixed characteristics as well as the effect of the integration policy in the PUSD. The term $b_{it} - b_{i\tau}$ will equal 1 for the PUSD if $\tau_i < 1970 < t_i$. If $\tau_i < 1970 < t_i$ is not true, then $b_{it} - b_{i\tau}$ will equal 0 for the PUSD, while $b_{it} - b_{i\tau} = 0$ will always hold for SMUSD.

The previous equations can also be re-expressed using discrete time dummies in place of a continuous time trend. For the discrete case, the estimation equation for the first sale will take the form

$$\ln(P_{i\tau}) = C + \ln(Z_i)\beta_1 + D_i\beta_2 + \beta_3 b_{i\tau} + T_{i\tau}\theta \tag{8}$$

where $T_{i\tau}$ is a row vector of time dummies with a 1 in the τth place and θ is a conformable column vector of coefficients for each time dummy. The equation for the second sale is

$$\ln(P_{it}) = C + \ln(Z_i)\beta_1 + D_i\beta_2 + \beta_3 b_{it} + T_{it}\theta \tag{9}$$

where T_{it} is a row vector of time dummies with a 1 in the *t*th place. As above in the continuous case, equation (8) is rearranged and substituted into equation (9) such that the new equation becomes

$$\ln(P_{it}) - \ln(P_{i\tau}) = \beta_3(b_{it} - b_{i\tau}) + (T_{it} - T_{i\tau})\theta \quad (10)$$

$T_{it} - T_{i\tau}$ is the differenced time dummy vector where the first sale is denoted by −1 and the second sale by 1, so that $(T_{it} - T_{i\tau})\theta = \theta_{it} - \theta_{i\tau}$, the change in price of house i over the time interval. Again, equations (8) and (10) can be stacked and estimated by generalized least squares as follows:

$$\begin{bmatrix} \ln(P_{j\tau}) \\ \ln(\frac{P_{it}}{P_{i\tau}}) \end{bmatrix} = \begin{bmatrix} 1 & \ln(Z_j) & D_j & b_{j\tau} & T_j \\ 0 & 0 & 0 & (b_{it} - b_{i\tau}) & (T_{it} - T_{i\tau}) \end{bmatrix} \begin{bmatrix} C \\ \beta_1 \\ \beta_2 \\ \beta_3 \\ \theta \end{bmatrix} \quad (11)$$

4 The Effect of Busing

4.1 Difference-in-Difference Results

This section reports and discusses the estimation results for the difference-in-difference method. All t-statistics reported are computed using robust White standard errors.

Table 2: Difference-in-Difference Estimation

	Coefficient*	t-statistic**
Constant	-1.19	-0.73
lot size (ln)	0.62	4.14
house size (ln)	0.73	2.41
stories	0.13	0.74
beds	-0.14	-2.66
baths	-0.06	-0.91
Exterior type	0.63	2.27
age	0.01	1.80
β_3	-0.11	-0.76
β_4	0.28	1.88
β_5	-0.09	-0.49
F	10.83	
Log Likelihood	-58.27	

* Coefficients measure percentage changes except for lot and house size, which are elasticities

** Reported t-statistics are computed with White standard errors.

Table 2 reports the estimation of the difference-in-difference equation (1). The coefficient of interest, β_5, measures the percentage impact of the busing policy on housing prices. The shock of the busing policy reduces housing prices by 8.6 percent, but the coefficient is not statistically significant. Table 3 reports results of two alternate specifications for the difference-in-difference estimation. The first specification uses yearly time dummies with the omitted year being 1965. The second reports the regression with a continuous time trend. As shown in Table 3, β_5 increases marginally from the estimation in Table 2. Under the difference-in-difference estimation with year dummies, the effect of busing is a 9.3 percent reduction in price[8]. With a continuous time trend, the busing effect is a 14.7 percent reduction in prices. Both coefficients, however, are insignificant. Possible explanations for the insignificant results are subsequently discussed.

Table 3: Difference-in-Difference Estimation with time dummies and trend.

	Coefficient*	t-statistic**		Coefficient*	t-statistic**
Constant	-0.08	-0.05	Constant	-0.32	-0.19
lot size (ln)	0.57	4.27	lot size (ln)	0.54	3.83
house size (ln)	0.71	2.42	house size (ln)	0.71	2.39
stories	0.17	1.08	stories	0.19	1.07
beds	-0.13	-2.31	beds	-0.11	-2.02
baths	-0.08	-1.14	baths	-0.10	-1.38
Exterior type	0.52	1.93	exterior type	0.53	1.97
age	0.01	1.52	age	0.00	0.71
β_3	-0.15	-1.10	β_3	-0.11	-0.92
β_5	-0.09	-0.53	β_5	-0.15	-0.97
			time trend	0.06	2.82
F	6.82		**F**	11.67	
Log Likelihood	-50.90		**Log Likelihood**	-56.03	

* Coefficients measure percentage changes except for lot and house size, which are elasticities.
** Reported t-statistics are computed with White standard errors.

Tables 2 and 3 show similar price effects for the other control variables. Both the lot and house size coefficients, measured as elasticities, are positive and significant. Table 2, for example, reports that increasing house size by one percent increases the house price by .728 percent. Increases in the number of stories or the age of the house do not yield statistically significant impacts on price, although both coefficients are positive. Having a stucco exterior, however, significantly raises the price of the house.

A seemingly counterintuitive feature of the results in Tables 2 and 3 is the significantly negative coefficient on bedrooms, which indicates that increasing the number of bedrooms reduces the house price. Recall however, that the square footage of the house is held constant in the regression, which means that increasing the number of bedrooms makes the bedrooms smaller and likely less valuable, thus apparently leading to a negative coefficient. Some recent examples of papers containing this same empirical result are Bowen et al. (2001), Boarnet and Chalermpong (2001) and Clark and Herrin (2000)[9]. This result is explored in detail by various sensitivity tests in a later section.

4.2 Hybrid Repeat-Sales Results

Table 4: Hyrbid Repeat-Sales Estimation with time trend.

	Coefficient*	t-statistic**
Constant	-2.15	-1.13
lot size (ln)	0.48	2.55
house size (ln)	1.02	2.56
stories	0.07	0.36
beds	-0.09	-1.61
baths	-0.13	-1.71
Exterior type	0.72	2.12
district dummy	-0.06	-0.44
β_3	-0.06	-0.39
γ_1	0.06	2.91
F	749.04	
Log Likelihood	-70.67	

* Coefficients measure percentage changes except for lot and house size, which are elasticities.

** Reported t-statistics are computed with White standard errors.

Table 4 reports the hybrid repeat-sales estimation results. The coefficient β_3 measures the impact of busing on housing prices under the hybrid repeat-sales model. A busing policy reduces prices by 5.8 percent, but the effect again is not statistically significant. Table 5 reports the results of the hybrid repeat-sales specification with discrete time dummies, where the dummy coefficients are not reported. Table 5 shows that the coefficient of interest, β_3, is actually positive but still insignificant. Both the house and lot size variables have positive and significant effects in the continuous and discrete time control regressions. The number of stories and exterior type have positive but insignificant coefficients while number of bedrooms and bathrooms have negative and insignificant coefficients. All coefficients are of similar size and magnitude across the continuous and discrete-time control specifications. Age of the house is not included in the model due to the fact that any differencing of age is perfectly correlated with the differencing of the continuous time variable[10].

Table 5: Hyrbid Repeat-Sales Estimation with discrete time controls.

	Coefficient*	t-statistic**
Constant	-1.516	-0.763
lot size (ln)	0.411	2.201
house size (ln)	1.062	2.808
stories	0.108	0.604
beds	-0.099	-1.715
baths	-0.105	-1.321
Exterior type	0.664	1.766
district	-0.15	-0.961
β_3	0.106	0.551
F	401.23	
Log Likelihood	-64.54	

* Coefficients measure percentage changes except for lot and house size, which are elasticities.

** Reported t-statistics are computed with White standard errors.

The results from both Tables 4 and 5 suggest that a busing policy has no significant effect on house prices, which is consistent with the difference-in-difference results. While the conclusion drawn from both methodologies presented here is not consistent with Clotfelter's results, it is indirectly consistent with the results of Angrist and Lang. Since they provided evidence that a busing policy did not hurt educational achievement, the policy's presence would not be expected to significantly reduce house prices, as shown in the above results.

4.3 Sensitivity

The tables above show results that indicate possible specification errors in the regression equation, namely, the negative coefficient on bedrooms and positive though insignificant coefficient on age of the house. This section describes how different model specifications were considered to explore the sensitivity of these results.

Close inspection of the data shows that there are a few exceptionally large houses in the sample. For example, these observations are such that the difference between the minimum and maximum values of lot size is greater than ten times the minimum. To appraise their effect, these observations were deleted from the sample and the data were analyzed again in the difference-in-difference framework of equation (1) and repeat-sales framework of equation (7). Without the large outliers, the results of the difference-in-difference estimation did not change in an appreciable manner. The coefficients for bedrooms and bathrooms showed marginal increases in size (changes of .01 and .04 respectively), where the bedrooms coefficient was statistically significant and the bathrooms coefficient was not. However, the original coefficient of interest, $\beta 5$, doubled in size (-.09 to -.18) but remained insignificant.

Removing outliers in the repeat-sales method also did not change the qualitative nature of the results. The signs and significance of all the coefficients remained the same as reported in Table 4, though coefficients for house size and number of bathrooms decreased slightly while coefficients for the district dummy and number of stories increased slightly.

Other sensitivity analyses included removal of variables[11]. As discussed previously, fixing the house size and increasing the number of bedrooms could in principle decrease the value of the house. But a regression without the house size variable still generated a significantly negative coefficient on bedrooms (-0.11), while the bathrooms coefficient changed to a positive value that was still insignificant. When all variables relating to the size of the house (lot size, house size and stories) were deleted, the coefficient for bedrooms remained negative but became insignificant and the coefficient for bathrooms became positive and significant.

To achieve more satisfactory results, a different specification was estimated using an approximation of the number of rooms in the house. The number of rooms was generated by the sum of bedrooms and bathrooms, plus the number three to represent a kitchen, living room and family/dining room. This variable replaces bedrooms and bathrooms in regressions with the size variables (lot size, house size and stories) and without the size variables. With the size variables, the coefficient on number of rooms is negative (-.11) and significant. Without size controls, it is positive (.04) and marginally significant ($p=.07$). This finding shows that sensible results can be generated using a composite rooms measure, even though the bedrooms variable does not perform well when used separately. Most importantly, the β_5 coefficient did not change magnitude, sign or significance in this specification.

The positive and marginally significant coefficient on age may be another sign of model misspecification. Discussions with people who have extensive knowledge of the area, however, indicate that this finding may reflect unusual features of the housing stock in Pasadena and San Marino. Older homes in these cities have unique architectural features not found in newer housing developments, and these features are valued by home buyers.

4.4 Discussion

There are some shortcomings to this study that could be addressed[12]. First, the officials at the PUSD could not provide detailed information regarding the magnitude and direction of the busing policy (i.e., whether students were bused to the schools in the sample neighborhoods or bused from the sample neighborhoods to other schools). Anecdotal evidence from interviews with William Bibbiani, director of research and school board member for the PUSD, indicates that by 1970, most of the white school population had left the PUSD (either by families moving or by enrolling in private school) and that, as a result, busing was not that extensive at its implementation. This pattern could be a contributing factor to the statistically insignificant results presented.

Other unavailable controls were the ethnic and family composition of the transacting parties[13]. If minorities were involved in a transaction, their preference for a busing policy would lead to higher asking or offering prices. Family composition would also be important, in that a busing policy would only affect families with school-aged children. Transacting parties without children would not view the school system as a valuable amenity.

5 Conclusion

This paper uses multiple estimation methods and specifications to measure the effect of the implementation of a busing policy on house prices. Both the traditional difference-in-difference and more-appropriate hybrid repeat-sales analysis show that there is no evidence of a significant impact on house prices, a finding that is contrary to the results of Clotfelter (1975) but consistent with the results of Angrist and Lang (2004). However, though Pasadena and San Marino are both fairly representative of suburban communities, it may be inappropriate to generalize the results to any other suburban area, especially given the relatively small size of the current sample.

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[1] www.watson.org/lisa/blackhistory/post-civilwar/plessy.html
[2] www.watson.org/lisa/blackhistory/post-civilwar/brown.html
[3] etext.lib.virginia.edu/journals/eh/eh37/gray.html, also see Gray's reference in the References Section
[4] There was no record in the assessor's office that the selected properties underwent any structural renovations that changed the physical characteristics during the sample period.
[5] This situation could arise if the house sold with a lien on it. The stamp tax would be computed from the sale price minus the value of the lien. Therefore, the fill dollar amount of the sale could not be determined from the deed.
[6] For a comprehensive review of the hedonic versus repeat-sales methods, see Case et al. (1991).
[7] Since time controls are included in the model, there is no need for using deflated prices.
[8] The model in Table 2 can easily be compared to the first model in Table 3, as the former is a restricted form of the latter. The difference-in-difference specification with individual time dummies allows for each year to have its own effect on the sale price, where β_{1965} through β_{1975} have individual values. The difference-in-difference specification in equation (1) requires that $\beta_{1965} = \beta_{1966} = ... = \beta_{1969}$ and $\beta_{1970} = ... = \beta_{1975}$. The validity of these restrictions and, hence, the validity of the model can be tested with a likelihood ratio test. The χ^2 statistic with 9 degrees of freedom is 14.75 with a P-value of .098, which leads to a rejection of the model in equation (1) at the 10 percent level.
[9] This result is also an example in Wooldridge's (2001) text, *Introductory Econometrics; A Modern Approach*.
[10] It is possible that the hybrid structure of the model can relieve perfect collinearity by including the actual age in the top part of the stacking mentioned in (7). Estimates of the model with the age variable do not significantly change the nature of the other coefficients while the actual effect of age is negligible with an insignificant coefficient of .0008.
[11] All specifications discussed in this part are done both with and without the outliers. The results are robust to the choice of the data set.
[12] One concern for a study such as this is that there is only a one time policy shock to the housing stock. Though one time policy shocks are the norm for housing issues, it would be ideal if the busing policy were implemented multiple times so that a more accurate measurement of the policy effect could be made.
[13] Though the names of the transacting parties are on the deeds in the County Recorders office, accurate identification of race based on name alone is impossible.

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Appendix

This section provides additional empirical results that were not crucial to the conclusions of this paper.

If residents anticipated the implementation of the busing policy, this anticipation would change the temporal significance of the year 1970 as the starting time of the policy treatment. To explore this issue, difference-in-difference estimation was performed with the treatment time changed to 1968 or 1969. The estimation equations would appear as follows:

$$\ln(P) = C + \ln(Z)\beta_1 + D\beta_2 + \beta_3 dist + \beta_4 d_{1968} + \beta_5 b \qquad (12)$$

and

$$\ln(P) = C + \ln(Z)\beta_1 + D\beta_2 + \beta_3 dist + \beta_4 d_{1969} + \beta_5 b \qquad (13)$$

where β_5 is the coefficient term corresponding to the interaction of the district variable and the time variables for the respective years. Table 6 shows that, even when controlling for anticipation, busing has no significant effect on housing prices.

Another consideration to examine is how the busing policy might affect the distribution of home prices, as opposed to just the mean. It is possible that a policy such as this may have different effects on certain blocks of homes in different price groups (e.g. The policy affects expensive homes more than homes near the median house price). Quantile regressions are estimated to determine if the busing policy affected certain parts of the distribution more than others. Table 7 reports results of the quantile regression for the 20th, 50th and 80th percentiles of the distribution, where 1970 is considered the treatment year. The results show that the effect of busing is insignificant across quantiles. More importantly, it seems that the effect was close to uniform across quantiles.

Table 6: Difference-in-Difference Estimation

	Diff-in-Diff for 1968		Diff-in-Diff for 1969	
	Coefficient*	t-statistic**	Coefficient*	t-statistic**
Constant	-0.55	-0.35	-0.54	-0.34
lot size (ln)	0.60	4.42	0.58	4.25
house size (ln)	0.65	2.22	0.67	2.30
stories	0.20	1.20	0.21	1.26
beds	-0.12	-2.19	-0.12	-2.21
baths	-0.07	-1.10	-0.08	-1.12
exterior type	0.57	2.32	0.58	2.30
age	0.01	1.21	0.01	1.22
β_3	0.00	-0.02	-0.03	-0.14
β_4	0.48	2.38	0.44	2.33
β_5	-0.21	-0.93	-0.18	-0.86
F	12.22		11.95	
Log Likelihood	-54.62		-55.31	

* Coefficients measure percentage changes except for lot and house size, which are elasticities.

** Reported t-statistics are computed with White standard errors.

Table 7: Quantile Regression Estimation.

	20th Percentile		50th Percentile		80th Percentile	
	Coefficient*	t-statistic**	Coefficient*	t-statistic**	Coefficient*	t-statistic**
Constant	0.56	0.18	0.41	0.20	0.26	0.09
lot size (ln)	0.62	2.94	0.65	4.12	0.67	3.21
house size (ln)	0.38	1.14	0.53	2.29	0.54	2.14
stories	0.43	1.94	0.35	1.95	0.12	0.60
beds	-0.26	-3.74	-0.14	-2.05	-0.14	-2.10
baths	0.11	1.03	-0.05	-0.58	-0.02	-0.25
exterior type	1.26	1.84	0.27	0.91	0.27	0.96
age	0.00	0.10	0.01	1.48	0.01	2.12
β_3	0.00	0.00	-0.25	-1.41	-0.21	-1.30
β_4	0.21	0.42	0.17	0.87	0.15	0.92
β_5	-0.16	-0.28	-0.11	-0.58	-0.12	-0.66

* Coefficients measure percentage changes except for lot and house size, which are elasticities.

** Reported t-statistics are computed with White standard errors.

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