ESSAYS IN THE ECONOMICS OF EDUCATION

By

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A DISSERTATION PRESENTED TO THE GRADUATE SCHOOL
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To my husband

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of the University of Florida in Partial Fulfillment of the
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In this work, I present three separate studies. In the first study, I examine the impact of childhood overweight on classroom outcomes. I investigate whether height and/or weight have an impact on student test scores. I find that overweight students receive lower test scores than healthy weight students. While I find a negative impact of overweight among all adolescents, white females are especially at a disadvantage, receiving test scores 0.19 to 0.29 standard deviations lower than white females of recommended weight. I also find that students in the bottom fifth percentile for height receive lower test scores and that growth spurts are positively related to test scores among white males.

In the second study, I consider the impact of restricting school district size on student outcomes. Tiebout theory and empirical research tell us that within a metropolitan area people will sort themselves based on income and preference for schooling. Often, however, local and state government policies limit Tiebout choice. I contribute to the literature by using a unique method of dealing with the endogenous nature of the number of school districts. I compare student learning among states that exogenously limit Tiebout choice with student performance in other states. I find strong evidence that restricting competition among public school districts negatively impacts student learning. Binding laws that mandate county or state-wide school

districts negatively impact student test scores by 0.09 to 0.40 standard deviations. In the largest school districts with the most students, these restrictive mandates are especially harmful.

In the final study, I explore the evolution of the system of voter representation in school decisions after Florida adopted countywide districts. I consider the vote on a 1956 amendment to the Florida constitution. The amendment eliminated a school administrative office and eliminated representation for portions of each county-wide school district. I find that the support for the amendment was strongest in rural, heterogeneous counties.

CHAPTER 1
INTRODUCTION

I conduct three separate studies in this paper: (1) Does this test make me look fat? Economic consequences of adolescent weight and stature, (2) Evidence of the effects of inter-school district competition: comparisons of state-limited school districts with other states, (3) Analysis of Florida constitutional amendment, eliminating the office of school district trustees, 1956.

In the first study, I examine the impact of childhood height and weight on test scores. Adolescents receive differential treatment from peers based on outward physical characteristics. This attention may preoccupy the student, causing her to absorb less information in the classroom. I use the National Longitudinal Survey of Youth (NLSY97) to investigate whether height and/or weight have an impact on student test scores. I find that overweight students receive lower test scores than healthy weight students. While I find a negative impact of overweight among all adolescents, white females are especially at a disadvantage, receiving test scores 0.19 to 0.29 standard deviations lower than white females of recommended weight. Regression results also reveal that students in the bottom fifth percentile for height receive lower test scores and that growth spurts are positively related to test scores among white males.

In my next study, I examine the impact of limiting the number of public school districts on student outcomes. Tiebout theory and empirical research tell us that within a metropolitan area people will sort themselves based on income and preference for schooling. Often, however, local and state government policies limit Tiebout choice. The difficulty in assessing the impact of limiting Tiebout choice on academic performance is that the degree of competition within a market is usually endogenous. I contribute to the literature by using a unique method of dealing with the endogenous nature of the number of school districts. I compare student learning among states that exogenously limit Tiebout choice with student performance in other states. I find strong evidence that restricting competition among public school districts negatively impacts student learning. Binding laws that mandate county or state-wide school districts negatively impact student test scores by 0.09 to 0.40 standard deviations. In the largest school districts with the most students, these restrictive mandates are especially harmful.

In my final chapter, I explore voting on a Florida constitutional amendment. The 1956 amendment that I study eliminates the position of school district trustees. This change reduces representation of certain communities within each school district. I find that in 1956, support for this amendment was related to county homogeneity. Specifically, counties that strongly supported abolishing school district trustees were predominately wealthy, white, urban counties where Tiebout sorting was complete.

CHAPTER 2
DOES THIS TEST MAKE ME LOOK FAT? ECONOMIC CONSEQUENCES OF ADOLECENT WEIGHT AND HEIGHT

Introduction

Economists have extensively investigated the effects of physical characteristics (including race, gender, height, weight, and beauty) on labor market outcomes. Sargent and Blanchflower (1994), Averett and Korenman (1996), and Cawley (2004) find that obesity is associated with lower wage rates. Persico, Postlewaite, and Silverman (2004) and Sargent and Blanchflower (1994) find a positive relationship between height and earnings. Hamermesh and Biddle (1994) find that plain men and women earn five to ten percent less than their average looking colleagues.

Some of the wage premium received by healthy weight and tall people may be due to their being more productive than their counterparts. Hamermesh and Biddle (1994), Averett and Korenman (1996), and Persico et al (2004) attempt to control for productivity differences by including a variable for the highest grade attained in each of their regressions.[1] However, if individuals with less desirable physical characteristics learn less in any given grade of school, they should be less productive in the labor market and some portion of the estimated beauty premium would actually be due to productivity differences. There has been very little research on the effects of physical characteristics on educational outcomes. This would provide valuable evidence on whether those with healthy weight and those who are taller have better cognitive skills. I contribute to the discipline by filling in the gap in this literature.

There are many reasons that we may expect to see a negative relationship between height/weight and student outcomes. Adolescents receive differential treatment from peers based

[1] Only Sargent and Blanchflower (1994) use a different measure, test scores, to control for education level.

on outward physical characteristics. A student whose appearance is different from others in height and/or weight is often a victim of bullying and teasing (Jansen et al, 2004), which is likely to lead to more absences. In addition to negative attention from peers, the student may receive negative attention or less instruction from her teachers and parents. One would expect a suboptimal learning environment to be reflected in student outcomes. It is also possible that poor student outcomes may cause weight gain. A student who performs poorly in school may experience stress, causing her to turn to food for comfort. Finally, there may be a third factor causing both poor student performance and an unhealthy weight. It may be that a disadvantaged home life causes both weight gain and low test scores.

On the other hand, there could be a positive relationship between student weight and academic outcomes. A student whose appearance is different from others may choose to spend more time studying instead of socializing with peers. Her teachers may see her potential and give her more attention than her average looking peers. This may lead to better student outcomes.

Let us turn to the few studies of the effects of appearance on academic outcomes. Falkner et al (2001) find that underweight adolescent boys are more likely than their healthy weight peers to dislike school and less likely to expect to finish college. Datar, Sturm, and Magnabosco (2004) find that being overweight does not impact kindergartners' test scores once socioeconomic characteristics are controlled for. Sabia's (2007) research is closest to that done in this paper. He finds that a two standard deviation increase in weight leads to a 9 percent decrease in grade point average (GPA) among white females, but was unable to find a consistent impact of weight on outcomes among males or nonwhite females on the GPA.

This paper uniquely contributes to the literature in three ways. First, student test scores are used instead of the student's GPA as one of the dependent variables. While the test scores measure the student's cognitive skills, the GPA at least in part reflects the student's position within the school. There have been no studies of the effect of appearance on test scores for students past kindergarten. Second, to my knowledge I am the first to explore the impact of height on student outcomes. Finally, I explore the impact of student height and weight on student absences, which provides important evidence on the mechanism by which appearance affects test scores. This paper uses various measures of weight and three different statistical methods: ordinary least squares (OLS), instrumental variables (IV) and fixed effects (FE) models.

I find that students with undesirable physical traits indeed learn less in school than other students. Specifically, weight negatively impacts test scores for white females, black females, and white males. Additionally, holding weight constant, height positively impacts test scores for white females, black females, and white males. The beauty premium found in the labor market thus reflects some productivity differences. I also find that those with healthy weight and who are taller miss fewer days of school; numerous studies have found that students who miss fewer days have higher test scores.

Data

The 1997 National Longitudinal Survey of Youth (NLSY) follows a sample of 8,984 students in their transition from school to work beginning in 1997. This group is still being followed annually, and the most recent data available are from 2005. Only in the initial 1997 survey were parents interviewed and all students tested. A fraction of students took a standardized math exam in subsequent years. During each interview students were asked their height, and weight. [2] Because much more information is available for students in 1997, I analyze the cross section in addition to a five year panel. Many of the independent variables explained below are used only in the cross sectional analysis because data are not available in following years.

The outcomes that I use are self reported absences from school in the fall of 1997 and the students' score on the Peabody Individual Achievement Test (PIAT) Math Assessment. The PIAT is a computer administered exam that has been found to reliably measure mathematic achievement. During the first interview, students were asked to take the math exam if they were in or below the ninth grade; 6,046 students born 1980-1984 took the exam in 1997. However, in subsequent interviews, only students born in 1984 retook the test. The exam begins with a few questions of varying difficulty, based on the students' grade level. The computer then presents more complicated questions if a student's prior answers were correct and easier questions if his prior answers were wrong. Raw exam scores are reported on a scale of zero to one hundred. As expected, students in higher grades receive higher scores. To better track a student's relative progress over time and to be able to compare students across grades, I normalize the raw score with respect to grade.[3] That is, I take each student's raw test score, subtract the mean score for that student's grade level and then divide by the standard deviation for that student's grade level. Therefore, within grade level, the learning measure that I use has a mean of zero and standard deviation of one.

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[2] While adults tend to under report weight and over report height, no similar studies have been conducted concerning the reliability of adolescent self-reported height and weight.

[3] I also used raw scores as the dependent variable in all regressions, including grade dummies. I do not report these results here, as they were very similar.

The independent variables of interest are measures of weight, height and body mass index (BMI).[4] A child is considered overweight[5] by the Centers of Disease Control and Prevention (CDC) if she has a BMI (kg/m^2) greater than 95% of her peers.[6] She is considered at risk for becoming overweight if she is at or above the top 85th percentile of BMI for age and underweight if it is at or below the bottom 5th percentile.

The CDC stature-for-age and weight-for-age growth charts were originally created in 1977 and were based on information gathered using the second National Health Examination Survey (NHES II, 1963-1965) and the second National Health and Nutrition Examination Survey (NHANES II, 1976-1980). In 2000, the CDC issued revised the stature-for-age charts and introduced BMI-for-age charts.[7] The revised charts employ the same data as the 1977 charts, but use slightly different statistical methods. Since the CDC growth charts and definitions of overweight are based on a trimmer population of adolescents, currently fifteen percent of children are in the "top 5th percentile" of BMI and considered overweight.[8] A fourteen year old girl who is 5'3" tall is overweight if she weighs more than 154 pounds, and is at risk for becoming overweight if she 132 pounds. She is underweight if she weighs less than 89 pounds. Further examples of overweight, at risk for overweight, and underweight for both males and

[4] I discard observations with improbable height and weight. I do not use observations when reported height is greater than 78 inches or less than 48 inches or when BMI is greater than 140 or less than 11.

[5] To avoid stigma, the NCHS avoids characterizing any youth as obese. However many researchers classify youth as obese and overweight when they are in the 95th and 85th percentiles of BMI-for-age, respectively. Throughout this paper, I will use the terms "overweight" and "at risk for overweight" when referring to these students.

[6] Separate growth charts are used for males and females.

[7] The weight-for-stature chart was also revised in 2000, but the NCHS recommends using the BMI-for-age chart to assess weight in relation to stature for children ages two through 20.

[8] See Philipson (2001) or Hedley et al (2004) for further information about recent trends in overweight and obesity.

females are presented in Table 2-1 and Table 2-2. I use the national BMI-for-age charts to assign each student in my sample to one of the four weight categories.[9]

To gather information on the students' daily life, NLSY interviewers asked the following pair of questions: "How many times have you been threatened at school?" "How many times have you had something stolen from school?"[10] These questions may be viewed as indicators of both school quality and student effort. Surprisingly, these two variables have a correlation coefficient of only 0.16, and I am able to include both in my analysis. The other gauges of school quality are the student teacher ratio and school size, which NLSY interviewers obtained directly from the school.

One parent from each household was interviewed in 1997. About ten percent of students surveyed had no parent interview recorded and were excluded from my analysis. The student's biological mother was the respondent for 80% of completed parent interviews. The parent was asked to report her own height, weight, and education level and the student's biological father's height, weight, education level and whether he still lived at home. The interviewer also asked if the biological mother or another family member attended PTA meetings or volunteered at the student's school (correlation coefficient of 0.29).

In addition to height and weight, the NLSY parent interview provides biological mother and father's education (missing in 6% and 18% of observations, respectively). If the education level of a biological parent is missing, I use the resident parent's education instead. Summary statistics for the 1997 sample are presented in Table 2-3.

[9] Stature-for-age and body mass index-for age charts are available at http://www.cc.gov/growthcharts.

[10] I discard observations where a student reports having something stolen or being threatened over 90 times in a semester.

Methods

I first use ordinary least squares (OLS) to examine the effect of physical appearance on student absences, employing an education production function:

$$learning = f(student\,inputs, parental\,inputs, school\,quality)\,. \tag{2-1}$$

I consider two learning measures: score on the PIAT and self reported absences from school in the fall of 1997. The student inputs that I am most interested in are measures of height and weight. I use three different specifications of height and weight. I look at BMI, height and weight in pounds, and finally I use three dummy variables underweight, at risk for overweight, and overweight.

Throughout my study, I estimate separate regressions for white females, black females, white males, and black males since I expect personal appearance to impact these groups differently.[11] Averett and Korenman (1999) find that white women have a lower ideal BMI and report having more negative feelings about their bodies than black women. I expect the coefficient on the weight variables to be bigger in magnitude for white females than black females. I also expect weight to impact females more severely than males. Adolescent females, especially those who are overweight, experience greater preoccupation with their weight and express dissatisfaction with their bodies more often than males (Rosenblum and Lewis, 1999). I find that the same is true for the NLSY sample.

Each year of the NLSY students were asked what they were currently doing about their weight. Response options were, “trying to lose weight,” “trying to gain weight,” “trying to stay the same weight,” and “doing nothing about weight.” Student responses by gender and race are presented in Figure 2-1. Approximately two thirds of the females in the sample want to lose

[11] Cawley (2004) and Sabia (2007) also estimate separate regressions for different sex-race groups. Both authors reject the null hypothesis that the coefficients on BMI are equal across groups.

weight, while only one third of males want to lose weight. Student answers also reveal that white females have a lower ideal weight than black females: a greater proportion of white females are trying to lose weight even though overweight is 50% more prevalent among the black females in my sample.

All education production function regressions include student, school, and parental inputs. Parental inputs must include measures of both quality and quantity of time that parents contribute to their child's learning. I use the mother's and father's highest grade attained as measures of parent quality. Quantity of time the parents contribute to learning is measured by indicators of the biological father living with the student, a parent volunteering in the classroom, parent PTA membership, and a variable for the number of children under eighteen living in the household.

School quality is measured by student teacher ratio, school size, number of times a student has had something stolen from school, and number of times he was threatened at school. The NLSY surveyors ask students how many times the student has had something stolen from school in the semester. Students indicating that they have had items stolen multiple times are likely attending a lower quality school and will therefore learn less, all else equal. The number of times a student was threatened is also an indicator of school quality and student learning. Threatened students would learn less since they would be preoccupied with their safety. The NLSY gathered the student teacher ratio and enrollment numbers directly from the school that the student attended in 1997. However, the student teacher ratio and school size are assigned only to a range. I deal with this by assigning the midpoint to each group. The two school variables are missing 12% of the time; I include flags to account for this. A complete list of independent variables and the expected signs of their OLS coefficients is presented in Table 2-4.

As explained above, endogeniety of the weight variable is a concern. That is, test scores could cause weight change. I use an instrumental variables method to deal with simultaneity. A good instrument will eliminate any bias in the coefficient estimate and must satisfy two assumptions. The first assumption is that the instrument is correlated with the weight variable. The second assumption is that the instrument is not correlated with learning except through weight. I use parental overweight as my instrument. This variable takes a value of one if either biological parent has a BMI greater than or equal to twenty-five. The variable has a value of zero if neither parent is overweight. For the instrumental variables regressions, I drop observations where no biological parent BMI is recorded.

Studies have shown that biological parent weight is strongly correlated with child weight; approximately half of the variation in weight between child and parent can be explained by genetic variation (Comuzzie and Allison 1998). Cawley (2004) uses biological sibling weight as an instrument for respondent weight. Sabia (2007) uses parental self-reports of obesity as an instrument for student weight. In the author's data set, parents were asked to report if the biological father or mother "suffers from an obesity problem." This study improves on the work by Sabia in that I use a more objective measure of overweight and am able to calculate BMI directly instead of relying on parent's self perception of overweight.

One may be concerned that unobserved family characteristics such as motivation and work ethic cause both child and parent weight. However, adoption studies have shown that it is only genetics and not family environment that contributes to weight.[12] That is, the weight of adopted children is not correlated with the weight of their adoptive parents or siblings. Twin studies have

[12] Stunkard et al 1986

also supported these findings. Twins raised in different homes have body weight that is as highly correlated as twins who were raised together.[13]

As a final test, I use panel data from 1997 and 1998 along with a fixed effects (FE) model to control for unobserved heterogeneity. The FE model controls for any unobserved individual-level, time-invariant characteristics. The downside of the FE model is that it uses individual changes in weight and test score to identify the impact of weight on learning and exacerbates any measurement errors present in the data. There must be significant individual level variation in both weight and test score to detect a statistically significant effect.

Empirical Results

Example coefficient estimates for control variables can be found in Table 2-5. In the remaining tables, I present the main findings of this paper. For the sake of space, I only present coefficient estimates on the independent variables of interest. All control variables have the expected sign.[14]

Effects of Height and Weight on Test Score Using OLS

The results of OLS regressions with test score as the dependent variable are presented in Table 2-6. Three different regressions were run for each group of students, using three different measures of weight and height. In Column 1, all three different measures produce statistically significant results for white females. A one standard deviation increase in BMI is associated with a 0.011 standard deviation drop in test score.[15] The coefficient on pounds indicates that, for white females, a one standard deviation weight gain is associated with test scores 0.002 standard

[13] Grilo and Pogue-Geille 1991

[14] One may hypothesize that the impact of weight will vary as the fraction of the population that is overweight varies. State level measures of adult overweight did not change regression results and were not statistically significant. They were therefore excluded from final regressions.

[15] The average white female in my sample has a BMI of 21.3 and raw test score of 73.61; this means that a one standard deviation increase in BMI (to 25.3) is associated with a test score drop to 73.43.

deviations lower. Also, this regression indicates that a one standard deviation increase in height is associated with a test score that is 0.031 standard deviations higher. Finally, results show that white females who are overweight are expected to receive test scores 0.279 standard deviations lower than their healthy weight peers.

Using OLS, no statistically significant results were obtained for either black females (Column 2) or black males (Column 4). However, underweight white males receive test scores that are 0.237 standard deviations lower than their healthy weight, white counter parts. This “penalty” is similar in magnitude to test score decrease experienced by overweight white females.

Effects of Height and Weight on Test Score Using IV

Results of instrumental variables (IV) regressions are presented in Table 2-7. The sample size is slightly smaller than that used in OLS since observations must also have the height and weight of at least one biological parent. Coefficient estimates on height and weight variables for white females, black females, and white males are statistically significant and larger in magnitude than OLS estimates, indicating that IV has eliminated upward bias in the endogenous variable.   In Column 1, results for white females are presented. A one standard deviation increase in BMI is associated with a drop in test score of 0.057 standard deviations. A weight gain of 26 pounds (one standard deviation) is associated with a drop in test sore of 0.010 standard deviations. Height is positively related to test score. A growth spurt of three inches (one standard deviation) is associated with a test score that is 0.065 standard deviations higher. Finally, overweight white females can expect to receive test scores 1.54 standard deviations lower than their healthy weight counterparts.

Instrumental variable regressions indicate that weight is a predictor of student performance not only for white females, but for black females and white males as well. In fact, coefficient estimates are smaller for white females than they are for black females and white males. Coefficient estimates in Column 2 indicate that a one standard deviation increase in BMI among black females is associated with a drop in test score of 0.74 standard deviations. A weight gain of 33.7 pounds (one standard deviation) is associated with a drop in test score of nearly one standard deviation. An increase in height of three inches (one standard deviation) is associated with a test score 0.42 standard deviations higher. Results also indicate that overweight black females can expect to receive test scores 1.8 standard deviations lower than their healthy weight counterparts.

Results for white males, presented in Column 3, are quite similar to results for black females. A one standard deviation increase in BMI among white males is associated with a drop in test score of approximately one-half standard deviation. A weight gain of 35.3 pounds (one standard deviation) is associated with a 0.78 decrease in test score and a one standard deviation increase in height (4 inches) is associated with a 0.46 increase in test score. Results indicate that overweight white males receive test scores that are 2.51 standard deviations lower than their healthy weight counter parts.

Effects of Height and Weight on Test Sore Using FE

Sample sizes used in the FE regressions are rather small since they require the student have test score and height/weight information in both 1997 and 1998. In order to obtain statistically significant results using a FE model, there must be enough individual level variation in both test score and weight. The great majority of students (80%) are a healthy weight in both 1997 and 1998. Fixed effects regressions using the dummy variables, which are presented the last rows of Table 2-8 do not utilize the data to its full potential, identifying off of a very small number of observations. Because of the small identifying sample, coefficients on underweight, at risk for overweight, and overweight are not statistically significant for any sex-race group.

However, when the variables BMI or pounds are used instead of dummy variables, I do obtain small but statistically significant coefficients for both white females and white males. The results presented in Column 1 of Table 2-8 indicate that, among white females, a BMI increase of one standard deviation is associated with a decrease in test score of 0.02 standard deviations. A weight gain of 26 pounds is associated with a test score decrease of 0.05 standard deviations.

The coefficients on BMI and pounds are positive for white males, indicating that heavier white males perform better than their thinner counter parts. Results indicate that a one standard deviation increase in BMI is associated with a 0.12 standard deviation increase in test score and a weight gain of 35 pounds is associated with a 0.17 increase in test score.

Effects of Height and Weight on Student Absences Using OLS

In addition to student test scores, being over or underweight may affect student absences. A student who is over or underweight may try to avoid school because of teasing from her peers. While missing school is a concern in itself, the negative impact of student absences on overall academic performance is well documented (Bos, Ruijlers, Visscher, 1992; Lamdin, 1996). To see whether student absences are affected by height or weight, I use OLS and IV regressions with student absences as the dependent variable, presented in Tables 2-9 and 2-10[16].

Using OLS, I find statistically significant and similar results among white females, black females, and white males. For these groups, a one standard deviation increase in BMI or in pounds is associated with missing approximately an additional half day of school per semester. Results also indicate that black females who are at risk for becoming overweight miss one and one half more days of school than their healthy weight counterparts. Surprisingly, results

16 Unfortunately, student absences are only reported in 1997 and further analysis is not possible with this data set.

indicate that overweight white males are absent less than their healthy weight peers. These results are economically significant, since the median number of student absences is only three.

Effects of Height and Weight on Student Absences Using IV

Other results indicate that instrumental variables regressions are not at all similar to OLS regressions. I estimate no statistically significant impact among white females, black females, or black males. Among white males, heavier students miss more school. The estimated impact is quite large in magnitude and statistically significant. A one standard deviation increase in BMI is associated with missing 1.5 additional days of school. A weight gain of 35 pounds is associated with missing 1.6 additional days of school. Finally, overweight white males miss nearly five and one half additional days of school per semester. All these results suggest that heavier students are absent more frequently. These results are economically significant, considering the median number of days absent is only three.

Conclusion

The strongest evidence that heavier or shorter children do not do as well in school as their classmates comes from white females. For this group, some measure of the student's weight has a significantly negative impact on her test score in OLS, IV, and FE specifications. The hypothesis that taller students perform better is supported in the OLS and IV regressions. For black females, only the IV regressions provide statistical support for the overweight and height hypotheses. For both female groups, there is evidence in the OLS regressions that heavier students are absent from school more often. These results suggest that at least part of the fall in test scores due to being overweight is attributable to less time being spent in school.

Body features have less impact on male test scores. None of the weight and height measures are significant in the regressions for black males. The evidence is less consistent for white males. In the OLS regressions, underweight boys have lower test scores. In the IV regressions, heavier and shorter males have lower test scores. On the other hand, heavier boys are estimated in the FE regressions to have higher test scores. There is stronger evidence in the white male regressions than in the female regressions that heavier students miss more school. The additional support comes from two of the three OLS regressions in which some measure of the student's weight is significant.

Overweight students may be victims of bullying by peers, they may receive differential treatment from teachers, or they may experience a less favorable home environment. Undoubtedly, students who do not perform to their potential in school will face academic as well as labor market consequences. The American Obesity Association reports that overweight children have a 79% chance of being overweight adults.[17] If overweight individuals learn less as students, then the labor market "beauty premium" is partially a productivity premium and not solely due to employer discrimination.

17 http://www.obesity.org/subs/fastfacts/obesity_youth.shtml

Table 2-1. NCHS' definitions of overweight, at risk for overweight, and underweight based on median height for females

Age	Median height	Overweight (>95%)	Risk for overweight (>85%)	Underweight (<5%)
12	4'11"	129 lbs	111 lbs	76 lbs
13	5'2"	145	124	84
14	5'3"	161	137	93
15	5'3"	169	144	98
16	5'4"	175	149	102
17	5'4"	179	151	103
18	5'4"	184	154	104

Table 2-2. NCHS' definitions of overweight, at risk for overweight, and underweight based on median height for males

Age	Median height	Overweight (>95%)	Risk for overweight (>85%)	Underweight (<5%)
12	4'11"	121 lbs	105 lbs	74 lbs
13	5'1"	137	119	84
14	5'5"	156	136	96
15	5'7"	173	151	107
16	5'9"	186	164	115
17	5'9"	193	170	121
18	5'9"	200	177	126

Table 2-3. Summary statistics for 1997 cross section

	Females N=2,155			Males N=2,526		
	Mean	Min	Max	Mean	Min	Max
PIAT score	71.61	1.00	100.00	71.84	1.00	100.00
PIAT normalized by grade	0.01	-4.26	2.22	0.04	-4.31	2.22
Days absent from school	4.41	0.00	88.00	4.35	0.00	75.00
BMI	21.47	14.13	39.57	21.60	14.06	39.87
BMI percentile	58.54	0.20	99.54	60.76	0.01	99.66
Overweight	0.09	0.00	1.00	0.117	0.00	1.00
At risk for overweight	0.14	0.00	1.00	0.15	0.00	1.00
Underweight	0.03	0.00	1.00	0.03	0.00	1.00
Age	13.60	12.00	17.00	13.70	12.00	17.00
Grade	7.83	6.00	9.00	7.77	6.00	9.00
Black	0.28	0.00	1.00	0.30	0.00	1.00
Mother’s years of education	12.65	2.00	20.00	12.71	1.00	20.00
Father’s years of education	12.71	2.00	20.00	12.76	1.00	20.00
Live w/ biological father	0.53	0.00	1.00	0.54	0.00	1.00
Parent volunteers at school	0.52	0.00	1.00	0.50	0.00	1.00
Parent member of PTA	0.69	0.00	1.00	0.69	0.00	1.00
Household members <18	2.47	1.00	9.00	2.47	1.00	9.00
Threats at school	0.59	0.00	25.00	0.86	0.00	25.00
Theft at school	0.39	0.00	20.00	0.54	0.00	20.00
Student teacher ratio	17.00	10.00	26.00	16.90	10.00	26.00
School size	845.00	50.00	1250.00	829.00	50.00	1250.00

Table 2-4. Independent variables’ expected impact on test scores and school absences

Independent variables	Test score	School absences
Student Inputs		
BMI	-	+
Pounds	-	+
Height	-	+
Overweight	-	+
Risk for overweight	-	+
Underweight	-	+
Parent Inputs		
Mother’s years of education	+	-
Father’s years of education	+	-
Live with father	+	-
Parent volunteers at school	+	-
Parent member of PTA	+	-
Number of household members <18	-	+
School inputs		
Threats at school	-	+
Theft at school	-	+
Student teacher ratio	-	+
School size	+	-

Table 2-5. Cross section regression results, effect of weight on test score; dependent variable is grade normalized PIAT math test score

	White females	Black females	White males	Black males
Underweight	-0.270	0.016	-0.237***	0.210
	[0.120]	[0.280]	[0.120]	[0.193]
Risk for overweight	-0.002	-0.133	-0.059	-0.113
	[0.067]	[0.110]	[0.058]	[0.112]
Overweight	-0.279***	0.126	-0.063	-0.134
	[0.095]	[0.110]	[0.066]	[0.110]
Mom's years of education	0.069	0.078	0.062	0.079
	[0.009]***	[0.022]***	[0.009]***	[0.020]***
Dad's years of education	0.04	0.024	0.067	-0.002
	[0.009]***	[0.024]	[0.008]***	[0.021]
Live w/ biological dad	0.139	0.027	0.04	0.099
	[0.048]***	[0.091]	[0.046]	[0.086]
Parent volunteers at school	0.204	0.061	0.087	0.107
	[0.049]***	[0.085]	[0.045]*	[0.080]
Parent PTA member	0.038	0.014	0.05	0.003
	[0.049]	[0.099]	[0.047]	[0.088]
Household members <18	0.006	-0.091	0.01	0.028
	[0.019]	[0.028]***	[0.019]	[0.027]
Student threatened at	-0.025	-0.008	0.004	-0.006
School	[0.013]*	[0.017]	[0.007]	[0.017]
Something stolen from	0.007	0.014	-0.048	0.006
School	[0.023]	[0.029]	[0.016]***	[0.020]
Student teacher ratio	-0.007	-0.027	-0.008	-0.002
	[0.005]	[0.009]***	[0.004]*	[0.008]
School size <100	-0.357	0.000	-0.106	0.000
	[0.355]	[0.001]	[0.354]	[0.001]
100<school size<300	0.096	-0.285	-0.005	0.113
	[0.113]	[0.246]	[0.099]	[0.224]
300< school size<500	-0.014	-0.401	0.03	0.177
	[0.080]	[0.180]**	[0.074]	[0.146]
500<school size<750	0.027	-0.143	0.032	0.077
	[0.063]	[0.112]	[0.059]	[0.102]
570<school size<1000	-0.031	0.07	0.01	0.039
	[0.066]	[0.110]	[0.065]	[0.099]
Observations	1545	610	1777	749
R-squared	0.17	0.11	0.17	0.05

*Significant at the 10% level. **Significant at the 5% level. ***Significant at the 1% level. Standard errors are in brackets. Flags are included when mother's education (missing 5%), father's education (missing 15%), and school information (missing 12%) are not observable.

Table 2-6. OLS regression results, effect of weight on test score; dependent variable is grade normalized PIAT math test score

	(1) White Female	(2) Black Female	(3) White Male	(4) Black male
BMI				
Coefficient	-0.011*	-0.012	-0.004	0.003
Standard error	0.006	0.008	0.005	0.008
R^2	0.17	0.11	0.17	0.04
Pounds				
Coefficient	-0.002*	-0.002	-0.001	0.001
Standard error	0.001	0.001	0.001	0.001
Height				
Coefficient	0.031***	0.019	0.001	0.004
Standard error	0.008	0.013	0.001	0.011
R^2	0.17	0.11	0.17	0.04
Underweight				
Coefficient	-0.027	0.016	-0.237***	-0.210
Standard error	0.120	0.280	0.120	0.193
Risk for overweight				
Coefficient	-0.002	-0.133	-0.059	-0.113
Standard error	0.067	0.110	0.058	0.112
Overweight				
Coefficient	-0.279***	-0.126	-0.063	-1.134
Standard error	0.095	0.110	0.066	0.110
R^2	0.17	0.11	0.17	0.05
Observations	1545	610	1777	749

*Significant at the 10% level. **Significant at the 5% level. ***Significant at the 1% level. Flags are included when mother's education (missing 5%), father's education (missing 15%), and school information (missing 12%) are not observable. Control variables include mother's education, father's education, live w/ bio dad, parent volunteer, parent PTA, number of household members under 18 years old, threatened at school, stolen from school, student teacher ratio, school size, and a constant.

Table 2-7. IV regression results, effect of weight on test score; dependent variable is grade normalized PIAT math test score

	(1) White Female	(2) Black Female	(3) White Male	(4) Black male
BMI				
Coefficient	-0.057**	-0.146*	-0.128***	0.016
Standard error	0.026	0.084	0.029	0.056
F-stat on instruments	10.02	2.31	8.09	2.57
First-stage R^2	0.13	0.07	0.09	0.07
R^2	0.13	0.01	0.01	0.03
Pounds				
Coefficient	-0.010**	-0.029*	-0.022***	0.003
Standard error	0.004	0.017	0.005	0.010
F-stat on instruments	34.26	10.90	75.58	18.41
First-stage R^2	0.32	0.29	0.48	0.36
Height				
Coefficient	0.065***	0.140*	0.114***	0.022
Standard error	0.020	0.080	0.025	0.046
R^2	0.07	0.01	0.01	0.03
Overweight				
Coefficient	-1.544**	-1.807*	-2.514***	-0.252
Standard error	0.744	1.031	0.658	0.900
F-stat on instruments	3.54	2.73	4.18	2.09
First-stage R^2	0.05	0.09	0.05	0.06
R^2	0.06	0.01	0.02	0.02
Observations	1376	509	1555	614

*Significant at the 10% level. **Significant at the 5% level. ***Significant at the 1% level. The first stage is not statistically significant when the F-statistic is less than five; this is likely due to the small sample size. Flags are included when mother's education (missing 5%), father's education (missing 15%), and school information (missing 12%) are not observable. Control variables include mother's education, father's education, live w/ bio dad, parent volunteer, parent PTA, number of household members under 18 years old, threatened at school, stolen from school, student teacher ratio, school size, and a constant.

Table 2-8. Panel regression results, effect of weight on test score; dependent variable is grade normalized PIAT math test score

	(1) White Female	(2) Black Female	(3) White Male	(4) Black male
BMI				
Coefficient	-0.005**	0.007	0.034**	0.003
Standard error	0.002	0.024	0.015	0.023
R^2	0.12	0.05	0.23	0.18
Pounds				
Coefficient	-0.002*	-0.001	0.005**	0.000
Standard error	0.001	0.004	0.002	0.003
Height				
Coefficient	0.017	0.005	0.013	0.008
Standard error	0.019	0.032	0.016	0.025
R^2	0.13	0.05	0.23	0.18
Underweight				
Coefficient	0.156	-0.020	0.383	-0.167
Standard error	0.189	0.190	0.287	0.350
Risk for overweight				
Coefficient	0.096	-0.222	0.235	-0.182
Standard error	0.144	0.182	0.217	0.183
Overweight				
Coefficient	0.197	0.065	0.229	-0.488
Standard error	0.222	0.340	0.152	0.311
R^2	0.13	0.07	0.23	0.02
Observations	544	234	601	217

*Significant at the 10% level. **Significant at the 5% level. ***Significant at the 1% level.

Table 2-9. OLS regression results, effect of weight on student absences; dependent variable is number of absences in the 1997 fall semester

	(1) White Female	(2) Black Female	(3) White Male	(4) Black male
BMI				
Coefficient	0.088***	0.129***	0.097***	0.071
Standard error	0.034	0.042	0.030	0.045
R^2	0.07	0.08	0.06	0.05
Pounds				
Coefficient	0.016***	0.021***	0.021***	0.009
Standard error	0.006	0.007	0.004	0.007
Height				
Coefficient	-0.009	0.019	0.022	-0.018
Standard error	0.049	0.075	0.037	0.061
R^2	0.07	0.08	0.06	0.05
Underweight				
Coefficient	-0.536	1.527	-0.642	0.076
Standard error	0.750	1.470	0.720	1.193
Risk for overweight				
Coefficient	0.479	1.629***	-0.059	-0.452
Standard error	0.427	0.590	0.355	0.642
Overweight				
Coefficient	-0.147	0.983	-0.890**	0.132
Standard error	0.575	0.620	0.406	0.599
R^2	0.07	0.08	0.06	0.05
Observations	2305	945	2531	1005

*Significant at the 10% level. **Significant at the 5% level. ***Significant at the 1% level. Flags are included when mother's education (missing 5%), father's education (missing 15%), and school information (missing 12%) are not observable. Control variables include mother's education, father's education, live w/ bio dad, parent volunteer, parent PTA, number of household members under 18 years old, threatened at school, stolen from school, student teacher ratio, school size, and a constant.

Table 2-10. IV regression results, effect of weight on student absences; dependent variable is student absences

	(1) White Female	(2) Black Female	(3) White Male	(4) Black male
BMI				
Coefficient	-0.017	0.551	0.293**	-0.414
Standard error	0.170	0.372	0.140	0.286
F-stat on instruments	12.38	1.98	10.76	4.40
First-stage R^2	0.10	0.04	0.08	0.08
R^2	0.07	0.01	0.05	0.01
Pounds				
Coefficient	0.003	0.095	0.045*	-0.072
Standard error	0.029	0.077	0.024	0.046
F-stat on instruments	45.78	11.61	114.50	33.43
First-stage R^2	0.30	0.21	0.50	0.42
Height				
Coefficient	0.068	-0.269	0.148	0.435
Standard error	0.120	0.310	0.125	0.246
R^2	0.07	0.01	0.05	0.01
Overweight				
Coefficient	0.466	7.778	5.405*	-7.243
Standard error	4.776	5.414	0.029	5.070
F-stat on instruments	4.14	2.58	5.14	2.18
First-stage R^2	0.04	0.05	0.04	0.06
R^2	0.07	0.01	0.02	0.02
Observations	2057	786	2225	836

*Significant at the 10% level. **Significant at the 5% level. ***Significant at the 1% level. Control variables include mother's education, father's education, live w/ bio dad, parent volunteer, parent PTA, number of household members under 18 years old, threatened at school, stolen from school, student teacher ratio, school size, and a constant. Flags are included when mother's education (missing 5%), father's education (missing 15%), and school information (missing 12%) are not observable.

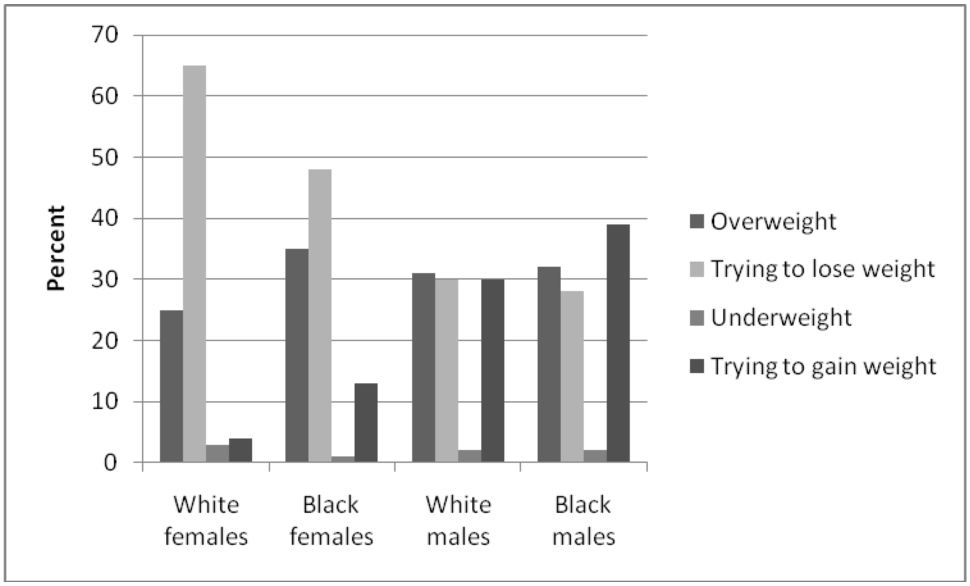

Figure 2-1. Students actual weight and students trying to gain or lose weight

CHAPTER 3
EVIDENCE ON THE EFFECTS OF INTER-SCHOOL DISTRICT COMPETITION: COMPARISIONS OF STATE-LIMITED SCHOOL DISTRICT STATES WITH OTHER STATES

Introduction

Tiebout theory and empirical research tell us that within a metropolitan area people will sort themselves based on income and preference for schooling.[1] That is, a high-income family with many children will live in a neighborhood with higher local public school taxes and expenditures than a retired couple with no school aged children. Often, however, local and state government policies limit Tiebout choice. When Tiebout choice is restricted or absent, families have fewer options as to where to send their children to school. This reduces the competition among schools within any given market area. When schools do not have to compete with one another for students, they have fewer incentives to use their limited resources efficiently. When schools are inefficient and spend money wastefully, classroom learning is sub-optimal. On the other hand, when there are more school districts in a metropolitan area, it is more evident which districts are inefficient. Poorly run school districts will have lower test scores, ceteris paribus, which will cause house values to fall. Homeowners have an incentive to avoid the capital loss by making the schools more efficient.

The difficulty in assessing the impact of Tiebout choice on academic performance is that the degree of competition within a market is usually endogenous. That is, the number of school districts (and therefore the amount of competition) and academic performance are determined simultaneously. For example, imagine two neighboring districts, one with strong performance in math the other with strong English skills. If these districts decide to merge, it is conceivable that average academic achievement would increase. History has also shown that efficient districts

1 See Tiebout (1956), Eberts and Gronberg (1981), Munley (1982), Schmidt (1992).

with administration effective at managing school funds have absorbed ineffective school districts (Hoxby, 2000). These are examples of student learning *causing* the number of districts. On the other hand, the number of districts can impact learning through school competition and scale efficiencies. I contribute to the literature by using a unique method of dealing with the endogenous nature of the number of school districts. Specifically, I compare student learning among states that exogenously limit Tiebout choice with student performance in other states.

Nine U.S. states and the District of Columbia have eliminated the simultaneous nature of learning and Tiebout choice. In each of these nine states and DC, the number of school districts has not changed significantly since before 1950 (Kenny and Schmidt, 1994).[2] Florida, Maryland, Nevada, Virginia, and West Virginia all have laws in place that mandate that each county in the state have one and only one school district. The District of Columbia has had a single federal district-wide public school district since before 1950. Hawaii has had a single state-wide public school district since it became a state in 1959. The number of school districts has also remained relatively constant for the past half century in Georgia, Louisiana, and Utah. Between 1947 and the late 1970s, the number of public school districts in Georgia's 159 counties has been as great as 198 and as few as 186. Since the late 1970s the number of school districts in Georgia has remained at 187. Louisiana has 66 public school districts in 64 counties since before 1970. Finally, Utah has had 40 public school districts in 29 counties since before 1947. None of the aforementioned states nor any other states have replaced their county or state-wide school districts with multiple districts. These nine states and D.C. are in stark contrast to the remaining states which consolidated school districts from 1950 to 1980. During this time, the number of school districts in the U.S. fell from 83,642 to 15,987 (Kenny and Schmidt, 1994).

[2] The exception is Nevada. Nevada had 196 school districts in 1952 but due to a funding crisis, consolidated to 17 districts after 1954 (Strang, 1987).

Table 3-1 lists the number of districts in the nine states and D.C. with state-limited districts from 1947[3] to 1997.

Small counties like St. James, Louisiana[4] have few students and would most likely have only one school district even if the law permitted them to have many more. I expect that since the law mandating a county-wide district is not binding in a small county, it has no impact on student learning. However, in larger markets like Washington DC and Broward County, FL, mandating a single district significantly restricts competition, since many school districts would exist in their absence. In fact, the MSAs of Huston, TX, Atlanta, GA, and Miami, FL have very similar populations. Unrestricted Huston has sixty-eight independent public school districts within its eight counties. Georgia law mandates that counties have a single district per county; Atlanta is made up of twenty-eight counties and therefore has twenty-eight school districts. Miami is made up of only one county and has only one public school district to serve its nearly four million residents.

I expect that in markets where the laws or traditions that restrict the number of districts are binding, student learning is hindered. Additionally, I expect that the laws or traditions that are the most binding and cause the most distortion will have the greatest impact on student learning.

Literature Review

Economists have studied the impact of competition among public school districts on student outcomes; some authors have attempted to deal with the endogeniety of the number of public school districts and some have not. Despite the extensive research on the topic, economists have not been able to reach a consensus: some authors have found that competition

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[3] The earliest data available are from 1947 and obtained from *The Book of the States*.

[4] The county of St James, Louisiana has a population of under 21,000, land area of 246 mi^2 and population density of 84 people/ mi^2.

among districts has a positive effect on learning; other authors have found that competition has no impact on learning.

Authors that do not attempt to control for the endogenous nature of the number of public school districts are Zanzig (1997) and Borland and Howsen (1992). Zanzig uses a spline and finds that counties with four or more school districts, and therefore more competition, perform better than counties with fewer school districts and less competition. Borland and Howsen use a Herfindahl index as their variable for school competition and find that positive correlation between competition and student achievement in Kentucky.

Papers that specifically deal with the endogenous nature of the number of public school districts and consider the impact on student learning are described below. Hoxby (2000) uses the number of rivers in a metropolitan area to instrument for the number of districts and finds that in markets with greater Tiebout choice, students in public schools perform better academically. Additionally, Hoxby finds that per-pupil spending is lower in metropolitan areas with greater choice. Rothstein (2007) argues that Hoxby's instrument is very difficult to implement and that there was little evidence of an effect of inter-school competition on test score. Another paper by Rothstein (2006) uses the number of districts in 1942 to instrument for the number of districts in 1997. The author looks at SAT scores and data from the National Educational Longitudinal Survey 1998 and concludes that increasing Tiebout choice does not increase academic performance among students.

Only one paper assesses the impact of mandated state-wide or county-wide districts on school efficiency. Kenny and Schmidt (1994) find that state-wide and county-wide districts are less efficient than districts where competition is present. The laws that prevent within county competition lead to a higher cost of education. As a result, these monopoly-like school districts spend an additional $866.5 million each year (1992 dollars). I contribute to the literature by assessing the impact of restricting the number of public school districts on student achievement.

Empirical Model

To assess the impact of restricting Tiebout choice on student learning, I use a spline model with one break point and an education production function:

$$\begin{aligned} Learning_{icsv} &= \beta_0 + \beta_1 StateLimitedDistrict_s + \beta_2 MarketSizeSpline1_c \\ &+ \beta_3 MarketSizeSpline2 + \beta_4 StateLimitedDistrict_s * MarketSizeSpline2 \\ &+ StudentInputs_i \chi + ParentalInputs_i \lambda + SchoolInputs_s \theta + \varepsilon_{icsv} \end{aligned} \quad (3\text{-}1)$$

$$MarketSizeSpline1 = \begin{cases} MarketSize & \text{if } MarketSize \le M^* \\ M^* & \text{if } MarketSize > M^* \end{cases} \quad (3\text{-}2)$$

$$MarketSizeSpline2 = \begin{cases} 0 & \text{if } MarketSize \le M^* \\ MarketSize - M^* & \text{if } MarketSize > M^* \end{cases} \quad (3\text{-}3)$$

Where *i* indicates that the variable is measured at the individual level, *c* indicates that the variable is measured at the market level, *s* indicates that the variable is measured at the state level and *v* indicates that the variable is measured at the school level. The spline is a continuous function with a discrete change in the marginal effect (slope) at the breakpoint. I search for the appropriate breakpoint by finding the market size breakpoint, M* which gives the best fit, that is the M* which minimizes the root mean squared error. I define a public school market is in one of two ways: either the county or the metropolitan statistical area (MSA). The independent variables of greatest interest are *StateLimitedDistrict*, *MarketSizeSpline1*, *MarketSizeSpline2*, and the interaction term *StateLimitedDistrict*MarketSizeSpline2*. The variable *StateLimitedDistrict* is a dummy that equals one in the states where the number of public school districts is exogenous.[5] In the remaining states, where residents' preference for education, income heterogeneity, population, population density, and land area determine the number of school districts, the variable *StateLimitedDistrict* equals zero. I expect that the coefficient on *StateLimitedDistrict*, β_1, will not be statistically distinguishable from zero. I do not believe that a law or tradition limiting the number of districts will impact learning in itself, however I expect the law or tradition will impact learning as the size of the market grows and the law becomes binding. This effect is picked up in the variables *MarketSizeSpline1*, *MarketSizeSpline2*, and the interaction *StateLimitedDistrict*MarketSizeSpline2*.

In Equations 3-2 and 3-3, the variable *MarketSize* can be one of four variables that I use, one at a time, to represent the size of the market for education. The four variables used to represent *MarketSize* are MSA population, MSA population density (people/mi^2), county population, and county population density (people/mi^2). The MSA is a better measure of the market since parents do not often send their children to school in another MSA but sometimes send their children to school in a neighboring county.[6] However I also use county measures because 1,148 (22%) of the students in my sample do not live in an MSA.

There is a tradeoff between having a larger number of districts (more Tiebout choice) and having fewer but bigger districts that take advantage of economies of scale. Only one or two districts are found in small markets. The benefits of taking advantage of scale economies by having only one district appear to dominate the benefit from having more choice in school quality, in a market with many relatively homogeneous districts, each having only a small number of students. In states without laws limiting competition, as *MarketSize* increases, the

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5 For the remainder of the paper, I refer to the District of Columbia, Florida, Georgia, Hawaii, Louisiana, Maryland, Nevada, Utah, Virginia, and West Virginia as "limited-district states" for simplicity. Admittedly, this is a slight misnomer since DC is a federal district and not a state.

6 See Hoxby (2000), Zanzig (1997), and Rothstein (2006).

number of school districts within that market also increases. Residents are able to better take advantage of economies of scale *and* to better sort themselves according to their preference for school quality. The number of public school districts increases as the size of the market increases because people are sorting themselves more completely according to their preference for education. Regression estimates from Fisher and Wassmer (1998) indicate that unrestricted MSAs with populations of a quarter million, half a million, and one million people have (respectively) three, five and ten times the number of districts as an MSA with a population of only one hundred thousand residents, all else constant.

The variables *MarketSizeSpline1* and *MarketSizeSpline2* allow me to search for the threshold market size when the restriction on the number of districts becomes binding. To find the threshold market size, *M**, I search over the range of market size for the empirical model's best fit. That is, I find the value of *M** that produces the r-squared closest to one. The variable *MarketSizeSpline1* is equal to the size of the market when the market is relatively small and limiting the number of public school districts to one per county does not impact learning. This variable is equal to the threshold market size, *M**, in large markets when the restrictive mandate is binding. I expect the coefficient on *MarketSizeSpline1*, β_2, will be positive since this variable picks up the impact of economies of scale. A very small school district in a rural area with few residents will not be as efficient as a slightly larger school district.

The variable *MarketSizeSpline2* is equal to zero when the size of the market is less than *M**. It is equal to the difference of *M** and *MarketSize* when the market is large and the mandate is binding. I expect that the coefficient on *MarketSizeSpline2*, β_3, will be positive. The coefficient β_3 picks up additional economies of scale and the effect of more competition in larger markets.

The interaction term, *StateLimitedDistrict*MarketSizeSpline2* is of greatest interest. It picks up the impact of restricting the number of public school districts in large markets. The variable takes a value of zero when the state or federal district has no restriction on the number of school districts. This variable also equals zero when *StateLimitedDistrict* = 1 and *MarketSize* is "small." In this case, the mandate is not binding and there is little to no market distortion and the mandate will have little or no impact on learning. When *StateLimitedDistrict* = 1 and *MarketSize* is "large" and the restriction is therefore binding, the variable *StateLimitedDistrict*MarketSizeSpline2* equals the size of the market minus the breakpoint value, M*. I predict that when the market becomes large enough, the mandate will negatively impact student learning. Additionally, as the size of the markets surpasses M* and continues to grow, there will be further and further deterioration in the performance of students in restricted states relative to students in unrestricted states. In terms of Equation 3-1, I expect $\beta_4 < 0$. These concepts are illustrated graphically in Figure 3-1.

Data

The variable *MarketSize* is measured in four different ways and is calculated using data from the 2000 census. Summary statistics for these variables are presented in Table 3-2. I match each *MarketSize* variable with information from the 1997 National Longitudinal Survey of Youth (NLSY97). All individual and school level data that I use come from the NLSY97 survey data. The NLSY97 follows a sample of 8,984 students in their transition from school to work beginning in 1997. These data are weighted to be representative of the U.S. population. During the first round of interviews, 6,039 students were giving the Peabody Individual Achievement Test (PIAT) Math Assessment. The variable *Learning* is the students' score on the PIAT. This test is a computer administered exam that has been found to reliably measure mathematic achievement (Markwardt, 1998). The PIAT begins with a few questions of varying difficulty, based on the students' grade level. The computer then presents more complicated questions if a student's prior answers were correct and easier questions if his prior answers were wrong. Raw exam scores are reported on a scale of zero to one hundred. As expected, students in higher grades receive higher scores. To better track a student's relative progress over time and to be able to compare students across grades, I normalize the raw score with respect to grade.[7] That is, I take each student's raw test score, subtract the mean score for that student's grade level and then divide by the standard deviation for that student's grade level. Therefore, within grade level, the learning measure that I use has a mean of zero and standard deviation of one.

The vector *StudentInputs* is measured using three different dummy variables (Black, Hispanic, and female), and the student's age. The vector *ParentalInputs* consists of six different variables: mother's years of education, father's years of education, the number of children under eighteen living at home, an indicator equal to one if the biological father lives at home, an indicator equal to one if a family member volunteered at school, and an indicator equal to one if a family member attended a PTA meeting in the last month. In 1997, one parent from each NLSY household was interviewed. About ten percent of students surveyed had no parent interview recorded and were excluded from my analysis. The student's biological mother was the respondent for 80% of completed parent interviews. The parent was asked questions about her education level and about the student's biological father's education level and if he still lived at home. If the education level of a biological parent is missing, I use the resident parent's education instead. The interviewer also asked if the biological mother or another family member attended PTA meetings or volunteered at the student's school (correlation coefficient of 0.29).

7 I also used raw scores as the dependent variable in all regressions, including grade dummies. I do not report these results here, as they were very similar.

The vector *SchoolInputs* is made up of three different pieces of school and individual level information. To gather information on the students' daily life, NLSY interviewers asked, "Have you ever been threatened at school?" This question may also be viewed as indicator of student effort. The other gauges of school quality are the student teacher ratio and school size, which NLSY interviewers obtained directly from the school. The final sample that I use consists of 710 students who live in areas where state law restricts the number of school districts, and 4,587 students from states without a potentially restrictive mandate. Summary statistics are presented in Table 3-3.

Results

The coefficients on variables *StateLimitedDistrict*, *MarketSizeSpline1*, *MarketSizeSpline2*, and the interaction term are presented in Table 3-4. All definitions of *MarketSize*, except county population density, indicate that restricting competition among public school districts within a market hurts test scores. Full results for regression 1 are presented in Table 3-5. The magnitude and sign of all variables presented in Table 3-5 are quite similar to results obtained from regressions 2 – 4. Results indicate that males and females perform equally well on the Math PIAT. However, Black and Hispanic students earn grades approximately 0.6 and 0.2 standard deviations lower than white students, respectively. Since the test scores are normalized by grade, it is not surprising that the coefficient on *Age* is negative. This indicates that if grade is held constant, older students (perhaps students that have been held back a grade) do not perform as well on the exam. Both mother and father's education positively impact test scores. Results indicate that students whose mother or father has a four-year college degree will likely score 0.2 standard deviations better on the exam than a student whose parents have not finished at least a year of college. Students who live with their biological father perform, on average, 0.1 standard deviations better than students who do not live with their biological father. Finally, I find that the student teacher ratio is inversely related to a students score on the exam. Specifically, an average student at a school with a teacher for every ten students will score 0.07 standard deviations better on the exam that an average student at a school with a teacher for every twenty-five students. Let us turn to the results for the variables of interest. The results reported below are insensitive to excluding Georgia, the restricted state with the most variation in the number of districts since 1947, or to excluding DC.

Turning back to Table 3-4, I find that mandating only one school district per county does not negatively impact test scores until MSA population reaches approximately 91,000. An MSA with population density of up to 480 people per square mile is small enough to efficiently have only one school district. When the market is defined as the county, results indicate that having a single public school district for every 250,000 residents is efficient. I also find that counties with population densities less than 450 people per square mile are sufficiently small to contain only one school district.

All regression results indicate that β_1 is not statistically different from zero. Point estimates are positive when the market is defined as the MSA and negative when the market is defined as the county. This means that restrictive mandates do not have a negative impact on test scores in and of themselves when markets are relatively small. This result also rules out the possibility that states with restrictive mandates are somehow intrinsically different and less productive than states without mandates. It is only when the mandates are binding and effectively limit the number of school districts, that test scores are negatively impacted.

Point estimates of the coefficient β_2 suggest that in markets smaller than the threshold, M^*, learning improves as the market becomes larger. That is, economies of scale exist. However, this effect is only statistically significant when *MarketSize* is defined as the MSA population; the point estimate suggests that in small markets with less than 91,000 residents (i.e., M* = 91,000), each population increase of 10,000 people will be accompanied by a 0.12 standard deviation increase in test scores.

Point estimates of the coefficient β_3 offer mixed results. When the market is defined as the MSA, point estimates indicate that even when the size of the market is greater than *M**, economies of scale are not yet exhausted. When *MarketSize* is defined as the population density of an MSA, estimates suggest that in large markets with population density greater than 480 people per square mile each standard deviation increase in population density (275) is associated with a growth in test scores of 0.03 standard deviations. However results are different when the market is defined as the county. When *MarketSize* is defined as the county population, larger markets with population greater than 245,254 will experience a decrease in test scores of 0.01 for each standard deviation increase in population.

Three of four estimates indicate that as the market grows, students in restricted states are falling farther and farther behind students in unrestricted states; in other words, β_4 is negative and statistically significant. In Column 1 the size of the market is defined as the population within the MSA. Coefficient estimates suggest that for each standard deviation increase in MSA population over 91,000, test scores will drop 0.04 standard deviations. Since an MSA population of 91,000 represents only the 5^{th} percentile of MSA population, this means that 95% of state-limited MSAs would benefit from allowing the number of public school districts to increase. On average, a student living in a restricted state and in an MSA with population of 1,000,000 will earn a test score 0.02 standard deviations lower than a similar student living in an unrestricted state.[8] This disparity grows as the market size grows. In fact, in an MSA with a population of 10,000,000, the restrictive mandate hurts test scores by nearly a quarter of a standard deviation.

Columns 2 and 3 offer similar evidence that restrictive mandates hurt student performance. I estimate the largest impact when *MarketSize* is defined as the county population. For each standard deviation increase in MSA population density, the average student in a restricted state with population density greater than 480 will perform 0.14 standard deviations worse than his counterpart in an unrestricted state. In Column 3, *MarketSize* is defined as the county population. The coefficient on β_4 indicates that for each standard deviation increase in county population over 245,254, the average test score difference between students in restricted states and students in unrestricted states will grow by 0.05 standard deviations.

Using these estimates I present a list of the eight largest MSAs whose students are negatively impacted by restrictive mandates in Table 3-6. These markets serve between 60,000 and 400,000 students each. Using the regression coefficients in Table 3-4, I estimate that these markets have test scores 0.17 to 0.73 standard deviations lower than they would in absence of restrictive mandates. Notably impacted MSAs are Washington DC, Atlanta, GA, Miami, FL and Honolulu, HI. I estimate that if multiple public school districts were permitted Washington DC, test scores would be 0.17 to 0.40 standard deviations higher. Removing a restrictive mandate in Atlanta may lead to improvements in test scores from 0.09 to 0.34 standard deviations. Because of the high population density in Miami and Honolulu, I estimate that allowing more inter-district competition may improve test scores from 0.61 to 0.73 standard deviations. These are statistically and economically significant impacts. Relative to other findings in the education production literature, the negative impacts of these restrictive mandates are very large.

[8] I calculate this by multiplying β_3 by (1,000,000 – 91,000).

Conclusion

Despite the conflicting economic literature, I find strong evidence that restricting competition among public school districts negatively impacts student learning. I exploit markets where the number of school districts and Tiebout competition are exogenous. I find that binding laws that mandate county or state-wide school districts negatively impact student test scores by 0.09 to 0.34 standard deviations. It seems that in the largest school districts with the most students, these restrictive mandates are especially harmful. In smaller markets where having more than one school district is inefficient, restricting competition has no impact on student learning.

Table 3-1. Characteristics of states with an exogenous number of school districts

State	Districts in 1947	Districts in 1950	Districts in 1960	Districts in 1970	Districts in 1980	Districts in 1997	Mandate
DC	1	1	1	1	1	1	Yes
Florida	67	67	67	67	67	67	Yes
Georgia	189	186	198	190	187	187	No
Hawaii	1	1	1	1	1	1	Yes
Louisiana	67	67	67	66	66	66	Yes
Maryland	24	24	24	24	24	24	Yes
Nevada	222	196	17	17	17	17	Yes
Utah	40	40	40	40	40	40	Yes
Virginia	125	127	131	134	141	141	Yes
West Virginia	55	55	55	55	55	55	Yes

1947 data is from *The Book of the States*, 1947. 1950 – 190 data is from Kenny and Schmidt, 1994. 1997 data is from http://nces.ed.gov/programs/digest/d98/d98t092.asp. All states but Georgia have a law in place preventing the number of districts from changing. Florida consolidated from 720 to 67 school districts in 1947. Navada consolidated from 196 to 17 districts in 1952. In Virginia, the number of school districts equals the number of counties plus the number of independent cities; changes in the number of school districts are due to changes in the number of independent cities.

Table 3-2. *MarketSize* variables summary statistics

Variable	Mean	Std Dev	Min	Max
MSA Population	818,545	1,957,796	57,813	21,199,870
MSA Population Density (people/mi^2)	292	275	5.4	2,029
County Population	89,596	292,462	67	9,519,338
County Population Density (people/mi^2)	243	1,667	0.7	66,940

Table 3-3. Variable summary statistics

Variable	Mean	Std. Dev	Min	Max
Dependent Variable				
Normalized Test Score	0.000	1.000	-4.299	2.721
Student Inputs				
Female	0.472	0.499	0	1
Black	0.282	0.450	0	1
Hispanic	0.200	0.400	0	1
Age	13.63	1.17	12	17
Parent Inputs				
Mother’s Years of Education	12.47	2.89	1	20
Father’s Years of Education	12.48	3.19	1	20
Live with Biological Father	0.531	0.499	0	1
Volunteer at Student’s school	0.641	0.722	0	2
Attend PTA Meetings	0.933	0.745	0	2
Number of Children Under 18 Living in Household	2.52	1.27	1	12
School Inputs				
Threatened	0.224	0.42	0	1
Student Teacher Ratio	17.19	5.31	10	26
School Size	819	359	50	1250

Table 3-4. Regression results, the effects of limiting competition on student learning; dependent variable is grade normalized PIAT math test scores

	MarketSize Variable			
	(1) MSA Population	(2) MSA Population Density	(3) County Population	(4) County Population Density
β_0	0.8175	-0.2936	-0.3355	-0.3245
	(0.3140)	(0.2936)	(0.2419)	(0.2143)
β_1	0.0165	0.0539	-0.0503	-0.0853
	(0.1154)	(0.0796)	(0.0835)	(0.0625)
β_2	$1.200 \text{ X } 10^{-5}$***	$1.268 \text{ X } 10^{-4}$	$4.442 \text{ X } 10^{-3}$	$3.971 \text{ X } 10^{-5}$
	($1.268 \text{ X } 10^{-6}$)	($1.296 \text{ X } 10^{-4}$)	($4.687 \text{ X } 10^{-3}$)	($1.032 \text{ X } 10^{-4}$)
β_3	$1.771 \text{ X } 10^{-9}$	$1.103 \text{ X } 10^{-4}$***	$-2.909 \text{ X } 10^{-8}$*	$-3.576 \text{ X } 10^{-7}$
	($4.126 \text{ X } 10^{-9}$)	($3.830 \text{ X } 10^{-5}$)	($8.310 \text{ X } 10^{-9}$)	($2.719 \text{ X } 10^{-6}$)
β_4	$-2.272 \text{ X } 10^{-8}$***	$-4.997 \text{ X } 10^{-4}$***	$-1.608 \text{ X } 10^{-7}$*	$7.671 \text{ X } 10^{-6}$
	($1.010 \text{ X } 10^{-8}$)	($8.696 \text{ X } 10^{-5}$)	($9.502 \text{ X } 10^{-8}$)	($3.474 \text{ X } 10^{-5}$)
M*	91,000	480	245,254	450
(percentile)	(5^{th})	(80^{th})	(91^{st})	(92^{nd})
N	4,149	4,149	5,297	5,297
R^2	0.21	0.21	0.19	0.19

Standard errors are clustered at the state level and presented in parenthesis. Each regression is weighted. $\boldsymbol{\beta_1}$ is the value of the coefficient on the variable *StateLimitedDistrict*. $\boldsymbol{\beta_2}$ is the value of the coefficient on the variable *MarketSizeSpline1*. $\boldsymbol{\beta_3}$ is the value of the coefficient on the variable *MarketSizeSpline2*. $\boldsymbol{\beta_4}$ is the value of the coefficient on the interaction term, *StateLimitedDistrict*MarketSizeSpline2.*

Table 3-5. Regression results, education production function; dependent variable is grade normalized PIAT math test scores.

Variable	Coefficient	Standard Error
Student Inputs		
Female	-0.0338	0.0227
Black	-0.5546***	0.0496
Hispanic	-0.1922***	0.0538
Age	-0.0611***	0.0201
Parent Inputs		
Mother's Years of Education	0.0571***	0.0080
Father's Years of Education	0.0480***	0.0086
Live with Biological Father	0.1127***	0.0359
Volunteer at Student's school	0.0766***	0.0247
Attend PTA Meetings	-0.0172	0.0193
Number of Children Under 18 Living in Household	-0.0169	0.0142
School Inputs		
Threatened	-0.0824***	0.0273
Student Teacher Ratio	-0.0045**	0.0030
School Size	1.96×10^{-5}	5.54×10^{-5}

Table 3-5 presents the complete coefficient results for the first regression in Table 3-4. The market size variable is MSA population. Standard errors are clustered at the state level.

Table 3-6. Sample of MSAs negatively impacted by mandates restricting inter-county or inter-state competition among public schools.

MSA Name	Population	Negative Impact on Test Scores	Population Density	Negative Impact on Test Scores
Washington DC/ Baltimore, MD	7,608,070	0.17	794	0.40
Atlanta, GA	4,112,198	0.09	672	0.34
Miami/Fort Lauderdale, Florida	3,876,380	0.09	1,230	0.61
Tampa/St. Petersburg/Clearwater, FL	2,395,997	0.05	939	0.47
Norfolk/Virginia Beach, VA	1,569,541	0.04	668	0.33
Salt Lake City, UT	1,333,914	0.03	825	0.41
West Palm Beach/Boca Raton, FL	1,131,184	0.03	573	0.29
Honolulu, HI	876,156	0.02	1,461	0.73

Impact on test scores represents the estimated number of standard deviations lower the average test score is as a result of the restrictive mandate. In terms of Equation 3-1, these two columns are calculated by *MarketSize**$\boldsymbol{\beta}_4$.

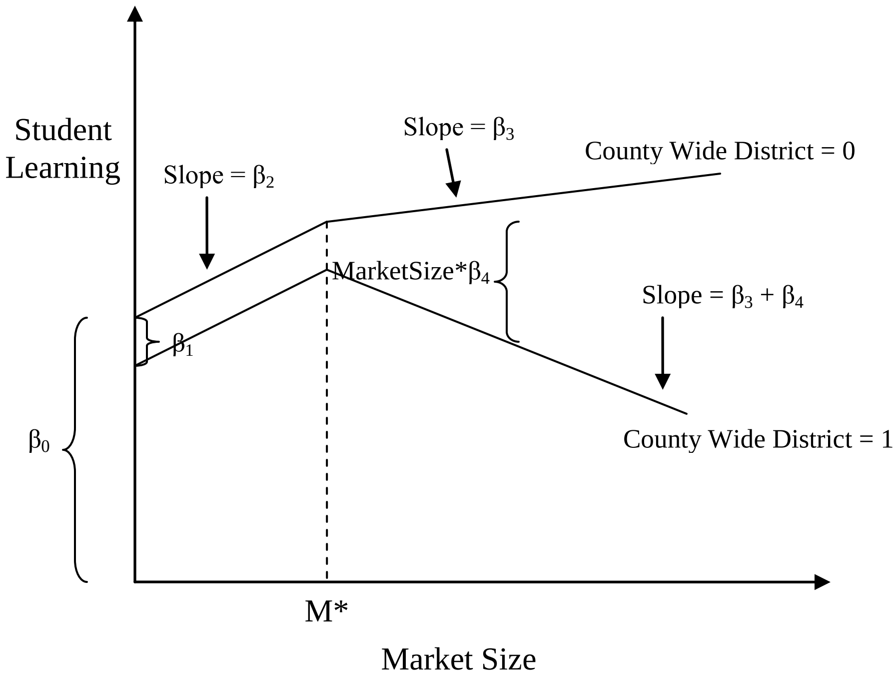

Figure 3-1. Impact of the market size on student learning as the market size increases.

CHAPTER 4
ANALYSIS OF FLORIDA CONSTITUTIONAL AMENDMENT ELIMINATING THE OFFICE OF PUBLIC SCHOOL TRUSTEES, 1956

Introduction

In November of 1956, Florida voters authorized an amendment to Article XII, Section 10 of the state constitution that would eliminate the office of school district trustees and give their powers and duties to the county school board. This amendment effectively reduced representation of certain residential districts within each county. Tiebout theory tells us that people will sort themselves into communities based on their preference for public services, including public schooling. In homogenous Florida counties, Tiebout sorting was complete and each residential district did not need separate representation since each residential district would have the same preferences for schooling and taxes. In heterogeneous counties, Teibout sorting was not complete and each residential district benefited from the ability to elect an official to represent them when decisions about school taxes and funding were made. I examine the votes of this constitutional amendment at the county level. I hypothesize that in homogeneous counties, voters preferred to streamline the administration of public schools, and supported the amendment. In heterogeneous counties, voters would not be as likely to support the amendment.

School District Trustees and School Boards

The 1956 statewide amendment vote gave Florida citizens a chance to choose how they would be represented in the relatively young county-wide school district system. The office of school district trustees was officially created in Florida in 1885, and eliminating the position was a controversial issue in some counties. While the trustee position was well established, their responsibilities changed significantly in 1947. In 1947, Florida had 720 school districts located within 67 counties, or 11 per county on average (Florida Citizens Committee on Education, 1947). Each school district held a biennial election and chose three school district trustees, meaning there were 2,160 trustees (11 sets of 3 trustees per county on average) in Florida in 1947. Each school district within the county levied its own taxes according to voter preference. One district within the county may have collected a school district tax as high as ten mills, and another school district in that same county may have chosen to collect no additional funds and pay only the minimum amount required by the county school board. After 1947, Florida consolidated school districts to one per county, eliminating all but three trustee positions per county. The duties of these remaining 201 trustees varied by county and were not set forth by the Florida legislature. The 1947 consolidation act also divided each county into residential (not school) districts. Before consolidation in 1947, each school district was homogeneous and there was no issue with voter preferences being poorly represented. After 1947, there was only one school district in each county. Heterogeneous counties were unable to offer different spending levels to different districts in the county, which would have brought about Tiebout sorting.

Florida has consistently had one school board of 5 members per county. After 1947 and before 1956 there were two overlapping groups: a countywide set of 3 trustees and a county wide school board of 5 members. Both the school board and the trustees were selected in elections in which all in the county voted but none of the 5 geographic districts could have more than one trustee or school board member. Thus each of the 5 geographic districts had one school board member and 3 of the 5 were represented by a trustee; this creates a fear of being in one of the 2 districts with no trustee. Doing away with the trustees would eliminate the risk associated with not being represented by a trustee. This was more of an issue in heterogeneous counties. While trustees answered to the county school board, they effectively exerted administrative and monetary control over their respective school districts.

Finally, unlike county board members, trustees were not nominated by a political party during the primaries, and any voter living within the county could run for office. Eliminating the trustee position would give more power to the political parties, specifically the Democratic Party, since there were few Republicans in Florida in the 1950s.

Senate Joint Resolution No. 638

The constitutional amendment abolishing the office of school district trustees began in the Florida Senate. Senate Joint Resolution No. 638 was passed on May 12, 1955. Thirty three senators voted yea on the bill and only Senator Connor from Citrus County voted nay. The House voted on the resolution on May 31, 1955. Sixty-six house members voted yea and five house members from Bay, Columbia, Hamilton, Lafayette, and Martin Counties voted nay. The amendment was then voted on in the general election on November 6, 1956. Fifteen counties opposed the amendment; the remaining fifty-two counties supported it.[1] Summary statistics on the general election vote are presented in Table 4-1.

Data

Information on the number of votes cast in each county is available in the Florida State Archives. I match this data to the 1960 Census Bureau data. I hypothesize that support for the amendment will be inversely related to the heterogeneity within the county. I measure heterogeneity using various variables of income, race, and rural population. I control for the county population and land area. Summary statistics are presented in Table 4-2

Hypotheses

The median voter model predicts that support for the amendment will be inversely related to the ratio of the median to the mean income. If the ratio of median to mean income is small

[1] Counties that did not pass the amendment were Calhoun, Dixie, Gilcrest, Glades, Hamilton, Holmes, Jefferson, Lafayette, Levy, Liberty, Madison, Martin, Taylor, Wakulla, and Walton.

and less than one, the median voter would elect trustees that would redistribute income away from the wealthy. Many wealthy voters could benefit if the ability to redistribute was taken away, that is I expect more support for the amendment if the ratio of median to mean income is small. As the ratio of median to mean income approaches one, income distribution becomes less skewed; the median voter has less of a chance to redistribute income toward himself and voters may be in favor of keeping the trustees to perform other duties. I also predict that the more heterogeneous the population in income, race or fraction rural, the less support for the amendment.

Within each county, residential districts with high voter turnout would be more likely to have had a trustee representing them and would therefore be less likely to vote for the amendment to do away with the position. Traditionally, the well educated and elderly populations have highest voter turnout. I expect to find that there was strong support for the amendment in urban areas. In urban areas, where population density was higher and transportation was easier, voters could easily participate in local school politics and would communicate more readily with their elected representatives, ensuring their voices be heard even after county board members were elected. In predominantly rural counties, the distribution of residents is spread thinly over the county. Residents would rely more heavily on their elected representative when school policy was made. Thus, rural areas would benefit from greater representation and from electing trustees.

Results

Regression results are presented in Table 4-3. I use seven different income variables separately in regressions. In the first two regressions, the income variables are median individual income and mean individual income. It is apparent that the amendment had greater support in wealthier, more populated areas. Each thousand dollar increase in the median income is associated with an increase of 0.08 percentage points in support of the amendment. Each thousand dollar increase in the mean income is associated with an increase of 0.07 percentage points in support of the amendment. It is possible that wealthy counties favored eliminating the trustees in order to streamline operations and transfer school funding away from administration and toward more educational purposes. If wealthier, more educated residents are more efficient at running their school districts then additional representation would not be necessary.

In the remaining columns I regress the fraction of the county in favor of the amendment on measures of income heterogeneity. I measure income heterogeneity using a ratio of the median to the mean income and with a Herfindahl Index (HHI) based on the number of residents falling into specific income categories, as explained below. As expected, I find that as the ratio of the median to the mean income increases, there is less support for the amendment. A one standard deviation increase in the ratio of median individual income to mean individual income is associated with a two percentage point decrease of support for the amendment. A one standard deviation increase in the ratio of median household income to mean individual income is associated with a four percentage point decrease of support for the amendment.

An additional measure of income heterogeneity is an income HHI. The 1960 census contains information on the number of residents within twelve different income brackets, adding the squares of each of these gives me an accurate measure of income heterogeneity. As this variable increases, the amount of heterogeneity decreases and I would expect coefficients to be positive. While the point estimate of the coefficient on the income HHI is positive, it is not statistically significant.

Interestingly, the greatest predictor of rejecting the amendment is the percent of the population living in a rural area. In fact, of the fifteen counties rejecting the amendment, eleven were completely rural and three were over 65% rural. The only county voting against the amendment that was predominantly urban was Taylor County. A one percentage point increase in the population living in a rural area is associated with a 0.2 percentage point decrease in support for the amendment.

Table 4-1. General election votes on amendment to abolish the office of school district trustees

Statewide information	
Number of votes against	116,897
Number of votes for	311,947
Fraction of votes for	0.727
Fraction voter turnout	0.087
County information	
Number of counties for	52
Fraction counties for	0.776
Median fraction of voters for	0.640
Mean fraction of voters for	0.613
Max fraction of voters for	0.839
Min fraction of voters for	0.195

Table 4-2. County level summary statistics

Variable	Mean	Standard deviation	Minimum	Maximum	
Median / mean income	0.737	0.083	0.207	0.881	
Median income (dollars)	1,980	511	714	3,563	
Mean income (dollars)	2,687	599	1,690	4,172	
Income HHI	0.125	0.058	0.089	0.496	
Population	73,903	145,781	2868	935,047	
Land area (sq mi)	810	395	240	2,054	
Percent nonwhite	23.3	11.5	3.2	59.4	
Percent rural	59.7	27.8	3.3	100	100

Table 4-3. Regression Results

	Median	Mean	Median / mean	Income HHI
Income coefficient	7.62×10^{-05}	6.91×10^{-05}	-0.27	0.22
	(2.42)**	(2.07)**	(1.59)*	(0.87)
Race HHI	0.001	0.018	0.064	0.115
	(0.01)	(0.14)	(0.49)	(0.89)
Log (population)	0.051	0.042	0.067	0.062
	(4.50)***	(3.06)***	(5.67)***	(5.45)***
Log (land area)	-0.048	-0.045	-0.043	-0.034
	(1.51)	(1.39)	(1.32)	(1.05)
Fraction rural	-0.196	-0.202	-0.221	-0.243
	(2.82)***	(2.88)***	(3.16)***	(3.38)***
Constant	0.392	0.416	0.124	0.271
	(1.72)*	(1.79)*	(0.47)	(1.10)
Observations	67	67	67	67
R-squared	0.53	0.52	0.51	0.49

*Significant at the 10% level. **Significant at the 5% level. ***Significant at the 1% level.
t-statistics are presented in parentheses. Income is measured at the individual level.

CHAPTER 5
CONCLUSION

In this work composed of three separate studies, I find that overweight, white adolescent females perform worse on the math PIAT than their healthy weight counterparts. Body features have less impact on male test scores. If overweight individuals learn less as students, then the labor market "beauty premium" is partially a productivity premium and not solely due to employer discrimination. In my second study, I examine the impact of limiting the number of school districts per county. I find that eliminating the choice of residents to separate into multiple districts hurts student outcomes. Finally, in my third study, I find that urban, white, wealthy, homogeneous counties in Florida supported the 1956 amendment to eliminate school district trustees.

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BIOGRAPHICAL SKETCH

Katie Ann Sherron Showman graduated from Hope College with a Bachelor of Arts in economics and mathematics in 2003. After college, Katie moved to Gainesville and began her graduate studies at the University of Florida Department of Economics. She earned her Master of Arts in economics in 2005 and graduated with a Doctor of Philosophy degree in August 2009. Katie keeps it real in Tallahassee, Florida with her husband Brian and their chocolate lab Boo.