

# Arts-Based Charter Schools as Urban Redevelopment Catalysts: Santa Ana, California's Orange County School of the Arts

(working paper)

Dr. Bartley R. Danielsen  
*North Carolina State University*

Dr. David M. Harrison  
*Texas Tech University*

Dr. Jing Zhao  
*North Carolina State University*

This project was supported in part or in whole by an award from the *Research: Art Works* program at the National Endowment for the Arts: Grant# 14-3800-7010.

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This draft:  
June 15, 2015

## **Abstract**

*This study examines the impact that the Orange County School of the Arts (OCSA) has had on the relocation decisions of families whose child attends the school. The school draws students from a relatively wide geographic area, and it exerts a strong attractive power on enrolled families.*

*Families who live near the school (in Santa Ana, California) are substantially less likely to relocate than families who live farther away. Hundreds of families (669) have moved closer to Santa Ana after enrolling a child in the school, and a substantial fraction (97 families) moved from a non-Santa Ana address into the city. While students matriculate into the school in grades 7 through 12, the attraction seems to be particularly strong for families enrolling a child at the beginning of the 9th grade. The reasons for the high level of attraction for 9th graders are unclear.*

*This finding calls for further research since it may have implications for how school-choice programs in general, and arts-based programs in particular, should be structured when one of the policy goals is to catalyze redevelopment of the urban environment.*

Contact Author:  
Dr. Bartley R. Danielsen  
North Carolina State University  
Raleigh, NC 27695-7229

919.513.0003 (v)  
brdaniel@ncsu.edu

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## **Executive Summary**

Conventional wisdom holds that families move into specific neighborhoods so that their children can attend their preferred schools. However, the opposite can also be true: families with children in charter schools might find it convenient to move closer to the schools, even though they don't have to.

“Arts-Based Charter Schools as Urban Redevelopment Catalysts: Santa Ana, California's Orange County School of the Arts” is a case study of the impact that the Orange County School of the Arts (OCSA) has had on the relocation decisions of families whose child attends the school. The school draws students from a relatively wide geographic area, and it exerts a strong attractive power on enrolled families. Since OCSA's establishment as a charter school in Santa Ana, the school has grown substantially. The area around the school has been revitalized. New businesses have opened nearby, and the local crime rate has fallen dramatically.

To place this research in proper context, it's important to provide some background on the school. OCSA is a public charter school for grades 7 through 12, and it emphasizes various arts training programs as well as a conventional academic curriculum. In 2000, the school moved to Santa Ana, which was one of the least financially prosperous communities in Orange County. Santa Ana's attractive feature to OCSA was the very low rental rates available in vacant downtown space.

Santa Ana's traditional public schools do not generally attract families with children. For example, as compared to the whole of Orange County, approximately 11 percent fewer elementary-school age children reside in Santa Ana than should be expected, given the number

of pre-school children. That is the lowest percentage in Orange County, and one of the lowest in Southern California. While OCSA is not an elementary school, this statistic tells us something about the perceived quality of public schools in the city.

In contrast to traditional public schools that draw students only from a prescribed catchment area, OCSA accepts students regardless of where they live – school district boundaries don't come into play. This is typical of charter schools across California, and it is the norm for many charter schools across the country also. Because the school operates without a catchment zone, students and their families can relocate without being forced to withdraw from the school. To evaluate the impact of the school on family relocation decisions, we examined home residence data of 7,002 students who attended OCSA between the 2000-2001 school year and the 2013-2014 school year. Families who live near the school (in Santa Ana, California) are substantially less likely to relocate than families who live farther away.

We find that 1,217 families moved during the period studied, and their moves were strongly biased toward the school. Figure 4 presents a rose diagram showing family moves. The areas shown in each segment of the diagram are proportional to the number of students who have relocated in any particular direction, relative to their original address at the center of the diagram. OCSA's location is shown at the "0" location on the circle. The fraction of relocating students who moved in a direction within 15 degrees of the school is shown by the largest wedge, which contains 21.4% of the observations. If moves were not biased toward the school, only 8.3% of the moves would be represented in each wedge. The magnitude of the school's attractive power can be expressed by a statistical measure called the "concentration parameter." If there were no attraction exerted by the school, the concentration parameter would be zero, and each slice would

be the same size. In Figure 4, the concentration parameter ( $\kappa$ ) is 0.6184. This concentration is very similar to that previously found for work places.

**Figure 4** Move Directions with 12 Bins

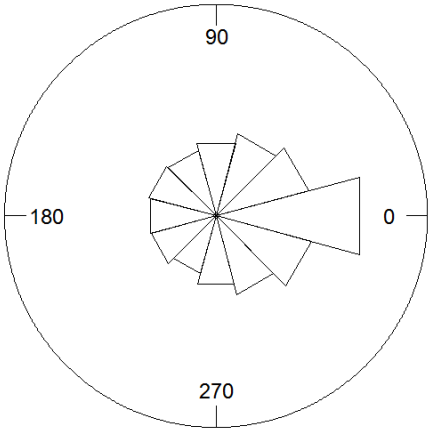
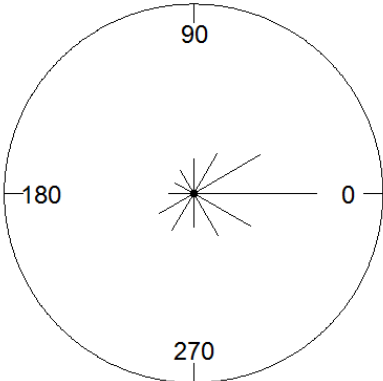


Figure 5 shows that students who moved toward the school were also likely to move farther than students who moved in other directions. The length of each line segment in Figure 5 is proportional to the average move distance for each cohort.

**Figure 5** Move Distances for 12 Bins



While students matriculate into the school in grades 7 through 12, the attraction seems to be particularly strong for families enrolling a child at the beginning of the 9th grade. Figure 6 shows the concentration parameter estimates for each enrollment grade.

**Figure 6** Concentration Parameter Estimates by Grade

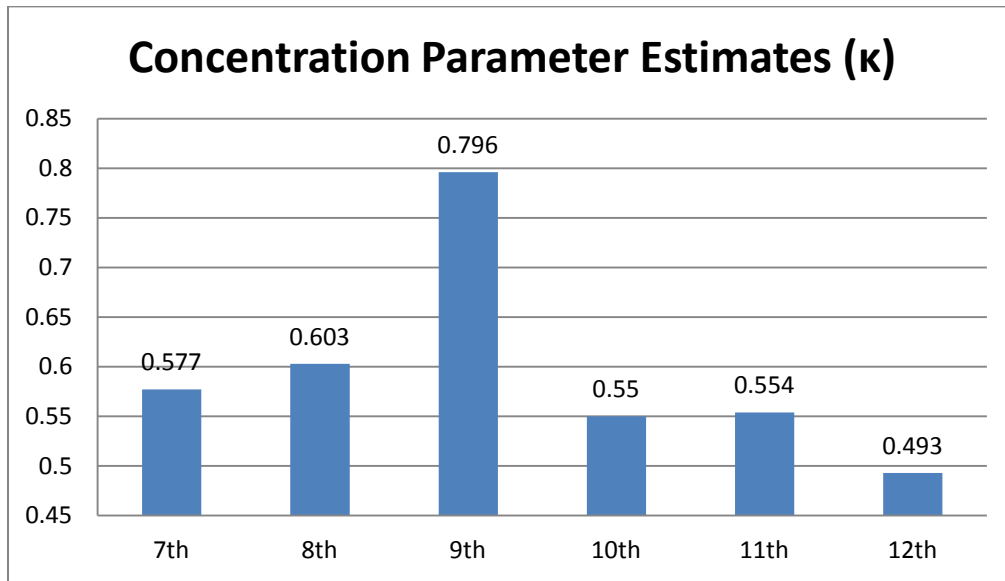
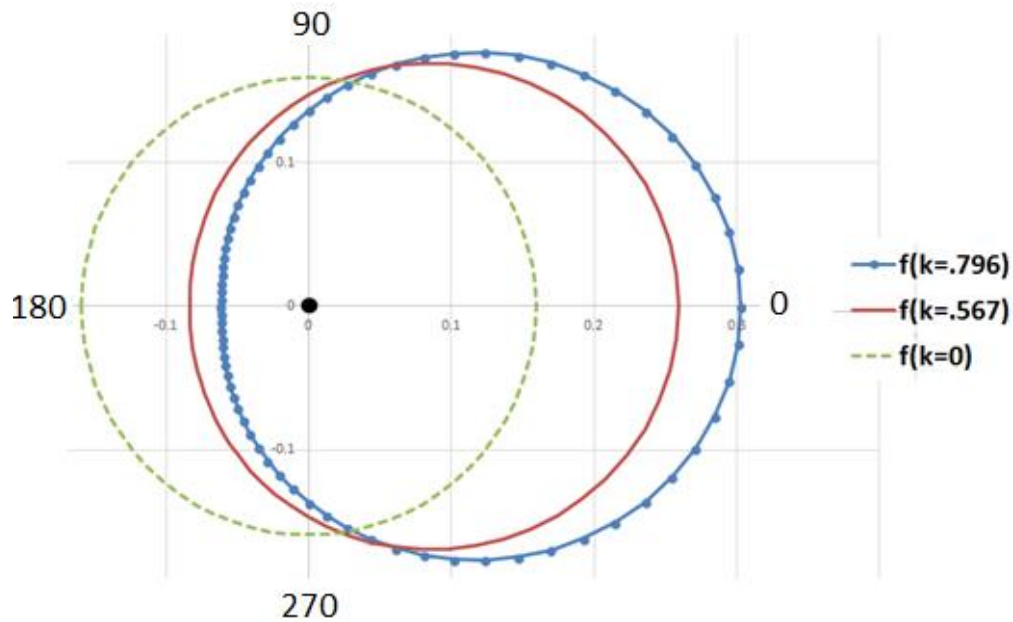


Figure 8 presents a continuous version of Figure 4. The rose diagram in Figure 4 has only 12 bins, but if there were several hundred bins, the diagram would take on an elliptical shape like the ones in Figure 8. The three ellipses are for students who enrolled as 9<sup>th</sup> graders [  $\rightarrow f(k=.796)$  ], non-9<sup>th</sup> graders [  $\rightarrow f(k=.567)$  ], and for a hypothetical distribution of “no bias” [  $\rightarrow f(k=0)$  ].

**Figure 8** Elliptical Density Functions for 9<sup>th</sup> Graders and non-9<sup>th</sup> graders



Overall, the level of attraction exhibited by OCSA must be viewed as relatively high. There are almost 2000 students, and several hundred employees who commute to downtown Santa Ana on a daily basis. The city would certainly view attracting an approximately 2500-employee firm downtown as a positive development for the city. Since the school exhibits a family attraction level similar to that previously found for employers, this may be an appropriate analogy. From an economic development perspective, it is worth noting that OCSA's arts focus may make it unusually attractive. During "after hours" when most schools are closed, OCSA students are engaged in over 150 performances and events each year. These performances draw students, families, and patrons back into the city where they also visit restaurants and other businesses.

While it is likely that non-arts-based charter schools are also developmentally attractive, cities seeking to foster economic development might find arts-based charter schools to be particularly impactful due to their after-hours spill-over effects in the community.

# Arts-Based Charter Schools as Urban Redevelopment Catalysts: Santa Ana, California's Orange County School of the Arts

## Introduction

Orange County School of the Arts (OCSA) is a 7th–12th grade public charter school located in downtown Santa Ana, Orange County, California. The school caters to middle and high school students with talents in the performing, visual, literary, and culinary arts. The educational program prepares students for higher education and professions in the arts.

Santa Ana is a highly unlikely location for a successful arts-based charter school. Santa Ana can be fairly characterized as a poorer, somewhat economically depressed, Hispanic city located in the middle of Orange County, a generally wealthier set of communities.

However, OCSA located in Santa Ana because it received early political support from the mayor and other local figures who expressed enthusiasm for arts-based education. The school also received financial assistance from the state of California which viewed the school's relocation to Santa Ana as an appropriate "infrastructure project" designed to revitalize Santa Ana's underutilized downtown area. The political and financial support made locating OCSA in Santa Ana feasible.

OCSA's appeal to applicants is primarily due to the unique educational environment that is offered by an arts-focused school. Academic programs run from 8:05 until 2:10 each day, and the academic elements of the school are rigorous. In 2009, 99% of OCSA students continued their education in college. However, from 2:15 until 4:50 each day, OCSA students participate in one of thirteen focused arts conservatories.

- Classical and Contemporary Dance
- Classical Voice
- Commercial Dance



- Creative Writing
- Culinary Arts and Hospitality
- Digital Media
- Film & Television
- Instrumental Music
- Integrated Arts
- International Dance
- Music and Theatre
- Production and Design
- Visual Arts

These conservatories offer aspiring artists an opportunity to refine their skills and flourish in a supportive artistic environment.

Because of the unique programmatic offerings at OCSA, over 1900 students are currently enrolled from more than 100 cities in Southern California. This broad geographic reach is significantly greater than would be observed in a general-education charter school. This also suggests that OCSA is likely to be a stronger family relocation draw than other charter schools might be.

The underlying purpose of this study is to document the magnitude of the “community creating” power of OCSA, and, by implication, the likely impacts of other “schools of the arts” in revitalizing urban areas. Urban redevelopment resources are frequently focused on for bringing jobs and affordable housing to downtown areas. However, Santa Ana’s experience suggests that arts-oriented schools may be even more powerful redevelopment tools. In order to effectively make this case, however, metrics need to be developed and tested. The measure provided by Danielsen, Harrison and Zhao (2014) is well suited to this task because it uses a “statistically powerful” test.

The research questions that are addressed in this study can be summarized as follows:

- Does an arts-based charter school attract families closer to the school's location?  
(a sign of economic stimulus to the area)
- If so, to what degree are relocations biased toward the school?

These questions are important both for attracting general funding support for arts-based schools and for informing urban redevelopment and design efforts.

### **Literature Review:**

Over the last several years, numerous papers have begun to document the impact of various “school choice” programs, such as charter schools and voucher programs on surrounding communities. In particular, studies have considered the potential impact of these school choice programs on residential property values. While we briefly summarize this literature here, we refer the reader to Danielsen, Fairbanks and Zhao (2014) for a more complete discussion of this topic.

Charles Tiebout's seminal paper describing the effects of catchment-area-based school assignments led to an early understanding of how school zones result in a spatial sorting that separate wealthier families from poorer families. The wealthier families enjoy better-funded and more successful schools paid for by higher property taxes. As observed in practice, Tiebout sorting is often referred to as people “voting with their feet”. A series of theoretical and simulation-based papers by Thomas Nechyba [ Nechyba (1999), Nechyba (2000), Nechyba (2003) ] and later Ferreyra (2007) investigated how systems that allowed families to choose schools other than an assigned public school could break down the sorting equilibrium and create areas with greater economic diversity (heterogeneity). This theoretic insight led to numerous empirical papers finding that school choice programs raise relative property values in otherwise

economically depressed areas. For examples see Walden (1990), Reback (2005), Fack and Grenet (2010), Machin, and Salvanes (2010), Merrifield, King-Adzima, Nesbit and Gunasekara (2011), Brunner, Cho, and Reback (2012), Shapiro and Hasset (2013), Schwartz, Voicu and Horn (2014), Cannon, Danielsen and Harrison (2014). A single study by Horowitz, Keil and Spector (2009) found no effect for charter elementary schools and a negative effect for charter (and noncharter) high schools in Dayton, Ohio.

Danielsen, Fairbanks and Zhao (2014) review both the theoretical and empirical literature relating to the impact of school choice programs, particularly voucher programs, on residential property values. Beginning with the seminal works of Charles Tiebout (1956) and Thomas Nechyba (1999, 2000, 2003), they describe the sorting equilibrium theories that arise in the context of public school assignments based strictly on geographic catchment areas. They then consider the implications of allowing students to attend schools other than those to which they are assigned, particularly in a school voucher context. Finally, they review the empirical tests of these theories. The important concepts that emerge from that analysis is that while assigned schools lead to a separating equilibrium that results in segregation of communities on the basis of income, school quality and property values, school choice programs undermine this separating equilibrium by severing the link between place of residence and school assignment.

Of more specific application to the case of the OCSA charter school, Danielsen et al. (2014) examine residential relocation of families whose children attend a K-12 charter school in Wake County, North Carolina. They develop a conceptual model that predicts where relocating families are likely to move, given ex ante distance and direction to the school. Their model is parameterized using data from student mailing address changes. They found that families are almost twice as likely to relocate toward the school as would be expected if the school did not

exert any attraction. Many of the techniques used in this study are based upon those developed in Danielsen et al. (2014). Although OCSA is also a charter school, many of the characteristics of the school differ from the school studied in Danielsen et al. (2014).

### **Contributions of This Paper**

The Orange County School of the Arts has a curricular and extracurricular focus on training students in the arts, as broadly defined. Because OCSA has a relatively highly-focused mission, it draws applicants from a wide geographic area. Students who have enrolled in OCSA may need to commute over relatively long distances to attend school. As a result, families may find it convenient to relocate in a manner that reduces these commutes. If so, it seems very likely that the school's impact on urban development might be quite significant. The method used in this paper allows us to compare the relocation-attractive power to previous studies that have measured charter school and work-place attraction. We find that the school exerts a strong and statistically robust attraction on students' families, and an unusually strong attraction on the families of children enrolling in the 9<sup>th</sup> grade.

## **Data, Hypothesis and Descriptive Interpretations**

Our data are provided by the Orange County School of the Arts. The data covers school years from 2000-01 to 2013-14. The data set includes students who have been admitted for the subsequent year, except for the 2014-15 data. Each student is identified by a student ID number. Other than the grade level and the address of record for each student, we do not have access to other information. We do not know the name or gender of any student, and we have no information regarding the academic success of the student before, during or after enrollment at the school.

Admission to the school is competitive. Approximately 2000 students apply to the school each year, and approximately 500 students are accepted. Students must qualify academically to be considered for admission. The current standard for admission is that the student's most recent (semester or trimester) report card must have no "F" grades and a minimum academic G.P.A of 2.0 or better. However, once the student satisfies this minimum academic threshold, the student is allowed to audition for one (or more) of the school's conservatories. OCSA states that "acceptance is primarily based upon the audition results." While siblings may attend the school, unlike most charter schools, attendance by a sibling does not assure preference in the admission process.

The data that we have collected identifies 7002 students for which we have at least one home address observation. The school's data on each student includes a single mailing address for each school year. We can identify the first school year for which a student's address exists in the dataset, and this year is deemed to be the student's last grade attended before enrolling at OCSA. This is the address at the time of application. Consistent with this assumption, while the school includes grades 7-12, there are 165 students listed as 6th graders in the 2012-2013 school year data. In a data run conducted in early 2014 (before new applicants were admitted for 2014-15) 163 of these 165 students were listed as 7th graders. There were also 5 students listed as 7th graders who did not appear as 6th graders in the prior year. We presume that these students completed the enrollment process after the end of their 6th grade school year, rather than during their 6th grade year.

For the 5 students in 2013-14 who entered the dataset for the first time as 7th graders, our system will misclassify these students as admitted in their 7th grade year and enrolled in their 8th grade year. For all other years and grades, it is impossible for us to identify such data errors.

For every year, we only observe one address, and we have no details about when the enrollment process was completed. If a child enters the data set identified as an 8th grader, we presume that he/she actually did not enroll until 9th grade. Assuming that the 7th grade class of 2013-14 is representative, our system correctly classified 163 of 168 7th graders as applying in the prior year, and the accuracy rate is 97%.

After the student is admitted, we observe changes in mailing addresses annually. If the student moved multiple times during the year, we cannot identify this behavior. We are also unable to determine exactly when a student moved. All addresses are presumed to be the student's physical residence. However, for some of our tests we presume that reported addresses that are very far from the school cannot be actual "home" for the student during the school week. For example, if a student's address is in San Francisco, which is more than 400 miles away from Santa Ana, it is probably impossible for that student to actually be residing in the reported address. Instead, the student probably has a parent residing in San Francisco, but the student resides with another relative or friend during the week. In any event, to prevent these outliers from biasing our results, for many tests we exclude students with addresses more than 50 miles away from the school. In some cases this probably improperly excludes students who applied to the school while living far away but who then moved near to the school after enrollment. Excluding these students will tend to underestimate the attraction exerted by the school.

We used ArcGIS Online from Esri to geocode the location of each address. We also geocoded 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. The attribute data table of each point contained the record ID, student address, and geographic latitude/longitude coordinates.

Finally, we used the "Calculate Movement Parameters" tool within Hawth's Tools, a third-party ArcGIS Desktop extension, to calculate the linear distance from each address to the school. Bearing and turn angle metrics are also calculated, which are discussed later in the paper. Hawth's Tools are designed specifically for ecology-related analyses such as this.

Table 1 presents summary statistics on the original linear distance between the school and the families whose children were admitted. The average distance is 20.05 miles while the median is 9.45 miles. When we focus on presumably the local families (i.e., with original linear distance of less than 50 miles from the school), the average distance reduces to 10.76 miles and the median becomes slightly shorter at 9.35.

**Table 1:** Original Linear Distance in Miles from Home to School for Enrolled Students

| Summary Statistics | Original Linear Distance<br>(in miles) | Original Linear Distance<br>(obs. w/ distance<=50) |
|--------------------|--|--|
| Mean               | 20.05                                  | 10.76  |
| Std. Dev.          | 129.81                                 | 7.28   |
| Q1                 | 0.74                                   | 0.72   |
| Q5                 | 1.58                                   | 1.57   |
| Q25                | 5.75                                   | 5.70   |
| Median             | 9.45                                   | 9.35   |
| Q75                | 14.96                                  | 14.74  |
| Q95                | 26.85                                  | 24.94  |
| Q99                | 61.73                                  | 35.38  |
| Min                | 0.11                                   | 0.11   |
| Max                | 2780.08                                | 49.80  |
| N                  | 7,002                                  | 6,893  |

*Note:* Table 1 presents the summary statistics of the original linear distance (in miles) from home to school for the full sample of enrolled students as well as families whose original linear distance is within 50 miles from the school.

Table 2 provides the summary statistics on pre-move linear distance conditional on admitted grade. Panel A focuses on the full sample. On average, students enrolled into middle schools (grade 7-8) are more likely to be from closer neighborhoods than those enrolled into high

school (grade 9-10). Panel B examines the subsample with original distance within 50 miles from the school, and as expected, the distinction in distance between middle school and high school enrolled students disappears (since all students in the subsample are local).

**Table 2: Original Linear Distance in Miles by Admitted Grade**

| Admitted Grade  | Original Linear Distance (in miles) |       |           |      |      |        |       |          |
|---|-------------------------------------|-------|-----------|------|------|--------|-------|----------|
|   | N                                   | Mean  | Std. Dev. | Min  | Q25  | Median | Q75   | Max      |
| Panel A: Full Sample                                  |                                     |       |           |      |      |        |       |          |
| 6   | 1,744                               | 12.44 | 63.39     | 0.11 | 5.90 | 9.02   | 13.35 | 2,573.94 |
| 7   | 1,195                               | 15.60 | 91.62     | 0.22 | 5.62 | 9.27   | 14.88 | 2,518.83 |
| 8   | 1,819                               | 19.16 | 127.59    | 0.19 | 5.44 | 9.47   | 15.82 | 2,780.08 |
| 9   | 1,012                               | 32.84 | 192.00    | 0.11 | 5.40 | 9.40   | 15.63 | 2,696.07 |
| 10  | 685                                 | 34.40 | 217.17    | 0.39 | 6.35 | 10.40  | 15.91 | 2,595.09 |
| 11  | 547                                 | 15.41 | 50.32     | 0.24 | 6.41 | 10.30  | 15.31 | 971.22   |
| Total   | 7,002                               | 20.05 | 129.81    | 0.11 | 5.75 | 9.45   | 14.96 | 2780.08  |
| Panel B: Subsample with Original Distance <= 50 miles |                                     |       |           |      |      |        |       |          |
| 6   | 1,731                               | 10.13 | 6.33      | 0.11 | 5.87 | 8.99   | 13.21 | 49.80    |
| 7   | 1,187                               | 10.47 | 7.02      | 0.22 | 5.62 | 9.24   | 14.75 | 47.93    |
| 8   | 1,792                               | 11.03 | 7.85      | 0.19 | 5.36 | 9.37   | 15.44 | 49.49    |
| 9   | 983                                 | 10.82 | 7.56      | 0.11 | 5.28 | 9.17   | 14.84 | 49.25    |
| 10  | 668                                 | 11.71 | 7.87      | 0.39 | 6.26 | 10.26  | 15.55 | 49.71    |
| 11  | 532                                 | 11.27 | 7.33      | 0.24 | 6.32 | 10.08  | 14.91 | 47.49    |
| Total   | 6,893                               | 10.76 | 7.28      | 0.11 | 5.70 | 9.35   | 14.74 | 49.80    |

*Note:* Table 2 presents the summary statistics of the original linear distance (in miles) from home to school of enrolled students by admitted grade for the full sample (Panel A) and the subsample with original linear distance within 50 miles (Panel B).

### *Which Families Moved?*

Comparing the application addresses to the subsequent mailing addresses, we find that 1,217 of the families changed addresses after they were admitted to the school, the remainder did not change addresses over our sample period. We assume that a change of mailing address constitutes a change of residence.



Assuming that families make relocation decisions on the basis of the child's grade at enrollment, we might expect that families whose child was admitted at lower grade, and hence expect a longer relationship with the school, would be more likely to relocate. To test this hypothesis, we specify the following probit model:

$$P(Moved_i = 1 | x_i) = \Phi(x_i \beta) \quad (1)$$

$$= \Phi(\beta_0 + \beta_1 Admitted\ Grade_i + \beta_2 Graduated_i + \beta_3 Dropped_i + \beta_4 Distance_i)$$

The marginal effects are:

$$\frac{\partial}{\partial t_j} P(Moved_i = 1 | x_i = t) = \frac{\partial}{\partial t_j} \Phi(t \beta) = \phi(t \beta) \beta_j \quad (2)$$

Where  $\Phi(\cdot)$  is the cumulative standard normal distribution function and  $\phi(\cdot)$  is standard normal density. ( $Moved_i = 1$ ) indicates that a family  $i$  moved after admission, and ( $Moved_i = 0$ ) indicates that the family did not move.  $Admitted\ Grade_i$  is the grade at enrollment. Families who enrolled a child into the school at a lower grade are more likely to move, in part because they have more time to do so before the student reaches graduation. They may also be more motivated to move because they have more years of expected school commuting. If younger children are more likely to move,  $\beta_1$  will be negative. We include several control variables in the regressions that likely affect a family's decisions to relocate.  $Graduated_i$  is an indicator variable equal to one if the student has graduated from the school and zero otherwise. In contrast,  $Dropped_i$  is an indicator variable equal to one if the student has dropped from the school during our sample period and zero otherwise. Everything else equal, we expect families to be more likely to move if their children graduated from the school and less likely to move if their kids dropped out of school. Thus, the coefficient  $\beta_2$  should be positive and  $\beta_3$  negative.  $Distance_i$  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. We

expect the coefficient  $\beta_4$  to be positive. We also control for the fixed effects of the calendar year at enrollment.

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

**Table 3: Probit Regressions Predicting the Probability of Moving**

| Dep. Var.<br>= Moved (1/0)                                  | Model (1)                  |                               | Model (2)                  |                               | Model (3)                  |                               |
|---|----------------------------|-------------------------------|----------------------------|-------------------------------|----------------------------|-------------------------------|
|   | Marginal effect<br>[dy/dx] | Elasticity<br>[d(lny)/d(lnx)] | Marginal effect<br>[dy/dx] | Elasticity<br>[d(lny)/d(lnx)] | Marginal effect<br>[dy/dx] | Elasticity<br>[d(lny)/d(lnx)] |
| Panel A: Full Sample  |                            |                               |                            |                               |                            |                               |
| <i>Admitted Grade</i>                                       | -0.0204***<br>(-6.91)      | -0.9506***<br>(-6.85)         | -0.0267***<br>(-8.57)      | -1.2832***<br>(-8.47)         | -0.0286***<br>(-9.17)      | -1.391***<br>(-9.06)          |
| <i>Graduated</i>  |                            |                               | 0.0343*<br>(1.72)          | 0.0900*<br>(1.72)             | 0.0304<br>(1.53)           | 0.0808<br>(1.53)              |
| <i>Dropped</i>  |                            |                               | -0.0876***<br>(-4.87)      | -0.1900***<br>(-4.85)         | -0.0934***<br>(-5.21)      | -0.2059***<br>(-5.19)         |
| <i>Distance</i>   |                            |                               |                            |                               | 0.0003***<br>(5.63)        | 0.0374***<br>(5.63)           |
| Admitted Year FE  |                            | Yes                           |                            | Yes                           |                            | Yes                           |
| Log Pseudo likelihood                                       |                            | -3172.0354                    |                            | -3100.1655                    |                            | -3057.5956                    |
| Pseudo R <sup>2</sup>                                       |                            | 0.0171                        |                            | 0.0394                        |                            | 0.0526                        |
| Predicted Prob.   |                            | 0.1701                        |                            | 0.1644                        |                            | 0.1627                        |
| Observations  |                            | 6,967                         |                            | 6,967                         |                            | 6,967                         |
| Panel B: Subsample with Original Linear Distance <=50 miles |                            |                               |                            |                               |                            |                               |
| <i>Admitted Grade</i>                                       | -0.0225***<br>(-7.63)      | -1.0901***<br>(-7.56)         | -0.0286***<br>(-9.25)      | -1.4351***<br>(-9.12)         | -0.0298***<br>(-9.58)      | -1.5022***<br>(-9.44)         |
| <i>Graduated</i>  |                            |                               | 0.0329*<br>(1.65)          | 0.0901*<br>(1.65)             | 0.0331*<br>(1.67)          | 0.0913*<br>(1.67)             |
| <i>Dropped</i>  |                            |                               | -0.0849***<br>(-4.74)      | -0.1929***<br>(-4.72)         | -0.0865***<br>(-4.84)      | -0.1979***<br>(-4.82)         |
| <i>Distance</i>   |                            |                               |                            |                               | 0.0026***<br>(4.31)        | 0.1810***<br>(4.29)           |
| Admitted Year FE  |                            | Yes                           |                            | Yes                           |                            | Yes                           |
| Log Pseudo likelihood                                       |                            | -3047.6732                    |                            | -2978.6242                    |                            | -2968.757                     |
| Pseudo R <sup>2</sup>                                       |                            | 0.0203                        |                            | 0.0425                        |                            | 0.0457                        |

|                 |        |        |        |
|-----------------|--------|--------|--------|
| Predicted Prob. | 0.1629 | 0.1573 | 0.1566 |
| Observations    | 6,858  | 6,858  | 6,858  |

*Note:* Table 3 reports marginal effects and elasticity from probit regressions predicting the probability of moving. Panel A uses the full sample and Panel B uses the subsample of families that lived originally within 50 miles from the school. The dependent variable (*Moved*) is a binary variable that equals one if the family moves and zero otherwise. The independent variables include original grade (*Admitted Grade*), an indicator variable whether the student graduated (*Graduated* = 1/0), an indicator variable for whether the student dropped out (*Dropped* = 1/0), the original commute distance in miles (*Distance*), and fixed effects for the calendar year admitted (omitted from the table). Each specification builds on the previous one. The partial derivatives and elasticities of the dependent variable with respect to the independent variables are evaluated at the mean for each independent variable. Robust z-statistics are reported in parentheses. \*\*\*, \*\*, and \* denote significance at the 1%, 5%, and 10% levels, respectively, in a two-tailed test.

Panel A uses the full sample. In the first specification, the only independent variable considered is *Admitted Grade*. The coefficient is negative and statistically significant suggesting that indeed the lower the grade at enrollment, the more likely the student's family would move. The second specification incorporates indicator variables for whether the student graduated or dropped over our sample period. As expected, for students who actually graduated, their families were more likely to move after the students were enrolled ( $\beta_2 > 0$ ). We note that the coefficient  $\beta_2$  is only significant at 10% level. This is probably driven by the fact that there are still students in our sample that would graduate later but not yet during our sample period. In comparison, for students who have dropped out of school, their families were less likely to move after enrollment. The coefficient  $\beta_3$  is negative, and highly significant.

The third specification incorporates the original linear distance between the family and school for enrolled students. 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 distance that the family originally commuted to school is also positively correlated with the move probability. Panel B uses the subsample with the original linear distance of less than or equal to 50 miles. This local subset exhibits similar results.

### *Did the Movers Move Closer? Some Non-Parametric Tests*

We now focus our attention on the 1,217 families in the full sample that moved after their child was enrolled in the school. Let  $d_O$  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  $(d_O - d_N)$ . If  $(d_O - d_N) > 0$ , the family moved closer to the school. In fact, the average value of  $(d_O - d_N)$  was 22.5 miles. The one-tailed t-test probability of obtaining this mean, assuming that the null hypothesis ( $H_0$ : mean=0) is true, would be  $p=0.0103$ .

Applying the sign test, 669 of the 1,217 movers moved in the direction of the school, and 548 moved away from the school. If the true underlying  $\Pr(d_O - d_N > 0) = 0.5$ , the chance of observing 669 or more positive values of  $(d_O - d_N)$  is  $p=0.0003$ . Similarly, the Wilcoxon sign-rank test rejects the null ( $H_0$ : mean=0) with a one-tailed p-value of 0.0000.

We also conduct analogous tests for the subsample (1,140 unique student obs.) with original distance (and ending distance) of less than or equal to 50 miles from school. The average value of  $(d_O - d_N)$  is 1.54 miles and the p-value of the one-sided t-test ( $H_a$ : mean > 0) is 0.000. The sign test shows that 609 of the 1,140 local movers actually moved towards the school, and 531 moved away from the school. If the true underlying  $\Pr(d_O - d_N > 0) = 0.5$ , the chance of observing 609 or more positive values of  $(d_O - d_N)$  is  $p=0.0113$ . Finally, the Wilcoxon sign-rank test rejects the null ( $H_0$ : mean=0) with a one-tailed p-value of 0.0001.

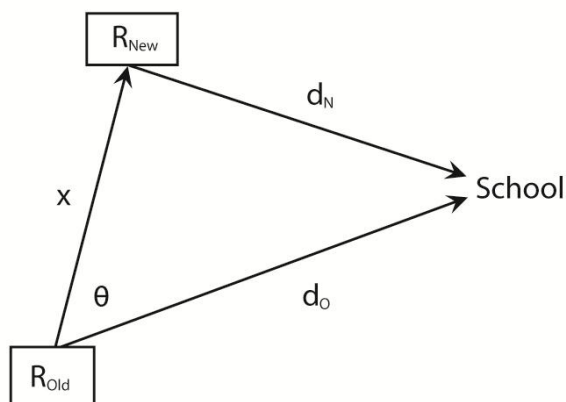
## A Model of School Attraction

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 spatial 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.

For simplicity we will adopt the description of the model used by Danielsen et al. (2014). Consider a family's residential relocation as shown in Figure 1.

**Figure 1**

A Vector Structure of the School-Residence Relationships



*Note:* Figure 1 plots a vector structure of the school-residence relationships.  $R_{Old}$  is the old residence of the student prior to enrolling in the school.  $d_O$  is the distance from  $R_{Old}$  to the school.  $R_{New}$  is the new residence of the student, and  $d_N$  is the new commuting distance to the school. The distance moved from  $R_{Old}$  to  $R_{New}$  is designated as vector  $X$ .  $\theta$  is the angle formed by moving from vector  $d_O$  to vector  $X$ . If a student moved directly toward the school,  $\theta$  would be zero.

In the Figure 1 diagram, the student lives at the residence  $R_{Old}$  prior to enrolling in the school. The distance 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  $R_{New}$ . The distance moved from  $R_{Old}$  to  $R_{New}$  is designated as vector  $X$ . After moving to  $R_{New}$ , 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  $R_{Old}$  to  $R_{New}$ , and the commute distance to the school changed from  $d_O$  to  $d_N$ .

In addition to the distances that have been identified, another important aspect of this conceptualization concerns the angle theta ( $\theta$ ). 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 1 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). Unlike those studies, which model move distances using an exponential distribution, we adopt the gamma distribution used by Danielsen et al. (2014). This is a more general model that allows the data to select an exponential distribution if that provides the best fit.

$$g(X; \varphi, \alpha) = \frac{\alpha^\varphi}{\Gamma(\varphi)} X^{\varphi-1} e^{-\alpha X}, \quad X > 0 \text{ and } \varphi, \alpha > 0. \quad (3)$$

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.

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  $\mu$  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  $\mu=0$  (an assumption that is subject to subsequent testing). For  $\mu=0$ , the density function is defined as

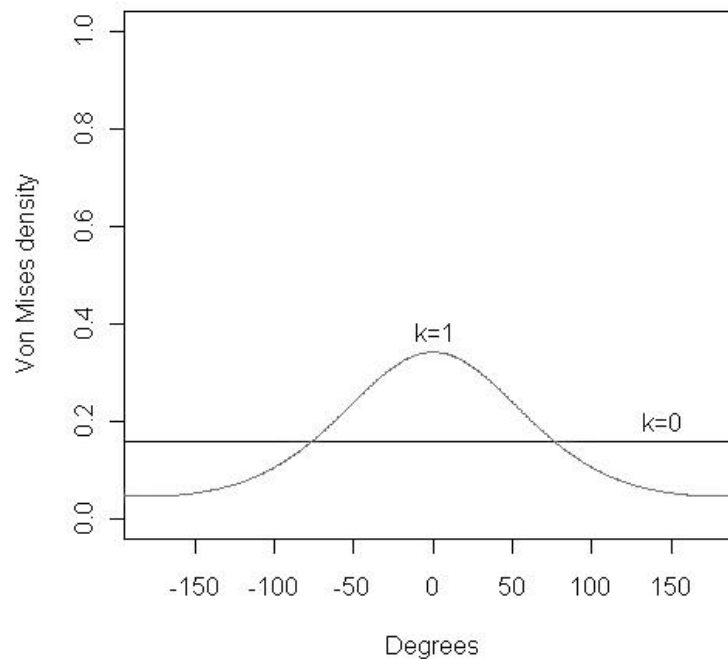
$$v(\Theta) = \frac{1}{2\pi I_0(k)} e^{k \cos(\Theta)}, \quad -\pi < \Theta < \pi, k \geq 0 \quad (4)$$

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.

Figure 2 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 the normal distribution, the horizontal axis in Figure 2 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 2** The Density Function of the von Mises distribution

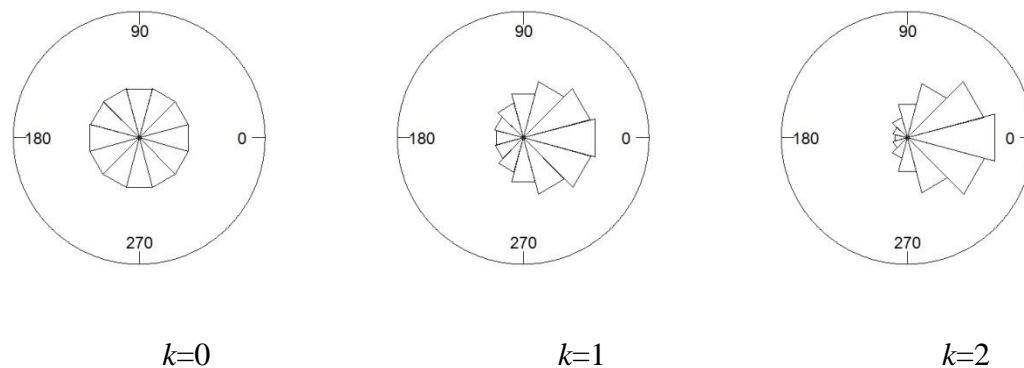


*Note:* Figure 2 depicts the density function of the von Mises (circular-normal) distribution. The horizontal axis extends from  $-180^\circ$  to  $+180^\circ$ . These two are the same point on the circle so that the horizontal axis wraps around the circle. For larger values of  $k$ , the concentration at the origin increases and the standard deviation decreases. For  $k = 0$ , the distribution becomes a circular uniform distribution.



Figure 3 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 altering 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. For  $k=0$ , the move directions are uniform, but for  $k=2$ , the moves are strongly concentrated toward  $\mu=0$ .

**Figure 3** Rose Diagrams of Movement Concentration toward  $\mu=0$  for Various Values of  $k$



*Note:* Figure 3 depicts theoretical rose diagrams for various concentrations of movement toward  $\mu=0$ . For each diagram, moves that occur in common directions are aggregated into bins, where each bin includes  $30^\circ$ . For  $k=0$ , the move directions are uniformly distributed; for  $k=2$ , the moves are strongly concentrated toward  $\mu=0$ .

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 et al. (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

$$c(X, \theta) = g(X)v(\theta) \quad (5)$$

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

$$P(X_1 < X < X_2, \theta_1 < \theta < \theta_2) = \iint_{X_1 \theta_1}^{X_2 \theta_2} c(X, \theta) d\theta dX \quad (6)$$

where

$$c(X, \theta) = g(X)v(\theta) = \left( \frac{\alpha^\varphi}{\Gamma(\varphi)} X^{\varphi-1} e^{-\alpha X} \right) \left( \frac{1}{2\pi I_0(k)} e^{k \cos(\theta)} \right)$$

Recall from Figure 1 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

$$(d_N)^2 = (d_O)^2 + (X)^2 - 2(d_O X) \cos \theta \quad (7)$$

Thus,

$$\begin{aligned} P(d_N < d_O) &= P((d_N)^2 < (d_O)^2) \\ &= P((d_O)^2 + (X)^2 - 2(d_O X) \cos \theta < (d_O)^2) \\ &= P(X < 2(d_O) \cos \theta) \\ &= \int_{-\pi/2}^{\pi/2} \int_0^{2(d_O) \cos \theta} c(X, \theta) dX d\theta \end{aligned} \quad (8)$$

$$P(d_N < d_O) = 2 \int_0^{\pi/2} \int_0^{2d_0 \cos \theta} c(x, \theta) dx d\theta$$

$$\begin{aligned}
&= 2 \int_0^{\frac{\pi}{2}} \int_0^{2d_0 \cos \theta} \left( \frac{\alpha^\varphi}{\Gamma(\varphi)} x^{\varphi-1} e^{-\alpha x} \right) \left( \frac{1}{2\pi I_0(k)} e^{k \cos \theta} \right) dx d\theta \\
&= \frac{\alpha^\varphi}{\pi I_0(k) \Gamma(\varphi)} \int_0^{\frac{\pi}{2}} e^{k \cos \theta} \int_0^{2d_0 \cos \theta} x^{\varphi-1} e^{-\alpha x} dx d\theta
\end{aligned}$$

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

Because  $\cos^2 \theta + \sin^2 \theta = 1$ ,  $d\theta = \frac{1}{-\sin \theta} dt = -\frac{1}{\sqrt{1-t^2}} dt$ .

$$P(d_N < d_0) = \frac{\alpha^\varphi}{\pi I_0(k) \Gamma(\varphi)} \int_0^1 \frac{1}{\sqrt{1-t^2}} e^{kt} \int_0^{2d_0 t} x^{\varphi-1} e^{-\alpha x} dx dt \quad (9)$$

Equation 9 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  $d_0$ .

## Tests of School Attraction

Assuming that the observed move distances are drawn from the gamma distribution, for the subset of families originally living in the 50-mile locality, we find MLE parameter estimates of  $\alpha = 0.079$ , and shape parameter  $\varphi = 0.685$ . The mean of the gamma distribution,  $(\alpha-1)(\varphi)$ , is 8.67 miles. The move distance corresponds to the length of the X vector in Figure 1, and it is also the value of X in the theoretical distribution from Equation 3.

Turning to our tests of move direction, the direction of each move in the sample can be represented by a vector with direction  $\theta$  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 R, where  $\theta_R = \tan^{-1} \frac{1/n \sum \sin \theta_i}{1/n \sum \cos \theta_i}$  is a measure of mean move direction. The length of vector 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,

$$\bar{R} = \frac{R}{n} = \frac{\sqrt{(\sum \sin \theta_i)^2 + (\sum \cos \theta_i)^2}}{n}, \bar{R} \text{ is a function of the concentration parameter } k \text{ by virtue of}$$

$$\bar{R} = \frac{I_1(\hat{k})}{I_0(\hat{k})}, \text{ where } I_0(k) \text{ is a modified Bessel function of the first kind and zero order. Solving for}$$

$k$  requires numerical approximation. We used the circular statistics package found at

<http://cran.r-project.org/web/packages/circular/circular.pdf>.

Of the 1,140 students in the subsample, there are 1,086 unique beginning addresses. We assume some families have multiple students in the school and that a single address represents a single family. For the analysis which follows, “families” refers to the 1,086 individual addresses. For the sample of relocating families in the current study,  $\theta_R$  equals 0.081 radians, or 4.64 degrees. The clustering index  $\bar{R}$  equals 0.295, yielding concentration parameter  $k = 0.6184$ . For the von Mises distribution of 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. In this test the value is 189.5, which is far above the cutoff value of 5.99 for  $p=0.05$ .

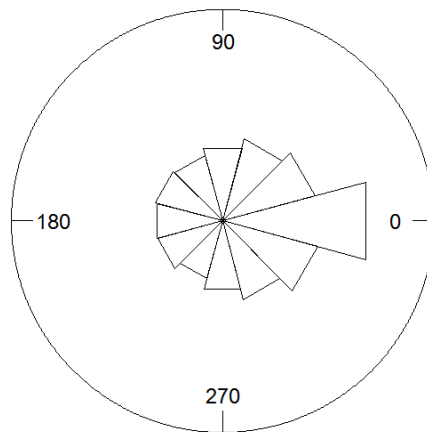
Given a move direction bias, we test the assumption that the move directions are biased toward the school. This test assumes the school is the attractor and tests whether or not we can reject that assumption. The 95% confidence interval around the school direction can be written as  $0 \pm 1.96/\sqrt{nk\bar{R}} = 0 \pm 1.96/\sqrt{(1086)(0.6841)(0.295)} = 0 \pm 0.139$  radians. Because  $0.139 < \theta_R < 0.139$ , we accept the hypothesis (i.e. cannot reject) that the move directions are concentrated toward the school.

As a point of reference, Clark and Burt (1980) and Clark et al. (2003) that considered workplace attraction found concentration parameter estimates of  $k=0.638$  and  $k=0.668$ . Notice

that the school's attraction ( $k=0.6184$ ) is very similar to the reported work-place attraction measures. However, Clark et al. (2003) report that approximately 8.7% of the observed sample changed residence, while 17.3% of the families attending this school changed residence. Therefore, while the magnitude of the attraction is similar for those who moved, the propensity to move may be stronger in the school sample.

To help the reader more clearly visualize the move pattern of relocating families, we present a rose diagram in Figure 4. Similar to those presented in Figure 3, this rose diagram aggregates moves that occur in common directions into several bins. However, while the diagrams in Figure 3 are produced from theoretical von Mises distributions, Figure 4 depicts actual empirical observations from the data.

**Figure 4** Move Directions with 12 Bins



*Note:* Figure 4 presents the observed density of family moves as a rose diagram. The circle is segmented 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  $\theta = 0$ . The length of each wedge is proportional to the square root of the number of observations. The fraction of the observations represented by the largest wedge is 21.4%, and the fraction represented by the smallest wedge shown is 4.2%.

Again, 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  $\theta = 0$ . 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 21.4%, and the fraction represented by the smallest wedge shown is 4.2%. The three wedges which comprise the fourth of the circle closest to the school contain 44.1% of the moves. In this framework, the magnitude of the family relocation bias seems obvious.

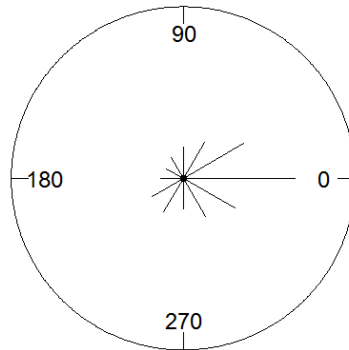
### *Further Analysis*

Returning to the rose diagram shown in Figure 4, we have also calculated the mean distance moved by the families in each of the 12 bins. The mean move distances are graphically depicted in Figure 5, with the values for the mean and standard deviations shown below the figure.

The group names in the legend reflect the geographic bounds on each bin. The bounds are identical to those used to construct Figure 4. 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&>345”. The bins in the table are listed in a counter-clockwise direction from the school.

Obviously, families moving toward the school move much farther, on average, than those moving away. The mean distance moved toward the school is 16.98 miles, and the mean distance moved directly away from the school is only 3.21 miles. We conclude that the distance moved is affected by the direction, and the assumption that distance and direction are independent is not, in fact, valid.

**Figure 5 Move Distances for 12 Bins**



**Mean move distances by bin**

| Group     | Mean  | Std    | n   |
|-----------|-------|--------|-----|
| <15&> 345 | 16.98 | 13.427 | 230 |
| 15-45     | 10.39 | 10.746 | 120 |
| 45-75     | 6.18  | 7.615  | 93  |
| 75-105    | 4.58  | 6.193  | 76  |
| 105-135   | 3.48  | 3.834  | 60  |
| 135-165   | 2.77  | 3.272  | 64  |
| 165-195   | 3.21  | 5.582  | 58  |
| 195-225   | 5.33  | 6.044  | 58  |
| 225-255   | 5.84  | 6.519  | 46  |
| 255-285   | 4.58  | 6.350  | 65  |
| 285-315   | 6.97  | 8.382  | 90  |
| 315-345   | 8.89  | 9.837  | 126 |

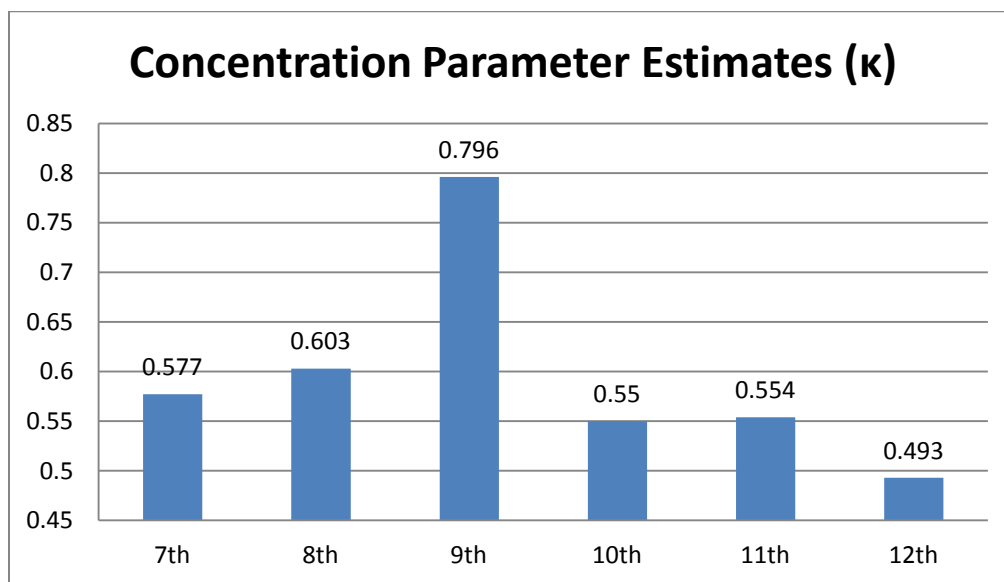
*Note:* Figure 5 depicts the mean distance moved by families in each of the 12 bins depicted in Figure 4. The mean and standard deviations for these values are shown below the figure. Group names in the legend reflect the geographic bounds on each bin. The first group is for moves most towards the school which includes moves between  $+15^\circ$  to  $-15^\circ$  (345 degrees). This group is labeled as group “<15&>345”. The bins in the table are listed in a counter-clockwise direction from the school.

### **Grade-by-Grade Analysis**

Because students enroll in the school for the first time at various ages (grades), we might expect that the grade when the child first enrolled to exert some influence over the level of

attraction demonstrated by the school. For example, for a family whose child enrolls for the first time in the 12<sup>th</sup> grade, we might expect that the school's attraction would be relatively low since the child will only attend one year of classes at the school before graduating. In contrast, there may be a strong school attraction for the families of 7<sup>th</sup> graders simply because the child may attend the school for the next six years. To examine the influence of the child's grade of matriculation into the school, we calculate concentration parameters  $\kappa$  for students grouped by the grade of matriculation. These values are shown in Figure 6.

**Figure 6** Concentration Parameter Estimates by Grade



Surprisingly, we find that the concentration parameter for students entering the ninth grade is significantly higher than for any other grade. The 9<sup>th</sup> graders  $\kappa$  value is 0.796, and the  $\kappa$  values for all other grades range from 0.496 to 0.603 with an overall  $\kappa$  value for non-9<sup>th</sup> graders of 0.567.

To test whether this difference is statistically significant, we utilize the bootstrapping technique described in Danielsen et al. (2014). Specifically, we treat the observed values as the



sampling population and take repeated samples from the population. Using these repeated samples we calculate the parameter estimates and observe the variation from bootstrap across samples. We use this variability estimate as the estimate of the standard error. When testing for the difference between groups  $\kappa_9$  and  $\kappa_{other}$ , we repeat this sampling process 10,000 times, then we calculate the standard deviation of the differences. The bootstrap-sample means produce a near-normal distribution. Using this standard deviation and assumed normality, we calculate a confidence interval for the difference in  $\kappa$  values. The confidence interval can be used to test the hypothesis that  $\kappa_9$  and  $\kappa_{other}$  are significantly different. We find that the difference is large (0.242) and statistically significant. Note that the bootstrap estimates of  $\kappa$  are very close to, but not identical to, the values observed in the underlying sample.

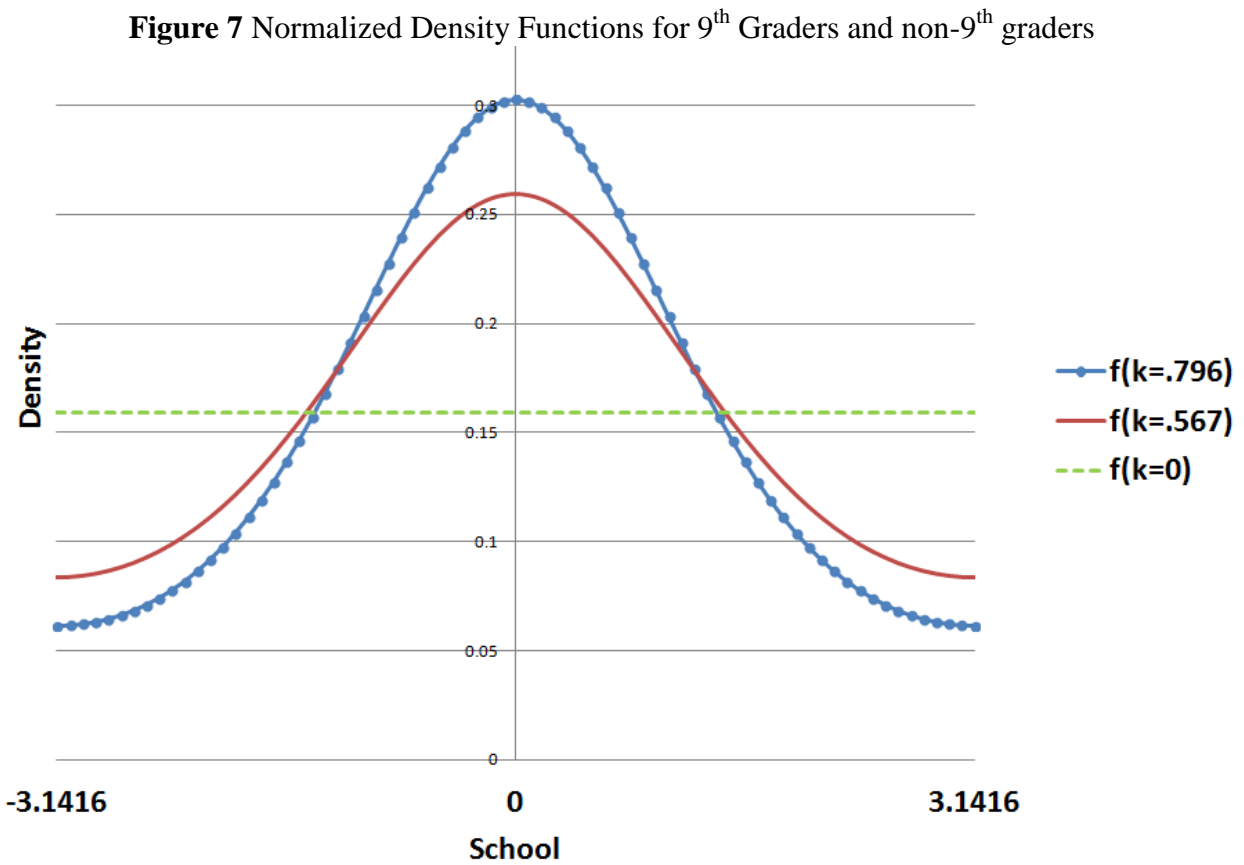
| Grade | Bootstrap estimate for $\kappa$ | Difference | Confidence interval |
|-------|---------------------------------|------------|---------------------|
| 9th   | 0.798                           |            |                     |
| Other | 0.556                           | 0.242      | (0.025,0.459)       |

While we do observe lower parameter estimates for students entering the grades above 10<sup>th</sup>, 11<sup>th</sup> and 12<sup>th</sup> grades than 7<sup>th</sup>, 8<sup>th</sup> grades, as we hypothesized, the differences among the grades (other than the 9<sup>th</sup> grade) are not statistically significant.

In order to better visualize the level of the move direction bias that these  $\kappa$  values represent, in Figure 7 we present smoothed von Mises density values using the same format as was presented previously in Figure 2. As a baseline, the density for  $k=0$  [  $f(k=0)$  ] results in a uniform density of 0.1592. Notice that  $\frac{1}{2\pi} = 0.1592$ . For every von Mises distribution, the average density around  $2\pi$  radians will be 0.1592 because the cumulative density around  $2\pi$  radians must equal one, by definition.

For non-9<sup>th</sup> graders ( $\kappa=0.567$ ), the density function reaches as high as 0.259, and the density function for 9<sup>th</sup> graders ( $\kappa=0.796$ ) reaches as high as 0.303.

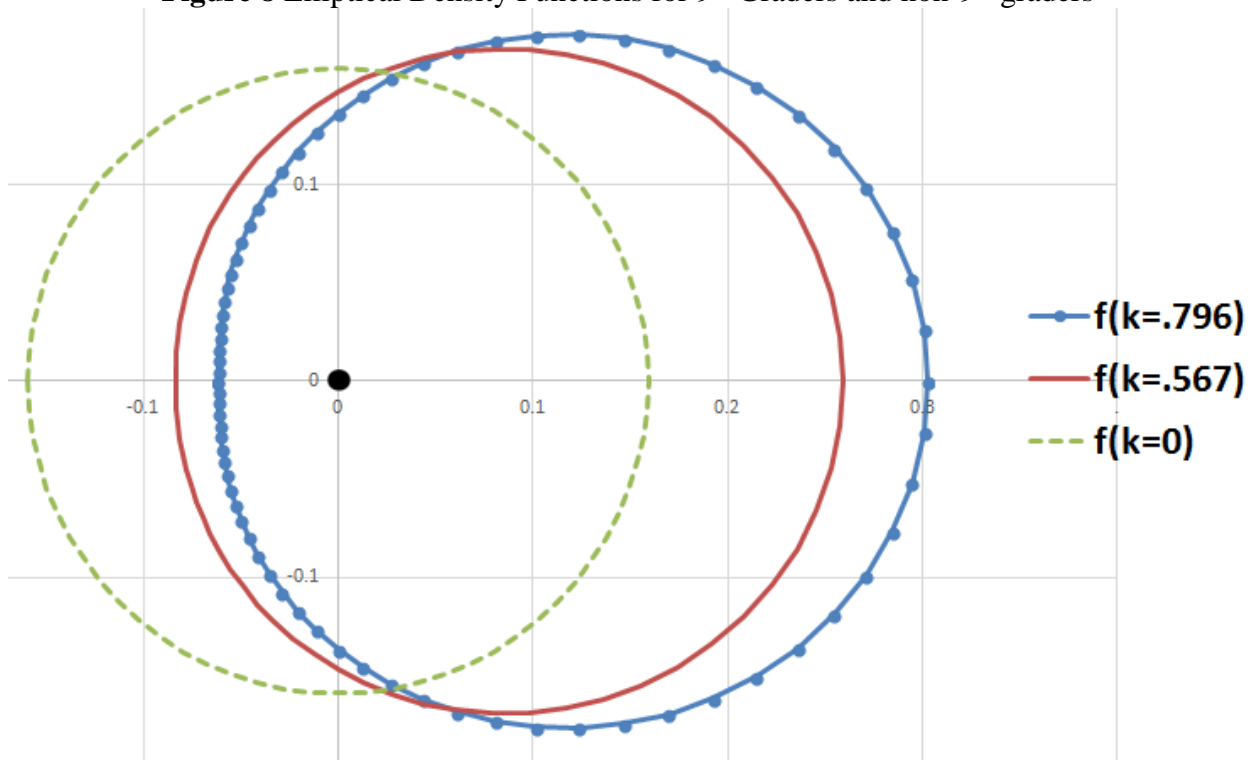
An alternative representation of the density function can be created by wrapping the function around the origin to form an elliptical graph. We do this in Figure 8 where we once more present the baseline case of no attraction ( $\kappa=0$ ). The density function for this case is represented by a circle focused on the origin (0,0) because the density (0.1592) is identical around the focus. The other two ellipses also have their focus at the origin, but the density for each varies depending upon the direction represented. The school's location would be in the direction of the bias.



The average length from the focus to the exterior of the ellipse is  $\frac{1}{2\pi} = 0.1592$  for each curve. Because the average density is the same around the focus of each density function, the area inside the curve becomes larger as  $\kappa$  becomes larger. Consider the 9<sup>th</sup>-grade ellipse which has a mark at every 5 degrees around the curve. The marks on the right are more widely spaced

than the marks on the left. This is because the distance from the focus is greater in this direction. While the ellipse's average distance from the focus is 0.1592, the area inside the ellipse over each 5 degrees changes depending on the distance from the focus. Because the area around the ellipse increase with the square of the distances; the area is minimized when the density is uniform, and increases as the figure becomes more elliptical. This must be true because the average density remains at  $\frac{1}{2\pi} = 0.1592$ . In fact, while the differing areas for the three ellipses are obvious, they are unimportant. The variation around the origin for each is of importance.

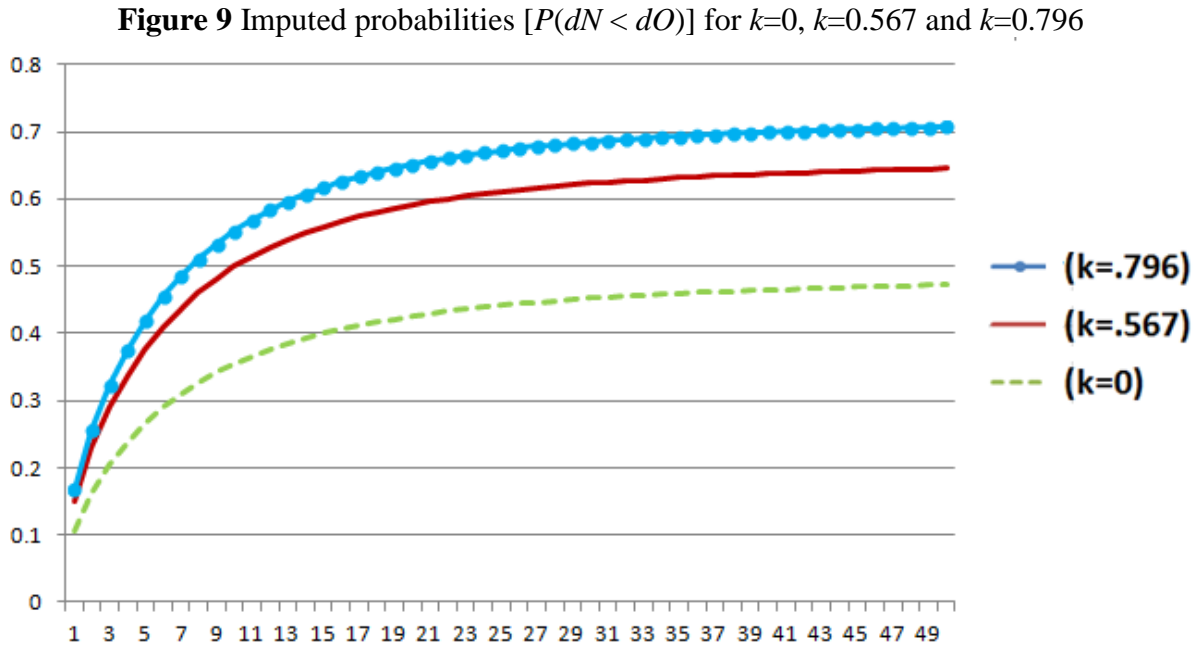
**Figure 8** Elliptical Density Functions for 9<sup>th</sup> Graders and non-9<sup>th</sup> graders



### Imputed Move Probabilities

Given the observed attraction exerted by the school, we next assess the probability that a family will move closer by reevaluating Equation 9 for various values of  $d_0$ . Figure 9 provides a

visual depiction of the increase in  $P(d_N < d_O)$  for  $1 \leq d_O \leq 50$  under the baseline assumption ( $\kappa=0$ ) and under the  $\kappa$  values displayed by 9<sup>th</sup> graders and non-9<sup>th</sup> graders.



Note: Figure 9 graphs the increase in  $P(d_N < d_O)$  for  $1 \leq d_O \leq 50$  under the baseline assumptions ( $k=0$ ), ( $k=0.567$ ) and ( $k=0.796$ ).

For discussion purposes, consider a family living 9.45 miles from the school at the time of acceptance. This is the median  $d_O$  value in the sample.

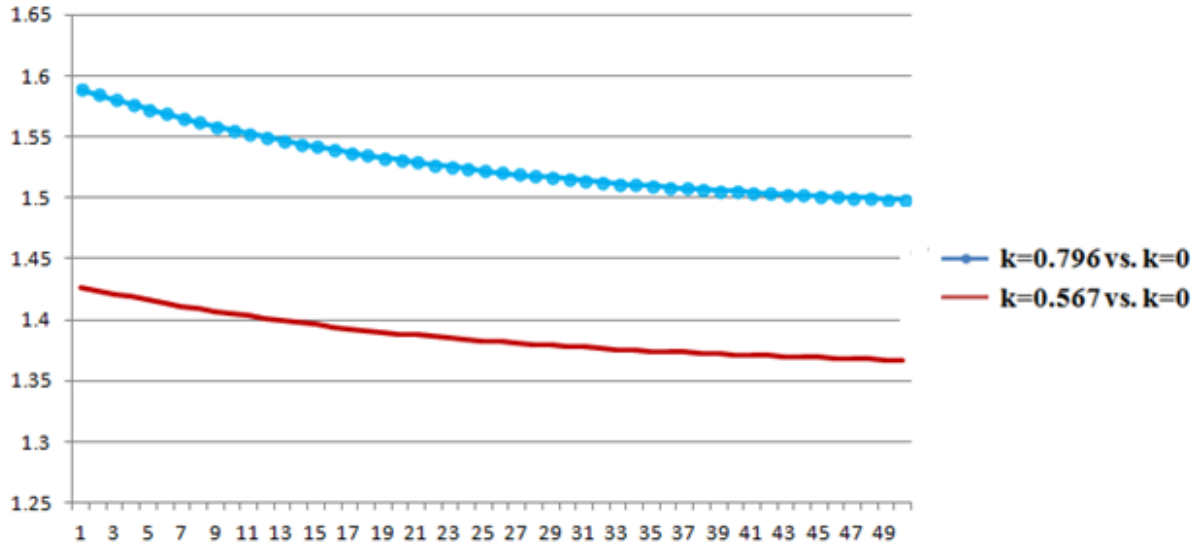
| Group           | $d_O$   | $\kappa$ | $P(d_N < d_O)$ | $\frac{P(d_N < d_O)}{P(d_N < d_O) _{\kappa=0}}$ |
|-----------------|---------|----------|----------------|---|
| Baseline        | 9.45 mi | 0.000    | 0.348          |   |
| non-9th graders | 9.45 mi | 0.567    | 0.489          | 1.41  |
| 9th Graders     | 9.45 mi | 0.796    | 0.542          | 1.56  |

At a distance of 9.45 miles, the non-9<sup>th</sup> grader's family is 41% more likely to move closer to the school than would be expected for a family that is not attracted to the school. The baseline probability of 0.348 has increased to 0.489. A ninth grade family is 56% more likely to move closer to the school than should be expected under the baseline case.

Figure 10 depicts the ratios of the observed probabilities for  $1 \leq d_o \leq 50$  for non-ninth graders and ninth graders relative to the baseline probability. Mathematically these values are

$$\frac{P(d_N < d_o)|\kappa=0.567}{P(d_N < d_o)|\kappa=0} \text{ and } \frac{P(d_N < d_o)|\kappa=0.796}{P(d_N < d_o)|\kappa=0} .$$

**Figure 10** Increase in the probability of moving closer to the school



Note: Figure 10 graphs the ratio of  $P(d_N < d_o)|\kappa=0.567$  to  $P(d_N < d_o)|\kappa=0$  and of  $P(d_N < d_o)|\kappa=0.796$  to  $P(d_N < d_o)|\kappa=0$  for  $1 \leq d_o \leq 50$ .

Depending upon the initial distance from the school, non-ninth graders are 37% to 43% more likely to move closer to the school than would be expected by random chance. Ninth graders are 50% to 59% more likely to move closer.

| $d_o$    | Non-9 <sup>th</sup> Graders                                   | 9 <sup>th</sup> Graders                                       |
|----------|---|---|
|          | $\frac{P(d_N < d_o) \kappa = 0.567}{P(d_N < d_o) \kappa = 0}$ | $\frac{P(d_N < d_o) \kappa = 0.796}{P(d_N < d_o) \kappa = 0}$ |
| 1 mile   | 1.43  | 1.59  |
| 10 miles | 1.41  | 1.56  |
| 25 miles | 1.38  | 1.52  |
| 50 miles | 1.37  | 1.50  |

## **Conclusion with Comparisons to a Previous Study**

This study examines the impact that the Orange County School of the Arts (OCSA) has had on the relocation decisions of families whose child attends the school. The school draws students from a relatively wide geographic area, and it exerts a strong attractive power on enrolled families. Families who live near the school (in Santa Ana, California) are substantially less likely to relocate than families who live farther away. Hundreds of families (669) have moved closer to Santa Ana after enrolling a child in the school, and a substantial fraction (97 families) moved from a non-Santa Ana address into the city. While students matriculate into the school in grades 7 through 12, the attraction seems to be particularly strong for families enrolling a child at the beginning of the 9th grade. The reasons for the high level of attraction for 9th graders are unclear. This finding calls for further research since it may have implications for how school-choice programs in general, and arts-based programs in particular, should be structured when one of the policy goals is to catalyze redevelopment of the urban environment.

We find that the school's attractive power is of the same general magnitude as workplaces previously examined. The school has almost 2000 students currently enrolled, it may be reasonable to consider its relocation impact as similar to that of a work place with a similar number of employees.

However, because this is a case study of a single school, we should be careful to consider what factors may be unique to this school, and which are likely to be generalizable. We can also make some comparisons to the results of a similar study published by Danielsen et al. (2014) who studied a K-12 charter school in North Carolina.

If a school exhibited no attraction on families ( $\kappa = 0$ ), the percentage moving in the direction of the school would be 25%, where the term "in the direction of the school" is defined

as a ninety-degree span of a circle with the school's direction from the original address at the center of the ninety degree span. The concentration parameter estimate found for OCSA was  $\kappa = 0.618$ , meaning that approximately 42% of families in the study moved "in the direction of the school. The North Carolina school showed approximately 59% moving in the direction of the school ( $\kappa = 1.128$ ). Although the attraction by OCSA should be viewed as relatively large, there are several factors that are likely to explain its lower level of attraction, relative to the North Carolina School.

First, the North Carolina school is a K-12 school. A student first enrolled in kindergarten can remain enrolled for 13 years before graduating. OCSA is a 7-12 school, and no student can expect to be enrolled for more than 6 years. A long expected enrollment period would increase the benefits of moving closer to school.

Second, the North Carolina school guarantees admission for the siblings of currently enrolled students. OCSA does not. All OCSA students are evaluated on artistic talent before being admitted. The North Carolina school has far more multi-student families enrolled than OCSA. If siblings are not enrolled in OCSA, the family must also consider the schooling options of the other children in the family. This would mitigate against moves toward OCSA.

A third factor that can impact a school's attraction is the perceived financial stability of the school itself. The North Carolina school was founded by a successful businessman who had already founded another well-regarded private school. Families who were aware of this fact probably recognized that the new charter school was likely to succeed, both academically and financially. OCSA's viability was not always assured. Over time it has developed an excellent reputation, and it turns away many applicants. The school is probably now viewed as a relatively low-risk opportunity by families, but this may not have been true initially. We have not

examined whether the attractive power of the school has increased over time, but this is a potential area for further study

Fourth, OCSA has very specialized and focused extracurricular programs. Some families may be unsure whether those programs will prove to be acceptable to their children. In fact, some students find that OCSA's demanding programs are "too much of a good thing." The probit analysis in this study shows that students who dropped out of OCSA were less likely to move closer to the school.

A fifth consideration is related to this fact. The North Carolina school may simply be viewed as a more attractive location for a family, relative to the alternatives in the area. That school is located in Wake County, which is generally considered to have a relatively high-quality traditional public school system. As a reflection of this, in the 2010 census, there were 4% *more* five-to-nine year olds in Wake County NC than zero-to-four year olds. Santa Ana has 7% *fewer* five-to-nine year olds than zero-to-four year olds. These ratios are likely to reflect perceptions of the quality of life (and particularly of traditional public schools) in Santa Ana relative to nearby communities. For a student enrolled in OCSA who may decide to leave OCSA and return to an assigned school, the family may consider the alternatives offered by the Santa Ana district inferior to the alternative assigned school in the family's current (original) location. If so, a move into Santa Ana could be viewed as a strong indicator that the child intends to remain enrolled at OCSA.

Overall, the level of attraction exhibited by OCSA must be viewed as relatively high. Almost 2000 students attend OCSA, and more than 500 full or part-time employees of the school. The city would certainly view attracting a near-2500-employee firm downtown as a very positive



development for the city. Given that the school exhibits a family attraction level similar to that previously found for employers, this may be an appropriate analogy.

While it is likely that non-arts-based charter schools are also developmentally attractive, cities seeking to foster economic development might find arts-based charter schools to be particularly impactful due to their after-hours spill-over effects in the community.

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