It Makes a Village:
Residential Relocation after Charter School Admission

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Abstract

Although numerous studies investigate how student achievement is impacted by educational vouchers and charter schools, there appears to be no research on how these programs impact the surrounding environment. This study examines residential relocation of families whose children attend a charter school. We develop a conceptual model which predicts where relocating families are likely to move, given ex-ante distance and direction to the school. The model is parameterized using data from student mailing address changes. We find that families are almost twice as likely to relocate toward the school than would be expected if the school did not exert any attraction. Moreover, although families are not required to live near the school, the child’s school exerts a significantly stronger attraction than parent workplaces. This result may have important implications for mitigating urban sprawl, fostering urban renewal, and promoting sustainable real estate development.

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Although numerous studies investigate how student achievement is impacted by educational vouchers and charter schools, there appears to be no research on how these programs impact the surrounding environment. This study examines residential relocation of families whose children attend a charter school. We develop a conceptual model which predicts where relocating families are likely to move, given ex-ante distance and direction to the school. The model is parameterized using data from student mailing address changes. We find that families are almost twice as likely to relocate toward the school than would be expected if the school did not exert any attraction. Moreover, although families are not required to live near the school, the child’s school exerts a significantly stronger attraction than parent workplaces. This result may have important implications for mitigating urban sprawl, fostering urban renewal, and promoting sustainable real estate development.
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I. Introduction
Real estate professionals have long known that housing prices are higher in areas with good public schools. An indicator of the importance of schools to homebuyers is that while crime rates and transportation options are also understood to affect housing prices, only schools are a searchable field on Multiple Listing Service databases. It is no surprise that academic studies conducted in many countries show parents are prepared to pay substantially more for homes in better-performing school districts.

Most kindergarten through 12th grade education in the United States is provided by public schools where attendance is linked to home location based on district boundaries, or catchment areas. Students who live in a particular catchment area are assigned to a specific school. Families can exercise choice over which schools their children attend by buying a home in the catchment areas of their preferred schools. It is evident that people pay more for homes in catchment areas where school quality, as measured by student outcomes, is higher. However, it is not clear that parents are willing to pay more for higher-quality schools as measured by inputs—that is, the amount spent per pupil.

Occasionally, districts alter the boundaries of catchment areas to fill available school spaces or reduce overcrowding, eliminate spare capacity, or promote other goals such as equalizing perceived school quality or promoting racial or ethnic integration. As one would expect, research suggests that homes reassigned to lower-performing catchment areas decline in value. Subsequent uncertainty about future student assignment policy also lowers housing prices. Cheshire and Sheppard (2004) note that buyers appear to be less eager to purchase a home in a high-quality school catchment zone if history suggests changing policies may result in the home being assigned to another school.

An unfortunate effect of the current assignment-by-catchment-area model can be seen in the pattern of development in most major urban areas. To choose a better school, parents must choose a better
home—or at least a better catchment area. This home-to-school linkage has led to middle-income families migrating from catchment areas of underperforming urban schools to areas with higher-performing suburban schools. Baum-Snow (2007) observes that “between 1950 and 1990, the aggregate population of central cities in the United States declined by 17 percent despite population growth of 72 percent in metropolitan areas as a whole.” Numerous factors have been cited as drivers of this long-term trend, but the most often cited culprit has been a middle-class migration from poorer inner-city schools to preferred suburban schools.

Growing discontent with the quality of assigned public schools—particularly inner-city schools—has led to some growth in attendance at private schools and in home schooling. However, more significant, the U.S. Department of Education reports that between 1993 and 2007, there was more than a 57 percent increase in the number of students enrolled in public school choice programs. Such programs allow students to enroll in schools other than those to which they are otherwise assigned.

Public school choice is a catch-all description for a wide array of school programs. Some choice programs allow students to attend a traditional public school in another catchment area. Others allow students to attend a magnet school in the same district. Some programs allow students to attend charter schools operated by not-for-profit entities. Eligibility differs for each of these programs. Some choice programs are means tested—offered to poor families but not to those with a higher income. Minnesota’s Enrollment Options Program allows the state education agency to prevent white students from transferring out of districts that have high percentages of minorities [Reback (2005)].

Not only do school-choice programs come in many forms, the number of school choice programs has grown substantially over the past two decades. This seems to be a particularly appropriate time to consider the environmental impact of these schools, as the nation appears to be nearing a tipping point that will see a substantial increase in the percentage of students educated outside the assigned-school model. For example, a cap limiting the number of charter schools in North Carolina to 100 was eliminated in 2011 by an overwhelming bipartisan vote: only five of 113 legislators voted to retain the cap. Similar changes have occurred recently in more than a dozen states.
This paper presents a case study of residential relocation patterns for families whose children attend one charter school in the Raleigh-Durham area. There are at least two important characteristics of this school that make it a good laboratory for initiating an investigation of how families are likely to relocate when their children attend such schools. First, the rules for attending the school are very liberal. No students are assigned to the school, and there is no attendance zone that restricts admission other than the state’s borders. There is also no tuition. Students are admitted by lottery without regard to academic ability, income or race. In this sense, student attendance is by parental choice in a relatively unrestrictive and pure sense. Second, the school has been successful, in the sense that it has survived and grown for more than a decade. Families can be reasonably certain that the school will continue operations, and a sufficient history exists to track the relocation patterns of numerous families. These families may relocate anywhere in the state without jeopardizing the student’s right to continued enrollment, and school reassignment by the local district need not be a concern in their residence selection.

Before describing the details of the current research, it is worthwhile to summarize some of the literatures that have developed around school assignment policy and school choice. While school assignments are of interest in many disciplines, we will limit this review to two important streams: real estate valuation, and racial sorting. The findings in this paper are clearly relevant to the first (albeit indirectly), and may be important to the second. In any event, the methods used in this paper are markedly different from those used before. However, to understand why this divergence is required, one must first understand what questions these literatures have sought to address.

A. Literatures Review
Many studies have examined the impact of school quality on home prices, but only a few have focused specifically on the effects of school choice on home values. For example, in 1997, Oslo, Norway, scrapped its zone-based school assignment system in favor of choice-based open enrollment. Before the change, a catchment area with pupil test scores significantly above average registered home
prices 7 to 10 percent higher than average. After the policy change, about half the price premium for these homes disappeared.

In 1990, Minnesota implemented a statewide system of interdistrict open enrollment that allowed students to attend a school outside their own district. As a result, students in poor-performing districts were able to attend schools in better-performing districts. Eight years later, home prices were found to have appreciated more in districts where higher percentages of students transferred out to preferred districts [Reback (2005)]. The explanation for the home value changes in both Minnesota and Oslo is that after the policy change, families could get access to the premium-quality schools without paying for premium-priced homes in a preferred catchment.

The impact of charter schools, which typically operate without catchment areas, on home values has not been studied extensively. The influence of publicly funded private schools on home prices, in parallel with catchment-based public schools, has been studied by Fack and Grenet (2010) using data from Paris, France. Paris has a catchment-based school assignment system as well as a well-developed publicly funded private school system—based on vouchers—that operates without catchments.

One-third of all middle schools and high schools in France are private. However, the distribution of private schools is not uniform, with some areas having few private schools and others having several. In areas with few private school options, homes are worth more in the catchment with desirable public schools. However, where many publicly funded private schools exist, public school assignment boundaries apparently have no impact on home prices. To the extent that charter schools are similar to publicly funded private schools, one might expect that the proliferation of such schools would similarly smooth home values across school district boundaries.

Of course, school assignment policies (or the absence of assignment policies) are viewed as critically important for social issues beyond local real estate valuation. In particular, legally enforced racial segregation, and subsequent efforts to end this practice have occupied center-stage in the school assignment process for the last sixty years. A substantial academic literature has developed to connect school assignment policy with racial geographic sorting in urban areas. This important literature is too
voluminous to cover fully in this paper, but in order to fully understand how this charter school case study departs from the racial-sorting literature, it is appropriate to consider a few of the important ideas in the racial sorting literature.

Tiebout (1956) motivated the idea that a sorting equilibrium can arise as households "vote with their feet" by choosing residential locations with the most desired package of local public goods (e.g., public schools). Numerous papers build on this paradigm; a recent example being Baum-Snow and Lutz (2011) who examine changes in racial sorting within 92 Metropolitan Statistical Areas after judicial desegregation orders were imposed. They conclude that in response to court-ordered desegregation white populations in southern central city school districts declined, and black populations in non-southern central city school districts grew.

Weinstein (2011) investigates neighborhood racial sorting in response to changes in school assignments that resulted from the termination (as opposed to the earlier imposition) of court-ordered racial desegregation in the Charlotte-Mecklenburg Public School District. In Fall 2001, Charlotte-Mecklenburg schools were ordered to dismantle a race-based student assignment plan that had been in effect for 30 years. A district-wide plan was approved for the 2002-2003 school year, with school assignment zones dramatically redrawn to give each student a guaranteed seat at a school close to her residence. Approximately half of families were reassigned to different schools, causing large changes in school racial compositions across the district. Weinstein shows that these reassignments produced a new sorting of families within the city. An increase in the fraction of students in an elementary school who are black produced a positive and statistically significant increase in the percent black of the surrounding neighborhood over the subsequent five-year period.

**B. The Contributions of this Paper**

This study examines residential relocation of families whose children attend a charter school. We develop a statistical model which describes where relocating families move, relative to the school, given ex-ante distance and direction to the school. The model is parameterized using data from student mailing
address changes. Baseline probabilities are presented to describe the distribution of moves that could be expected for random movers and compared to the actual data.

For reasons discussed below, rather than adopting methods used in previous studies of school assignment impacts, this paper utilizes methods developed to link housing location choice with adult workplaces. With very rare exception, employers do not require that workers live in a particular catchment area as a condition of employment. Employees are also free to change residences as they wish without jeopardizing their continued employment. In this sense, families whose children attend a non-catchment-based charter school confront a relocation decision where the school’s rules mirror their employers’ rules: they can live wherever they choose. This differs markedly from the relocation decision faced by families in the catchment-based systems studied in most prior literatures.

Families who are freed of the need to relocate into a specific school catchment zone (or district) may choose to relocate in two distinct patterns that can have environmental, urban planning, real estate development, transportation, and urban sprawl ramifications. On one hand, families may choose to live closer to the schools that their children attend. On the other, being no longer geographically tied to the school by assignment policy, families may choose to move farther away from the school.

Previous research on housing location choices, as they relate to adult employment location, lends support to the hypothesis that families may choose to live closer to schools that their children attend. For example, Clark, Huang and Withers (2003) observe that people tend to relocate closer to their work locations when they move. Two-worker families consider the commutes of both parties when choosing to relocate. Interestingly, in many instances, two-earner households are more likely to move closer to the wife’s workplace than the husband’s. This pattern may be attributable to females’ greater need to balance the dual role of mother and worker. A similar logic would suggest that home-to-school commutes are likely to be an important relocation driver.

Empirical evidence that families move toward their children’s schools when relocation is not compelled by a “neighborhood schools” policy would suggest that urban school choice programs may
produce subsequent relocation behaviors that decrease urban sprawl and reduce environmental impacts (air pollution and carbon footprints).

However, school choice may have an alternative impact on family housing choices as it relates to urban sprawl. Geographically based school assignments usually require families to live in close proximity to the schools that they attend. Freed from an explicit geographic tether, families with students attending schools of their own choice might decide to move farther from the school and increase the school commute. Consider, for example, the work-commuting choices that people make. We know that households work-commuting distance is not the only reason for residential relocation. Accessibility to work is only one variable. In fact, it appears that many moves within the city, in effect, hold the distance to work as a constant. Previous work describes an ‘indifference zone’ within which commuters are relatively indifferent to access to work (Getis, 1969). Brown (1975) found that households with employment changes outside their original work zone were much more likely to move than were households within the original work zone. In fact, there appears to be a marked tendency for households to move closer to their workplace as the ex-ante separation increases. Simply put, if a household is a long distance from the workplace, when the household moves it is likely to move nearer the workplace. Thus, we might expect that home-to-school commutes will follow a similar dynamic. Even if families who live far from a school tend to move closer, those who live near the school may choose to live further away, simply because their housing choice no longer predetermines school enrollment.

Taken together, we can expect that families who have freedom of choice that is disentangled from geographic eligibility will occasionally move closer to the school, and occasionally move away. It is an open question as to which choice will dominate. The resolution of this issue is critical to assessing whether school choice will increase urban sprawl and accelerate inner-city decline, or decrease sprawl and improve inner city schools.

This study differs from previous investigations in at least three additional respects. First, while many previous studies reference “school choice plans” or a similar reference to “choice”, the nature of the choices exercised by families in this study are very different from those mentioned in other studies. For
example, Weinstein notes that in his Charlotte-Mecklenburg study “a district-wide public school choice plan was approved … with school assignment zones dramatically redrawn to give each student a guaranteed seat at a school close to her residence, typically the closest (students could gain admission to other schools in the district through a lottery process) [emphasis added].” Notice that while the plan is referred to as a “choice” plan, in fact students are assigned to a neighborhood school and must request a transfer only after the assignment has occurred. The school district’s website notes that the district has discretion as to whether to approve a transfer, and only students who attend a failing school are assured that they can transfer; after the school has been failing for 3 years. The Charlotte-Mecklenburg schools are more accurately described as adhering to a “neighborhood plan” than a “choice plan”. In Charlotte, the only way to be guaranteed a particular school is to move into the assigned catchment area, ex-ante.

In contrast, the students who attend the charter school studied here are not assigned to the school. There is no catchment area, and home location plays no role in admission. Family residence choice may be impacted by the school’s location, but not because it assures admission. We are not familiar with any study that documents the magnitude of school attraction (even indirectly) in the complete absence of any school assignment criteria.

A second difference between this study and previous ones is that extant studies look at neighborhood composition (or home price levels) before and after changes in assignment policies. Then they infer that families have voted with their feet in a Tiebout sorting. While this is a reasonable inference, it seems likely that researchers would prefer to track individual families, if the data were available. After all, biologists have used tracking tags to study animal migration for over 200 years. Unlike prior school-and-housing studies, this study uses actual address changes, and we observe individual families moving. This has the advantage of offering a much more powerful test of the school’s attraction level. Of course there is a trade-off; we cannot apply traditional tools that examine differences between schools and their surrounding neighborhoods. All of the students in this study attend the same school.
Third, extant studies generally focus on comparisons of school district assignment zones or census tracts with well-defined boundaries. This is a natural consequence of collected data inputs being pre-aggregated using these geographic boundaries. Moreover, because the vast majority of families in an assignment zone will probably send their children to the assigned school, it is reasonable to infer that changes in the local school will result in observable changes in the neighborhood. In contrast, consider families living in the Upper East Side of Manhattan where school-age children make up less than 10% of the population, and more than half of all elementary children attend private school. While the Upper East Side may be modestly impacted by public school quality or assignment changes, it seems unlikely that the response would be as dramatic as in a child-dense, public-school-dominant environment.

Analogously, the students who attend the charter school studied here are scattered across numerous census tracts where they make up a very small fraction of the total school-age population. There are approximately 250 traditional public schools in the MSA, and the fraction of students attending this charter school is far less than 1% of the total. Moreover, between 2000 and 2009, the Raleigh-Durham area was the fastest-growing large MSA in the country. Considering both of these factors, it would be very difficult (and inappropriate) to attribute changes in specific neighborhoods or census tracts to migration by charter school families. Fortunately, by tracking the families themselves, we can reach conclusions and make inferences that would be impossible to coax from census tract data.

II. Data, Hypothesis and Non-Parametric Descriptive Interpretations

The data used to conduct this analysis is provided by a charter school in the Raleigh-Durham, North Carolina area. By state law, admission to charter schools is conducted by lottery. Because North Carolina capped the number of state charter schools at 100 during the period studied in this paper, it was not uncommon for the demand for charter schools to exceed the available seats. This is the case for the school in question. Application to the school entitled the applicant to participate in the lottery, but there was no guarantee that the student would be admitted.
Preference is granted to applicants who have a sibling already enrolled at the school. If there are more seats available in the class than the number of sibling students who apply, all of the sibling students are admitted, and a lottery is held for the remaining seats. If there are fewer seats than sibling students, the lottery is held for the sibling students only, and no outside applicants are admitted.

Each applicant must complete an application containing, among other data, the mailing address of the applicant’s family. Once the student is admitted, this application is retained in the student’s permanent record. Using the permanent record files, we have assembled the initial mailing addresses for all students attending the school. The school continuously updates student mailing addresses for general purposes, and by comparing the address on each student's application to his/her subsequent mailing list address, we are able to determine which students have moved since being admitted to the school. In addition, by matching the last names and mailing addresses for students, we are able to determine which students are members of a single-family. Moreover, we can identify which student in any family was the first admitted sibling. The data on these students is of interest in this research.

Because siblings are granted priority admission, a family who has one student admitted to the school can expect that siblings will gain admission in a later year. This may be important for families with multiple children, even if younger children are not yet of school age. Enrolling a child in the school creates a pathway for enrolling all other school-aged siblings once they are ready to attend the school. In other words, the family secures the right for each child to attend the school once the first child is admitted. Thus, admission of the first child to the school confers a valuable right which may impact the family’s residential location choice.

With this in mind, admission of the family's first child would appear to be a triggering event most likely to alter a family’s optimal residential location choice. Therefore, for each family, we identify both the family residence location prior to the first admission to the school, and the subsequent mailing address as of January 2009.

The data we have collected reveals 662 families had at least one student attending the school. The application mailing addresses for the first-admitted child in four instances cannot be ascribed to a true
place of residence because a Post Office Box is given. The other addresses described are presumed to be true residential addresses.

We geocoded each address using the ArcGIS 9.2 "Geocode Addresses Tool," which utilizes street centerline data for address ranges. Specifically, we used the North Carolina Department of Transportation's 2007 Integrated Statewide Road Network database. \(^1\) We also geocode the school’s location. The result of the geocoding is a shapefile of points, with each point representing the address location (longitude and latitude) for a single record in the data table. Any addresses that did not properly geocode had points created based upon manual searches using Mapquest and Google Earth. The attribute data table of each point contained the record ID, student address, and geographic latitude/longitude coordinates.

Using the January 2009 mailing addresses of all students, we identified families which moved after the family’s first child was admitted to the school. For these families, we repeated the process and geocoded the new addresses.

Finally, we use Hawth’s Tools, an ArcGIS 9.2 extension, to calculate the linear distance from each address to the school. We also calculate bearing and turn angle metrics which are discussed later in the paper. \(^2\) Hawth’s Tools are designed specifically for ecology-related analyses such as this. We also access Google maps to calculate the nonlinear road-commuting distance and the estimated commuting time from each address to the school.

We expect that family relocation decisions are likely to be determined by commuting time and distance rather than linear distance. However, the geographic model which we construct later in the paper uses trigonometric functions that presume linear movements. In order to obtain some comfort that linear distance provides a reasonable proxy for families’ more likely decision variables of nonlinear road

\(^1\) See [http://www.lib.ncsu.edu/gis/ncdot.html](http://www.lib.ncsu.edu/gis/ncdot.html) and [http://www.ncdot.org/it/gis/DataDistribution/DOTData/default.html](http://www.ncdot.org/it/gis/DataDistribution/DOTData/default.html)

\(^2\) The Hawth’s Tool module used is “Calculate Movement Paramenters”. Documentation can be found at the following: [http://www.spatailecology.com/htools/moveparamssimple.php](http://www.spatailecology.com/htools/moveparamssimple.php)
commuting distance and commuting time, we have calculated the correlation between each of these three measures. These correlations are presented in Table 1.

Table 1: Correlation of Linear Distance, Drive Distance, and Drive Time for Accepted Applicants (First in Family)

<table>
<thead>
<tr>
<th></th>
<th>Linear distance</th>
<th>Drive distance</th>
<th>Drive Time</th>
</tr>
</thead>
<tbody>
<tr>
<td>Linear distance</td>
<td>1.0000</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Drive distance</td>
<td>0.9901</td>
<td>1.0000</td>
<td></td>
</tr>
<tr>
<td>Drive Time</td>
<td>0.9554</td>
<td>0.9638</td>
<td>1.0000</td>
</tr>
</tbody>
</table>

Notice that all of these variables are very highly correlated. In particular, the drive distance is highly correlated with the linear distance. The very-high level of correlation appears to be related to the fact that the school location is common to each commute. Given that the last leg of the commute follows the same few paths for all commuters, the linear distance maps very closely to the drive distance.

We are able to identify a residential address at the time of application for 658 of the 662 families admitted to the school. Table 2 provides descriptive statistics concerning linear distance, in miles, from each family’s original address to the school’s location. Admitted applicants, on average, lived 5.77 miles from the school, and the median distance from the school was 4.59 miles. Less than one percent of the admitted students lived within a quarter of a mile from the school. Approximately 95% live within 15 miles.

Table 2: Original Linear Distance in Miles from Home to School for Accepted Applicants (First in Family)

<table>
<thead>
<tr>
<th>Summary Statistics</th>
<th>Original Linear Distance</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean</td>
<td>5.7788</td>
</tr>
<tr>
<td>Std. Dev.</td>
<td>4.9696</td>
</tr>
<tr>
<td>Q1</td>
<td>0.2612</td>
</tr>
<tr>
<td>Q5</td>
<td>0.9200</td>
</tr>
<tr>
<td>Q25</td>
<td>2.5725</td>
</tr>
<tr>
<td>Median</td>
<td>4.5993</td>
</tr>
<tr>
<td>Q75</td>
<td>7.2459</td>
</tr>
<tr>
<td>Q95</td>
<td>14.3403</td>
</tr>
<tr>
<td>Q99</td>
<td>24.8256</td>
</tr>
<tr>
<td>Min</td>
<td>0.1030</td>
</tr>
<tr>
<td>Max</td>
<td>56.5721</td>
</tr>
<tr>
<td>N</td>
<td>658</td>
</tr>
</tbody>
</table>
A. Which families moved?

Comparing the application addresses to the subsequent mailing addresses, we find that 176 of the families changed addresses after they were admitted to the school, the remainder did not change mailing addresses. We assume that a change of mailing address constitutes a change of residence, but this need not be the case. For instance, a family might use a business address or a post office address for receiving personal correspondence. In that case, the change will be misinterpreted as a change of residence. School administrators also point out that a small number of students have divorced parents with joint custody. We cannot systematically identify these students, and we have no means of determining what impact these family arrangements might have on the data. In any event, noise that is introduced by these factors should bias against finding school commute to be an important factor in relocation decisions.

Assuming that families make relocation decisions on the basis of commute time, we might expect that families who live a long distance from the school would be more likely to relocate. To test this hypothesis, we specify the following probit model:

\[ P(\text{Moved} = 1 | x_i) = \Phi(x_i \beta) = \Phi(\beta_0 + \beta_1 \text{Distance}_i + \beta_2 \text{Years}_i + \beta_3 \text{HomeValue}_i) \]

The marginal effects are:

\[ \frac{\partial}{\partial \beta} P(\text{Moved} = 1 | x_i = t) = \frac{\partial}{\partial \beta} \Phi(t \beta) = \phi(t \beta) \beta \]

Where \( \Phi(\cdot) \) is the cumulative standard normal distribution function and \( \phi(\cdot) \) is standard normal density. \( (\text{Moved}_i = 1) \) indicated that a family \( i \) moved after admission, and \( (\text{Moved}_i = 0) \) indicates that the family did not move. Distance, is the pre-move linear distance from the school. We expect that families with longer home-to-school commutes are more likely to move in order to reduce the commute time and distance. If this is true, \( \beta_1 \) will be positive. Years, is the number of years that the student has been enrolled at the school. Students who have attended the school for a longer period of time, are more likely to have moved, without regard to motivation. Thus, the coefficient \( \beta_2 \) should be positive.
is an estimate of the value of the family's original residence. The decision to relocate may also be impacted by a family’s wealth and/or income level. However, we do not have access to these measures. However, the value of the family’s home is likely correlated with wealth and income. One might expect that higher wealth and/or income would facilitate relocation for a family. However, because relocation will be more costly if one must dispose of an expensive home in order to acquire another of similar value, may be negatively correlated with . The value of each home is taken from Zillow.com using value estimates in July 2011. Zillow.com estimates are notoriously poor when used for appraisal purposes because they ignore all qualitative factors, including property condition. However, to the extent that Zillow.com provides a noisy estimate of home value, results will be biased against finding that the variable is a determinate of move probability.

Where Zillow.com reported a value estimate for an address, that value has been used. If Zillow.com did not report a value estimate, the value of a nearby home of approximately the same size was used instead. If Zillow.com reported no building at a particular address, the estimated value of the closest residence was utilized.

Table 3 presents the results of the hypothesized model with variations. Below the partial effect of each independent variable, -values are reported in parentheses. Elasticities with respect to each independent variable are also calculated with -statistics shown underneath. Both the partial effects and elasticities are measured at the mean value.

In the first specification, the only independent variable considered is . While the sign on the partial effect is positive, and statistically significant, the magnitude of the partial is quite small. The second specification incorporates the Zillow.com generated (in thousands) and . The average home value for all families in the regression is $226,425, and the average number of years attended by the students in the sample is 4.06.
Table 3: Probit Regression Predicting the Probability of Moving

This table reports marginal effects and elasticity from probit regressions predicting the probability of moving. The dependent variable is Moved, which is a binary variable that equals one if the family moves and zero otherwise. The independent variables include original commute distance (Distance), home value from Zillow (Home Value), years in school (Years), original grade (Admitted Grade) and current grade (Current Grade). There are 3 specifications that build on one another. The partial derivatives and elasticities of the dependent variable with respect to the independent variables are evaluated at the mean value for continuous variables and at zero for binary variables. Robust z-statistics are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively, in a two-tailed test.

<table>
<thead>
<tr>
<th>Dep. Var.= Moved (1/0)</th>
<th>Model (1)</th>
<th>Model (2)</th>
<th>Model (3)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Marginal effect [dy/dx]</td>
<td>Elasticity [d(lny)/d(lnx)]</td>
<td>Marginal effect [dy/dx]</td>
</tr>
<tr>
<td>Distance</td>
<td>0.0050*** (2.38)</td>
<td>0.177* (2.36)</td>
<td>0.0035 (1.65)</td>
</tr>
<tr>
<td>Home Value</td>
<td>-0.0007*** (-3.69)</td>
<td>-0.7928*** (-3.51)</td>
<td>-0.0007*** (-3.68)</td>
</tr>
<tr>
<td>Years</td>
<td>0.0451*** (7.27)</td>
<td>0.8581*** (6.85)</td>
<td></td>
</tr>
<tr>
<td>Admitted Grade</td>
<td>-0.0443*** (-6.16)</td>
<td>-0.5195*** (-5.93)</td>
<td>-0.0455*** (6.96)</td>
</tr>
<tr>
<td>Current Grade</td>
<td>0.2682</td>
<td>0.2133</td>
<td>0.2132</td>
</tr>
<tr>
<td>Log</td>
<td>-375.9008</td>
<td>-311.5190</td>
<td>-311.5003</td>
</tr>
<tr>
<td>Pseudolikelihood</td>
<td>0.0072</td>
<td>0.1335</td>
<td>0.1336</td>
</tr>
<tr>
<td>Pseudo R-squared</td>
<td>0.2682</td>
<td>0.2133</td>
<td>0.2132</td>
</tr>
<tr>
<td>Predicted Prob.</td>
<td>650</td>
<td>635</td>
<td>635</td>
</tr>
</tbody>
</table>

As expected, the number of years that the student has attended the charter school is highly correlated with the probability of a move. Obviously, the more time that has elapsed between the two observation points, the more likely it is that a move will have occurred. The distance that the family originally commuted to school is also positively correlated with the move probability. The family’s HomeValue is negatively correlated with the move probability. Of the 635 observations in the sample, 160 of the families moved. The average mover’s home was valued at $174,944 in July 2011. The mean HomeValue for non-movers was $243,766 (almost 40% higher).
The third specification in Table 3 decomposes the time that the student has been enrolled at the school into the student’s Current Grade and the student’s Admitted Grade. The difference between Current Grade and Admitted Grade is the value of Years in the second specification. The negative partial effect on Admitted Grade indicates that the younger the student was when he was admitted, the more likely the family was to relocate. This is consistent with families choosing to relocate when they expect that their children will be enrolled at the school for a long period of time. For families that expect to be affiliated with the school for many years, the relative benefits of moving increase. The positive coefficient on Current Grade indicates that older students are more likely to have moved since enrolling. Finally, Model (3) shows that the elasticity of moving probability \((\text{Moved})\) is 0.1556 with respect to Distance, -0.7946 with respect to HomeValue, -0.5195 with respect to Admitted Grade, and 1.3988 with respect to Current Grade, all evaluated at the respective mean value. Overall, these magnitudes are economically non-trivial. Results using the average elasticities (not tabulated but available upon request) are slightly stronger.

**B. Did the movers move closer? Some Non-Parametric Tests**

We now focus our attention on the 176 families that moved after the first child was enrolled in the school. Let \(d_0\) be the distance between the family’s original home and the school, and let \(d_N\) be the distance between the family’s new home and the school. Thus, we calculated the direction of the move relative to the school as \((d_0-d_N)\). If \((d_0-d_N) > 0\), the family moved closer to the school. In fact, the average value of \((d_0-d_N)\) was 1.48 miles. The one-tailed t-test probability of obtaining this mean, assuming that the null hypothesis \((H_0: \text{mean}=0)\) is true, would be \(p=0.0045\).

Applying the sign test, 99 of the 176 movers moved in the direction of the school, and 77 moved away from the school. If the true underlying \(\text{Pr}(d_0-d_N > 0)=.5\), the chance of observing 99 or more positive values of \((d_0-d_N)\) is \(p=0.0566\). Similarly, the Wilcoxon sign-rank test rejects the null \((H_0: \text{mean}=0)\) with a one-tailed \(p\)-value of 0.023.
The above tests make the implicit assumption that conditional upon a family moving, we would expect $\Pr(d_O-d_N>0)=.5$ if the family is not attracted to the school. However, this assumption is inappropriate. In fact, if a family is indifferent to the distance from the school, the mean of $(d_O-d_N)$ should be negative! To illustrate this point, consider two childless individuals in Figure 1, neither of whom has any interest in, nor affiliation with, the school shown at the middle of the figure.

Figure 1

If Individual A moves, she is highly unlikely to move closer to the school because the area inside the small circle represents a small fraction of the total potential move locations. Individual B has a higher probability of moving closer to the school simply because there are more addresses inside the larger circle that satisfy the condition $d_N < d_O$. Even for Individual B, the probability that $(d_O-d_N>0)$ is less than half. $\Pr(d_O-d_N>0) = 0.5$ is only asymptotically true. For example, if an uninterested party lives 1000 miles due west of the school, then approximately half of the possible relocation moves would take him slightly east of his starting location, and approximately half the moves would take him west.

We will later establish an approximate benchmark for the move probabilities that a disinterested party actually faces. For the moment, it is sufficient to recognize that the farther a relocating family
originally lives from the school, the more likely it will relocate closer to the school, because the area \( A = \pi d_0^2 \) of condition-satisfying moves that are closer to the school grows geometrically with \( d_0 \). With this in mind, we repeat the Wilcoxon sign-rank test while weighting each observation by \( \pi d_0^2 \). Testing the null hypothesis \( H_0: (d_O - d_N) \times (\pi d_0^2) = 0 \), we reject the null with a one-tailed p-value of 0.0001.

### III. A Model of School Attraction

The foregoing frequency distributions and probit analyses are helpful in describing the relationship between school location and relocation choice. However, if we wish to fully understand the magnitude of the school’s attraction in residential relocation decisions, a two-dimensional spacial model of the relocation decision is useful. Ideally, a model of school attraction will (1) provide testable hypotheses concerning the probability of moving closer to or further from the school, and (2) provide testable hypotheses concerning the effect of distance on school site attraction.

In order to simplify exposition of the model that will follow, let us first consider a simple conceptualization of one family’s residential relocation. Figure 2 presents a vector structure of the school-residence relationships. In the Figure 2 diagram, the student lives at the residence \( R_{\text{Old}} \) prior to enrolling in the school. The distance that the student lives from the school is identified as \( d_O \). After being admitted to the school, the student moves to a new residence, designated as \( R_{\text{New}} \). The distance moved from \( R_{\text{Old}} \) to \( R_{\text{New}} \) is designated as vector \( X \). After moving to \( R_{\text{New}} \), the new commuting distance to the school is designated by the vector \( d_N \). Summarizing the distances involved in this move, the student moved \( X \) miles from \( R_{\text{Old}} \) to \( R_{\text{New}} \), and the commute distance to the school changed from the \( d_O \) to \( d_N \).
In addition to the distances that have been identified, another important aspect of this conceptualization concerns the angle theta. Theta is the angle formed by moving from vector \( d_o \) to vector \( X \). If a student moved directly toward the school, the value of theta would be zero. For movements in a counter-clockwise direction from the original school bearing, the value of theta is between \(-\pi\) and zero \((-\pi < \theta < 0\)). In the Figure 2 example, the value of \( \theta \) would be approximately \(-\pi/4\), corresponding to a 45 degree angle moving counter-clockwise. Similarly, for movements in a clockwise direction from the original school bearing, the value of theta is between zero and \( \pi \) \((0 < \theta < \pi)\). The importance of theta will be seen in the further development of the model.

We are interested in the relationship between distances from the student’s residence before and after the move. The conceptualization of this relationship can now be structured as a model with two parameters in which each student’s move is described by the vector \( X \), which has both a length and a direction. Thus, the distribution of these moves across the full sample is a joint distribution of directions and lengths for all \( X \)’s.

This brings us to a formal model of the relationships conceptualized in Figure 1. Quigley and Weinberg (1977), Clark and Burt (1980), and Clark, Huang and Withers (2003) consider relocations as a function of move distances from workplaces (analogous to this study of moves related to school location).
These papers, using census tract data, make the empirical observation that move distances are distributed exponentially:

\[ f(X; \alpha) = \alpha e^{-\alpha X} , \quad X > 0 \text{ and } \alpha > 0 \]  

where \( X \) is the distance in miles. Here \( \alpha \) is the rate parameter of the distribution, and the distribution is supported on the interval \([0, \infty)\).

The data used in this study are not coded by census tract. Instead, we are fortunate to have actual street addresses, and we are better able to observe short-distance moves than has been possible in prior research. Foreshadowing later results, it is helpful to adopt a more general distributional assumption than the exponential distribution, which is a special case of the gamma distribution,

\[ g(X; \varphi, \alpha) = \frac{\alpha^\varphi}{\Gamma(\varphi)} X^{\varphi-1} e^{-\alpha X} , \quad X > 0 \text{ and } \varphi, \alpha > 0 \]  

This gamma distribution is parameterized in terms of a shape parameter \( \varphi \), as well as the rate parameter \( \alpha \). The function \( \Gamma(\varphi) \) is defined to satisfy \( \Gamma(\varphi) = (\varphi - 1)! \) for all positive integers \( \varphi \), and to smoothly interpolate the factorial between integers. For the special case of the shape parameter \( \varphi = 1 \), the gamma distribution in equation 2 becomes the exponential distribution of equation 1.

A second assumption of our model is that the move directions for students follow a von Mises distribution (Gaile and Burt, 1976). The von Mises distribution is also known as the circular normal distribution. Accordingly, it can be viewed as an analogue to the normal distribution that is useful for analyzing two-dimensional data. The parameters of the von Mises distribution are \( \mu \) and \( \kappa \), which are analogous to the normal distribution’s parameters \( \mu \) and \( \sigma^2 \). Actually, \( \kappa \) is analogous to the inverse of \( \sigma^2 \), \( (1/\sigma^2) \).

The assumption that student movements are, on average, in the direction of the school is captured as \( \mu = 0 \). (This assumption is subject to subsequent testing.) For a mean direction of zero, the von Mises density function is defined as

\[ \nu(\theta) = \frac{1}{2\pi I_0(\kappa)} e^{\kappa \cos(\theta)} , \quad -\pi < \theta < \pi, \kappa \geq 0 \]
where $\theta$ is the move direction described in Figure 1, measured in radians. $I_0$ is a modified Bessel function of the first kind and order zero.

As noted above, the dispersion of the von Mises distribution is a function of $k$. Figure 3 depicts several potential values of $k$ for a distribution with mean direction of movement $\mu$.

**Figure 3**

When $k = 0$, movements are in no preferred direction, without regard to the value of $\mu$. However, as $k$ increases, the magnitude of movements in the $\mu$ direction increases. One test which follows will estimate the magnitude of $k$, with $k$ serving as a measure of the attraction on the family that is exerted by the school location. The larger $k$ is, the stronger the relocation attraction of the school.

Because many readers may be unfamiliar with the von Mises distribution, it is helpful to view other representations of the distribution as functions of $k$. 

![Figure 3](image-url)
Figure 4 clarifies why the von Mises distribution is also described as the circular-normal distribution. Notice that for k=1, a graph of the density function looks very similar to a normal distribution. However, unlike for the normal distribution, the horizontal axis in Figure 4 does not extend from $-\infty$ to $\infty$. Instead, the axis extends from $-180^\circ$ to $+180^\circ$. Of course, these two values represent the same point on the circle so that the horizontal axis actually wraps around the circle. For larger values of k, the concentration at the origin increases and the standard deviation decreases. For k = 0, which also is depicted in the figure, the distribution becomes a circular uniform distribution.

Figure 5 presents a series of rose diagrams which allow the reader to visualize the concentration of movement toward $\mu=0$ for various values of k. Each rose diagram is generated from a theoretical von Mises distribution with alternative values of the concentration parameter k. For each diagram, moves that occur in common directions are aggregated into various bins. Rose diagrams resemble pie charts, except
that each bin (sector) has an equal angle. Rather than alter the central angles to account for different numbers of observations in each sector, we extend each sector from the center of the circle by varying distances to illustrate the number of moves that occur in a particular direction.

Figure 5

Notice that for \( k=0 \), the move directions are uniform, but for \( k=2 \), the moves are strongly concentrated toward \( \mu=0 \). Referring back to Figure 3 we see continuous versions of these same images. If Figure 5 presented an infinite number of bins for each rose diagram, the rose diagrams would match the continuous shapes depicted in Figure 3.

In combining move directions and distances, we will assume that the move directions and distances are independent of one another. This assumption aids tractability but biases against finding confirming empirical support if the assumption is invalid. Thus, as noted by Clark, Huang and Withers (2003) “if the fit between observed and expected is good, we are confident of the results of the model.” Accordingly, the joint probability distribution of movement distance and direction is described by

\[
c(X, \theta) = g(X) \nu(\theta)
\]  

(3)

Given these assumptions we develop a model of the likelihood that a student will move into a particular area defined by two distances \((X_1 \text{ and } X_2)\) and two angles \((\theta_1 \text{ and } \theta_2)\),

\[
P(X_1 < X < X_2, \theta_1 < \theta < \theta_2) = \int_{X_1}^{X_2} \int_{\theta_1}^{\theta_2} c(X, \theta) d\theta \ dX
\]  

(4)
where
\[
c(X, \theta) = g(X)\nu(\theta) = \left(\alpha^\varphi \Gamma(\varphi) X^{\varphi-1}e^{-\alpha x}\right) \left(\frac{1}{2\pi l_0(k)} e^{k\cos(\theta)}\right)
\]

Recall from Figure 2 that students move closer to the school for \(d_N < d_O\). Thus, we are specifically interested in the region where \(d_N < d_O\). Specifically, we wish to solve for \(P(d_N < d_O)\). From the law of cosines
\[
(d_N)^2 = (d_O)^2 + (X)^2 - 2(d_OX) \cos \theta
\]

(5)

Thus,
\[
P(d_N < d_O) = P((d_N)^2 < (d_O)^2 )
\]
\[
= P((d_O)^2 + (X)^2 - 2(d_OX) \cos \theta < (d_O)^2 )
\]
\[
= P(X < 2(d_O) \cos \theta )
\]
\[
= \int_{-\pi/2}^{\pi/2} \int_0^{2(d_O) \cos \theta} c(X, \theta)dX\ d\theta
\]

(6)

\[
P(d_N < d_O) = 2 \int_0^{\pi/2} \int_0^{2d_O \cos \theta} c(x, \theta)dx\ d\theta
\]
\[
= 2 \int_0^{\pi/2} \int_0^{2d_O \cos \theta} \left(\frac{\alpha^\varphi}{\Gamma(\varphi)} X^{\varphi-1}e^{-\alpha x}\right) \left(\frac{1}{2\pi l_0(k)} e^{k\cos(\theta)}\right)dxd\theta
\]
\[
= \frac{\alpha^\varphi}{\pi l_0(k)\Gamma(\varphi)} \int_0^{\pi/2} e^{k\cos \theta} \int_0^{2d_O \cos \theta} X^{\varphi-1}e^{-\alpha x}dxd\theta
\]

Let \(t = \cos \theta\), \(dt = d\cos \theta = -\sin \theta \ d\theta\).

Because \(\cos^2 \theta + \sin^2 \theta = 1\), \(d\theta = \frac{1}{-\sin \theta} \ dt = -\frac{1}{\sqrt{1-t^2}} \ dt\).
Equation 7 can be evaluated for various values of $k$ and $d_0$ using numerical integration, this allows us to establish the relationship between $P(d_N < d_0)$ and $d_0$.

IV. Tests of School Attraction

The tests conducted in this subsection take place in two steps. The first step fits the distributions of observed and expected move distance. The second step considers observed and expected move directions.

Although previous research has concluded that residential relocation distances follow an exponential distribution, we should consider whether this distribution fits our particular sample. Much prior research examines movements between zip codes of census groups or blocks. Thus, no moves of very short distances are resident in the data. By necessity, under those circumstances, fitting to the exponential distribution (or any distribution) is conducted without the benefit of very-short-distance moves. We have finer data in that we use actual street address coordinates. Although the mean move distance is 7.73 miles, a quarter of the moves observed are less than 2.7 miles. Thus, we are in a position to fit the data more precisely than prior researchers have been able to do.

The Kolmogorov–Smirnov statistic quantifies the distance between the empirical data and the hypothesized cumulative distribution function. Given that the mean move distance is 7.73 miles, if the hypothesized distribution of move distances is exponential, the rate parameter ($\alpha = 1$/mean distance moved) is 0.129.

Testing the null hypothesis that the sample is drawn from an exponential distribution with rate parameter $\alpha$ equal to 0.132, The Kolmogorov-Smirnov Goodness-of-Fit test yields a p-value = 0.009. Therefore we must reject that the exponential is the appropriate distribution to use for mean distance
moved. Since move distance is not distributed exponentially, we next consider the more flexible gamma
distribution.³

Assuming that the observed moves are drawn from the gamma distribution, we find parameter
estimates of $\alpha = 0.166$, and shape parameter $\phi = 1.28$. Figure 6 plots the fitted exponential density
function and the fitted gamma density function against the move distance. The mean of the gamma
distribution, $(\alpha^{-1})(\phi)$, is also 7.73 miles.

The move distance corresponds to the length of the X vector in Figure 2, and it is also the value of X in the theoretical distributions from Equation 1 and Equation 2. Notice that the fitted exponential
function (dashed curve) has a modal value of zero. This distribution would suggest that the most likely
move distance for any residential relocation is to the nearest alternative residence – a move to the house
next door. The fitted gamma distribution (the solid curve) produces a modal move 1.7 miles from the
original location. This seems to be a reasonable finding. Rather than changing homes within the same
neighborhood, the gamma function suggests that relocaters are more likely to move to a nearby
neighborhood than immediately next door.

³ The exponential distribution is a constrained form of the gamma distribution with the shape parameter equal to 1.

Figure 6

Exponential vs. Gamma Density Functions

<table>
<thead>
<tr>
<th>Probability Density</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.14</td>
</tr>
<tr>
<td>0.12</td>
</tr>
<tr>
<td>0.1</td>
</tr>
<tr>
<td>0.08</td>
</tr>
<tr>
<td>0.06</td>
</tr>
<tr>
<td>0.04</td>
</tr>
<tr>
<td>0.02</td>
</tr>
</tbody>
</table>

0.0  5.0  10.0  15.0  20.0

Gamma density — Exponential Density
The Kolmogorov-Smirnov Goodness-of-Fit test for the gamma function yields a p-value = 0.356, and we fail to reject the hypothesis that the move distances are drawn from this maximum-likelihood-estimated fitted distribution. Figure 7 graphically compares the goodness of fit for the exponential and gamma distribution. Notice that the smooth theoretical curve for the exponential function lies above the rough “actual” line for move distances less than 5 miles. This means that the exponential function overestimates the number of short-distance moves. For the Gamma distribution, the theoretical curve fits closer to the observed data.

Figure 7

![Exponential distribution goodness of fit](image)

![Gamma distribution goodness of fit](image)

Turning to our tests of move direction, the direction of each move in the sample can be represented by a vector with direction θ whose length is one (unit vector). The use of unit vectors
conforms to the theoretical assumption that move direction and move length are independent. Summing all the sample vectors results in a vector $\mathbf{R}$ where

$$\theta_R = \tan^{-1} \left( \frac{1/n \sum \sin \theta_i}{1/n \sum \cos \theta_i} \right)$$

is a measure of mean move direction. The length of vector $\mathbf{R}$ also reflects the extent of clustering in the sample’s mean direction. This clustering is analogous to the variance in non-directional data.

Standardizing by the number of observations in the sample yields an index $\bar{R}$ with a value between zero and one.

$$\bar{R} = \frac{R}{n} = \frac{\sqrt{(\sum \sin \theta_i)^2 + (\sum \cos \theta_i)^2}}{n}$$

$\bar{R}$ is a function of the concentration parameter $k$ by virtue of

$$\bar{R} = \frac{I_1(k)}{I_0(k)}$$

where $I_0(k)$ is a modified Bessel function of the first kind and zero order.

For the sample of relocating families in the current study, $\theta_R$ equals 0.136 radians, or 7.79 degrees. The clustering index $\bar{R}$ equals 0.522, yielding concentration parameter $k = 1.218$.

For the von Mises distribution parent population when $n$ is large and $k = 0$ the statistic $2n\bar{R}^2$ is approximately $\chi^2$ distributed with two degrees of freedom. For the current test, the value is 95.88 which is far above any reasonable cutoff value ($p=0.05$, cutoff value=5.99). Thus, we reject the null hypothesis of $k=0$ (no bias).

Given a move direction bias, we test the assumption that the move directions are biased toward the school. This test assumes the school is the attractor and tests whether or not we can reject that assumption. The 95% confidence interval around the school direction can be written as

$$0 \pm 1.96/\sqrt{nk\bar{R}}$$

4 See Mardia (1972).
= 0 ± 1.96/\sqrt{(176)(1.218)(0.522)} = 0 ± 0.1853 radians. Because -0.1853 < θ_r < 0.1853, we accept the hypothesis (i.e. cannot reject) that the move directions are concentrated toward the school.

As a point of reference, previous studies by Clark and Burt (1980) and Clark, Huang and Withers (2003) consider workplace attraction. The first paper studied workplace attraction in the Milwaukee metropolitan area. This study found a concentration parameter k=0.638. The second study conducted similar tests to gauge Seattle area work-place attraction and yielded a parameter k=0.668. Notice that the value associated here with school attraction (k=1.218) is significantly larger than previously reported work-place attraction measures.

A. Imputed Probabilities of Toward-School Migration

Conditional upon a family moving, we are interested in assessing the probability that it will move toward the school. Figure 8 provides a simple graphic representation of the question. Given that the family’s original home, R_{Old} is a distance d_o from the school, we are interested in the probabilities that the family will move to a location that is closer to school - the shaded area in the figure.

Figure 8

1. Base case probabilities (k=0)

There is some probability that the family would move closer to the school even if the school were not a relocation attractor. This is the probability when k=0. To obtain this baseline probability, we numerically solve equation 7 for various values of d_o, given k = 0, α = 0.166 and φ = 1.28.
Although each mover must move either closer to the school or farther away from the school, the probability of moving closer is not 50%. For families already living near the school, the probability that they will move closer is small simply because the area inside the circle is small, as previously addressed in the discussion of Figure 1. For \( k = 0 \), \( \alpha = 0.166 \) and \( \varphi = 1.28 \), a family living a mile from the school \((d_o=1)\) only has a 0.055 probability of moving closer. However, for \( d_o=10 \), the probability of moving closer rises to 0.367. Only in the limit does the probability rise to 50%.

2. **Imputed move probabilities** (\( k=1.218 \))

Given the observed attraction that the school exerts, we next reassess the probability that a family will move closer by reevaluating equation 7 for all values of \( d_o \), given \( k = 1.218 \). The parameters \( \alpha \) and \( \varphi \) are unchanged. For families already living a mile from the school, the probability of moving closer nearly doubles, rising from 0.055 to 0.106. For \( d_o=10 \), the probability rises from 0.367 to 0.669.

Although the increase in probability can be estimated for longer initial commutes, only 8% of the movers had initial commutes of over 15 miles. With relatively few actual observations, we are not confident that the imputed probabilities would be meaningful for extreme values of \( d_o \). For example, if we fit the model for \( d_o =100 \), \( P(d_N < d_o) = 0.815 \), but no initial commutes were this long, and it seems likely that the parameters of the fitted gamma distribution would be altered if an observed \( d_o =100 \) had existed.

Figure 9 provides a visual depiction of the increase in \( P(d_N < d_o) \) for \( 1 \leq d_o \leq 15 \) under the baseline assumption (\( k=0 \)) and under the assumption that \( k=1.218 \) as observed from the actual data.
Figure 9
Imputed probabilities \([P(d_N < d_O)]\) for \(k=0\) and \(k=1.218\)

Figure 10 depicts the ratio of \(P(d_N < d_O)\k_{k=1.218}\) to \(P(d_N < d_O)\k_{k=0}\) for \(1 \leq d_O \leq 15\). As noted above, for families already living a mile from the school, the probability of moving closer nearly doubles. Even for families living 15 miles away from the school, the probability of moving closer is almost 1.8 times greater.

Figure 10
Increase in the probability of moving closer to the school
\[
\frac{P(d_N < d_O)\k_{k=1.218}}{P(d_N < d_O)\k_{k=0}}
\]
**B. Further Analysis**

To help the reader more clearly visualize the move pattern of relocating families, we present a rose diagram in Figure 11. Similar to those presented in Figure 5, this rose diagram aggregates moves that occur in common directions into several bins. However, while the diagrams presented in Figure 5 are produced from theoretical von Mises distributions, that depicted in Figure 11 depicts the empirical observations from the data.

Families can move in any direction, and we have segmented the circle into twelve 30-degree bins. The right-most segment is centered on the school so that this bin contains all observations for families moving in a direction within 15 degrees of θ = 0. In order to make the constructed areas proportional to the frequencies, the length of each wedge is proportional to the square root of the number of observations. In this graph, the fraction of the observations represented by the largest wedge is 32.4%, and the fraction represented by the smallest wedge shown is 1.70%. In this framework, the magnitude of the family relocation bias is obvious.

![Figure 11: Move Directions with 12 Bins](image)
Although this study examines how families relocate, the reader will probably take an interest in the ex-ante and ex-post residency patterns for these movers. Figure 12 presents a graph of ex-ante (OLD) and ex-post (NEW) residences of relocating families relative to the school’s location at the center of the graph. The grid is for an area covering 6400 km² (2471 mi²), and it does not include 4 observations that would lie outside the graphs borders (1 “NEW” and 3 “OLD” observations). Notice that the black NEW residences are more tightly clustered than the lighter shaded OLD residences.

**Figure 12:**
**Heat Map of Ex-Ante (Grey-Shaded) and Ex-Post (Black-Shaded) Residence Locations of Movers**

To further evaluate the residency patterns for movers, in Figure 13, we present a graph of the ex-ante and ex-post spatial “footprints” for various percentiles of school commutes by relocating families. The four sets of concentric circles represent the 25th, 50th, 75th and 90th percentiles on both an ex-ante
and ex-post relocation basis, where the grey circle indicates pre-move distance to school (located at the center of the circle), and the dark circle indicates the post-move distance. First consider the largest concentric circles in the lower right corner of the chart. These circles represent the 90th percentiles of commute distances for ex-ante and ex-post of residences. Ex-ante, 90 percent of the moving families lived within 13.5 km of the school. This distance is represented by the large light-shaded circle. Ex-post, 90 percent of the families lived within 10.7 km of the school, as represented by the smaller black circle. The same pattern also exists for the 25th, 50th, and 75th percentiles.

**Figure 13:**
Percent of Moving Households (Ex-Post and Ex-Ante)

<table>
<thead>
<tr>
<th>Percentile</th>
<th>Ex-Ante Pre-Move</th>
<th>Ex-Ante Post-Move</th>
<th>Ex-Post Pre-Move</th>
<th>Ex-Post Post-Move</th>
</tr>
</thead>
<tbody>
<tr>
<td>25th</td>
<td>4.2 km</td>
<td>3.6 km</td>
<td>4.2 km</td>
<td>3.6 km</td>
</tr>
<tr>
<td>50th</td>
<td>7.0 km</td>
<td>6.5 km</td>
<td>7.0 km</td>
<td>6.5 km</td>
</tr>
<tr>
<td>75th</td>
<td>10.7 km</td>
<td>13.5 km</td>
<td>10.7 km</td>
<td>13.5 km</td>
</tr>
<tr>
<td>90th</td>
<td>22.6 km</td>
<td>15.6 km</td>
<td>22.6 km</td>
<td>15.6 km</td>
</tr>
</tbody>
</table>

Notice that density does not increase substantially in the 25th and 50th percentiles. However, at the 75th and 90th percentiles the families exhibit a clear preference to avoid longer commute distances. This finding is similar to what others have observed concerning preferences for home-to-work commutes: concerning short commutes “there is an ‘indifference zone’ within which commuters are relatively indifferent to access to work (Clark et al. (2003).”
It is worth emphasizing that 77 of the 176 families actually moved away from the school. The
tighter ex-post circles point to the fact that those moving away appear to have stayed relatively close
while those moving closer moved a greater distance.

Concerning these move distances, we have also calculated the mean distance moved by the
families in each bin shown in Figure 11. The mean move distances are graphically depicted in Figure 14,
with the values for the mean and standard deviations shown below the figure.

Figure 14:
Move Distances for 12 Bins

<table>
<thead>
<tr>
<th>group</th>
<th>mean</th>
<th>std</th>
<th>n</th>
</tr>
</thead>
<tbody>
<tr>
<td>&lt;15&amp;&gt;345</td>
<td>11.2622</td>
<td>10.21312</td>
<td>54</td>
</tr>
<tr>
<td>15-45</td>
<td>6.841459</td>
<td>5.331118</td>
<td>28</td>
</tr>
<tr>
<td>45-75</td>
<td>7.466875</td>
<td>8.153274</td>
<td>17</td>
</tr>
<tr>
<td>75-105</td>
<td>3.645407</td>
<td>2.113573</td>
<td>11</td>
</tr>
<tr>
<td>105-135</td>
<td>4.283388</td>
<td>4.50675</td>
<td>5</td>
</tr>
<tr>
<td>135-165</td>
<td>3.08801</td>
<td>3.811275</td>
<td>5</td>
</tr>
<tr>
<td>165-195</td>
<td>1.692871</td>
<td>1.131968</td>
<td>4</td>
</tr>
<tr>
<td>195-225</td>
<td>4.719975</td>
<td>2.542676</td>
<td>9</td>
</tr>
<tr>
<td>225-255</td>
<td>2.829729</td>
<td>1.149862</td>
<td>3</td>
</tr>
<tr>
<td>255-285</td>
<td>3.343041</td>
<td>1.348591</td>
<td>8</td>
</tr>
<tr>
<td>285-315</td>
<td>8.121195</td>
<td>5.655127</td>
<td>7</td>
</tr>
<tr>
<td>315-345</td>
<td>8.644745</td>
<td>6.705769</td>
<td>25</td>
</tr>
</tbody>
</table>
The group names in the legend reflect the geographic bounds on each bin. The bounds are identical to those used to construct Figure 11. The first group is for movers in the direction of the school which includes moves between $+15^\circ$ to $-15^\circ$ (345 degrees). This group is labeled as “group $<15^\circ & >345$”. The bins in the table are listed in a counter-clockwise direction from the school.

Causal observation suggests that families moving toward the school move much farther, on average, than those moving away. The mean distance moved toward the school is 11.3 miles, and the mean distance moved directly away from the school is only 1.7 miles. (Group 165-195 is centered on 180 degrees from the school.) More rigorously, based on a small ANOVA test p-value ($p =.0052$), we conclude that the distance moved is affected by the direction, and the assumption that distance and direction are independent does not hold.

### C. Assessing the Direction of Causality

The previous sections of this paper document that families who enrolled a child in this charter school tend to subsequently relocate closer to the school at an unexpectedly high rate. The presumption has been that the correlation is confirmation of the school as a relocation magnet. However, it is possible that the direction of causality is actually in the opposite direction. It is possible that families are applying to the school because they already intend to move close to the school. It is also possible that the direction of causality flows in both directions: some families apply because they plan to move closer, and other families move because they have been accepted already. In this subsection we will attempt to assess the direction of causality by (1) considering the timing of moves by families, relative to admission, (2) by surveying moving families to inquire as to their motivations, and (3) by considering parental work locations, the most likely alternative attractors for moving families.

**Quick vs. Slow Movers**

We are fortunate to have survey data available for a subset of moving families. This survey data allows us to identify the year in which 89 of the 176 moving families changed addresses.
Additionally, 85 of these 89 families provided parent work histories that are sufficient for us to identify where one or both parents worked at the time they moved.

In the first test, we split the sample into two groups: families which move shortly after being admitted, and those who wait more than 6 months before moving. To the extent that families are motivated to apply to the charter school because they expect to move toward the school anyway, we should see a high concentration parameter for “quick movers”. “Slow movers” who take more than 6 months to relocate are more likely to be moving because they were already accepted to the school, then the school attracted them closer. If the concentration parameter is high for these movers, it suggests that the direction of causality runs in the direction we have previously hypothesized.

We will refer to the alternative θ values in this section as θ_quick and θ_slow. Concentration parameters will be referred to as κ_quick and κ_slow.

<table>
<thead>
<tr>
<th>Table 4: Quick vs. Slow Movers</th>
</tr>
</thead>
<tbody>
<tr>
<td>Theta (degrees)</td>
</tr>
<tr>
<td>95% Lower Limit</td>
</tr>
<tr>
<td>95% Upper Limit</td>
</tr>
<tr>
<td>Confidence Interval Range</td>
</tr>
<tr>
<td>Kappa</td>
</tr>
<tr>
<td>Test statistic</td>
</tr>
<tr>
<td>Reject no bias cutoff = 5.99</td>
</tr>
<tr>
<td>Obs.</td>
</tr>
</tbody>
</table>

The first column of Table 4 reports results for the 15 responding families who moved within 6 months of admission. These families had a mean move direction of 4.1° and a concentration parameter κ_quick = 4.253. The magnitude of κ_quick is surprisingly large, and it is consistent with the hypothesis that these families already intended to move closer to the school before their child was admitted. In
untabulated results, 31 families reported moving within 18 months of their child being admitted to the school (16 additional families). For this 31-family group, $\kappa = 2.143$.

The slow-to-move families (those moving more than 6 months after admission) have a concentration parameter $\kappa_{\text{Slow}} = 1.470$, which is also statistically significant. The behavior of these families is consistent with the school serving as a relocation attractor. For reasons we cannot explain, the families who did not respond to the survey have a lower $\kappa$ value than those who responded.

Overall, we interpret the results in Table 4 as indicating that the direction of causality flows in both directions: some families apply because they plan to move closer, and other families move because they have already been accepted.

\textit{Survey of Mover Motivations}

In a separate online survey, we asked families what motivated their moves. The survey asked only two questions:

- Did you apply to (the school) because you already expected to move closer to (the school) anyway?
- When you decided to move, did you consider your shorter commute distance to the school as one of the factors?

A total of 36 families responded to this survey. We tabulate the responses as Table 5.

\textbf{Table 5: Survey of Mover Motivations}

<table>
<thead>
<tr>
<th>Did you apply to (the school) because you already expected to move closer to (the school) anyway?</th>
</tr>
</thead>
<tbody>
<tr>
<td>Answer Options</td>
</tr>
<tr>
<td>-----------------</td>
</tr>
<tr>
<td>Yes</td>
</tr>
<tr>
<td>No</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>When you decided to move, did you consider your shorter commute distance to the school as one of the factors?</th>
</tr>
</thead>
<tbody>
<tr>
<td>Answer Options</td>
</tr>
<tr>
<td>----------------</td>
</tr>
<tr>
<td>Yes</td>
</tr>
<tr>
<td>No</td>
</tr>
</tbody>
</table>
We interpret the results in Table 5 as suggesting that while some families expected to move to the area before they applied to the school, most families did not. Moreover, a significant minority of the moving families consciously considered the family’s home-to-school commute when they moved.

D. Workplace vs. School Attraction

Finally, we examine the magnitude of parent-work-place attraction for the moving families. We do this for two reasons. First, since we are considering move causality, it makes sense to consider the most-important alternative family-specific factors that might be relevant. Second, measuring work-place attraction for this sample allows us to consider whether the families in this study otherwise behave in a “normal” manner. In other words, have these families’ movements been consistent with what has been previously observed and documented relative to work locations as studied by Clark and Burt (1980) and Clark, Huang and Withers (2003).

To address this question, we return to the original survey referenced in the “Quick vs. Slow Movers” subsection. Eighty-nine families responded to the survey, and 85 of these responses provided adequate data to assess relevant work addresses for one or both parents. The surveys requested information about (1) how long the family had lived at the current address, (2) how long the mother (and/or father) worked at their current employment address, (3) the street address where parents were employed, and (4) the previous street address where parents were employed. From this data we are able to determine where a parent was working at the time they moved to their new (current) residence. We then repeat the procedures used to develop $\theta_R$ and $\kappa$: calculating $\theta_R$ angles relative to the school, the mother’s work location, and the father’s place of employment. We will refer to the alternative $\theta_R$ values in this section as $\theta_{\text{School}}$, $\theta_{\text{Mother}}$ and $\theta_{\text{Father}}$. Concentration ratios will be referred to as $\kappa_{\text{School}}$, $\kappa_{\text{Mother}}$ and $\kappa_{\text{Father}}$, respectively.

Of the 85 respondents, 55 reported that the mother worked outside the home at the time of the relocation. There were 59 fathers working outside the home at the same time. Several families reported
that only one parent lived in the home, but we have not incorporated this information into the analysis.

Results are shown in Table 6.

**Table 6: School vs. Work Attraction**

<table>
<thead>
<tr>
<th></th>
<th>School</th>
<th>Mother Work</th>
<th>Father Work</th>
</tr>
</thead>
<tbody>
<tr>
<td>Theta (degrees)</td>
<td>9.8°</td>
<td>-12.6°</td>
<td>-19.9°</td>
</tr>
<tr>
<td>95% Lower Limit</td>
<td>-1.7°</td>
<td>-40.1°</td>
<td>-90.5°</td>
</tr>
<tr>
<td>95% Upper Limit</td>
<td>20.6°</td>
<td>11.5°</td>
<td>38.4°</td>
</tr>
<tr>
<td>Confidence Interval</td>
<td>22.3°</td>
<td>51.6°</td>
<td>128.9°</td>
</tr>
<tr>
<td>Kappa</td>
<td>1.485</td>
<td>0.867</td>
<td>0.386</td>
</tr>
<tr>
<td>Test statistic</td>
<td>59.999</td>
<td>17.405</td>
<td>4.236</td>
</tr>
<tr>
<td>Reject no bias cutoff</td>
<td>Yes</td>
<td>Yes</td>
<td>No</td>
</tr>
<tr>
<td>Obs.</td>
<td>85</td>
<td>55</td>
<td>59</td>
</tr>
</tbody>
</table>

Of the 85 families for which we have survey data, the mean $\theta_{\text{School}}$ value is 9.8°. A 95% confidence interval centered on this value spans 22.3° and brackets the origin at $\theta=0$. Thus, for this subsample, we once again fail to reject the hypothesis that families are moving toward the school. The concentration parameter, $\kappa_{\text{School}}$ ($\kappa_{\text{School}} = 1.485$) is greater than zero and the $\chi^2$ test again rejects the null hypothesis of $\kappa_{\text{School}} = 0$. Although the kappa value is higher for this surveyed subset than for the full sample, the $\chi^2$ test statistic is lower, reflecting fewer observations. The $\kappa_{\text{School}}$ value for the full population is not statistically different from the subsample $\kappa_{\text{School}}$ reported here.

Regarding the attraction of mothers’ work locations, the mean $\theta_{\text{Mother}}$ is -12.6°, and the $\kappa_{\text{Mother}}$ concentration parameter is 0.867. Due to fewer observations and lower concentration, the confidence interval for $\theta_{\text{Mother}}$ spans 51.6°. Again, we cannot reject that families are moving toward mothers’ work locations, and the concentration parameter is very close to that found for women in Seattle by Clark, Huang and Withers (2003). In that study the $\kappa$ value for women was found to be 0.831.

Clark, Huang and Withers (2003) found the concentration parameter for men to be 0.536, but we find a $\kappa_{\text{Father}}$ of only 0.386 in our analysis. In fact, the $\chi^2$ test statistic of 4.236 is less than the 95% cutoff of
5.99, and we cannot reject the hypothesis $H_0: \kappa_{\text{Father}} = 0$. Thus, we cannot reject the idea that these families have no bias toward the fathers’ work locations.

We also compare within this sample these $\kappa_{\text{School}}$, $\kappa_{\text{Mother}}$ and $\kappa_{\text{Father}}$ values. We utilize a bootstrap resampling approach. In the bootstrap approach we treat the observed values as the sampling population and take repeated samples from the population. Using these repeated samples we calculate the statistic of interest and observe its variation from bootstrap sample to sample. We use this variability estimate as the estimate of our standard error.

Thus, when testing for the difference between $\kappa_{\text{School}}$ and $\kappa_{\text{Mother}}$, we take a random sample with replacement of size 85 from the home-to-school thetas as well as a random sample with replacement of size 55 from the home-to-mother’s-work thetas. Using this sample we estimate $\kappa_{\text{School}}$ and $\kappa_{\text{Mother}}$ and then calculate their difference. We repeat this sampling process 10,000 times, then calculate the standard deviation of the differences. We find the bootstrap-sample means to produce a near-normal distribution. Using this standard deviation and reasonably-assumed normality, we calculate a confidence interval for the difference in $\kappa$ values. The confidence interval can be used to test the hypothesis that $\kappa_{\text{School}}$ and $\kappa_{\text{Mother}}$ are significantly different.

The findings: at a 10% significance level, we find that $\kappa_{\text{School}} > \kappa_{\text{Mother}} > \kappa_{\text{Father}}$. An important implication of this analysis is that it extends the finding of Clark, Huang and Withers (2003) that women’s job locations are a stronger relocation draw than men’s work locations. We find that the children’s school is a stronger draw than either, even without the presence of a geographic catchment zone.

V. Caveats Concerning Generalizing the Results

This study provides a conceptual foundation for considering environmental implications of school choice plans. However, the data considered is provided by a single North Carolina charter school. Careful interpretation requires that we consider what factors may be unique to this school, and which are likely to be generalizable.
First, it is possible that this school is located in an area that is unusually attractive to families. If so, movement toward the school may be a function of available amenities rather than the school itself. At a minimum, the absence of “negative amenities” may augment the school’s attractiveness. If the school were located next to hazardous waste site (It is not.), we would certainly expect that the school would exhibit a less powerful attraction. Nothing in this study allows us to gauge the direct relative attraction of this school against other nearby attractors. We can say that this school appears to be more attractive to families than work locations in Seattle and Milwaukee as documented in prior studies.

A second factor that seems likely to be important to the school’s attraction is that this school enrolls students from kindergarten through 12th grade. It also gives admission preference to the families of current students. Both of these policies seem likely to lead to greater family attraction because they create greater family-school stability.

A third factor which may impact the school’s attraction is the financial stability of the school itself. This charter school was founded by a successful businessman who has also founded other successful private schools. Families who were aware of this fact probably recognized that the school was likely to succeed, both academically and financially. A school with a short history, founded by a sponsor without a legacy of financial and/or academic success might be less likely to produce similar environmental impacts.

Fourth, while there is reason to believe that other types of schools may produce qualitatively similar attractions, the magnitude of the attraction might be greater for an independent charter school than for a private school or a “magnet school” which is operated by an elected school board. Unlike a private school, this school is publicly funded and charges no tuition. Because the school is free, families may perceive that their connection to the school is likely to be more permanent than would be the case with a private school. Private school parents must continue to pay fees to retain the services of the school. Recognizing this cost of continuing the relationship, private school families may view their long-term connection to a private school as more uncertain. If so, we would expect the enrollment in a charter school to be more stable, and the attraction level to be greater.
Various school districts also utilize “magnet” programs which allow families to enroll children in district-operated schools of their choice. It is an open question whether these magnet schools would exert environmental effects that are quantitatively similar to the subject school. The sometimes transitory nature of school-district policy may suggest otherwise. For example, in Wake County, North Carolina, where this school is located, the election of a new school board in 2009 led to uncertainty about the fate of the district’s magnet programs. Students attending charter schools (or private schools) are probably less subject to political uncertainties that might undermine a family’s long-term commitment to the school. In a sense, having a property right that allows all of a family’s children to attend the school is likely to provide greater school-family stability than can be achieved when each school-board election may usher in new assignment policies. Districts with hotly contested school board elections may have a particularly difficult time achieving the level of stability that will lead to strong levels of family attraction for their magnet schools.

Fifth, the quality of surrounding “traditional” public schools may have an impact on the success of a charter school, and the magnitude of its impact on the surrounding area. In general, the Wake County N.C. schools are considered to be the best in the state of North Carolina. However, school assignment policy in Wake County has been designed to increase within-school diversity and to minimize between-school diversity. We offer no hypothesis concerning how our results would be impacted if the near-by traditional public schools’ quality is unusually poor (or good). Addressing this question would require an examination that includes data from multiple charter schools.

Further study involving alternate locations, differing school finance mechanisms (e.g. public funding vs. private), and alternative school governance/stability formats is needed to fully understand the environmental effects that various school-choice alternatives may produce.

VI. Conclusion

This study is a first effort at developing a conceptual foundation for considering environmental implications of school choice plans. More narrowly, we develop a model of move distance (distributed
gamma) and direction (distributed von Mises) to predict family relocation choice, relative to school location. The model is parameterized using data from student mailing-address changes. The fitted data suggest that families attending the school in question are almost twice as likely to relocate toward the school than could be expected if the school did not exert any attraction. Because move distance and direction in the sample are not independent, the theoretical model probably underestimates the true magnitude of the school’s attraction. This result may have important implications for the potential role of charter schools and other non-catchment-area based school choice plans (such as private school tax credits, vouchers, and magnet school programs) in mitigating urban sprawl, fostering urban renewal, and promoting sustainable real estate development.

This study has implications even where various forms of school choice already exist. For example, Milwaukee’s voucher program excludes students from families with incomes above 175% of the federal poverty level; $37,439 for a family of four in 2008-09. The threshold is apparently intended to focus resources on students from poor families. However, an unintended consequence of restrictive eligibility may be to further concentrate poor families in the inner city, while middle-class families relocate to the suburbs. When one considers the greater environmental impact of the voucher policy, a better design might allow wealthier families, including suburban families not resident in Milwaukee, to enroll. Subsequent migration into the city by these suburban families would produce environmental externalities that are usually considered to be positive in terms of reducing sprawl, reducing pollution, and promoting urban renewal.
References:


