Student Demographics, Teacher Sorting and Teacher Quality: Evidence From the End of School Desegregation

Clement (Kirabo) Jackson
Cornell University, ckj5@cornell.edu

"STUDENT DEMOGRAPHICS, TEACHER SORTING AND TEACHER QUALITY: EVIDENCE FROM THE END OF SCHOOL DESEGREGATION"[+]

C. Kirabo Jackson *Draft Date July 17, 2008.*

Abstract: The reshuffling of students due to the end of student busing in Charlotte-Mecklenburg provides a unique opportunity to investigate the relationship between *changes* in student attributes and *changes* in teacher quality that are not confounded with changes in school or neighborhood characteristics. Comparisons of OLS and IV results suggest that the spatial correlation between teachers' residences, students' residences and schools could lead to spurious correlation between student attributes and teacher characteristics. The re-shuffling of students led to teacher re-sorting so that schools that experienced a repatriation of black students experienced a decrease in various measures of teacher quality (including estimated value-added). I provide evidence that this was primarily due to a labor supply response.

1 Motivation and Introduction

In 2002, Charlotte-Mecklenburg (CM) school district ended its long-standing school integration policy which entailed busing students across neighborhoods to maintain racial balance of the student bodies across schools. Since CM schools were compelled to have student populations that were similar to the district average during busing, the demographic make-up of schools quickly converged to those of their surrounding neighborhoods in 2002 while other school attributes and neighborhood characteristics were largely unchanged.[1] Since student characteristics affect the working conditions for teachers, this policy change provides a unique opportunity to better understand the relationship between student demographics and teacher quality and to determine whether teachers have preferences for particular types of students.

While the research is mixed, there is evidence that years of teaching experience, the selectivity of undergraduate institution, teachers' test scores, and regular licensure are associated with higher student achievement [Brewer and Ehrenberg (1994); Hanushek

[+] I am very grateful for advice and feedback I received from Caroline Hoxby and Lawrence Katz. I would like to thank Kara Bonneau of the North Carolina Education Research Data Center. All errors are my own.

[1] Only 48 percent of students in the county attended a school that deviated from the district average percent of minority students by more than 15 percentage points in 2000-1, while in 2004-5, after the policy change, that number increased to 74 percent. Source: NAACP.

(1997); Brewer and Goldhaber (2000); Anthony and Goldhaber (2007); Clotfelter, Ladd and Vigdor (2006)]. Studies that identify teachers associated with student test-score gains show that a one standard deviation increase in teacher quality leads to between a tenth and a fifth of a standard deviation increase in math and reading scores [Rockoff (2004); Aaronson, Barrow and Sander (2007); Rivkin, Hanushek and Kain (2005)] and Jacob and Lefgren (2008) find that principals' subjective evaluations of teachers are highly correlated with subsequent increases in student achievement.

Since salaries do not vary across schools within a district, teachers have little financial incentive to teach at undesirable schools. Since observably better teachers will be hired over weaker teachers, and all teachers are likely to apply for the most desirable jobs, schools with undesirable working environments will have teachers of lower average quality. If teachers prefer working environments with students of a particular demographic, teacher quality would be endogenous to student demographics and, *ceteris paribus*, students who teachers find undesirable will be exposed to teachers of lower quality. Desegregation orders and school choice policies are predicated on the hypothesis that it is helpful to reshuffle peers while keeping other things roughly the same. While this may be true, it may be impossible to keep teaching "roughly the same" if teacher quality is endogenous to student characteristics. For example, the movement of high-quality teachers out of schools with growing black enrollment shares may be partially responsible for the costs of school segregation to black students documented by Guryan (2004) and Lutz (2005) and the finding that high black enrollment shares are associated with lower test scores [Hanushek, Rivkin and Kain (2004), Hoxby (2000)].

Researchers have found that high-poverty schools tend to have teachers with lower qualifications than low-poverty schools and that teachers tend to move from schools with low-achieving, poor, heavily minority school districts, particularly when there are vacancies at higher-achieving, affluent schools. This evidence is based on observing teacher attributes, or changes in teacher attributes at schools whose student populations are unchanging or are changing due to unobserved factors that could also affect teacher labor supply. I provide an overview of this literature and discuss why, based on previous studies, one cannot say whether the observed differences are caused by (a) school attributes that are correlated with student characteristics (b) unobserved neighborhood attributes that are correlated with student characteristics or (c) mobility of teachers toward their residences that happens to move them out of inner-city schools.

The sudden changes in student attributes *within* schools over time due to the policy change allow me to address these issues and provide a unique opportunity to observe teachers' reactions to exogenous changes in student attributes that were uncorrelated with changes in neighborhood and school characteristics.[2] While a faculty desegregation order was issued in 1972, it had not been exercised in over twenty years and there was no change in the district's hiring or teacher/principal placement practices over the sample period.[3] Also, CM has a policy of not forcibly relocating teachers across schools.[4] As such, I interpret changes in teacher mobility to be *primarily* a labor supply response. Anecdotal and empirical evidence suggests that the changes were not driven by changes in teacher demand so that this analysis may provide empirical evidence of the sorting suggested by the theory of compensating differences. Similar to Hanushek, Kain, O'Brien and Rivkin (2005), I use student achievement gains to estimate teacher value-added. This allows me to observe the change in the distribution of teacher value-added within a school in response to a quasi-exogenous change in student demographics.

Since a racially integrated school in a predominantly black neighborhood would have experienced a larger inflow or repatriation of black students after busing ended than a predominantly black school in an identical neighborhood, I use the difference between the proportion of black students at the school and the proportion of black residents in its surrounding neighborhood *before the policy change* to predict the exogenous inflow of black students due to the policy change. While the policy change allows me to observe exogenous movement of students, I am unable to disentangle race from other student characteristics endogenous to race. As such, as in other studies, student race is a summary statistic for a variety of student attributes and the results should be interpreted in that light.

I find that schools that had an inflow of black students, due to the policy change, had a decrease in the share of high-quality teachers, as measured by years of experience,

---

[2] Other researchers have used this policy change in CM as a way to study the effects of school choice on student outcomes [Hastings, Kane and Staiger (2006); Hastings and Weinstein (2007); Hastings, Van Weelden and Weinstein (2007)] and to study the relationship between school characteristics and housing prices [Kane, Staiger and Riegg (2005)].

[3] Employees from the Charlotte-Mecklenburg legal office, personnel office and superintendent's office have all corroborated this statement.

[4] However, the superintendent has forcibly relocated two school principals *after the sample period*.

certification test scores, and estimated teacher effectiveness in math and reading. These changes were largely driven by changes in the attributes of teachers who remained in these schools– indicating that experienced, white and high value-added teachers were relatively more likely to leave these schools. I find that black teachers were more likely to stay in these schools while white teachers were relatively unaffected. The relationship between teacher characteristics and student race differs in the within-school instrumental variables regressions and in the cross-section, suggesting that some of the well documented correlations are an artifact of residential segregation. This paper presents the first compelling evidence that the relationship between student demographics and teacher quality may be causal. The direction of the flow of black students is not correlated with hiring more teachers (vacancies) – suggesting changes were not demand driven.

The data show that *all* CM schools experienced increased teacher turnover (leaving) and within-district switching the year before students were re-assigned. This shows that the teacher movement was probably not in response to vacancies at schools that had decreasing black enrollment shares- suggesting a labor supply response. These patterns are consistent with a compensating differentials equilibrium where teachers have heterogeneous tastes for student attributes so that teachers re-sorted in the face of an anticipated change in working conditions. The findings suggest that the widening black-white achievement gap associated with residential and school segregation and the negative relationship between student achievement and the percentage of black students at the school[5] are due, in part, to the endogeneity of teacher quality with respect to student characteristics. The findings underscore that policy-makers should be careful to consider how teachers may re-allocate themselves when students are moved across schools through vouchers, school choice, district consolidation, or school busing.

The remainder of the paper is structured as follows. Section II reviews the literature on teacher quality and student attributes; Section III describes the policy change and documents its effect on student characteristics. Section IV shows the effect of the policy change on teacher characteristics. Section V presents a graphical analysis of teacher turnover. Section VI uses disaggregated teacher data to explain the observed results in the aggregate, and section VII concludes.

[5] Guryan (2004); Lutz (2005); Hanushek, Rivkin and Kain (2004), Hoxby (2000).

II Research on Student Attributes and Teacher Mobility

It has been well documented that inner-city, minority-majority, high-poverty schools across the United States tend to have teachers with lower qualifications than low-poverty schools [Betts, Reuben and Danenberg (2000), Clotfelter, Ladd, Vigdor and Wheeler (2007), Lankford, Loeb, and Wyckoff (2002), Scafidi, Sjoquist and Stinebrickner (2007) Hanushek, Kain and Rivkin (2003), Hanushek and Rivkin (2004)]. These researchers also find that low-income inner-city schools experience higher teacher turnover, particularly among white teachers, than affluent high-achieving suburban schools. While greatly informative, these studies compare the stock or the flow of teachers across schools where student attributes are either unchanging or changing for reasons that may exert an independent effect on teacher labor supply decisions.[6]

Exploiting the movement of individual teachers, researchers have found that teachers in schools with low-achieving students, particularly those with more experience, move to higher-achieving schools, leaving many high-poverty minority-majority districts with vacancies and unqualified instruction [Betts, Rueben and Danenberg (2000), Bohrnstedt and Stecher (1999); Lankford (1999), Lankford, Loeb and Wyckoff (2002); Hanushek, Kain and Rivkin (2004), Hanushek, Kain, O'Brian and Rivkin (2005)]. Hanushek and Rivkin (2004) find that this movement is stronger for white teachers than for black teachers- suggesting that teachers may prefer own-race students.

Analyzing New York teachers, Boyd, Lankford, Loeb and Wycoff (2005) find that the geographic location of a school *vis a vis* a teacher's home plays a strong role in labor supply decisions. They find that teacher labor markets tend to be geographically very small and that teachers express preferences to teach close to their residences, which in turn tend to be close to where they grew up. The implications of the geospatial nature of teacher labor markets are that the spatial correlation between teachers' residential locations and those of the schools could generate *both* the cross-sectional relationship and the dynamics documented by researchers even if teachers have no preference for student or school attributes *per se*.

[6] As noted by several researchers, attempting to separate the contribution of student attributes from those of school or neighborhood attributes (which are highly collinear and jointly determined) is a dubious exercise without independent exogenous variation. While including school and neighborhood proxies can mitigate this problem, the strong collinearity between student demographics, school attributes and neighborhood attributes render this solution unsatisfactory.

Consider the observation that experienced teachers leave inner city schools when vacancies are available in affluent, suburban schools and the observation that experienced teachers are less likely to teach at inner city schools serving poor, minority populations. Since more experienced teachers are often given preference for new teaching positions, they have greater ability to express their preferences for schools. Since teachers, especially older teachers who are likely to have families, tend to live in suburban areas with reasonably good schools, their moving towards schools that are close to their homes will systematically move them out of inner-city schools that serve low-income ethnic minority neighborhoods. In such a scenario, teachers' *endogenous* movements, especially those of experienced teachers, would be due to the spatial correlation between school demographics, neighborhood characteristics and teachers' residential locations rather than a reflection of teachers' preferences for teaching at the schools *per se*. If the documented relationship between student and teacher attributes is an artifact of residential segregation, the interpretation of the evidence is very different, and policy prescriptions with regards to teacher recruiting and retention would be vastly different.[7]

To address this spatial correlation bias, one would like to observe changes in teacher labor supply decisions at schools in which student demographics are changing, but for which the geospatial relationship between the school and their homes are unchanged. Given the limitations associated with observing endogenous movement of teachers across schools whose student populations are associated with a variety of other factors (including distance to home), the relatively sudden change in schools' student demographics caused by the end of the desegregation order in CM may provide some new insights into the relationship between student attributes and teacher sorting.

III The Policy Change and its Effect on Student Characteristics

In 1971, the United States Supreme Court held that busing was an appropriate way to ensure that all students would receive equal educational opportunities regardless

[7] For example, policies that improve the quality of neighborhoods surrounding a school may make it easier to attract teachers to schools with large ethnic minority shares. Alternatively, policies that make it easier to live farther away from schools in undesirable neighborhoods could improve teacher retention. Schools could also actively recruit teachers who grew up close by or in similar neighborhoods. However, if teachers react to the demographics of students rather than the neighborhoods of their schools, such policies would be largely ineffective.

of their race.[8] Following this ruling, CM adopted a race-based student-busing policy so that many students attended schools that were not located in their own residential neighborhood. The plan stated that no school was to be more than fifty percent black and the “the burdens of busing” were to be shared equally. To achieve this goal, the plan used noncontiguous satellite zones and the pairing of inner-city black schools with outlying white schools.[9,10] Since faculties were also segregated by race, teachers were re-assigned to schools in 1972 on the basis of their race. After the initial period of reassignment, teacher race was not used in the placement or re-assignment of teachers to schools.[11] Teachers who were dissatisfied with their schooling assignment in 1972, would have had almost three decades to undo any undesirable forcible relocation before the policy change in 2002. As such, any increased re-shuffling observed in 2002 can be reasonably be attributed to changes in student attributes.

In 1997, the CM school system was sued by a parent charging that his daughter was twice denied entrance to a magnet school because the non-black slots were filled and she was not black. This suit was the catalyst for a lengthy legal battle that resulted in the implementation of a neighborhood based school choice plan for the 2002-3 school year.[12] Under the new policy, students would no longer be bused into schools across neighborhoods and parents would list three schools that they would like their child to attend. If the neighborhood school was the parent’s first choice, the student was guaranteed admission. If the parent’s most preferred school was not their neighborhood school, their child would have to enter a lottery in which low-income students were given preference. If a student was not admitted to one of their three choice schools, they were sent to their neighborhood school. Under the new plan, the likelihood that a student would attend a school outside of their own neighborhood was significantly reduced.

During this period of student shuffling, teacher assignment policies remained unchanged. Going as far back as 1990, the teacher allocation system has operated as

---

[8] Swann versus Charlotte-Mecklenburg Board of Education

[9] The plan was subsequently tweaked to accommodate the growth of the black student population and the emergence of magnet schools, however, the plan remained largely the same.

[10] Legal briefs from Capacchione versus CM Board of Education http://www.usdoj.gov/crt/briefs/belk.pdf

[11] This statement has been verified by various members of the CM board of education. Specifically the chief communications officer, lawyers at the CM office of general council and the director of the employee relations. The logic of no longer enforcing the teacher desegregation order is that once students were integrated, teachers could not segregate themselves from students of another race.

[12] http://www.cms.k12.nc.us/discover/narrative.asp

follows. Teachers in CM can either apply to the school district or they may apply for an advertised position at a particular school. Advertised positions are those that could not be easily filled by applicants in the general pool. For advertised positions, applications may be sent to several schools and the applicant is assigned to the school that accepts her application the soonest. For other openings, principals are given a list of eligible applicants from the pool (based on qualifications, and proximity to the teacher's home) and make their selection of teachers, which are then sent back to the district. Teachers who are not selected within this group are sent back to the applicant pool to be eligible for other positions. After being assigned, teachers are eligible for a voluntary transfer after having spent two years in their current position (unless they wish to move to an understaffed or underperforming school). The transfer application and assignment policy is identical to the application procedure for advertised positions in the district.

I use school level aggregate data from the Common Core of Data available from the National Center of Education Statistics for the years 2000 though 2005 to determine the impact of this policy change on the demographic make-up of students at CM schools. I augment this dataset with school-level achievement and teacher data from the North Carolina Education Research Data Center and neighborhood (block group [13]) demographic data from the 2000 decennial census. Since CM is the largest and most urban school district in North Carolina, it is most appropriate to use other large urban school districts as comparison districts. The top panel of Table 1 summarizes the school-level student demographic, achievement and census data for the busing years and the post busing years for schools in CM district, the three next largest school districts [Wake, Guilford, and Cumberland] and all other schools in North Carolina.

It is clear that CM is not representative of North Carolina and CM schools are much more similar to those in the three next-largest school districts. The CM schools are very similar in enrollment to the comparison schools, but much larger than other North Carolina schools. CM is the most urbanized district (about 81 percent of schools are in a large or mid-sized city) with the highest share of black students (about 49 percent) and the lowest share of white residents (about 59 percent). The comparison schools are somewhat less urbanized (almost 70 percent of schools are in a large or mid sized city)

[13] Zip code data are used where block group data are not available.

have lower black enrollment shares (about 41 percent) and a higher share of white residents (about 66 percent). In the rightmost panel, one can see that only 27 percent of schools in the rest of the state are located in a large or mid-sized city, the average black enrollment share is just over 30 percent, and whites make up 72 percent of the residents.

Table 1

Summary statistics for CM, comparison districts (Wake , Guilford and Cumberland) and the rest of North Carolina: By pre and post policy change

	Charlotte/Mecklenburg		Comparison Districts		Rest of North Carolina	
	2000-2002	2003-2005	2000-2002	2003-2005	2000-2002	2003-2005
Black Differential (2000)	13.96	13.96	12.55	12.55	8.81	8.81
	(19.96)	(19.96)	(20.11)	(20.11)	(15.98)	(15.98)
School Enrollment	762.16	837.66	724.79	727.58	556.57	561.57
	(497.13)	(524.19)	(427.2)	(447.66)	(318.16)	(332.08)
% Black Students	48.11	49.43	40.78	42.12	30.99	30.58
	(18.93)	(24.49)	(21.61)	(22.32)	(26.5)	(25.97)
% White Students	40.89	35.61	50.57	46.95	61.79	59.95
	(21.59)	(26.95)	(22.33)	(22.62)	(27.88)	(27.89)
% Hispanic Students	6.29	10.21	4.64	6.66	4.25	6.40
	(6.61)	(9.59)	(3.99)	(4.83)	(5.55)	(7.73)
% Asian Students	4.11	4.07	3.18	3.45	1.14	1.23
	(2.41)	(2.45)	(3.21)	(3.55)	(2.35)	(2.38)
% Students Free lunch Eligible	38.01	44.90	32.05	36.02	37.29	37.63
	(21.35)	(27.4)	(20.43)	(21.67)	(20.56)	(23.49)
Median HH Income (2000 census)	48366	48272	47225	46868	35993	36031
	(15612)	(15774)	(15805)	(15598)	(8068)	(8154)
% Black residents (2000 census)	35.30	35.30	28.03	28.03	22.69	22.69
	(23.69)	(23.69)	(20.95)	(20.95)	(18.71)	(18.71)
% White residents (2000 census)	59.01	58.44	66.13	65.79	72.41	72.41
	(23.15)	(23.81)	(20.99)	(20.98)	(20.2)	(20.26)
City	0.80	0.82	0.66	0.72	0.26	0.27
	(0.4)	(0.39)	(0.47)	(0.45)	(0.44)	(0.44)
% at or above grade level: Math	78.01	85.30	83.05	87.48	80.56	86.32
	(13.42)	(12.31)	(12.53)	(10.74)	(14.39)	(11.67)
% at or above grade level: Reading	72.80	79.39	79.26	83.43	76.08	81.84
	(14.53)	(12.95)	(13.2)	(11.36)	(14.14)	(11.11)
% Teachers: 0-3 years experience	32.06	30.99	25.42	25.72	22.44	21.45
	(12.1)	(11.84)	(11.88)	(10.7)	(11.)	(10.39)
% Teachers: 4-10 years experience	27.33	30.36	26.49	27.60	24.96	26.22
	(7.68)	(8.17)	(9.88)	(8.78)	(9.01)	(8.77)
% Teachers: 11+ years experience	40.61	38.65	48.09	46.69	52.60	52.27
	(11.42)	(12.37)	(13.41)	(12.33)	(12.9)	(12.57)
One Year Teacher Turnover Rate*	27.65	25.23	24.94	22.85	21.39	18.98
	(13.26)	(13.06)	(10.94)	(10.41)	(11.11)	(10.21)
% Teachers: Black	23.78	24.57	20.91	23.44	13.41	13.45
	(15.47)	(17.56)	(17.21)	(18.14)	(17.22)	(18.25)
% Teachers: White	74.40	72.40	77.12	73.49	84.66	84.39
	(15.81)	(18.22)	(17.64)	(19.04)	(18.61)	(19.66)
% Teachers: Advanced Degree	19.59	21.66	17.37	18.10	11.70	11.94
	(14.43)	(15.09)	(12.02)	(12.81)	(8.36)	(8.7)
% Teachers: Score in top 25%	47.12	47.86	46.59	48.55	42.56	45.24
	(10.12)	(11.18)	(12.67)	(13.43)	(13.91)	(14.22)
% Teachers: Score in top 50%	73.28	75.55	71.92	74.39	69.76	45.24
	(9.97)	(9.67)	(12.44)	(12.39)	(13.83)	(13.66)
% Teachers: Top 100 College	9.06	12.80	12.87	15.46	7.94	10.00
	(5.4)	(6.33)	(10.58)	(11.31)	(7.45)	(8.76)
Number of Schools	152		358		2220	

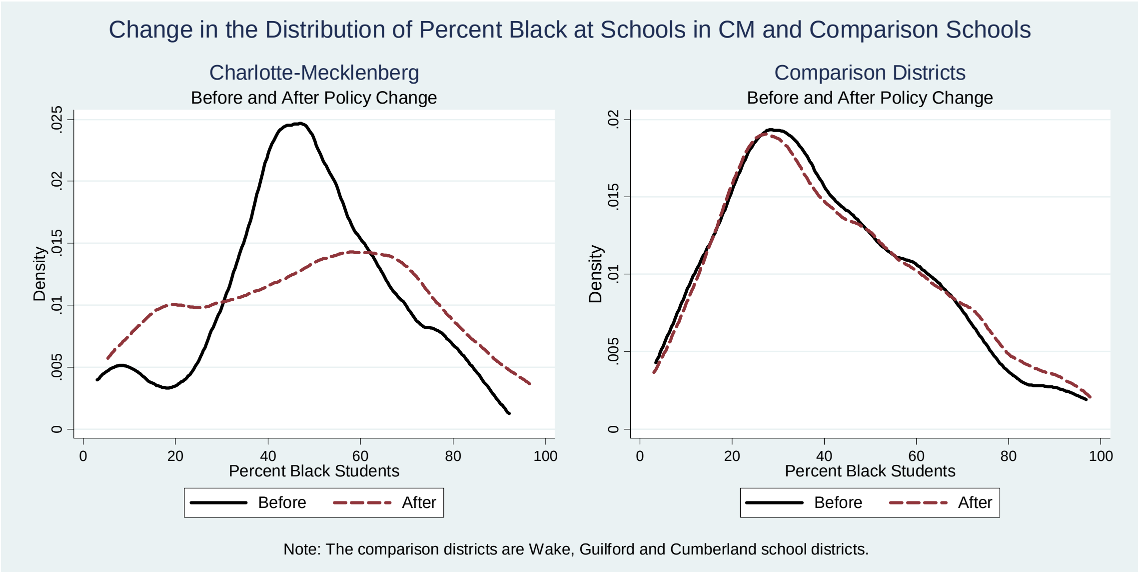
Standard errors in parenthesis. The unit of observation is a school year, such that each school has one observation in each year in sample. Since the panel is not balanced due to new schools or school closings, variables that do not vary over time may change on average across time due to composition effects.

Black Differential is defined as the percentage of black students at the school in the year 2000 minus the percentage of black residents in the census block group (or zip code if black group data are not available) of the school in the 2000 census. In Charlotte-Mecklenburg this variables ranges from -31.34 to +57.06. note that the teacher turnover rate is computed in sample so that errors in the data classification or missing data would lead to an inflated estimate of teacher turnover. This should not affect the regression results which are based on changes in this variable.

The CM schools and those in the comparison districts are located in neighborhoods with median census household incomes between 46 and 49 thousand dollars a year, compared to only about 36 thousand dollars for the rest of the state. While all schools in the state became increasingly Hispanic during the sample period, there was a somewhat larger increase in CM schools. Across the two time periods, the percentage of students on free lunch went up about 7 points in CM compared to 4 points in comparison schools, and less than 1 point in other schools.

To illustrate the effect of the policy change on the percent black in CM, figure 1 shows kernel density plots of the distribution of %Black in CM schools and comparison schools in the years before and after the policy change. Figure 1 shows that before the policy change (2000 – 2002) the distribution of percent black at the schools was relatively similar between CM and the comparison districts. The figure also shows that the distribution of percent black became much more dispersed after the policy change (2003-2005) in CM, while there was almost no change for the comparison districts.

Figure 1



The Black Differential (BD) variable at the top of Table 1 is the percentage of black students at the school in the year 2000 minus the percentage of black residents in the local neighborhood's block group (zip code data are used when there are no block group data available) in the year 2000. This variable does not change for a school over time since it is based on data from the year 2000. Schools in CM and comparison districts are located in areas with about 13 percentage points more black students than percent black in the surrounding neighborhoods compared to 9 percentage points for other schools. This difference may be due to black families in North Carolina being more likely to have school-age children than white families, or it may reflect the fact that white households are more likely to send their children to private schools. The difference in the gap across school districts could also reflect greater private school going for white students in urban environments.[14]

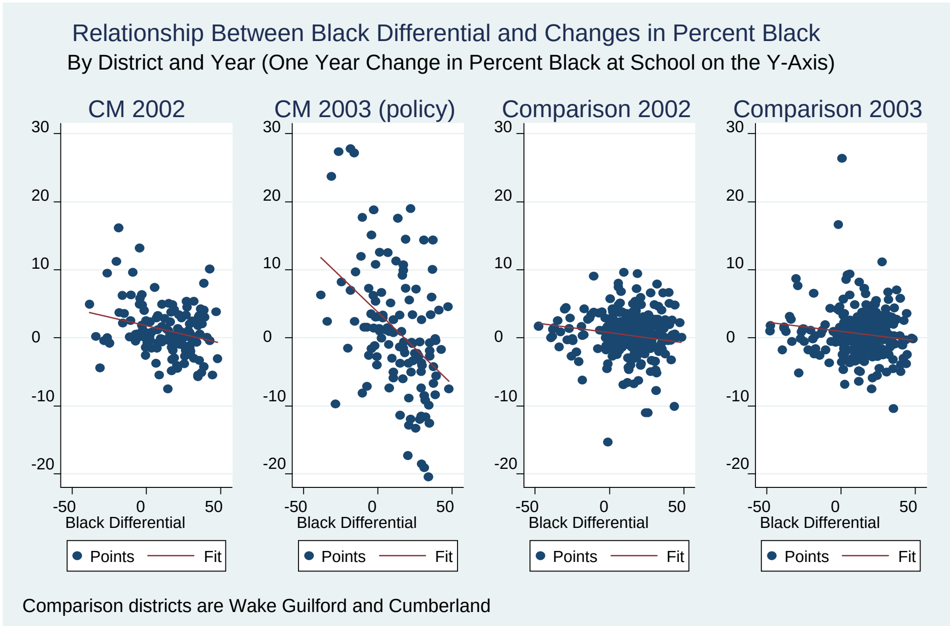
Since the busing policy that ended in 2002 maintained school integration despite much residential segregation, the schools that would be expected to have experienced the greatest change in student demographics are schools that had proportionately more blacks/whites in the school than the surrounding area.[15] A school with 10 percent black students located in an area with 50 percent black residents (a BD of minus 40) will have a larger inflow of black students at the end of busing than a school with 90 percent black students in a neighborhood in which 100 percent of the residents are black (a BD of minus 10).

The BD predicts the outflow of black students that would occur if all schools had student populations that were exactly representative of the surrounding neighborhoods. A variable denoting post-busing, equal to one after 2002 and zero otherwise, would identify the year in which schools are most likely to have student populations that mirror the attributes of the surrounding neighborhoods. By interacting the BD variable with a “post” variable one can predict the exogenous change in the share of black students that is due to the policy change. To illustrate this point, Figure 2 shows the relationship between the BD of a school in 2000 and the change in the percentage of black students between 2001 and 2002 (the year before the policy change) and between 2002 and 2003 (the year of the policy change).

[14] Even though the comparison districts did not have student busing during the sample period, they all did in the past so that old district lines still cross neighborhoods where possible to maintain diversity within schools. Wake county, the second largest county moved from a race based to an income based busing system in 2000 so that there are still forces keeping the BD high in Wake. While Cumberland and Guilford do not have student busing policies, they both explicitly aim to maintain racial diversity across school districts when drawing and re-drawing school enrollment areas.

[15] In regressions that predict the change in the percentage of black students in schools, the difference between the percent black in the school and the percentage of black residents in the neighborhood has a much larger F-statistic than simply using the percentage of black residents in the neighborhood.

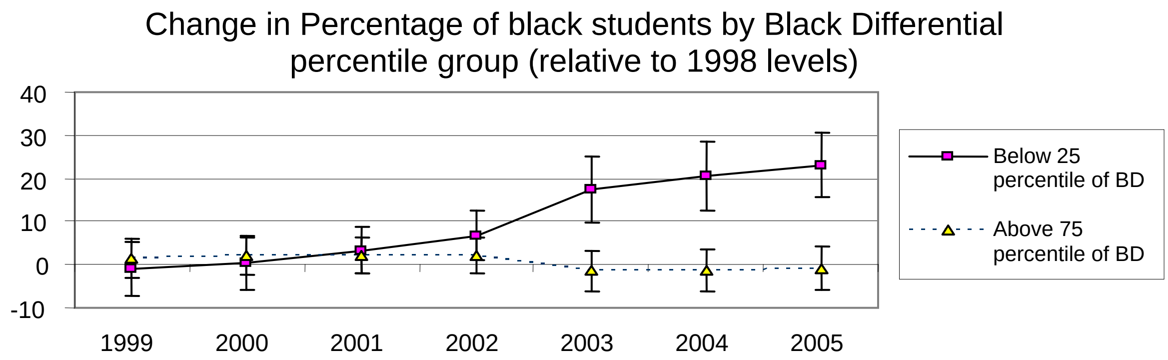
Figure 2



On the left, the panel shows the sizable difference in the relationship between BD and changes in the percentage black students before and after the policy change in 2003 in Charlotte-Mecklenburg. As one would expect, the right panel shows very little difference over time for the comparison districts. The BD predicts small changes in the percentage of black students in a school for CM in the pre policy year and for the comparison districts for all years, such that schools with negative BD's (fewer blacks than predicted by neighborhood) experienced small increases in the share of black students.[16] In contrast, the BD predicts large changes in the percentage of black students in CM during the policy change year (2002-2003). Figure 2 illustrates the mechanics of the instrument that uses the *difference* in the *change* in the relationship between BD and the percent black at the school before and after the policy change between CM and the comparison schools. Readers should note that most schools that experienced large inflows of black students in 2003 were located in predominantly black neighborhoods while most schools that experienced a large outflow of blacks in 2003 were located in predominantly white neighborhoods. As such, the instrument predicts the local average treatment effect –the effect of an inflow/outflow of black students on schools in largely black/white neighborhoods.

[16] Note that one cannot reject the hypothesis that the relationship between BD and the change in percent black within the school from 2001 to 2002 is the same at traditional levels –indicating the comparison districts would form a good counterfactual group.

Figure 3



This figure plots the estimated year fixed effects from a linear regression that includes individual school indicator variables on the two sub-samples of schools (those schools below the 25th percentile and those above the 75th percentile of the black differential distribution).

To show further that the BD variable predicts a sudden inflow of black students in 2002 above and beyond that in other years, I estimate the within school change from 1998 levels in the proportion of black students, for those CM schools with a BD above the 75th percentile and those CM schools with a BD below the 25th percentile. Figure 3 shows that schools with BDs above the 75th percentile (predictive of an outflow of blacks) experienced a slight decrease in the share of black students between 2002 and 2003, while schools with BDs below the 25th percentile (predictive of an inflow of blacks) experienced an increase in the share of black students between 2002 and 2003. The figure suggests that the BD predicts relatively sudden *differential* changes in the share of black students the year of the policy change.[17]

Effect of the policy change on student characteristics

To describe the change in student characteristics that teachers were exposed to i.e. the treatment, I run regressions to determine the effect of the policy change on various student characteristics. While the final analysis uses the percentage of black students as the treatment, teachers are exposed to all other student characteristics that are associated with black students. Therefore, it is instructive to look at other students characteristics. It is useful to consider the student demographics regressions first stage regressions where

[17] In addition to the movement of students across public schools, the change in the share of black students could also reflect movement of white students from private schools back into public schools that lost a large fraction of black students in 2003.

the coefficients on the instruments predict the treatment that schools and teachers are exposed to.

Since the policy change had a differential effect on high-BD versus low-BD schools, one could, in principle, identify the effect of the policy change using a difference in difference (DID) estimator - comparing the difference in the change in outcomes between 2002 and 2003 across high-BD and low-BD schools in CM. This DID strategy would be valid if high-BD schools and low-BD schools would have experienced the same change in outcomes in the absence of the policy change. Since high-BD and low-BD schools are located in different neighborhoods and serve different populations, the assumption that they have the same underlying dynamics is implausible. In addition, statewide policies aimed at particular types of schools (low-income, low-performing) may have differential effects across school types and would invalidate the exclusion restriction in a standard DID approach. For example, the North Carolina Bonus Program that paid teachers for locating in low-performing schools was implemented in 2001 and differentially affected teacher turnover across high and low income schools in 2002.[18]

To address this concern, I use schools from the three next-largest school districts (Guilford, Wake and Cumberland) as comparison schools, allowing me to introduce another round of differencing and implement a difference in difference in differences (DIDID) estimator.[19] Identification in this triple differenced model compares the difference in the change in outcomes between high-BD and low-BD schools within CM (which had the policy change) to that of other school districts (which did not have the policy change). The identifying assumption is that the difference in the change in outcomes between high-BD and low-BD schools in the control districts is the difference in the change in outcomes that would have occurred in CM between high-BD and low-BD schools had there been no policy change. Figures 1 and 2 suggest that this assumption is plausible. This assumption is more compelling than that for the standard DID approach

[18] This program's effects on teacher mobility were analyzed in Clotfelter, Glennie, Ladd, Vigdor (2008).
[19] There is an efficiency/consistency tradeoff in increasing the sample to all schools in North Carolina. Since CM is the largest most urbanized school district in the state, restricting the control sample to other large, urban school districts is desirable. I chose the four largest school districts because the size and urbanicity of school districts changes rather suddenly as one goes beyond the first few districts. For example the year 2000 enrollment for the four largest districts was 103, 99, 63, and 51 thousand students. For the next districts the enrollment was 44, 30 and 30 thousand respectively. Restricting the analysis to the top three districts results in less power but does not change the results in any meaningful way.

since the DIDID approach will "net out" any statewide policies or differential migration that could have had a different time-effect across different types of schools. Since the predictor for an inflow of black students (the BD) is computed based on data in 2000, the estimation sample does not include data before 2000 to avoid any mechanical endogeneity between the instrument and the variables of interest.[20] The first set of basic DIDID estimates are implemented by estimating the following equation by OLS on the schools in the four largest school districts in the state. All subsequent analyses are based on this sample of schools.

$$Y_{it} = \delta \cdot POST_t \times CM_i \times BD_i + \omega_1 POST_t + \omega_2 POST_t \times BD_i + \omega_3 POST_t \times CM_i + \theta_i + \varepsilon_{it} \qquad [1]$$

Where Y_{it} is the outcome for school i at time t, $POST_t$ is an indicator variable equal to one in the year 2003 onwards and zero otherwise, CM_i is an indicator variable equal to one if school i is in Charlotte-Mecklenburg and equal to zero otherwise, BD_i is the black differential for school i, θ_i is a school specific intercept, and ε_{it} is the idiosyncratic error term. The school dummies θ_i subsume the necessary one-way and two-way effects between CM and BD. The parameter of interest is δ, the coefficient on the three-way interaction $POST_t \times CM_i \times BD_i$ that predicts an outflow of black students.

The regression results in Table 2 show that the policy had a strong effect on the racial composition of students at the affected schools, and that CM schools that had more black students than the neighborhood demographics would predict experienced an outflow of black students and an inflow of white students after busing ended in 2002. Specifically, the -0.253 coefficient for the variable $POST_t \times CM_i \times BD_i$ in column 1 indicates that a school in CM would have had a 0.253×20=5.06 point greater increase in the percentage of black students after 2002 than a school in CM over the same time period with a black differential 20 points higher (a one standard deviation difference in BD). The t-statistic on the coefficient is 4.77 indicating a strong first stage. The odd numbered columns show that a school in CM with a BD of 20 would have had a 5.06 point decrease in the percentage of black students, a 3.6 point increase in the percentage of white students, and a 6.16 point decrease in the percentage of students who are on free-

[20] Excluding data for the year 2000 is unnecessary since all regression specifications are differenced.

lunch, all relative to a school with a BD of 0. CM schools also experienced changes in student achievement. Note that changes in achievement could also reflect the effect of teacher mobility, peer quality, or other unmeasured inputs that may be endogenous to student race rather than simply changes in the ability of students. A school in CM with a black differential of 20 would have experienced a 2.08 and 3.34 point increase in the percentage of 3rd through 8th grade students at or above grade level in math and reading respectively, relative to a CM school with a BD of 0 over the same time period.

Table 2

OLS Estimates of Policy Change on Effect on School Attribtes. The Dependent Variable is Above Each Column. (First Stage is Column 1)

	1	2	3	4	5	6	7	8	9	10
	OLS	OLS	OLS	OLS	OLS	OLS	OLS	OLS	OLS	OLS
	%Black Students	%Black Students	%White Students	%White Students	% Student Free-Lunch Eligible	% Student Free-Lunch Eligible	% at Grade Level (Math)	% at Grade Level (Math)	% at Grade Level (Reading)	% at Grade Level (Reading)
Post*CM*BD	**-0.253**	**-0.2431**	**0.18**	**0.1815**	**-0.308**	**-0.2156**	**0.104**	**0.154**	**0.167**	**0.1965**
	[0.053]**	**[0.0480]****	**[0.054]****	**[0.0488]****	**[0.079]****	**[0.0815]****	**[0.050]***	**[0.0504]****	**[0.056]****	**[0.0583]****
Post*CM	5.249	-	-5.896	-	9.103	-	-0.206	-	-1.911	-
	[1.349]**	-	[1.397]**	-	[2.064]**	-	[1.294]	-	[1.482]	-
Post	2.485	-	-4.942	-	4.689	-	4.259	-	4.114	-
	[0.391]**	-	[0.585]**	-	[0.599]**	-	[0.616]**	-	[0.563]**	-
Post*BD	-0.061	-	0.059	-	0.026	-	0.031	-	0.024	-
	[0.026]*	-	[0.025]*	-	[0.031]	-	[0.018]+	-	[0.015]	-
School Dummies	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Locale*Year Dummies	NO	YES	NO	YES	NO	YES	NO	YES	NO	YES
Census %Black Decile*Year Dummies	NO	YES	NO	YES	NO	YES	NO	YES	NO	YES
District*Year Dummies	NO	YES	NO	YES	NO	YES	NO	YES	NO	YES
Observations	2542	2503	2503	2503	2514	2475	1801	1777	1801	1777
Number of group(lea schlcode)	431	419	419	419	431	419	370	358	370	358
R-squared	0.22	0.31	0.35	0.45	0.2	0.32	0.3	0.42	0.3	0.42

Robust standard errors in brackets. Clustered at the zip code level. (sample is CM, Wake, Guilford and Cumberland districts)

+ significant at 10%; * significant at 5%; ** significant at 1%

Note: BD is the percentage of black students at the school (in 2000) minus the percentage of black residents in the block group or zip code (in 2000) in whitch the school is located. CM stands for Charlotte-Mecklenberg and Post denotes after the policy change (2003 onwards). The POST*CM*BD variable is a difference in difference in difference estimate.

While the DIDID specification is instructive, I augment model [1] to control for neighborhood characteristics and to allow for a more flexible specification. Specifically, I include year effects instead of a simple before/after dummy, I use district fixed effects instead of a simple CM dummy and I include neighborhood characteristics interacted with year fixed effects. Specifically, I estimate equation [2] below by OLS.

$$Y_{it} = \delta \cdot POST_t \times CM_i \times BD_i + \omega_2 POST_t \times BD_i + \omega_{3,r} \sum_r^6 I_{year=r} \times LOC_i$$
$$+\omega_{4,r} \sum_r^6 I_{year=r} \times DEC_i + \omega_{5,r} \sum_r^6 I_{year=r} \times DISTRICT_i + \theta_i + \varepsilon_{it} \qquad [2]$$

Where all common variables are defined as before and $I_{year=r}$ is an indicator variable equal to 1 if the observation year is year r and zero otherwise. To control for underlying dynamics that may have had a differential effect across school districts, urban environments, and neighborhoods with different shares of black residents, I include interactions of $I_{year=r}$ dummies with indicators for each school district $DISTRICT_i$, indicators for the urbanity of the surrounding area LOC_i, and dummies denoting the ten deciles of the distribution of the percentage of black residents in the surrounding area DEC_i. The results of this more flexible model are presented in the even numbered columns of Table 2. The flexible specification yields similar results to those of equation [1] and is used for all subsequent analysis. In sum, Table 2 shows that the student body changed in a variety of ways associated with student race, such as income levels and achievement levels. For the remainder of the paper I use the change in percentage of black students to categorize the change in student demographics. As such the results on teacher characteristics *must not* be interpreted as being the result of teachers having preferences for student race *per se*, but the result of teachers having preferences for student or school characteristics that are endogenous to student race.

IV Effect of policy change on teacher characteristics

In this section I analyze aggregate teacher data to determine the effect of this policy change on teacher attributes. The teacher data were created by computing school aggregate statistics from individual teacher data from the North Carolina Education Research Data Center. The rankings of the colleges or universities teachers attended were obtained by linking US News rankings from 2005 to the undergraduate institution data from the teacher education files. Teacher license score data were created by comparing each teachers score on the exam to all other teachers in the state in that year. Variables were created denoting if the teacher scored above the 75^{th} percentile or the median on that exam in that year. Since teachers may have taken more than one exam, I code a teacher as having scored above the 75^{th} percentile or the median if she has at least one score above the 75^{th} percentile or the median on any one of her exams. As such, more than half of the teachers would be expected to score above the median. Teacher value-added was computed by linking the student end-of-year test files with individual teacher data. Since teacher effectiveness could have been affected by changes that take place due to students' demographics changing or teacher demographics changing in 2002, teacher value-added is estimated “out of sample” for the years 1995 through 2000.

There are several specifications used in the literature to estimate teacher value-added, however, the estimated teacher fixed-effects across studies are surprisingly robust to the chosen specification. [21] To identify effective teachers, I estimate teacher fixed-effects in a test score growth model of the form [3] using data from 1995 through 2000.[22]

$$A_{ijgt} - A_{ijg-1t-1} = \psi_1 A_{ijg-1t-1} + \psi_2 \overline{A}_{i'jg-1t-1} \psi_3 X_i + \psi_4 Z_{st} + \psi_5 W_{jt} + \tau_j + \tau_t + \tau_g + \varepsilon_{ijgt} \qquad [3]$$

In [3] A_{ijgt} is the achievement score of student i with teacher j in grade g in year t, $\overline{A}_{i'jg-1t-1}$ are the average incoming test scores of a student’s classmates, X_i is a vector of student characteristics such as ethnicity, gender and parental education level. W_{jt} is a vector including teacher experience, class-size and variables denoting the gender and ethnic match between the student and the teacher.[23] Z_{st} is a vector of school attributes including the percent black, percent white, percent Hispanic, the percent free-lunch eligible students and the urbanicity of the school (whether the school is in a large city, medium sized city, urban fringe, suburban or rural area), τ_t is a year fixed effect, τ_g is a grade fixed effect, τ_j is a teacher effect and ε_{ijgt} is the idiosyncratic error term. Since I need estimates of teacher value-added that are comparable across schools, grades and classes I *do not* include school or student fixed-effects but rather include a set of demographic controls for the students and schools.[24] Readers may be concerned that the

---

[21] For a detailed discussion of the theoretical and econometric assumptions underlying value-added specifications see Todd and Wolpin (2003).

[22] Researchers have pointed out that measurement error in the lagged test score could bias estimates of the coefficient of lagged test scores on test score growth. The common fix for this problem is to assume there is no serial correlation in the error terms over time and (where there is enough data) to instrument for lagged test scores with the second lag of test score. The main results do not use this approach since it results in a small estimation sample that makes identification of teacher fixed-effects difficult. (I lose one additional year of data to include the second lag, resulting in an estimation sample of three years). I do however present results in Appendix Table 2 showing that making this correction yields similar results to the chosen specification despite producing noisier estimates.

[23] The value-added results are robust to omitting the gender and ethnic match variables.

[24] Specifications that include student or school fixed-effects identify teacher value-added based on within-school or within-student variation. If teachers are very different across schools, then much of the variation in teacher quality (i.e. the cross-school variation) will be absorbed by the school fixed-effect, making estimated effects across schools impossible to compare. Including student fixed-effects further exacerbates this problem by only allowing comparisons of teachers who teach the same groups of students. If those teachers who teach the gifted and talented students are of different average quality than those who teach the regular students, the estimated teacher value-added can only be used to compare teachers who share the

included covariates do not adequately capture measures of school quality so that the teacher effects capture school, principal and other unobserved effects.[25] While this is possible, these estimates are used in a within-school model on an out of sample period so that changes in the distribution of these estimates *within schools* over time will not be confounded with those unobservable school inputs. The estimates of regression equation [3] are in Appendix Table 1; all variables have the expected signs and magnitudes. The teacher value-added estimates τ_j are standardized, normalized and linked to teachers in the 2000 through 2005 data and school level aggregates are computed. Under the assumption that true teacher value-added comes from a normal distribution and the estimates include random noise, I also compute shrinkage estimates, or Empirical Bayes (EB) estimates, that shrink noisy teacher value-added estimates toward zero for greater statistical precision. Specifically I use the EB estimate $\tau_j^{EB} = \tau_j \cdot (\sigma_\tau^2 / (\sigma_\tau^2 + \sigma_{u_j}^2)$ where σ_τ^2 is the sample estimate of the variance of true teacher value added distribution and $\sigma_{u_j}^2$ is the sample estimate of the variance of teacher *j*'s value-added estimate. The details of how these EB estimates are constructed are described in the appendix. Results using the normalized teacher estimates directly from the regression are almost identical to those using the normalized EB estimates. It should be noted that not all teachers have estimated teacher effects since not all teachers teach basic English and math, and teachers who were not in the sample in 2000 would not have estimated teacher value-added. As such, changes in the distribution of estimated teacher value-added within schools over time reflect changes in the distribution of those teachers who were in the sample in the year 2000, but not necessarily of new teachers or teachers who have experience but came from outside of North Carolina.

The lower panel of Table 1 summarizes the teacher variables used. Teacher turnover was somewhat higher in the large school districts than in the rest of the state (about 26 percent for CM, and 23 percent for the three comparison districts compared to about 20 percent for the rest of the state). Consistent with this, CM and the comparison

same students so that comparing teachers who teach different students (even within the same school) may be misguided.

[25] Note that using within-school or within-students variation to identify teacher value-added loads any common effectiveness at a school on the school even if they are due to the teachers. Such models also lead to attenuated teacher effects if there are spillovers across teachers. However, results using student fixed effects are qualitatively similar.

districts have larger shares of rookie teachers and lower shares of experienced teachers. These districts also have a greater share of black teachers (about 24 percent for CM, and 22 percent for the three comparison districts compared to about 13.5 percent for the rest of the state), a greater share of teachers with advanced degrees and a greater share of teacher who attended a top 100 college than other schools in the state.

To determine whether the change in student demographics affected schools' overall teacher makeup, I run regressions of teacher characteristics on the percentage of black students. To use only variation in black enrollment shares that are attributable to the policy change, I instrument for the percentage of black students with the triple differenced $POST_t \times CM_i \times BD_i$ variable from equation [2]. Specifically, I estimate the following system of equations by 2SLS.

$$\begin{aligned}\%Black &= \pi_1 \cdot POST_t \times CM_i \times BD_i + \pi_2 POST_t \times BD_i + \pi_{3,r} \sum\nolimits_r^6 I_{year=r} \times LOC_i \\ &+ \pi_{4,r} \sum\nolimits_r^6 I_{year=r} \times DEC_i + \pi_{5,r} \sum\nolimits_r^6 I_{year=r} \times DISTRICT_i + \theta_{1i} + \varepsilon_{1it}\end{aligned} \quad [4]$$

$$\begin{aligned}Y_{it} &= \delta_2 \cdot (\%Black_{it}) + \phi_2 POST_t \times BD_i + \phi_{3,r} \sum\nolimits_r^6 I_{year=r} \times LOC_i \\ &+ \phi_{4,r} \sum\nolimits_r^6 I_{year=r} \times DEC_i + \phi_{5,r} \sum\nolimits_r^6 I_{year=r} \times DISTRICT_i + \theta_{2i} + \varepsilon_{2it}\end{aligned} \quad [5]$$

All variables are defined as in [2] and equation [4] is equation [2] with % Black as the dependent variable shown in column 2 of Table 2. In the second stage regression, the fitted values from [4] are used in place of $\%Black_{it}$ in [5]. The excluded instrument in [5] is the three way interaction $POST_t \times CM_i \times BD_i$ and Y_{it} is the teacher outcome for school *i* at time *t*. Since the model includes year effects by district, locale, and percent black in the neighborhood decile for each year, the parameter δ_2 identifies the effect of an inflow of black students that is arguably uncorrelated with those changes that may have naturally occurred across different neighborhoods over time.

To highlight the differences between the cross-sectional relationships and the relationships one observes based on the policy change, I also estimate a simple model of the outcome of interest on *%Black* and a constant (OLS regression). Table 4 documents the cross-sectional relationship between the percentage of black students at a school and various teacher characteristics in column 1 and the Instrumental Variables DIDID (DIDID-IV) regression described above in column 2. Table 4 reports the coefficient on *%Black* for each outcome and each model.

Table 4

The effect on the percentage of black students at the school on teacher characteristics: The coefficient on the %Black at the school is reported. %Black ranges from 0 to 100.

		1		2		3	
		OLS		DIDID-IV		DIDID-IV	
	Dependent Variable	Coef.	SE	Coef.	SE	Coef.	SE
1	Mean Teacher experience	**-0.028**	**[0.006]****	**-0.087**	**[0.038]***	**-0.088**	**[0.032]****
2	% Teachers: 1-3 years	**0.153**	**[0.020]****	0.163	[0.185]	**0.256**	**[0.1390]+**
3	% Teachers: 4-9 years	-0.006	[0.018]	**0.184**	**[0.099]+**	0.0982	[0.0833]
4	% Teachers: 10 to 20 years	**-0.096**	**[0.013]****	-0.156	[0.125]	-0.1526	[0.1108]
5	% Teachers: 21 years	**-0.051**	**[0.018]****	**-0.191**	**[0.083]***	**-0.2016**	**[0.0718]****
6	% Teachers: leave current school	**0.186**	**[0.023]****	-0.123	[0.174]	-0.0907	[0.1588]
7	Lag % teachers leave current school	**0.167**	**[0.020]****	-0.342	[0.230]	-0.1394	[0.1514]
8	% Teachers: Black	**0.526**	**[0.039]****	**0.373**	**[0.159]***	**0.3566**	**[0.1618]***
9	% Teachers: White	**-0.528**	**[0.038]****	**-0.299**	**[0.178]+**	**-0.2963**	**[0.1801]+**
10	% Teachers: Higher degree	**-0.073**	**[0.019]****	0.077	[0.145]	-0.0722	[0.1242]
11	% Teachers: Top 50 college	**-0.05**	**[0.008]****	0.006	[0.047]	-0.0065	[0.0542]
12	% Teachers: Top 100 college	**-0.086**	**[0.013]****	-0.011	[0.071]	-0.0327	[0.0741]
13	% Teachers: Top 10 score	**-0.133**	**[0.018]****	-0.13	[0.163]	**-0.2081**	**[0.1215]+**
14	% Teachers: Top 25 score	**-0.205**	**[0.019]****	-0.177	[0.228]	-0.2556	[0.1947]
15	% Teachers: Top 50 score	**-0.211**	**[0.022]****	-0.099	[0.159]	-0.1465	[0.1325]
16	Mean teacher value added math	**-0.002**	**[0.001]***	**-0.015**	**[0.005]****	**-0.0134**	**[0.0045]****
17	Mean teacher value added math (EB)	**-0.002**	**[0.001]****	**-0.015**	**[0.006]***	**-0.0157**	**[0.0061]***
18	Mean teacher value added reading	0.0002	[0.001]	**-0.013**	**[0.007]***	**-0.013**	**[0.0063]***
19	Mean teacher value added reading (EB)	-0.001	[0.001]	**-0.014**	**[0.006]***	**-0.016**	**[0.0061]****
	School Effects	NO		YES		YES	
	Year-by-District Effects	NO		YES		YES	
	% Black decile-by-years effects	NO		YES		YES	
	Locale-by-year effects	NO		YES		YES	
	Excluded Instrument	-		POST*CM*BD		(POST*CM*BD)*Qi	

Robust standard errors in brackets to the right of point estimates. Standard errors clustered at the zip code level.
+ significant at 10%; * significant at 5%; ** significant at 1%

Note: Each columns-Row combination represents a different regression. BD is the percentage of black students at the school (in 2000) minus the percentage of black residents in the block group or zip code (in 2000) in which the school is located. CM stands for Charlotte-Mecklenburg and Post denotes after the policy change (2003 onwards). The POST*CM*BD variable is a difference in difference in difference estimate. Qi denotes which of the five quintiles of the percentage of black residents distribution the school falls into. Sample is CM, Wake, Guilford and Cumberland districts.
Excluded instruments in column 2 is the black differential of the school interacted with a dummy denoting CM district interacted with a dummy variable denoting after 2002. Excluded instruments in Column 3 interacts CM*BD*POST with indicator variables denoting five quintiles of the distribution of percent black in the surrounding neighborhood.

The standard deviation of the change in *%Black* in CM between 2002 and 2003 is just over 10. This is also approximately the amount of variation associated with a two standard deviation difference in BD. Column 1 shows that in the cross-section, a school with 10 points higher percentage of black students would have 1.53 percentage points more teachers with zero to three years of experience, a teacher turnover rate 1.86 points higher, 5.26 percentage points more black teachers, 5.28 percentage points fewer white teachers, 0.73 percentage points fewer teachers with an advanced degree, 0.86 percentage points fewer teachers who attended a college ranked in the top 100, have about 2 percentage points fewer teachers who score above the 75th percentile and the median on their certification exams and would have a 0.02 standard deviations lower mean teacher value-added in math. In sum, schools with large black enrollment shares have teachers with weaker observable characteristics on average.

Column 2 of Table 4 documents the relationship between student demographics and teacher characteristics using that variation that is due to the policy change. The instrumental variables DIDID estimates show that a 10 point increase in the percentage black students due to the policy change is associated with a decrease of 0.8 years in the average experience of teachers at the school. This is much larger than the OLS estimate of only 0.27 years. Rows 2 through 5 indicate that this is due to an increase in the share of teachers with less than ten years of experience and a decrease in the share of teachers with ten or more years of experience.

Row 6 shows the surprising result that schools that had an inflow of black students did not experience a greater increase in turnover than schools that had an outflow. While schools with larger black enrollment shares have higher teacher turnover in the cross-section, this relationship does not hold in the instrumental variables results (in fact the point estimate is negative and not statistically significant). Since there was a period after which teachers would have known about the policy change but before students were actually moved, I also include the one year lag of turnover as a dependent variable. There was no statistically significant relationship between lagged turnover and an inflow of black students, and the point estimate is negative. The graphical analysis of teacher turnover in Section VI puts this surprising result in perspective.

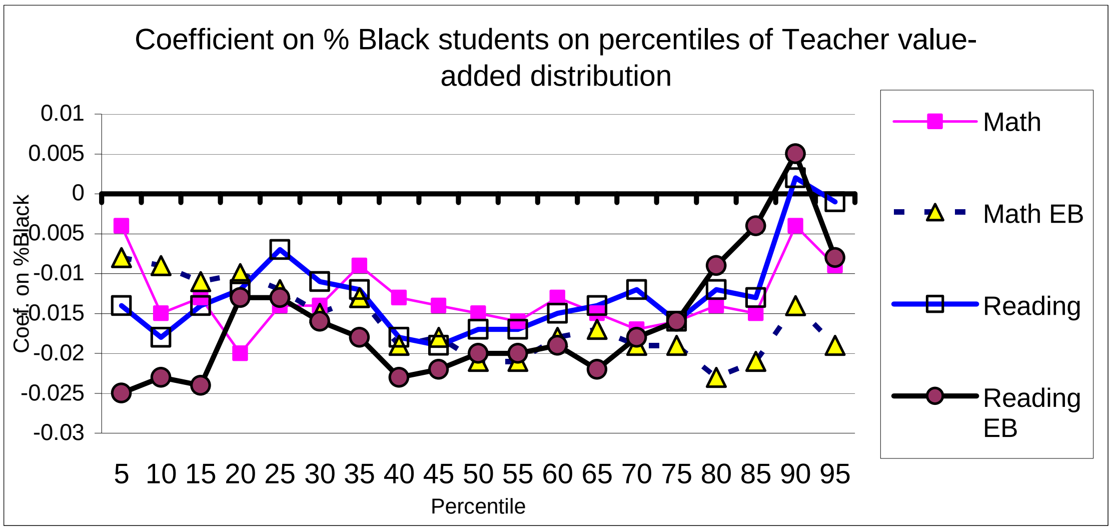
Rows 8 and 9 show that the relationship between teacher race and student race is robust across specifications. However, the IV estimates indicate that a 10 point increase in the black enrollment share is associated with a 3.5 point increase in the black teacher share compared to 5.3 point in the OLS. The IV-DIDID coefficient is about two thirds as large as the OLS coefficient, suggesting that much of the correlation between teacher race and student race is an artifact of residential segregation. The fact that there is still a strong relationship in the DIDID-IV results is compelling evidence that the relationship between teacher race and student race is not simply an artifact of co-location due to residential segregation, but is due to something systematic about how teachers apply to or are placed in schools. Since there was no change in teacher placement policy, and race is not explicitly used in the teacher hiring or placement procedure, it is reasonable to interpret this as a teacher labor supply response.

The results in Column 2 of Table 4 show no systematic relationship between the percentage of black students and the percentage of teachers with an advanced degree or the percentage of teachers who attended top 50 or top 100 colleges. The point estimates have the opposite sign of the OLS estimates. The point estimates in rows 13 through 15 suggest that an inflow of black students is associated with teachers with lower scores on their certification exams, but these estimates are not statistically significant at traditional levels. Rows 16 through 19 document the relationship between estimated teacher value-added (based on a pre-sample period) and the percentage of black students at the school. The DIDID-IV results indicate that a 10 point increase in the share of black students is associated with a 0.15 and 0.13 standard deviation decrease in the average teacher value added in math and reading respectively. Using the Empirical Bayes teacher effects (rows 17 and 19) a 10 point increase in the share of black students is associated with a 0.145 and 0.143 standard deviation decrease in the average teacher value added in math and reading respectively.

In column 3, I interact the $POST_t \times CM_i \times BD_i$ variable with Q_i (the quintile of the school in the percentage black in neighborhood distribution) to allow the instrument to have a differential effect on schools located in largely black neighborhoods as opposed to largely white neighborhoods. Figure 3 indicates that this is likely to improve the fit of the first stage and reduce noise in the second stage. Making this adjustment to the excluded instrument reduces the standard errors on most estimates. The results are largely the same as those of column 2, however in columns 3, an increase in the share of black students is associated with a decrease in the share of teachers who score in the top 10% of the certification exam. This relationship is significant at the 10 percent level. In column 3, even those outcomes that are not statistically significant have the expected sign and tell the same consistent story – schools that had an exogenous increase in the black enrollment share experienced a decrease in the observable and unobservable quality of teachers on average.

To provide a more nuanced picture of how the distribution of estimated teacher value-added changed within schools due to the policy change, Figure 4 shows the marginal effects of an inflow of black students on different percentiles of the value-added distribution for reading and for math. The regression coefficients are reported in Appendix Table 2. Whether one uses EB estimates or the estimated teacher effects, the results are qualitatively the same – an increase in the share of black students is associated with a statistically significant decrease in the value-added of teachers at the school at all points in the value-added distribution.[26]

Figure_4



To put these results into perspective consider the following "back of the envelope" calculation. Assume that under student busing the average black/white student attended a school that was 60 percent black/white, and after busing attended a school that was 75 percent black/white. Then they would, on average, be faced with teachers with approximately 0.225 standard deviations lower/higher value-added in math and reading. This ignores any pre-existing differences that may exist across schools during busing. This would imply an increased teacher quality gap of about 0.45 standard deviations which would imply an increased performance gap of between 4.5 and 9 percent of a

[26] Appendix Table 1 shows results using the serial correlation adjusted value-added estimates, which are qualitatively similar. Using the second lag of test scores to correct for measurement error in lagged test scores reduces the sample of teachers with estimated effects to less than half of those when one uses the lagged test scores as is. This would explain the additional noise.

standard deviation.[27] This is roughly the magnitude of having a first year teacher as opposed to a more experienced teacher. Since the black-white test score gap is estimated to be between 0.6 and 1 standard deviations [Fryer and Levitt (2004)] this crude calculation suggests that the endogenous sorting of teachers with respect to student race could potentially explain between 4.5 and 15 percent of the black-white test score gap.

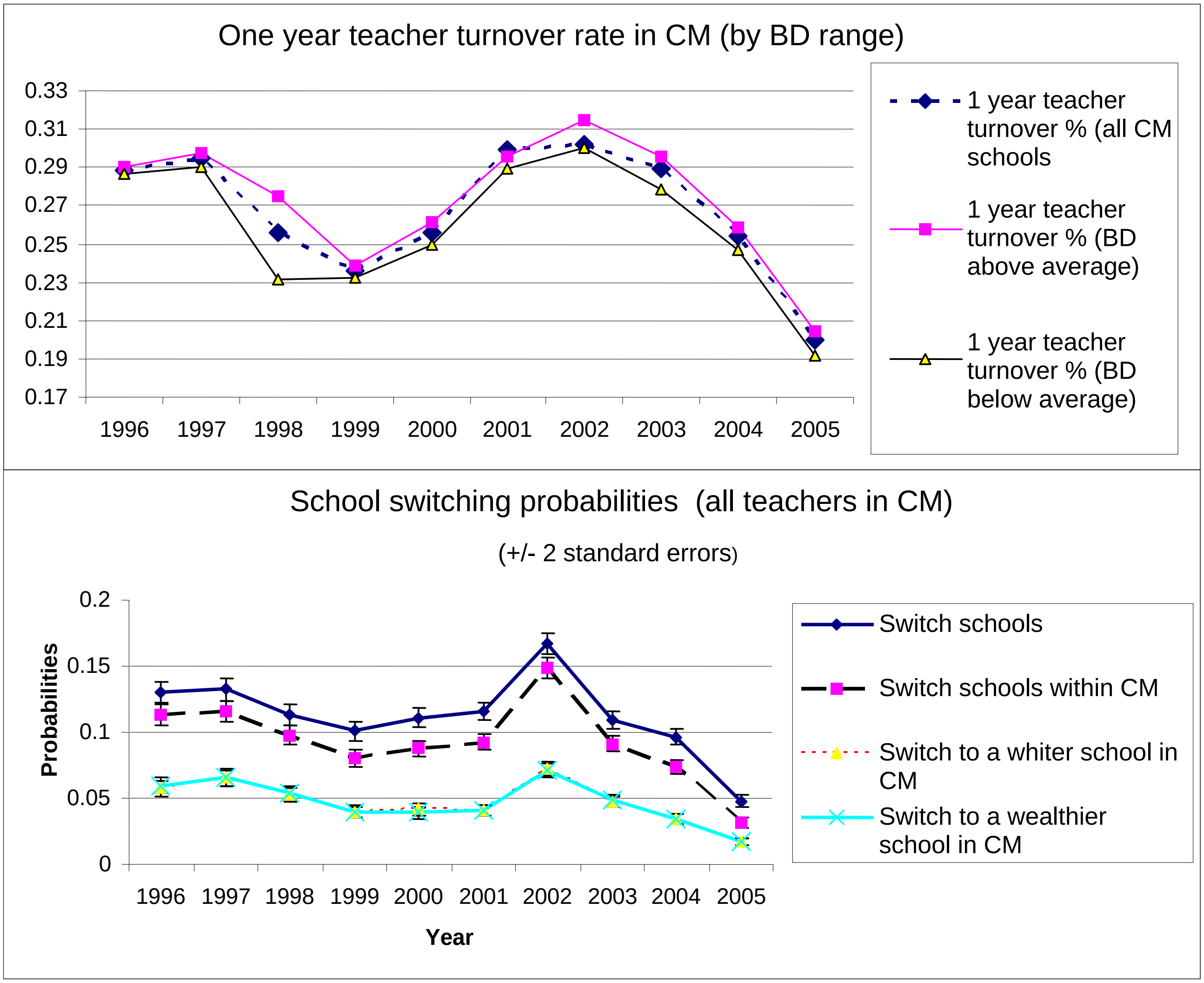
V. A graphical analysis of teacher turnover.

It is somewhat surprising that the DIDID-IV regression results in section IV indicate that black students are not associated with higher turnover so I present descriptive statistics about teacher turnover to put these regression results in perspective. The top panel of Figure 5 shows the one-year turnover rates (leaving their current school) by year for those CM schools with BDs above average and those with BDs below average. The first notable pattern is that while there are differences in turnover rates between low-BD and high-BD schools (i.e. low-BD schools with low black enrollment shares have slightly higher turnover than high BD schools with large black enrollments), the increases in turnover over time are almost identical for all schools. This is consistent with finding a statistically significant effect of percent black on turnover in the cross-section but no statistically significant differential effect of percent black on turnover in the IV-DIDID estimates in columns 2 and 3 of Table 4. The second notable pattern is that turnover is elevated for all CM schools between 2001 and 2003, suggesting that teachers may have been reacting to the change in student demographics, and to the *anticipated* change in student demographics. Since a teacher sorting explanation would involve teachers switching schools rather than simply leaving their current school, the lower panel of Figure 5 looks specifically at teachers switching schools. The lower panel of figure 5 shows a clear increase in teachers switching schools in 2002 that was obscured by looking at aggregate teacher turnover. Using simply t-tests, one can reject the hypothesis that switching is the same in 2002 as in 2001 or 2003 at the five percent level. The figure also shows that the vast majority of teacher switching is due to switching schools within CM rather than switching to schools outside the district. There is some

[27] The estimates for the standard deviation change in student scores associated with a one standard deviation increase in teacher quality range between 0.25 [Jacob and Lefgren (2007)] to a more modest 0.1 [Rockoff (2004); Hanushek, Kain and Rivkin (2005)].

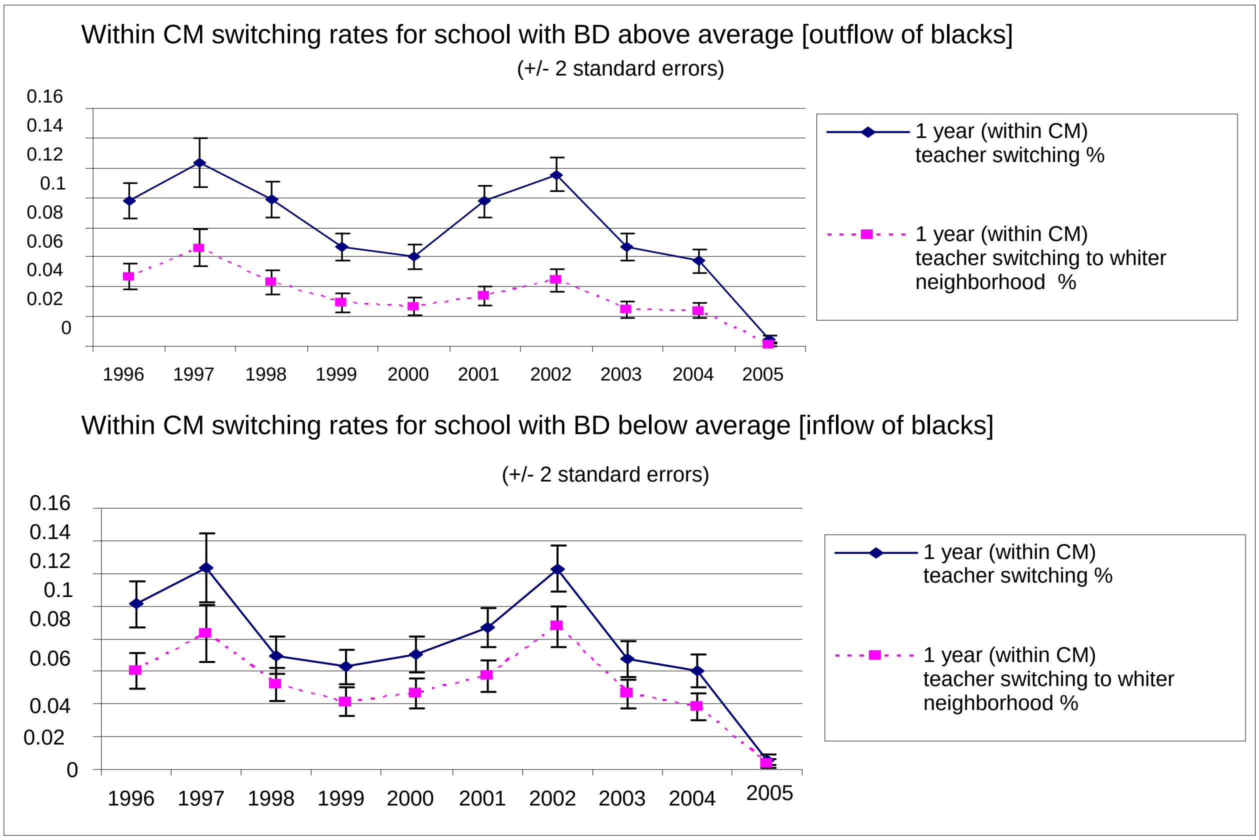
evidence of increased switching to whiter neighborhoods in 2002, but some of this may simply be due to mean reversion.

Figure5



If teachers were switching schools in 2002 because they *all* preferred to teach in schools that had a lower share of black students, one would observe (1) an increase in turnover for those schools that had an increase in the share of black students (2) a decrease in turnover for those schools that had a decrease in the share of black students (3) most of this change in turnover would be due to school switching. The dynamics documented in Figure 6 show that this was not the case. Both high-BD and low-BD schools experienced an increase in teachers switching out of their schools to other schools in the district in 2002. This dynamic is much more consistent with there being heterogeneity in teachers' preferences for students, such that some teachers like teaching in schools with high shares of low-income minority students while other teachers do not.[28] This would also explain why the aggregate regression results show no differential change in teacher turnover across schools despite a clear change in the characteristics of teachers within schools over time.

Figure 6



Readers may wonder if the movement of students systematically created job openings at schools that had an outflow of black students due to the policy change leading to a change in teacher demand. Instrumental variables regressions of the share of teachers that are new hires yields a coefficient on %Black of 0.009 and a standard error of 0.012. The standard error of the same OLS regression is 0.01 showing that this lack of significance is not due to increased noise from the IV procedure. If teachers had no preferences for student demographics, since there were not disproportionately more new

[28] Anecdotal evidence suggests that many teachers avoid inner-city schools because they find those working conditions difficult, while other teachers seek them out because they want to make a difference to students who really need the help.

hires (vacancies filled) at schools that lost or gained black students due to the policy change, they would be no more likely to apply for a transfer or leave their schools as before. Since the school district *did not* compel teachers to leave schools, the aggregate increase in teacher switching for all schools further suggests that the changes in mobility were likely due to a labor supply rather than a demand response.

VI The effect of the policy change on incumbent teachers and new hires.

The changes in the aggregate documented in section IV, may have occurred for three reasons; (1) schools that had an inflow of black students may have experienced an increased outflow of highly-qualified teachers, (2) schools that had an inflow of black students may have found it more difficult to attract new highly-qualified teachers than before the inflow of black students or (3) some combination of the two. I attempt to disentangle these two margins by looking at changes in the characteristics of teachers who remain in a school (teachers who did not leave their school the previous year) and changes in the characteristics of newly hired teachers. All the analyses in this section uses the DIDID-IV specification to remove potential endogeneity bias.

Table 5 reports the coefficient on *%Black* at the school on the characteristics of individual teachers. Columns 1 through 9 are based on the sample of teachers who remain in their school from the previous year, and columns 10 through 18 are based on the sample of new teachers. Table 5 reports the DIDID-IV results where all models include the year-by-district fixed effects, year-by-locale fixed effects school effects and post-by-BD effects. The results for incumbent teachers in columns 1 through 9 echo the aggregate teacher results. A school with a 10 point increase in the share of black students experienced 1 year a decline in the average years of experience among teachers who stayed in the school. These teachers who stayed after the policy change were about 3 percentage points more likely to be black, and had about 0.11 standard deviations lower value added in math and reading. These results imply that within a school, those teachers that left schools that experienced an inflow of black students were on average more experienced, whiter, and had higher value-added than those who stayed.[29]

[29] Regression models that estimate the probability that a teacher leaves her current school indicate that this was the case; however these point estimates are not statistically significant for the experience and value-

Table_5

Effect of change in percent black students on characteristics of incumbent teachers and new hires

	Incumbent Teachers								
	1	2	3	4	5	6	7	8	9
	Years of experience	less than 4 years	4 to 10 years	11 to 20 years	more than 20 years	White	Black	math effect EB	reading effect EB
Percent Black at school	**-0.10729**	**0.0037**	**0.00226**	-0.00153	**-0.00349**	-0.00244	**0.00299**	**-0.01163**	**-0.01058**
	[0.03582]**	**[0.00155]***	**[0.00135]+**	[0.00109]	**[0.00154]***	[0.00151]	**[0.00149]***	**[0.00473]***	**[0.00532]***
Observations	119368	128105	128105	128105	128105	128105	128105	26524	26524
Number of schools	419	419	419	419	419	419	419	412	412

	New Hires								
	10	11	12	13	14	15	16	17	18
	Years of experience	less than 4 years	4 to 10 years	11 to 20 years	more than 20 years	White	Black	math effect EB	reading effect EB
Percent Black at school	0.04085	-0.00187	-0.00058	0.00105	0.00061	-0.00281	0.00228	-0.01929	-0.01242
	[0.06102]	[0.00223]	[0.00152]	[0.00137]	[0.00146]	[0.00381]	[0.00332]	[0.01267]	[0.01730]
Observations	20550	24464	24464	24464	24464	23969	23969	2580	2580
Number of schools	419	419	419	419	419	419	419	345	345

Robust standard errors in brackets. Standard errors clustered at the zip code level.
+ significant at 10%; * significant at 5%; ** significant at 1% (sample is CM, Wake, Guilford and Cumberland districts)

Note: All regressions are based on the same IV-DIDID specification detailed in equations [4] and [5]. All regressions include year effects interacted with the school district, the decile of the school in the distribution of percent black in the neighborhood, and the locale. All specifications include school fixed effects and a POST*BD variable. The excluded instrument in these models is the POST*BD*CM variables interacted with the quintile of the school in the distribution of percent black residents from the 2000 census.

Columns 10 through 18 look at the attributes of new teachers that a school hires. None of these point estimates are statistically distinguishable from zero, suggesting that either the sample of new teachers is too small to detect differences, or there is no strong systematic difference in the characteristics of new teachers that a school hired after the policy change. The point estimates, however, do suggest that schools that experienced an inflow of black students were more likely to hire black teachers, and teachers with lower value-added than before the policy change.

The results in Table 5 suggests that white teachers, more experienced teachers, and teachers with higher value-added were more likely to leave schools that experienced an inflow of black students than black teachers, teachers with less experience, and teachers with low estimated value-added. Direct tests for differential mobility across experience and value-added groups yield statistically insignificant results that are not generally robust across models. However, differential mobility by teacher race is a consistent finding across all models and I present these results in Table 6.

added variables and are as such not reported. Differences in the likelihood of leaving by teacher race are detailed in Table 6.

Table 6

Difference in Mobility response by Race

	1	2	3	4	5	6
	IV-DIDID	IV-DIDID	IV-DIDID	IV-DIDID	IV-DIDID	IV-DIDID
	Black Teachers			White Teachers		
	Leave current school	Leave current school	Leave current school	Leave current school	Leave current school	Leave current school
Percent Black	**-0.00617**	**-0.00761**	-	-0.00155	-0.00159	-
	[0.00325]+	**[0.00357]***	-	[0.00181]	[0.00175]	-
Percent Black in the following year	-	-	**-0.00095**	-	-	0
	-	-	**[0.00043]***	-	-	[0.00019]
Excluded Instruments	1	2	1	1	2	1
Observations	16706	16706	13480	64811	64811	52922
Number of schools	408	408	402	418	418	418

Robust standard errors in brackets. Standard errors clustered at the zip code level.
+ significant at 10%; * significant at 5%; ** significant at 1%

Note: All regressions are based on the same IV-DIDID specification detailed in equations [4] and [5]. All regressions include year effects interacted with the school district, the decile of the school in the distribution of percent black in the neighborhood, and the locale. All specifications also include school fixed effects and a Instrument 1 is the three way interaction BD*POST*CM, and instrument 2 is BD*POST*CM interacted with the quintile of the school in the percent black residents distribution. (sample is CM, Wake, Guilford and Cumberland districts)

The dependent variable in Table 6 is leaving the current school in that year. The coefficient on percent black is reported and all models include the full set of control variables in model [4] and instrument for percent black using 2SLS. Columns 1 through 3 show the effect on leaving the current school for black teachers and columns 4 through 6 show the results for white teachers. Columns 1 and 3 that use the three way interaction as the excluded instrument shows that black teachers are 6 percentage points less likely to leave a school when the share of black students increases by 10 percentage points, while white teachers are 1.5 percentage points less likely. The effect on black teachers is statistically significant at the 10 percent level while that for white teachers (who are more numerous) is not significant at traditional levels. Columns 2 and 5 use the instrument interacted with the quintile of the percent black of the neighborhood as used in Table 4. These results are largely the same, but now the effect for black teacher is statistically significant at the 5 percent level. Since the analysis in Section V indicates that much teacher turnover and switching took place in 2002 rather than 2003 in anticipation of the change in student attributes, columns 3 and 6 use the percent black the following year as the independent variable. The instruments are also altered so that $POST_t$ denotes the year before students moved. The results from this model indicate that black teachers were about 1 percentage point less likely to leave a school when the share of black students was expected to increases by 10 percentage points, while there is no statistically significant differential effect for white teachers.

In sum, schools that experienced an exogenous increase in the black enrollment share were *relatively* more likely to lose white teachers, experienced teachers and effective math and reading teachers. The DIDID-IV estimates indicate that black teachers were less likely to leave schools, while white teachers were not differentially affected by an exogenous inflow of black students. While the point estimates show that schools that had increasing black enrollment shares hired new teachers with lower estimated value-added than before the inflow, these new hire results are not statistically significant.

VI Concluding remarks

The regression estimates show that the change from a race-based busing policy to a neighborhood-based controlled school choice model changed the student make-up of schools in CM in a clear and foreseeable way. As predicted by the instrument, schools that had a greater share of black students at the school than black residents in the surrounding neighborhood experienced an outflow of black students and an inflow of white students. The converse was also true. The sudden inflow or outflow of black students as a result of the policy change was associated with systematic changes in the make-up of teachers at the affected schools. Schools that experienced an increase in the black enrollment share saw a decrease in the proportion of experienced teachers, a decrease in the proportion of teachers with high scores on their licensure exams and a decrease in teacher value-added. Evidence on the characteristics of teachers who remain in schools and the profiles of new teachers within schools before and after the policy change indicate that the aggregate decline in teacher quality in schools with increased black enrollment shares was due to these schools losing experienced and effective teachers and possibly being less able to hire teachers with high value-added. I find that white teachers were no more likely to leave schools that experienced an inflow of black students than other schools, while black teachers were more likely to stay in schools that had an exogenous increase in the black enrollment share. This suggests that the relationship between teacher race and student race is not a mere artifact of co-location but likely the result of teacher preferences for student attributes that are correlated with race. It is true that discrimination against black teachers at schools that had increasing white enrollment shares could lead to this result, however, given that these are public schools and discrimination is illegal, this is not likely.

Anecdotal evidence and assertions from district employees suggest that these changes in teacher characteristics are driven by teacher labor supply. In addition, empirical evidence supports this interpretation. Specifically: (1) New teacher hiring (vacancies) is not correlated with the direction of the flow of black students due to the policy change, (2) all schools in the district experienced increased turnover, suggesting a re-sorting of teachers rather than a general movement of teachers from certain schools to others with vacancies and (3) teachers switched schools in anticipation of the demographic changes. While I cannot definitively rule out a demand side explanation, the bulk of the evidence supports a labor supply interpretation.

The dynamics of teacher turnover are consistent with a world in which some teachers prefer to teach in inner-city schools with low-income ethnic minority students while others prefer not to. These preferences appear to be correlated somewhat with teacher race, such that black teachers may have a greater preference for teaching in schools with larger shares of black students. The theory of compensating differentials predicts that where teachers have heterogeneous preferences for student characteristics, if students are re-shuffled (as they were), teachers would also re-sort across schools. In fact, this is exactly the type of dynamic one observes in the data. The fact that movers and "stayers" may have very different preferences, as a result of sorting, suggests that estimates that look at changes in teacher behaviors could grossly overstate or understate the overall or average effect of school characteristics on teacher mobility. This also suggests that compensating differentials estimated based on mobile teachers may be very different from that for the average teacher.

Overall, the findings present some of the first compelling evidence that teacher characteristics and teacher quality are endogenous to student demographics. One can reject the hypothesis that that the correlation between teacher quality and student demographics is merely an artifact of geography or residential segregation. The teacher sorting is probably responsible for some of the disparities in teacher qualifications that exist between low-income inner-city schools and affluent suburban schools, which in turn may be responsible for some of the cross-school achievement gaps that exist.

The endogeneity of teacher quality with respect to student characteristics also suggests that the movement of effective teachers out of schools in predominantly black neighborhoods may be partially responsible for the increase in the black-white achievement gap associated with the end of school desegregation and residential segregation. Back of the envelope calculations suggest that such endogenous movement could explain a non-trivial portion of the increased achievement gap. An important implication of these findings is that policy-makers should be cautious when advocating policies that require the re-shuffling of students across schools such as vouchers, school choice, district consolidation, or school busing. Insofar as student characteristics affect where teachers teach, the change in teacher attributes caused by the re-shuffling of students across schools needs to be taken into account to determine the overall anticipated effect of such policies.

References

Aaronson, D., L. Barrow, and W. Sander. (2007). “Teachers and Student Achievement in the Chicago Public High Schools.” *Journal of Labor Economics*, University of Chicago Press, vol. 25, pages 95-135.

Angrist, J., and K. Lang. (2004). “How important are classroom peer effects? Evidence from Boston’s Metco Program.” Cambridge: Mass.: National Bureau of Economic Research Working Paper 9263.

Anthony, E., and D. Goldhaber, (2007). “Can Teacher Quality be Effectively Assessed? National Board Certification as a Signal of Effective Teaching.” *Review of Economics and Statistics.* MIT Press, vol. 89(1), pages 134-150, 01.

Betts, J. R., Rueben, K.S., and Danenberg, A. (2000). “Equal resources, equal outcomes? The distribution of school resources and student achievement in California.” San Francisco: Public Policy Institute of California.

Bifulco, R., and H. Ladd. (2005a). “The Impact of Charter Schools on Student Achievement: Evidence from North Carolina.” Forthcoming, *Education Finance Policy.*

Bifulco, R., and Ladd, H. (2005b). “Race and Charter Schools: Evidence from North Carolina.” Unpublished manuscript at University of Connecticut.

Brewer, D., and R. Ehrenberg. (1994, March). “Do school and teacher characteristics matter? Evidence from High School and Beyond.” *Economics of Education Review*, *13*(1), 1-17. (EJ 483 386).

Brewer, D., and D. Goldhaber. (2000). “Does Teacher Certification Matter? High School Teacher Certification Status and Student Achievement.” *Educational Evaluation and Policy Analysis*, 22(2), 129-145.

Bohrnstedt, G., and B. Stecher, (1999). "Class size reduction in California: Early evaluation findings, 1996–1998." Palo Alto: CSR Research Consortium, Year 1 Evaluation Report, American Institutes for Research.

Boyd, D., H. Lankford, S. Loeb, and J. Wyckoff. (Winter 2005) "The Draw of Home: How Teachers' Preferences for Proximity Disadvantage Urban Schools." *Journal of Policy Analysis and Management*, Vol. 24, No.1, 113-132.

Buddin, R., and R. Zimmer. (2005). "A Closer Look at Charter School Student Achievement." *Journal of Policy Analysis and Management*, 24(2): 351-372.

Clotfelter, C., E. Glennie, H. Ladd, and J. Vigdor. (2008). "Teacher Bonuses and Teacher Retention in Low Performing Schools: Evidence from the North Carolina $1,800 Teacher Bonus Program." *Public Finance Quarterly*, Vol. 36, No. 1, 63-87.

Clotfelter, C., H. Ladd and J. Vigdor. (2007). "How and Why Do Teacher Credentials Matter for Student Achievement?" National Bureau of Economic Research Working Paper No. 12828.

Clotfelter, C., H. Ladd, J. Vigdor, and J. Wheeler. (June, 2007) "High Poverty Schools and the Distribution of Teachers and Principals." *North Carolina Law Review* 85.5: 1345-1380.

Clotfelter C., H. Ladd and J. Vigdor, (2006) "Who Teaches Whom? Race and the Distribution of Novice Teachers" *Economics of Education Review, Vol. 24, No. 4, Pp. 377-392.*

Dee, T. (May 2005) "A Teacher Like Me: Does Race, Ethnicity or Gender Matter?" *American Economic Review* 95(2), pages 158-165.

Fryer, R. and S. Levitt. (May 2004). "Understanding the Black-White Test Score Gap in the First Two Years of School," *Review of Economics and Statistics* 86, no. 2 pp. 447–64.

Guryan, J. (2004) "Desegregation and Black Dropout Rates." *American Economic Review*. 94(4): 919-943.

Hanushek, E., (1997) "Assessing the Effects of School Resources on Student Performance: An Update." *Educational Evaluation and Policy Analysis*, 19(2), 141-164.

Hanushek, E., J. Kain, and S. Rivkin. (Spring, 2004) "Why Public Schools Lose Teachers" *The Journal of Human Resources*, Vol. 39, No. 2., pp. 326-354.

Hanushek, E., J. Kain, and S. Rivkin. (2005). "Teachers, Schools and Academic Achievement." *Econometrica*, 73(2), 417-58.

Hanushek, E., J. Kain, D. O'Brien, and S. Rivkin. (February 2005) "The Market for Teacher Quality." National Bureau of Economic Research Working Paper No. W11154.

Hanushek, Eric A., and Steven G. Rivkin (2006) "School Quality and the Black-White Achievement Gap." NBER Working Paper #12651.

Hanushek, Eric A., John F. Kain and Steven G. Rivkin (2004) "New Evidence about Brown v. Board of Education: The Complex Effects of School Racial Composition on Achievement." Working Paper, Hoover Institution, Stanford University.

Hastings, J., T. Kane, and D. Staiger. (2006) "Preferences and Heterogeneous Treatment Effects in a Public School Choice Lottery," National Bureau of Economic Research working paper No 12145.

Hastings J., R. Van Weelden, and J. Weinstein. (2007) "Preferences, Information, and Parental Choice Behavior in Public School Choice" National Bureau of Economic

Research Working Paper No. 12995.
Hastings, J., and J. Weinstein. (2007) “No Child Left Behind: Estimating the Impact on Choices and Student Outcomes” National Bureau of Economic Research Working paper No. 13009.
Hoxby, C. (2000) “Peer Effects in the Classroom: Learning from Gender and Race Variation.” National Bureau of Economic Research Working Paper 7867.
Hoxby, C., and J Rockoff. (2004) “The Impact of Charter Schools on Student Achievement: A Study of Students Who Attend Schools Chartered by the Chicago Charter School Foundation.” Cambridge, MA: Department of Economics, Harvard University.
Jacob, B. and Lefgren, L. (2008). “Principals as Agents: Subjective Performance Assessment in Education.” *Journal of Labor Economics*, 26:1, 101-136.
Kane, T., D. Staiger, and S. Riegg, (2005) School Quality, Neighborhoods and Housing Prices: The Impacts of school Desegregation” National Bureau of Economic Research Working Paper No. 11347.
Lankford, H., (1999) “A descriptive analysis of the New York State and New York City teaching force.” Report prepared for the New York Supreme Court case Campaign for Fiscal Equity v. New York State.
Lankford, H., S. Loeb, and J. Wyckoff. (2002). Teacher sorting and the plight of urban schools: A descriptive analysis. *Educational Evaluation and Policy Analysis, 24*(1), 37-62.
Lutz, B. (2005) “Post Brown vs. the Board of Education: The Effects of the End of Court-Ordered Desegregation.” Federal Reserve Board, Finance and Economics Discussion Series Working Paper 2005-64.
Ludwig, J., and J. Vigdor. (2007) “Segregation and the Black-White Test Score Gap” National Bureau of Economic Research Working Paper 12988.
NAACP “Impact of Race Neutral Alternatives” Web source: http://www.naacpldf.org/
Rockoff, J. (2004) “The Impact of Individual Teachers on Student Achievement: Evidence from Panel Data.” *American Economic Review*, 94(2), 247-52.
Scafidi, B., D. Sjoquist and T. Stinebrickner. (2007) “Race, poverty, and teacher mobility”, *Economics of Education Review* Volume 26, Issue 2, Pages 145-159.
Smith, C. (January 18, 2004) “Resegregation; When Busing Ends.” Education Life Supplement Late Edition - Final, Section 4A, Page 30, Column 1. New York Times
Summers, A., and B. Wolfe, (1977). “Do Schools Make a Difference?” *American Economic Review*, 67, 639-652.
Todd, P., and K. Wolpin, (2003) “On the Specification and Estimation of the Production Function for Cognitive Achievement”, *The Economic Journal* 113 (February), F3-F33 Royal Economic Society.

APPENDIX

Appendix Table 1

Regression Estimates of Test Score Growth

	-1	-2
	Math	Reading
lagged score	-0.2522	-0.2594
	[0.0036]**	[0.0018]**
Peers: lagged score	-0.1405	-0.0873
	[0.0077]**	[0.0077]**
Student: Male	-0.0085	-0.0489
	[0.0015]**	[0.0016]**
Student: Black	-0.257	-0.1879
	[0.0049]**	[0.0043]**
Student: Hispanic	-0.1077	-0.0447
	[0.0055]**	[0.0055]**
Student: American Indian	-0.2108	-0.1294
	[0.0070]**	[0.0072]**
Student: Mixed	-0.1563	-0.0764
	[0.0070]**	[0.0074]**
Student: White	-0.1151	-0.0396
	[0.0045]**	[0.0045]**
Parental Education: High-school graduate	0.1246	0.1317
	[0.0023]**	[0.0021]**
Parental Education: Some College	0.1943	0.2004
	[0.0033]**	[0.0030]**
Parental Education: Professional graduate school	0.2127	0.223
	[0.0032]**	[0.0026]**
Parental Education: Junior College graduate	0.2916	0.291
	[0.0037]**	[0.0027]**
Parental Education: College	0.3421	0.3352
	[0.0044]**	[0.0032]**
Parental Education: Grad School	0.3865	0.3741
	[0.0062]**	[0.0053]**
Teacher and Student are same Race	0.0022	-0.0013
	[0.0019]	[0.0019]
Teacher and Student are same Sex	0.0058	-0.0015
	[0.0015]**	[0.0016]
Teacher: 0 years experience	-0.0478	-0.0201
	[0.0196]*	[0.0171]
Teacher: 1-3 years experience	-0.0036	-0.0063
	[0.0182]	[0.0164]
Teacher: 4-10 years experience	0.0118	-0.0081
	[0.0179]	[0.0163]
Teacher: 10-24 years experience	0.0177	0.0008
	[0.0187]	[0.0170]
Teacher: 25+ years experience	-0.0015	-0.007
	[0.0207]	[0.0183]

Cont'd

	1	2
	Math	Reading
Class Size	-0.0021	-0.0011
	[0.0004]**	[0.0003]**
School: Urban fringe (Large City)	0.0042	0.0476
	[0.0202]	[0.0178]**
School: Mid sized City	-0.042	0.0005
	[0.0205]*	[0.0166]
School: Urban fringe (mid-sized City)	-0.0285	0.0282
	[0.0205]	[0.0179]
School: Large town	0.068	0.0727
	[0.0392]+	[0.0337]*
School: Small town	-0.0157	0.0381
	[0.0223]	[0.0191]*
School: Rural (inside CBSA)	-0.0104	0.0387
	[0.0204]	[0.0178]*
School: Rural (outside CBSA)	-0.0074	0.0344
	[0.0197]	[0.0174]*
School: Log Enrollment	-0.0051	0.0041
	[0.0099]	[0.0078]
School: %White	0.3944	0.2903
	[0.0891]**	[0.0725]**
School: %Hispanic	0.3164	0.226
	[0.1261]*	[0.1014]*
School: %Black	0.1812	0.1749
	[0.0899]*	[0.0733]*
School: %Free-Lunch Eligible	-0.0093	-0.0518
	[0.0232]	[0.0190]**
Observations	1257510	1249391
Number of encrypted teacher id	30974	30888
Fraction of variance due to TFX	0.321	0.273
R-squared	0.18	0.16

Robust standard errors in brackets
+ significant at 10%; * significant at 5%; ** significant at 1%
All regressions include an indicator for missing parental education. The reference teacher experience group is teachers with missing experience data. Coefficients for the "other" student ethnicity category are suppressed.

Appendix Note 1: Empirical Bayes Estimates

It has been pointed out that while teacher effects that come directly from [3] should yield consistent estimates of teacher value-added under the identifying restrictions, these estimates are not the most efficient. The most efficient estimate of teacher value-added is the Empirical Bayes (EB) estimate that shrinks value-added estimates that are noisy. Since the estimates are estimated with noise then $\hat{\tau}_j = \tau_j + u_j$, and the total variance of the estimated effects is $Var(\hat{\tau}_j) = Var(\tau) + Var(u_j)$, where $\tau_j \sim N(0, Var(\tau))$ and u is random estimation error. It is straightforward to show that

$E[\tau_j \mid \hat{\tau}_j] = (\sigma_\tau^2 / (\sigma_\tau^2 + \sigma_{u_j}^2)) \cdot \hat{\tau}_j$. This conditional expectation is the Empirical Bayes estimate of the teacher value-added.

While σ_τ^2 and $\sigma_{u_j}^2$ are unknown, they can be estimated and used to construct the empirical analog of the EB estimate. I estimate $\hat{\sigma}_{u_j} = \hat{\sigma}_j / \sqrt{N_j}$ where $\hat{\sigma}_j$ is the variance of the residuals (outcome minus observed explanatory variables) of all students in class with teacher *j* from equation [3], and N_j is the number is students is class with teacher *j*. Since $Var(\tau_j) = Var(\hat{\tau}_j) - Var(u)$, I can create a sample estimate of the variance of the true effect τ_j by subtracting off the average measurement variances from the variance of the estimated effects. This method is intuitively appealing as it uses all the available information to "shrink" noisy teacher value-added estimates to yield efficient value-added estimates. In practice, this adjustment does not change the results in any meaningful way.

Appendix Table 2

Coefficient on percentage of lack student at the school on different percentiles of the value-added distribution

Percentile	Math		Math EB		Reading		Reading EB		Math Adjusted		Reading Adjusted	
5	-0.004	[0.013]	-0.008	[0.012]	-0.014	[0.013]	**-0.025**	**[0.011]***	-0.009	[0.012]	**-0.021**	**[0.011]+**
10	**-0.015**	**[0.009]+**	-0.009	[0.010]	-0.018	[0.011]	**-0.023**	**[0.011]***	-0.011	[0.010]	-0.015	[0.010]
15	-0.013	[0.010]	-0.011	[0.008]	-0.014	[0.013]	**-0.024**	**[0.010]***	-0.008	[0.009]	-0.009	[0.009]
20	**-0.02**	**[0.010]+**	-0.01	[0.009]	-0.012	[0.015]	-0.013	[0.012]	-0.009	[0.009]	-0.001	[0.010]
25	-0.014	[0.010]	-0.012	[0.010]	-0.007	[0.014]	-0.013	[0.012]	-0.01	[0.009]	-0.001	[0.009]
30	**-0.014**	**[0.008]+**	-0.015	[0.009]	-0.011	[0.012]	-0.016	[0.012]	-0.008	[0.008]	-0.002	[0.008]
35	-0.009	[0.007]	-0.013	[0.009]	-0.012	[0.008]	**-0.018**	**[0.010]+**	-0.005	[0.007]	-0.002	[0.007]
40	**-0.013**	**[0.007]+**	**-0.019**	**[0.009]***	**-0.018**	**[0.007]***	**-0.023**	**[0.009]****	-0.009	[0.008]	-0.005	[0.006]
45	**-0.014**	**[0.007]***	**-0.018**	**[0.008]***	**-0.019**	**[0.007]****	**-0.022**	**[0.009]****	-0.01	[0.008]	-0.008	[0.006]
50	**-0.015**	**[0.006]***	**-0.021**	**[0.008]****	**-0.017**	**[0.006]****	**-0.02**	**[0.008]****	-0.011	[0.007]	-0.006	[0.005]
55	**-0.016**	**[0.005]****	**-0.021**	**[0.008]****	**-0.017**	**[0.006]****	**-0.02**	**[0.008]****	**-0.011**	**[0.007]+**	-0.006	[0.006]
60	**-0.013**	**[0.005]***	**-0.018**	**[0.007]***	**-0.015**	**[0.006]***	**-0.019**	**[0.007]****	**-0.011**	**[0.006]+**	-0.005	[0.006]
65	**-0.015**	**[0.006]****	**-0.017**	**[0.007]****	**-0.014**	**[0.005]****	**-0.022**	**[0.006]****	-0.01	[0.007]	-0.006	[0.007]
70	**-0.017**	**[0.005]****	**-0.019**	**[0.006]****	**-0.012**	**[0.005]****	**-0.018**	**[0.006]****	**-0.014**	**[0.007]+**	-0.006	[0.008]
75	**-0.016**	**[0.007]***	**-0.019**	**[0.006]****	**-0.016**	**[0.006]***	**-0.016**	**[0.006]***	**-0.018**	**[0.008]***	-0.011	[0.009]
80	**-0.014**	**[0.008]+**	**-0.023**	**[0.007]****	**-0.012**	**[0.007]+**	-0.009	[0.007]	**-0.023**	**[0.009]***	-0.013	[0.009]
85	**-0.015**	**[0.009]+**	**-0.021**	**[0.008]****	-0.013	[0.008]	-0.004	[0.008]	**-0.028**	**[0.011]****	**-0.017**	**[0.010]+**
90	-0.004	[0.009]	-0.014	[0.009]	0.002	[0.008]	0.005	[0.008]	-0.016	[0.011]	-0.007	[0.009]
95	-0.009	[0.010]	**-0.019**	**[0.011]+**	-0.001	[0.012]	-0.008	[0.008]	-0.012	[0.012]	-0.01	[0.013]

Robust standard errors in brackets

+ significant at 10%; * significant at 5%; ** significant at 1%

Note: All regressions are based on the same IV-DIDID specification detailed in equations [4] and [5]. All regressions include year effects interacted with the school district, the decile of the school in the distribution of percent black in the neighborhood, and the locale. All specifications also include school fixed effects and a POST*BD variable. The excluded instrument is the three way interaction BD*POST*CM interacted with the quintile of the school in the percent black residents distribution. Math and Reading are the normalized value-added estimates that come directly from equation [3]. The Math EB and reading EB are the Empirical Bayes estimates from equation [3]. Math Adjusted and Reading Adjusted are the normalized value-added estimated obtained from a 2SLS procedure that uses the second lag or test scores as an instrument for the first lag of test scores in equation [3]. the lack of statistical significance for these two outcome reflect the fact that the sample of teachers with estimate value-added under this method effectively shrinks by half.