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RANKING UP BY MOVING OUT: THE EFFECT OF THE TEXAS TOP 10% PLAN ON PROPERTY VALUES

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Texas engaged in a large-scale policy experiment when it instituted the Top 10% Plan. This policy guarantees automatic admission to their state university of choice for all high school seniors who graduate in the top decile of their high school class. We find evidence that households reacted strategically to this policy by moving to neighborhoods with lower-performing schools, increasing property values in those areas. The effect is strongest among schools that were very low-performing before the change in policy. We also find evidence that these strategic reactions were influenced by the number of local schooling options available, as these effects of the Top 10% Plan were weaker in areas that had fewer school choices.

Keywords: property values, college choice, affirmative action, top 10% plan

JEL Codes: H31, H41, H73, I20

I. INTRODUCTION

Texas engaged in a large-scale experiment when it replaced affirmative action policies in its college admissions with the Top 10% Plan admissions policy. The Top 10% Plan guarantees admission into any of Texas' public universities to all high school seniors who finish within the top decile of their graduating class. This includes the two most selective state universities: The University of Texas at Austin (UT-Austin) and Texas A&M University at College Station (Texas A&M). For school districts that had poor acceptance rates to postsecondary institutions, this admissions policy suddenly provided a valuable local amenity — improved access to state universities. This amenity was highly valued by households who went so far as to change schools in order to take advantage of the increased chance of college admission (Cullen, Long, and Reback, 2013).

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In this study, we analyze the effect of the Top 10% Plan on property values. More specifically, we analyze whether the change in admissions policies led to an increase in the value of residential homes in school districts with lower-performing high schools relative to school districts with higher-performing high schools. Though theoretically it is possible for the property values in any school district to increase relative to any other district with higher initial school quality as a result of the policy change, we find that school districts with the lowest-performing high schools are the areas where property values are most responsive to the policy change. This is plausible because it is at these schools where *access* to selective public colleges and universities was improved the most, i.e., the largest increase in the probability of guaranteed acceptance was in the lowest performing schools. We find smaller effects of the Top 10% Plan in areas with high-performing schools; these schools were more likely to place the top 10 percent of their graduates in highly ranked postsecondary institutions prior to the reform, so the Top 10% Plan did much less to increase access.

Using a difference-in-differences framework, we find that, as a consequence of the change in admissions policy, residential property values in the areas served by schools in the bottom quintile of school quality grew more rapidly relative to areas served by schools in the 2nd quintile (second from the bottom). We also find that the bottom quintile grew relative to other quintiles in the school quality distribution, although the effect attenuates with distance from the bottom of the distribution. We also analyze the top two quintiles and find that the growth in home values did not occur in the top end of the school quality distribution.

Furthermore, we observe that changes in property values are sensitive to the number of schooling options locally available. If a household is going to react strategically to the Top 10% Plan by moving, then moves would be easier in areas with a large number of local schooling options (e.g., moving a shorter distance to find a new school would not require finding a new job). Specifically, we find that the lower a county's Herfindahl-Hirschman Index (HHI) for schooling, which is an indicator of more schooling options, the more property values increased in response to the Top 10% Plan.

Lastly, our analysis estimates that the Top 10% Plan caused a 4.8 percent gain in relative average property values in school districts in the lowest quintile of school quality compared to districts in the 2nd quintile of school quality. As property values vary greatly from district to district before the policy shift and property tax rates also vary greatly, the Top 10% Plan had a powerful impact not only on admissions decisions, but also on school finance and local taxation decisions.

II. BACKGOUND AND LITERATURE REVIEW

A. The Top 10% Plan

The 5th Circuit Court's decision in *Hopwood v. University of Texas Law School* banned the use of race as a criterion in admissions decisions in all public postsecondary institutions in Texas.[1] The end of affirmative action admissions policies had a significant impact, especially at the two most selective public institutions, UT-Austin and Texas A&M, where the number of minority enrollees plummeted. For example, the acceptance rate for Hispanic students dropped 11.6 percentage points from 79.9 percent to 68.3 percent at Texas A&M in the year following the Hopwood ruling (Tienda et al., 2003; Bucks, 2003; Walker and Lavergne, 2001). In response to this ruling, the Texas legislature on May 20, 1997 passed H.B. 588 — commonly known as the Top 10% Plan. The Top 10% Plan guarantees automatic admission to any public university of choice to all seniors who graduate in the top decile of their graduating high school class.[2] [3] This plan is similar to those in other states (e.g., California and Florida), but is unique in the sense that it gives students the choice of which public institution they would like to attend rather than assigning students to a specific institution.[4] The Top 10% Plan has been controversial in the 15 years it has been in place and has had its constitutionally challenged under the 14th Amendment in the Supreme Court in the Fisher v. University of Texas case.[5] Currently the case has been remanded to a lower court, and the constitutionality of the policy is still being debated.

Proponents of the plan believed that it would restore campus diversity because of the high degree of segregation among high schools in Texas. Their logic was that the number of minority students who would be rank-eligible under the Top 10% Plan would be sufficient to restore campus diversity in the university system. Even though the goal of the Top 10% Plan was to improve access for disadvantaged and minority students, the use of a school-specific standard to determine eligibility may have had some unintended consequences if households responded strategically. In a recent study, Cullen, Long, and Reback (2013) find that a large number of students increased their chances of being in the top 10% by choosing a high school with lower-achieving peers. They analyze student mobility patterns between the 8th and 10th grades before and after the policy change and conclude that the change in admissions policies in Texas did indeed influence the high school choices of students. This evidence of students changing districts strategically may help to explain the changes in college enrollment probabilities for minority and non-minority students found in Walker and Lavergne (2001), Tienda et al. (2003), Bucks (2003), Niu, Tienda, and Cortes (2006), Niu and Tienda (2006), and Cortes (2010).[6]

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1 *Hopwood v. University of Texas Law School* 78 F.3d 932, 944 (5th Cir. 1996).

2 In 2009, Texas placed a limit on student choice: UT-Austin is now allowed to cut off the proportion of Top 10% Plan students in a given freshman class at 75 percent.

3 Although private universities are subject to the *Hopwood* ruling, they are not subject to the automatic admissions guarantee (Tienda et al., 2003).

4 In both California and Florida, students are accepted into the state university system by rank eligibility but are not given a choice of which institution they would like to attend.

5 *Fisher v. University of Texas*, 570 U.S. (2013).

6 Low socioeconomic status and minority students saw a decrease in enrollment probabilities under the Top 10% Plan relative to affirmative action. It is possible that some of this decrease is due to students who changed high schools taking up slots in the top of their high school classes.

If households are moving strategically between schools, then their valuations of those schools must have changed. Our analysis explores this idea by looking for evidence of these changes in valuation as reflected in households' maximum willingness to pay for housing services as captured by changes in property values in school districts whose desirability changed when the Top 10% Plan was implemented.

B. Related Literature

The Top 10% Plan changed how much some households were willing to pay for school district quality through their housing prices; such a response is predicted by bidding and sorting models, which have a long tradition in the local public finance literature. This branch of the literature is widely seen as starting with Tiebout (1956) who argued that households shop for property tax and public service packages through their choice of location. This forms the cornerstone of bidding and sorting models in which households with different incomes and tastes sort themselves based on their maximum willingness to pay for a quality-adjusted unit of housing in communities with different tax and service packages. Ross and Yinger (1999) provide a discussion of this model as well as a review of the capitalization literature that analyzes how differing property tax or public service levels are reflected in housing prices.

The part of this literature that is germane to our analysis deals with estimating the capitalization of school district characteristics.[7] The main empirical hurdle with these studies is disentangling the capitalization of school district characteristics from the capitalization of neighborhood characteristics and taxes because these attributes are also spatially linked. A popular solution to this empirical hurdle is to use school districts that contain more than one school and identify capitalization effects using variation across boundaries within the school district. Variations on this strategy have been used by Bogart and Cromwell (1997), Black (1999), and Weimer and Wolkoff (2001).

Another possibility is to use panel data and difference out the undesired effects; this allows analysis of the capitalization of school district characteristics that vary over time. Barrow and Rouse (2004) use school district fixed effects to examine how differences in state aid to schools are capitalized into property values. Their identification strategy is similar to Clapp, Nanda, and Ross (2008) who use census tract fixed effects to study the capitalization of differences in state standardized test scores and school district demographics over time. Also, a study by Figlio and Lucas (2004) uses repeat sales data, which allows for property level fixed effects, to look at the effects of school report card grades on property values.

Our identification strategy is closer to the second set of papers, as we control for neighborhood and tax effects by differencing over time as part of our difference-in-differences estimator. However, our analysis is different in that we are not interested

[7] Nguyen-Hoang and Yinger (2011) provide a comprehensive review of the literature on the capitalization of school quality into housing values.

in the level of public service capitalization into property values as much as we are interested in how property values change in response to a policy shift. Few studies in the school quality capitalization literature take such an approach; the only paper that we are aware of is by Reback (2005), who analyzes how property values responded to the introduction of a school choice program in Minnesota.

III. THEORETICAL FRAMEWORK: THE EFFECT OF THE TOP 10% PLAN ON PROPERTY VALUES

Consider the following simple hedonic model of housing prices in a school district

$$(1) \quad P_{dt} = f(X_d, S_{dt}, M_t),$$

where P_{dt} represents the average value of housing in school district d at time t and is a function of time invariant school district level variables, X_d, such as geographic features and characteristics of the housing stock; time sensitive school district level variables, S_{dt}, which includes school quality characteristics; and the overall condition of the housing market, M_t.[8] The vector of time variant school district characteristics, S_{dt}, includes a variable that represents the quality of the top 10% of a school's graduating class, TTP_{dt}, as well as a variable that represents the quality of peers at a school in general, PE_{dt}. Before the implementation of the Top 10% Plan, both PE_{dt} and TTP_{dt} were positively related to property values, as were any other school quality measures. Parents are willing to pay for high quality schools, which would include high-achieving peers, and this translates to higher property values.

After the implementation of the Top 10% Plan, some students suddenly benefited from attending schools with lower-achieving peers in that school's top 10 percent. In these school districts, high-achieving students were suddenly able to automatically gain access to a state university by placing into the top 10 percent of their graduating class. Hence, lower-achieving peers in the top 10 percent suddenly became valuable, and higher-achieving peers in the top 10 percent were less valuable for certain students. If the parents of these students recognized this new relationship, it would change their maximum willingness to pay for housing, depending on the quality of best students in a school district. This can be expressed as TTP_{dt} having a negative relationship with willingness to pay for housing for some households. The relationship of peers in general, PE_{dt}, with willingness to pay would not change.[9] Parents would trade off the benefit of worse peers in the top 10 percent of the class coupled with the chance of a better college education, against the cost of worse peers in general. We will assume that for some proportion of parents the change in the effect of TTP_{dt} on willingness to

[8] The average characteristics of the housing stock as a whole change more slowly than the characteristics of a single home.

[9] The quality of the peer group in general might change after families move between districts; however, the relationship between general peer quality and willingness to pay is assumed to be stable.

pay for housing was enough to overwhelm the effect of PE_{dt} and increased their overall willingness to pay for housing in poorly performing school districts.

The effect of the policy on property values in an entire district would depend on what proportion of the district in question was made up of households for which poorly performing peers became attractive. We hypothesize that these would be school districts where access to top colleges was poor initially, so guaranteed access to the flagship universities (UT-Austin or Texas A&M) would have been considered quite valuable. These would be districts with low-achieving peers before the policy was enacted. Further, any effect on the district's property values would be exacerbated as additional parents with such preferences might migrate to the district to take advantage of its district's lower-quality peers.

The overall effect would be that school districts with low-achieving peers would experience an increase in property values, whereas the opposite would be true for school districts with high-achieving peers. These effects would be more pronounced in places where parents care a lot about access to colleges via the Top 10% Plan. In other words, a district where most students were already being admitted to universities of similar quality to UT-Austin or Texas A&M would experience a much smaller capitalization effect.

IV. EMPIRICAL STRATEGIES AND MODEL SPECIFICATION

A. Difference-in-Differences Analysis

We use a difference-in-differences analytic approach to study the effect of the Top 10% Plan on property values. We compare changes in home values before and after the Top 10% Plan was enacted by differencing property values in the pre-policy period (1994–1995 school year through 1996–1997 school year) from property values in the post-policy period (1997–1998 school year through 2005–2006 school year). This first difference removes any effects that are constant between the pre- and post-periods such as omitted neighborhood effects. The second difference is between the 1st and 2nd quintiles of school quality. These differences yield the net effect of the Top 10% Plan on home values in the 1st (bottom) quintile relative to the 2nd quintile. Our identification strategy hinges on the assumption that there were no other exogenous factors that could have caused these differences in this time frame.

Several models of the following form are estimated by ordinary least squares (OLS) with a focus on the parameter δ, the difference-in-differences estimator,

$$(2)\quad \ln\left(Y\right)_{jt} = \alpha + \sum_{k=1994,\, k\neq 1997}^{2005} \beta_k \cdot I\left(Year_t = k\right) + \beta \cdot Treatment_i + \delta \cdot Post_t \cdot Treat_i$$
$$+ X_{it} \cdot \theta + C_{kt} \cdot \lambda + \varphi + \varepsilon_{jt},$$

where the dependent variable $\ln(Y)_{jt}$ indicates the log of the average price of a single family home in school district j in year t, and $I(\cdot)$ is an indicator function associated with year t. The binary variable $Treatment_i$ indicates low-performing high school campuses (i.e., campuses with poor pre-policy access to universities); these campuses are identified by their median American College Test (ACT) scores (i.e., it is equal to 1 for the 1st ACT quintile or equal to 0 for the 2nd ACT quintile).[10] The binary variable $Post_t$ indicates the period after the law was passed (i.e., it is equal to 1 for the 1997–1998 through 2005–2006 school years or equal to 0 for the 1994–1995 through 1996–1997 school years). The product of $Post_t$ and $Treatment_i$ captures the interaction of these two indicator variables. The variable X_{it} is a vector of time varying characteristics associated with high school i in year t, C_{kt} is a vector of time varying characteristics associated with county k in year t, and φ is a vector of Metropolitan Statistical Area (MSA) fixed effects. Lastly, ε_{jt} is a normally distributed random error term.

More specifically, X_{it} is comprised of high school demographic controls and variables for the degree of urbanization at the high school's location. The high school demographic variables include the percentage of minority students, the percentage of economically disadvantaged students, the percentage of gifted students, average teacher experience, and the student-teacher ratio. The urbanization controls are dummy variables for the school campus being located in a large or small city, a large or small urban fringe, or in a town. Rural campuses are the omitted category. The vector C_{kt} includes time varying county characteristics and has controls for the percentage of the population that is black, the percentage of the population that is Hispanic, the average number of persons per housing unit, the percentage of housing units that are owner-occupied, the number of violent crimes per 1,000 people, and the percentage of county residents with a college degree.

Our difference-in-differences estimator does not discern whether the relative price change is driven by low-quality school districts gaining value or high-quality school districts losing value. However, the difference-in-differences estimator has some attractive properties in the face of some highly probable types of misspecification. Incorrect specification between the treatment and control groups will bias the estimator towards zero. For example, high school switching could realistically happen between any two schools of differential quality at the lower end of the school quality distribution. Not all switches will be from the 2nd ACT quintile of school quality to the bottom ACT quintile of school quality, as there is a possibility for intra-quintile switches. However, if we assume that all switches inspired by the policy change are from higher to lower-quality schools, then failing to capture price changes coming from these intra-quintile switches will bias the difference-in-differences estimation towards finding no effect from the legislative change.

Our estimation strategy allows the identification of effects from the part of the distribution of school quality that should be most responsive to the policy shift and provides the opportunity to check other parts of the distribution for policy effects. Specifically

[10] We can observe ACT scores at the individual high school level, but our dependent variable is measured at the district level. This introduces an aggregation bias towards finding no response from the policy change.

we can estimate the effect of the Top 10% Plan on all quintiles relative to the bottom quintile. We would expect to see the quintiles closest to the bottom of the distribution to have the largest effect, and to see the effects attenuate further and further away from the bottom quintile. This can be done by estimating,

$$(3) \quad \ln\left(Y\right)_{jt} = \alpha + \sum_{k=1994,\, k\neq 1997}^{2005} \beta_k \cdot I\left(Year_t = k\right) + \beta \cdot Qtile_i + \delta \cdot Post_t \cdot Qtile_i$$

$$+ X_{it} \cdot \theta + C_{kt} \cdot \lambda + \varphi + \varepsilon_{jt},$$

where *Qtile* is a vector of dummy variables for the 2nd, 3rd, 4th and top quintiles (the bottom quintile is the omitted category). The different realizations of δ, the coefficient on the interactions between the dummy variables and the post-period indicator will give the effect of the policy on the different quintiles relative to the bottom quintile.

We can also do the difference-in-differences analysis for the top two ACT quintiles of the school quality distribution. High schools with top levels of academic performance should be placing much more than their top 10% of graduates into quality institutions and thus should be largely unaffected by the implementation of the Top 10% Plan. If at the top end of the school quality distribution, relatively "poor" performing school districts (4th ACT quintile) are gaining in property value relative to better performing school districts (5th ACT quintile), then our proposed mechanism for property value changes at the bottom end of the school quality distribution would be called into serious doubt.[11] Such a result would show that migration from higher to relatively "lower" quality school districts occurred in a part of the school quality distribution where the Top 10% Plan should have little to no effect, making it likely that any changes observed in the bottom part of the school quality distribution were caused by some other phenomenon. Our hypothesis will be greatly strengthened if there are noticeable difference-in-differences between the bottom two (2nd and 1st) ACT quintiles but not between the top two (5th and 4th) ACT quintiles.

B. Herfindahl-Hirschman Index Analysis

Our second estimation strategy investigates if the number of schooling options available influenced the effect of the Top 10% Plan on property values. If it is costly to change

[11] Students from top quality schools who would have gotten into the flagship schools before the policy were not likely subject to crowd out by Top 10% Plan students. The entering freshman class at UT-Austin for example had 3,375 (58 percent) of its students from outside the top 10 percent in 1996 and 3,596 (55 percent) of its students from outside the top 10 percent in 1999. The flagships accommodated the new students by increasing freshman class sizes. (UT-Austin Office of Admissions, 2006).

school districts, which is one possible mechanism for property value changes, then it is less likely that households will react to the policy change.[12] Therefore, if there are more local schooling options then it should be less costly to change schools and there should be a larger reaction. For example, a move across the state to find a more strategic school seems unlikely because of the costs of finding new employment. However, a move of a smaller distance such as a few miles seems much more pluasible.[13]

One approach to measuring schooling industry concentration is to calculate the Herfindahl-Hirschman Index (HHI) at the county level, or

$$(4) \quad HHI_k = \sum_{i \in k} s_i^2 = \sum_{i \in k} \left(\frac{\text{Total number of students in each high school}_i}{\text{Total number of students in county}_k} \right)^2,$$

where s_i is the market share of each high school i in county k. For schooling, a measure of the market share is the number of students at a high school divided by the total number of students in the county. A HHI_k value close to 1 indicates a more monopolistic county, whereas a HHI_k value close to 0 indicates a more competitive county.

To analyze whether the number of schooling options available influenced the effect of the Top 10% Plan on property values, we interact the pre-policy county level HHI_k measure with our difference-in-differences estimator, yielding the following triple-difference specification,

$$(5) \quad \ln(Y)_{jt} = \alpha + \sum_{k=1994,\ k \neq 1997}^{2005} \beta_k \cdot I(Year_t = k) + \beta \cdot Treat_i + \delta \cdot Post_t \cdot Treat_i$$
$$+ \psi \cdot HHI_k + \phi \cdot Post_t \cdot HHI_k + \rho \cdot Treatment_i \cdot HHI_k + \pi \cdot Post_t \cdot Treatment_i \cdot HHI_k$$
$$+ X_{it} \cdot \theta + C_{kt} \cdot \lambda + \varphi + \varepsilon_{jt}$$

where π is now the parameter of interest, estimating the effect of the county HHI_k on the relative impact of the Top 10% Plan on property values. A negative value for the coefficient π would imply that counties with less school choice showed a smaller reaction to the Top 10% Plan.

[12] There is some uncertainty as to the specific mechanism by which property values change. Evidence presented by Cullen, Long, and Reback (2013) points towards changes in property values being driven by households making strategic moves. However, it is also possible that the relative change in property values is driven by households that change their willingness to pay for housing in their current district. These households could change residence without leaving the district and have their new willingness to pay capitalized into their property's value.

[13] It is not necessary for the household to move because of the policy change to experience the resulting change in property values. A change in values may be driven by households that were already planning to move and simply found lower-performing schools to suddenly be more desirable.

V. DATA SOURCES AND SAMPLE CHARACTERISTICS

A. Data Sources

The data for this study were compiled from five sources: the Texas Comptroller Property Tax Division (TCPTD), the Academic Excellence Indicator System (AEIS) from the Student Assessment Divisions of the Texas Education Agency, the National Center for Education Statistics (NCES), the U.S. Census Bureau, and the Federal Bureau of Investigation's Uniform Crime Reporting (UCR) database. The TCPTD, AEIS, and NCES all utilize Independent School District unique identification numbers that are identical across datasets and enable the linkage of variables in each of these datasets to their specific high school campuses.

The TCPTD database contains information on total appraised home values for all school districts from 1994–1995 to 2005–2006, which covers both pre- and post-policy years. This value is an aggregation of all residential homes that are served by a specific school district. Our analysis uses property values for single family homes only. We exclude multiple family dwellings and condominiums as well as all non-residential properties from our analysis. The TCPTD data also have information on the number of residential housing units in each school district. We use this information to construct our dependent variable by dividing the aggregate value of all residential homes in a school district by the number of housing units in that district. All home values are normalized to 1990 dollars.

Property appraisals in Texas follow a specific procedure. A property must be reappraised by its appraisal district at least once every three years, but can be reappraised more frequently. If a property is sold in a given year, then the sale price of the property is automatically used as the new appraised value of the property. Properties that do not sell are assigned a value based on how their characteristics compare to those of properties that were sold recently. The tax assessors generate a model based on recent sales and use that model to predict what the assessment should be for the unsold properties. There are also limits on how much an appraisal can increase over the previous year's appraisal.[14] Given how Texas calculates its home appraisals, our data account fairly well for property value changes as reflected by housing transactions.

We use the AEIS data in the pre-policy years (i.e., 1994–1995 through 1996–1997) to identify low-performing high school campuses using the median American College Test (ACT) scores of the graduating class. The mean of the median ACT scores in the pre-policy years is then used to sort campuses into quintiles. This allows the identification of poor-performing schools that are most likely to be targeted by parents who choose to move in order to increase the chances of their children being rank-eligible for automatic admission. While some states use the ACT as their assessment measure for the No Child Left Behind Act (NCLB) to hold schools accountable, this is not the case

[14] An appraisal may not increase to a value greater than the lesser of: (1) the sale price of the property if it sold that year, or (2) 110 percent of the previous year's appraisal plus the market value of any new improvements to the property.

in Texas. Texas has its own state assessment test, currently the Texas Assessment of Knowledge and Skills (TAKS), and formerly the Texas Assessment of Academic Skills (TAAS). Thus, using the ACT scores allows us to more reliably identify low-performing schools relative to higher-performing schools. Specifically, the ACT measures the quality of students who consider themselves to be college bound, which is closer to a measure of the top 10 percent of students than the TAAS or TAKS which is taken by all students. In other words, the ACT is a much better proxy for sorting districts based on the pre-policy TTP_{dt}.

The AEIS data also contain detailed information on student and teacher demographic variables, which allows the calculation of the percentage of minority students, the percentage of economically disadvantaged students (defined as those who qualify for reduced price school lunches), the percentage of students that participate in a gifted program, average teacher experience, and the student-teacher ratio at a given high school. Our analysis is restricted to "regular" high schools; any alternative or magnet high schools as well as any juvenile delinquency centers are dropped from the sample, as they cannot be associated with property value assessments.

The NCES data link high school campuses to the urbanization level of their surrounding area. For purposes of this study, campuses are considered to be located in a large city if they are in the central city of a Consolidated Metropolitan Statistical Area (CMSA) with a population greater than 250,000. Campuses are considered to be located in a small city if they are in the central city of a CMSA with a population less than 250,000. Campuses located in large and small fringe areas have addresses that are within the CMSAs for large and small cities respectively, but are not located in the central city of that CMSA. Campuses located in towns are in areas that are not incorporated into the above definitions and also have a population greater than or equal to 2,500. All other campuses are considered to be located in a rural setting, which is the omitted category in our analysis.

In addition, we use the U.S. Decennial Census and UCR data to merge in additional controls needed in the analysis. We use the 1990 and 2000 U.S. Decennial Censuses to create county-level variables to capture the trends in the percentage of the population that is black, the percentage of the population that is Hispanic, average persons per housing unit, and the percentage of housing units that are owner-occupied. Lastly, the UCR database provides county-level variables on violent crimes (i.e., murder, rape, robbery, and assault).[15] Combining the UCR data with the Census data allows us to use estimates of the county-level violent crime rate for the school years of interest.

B. Sample Characteristics

Table 1 reports means and standard deviations for the variables used in our analysis. It also reports the data for the relevant subsamples. For our main specifications, the subsample of interest is the bottom two quintiles of school quality as defined by ACT

[15] There are several measures of crime available in the UCR database. We use violent crimes because they are largely not financially motivated and thus exogenous with respect to local property values, as opposed to an alternate measure of property crimes (grand theft auto, larceny, etc.), which would be highly endogenous.

Table 1

Descriptive Statistics — Means and Standard Deviations

	School Quality Quintiles Based on ACT Scores		
	Both Subsamples	1st Quintile (Treatment)	2nd Quintile (Control)
Dependent Variable			
Average Home Value ($Thousands)	38.46	41.95	35.16
	(26.51)	(27.64)	(24.96)
High School Demographics			
Percent Minority Students	0.690	0.877	0.514
	(0.240)	(0.134)	(0.177)
Percent Disadvantaged Students	0.571	0.682	0.466
	(0.187)	(0.167)	(0.137)
Percent Gifted Students	0.093	0.093	0.094
	(0.066)	(0.065)	(0.067)
Average Teacher Experience	12.64	12.61	12.66
	(2.51)	(2.56)	(2.47)
Student-Teacher Ratio	13.06	13.86	12.30
	(3.28)	(3.14)	(3.24)
Urbanization Characteristics			
Percent in a Town	0.222	0.216	0.227
	(0.415)	(0.411)	(0.419)
Percent in a Small Fringe	0.061	0.056	0.066
	(0.240)	(0.230)	(0.249)
Percent in a Large Fringe	0.042	0.025	0.057
	(0.200)	(0.156)	(0.233)
Percent in a Small City	0.120	0.163	0.079
	(0.325)	(0.369)	(0.269)
Percent in a Large City	0.229	0.349	0.115
	(0.420)	(0.477)	(0.319)
Percent in a Rural Area	0.327	0.191	0.455
	(0.469)	(0.393)	(0.498)

Table 1 (Continued)

Descriptive Statistics — Means and Standard Deviations

	School Quality Quintiles Based on ACT Scores		
	Both Subsamples	1st Quintile (Treatment)	2nd Quintile (Control)
County Level Characteristics			
Percent Black	0.092	0.084	0.100
	(0.082)	(0.085)	(0.079)
Percent Hispanic	0.428	0.564	0.299
	(0.269)	(0.274)	(0.189)
Persons per Housing Unit	2.848	2.972	2.730
	(0.321)	(0.344)	(0.247)
Percent Owner Occupied	0.682	0.659	0.703
	(0.091)	(0.085)	(0.092)
Violent Crimes (per 1,000 People)	0.017	0.018	0.017
	(0.008)	(0.007)	(0.009)
Percent with College Degree	17.209	17.467	16.965
	(7.484)	(7.226)	(7.714)
Observations (school-by-year)	5,633	2,738	2,895

Notes: Numbers in parentheses are standard deviations. Average value per unit is reported in real terms of 1990$. The 1st quintile (the treatment group) is defined as the bottom fifth (0–20%) of school quality based on pre-policy ACT scores. The 2nd quintile (the control group) is defined as the lower middle (20–40%) of school quality based on pre-policy ACT scores

Sources: Texas Comptroller Property Tax Division (TCPTD), 1995 to 2006; Academic Excellence Indicator System (AEIS), Texas Education Agency (TEA), 1994–1995 to 2005–2006; National Center for Education Statistics (NCES), 1994–1995 to 2005–2006; U.S. Census Bureau Decennial Census, 1990 and 2000; and the Federal Bureau of Investigation's Uniform Crime Reporting (UCR) database, 1995 to 2006.

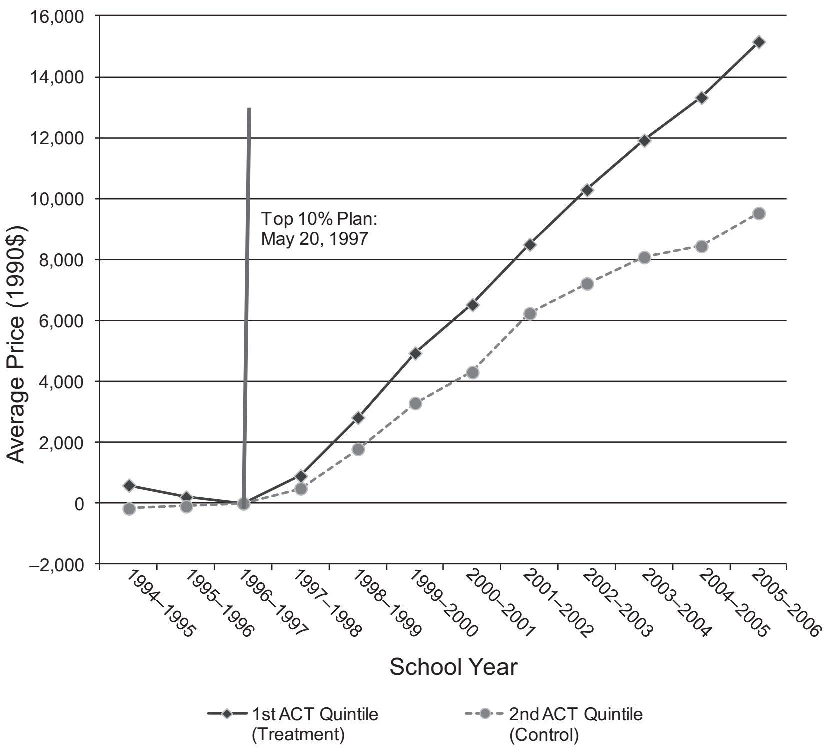
score distribution. The 1st quintile (bottom) serves as the treatment group and the 2nd quintile as the control group. The 1st quintile of schools represents schools that are most likely to be targeted by parents seeking to take advantage of the Top 10% Plan. The 2nd quintile is a good approximation for schools that a strategic parent would want to move their child from in order to gain the benefits available in the bottom quintile. This is because the 2nd quintile is most similar to the bottom quintile in terms of academic performance and pre-policy access to selective state colleges and universities.

It is immediately noticeable that the 1st and 2nd quintiles are actually quite different in many of their other characteristics. For example, property values are far greater in the bottom quintile than in the 2nd quintile. This is largely because the bottom quintile is made up of a larger percentage of urbanized areas. There are also differences in other observable characteristics, including school quality measures. These differences underscore the importance of controlling for school quality measures other than ACT scores, as parents are willing to pay for these characteristics as well.

Figure 1 shows the time trends for the property values of the treatment and control groups. The 1st and 2nd quintiles appear as if they may be on different growth paths

Figure 1

Average Housing Price by School Quality (ACT Quintiles)



Notes: The 1st quintile (the treatment group) is defined as the bottom fifth (0–20%) of school quality based on pre-policy ACT Scores. The 2nd quintile (the control group) is defined as the lower middle (20–40%) of school quality based on pre-policy ACT Scores.
Source: Texas Comptroller Property Tax Division and the Academic Excellence Indicator System from the Student Assessment Divisions of the Texas Education Agency, 1994–1995 to 2005–2006. Tabulations by authors.

in the post period. It appears at first glance that the 1st quintile experienced a spike in property values after the Top 10% Plan is enacted on May 20th, 1997; however, less of a discernible increase in property values is observed for the 2nd quintile. Figure 1 also indicates that prior to the implementation of the Top 10% Plan, the slopes of the treatment and control groups trend lines seem to be quite similar.

VI. DISCUSSION OF RESULTS

A. Overall Results: Difference-in-Differences Analysis

The results for the regression adjusted difference-in-differences analysis are summarized in Table 2. This table reports only the estimated coefficients on the post indicator interacted with the treatment indicator variable, and the treatment indicator variable.

Table 2

Difference-in-Differences Regressions
Log Average Price of Residential Homes (1990$)

	(1)	(2)	(3)	(4)
Bottom Two ACT Quintiles of School Quality				
Post × Treatment	0.050**	0.048**	0.049**	0.049**
	(0.023)	(0.023)	(0.023)	(0.024)
Treatment (1st ACT quintile)	–0.042	–0.058	–0.056	–0.049
	(0.050)	(0.051)	(0.051)	(0.052)
Constant	8.640***	8.534***	8.453***	8.555***
	(0.293)	(0.341)	(0.422)	(0.345)
Year dummies	Y	Y	Y	Y
High school demographics	Y	Y	Y	Y
Urbanization	Y	Y	Y	Y
County level	Y	Y	Y	Y
MSA fixed effects		Y	Y	Y
Previous year's ACT scores			Y	
Weighted by high school size				Y
Observations (school-by-year)	5,633	5,633	5,633	5,633
R^2	0.77	0.78	0.78	0.78

Notes: Numbers in parentheses are robust standard errors clustered by school district. The 1st quintile (the treatment group) is defined as the bottom fifth (0–20%) of school quality based on pre-policy ACT scores. The 2nd quintile (the control group) is defined as the lower middle (20–40%) of school quality based on pre-policy ACT scores. Asterisks denote statistical significance at the 1% (***), 5% (**), and 10% (*) levels.

All regression standard errors are robust and clustered at the school district level.[16] In Table 2, column (1) presents the baseline effects controlling for year fixed effects, high school demographics, urbanization characteristics, and county level controls. Column (2) is the fully controlled regression specification with the addition of MSA fixed effects. Column (3) further controls for high school ACT scores in the prior year, which would be the most recent year of information available to households looking to assess district quality. This variable helps control for school quality changes over time, but is also likely endogenous, so we present it in a separate regression to be used as a sensitivity check. Lastly, column (4) presents a regression specification weighted by high school size. The weighted regression checks whether small high schools have a disproportionate effect on our estimates.

There is a positive and statistically significant difference-in-differences estimate for all model specifications. The point estimate on the difference-in-differences estimator ranges between 0.048 and 0.050. Our preferred specification (shown in column (2)), estimates a 4.8 percent increase of housing prices in low-performing school districts, consistent with our hypothesis that the Top 10% Plan influences property values in districts in the lower end of the school quality distribution. Specifically, this suggests that the benefit offered by the increased likelihood of college admissions from attending a lower-quality school caused property values in school districts in the bottom quintile to increase in value relative to those in districts in the 2nd quintile. The magnitudes of the point estimates vary only slightly and are thus fairly robust across model specifications. Our point estimates are comparable in size to effects found in other studies looking at the capitalization of schooling attributes. Our results are larger than the estimated effect on property values of a one standard deviation increase in test scores of around 1 percent as found in studies such as Clapp, Nanda, and Ross (2008) and Black (1999), but smaller than the 7 percent effect found by Figlio and Lucas (2004) for top marks on school report card grades. Reback (2005), whose methods are closest to our own, finds around a 2 percent effect for gaining access to a high school choice program.

Turning to the control variables, the point estimate on the percentage of economically disadvantaged students is negative. Property values also appear to be positively related to schools with more teachers per student. The urbanization controls all have positive point estimates that increase with population. This is consistent with the standard urban economics result of higher land prices in more urbanized areas. Lastly, county education level has a positive and significant effect on property values.[17]

B. Analysis of Other Parts of the School Quality Distribution

The results for the other parts of the school quality distribution are presented in panels A and B of Table 3. Table 3 has the same structure as Table 2. Specifically, panel A shows the analysis using the top two quintiles of school quality instead of the bottom two quintiles. The treatment group is thus the 4th quintile and the control group is now

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[16] Clusters were chosen at the level of observation for our dependent variable.

[17] Full regression results are available from the authors upon request.

Table 3
Alternate Difference-in-Differences Regressions
Log Average Price of Residential Homes (1990$)

	(1)	(2)	(3)	(4)
Panel A: Top Two ACT Quintiles of School Quality				
Post × *Treatment*	0.006	0.005	0.007	0.005
	(0.015)	(0.015)	(0.015)	(0.014)
Treatment (4th ACT quintile)	–0.085***	–0.094***	–0.098***	–0.095***
	(0.033)	(0.033)	(0.033)	(0.033)
Constant	9.977***	10.090***	10.557***	10.068***
	(0.358)	(0.354)	(0.591)	(0.347)
Observations (school-by-year)	5,484	5,484	5,484	5,484
R^2	0.73	0.74	0.74	0.74
Panel B: All ACT Quintiles of School Quality				
Post × 2nd ACT quintile	–0.062**	–0.062**	–0.061**	–0.064**
	(0.028)	(0.028)	(0.028)	(0.030)
Post × 3rd ACT quintile	–0.057	–0.058*	–0.056	–0.060*
	(0.035)	(0.035)	(0.034)	(0.036)
Post × 4th ACT quintile	–0.008	–0.009	–0.005	–0.012
	(0.035)	(0.036)	(0.034)	(0.037)
Post × 5th ACT quintile	–0.009	–0.009	–0.007	–0.012
	(0.035)	(0.036)	(0.035)	(0.037)
2nd ACT quintile (20–40%)	–0.028	–0.017	–0.009	–0.020
	(0.048)	(0.048)	(0.048)	(0.049)
3rd ACT quintile (40–60%)	–0.036	–0.031	–0.023	–0.029
	(0.061)	(0.061)	(0.061)	(0.062)
4th ACT quintile (60–80%)	0.015	0.023	0.030	0.023
	(0.069)	(0.069)	(0.069)	(0.071)
5th ACT quintile (80–100%)	0.179**	0.189**	0.196**	0.187**
	(0.081)	(0.080)	(0.080)	(0.082)
Constant	8.997***	9.059***	9.315***	9.057***
	(0.233)	(0.251)	(0.330)	(0.250)
Observations (school-by-year)	13,910	13,910	13,910	13,910
R^2	0.75	0.76	0.76	0.76

Table 3 (Continued)

Alternate Difference-in-Differences Regressions
Log Average Price of Residential Homes (1990$)

	(1)	(2)	(3)	(4)
Year dummies	Y	Y	Y	Y
High school demographics	Y	Y	Y	Y
Urbanization	Y	Y	Y	Y
County level	Y	Y	Y	Y
MSA fixed effects		Y	Y	Y
Previous year's ACT scores			Y	
Weighted by high school size				Y

Notes: Numbers in parentheses are robust standard errors clustered by school district. In panel A, the 4th quintile (the treatment group) is defined as the upper middle fifth (60–80%) of school quality based on pre-policy ACT scores, and the 5th quintile (the control group) is defined as the top (80–100%) of school quality based on pre-policy ACT scores. In panel B, the 1st quintile is the omitted category and is defined as the bottom fifth (0–20%) of school quality based on pre-policy ACT scores. Asterisks denote statistical significance at the 1% (***), 5% (**), and 10% (*) levels.

the 5th quintile. The most noteworthy point about panel A is that all of the difference-in-differences point estimates are statistically insignificant. This is not the effect that one would expect to see if the Top 10% Plan had caused strategic high school switching at the top of the school quality distribution.

Next, the results for the entire distribution of school quality relative to the bottom of the distribution are shown in panel B. The negative point estimates for the interaction terms indicate that the quintile in question is losing value relative to the bottom quintile or that the bottom quintile is gaining relative to the quintile in question. This alternative analysis demonstrates a clear pattern for the distribution of school quality — the effect of the Top 10% Plan is strongest in the quintiles closer to the bottom of the distribution and attenuates with distance.

C. Robustness Analysis

It is possible that our findings could be the result of events other than the implementation of the Top 10% Plan. In this section, we present additional analyses that allow us to rule out alternative explanations of our results.

1. Pre-existing Trends

A well-known concern in a difference-in-differences analysis is that the treatment and control groups may be on different growth paths before the policy is enacted. In order for the previous analysis to provide unbiased estimates of the effect of the Top 10% Plan, it must be the case that the treatment and control groups exhibit common trends in the pre-policy period. This assumption in the difference-in-differences framework is commonly known as the parallel-trends assumption. Figure 1 suggests that this assumption holds for our analytic sample. We can also formally test the parallel-trends assumption. To do so, we drop all post-policy observations (i.e., 1997–1998 to 2005–2006) and redefine the "post" variable to a "fake year" (i.e., 1995–1996), choosing a year when the Top 10% Plan was not in effect. The results of this analysis are reported in panel A of Table 4. None of the regressions show any significant difference-in-differences point estimates, that is, there are no statistically significant differences between our treatment (1st ACT quintile) and the control (2nd ACT quintile) groups prior to the implementation of the Top 10% Plan.

Moreover, in 1995 Texas enacted *open enrollment laws* that gave students in poorly performing school districts the option to enroll in higher-quality schools without changing residence. This could have potentially increased property values in low-performing school districts, making the effects we are attributing to the Top 10% Plan simply a residual change from the enactment of open enrollment. However, it is very unlikely that the open enrollment laws had any effect on property values at the school district level, because even though school districts were required to accept transfer requests from within the district they were not required to accept out of district transfer requests. This made across district switches extremely rare and unlikely to influence property values. To verify this, the above test of the parallel trends assumption also coincides with the enactment of open enrollment laws. Since none of the regressions reported in panel A of Table 4 show any significant difference-in-differences point estimates, this helps to rule out open enrollment as an alternative explanation of the results.[18]

2. Robin Hood Plan

Another schooling policy that likely did influence property values in Texas was the "Robin Hood Plan."[19] The Robin Hood Plan, true to its name, was a scheme that redistributed tax revenues from school districts with a lot of property wealth per adjusted pupil to districts with little property wealth per adjusted pupil. It is very possible that

[18] It is also possible that our results might be explained by the passage of the No Child Left Behind (NCLB) Act on January 8, 2002. The goal of NCLB was to increase the quality of poorly performing school districts, and thus could also explain increasing property values in those areas. The first school year affected by the NCLB was 2002–2003. To check against such a possibility and gauge the stability of the point estimates shown in Table 2, we ran our difference-in-differences analysis using different sized post-period windows: (1) an eight-year period subsample that drops all of the school years in which NCLB was in effect (i.e., school years 2002–2003, 2003–2004, 2004–2005 and 2005–2006), and (2) a six-year sample (i.e., three years in the pre-policy period, and an equal number in the post-policy period). These difference-in-differences point estimates were positive and significant in all of the alternative subsample analyses. Thus, the results shown in Table 2 are robust to considering smaller windows around the implementation of the Top 10% Plan, and most importantly, these results helps rule out the passage of the NCLB Act as a factor driving our results.

[19] A thoughtful analysis of the Robin Hood Plan can be found in Hoxby and Kuziemko (2004).

Table 4

Difference-in-Differences Regressions — Robustness Checks

	(1)	(2)	(3)	(4)
Panel A: Pre-policy Analysis				
Post × *Treatment*	0.005	0.006	0.004	0.005
	(0.008)	(0.008)	(0.008)	(0.008)
Treatment (4th ACT quintile)	0.015	–0.002	–0.006	0.009
	(0.048)	(0.050)	(0.051)	(0.051)
Constant	8.599***	8.612***	8.838***	8.605***
	(0.353)	(0.401)	(0.605)	(0.410)
Observations (school-by-year)	1,409	1,409	1,409	1,409
R^2	0.76	0.77	0.77	0.77
Panel B: Testing for Robin Hood Plan[1]				
Post × *Treatment*	–0.007	–0.007	–0.007	–0.001
	(0.009)	(0.009)	(0.009)	(0.009)
Treatment (1st ACT quintile)	–0.014	–0.006	–0.010	–0.007
	(0.021)	(0.021)	(0.021)	(0.022)
Constant	8.928***	8.902***	9.111***	8.940***
	(0.132)	(0.154)	(0.241)	(0.155)
Observations (school-by-year)	4,237	4,237	4,237	4,237
R^2	0.70	0.71	0.71	0.71
Panel C: Excluding Longhorn Scholarship Eligible Schools				
Post × *Treatment*	0.039**	0.039**	0.039**	0.039*
	(0.020)	(0.020)	(0.020)	(0.021)
Treatment (1st ACT quintile)	–0.034	–0.052	–0.050	–0.045
	(0.051)	(0.051)	(0.051)	(0.051)
Constant	8.668***	8.517***	8.400***	8.538***
	(0.290)	(0.333)	(0.424)	(0.334)
Observations (school-by-year)	5,149	5,149	5,149	5,149
R^2	0.76	0.77	0.77	0.77

Table 4 (Continued)

Difference-in-Differences Regressions — Robustness Checks

	(1)	(2)	(3)	(4)
Year dummies	Y	Y	Y	Y
High school demographics	Y	Y	Y	Y
Urbanization	Y	Y	Y	Y
County level	Y	Y	Y	Y
MSA fixed effects		Y	Y	Y
Previous year's ACT scores			Y	
Weighted by high school size				Y

Notes: Numbers in parentheses are robust standard errors clustered by school district.
[1]In panels A and C, the dependent variable is log average price of residential homes (1990$), whereas in panel B the dependent variable is log spending per pupil. In panel A, the years of analysis are 1994–1995, 1995–1996, and 1996–1997 (pre-policy data). In panels A, B, and C, the 1st quintile (the treatment group) is defined as the bottom fifth (0–20%) of school quality based on pre-policy ACT scores, and the 2nd quintile (the control group) is defined as the lower middle (20–40%) of school quality based on pre-policy ACT scores. Asterisks denote statistical significance at the 1% (***), 5% (**), and 10% (*) levels.

the Robin Hood Plan lowered property values in property-rich districts relative to values in property-poor districts.

We can rule out any effects of the Robin Hood plan on our results for two reasons. The first is that Robin Hood was implemented in the 1993–1994 school year. This coincides with the beginning of our sample, so any time invariant effects of the Robin Hood Plan will be differenced out in our difference-in-differences estimator. It would also be possible for the Robin Hood Plan to serve as an alternative explanation for our results if the plan had time varying effects that intensified over time and if property-poor districts coincided with poorly performing districts. If this were the case, then we would expect the lowest quality school districts to receive a larger amount of funding as the effect of the Robin Hood Plan intensifies over time. We can test for this by running our difference-in-differences estimator with the amount of spending per pupil as a dependent variable. Panel B of Table 4 presents the results of this analysis. All estimates are both negative and insignificant, which further discredits the Robin Hood Plan as an alternative explanation of our results.

3. Longhorn Opportunity Scholarships

One further policy of note is the introduction of Longhorn Opportunity Scholarships in 2001. Longhorn Scholarships are offered through UT-Austin and are tied to the Top 10% Plan. The goal of these scholarships is to offer financial assistance to students from schools that did not historically place many students at UT-Austin. To be eligible a student must attend a school identified by UT-Austin as historically under or non-represented at UT-Austin and be rank eligible under the Top 10% Plan. These students get a scholarship of $5,000 per year for four years. It is possible that our results are inflated by the effect of the Longhorn scholarships.

To eliminate the effect of these scholarships, we re-estimate our difference-in-differences estimator after dropping all schools listed by UT-Austin as eligible for Longhorn Opportunity Scholarships from the sample.[20] The results of this estimation are reported in panel C of Table 4. These results are smaller in magnitude to those reported in Table 2, but are still quite sizeable and statistically significant, which rules out the effect of these scholarships as an alternative explanation for our results. We now estimate a 3.9 percent (column (2)) increase of housing prices in low-performing school districts, again consistent with our hypothesis that the Top 10% Plan influences property values in districts in the lower end of the school quality distribution.

D. School Competition: Herfindahl-Hirschman Index Analysis

The results from estimating (5) for the number of schooling options are presented in Table 5. All controls shown in column (2) of Table 2 are used in the regression for Table 5. The coefficient of interest is the interaction between the difference-in-differences estimator and the county level HHI_k. The interaction is negative and significant, implying that the more monopolistic the county, the less the property values in the school districts in that county were affected by the implementation of the Top 10% Plan. In other words, it is more difficult to switch schools in areas where there are not a lot of local high school options. The HHI analysis suggests that if the changes in property values are due to households moving strategically, then these moves likely cover a short distance. Furthermore, the HHI analysis reinforces the results presented in the previous section, as these results help to rule out alternative explanations. Many alternative explanations, such as the Robin Hood Plan mentioned previously, would likely be orthogonal to the number of schooling options available.

All that remains is the possibility that housing values in urban areas, which have many schooling options, experienced a sudden increase compared to those in rural areas. However, Texas did not experience the housing price bubble that preceded the 2008 financial crisis (which could have spiked property values in urban areas) nor the bust that followed (Chernick, Langley and Reschovsky, 2011; Martin, 2011).

VII. CONCLUSION

Since its implementation over 15 years ago, the Top 10% Plan has received mixed reviews. One of the main criticisms of this policy is that it is unfair to high-achieving

[20] During the time frame of our analysis, 44 schools were listed as eligible for Longhorn Opportunity Scholarships.

Table 5

Difference-in-Differences Regressions — Schooling Market Power

	Log Average Price (1990$)
Post × Treatment × HHI	–0.168**
	(0.078)
Post × Treatment	0.056**
	(0.026)
Post × HHI	–0.221***
	(0.056)
Treatment × HHI	0.221
	(0.140)
Treatment (1st ACT quintile)	–0.070
	(0.061)
Herfindahl-Hirschman Index (HHI)	–0.069
	(0.096)
Constant	8.875***
	(0.300)
High school demographics	Y
Urbanization	Y
County level	Y
MSA fixed effects	Y
Observations (school-by-year)	5,633
R^2	0.77

Notes: Numbers in parentheses are robust standard errors clustered by school district. Schooling market power is measured by Herfindahl-Hirschman Index (HHI) per pupils. The 1st quintile (the treatment group) is defined as the bottom fifth (0–20%) of school quality based on pre-policy ACT Scores. The 2nd quintile (the control group) is defined as the lower middle (20–40%) of school quality based on pre-policy ACT Scores. Asterisks denote statistical significance at the 1% (***), 5% (**), and 10% (*) levels.

students who attend elite high schools. Because the Top 10% Plan is solely based on class rank and this criterion is applied to all high schools that use grade point averages to rank students, there is redistribution in the university system from students who graduate from high-performing high schools to automatically admitted students who graduate from low-performing high schools. On the other hand, while the goal of the Top 10% Plan was to improve access for disadvantaged and minority students, the use of a school-specific standard to determine eligibility has led to some other unintended effects.

The estimate from our preferred specification implies that the implementation of the Top 10% Plan raised property values in poorly performing school districts by 4.8 percent. We can get a rough sense of the total effect on the tax base by estimating our main regression with the dependent variable of total appraised property value in a school district. The results of such a regression show a 16.4 percent increase in the total property tax base. If we arbitrarily divide the 16.4 percent evenly (i.e., assuming an 8.2 percent gain in aggregate property values in the bottom quintile and an 8.2 percent loss in aggregate property values in the second quintile) then one can see that the effect of the Top 10% Plan on the property tax base was potentially quite large. Applying a smearing estimator (Duan, 1983), we predict that the average district in the bottom quintile would have gained \$374.3 million in their tax base and the average district in the 2nd quintile would have lost \$162.5 million in their tax base. If we apply an arbitrary property tax rate of 0.4796 percent (i.e., the property tax rate in the city of Austin, Texas in 2008) then there would be an additional \$1.8 million in property taxes for the average district in the bottom quintile and \$0.78 million less in property taxes for the average district in 2nd quintile. These property tax estimates are by no means exact, especially since we do not know how the relative value shift is distributed between 2nd quintile losses and bottom quintile gains, and because these are only changes in single family homes and do not include changes in other taxable properties that could have been affected. However, these tax estimates do illustrate the type of effect that the Top 10% Plan had on the property tax landscape in Texas. Moreover, any future implementations of, or modifications to, such *top x-percent* admissions policies should bear in mind that the redistribution of educational resources will not be the only effect of such a policy change.

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