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# Estimates of The Effect of School Desegregation Plans on Housing Values Over Time

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**This study investigates the impact that school desegregation can have on the market values of affected residential properties. It improves upon previous studies in that it is able to estimate not only the "racial enrollment" effect but also "other" desegregation-related effects correlated with white perceptions of school quality, etc. Through the use of a controlled longitudinal and cross-sectional data set of property sales and a ridge-regression methodology, it is able to estimate these effects over time and separate them from amenity-related effects. Results are significant in that they predict substantial desegregation-related effects on house values over time, averaging 11.4% of property value, which correlate with school desegregation court rulings and other events. Furthermore, over one-third of the magnitude of this discount is related to desegregation factors other than actual racial enrollment patterns in the schools.**

## INTRODUCTION

The intent of this study is to estimate the impact that school desegregation in its various manifestations (the threat or reality of court orders, cross-district "busing," or racial enrollment changes) can have on the market values of affected residential properties. Documentation of such a relationship is important because its direction and intensity may represent the

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magnitude of demand shifts. These demand shifts, in turn, provide evidence of the "white flight" potential resulting from desegregation efforts. Some urban theorists feel the potential for white flight is substantial (e.g., Coleman 1975), but others (e.g., Giles, Gatlin, and Cataldo 1974, Rossell 1976) contend it is a long-standing trend resulting more from other factors such as decentralization of jobs and ghetto expansion. Beyond providing evidence of the potential for white flight, the magnitudes of any value discounts are important in policy decisionmaking in that they reflect part of the private costs which must be measured against the social benefits of school desegregation. The second section of this study discusses the findings of previous studies on this question. The third section indicates the ways in which the present study improves upon the estimates of previous research. The models and their empirical results are presented in the fourth section. A final section suggests some policy implications of our findings.

## PREVIOUS RESEARCH

Several previous studies in the economic literature have investigated this question. Two of the more influential and most complete are by Clotfelter (1975) and Jud and Watts (1981). Each is limited by the characteristics of its data set and, indeed, may be measuring only a part of the desegregation effect.

Clotfelter analyzed changes in home prices and rents in Atlanta across white-occupied census tracts over the decade 1960-1970 as a function of the increase in black enrollment in local high schools, controlling for changes in neighborhood racial composition, changes in accessibility, and average changes in measures of unit age and size. He found that school desegregation (i.e., school racial change) does seem to have a significant effect on home prices independent of neighborhood racial change, averaging 6 to 7% for the average 13.6% increase in black enrollment, but ranging up to 25%. The policy implications of this are rather pessimistic, for they suggest that the costs borne by white households are substantial and could be sufficient to affect segregation patterns.

Jud and Watts extended Clotfelter's line of investigation using disaggregate single-family sales and tax data from Charlotte, North Carolina for 1977. Their model is similarly a hedonic model of housing prices. In addition to a variable describing the racial composition of the local public school, however, they further included a variable acting as a proxy for school quality — namely, the score on the state test of reading skills for the third grade. Results suggest that the effect of non-white school enrollment is dominated by the school quality effect. (The two are highly collinear, but the

the latter is significant, the former not.) The school quality coefficient indicated an increase in sales price of 5.2 to 6.2% for every increase of one year in reading score (depending on whether the estimations are based upon the full sample or the non-ghetto sample). These results were transformed to a compensated demand model, as suggested by Rosen (1974) and Freeman (1979), indicating that an extra half year in grade-level performance means $675 to the average homeowner (.19% of average value) or a total of $48 million to the city of Charlotte. In contrast to Clotfelter's results, these results provide a basis for optimism. If desegregation is effective in increasing average reading scores, this could translate into a beneficial effect on housing values, and, by implication, on housing demand by the white middle class.

These studies bear strikingly different implications, but both have similar limitations that may restrict their usefulness. Both are only measuring one possible source for the effect of school desegregation on housing prices. They ignore what may be a much more important source. The racial enrollment variable in all studies is acting as a proxy for the perceived disutility by white residents either of busing their children to distant schools or of their children attending a local school with a high black enrollment. This factor would be expected to be important and to vary considerably across the school district. However, the entire school district could also suffer an adverse demand effect that is likely to be more uniform across at least the white neighborhoods of the district. This is the "image" created by the reality or uncertainty associated with school desegregation, regardless of whether or not the local area is affected by way of actual enrollment changes or busing. Such an effect is not capable of being measured in either study because the data in each case is drawn from a single school district.

Another difficulty is that both studies are cross-sectional and thus are incapable of extracting longitudinal variations in desegregation discounts. These could be expected to change, not only because of changes in the actual racial composition of local schools over time, but also because of other components of the school desegregation process, most notably the threat or reality of court orders or initiation of a cross-district busing program. It could be hypothesized that white discounts would increase after a major court decision in response to the uncertainty or anticipation of "the worst" and then stabilize and moderate later as the program is put into effect and uncertainty is replaced by experience.

## THE PRESENT STUDY

There are two difficulties associated with overcoming the above problems and adequately measuring the district-wide and longitudinal demand effects of school desegregation. First, such an analysis requires data from two different school districts, which also often represent different municipalities, neighborhoods, etc. This creates difficulty in separating out a school district demand effect. Second, different school districts may experience demand differences due to perceptions of status and quality differences, not to mention tax differentials, which may be totally independent of desegregation. The present study attempts to overcome these difficulties by use of 1) a unique data set and 2) a nontraditional estimation technique.

*The Data*

The present study makes use of disaggregate single-family sales transactions data over a ten-year-period (1971-1980) within a neighborhood that is as homogenous as possible in virtually every dimension (age, characteristics of the housing stock, accessibility, municipality, etc.) except school district. The transactions data was obtained through the North Texas Region of the Society of Real Estate Appraisers Market Data Center, which has compiled such information since 1971.

Part of the sample is drawn from Highland Park, "proper," i.e., an area that is in the municipality of Highland Park, Texas (an affluent inner suburb of Dallas) and is located in the Highland Park Independent School District (HPISD). The HPISD is virtually 100% white and has never experienced any significant threat of desegregation through inter-district busing.[1]

The rest of the sample is drawn from "West Highland Park," the immediately adjacent area to the east that is also in the municipality of Highland Park but is located within the Dallas Independent School District (DISD). The DISD, like most large central-city school systems, has experienced considerable controversy over court desegregation rulings and "busing" decisions since the early 1970s. A brief history of the DISD school desegregation case is provided in Figure 1.

The fact that the sample represents a single neighborhood in the same municipality overcomes many of the control problems discussed above which would force one to take into account multiple differences between areas in taxes, amenities, status, etc. It is true that differences in school taxes and "status" associated with the school district could affect any discounts that are found, thus supplementing any school desegregation effects. However, the use of a longitudinal data set beginning at the same time as significant desegregation rulings[2] will, under two assumptions, provide a separate estimate of the magnitude of the school desegregation-related effects. The first assumption is that status and tax effects were present prior to court desegregation rulings and remained roughly stable over time.[3] The second assumption is that major school desegregation events — significant court rulings, the initiation of major busing programs, and changes in racial composition of the local schools — would be expected to correlate highly

Figure 1

A Brief History of the Dallas Independent School District School Desegregation Case

The first District Court school desegregation order was handed down in August, 1971. Considerable controversy and anxiety over the impending desegregation was provoked in the white community, despite the fact that the 1971 order required minimal busing. Most desegregation was to be obtained through "pairing" via television in the classrooms, the redrawing of boundary lines, and voluntary majority to minority transfers. The Longfellow Elementary School, neighborhood school for the DISD study neighborhood, was to experience an influx of minority (predominantly black) students beginning in the 1972-73 school year through the redrawing of boundary lines.

The District Court Order was immediately appealed by both the school district and the NAACP. In August, 1975, the Fifth Circuit Court of Appeals rejected the 1971 plan and ordered the District Court to draw up a new plan. In March, 1976, the District Court ordered a new plan, to be first implemented in the 1976-77 school year, which involved a moderate amount of busing, but only in grades 4-9. The effect of the plan on Longfellow Elementary School enrollment was minimal, but it did increase black enrollment in the local middle school through busing. The plan was again appealed by both the school district and the NAACP, but implemented in the fall of 1976 amid considerable controversy in the white community and evidence of lowered white enrollments and "white flight."

In April, 1978, the Fifth Circuit again remanded the case to the District Court, ordering it to "show cause" why large numbers of schools were effectively left segregated in the 1976 plan. The effect of this ruling on the DISD study area was minimal at the elementary school level but potentially adverse to white concerns at the middle and high school levels. This decision was appealed to the Supreme Court, which decided in February, 1980, to let the Fifth Circuit Court ruling stand.[4]

with changes in the discount associated with the school desegregation effects. Under these conditions, any "preexisting" discounts may be interpreted largely as residual status and tax effects or the effects of any preexisting black enrollment in the local schools, while changes subsequent to 1971 may be interpreted as desegregation effects.

## *The Estimation Technique*

The estimation method used for analysis is ridge regression analysis; a biased estimation procedure designed to address problems created by multicolinearity among the explanatory variables. A high degree of multicollinearity is always present in hedonic modelling, especially in the present case in which the observations are made over time and a high level of interaction is expected between the amenity variables and time.

Briefly, the concept behind the ridge regression is that, at the cost of a small amount of bias, one may obtain a greatly reduced variance of the estimated coefficients. Hoerl and Kennard (1970a, 1970b), who first popularized ridge regression showed that among a family of ridge estimators $\hat{\beta}$ of $\hat{\beta}$, where $\hat{\beta}$ is the OLS estimate of the coefficient, at least one has a smaller mean squared error than $\hat{\beta}$. The biased estimators are constructed by adding small positive quantities of a scalar K to the diagonal elements of X′X:

$$\hat{\beta} = (X'X + KI)^{-1} X'Y \quad (1)$$

generally is tested between zero and 1.0. The "optimum" value of K is where the mean-squared error is minimized. Hoerl and Kennard demonstrated that ridge estimates can also be produced which tend to be closer to the true parameter values on the average than OLS estimates. Churchill (1975), Dempster, Schatzoff and Wermuth (1977), and others have supported this conclusion empirically using Monte Carlo simulation techniques.

One of the major difficulties in applying ridge regression, of course, is that one does not know the "true" parameter values, which would permit selection of the optimum K to minimize the mean-squared error (Vinod 1978). Hoerl and Kennard suggest a geometric method using the "ridge trace" in which the standardized coefficient estimates are plotted as a function of K. These typically change rapidly with a small increase in K and then become stable. They suggest the "appropriate" K is the smallest K (to minimize bias) that stabilizes the estimates. This approach has been criticized on several grounds. Conniffe and Stone (1973) and Thisted (1980), for example, show that the scale of the standardized coefficients could affect one's perceptions of where stabilization takes place. However, Marquardt and Snee (1975) have countered that for "typical" data sets the mean-squared error is lowered within a broad usage of K and furthermore the coefficient estimates are generally relatively stable within this range.

Recently, several more analytical methodologies for identifying the appropriate K have been developed. Marquardt (1970) and Marquardt and Snee (1975) suggest using the value of K for which the maximum "variance inflation factor" (VIF) for all of the coefficients is "between one and ten and closer to one." The VIF for a coefficient is the amount the variance of that coefficient is inflated by the correlations between the predictor variables. However, this procedure, like that of the ridge trace, only provides some indication of the minimum acceptable K value for analysis. It does not provide evidence for the "optimal" K or a range of acceptable K values.

Vinod (1976) suggests two heuristic methods which, in addition to identifying a "minimum" K ($K_{min}$), identify the largest "acceptable" biasing factor ($K_{max}$). Described as the "Index of Stability of Relative Magnitudes" (ISRM) and the "Numerical Largeness of More Significant Regression Coefficients" (NLMS), these measures are those used in the present study to identify the appropriate range of K.

Briefly, both the ISRM and the NLMS measures indicate the extent of deviation from orthogonality of the system used in estimation. That K at which the system is closest to orthogonality is considered to be the "optimal" K because it is the K at which the various explanatory variable effects are best able to be distinguished. A stable region for K exists where the system does not deviate significantly from orthogonality, in particular the region in which the system is closer to orthogonality than under OLS. The ISRM, which is based upon the magnitudes of the eigenvalues of the matrix of sample correlation coefficients between regressors, is minimized at the optimal K (and equals zero if the system is completely orthogonal). The NLMS, which is the correlation coefficient between the standardized coefficient absolute values and their statistics, is maximized at the optimal K. Both measures are discussed in greater detail in Appendix I.[5]

## THE MODEL AND RESULTS

### *Model Theory*

This study is an application of the traditional hedonic pricing model for residential properties, in which the value of the ith property ($P_i$) is composed of separate value contributions from a vector of individual structure, site, and neighborhood amenities ($S_i$, $L_i$, $N_i$), or

$$P_i = f(S_i, L_i, N_i). \quad (2)$$

Differentiating the hedonic price function with respect to individual amenities, yields the familiar hedonic, or implicit, price of the characteristic.

Both linear and various nonlinear specifications were estimated for the hedonic model in the present study. The linear specification performed best with respect to maximizing both the explanatory power of the equation and the significance of the coefficients. This is perhaps because of the significant controls inherent in the sample. Within the small range of variation permitted for the sample neighborhood, changes could be appropriately described as linear. This implies that hedonic prices could be considered constant over the range of the analysis.[6]

Furthermore, these hedonic prices shall be assumed to be interpretable as demand coefficients, properly reflecting changes in the demand for housing. This assumption is supported by Clotfelter's contention of inelastic housing supply in the short run and by the fact that, within the controlled neighborhood sample, both household incomes and tastes and the mix of attributes across sites are roughly constant.[7]

The dependent variable was PRLDFW, the real sales price of the property deflated to January, 1971 dollars using the Dallas-Fort Worth Consumer Price Index.[8] The explanatory variables included as structure, site, and neighborhood amenities included:

Structural Amenities ($S_i$)

BDRMS = number of bedrooms

BATHS = number of baths

OTHRMS = number of other rooms

AREA = air-conditioned area in square feet

SFPR = "spaciousness index." Interaction term representing square feet per room $\left(\frac{\text{AREA}}{\text{BDRMS} + \text{BATHS} + \text{OTHRMS}}\right)$

FRPLCE = number of fireplaces

AGE = age of structure in years

Site Amenities ($L_i$)

LOTSZ = lot size in thousands of square feet

Neighborhood Amenities ($N_i$)

HPISD = dummy variable representing a location within the Highland Park Independent School District

PCTBLK = percent black enrollment in the local elementary school[9]

Note that many other neighborhood amenities are controlled for by sample selection, including such traits as neighborhood socioeconomic status, accessibility, municipal characteristics, and differences in tax rates (except those for schools). This minimizes the problem Clotfelter faced of possible omission of relevant variables and removes the necessity of regressing on changes in amenity values rather than absolute values to eliminate specification bias.

One neighborhood amenity variable, which ideally one would desire to include to test the Jud and Watts hypothesis, is some proxy for school quality such as achievement test scores from the local elementary school. Unfortunately such data was not available. The Dallas and Highland Park Independent School Districts changed achievement tests and testing procedures over the sample period, and only over the last two years of the sample period were compatible scores available.

The sample contained all recorded sales transactions over the period 1971 to 1980. Since hedonic prices would be expected to change over time (Glaudemans and Miller 1976), proper specification of the pricing model must also include interactions of each amenity with time.

Summary statistics are displayed in Table 1. Note that HPISD homes were slightly larger (about 15%) on the average. Controlling for square

TABLE I

Summary Statistics

| | Total Sample | HPISD Sample | DISD Sample |
|---|---|---|---|
| Lot Size (LOTSZ) (1000 sq. ft.) | 8.4 | 9.0 | 7.7 |
| Number of Bedrooms (BDRMS) | 2.9 | 3.1 | 2.7 |
| Number of Baths (BATHS) | 2.2 | 2.4 | 2.0 |
| Number of Other Rooms (OTHRMS) | 2.3 | 2.3 | 2.3 |
| Floor Area (AREA) | 2274 | 2408 | 2093 |
| Spaciousness Index (Square Feet per Room, SFPR) | 303.6 | 308.1 | 297.4 |
| Number Fireplaces (FRPLCE) | 1.1 | 1.1 | 1.0 |
| Age in years (AGE) | 37.2 | 38.9 | 34.7 |
| HPISD Location (1 = Yes, 0 = No) | .577 | 1.0 | 0.0 |
| Percent Black Enrollment (PCTBLK) | | 0.0 | 60.9 |
| 1971 | | 0.0 | 39.3 |
| 1972 | | 0.0 | 47.5 |
| 1973 | | 0.0 | 51.6 |
| 1974 | | 0.0 | 65.8 |
| 1975 | | 0.0 | 63.6 |
| 1976 | | 0.0 | 64.6 |
| 1977 | | 0.0 | 67.5 |
| 1978 | | 0.0 | 65.2 |
| 1979 | | 0.0 | 60.0 |
| 1980 | | 0.0 | 61.7 |
| Average Real Sales Price (PRLDFW) ($) (Sales Price per Sq. Ft. in parentheses) | 67,157 (29.09) | 77,436 (31.61) | 53,141 (25.64 |
| 1971 | 43,339 (19.23) | 51,618 (18.51) | 35,061 (19.94) |
| 1972 | 60,748 (24.64) | 65,385 (25.24) | 39,880 (21.90) |
| 1973 | 65,807 (25.47) | 99,310 (30.87) | 42,612 (21.73) |
| 1974 | 57,117 (26.61) | 56,547 (29.33) | 58,177 (21.55) |
| 1975 | 57,048 (27.36) | 73,353 (29.89) | 38,931 (24.54) |
| 1976 | 60,941 (26.81) | 68,297 (29.65) | 52,206 (23.43) |
| 1977 | 64,017 (28.75) | 69,882 (30.61) | 54,893 (25.87) |
| 1978 | 79,398 (36.40) | 91,332 (39.58) | 68,658 (33.53) |
| 1979 | 112,111 (41.46) | 136,042 (44.26) | 76,215 (37.50) |
| 1980 | 100,478 (44.46) | 114,786 (51.24) | 76,632 (33.15) |
| N | 182 | 105 | 77 |

footage variation, the average sales price was about 23% higher over the observation period. This difference appeared to grow and peak in 1973. During the 1973-77 period, HPISD properties remained in the $29-30 per square foot range (in 1971 dollars), while DISD properties remained in the $21-22 range, until 1975 when they moved into the $24-25 range, where they stayed until 1978. In 1978, both DISD and HPISD property values began escalation, which was especially rapid in the HPISD sample. To some extent these trends reflect macro forces affecting the housing market, since the national market also experienced increases in real home prices in the 1971-73 and 1978-80 periods, with a period of relative price stability in 1974-77. To some extent, also, they reflect the imperfect control of the square foot variable alone; a number of other variations in structure and lot amenities between samples could account for these differences. Finally, the price differences between the DISD and HPISD sample could also be due to school district membership. It is, of course, the intent of the present analysis to control for as many of these other sources of variation as possible and isolate the school district membership influence.

Several sets of regressions were run to develop a sufficient understanding of the relationship between sales prices, time, and the desegregation-related variables HPISD and PCTBLK. In each case the dependent variable was PRLDFW, the real sales price per unit. Explanatory variables included the amenity variables as well as the desegregation-related variables. One set of regressions was run with the dummy variable HPISD as the only desegregation-related variable to isolate the total school district effect. A second set was then run with both HPISD and PCTBLK in an attempt to separate the effects of racial composition of the local school from other school district effects.

Continuous time interaction terms were included in a first set of regressions for both the amenity and desegregation-related explanatory variables to account for changes in hedonic price levels over time. These equations were then modified to include interaction terms derived from dummy variables for discrete time intervals. Such a modification permits a better assessment of hedonic price changes over time. Of particular interest is the change in the desegregation-related variable prices over time as various events in the desegregation process take place.[10]

## *Results*

Because significance tests have not yet been well-developed for ridge estimates, we cannot speak of significance of ridge coefficients in a purely theoretical sense. However, we shall consider "significant" in an informal sense any variable with a standard error that is half or less than the coefficient estimate. We have adopted this practice, in the absence of formal theory, to provide some (admittedly heuristic) feel for confidence in a coefficient estimate. Initial estimates consistently resulted in insignificance for the FRPLCE and AGE variables and their interactions with time and for the interaction of OTHRMS with time. These were eliminated in all succeeding runs. The insignificance of the FRPLCE and AGE variables could be explained by low variation (virtually all units had one fireplace and most were built at about the same time) or low sensitivity of price within the existing range of variation.

Both ISRM and NLMS measures (described in the third section of this study and Appendix I) were developed for each run to obtain an estimate of the "stable" range for K. The ISRM measure in all cases indicated a broad range of K from K = 0.05 to K = 0.50 to be a significant improvement over OLS estimates, with an "optimal" K at about 0.20. This range and the "optimal" K were generally shifted downward, however, when the NLMS measure was used. The NLMS measures for the continuous time specification found the entire range K = 0.05 to K = 0.50 to be superior to OLS estimates but the "optimal" K to range between 0.05 and 0.15. For the discrete time specification the NLMS measures suggested an acceptable range generally somewhat lower than K = 0.50 and an "optimal" K of between 0.05 and 0.10. In view of 1) this divergence in the "optimal" K estimate, 2) the broad range of apparently acceptable K, and 3) Marquardt and Snee's (1975) finding that for typical data sets the mean squared error is usually lowered over a broad range of K (where the coefficient estimates are usually relatively stable), we chose to present and view the ridge results over the entire range K = 0.00 (OLS) to K = 0.50, rather than simply selecting a single K for price estimation. This procedure also allows one to observe the sensitivity of the estimates to changes in K. When point estimates were required for calculation of percentage deviations, for the sake of consistency we chose to make use of the ridge estimation results at K = 0.20, which approximates the "optimal" K by the ISRM procedure, consistently improves estimates over OLS in all runs, and consistently represents a point of stability for the coefficients of interest.

Estimation results are presented in Tables 2 and 3.[11] The first three columns in each table represent results (at K = 0.00, K = 0.20, and K = 0.50) for the model specification excluding the PCTBLK explanatory variable. The last three columns represent results with the PCTBLK variable included. Table 2 presents the continuous time interaction variable results, and Table 3, the discrete time interaction variable results. Presented below each table are the adjusted $R^2$'s, the number of observations, and the ISRM and NLMS values.

Several general points should be noted concerning the results of the estimations. First, it is evident in all cases that the OLS estimates suffered from high multicollinearity, both among the amenities and between the

TABLE 2

Ridge Regression Estimation Results
PRLDFW Dependent Variable
Continuous Time Interaction Terms

| Explanatory Variable | Specification 1-1 Excluding PCTBLK Terms | | | Specification 1-2 Including PCTBLK Terms | | |
|---|---|---|---|---|---|---|
| | K = O (OLS) | K = .2 | K = .5 | K = O (OLS) | K = .2 | K = .5 |
| Constant | 18925.2 | 51576.7* | 45552.0* | 40374.9 | 45631.3* | 40628.9* |
| | (22280.3) | (6550.8) | (5595.1) | (31071.0) | (6799.7) | (5663.1) |
| LOTSZ | 3782.8* | 3439.8* | 2862.3* | 3726.8* | 3398.5* | 2822.6* |
| | (1268.8) | (389.7) | (294.1) | (1277.4) | (391.2) | (295.2) |
| BDRMS | 5304.6 | 1579.0 | 2597.5* | 10590.1 | 1346.2 | 2419.1* |
| | (6089.2) | (1389.1) | (1006.3) | (6549.3) | (1392.8) | (1005.9) |
| BATHS | 12535.2* | 6908.4* | 6157.9* | 13886.2* | 6787.0* | 6015.7* |
| | (4808.0) | (1395.1) | (923.0) | (4794.4) | (1401.6) | (926.2) |
| OTHRMS | 1493.3 | 2707.6* | 2382.7* | 1348.1 | 2751.6* | 2383.6* |
| | (2669.7) | (942.5) | (755.5) | (2637.9) | (943.3) | (757.2) |
| AREA | 22.31* | 8.96* | 7.90* | 26.41* | 8.71* | 7.75* |
| | (10.87) | (1.13) | (.72) | (11.10) | (1.12) | (.72) |
| SFPR | 103.55 | 49.35* | 53.50* | 133.79 | 48.29* | 52.84* |
| | (83.18) | (17.03) | (12.49) | (89.32) | (17.06) | (12.51) |
| HPISD | 1382.5 | 4976.4* | 5232.1* | 45607.3 | 1400.7 | 2607.8* |
| | (6524.7) | (2176.8) | (1477.2) | (25490.5) | (1890.6) | (1152.3) |
| PCTBLK | | | | 943.76* | 68.96* | 58.57* |
| | | | | (470.62) | (24.51) | (15.54) |
| TIME x LOTSZ | 173.5 | 199.0* | 174.9* | 200.2 | 212.8* | 183.8* |
| | (318.4) | (40.3) | (24.6) | (327.0) | (39.8) | (24.2) |
| TIME x BDRMS | 119.6 | 35.0 | 116.3 | 1395.3 | 77.5 | 141.3* |
| | (961.6) | (110.1) | (65.7) | (1150.1) | (107.6) | (64.6) |
| TIME x BATHS | 1530.6 | 209.4 | 292.4* | 2082.6 | 239.4 | 316.8* |
| | (1072.8) | (139.4) | (81.6) | (1091.7) | (140.2) | (81.0) |
| TIME x AREA | .785 | .502* | .461* | .155 | .520* | .481* |
| | (1.316) | (.119) | (.066) | (1.655) | (.120) | (.067) |
| TIME x SFPR | 11.63 | 2.77* | 2.32* | 21.02 | 3.41* | 2.71* |
| | (8.45) | (1.11) | (.63) | (14.19) | (1.03) | (.59) |
| TIME x HPISD | 1809.7 | 1059.3* | 886.3* | 1693.6 | 524.8 | 523.3* |
| | (1195.0) | (367.2) | (233.6) | (4167.4) | (295.2) | (179.4) |
| TIME x PCTBLK | | | | 21.14 | 8.84 | 7.10* |
| | | | | (66.42) | (5.43) | (3.27) |
| $R^2$ | .800 | .790 | .777 | .809 | .792 | .779 |
| N | 182 | 182 | 182 | 182 | 182 | 182 |
| ISRM | 24.09 | 3.25 | 5.57 | 55.56 | 6.41 | 8.79 |
| NLMS | .439 | .456 | .270 | .272 | .525 | .320 |

*Ratio of coefficient estimate to standard error greater than 2.0 in absolute value (significance tests are not well developed yet for ridge estimates).

TABLE 3

Ridge Regression Estimation Results
PRLDFW Dependent Variable
Discrete Time Interaction Terms: 1971-72, 73-74, 75-77, 78-80

| Explanatory Variable | Specification 2-1 Excluding PCTBLK Terms | | | Specification 2-2 Including PCTBLK Terms | | |
|---|---|---|---|---|---|---|
| | K = O (OLS) | K = .2 | K = .5 | K = O (OLS) | K = .2 | K = .5 |
| Constant | 69206.7* | 46593.0* | 40085.9* | 61961.1 | 42514.3* | 35613.4* |
| | (21917.0) | (6253.0) | (5438.3) | (37049.8) | (6438.3) | (5523.2) |
| LOTSZ | 6991.0* | 3552.2* | 2905.8* | 7411.9* | 3495.4* | 2854.8* |
| | (2015.6) | (376.8) | (284.6) | (2394.0) | (379.0) | (285.6) |
| BDRMS | 11821.1 | 3621.6* | 4268.2* | 12100.8 | 3548.9* | 4125.0* |
| | (6954.8) | (1376.8) | (1004.4) | (7960.6) | (1383.9) | (1011.6) |
| BATHS | 7161.6 | 7638.5* | 7011.4* | 9896.9 | 7246.4* | 6614.1* |
| | (3937.3) | (1393.8) | (923.5) | (5681.8) | (1388.5) | (918.4) |
| OTHRMS | 4416.8 | 2540.0* | 2117.4* | 3897.2 | 2796.0* | 2325.3* |
| | (2783.5) | (890.7) | (723.9) | (3156.6) | (903.8) | (734.2) |
| AREA | 3.35 | 9.73* | 8.62* | 0.75 | 9.47* | 8.47* |
| | (12.29) | (1.10) | (.71) | (13.11) | (1.10) | (0.71) |
| SFPR | 4.38 | 42.94* | 50.06* | 15.47 | 44.75* | 50.61* |
| | (71.39) | (16.62) | (12.35) | (82.48) | (16.71) | (12.44) |
| HPISD | 6042.6 | 5082.0* | 5630.2* | 20232.8 | 2173.2 | 3103.6* |
| | (8157.2) | (1854.7) | (1426.6) | (37882.2) | (1659.5) | (1014.2) |
| PCTBLK | | | | 285.06 | 43.64* | 49.66* |
| | | | | (805.06) | (17.42) | (13.14) |
| XLS7374** | 2827.5 | 223.7 | 280.2* | 3209.6 | 280.8 | 326.2* |
| | (2216.7) | (213.4) | (122.9) | (2486.6) | (215.5) | (123.2) |
| XLS7577 | 3755.7 | 58.2 | 113.4 | 4577.4 | 18.8 | 108.3 |
| | (2319.9) | (218.9) | (121.0) | (2672.8) | (216.3) | (118.7) |
| XLS7880 | 850.0 | 1049.7* | 882.2* | 841.3 | 1135.1* | 889.6* |
| | (2945.8) | (223.7) | (123.6) | (3227.7) | (220.9) | (118.0) |
| XBR7374 | 12352.0 | 1599.2* | 800.1 | 10952.5 | 1175.1 | 519.0 |
| | (6699.2) | (729.0) | (404.7) | (8756.3) | (687.0) | (371.6) |
| XBR7577 | 8035.9 | 481.1 | 162.0 | 10042.3 | 492.9 | 129.5 |
| | (6312.5) | (549.5) | (305.5) | (7416.0) | (542.7) | (299.1) |
| XBR7880 | 4907.3 | 2674.6* | 2431.2* | 2974.3 | 2714.8* | 2337.0* |
| | (7438.3) | (732.7) | (403.2) | (9584.9) | (666.6) | (355.9) |
| XBA7374 | 9380.0 | 1191.8 | 910.6* | 4802.8 | 1310.0 | 1039.7* |
| | (7869.2) | (807.0) | (433.5) | (9700.5) | (813.1) | (441.4) |
| XBA7577 | 1736.8 | 52.8 | 221.0 | 1889.0 | 40.8 | 295.0 |
| | (6875.7) | (715.7) | (395.3) | (8967.1) | (722.9) | (396.6) |
| XBA7880 | 404.8 | 724.7 | 1282.5 | 5050.8 | 1778.0* | 2188.3* |
| | (3312.3) | (1407.6) | (852.2) | (9283.4) | (893.5) | (472.9) |
| XAR7374 | 6.564 | .134 | .112 | 4.450 | .237 | .406 |
| | (11.120) | (.694) | (.404) | (13.914) | (.721) | (.398) |
| XAR7577 | 5.204 | .141 | .413 | 2.274 | .172 | .458 |
| | (9.913) | (.646) | (.367) | (12.736) | (.668) | (.371) |
| XAR7880 | 10.813 | 3.766* | 3.280* | 10.713 | 3.659* | 3.161* |
| | (10.164) | (0.852) | (.468) | (14.560) | (.810) | (.439) |
| XSF7374 | 154.30* | 2.93 | .80 | 164.74 | 7.07 | 1.84 |
| | (56.37) | (6.87) | (3.84) | (101.44) | (5.98) | (3.35) |
| XSF7577 | 194.16* | 15.97* | 7.10* | 129.99 | 14.32* | 7.06* |
| | (51.90) | (5.73) | (3.16) | (84.30) | (5.15) | (2.84) |
| XSF7880 | 14.41 | 8.77 | 13.72* | 44.59 | 11.86* | 14.18* |
| | (63.62) | (6.13) | (3.33) | (117.13) | (5.37) | (2.97) |
| XHP7374 | 15096.0 | 4918.6 | 3412.8 | 16878.9 | 1423.2 | 1073.9 |
| | (9969.9) | (3435.7) | (2461.4) | (30997.5) | (2954.0) | (2015.4) |
| XHP7577 | 17267.8 | 3659.4 | 2711.1 | 40472.2 | 4149.8* | 2205.6 |
| | (8962.4) | (2523.1) | (1788.8) | (29445.0) | (2018.6) | (1354.9) |

TABLE 3 - Cont'd

Ridge Regression Estimation Results
PRLDFW Dependent Variable
Discrete Time Interaction Terms: 1971-72, 73-74, 75-77, 78-80

| Explanatory | Specification 1-1 Excluding PCTBLK Terms | | | Specification 2-2 Including PCTBLK Terms | | |
|---|---|---|---|---|---|---|
| Variable | K = O (OLS) | K = .2 | K = .5 | K = O (OLS) | K = .2 | K = .5 |
| XHP7880 | 23410.9* (9738.3) | 11250.3* (3677.5) | 9502.6* (2606.6) | 20070.2 (37185.6) | 7526.4* (2976.7) | 7694.0* (2026.6) |
| XPB7374 | | | | 42.90 (646.22) | 105.53* (52.78) | 90.45* (36.92) |
| XPB7577 | | | | 425.97 (564.04) | 9.56 (35.38) | 4.98 (24.05) |
| XPB7880 | | | | 15.74 (667.69) | 89.76 (50.81) | 50.03 (36.45) |
| $R^2$ | .851 | .823 | .807 | .853 | .825 | .809 |
| N | 182 | 182 | 182 | 182 | 182 | 182 |
| ISRM | 81.07 | 8.97 | 14.89 | 166.02 | 14.40 | 21.34 |
| NLMS | .504 | .890 | .785 | .530 | .869 | .790 |

*Ratio of coefficient estimate to standard error greater than 2.0 in absolute value
**XLS7374 = Time Dummy Variable for 1973-74 x LOTSZ, etc.

amenities and their time interactions. Partial correlations between explanatory variables were often greater than between the explanatory variable and the dependent variable. Few coefficients (usually those for LOTSZ, BATHS, and AREA) were significant in the OLS estimates, and even these were often of questionable magnitude. Those that were insignificant were often of signs opposite from our a priori expectations (for example the coefficients for the BDRMS, HPISD, OTHRMS, and SFPR variables were frequently negative, as were several interaction terms with time). High collinearity between the desegregation-related variables HPISD and PCTBLK ($r = .989$) created problems, since whenever PCTBLK was added to the equation, the OLS coefficient estimate for HPISD would not only be insignificant, it would reverse in sign to negative. Thus, separating the effects of actual racial enrollment figures from other more general school district effects was virtually impossible using OLS.

Introduction of only a relatively small amount of bias (to K = 0.05) in virtually every case resulted in considerable increases in the number of significant variables and brought coefficient estimates more in line with a priori expectations. At K = 0.50 most, if not all, variable coefficients were significant, of appropriate signs and with magnitudes that were reasonable. Adjusted $R^2$'s were little affected through the introduction of such a degree of bias.

*The Desegregation-Related Variable Coefficients*

The OLS estimates resulted in HPISD coefficients that were negative or at least insignificantly positive. However when ridge regression analysis was undertaken, their signs were reversed at K = 0.10 or 0.20. They became significant at K = 0.30 or 0.40 when PCTBLK was included and at K = 0.10 when PCTBLK was excluded. The HPISD coefficient at K = 0.20 stabilized at about \$5000-5100 when PCTBLK was excluded from the equation (column 2 of Tables 2 and 3). This figure could be interpreted as an initial "school district" discount of 8.6 to 10.8% of average unit value in 1971. Such a discount would include all school district effects present at the beginning of the period of observation, including both status and tax effects and any desegregation effects, such as black enrollment then in the local schools.

When PCTBLK was included in the equation, the HPISD coefficient stabilized at about \$1400-\$2200 (column 5 of Tables 2 and 3). This figure could be interpreted as an initial school status and tax discount of 3.0-3.7% of average unit value in 1971. It excludes any desegregation effects present at the beginning of the period of observation caused by black enrollment then in the local schools. If it is assumed other desegregation effects did not exist in any measurable amount at the beginning of the observation period in 1971 (which may be a plausible assumption, since this was before any significant desegregation court orders affecting the DISD), this discount then could possibly be interpreted solely as a preexisting status and tax discount. The remaining 4.9-7.8% discount (roughly half of two-thirds the total school district effect) could then be attributed to the 39.3% black enrollment initially present in the local school.

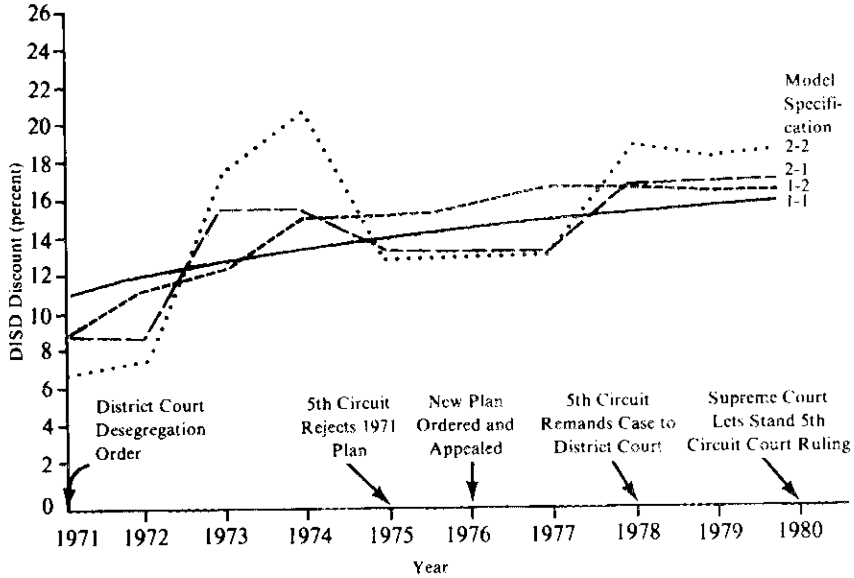
This estimate of the black enrollment effect is corroborated by observation of the PCTBLK variable coefficient behavior when PCTBLK is entered into the equation. The PCTBLK coefficient becomes significant between K = 0.00 and K = 0.15 and stabilizes at 44 to -69 (column 5 of Tables 2 and 3). Evaluated at the mean of the dependent variable and at the initial black enrollment of 39.3%, this could be interpreted as an initial "black enrollment" discount for DISD properties of 2.9 to 5.9%, roughly in line with the estimate above.

*Desegregation-Related Effects over Time*

Observation of the desegregation time interaction variable coefficients, either in continuous or discrete form, provided information about the behavior of the desegregation discount over time. Simulation results, in terms of total DISD discounts as a percentage of standardized HPISD unit value each year for each model specification, are shown in Figure 2. First consider results without the inclusion of the PCTBLK terms. There was definite evidence in the continuous time specification of an increasing

SCHOOL DESEGREGATION PLANS ON HOUSING VALUES

Figure 2
DISD Percent Discount by Year for Alternative Model Specifications (K = 0.20)




"school district" effect over time. The TIME x HPISD coefficient became significant at K = 0.10 and stabilized at about 1059 (column 2 of Table 2). This figure represents an annual increase in the DISD discount of 2.3% of average initial HPISD unit value or a total effect over the 1971-80 observation period of 23.1% of average initial unit value.[12] This increase, of course, could represent changing school status and tax effects as well as changing desegregation effects from all sources. However, to the extent that status and tax effects unrelated to desegregation could be considered relatively constant over time, it could be interpreted primarily as representing the total desegregation effect (excluding the effect of initial black enrollment in the local schools) during the 1970s, a period when the DISD experienced a number of major desegregation court orders and busing plans.

Discrete time interaction terms provide even more detail on the pattern of the school district effect over time. They provide evidence that there was an increase in the DISD desegregation discount, peaking at about $4900 in 1973-74, dropping back to a discount of about $3660 in 1975-77, and again increasing to a significant discount of $11,250 in 1979-80 (column 2 of Table

3). This result is equivalent to a changing discount associated with desegregation (as distinct from the initially present discount associated with racial enrollment, tax, and status) peaking at 7.6% of average HPISD unit value in 1973-74, dropping gradually to 5.5% in 1975-77, and climbing again to a new peak of 11.3% in 1978-80.

It is worthwhile to correlate these results with the major events relating to school desegregation in the DISD during the decades which were cited in Figure 1 and are indicated on the time axis in Figure 2. In general, it can be said that there appears to be considerable correlation between these court decisions (and the status of the desegregation case in general) and the "desegregation" discounts identified above. The discount was minimal in 1971 prior to significant court rulings. It peaked in 1973-74 in the wake of controversy and white fears during the first two years of the desegregation order. It then ebbed through the mid 1970s as households adjusted to the 1971 plan, awaiting the results of the appeal and the substance of the new plan. During the late 1970s it then grew, as the new, "tougher" plan was implemented. There did not appear to be significant "anticipation" effects for any of the desegregation events. In fact, quite the opposite seemed to be true. In both 1971 and 1975-76, major court rulings and plan implementation were followed by significant discount increases two years later.[13]

To what extent was this change in the total desegregation effect over time due to changes in actual black enrollment in the local schools, as opposed to other effects such as anxiety over possible future changes in the desegregation plan or changing attitudes about educational quality in the DISD? The racial enrollment time-interaction variable (TIME x PCTBLK) was entered in both continuous time and discrete time form to test for this effect. In both cases there was definite evidence of a separate negative "black enrollment" effect which varied over time. In the continuous time specification, the TIME x PCTBLK coefficient stabilized at about -8.8 and became significant at K = 0.40 (column 5 of Table 2). This magnitude represents an annual increase in the DISD discount of 0.6% of average initial HPISD value for the initial black enrollment of 39.3%, or a total effect over the 1971-80 observation period of 9.3% of average initial unit value, given actual black enrollment in 1980 of 61.7%. The coefficient of the TIME x HPISD variable, when PCTBLK is considered, is reduced from about $1059 to $525, implying that about half of the total desegregation effect over time is due to actual black enrollment changes, while about half is due to "other" influences.

The pattern of variation in the black enrollment effect over time can be better discerned by using the discrete TIME x PCTBLK interaction variable. Here an interesting, though not totally unexpected, result can be observed. There exists evidence that the negative effect of black enrollment is strongest in the 1973-74 period, very weak in the 1975-77 period, and again picks up moderate strength in 1978-80. The coefficients of the discrete TIME x PCTBLK interaction variables are a significant 105.5 in 1973-74, increasing to an insignificant 9.6 in 1975-77, and dropping again to 89.8 in 1978-80 (column 5 of Table 3). The coefficients of the discrete TIME x HPISD variable, on the other hand, increase over time from 1423 in 1973-74, to 4150 in 1975-77, to 7526 in 1978-80. Thus "other" desegregation effects beyond actual racial enrollment seem to become relatively more important over time in affecting desegregation discounts. This result would be consistent with a hypothesis of white household adjustment over time to accommodate a racially integrated schools situation, with an increase in sensitivity to integrated enrollments upon the first major desegregation order, subsequent adjustment to the reality of desegregation, and a later more moderate response to subsequent desegregation orders.[14] However, sensitivity to "other" issues affecting the relative desirability of the school districts (such as perceived educational quality differences, stability of the learning environment, fear of future court orders, etc.) appear to grow substantially over time.

The result in absolute dollar terms is supported when the relative magnitudes of the racial enrollment and "other" desegregation effects are observed on the basis of percentage discounts of standardized unit value over time. These results are shown in Table 4. Racial enrollment was responsible for a DISD discount of 2.9% in 1971. This discount grew to 15.1% in 1974, dropped to only 3.3% in 1976, and grew to 8.7% by 1978 (column 3 of Table 4). The "other" desegregation effects, however, represented by the discrete TIME x HPISD interaction variable, accounted for a continuously growing discount over time, from 0.0% in 1971, to 2.2% in 1974, to 6.2% in 1976, to 7.5% in 1978 (column 4 of Table 4). The racial enrollment effect accounted for 43.9% of the total discount in 1971 but 73.3% of the total discount in 1974. It then dropped off to 25.7% of the total in 1976, but again grew to 47.3% in 1978 (column 7 of Table 4). There is thus strong evidence, not only that the total desegregation discount varied considerably over time in response to certain events, but also that the composition of the total effect (a reaction to actual racial enrollment changes vs. "other" factors) also varied in expected directions and magnitudes.

## CONCLUSIONS AND POLICY IMPLICATIONS

Of course, the first general conclusion that may be drawn from the present analysis is that ridge regression analysis holds much promise for improved estimation of hedonic models. It is shown to reduce substantially the negative effects of multicollinearity and to improve significantly coefficient estimation while not seriously jeopardizing the predictive ability of the models.

TABLE 4

Model Simulation: Property Value Discounts by Year from Various Sources (Specification 2-2, K = 0.20)

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) |
|---|---|---|---|---|---|---|---|---|---|---|
| | | DISD Discount by Source (% of HPISD value) | | | | % of Total DISD Discount by Source | | | % of Total DISD Desegregation Discount by Source | |
| Year | Total DISD Discount (% of HPISD value) | Initial "Status" and Tax | Racial Enrollment | "Other" Desegregation | DISD Total Desegregation Discount ((3) + (4)) (% of HPISD value) | Initial "Status" and Tax ((2) ÷ (1)) | Racial Enrollment ((3) ÷ (1)) | "Other" Desegregation ((4) ÷ (1)) | Racial Enrollment ((3) ÷ (5)) | "Other" Desegregation ((4) ÷ (5)) |
| 1971 | 6.6 | 3.7 | 2.9 | 0 | 2.9 | 56.1 | 43.9 | 0.0 | 100.0 | 0.0 |
| 1972 | 7.2 | 3.7 | 3.5 | 0 | 3.5 | 51.4 | 48.6 | 0.0 | 100.0 | 0.0 |
| 1973 | 17.3 | 3.3 | 11.8 | 2.2 | 14.0 | 19.1 | 68.2 | 12.7 | 84.3 | 15.7 |
| 1974 | 20.6 | 3.3 | 15.1 | 2.2 | 17.3 | 16.0 | 73.3 | 10.7 | 87.3 | 12.7 |
| 1975 | 12.7 | 3.3 | 3.3 | 6.2 | 9.5 | 26.0 | 26.0 | 48.8 | 34.7 | 65.3 |
| 1976 | 12.8 | 3.3 | 3.3 | 6.2 | 9.5 | 25.8 | 25.7 | 48.4 | 34.7 | 65.3 |
| 1977 | 12.9 | 3.3 | 3.5 | 6.2 | 9.7 | 25.6 | 27.1 | 48.1 | 36.1 | 63.9 |
| 1978 | 18.4 | 2.2 | 8.7 | 7.5 | 16.2 | 12.0 | 47.3 | 40.8 | 53.7 | 46.3 |
| 1979 | 17.7 | 2.2 | 8.0 | 7.5 | 15.5 | 12.4 | 45.2 | 42.4 | 51.6 | 48.4 |
| 1980 | 17.9 | 2.2 | 8.2 | 7.5 | 15.7 | 12.3 | 45.8 | 41.9 | 52.2 | 47.8 |
| Unweighted Average | 14.4 | 3.1 | 6.8 | 4.6 | 11.4 | 25.7 | 45.1 | 29.4 | 63.5 | 36.5 |

**Note:** Figures may not add to 100% in every case due to rounding error.

The empirical results of this analysis clearly suggest the existence of property value discounts associated with school desegregation. Furthermore these discounts appear to vary over time depending on such conditions as the status of court decisions relating to desegregation, the initiation of desegregation plans, or changes in the racial composition of local schools. There does not appear to be any significant anticipation of such events as reflected in "leads" in property value changes, but instead a one-to-two-year lag appears to be more common. Finally, it is clear that the relative importance of the various sources of desegregation discounts also changes over time in response to various external forces and changed sensitivities of households. For example, the racial composition of the local school was found to be *the* dominant influence on discounts in the years immediately following the first desegregation order. However, this factor varied in influence in later years relative to the influence of "other" desegregation related factors, which include perceptions of school quality, stability in the educational process, or educational orientation. These "other" factors were found to grow in influence continuously from the time of the initial desegregation order.

The magnitude of the racial enrollment discount was generally in the same range as such discounts determined in previous studies, although it varied considerably over time. It ranged from a low of 2.9% of average unit value in 1971 to a high of 15.1% in 1974 and averaged an unweighted 6.8% over the observation period (column 3 of Table 4). This is in the same range as Clotfelter's results (6 to 7%) but for a substantially higher black enrollment (58.7% unweighted vs. 13.6% in the Clotfelter study). Elasticities in the present study were thus relatively low ranging from .05 (percent discount to percent black enrollment) to .23, averaging .12 unweighted. In the Clotfelter study elasticities were in the .44-.51 range. The source for this difference could be due to any number of factors, including both different household attitudes as well as different methodologies (e.g., the Clotfelter results also could be picking up some of the "other" desegregation effects that were separately estimated here).

School district effects unrelated to racial enrollment in the schools, which were not able to be estimated satisfactorily in previous studies, were also shown to have a significant influence on property value discounts. Such discounts ranged from 3.7 to 9.7% of property value and, depending upon the year, from 27 to 75% of the total discount (averaging 55%). If it can be assumed that preexisting school-district effects were unrelated to desegregation but those introduced after the first desegregation order were totally due to desegregation, then the "other" desegregation-related effects (besides actual racial enrollment) accounted for discounts ranging from 0.0 to 7.5% of property value, still accounting for zero to 65% of the total desegregation-related discount (averaging 37%, columns 4 and 10, Table 4). This is not an insignificant contribution. It is a factor that must be included in any evaluation of "total" desegregation effects on property values. The "total" desegregation effects, then, (eliminating consideration of preexisting status and tax effects) were found to range from 2.9 to 17.3% of average unit value, averaging 11.4% over the study period (column 5, Table 4).

These results have strong implications for public policy relating to school desegregation. If it can be assumed that each house occupied by a white household in the Dallas Independent School District suffered the same 11.4% average discount in value, this implies a total of $908 million loss in residential market value for the estimated 141,000 white-occupied units in the DISD, or $6453 per residential parcel.[15] At an average effective total tax rate of $1.22 per $100 taxable value, this implies a loss in tax revenues of $11.1 million annually or $78.73 per white-occupied residential parcel. This loss in public revenue and windfall loss in personal wealth must be balanced against the benefits that accrue from court-ordered desegregation plans. It ignores, of course, the additional adverse effects of any externalities that may flow from the downward filtering that takes place as a result of the devaluation. Another way of viewing the discount, if it is assumed that total revenue needs remain constant, is that it would be necessary to increase the tax rate within the DISD by an average 7.0%,[16] which could potentially have an adverse effect on migration patterns for both households and firms, supplementing the direct desegregation ("white flight") effect (Tiebout 1956), In toto it appears that this component of the direct economic cost of court-ordered desegregation plans can be substantial.

One more optimistic aspect of the results is the fact that white household sensitivity to desegregated enrollment patterns seems to wane several years after an integration plan is initiated. In later years, the factors causing a desegregation discount increasingly stem from "other" sources, including perceptions of school quality, educational orientation of the school district, etc. To the extent that the primary goal of school desegregation is integration in the classroom and the "other" factors are controllable through careful, deliberate policies, this implies that certain direct costs of court-ordered desegregation plans may be reduced in the long run, allowing potential increases in the net benefits from their implementation. However, even in this case, it must be recognized that such policy intervention strategies as affecting perceptions of school quality cannot be achieved costlessly.

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## Appendix I
## Quantification of the Concept of a Stable Region for K

Vinod (1976) has developed two heuristic measures, the Index of Stability of Relative Magnitudes (ISRM) and the Numerical Largeness of More Significant Regression Coefficients (NLMS), which provide quantitative evidence for a "stable" region for K, i.e., a region such that the reduction in variance outweighs the increase in bias and the mean square error of estimation and prediction is improved in comparison to OLS results. These are described briefly below.

*The Index of Stability of Relative Magnitudes (ISRM)*

The ISRM is a measure of the extent of deviation from orthogonality of the system used in estimation. The degree of orthogonality is affected each time a K is selected. Generally, for systems with high multicollinearity, initially (at low K) the system will approach orthogonality as the substantial reduction in variance overcomes the slight increase in bias. At higher levels of K, however, the orthogonality of the system is reduced as the bias effect begins to dominate. The "stable" region is considered to be the region in which the system does not deviate significantly from orthogonality, in particular where orthogonality is improved over OLS.

The ISRM is defined by the relationship:

$$\text{ISRM} = \sum_i \left[ (p\delta_i^2/\bar{S}\lambda_i) - 1 \right]^2 \tag{A1}$$

where $i$ = an index representing the explanatory variable number

$p$ = the number of explanatory variables

$\lambda_i$ = the $i^{th}$ eigenvalue of the matrix of sample correlation coefficients between the regressors.

$$\delta_i = \frac{\lambda_i}{\lambda_i + K}$$

$$\bar{S} = \sum_i \frac{\lambda_i}{(\lambda_i + K)^2}$$

$K$ = the degree of bias introduced in the ridge estimate

For completely orthogonal data, $\bar{S}$ becomes $\sum_i \frac{1}{(1 + K)^2} = p/(1 + K)^2$, and $\delta_i$ becomes $\frac{1}{1 + K}$ for all i. The expression in parenthesis in (A1) then becomes 1 and ISRM = 0. As the data deviates from orthogonality, the ISRM grows larger. It is thus possible to calculate the ISRM for a range of K and choose the "stable" region as those K where the ISRM does not greatly deviate from the minimum, in particular where it is lower than under OLS. One theoretical advantage of the ISRM is that it is not stochastic, whereas the standardized coefficients plotted in a ridge trace are stochastic, leading to a stochastic determination of K.

### *The Numerical Largeness of More Significant Regression Coefficients (NLMS)*

The second heuristic measure developed to quantify a "stable" region for K involves the monitoring of K for numerical largeness of more significant regression coefficients (NLMS). The idea behind this is that one would expect for orthogonal data that standardized regression coefficients which are numerically larger in absolute value (NL) also would be more significant (MS), in the sense of possessing a larger t-statistic. (This, of course, ignores the fact that significance tests are not well developed for ridge regression coefficients.) The NLMS test, therefore, correlates, for each K, the standardized coefficient absolute values against t-statistics for the set of explanatory variables. The ordinary correlation coefficient between the p pairs of values of $|b_i^*|$ and $|t_i|$, denoted by NLMS, is the scale free summary of this relationship. The "optimal" K then becomes the point where NLMS (or the correlation between $|b_i^*|$ and $|t_i|$) is maximized. The "stable" region of K is that region where NLMS does not greatly deviate from the maximum, in particular where it is greater than under OLS.

## NOTES

1. The HPISD was never considered in the original 1971 school desegregation court order. In the 1976 court order, it was deliberately excluded by the District Court (a decision that was approved by the Fifth Circuit Court of Appeals) after the plaintiffs requested it be included in the desegregation order. According to the District Court, the HPISD had exhibited "a twenty-year history of non-discrimination."

2. An attempt was made to acquire transactions data prior to 1971, the year of the first desegregation court order, to provide evidence of any anticipation of a desegregation order. However, the SREA data was not available prior to 1971, and other data sources, such as the MLS, were not compatible. Later findings indicate there appears to be a "lag" effect, rather than a "lead" effect of major court orders on property value changes. Thus, the effect of this limitation on data availability is thought to be minimal.

3. In the case of differential school tax effects, we may derive some notion of the potential magnitude of error in this assumption. The relative effective school tax rates between the DISD and the HPISD were as follows during the period 1971-80: 1971-1.51:1, 1972-1.56:1, 1973-1.59:1, 1974-1.65:1, 1975-1.45:1, 1976-1.40:1, 1977-1.38:1, 1978-1.37:1, 1979-1.10:1, 1980-0.82:1. Note the ratio was highest during the 1973-74 period and dropped off considerably in later years in response to relatively large property appreciations in Highland Park. Assuming tax rate differentials are fully capitalized into property value differentials and assuming a 10% discount rate, this implies DISD discounts due to school tax differentials would be in the range of 1.7 to +4.0%, based upon actual average house values and effective school tax rates each year. Except for the years 1979 and 1980, the discount stayed within the relatively narrow range of 3.1 to 4.0%. This would suggest most, if not all, of the initial status and tax discount of 3.7% consists of a tax discount and furthermore this discount would not be expected to change much over the study period (except for a significant drop in 1979-80). Thus, our model specification, which estimates a status and tax discount of 3.7% in 1971, dropping gradually to 2.2% in 1980, would not suffer serious specification error. The only potential problem might come in the years 1979-80, during which our model would overestimate the status and tax discount. The potential error, however, would be in the "right" direction in that it would result in underestimates of the desegregation discount during those years.

Of course, there is still a possibility that changes in status or locational effects not otherwise accounted for might have taken place during the study period. These are less easy to estimate. However, the fact that results presented later indicate that changes in discounts appear to correlate highly with court desegregation orders suggests that these sources of error either are correlated with such desegregation orders or, more likely, are relatively minor.

4. Since 1980 the DISD desegregation controversy has continued. In summer 1981, the District Court convened and ordered a new plan that it felt responded to the Fifth Circuit's mandate. The plan moderately increased the level of busing but still permitted significant numbers of one-race schools. The new plan was immediately appealed by both the school board and the NAACP. In 1982, the NAACP voted to drop its appeal.

5. Apart from the discussion about the appropriate K, numerous economists and statisticians have debated at length over other potential problems in the application of ridge regression (see Conniffe and Stone 1973, Smith and Campbell 1980, Thisted 1980, Marquardt 1980, van Nostrand 1980, Lindley 1980, Obenchain 1980, Peele and Ryan 1980, Vinod 1980, and Gunst 1980). These debates have focused on 1) ridge regression's inherent (unknown) bias characteristic, 2) the tendency to consider multicollinear data as "weak" rather than dealing with the underlying issues of multicollinearity, 3) the tendency to ignore the possibility that insignificant coefficients may be representing truly insignificant effects rather than being the effect of multicollinearity alone, and 4) the lack of behavioral basis for the introduction of bias. In addition, others (Goldstein and Smith 1974, Fraser 1982) have suggested modifications to "simple" ridge regression that are supposedly more general and better able to extract an estimate of the appropriate degree of bias introduction. We do not propose to enter into these debates in this paper. Most researchers (e.g., see Thisted 1980, Marquardt 1980, Vinod 1978) agree that ridge regression can be a useful alternative for OLS, especially for obtaining numerical values of regression coefficients (but possibly less useful for hypothesis testing). However, its usefulness is limited to those cases in which all "common sense" remedies for multicollinearity have preceded its use and all available prior information on proper specification has been employed. The present situation is one which satisfies these conditions: we have some a priori expectations about the proper inclusion of amenity variables affecting price and their coefficient signs and magnitudes, and the multicollinearity present is essential and a property of the data set. Moreover as Gunst (1980) observes, "Ridge regression has been successfully applied too frequently, when little formal prior information is available, for its use to be restricted to data sets for which the formal Bayesian priors are known to be valid."

6. Considerable discussion has arisen over the appropriate functional form for the hedonic equation and its exact meaning. There seems to be a general consensus that the single-equation coefficient estimates provide estimates of the hedonic prices, but that these prices are not constant for all individuals unless the functional form of the model is linear (Freeman 1979). Rosen (1974) and Freeman (1979) suggest that nonlinearity of the relationship is expected in general because the unit amenities are imperfectly separable from each other and from the site.

7. Hedonic prices have been shown not to be interpretable as demand coefficients unless 1) households are identical with respect to income and tastes for the amenity (Freeman 1971, 1974) or 2) the mix of attributes is constant across sites except for the attribute of interest, since the coefficient is evaluated at the mix of all other attributes (Cobb 1977). Rosen (1974) shows that even these conditions are not sufficient to obtain demand coefficients in the absence of linearity.

The suggested response to the problem, initially proposed by Rosen (1974), is an implicit market approach in which a two-stage procedure first estimates hedonic prices, and these are then used to estimate the demand for site traits. This is the procedure used by Jud and Watts. On the other hand, Clotfelter contends that since the supply of housing is relatively inelastic in the short run, an analysis of short-run price changes would reflect changes in the demand for housing only (although he acknowledges in the longer run this would cause additional changes in unit structure quality).

8. The Consumer Price Index was obtained quarterly for the Dallas-Fort Worth area. Linear interpolation was then used to provide monthly estimates for the CPI.

9. Obtained for Longfellow Elementary, the local school for the DISD study area, from records compiled by the Dallas Independent School District. It was felt black enrollment at the elementary school level would be more effective in influencing "white flight" tendencies than that at the high school level, as was used by Clotfelter.Note, this treats Hispanic enrollment as white, which may not be completely justified.

10. Attempts were made to estimate additional specifications which were unsuccessful for one reason or another. One set of regressions was run with PRLDFF, the real sales price per square foot, as the dependent variable. In the expectation that the square-footage adjustment provides adequate control for amenity features, the amenity-related explanatory variables were not included. Only the desegregation-related variables HPISD and PCTBLK were included. Results were unfavorable in that the explanatory power of the regressions was considerably reduced from those based on PRLDFW. An attempt also was made to increase the number of discrete time intervals to annual intervals. Such extreme discreteness in time would have been advantageous in that it would have provided maximum resolution of time variations in prices. However, restrictions in degrees of freedom and a 30-explanatory variable limitation in the ridge regression software package used prevented such extreme discreteness. One specification also considered the amenity-related interaction terms as continuous time while the desegregation-related amenity terms were entered as discrete time. This, of course, loaded all remaining price variability over time (beyond the linear component) onto the desegregation-related discrete interaction terms, which would tend to overstate their influence. The discrete time intervals used were obtained by testing model performance under a variety of alternative interval specifications.

11. Note that only a sample of all runs made is presented due to space limitations. Additional ridge results with different specifications are available from the first author.

12. Note that Figure 2 presents the *total* school district discounts by year and not just the marginal "desegregation" effects.

13. The finding of a "lag" rather than anticipatory effects is interesting. Causes for it are speculative, however. It may be due to greater attention to the *reality* of desegregation rather than the *anticipation*. Alternatively, it may be due in part to lags in transactions that reflect prior demand shifts. Little attention has been paid in the social science literature to the dynamics of such changes.

14. Of course, it must be recognized that part of this response could reflect a changing composition of DISD households, possibly with many of those most sensitive to desegregated schools moving out by 1977.

15. This estimate is a crude one and is meant only to provide some indication of the potential magnitude of the impact. It assumes the proportion of white-occupied units in the DISD is the same as the proportion in the city of Dallas in 1980 (the DISD proportion is actually somewhat lower). It also assumes average unit value is the same for black and white-occupied units. Finally, it assumes effective tax rates are identical in black and white neighborhoods and that there is no variation in the 11.4% discount across individual units which is, of course, not the case. Note that the magnitude of the average discount suggests that it may represent in part a capitalization of the cost of private schooling. The present value of a $1500 tuition payment over six years discounted at 10% is $6,530.

16. This percentage was obtained by weighting the 11.4% discount for white-occupied units by the proportion white-occupied units making up the total stock.

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