Signaling for Attention: Mobility and Student Performance in United Way's Promise Neighborhoods

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Abstract:

In this paper, we use a fixed effects linear least-squares regression to explore the relationship between student performance and student mobility in the Bethel School District in Eugene, Oregon. Our client, United Way of Lane County, has struggled with the topic of mobility, as it is important to its financial decision-making and education goals in its new Promise Neighborhood project. To provide context, we use voter registration data to estimate total mobility in Lane County and in the Promise Neighborhoods. Due to the structure of our data, we cannot determine the direction of causality with respect to student mobility and performance. Although we find a strong negative relationship between mobility and student performance, we can only conclude that mobility is merely a signal.

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Introduction:

United Way is a national non-profit organization that collects and allocates donations to benefit communities in need. With its headquarters in Eugene, Oregon, United Way of Lane County serves the entirety of Lane County. United Way has three primary goals centered on education, income, and health. These goals are: preparing children to succeed in school and life, moving families from poverty to financial stability, and ensuring people have access to basic health care. United Way's goals depend on its ability to understand, prioritize, and best respond to the needs of Lane County residents.

United Way's positive impacts on Lane County residents are a function of its projects and programs. The Promise Neighborhoods, a new project developed by United Way, will develop a continuum of "cradle through college and career" solutions to improve the educational and developmental outcomes of children living in Lane County's most distressed areas.[1] Inspired by the success of the Harlem Children's Zone, the Promise Neighborhoods project aimed at

[1] United Way. *Lane County Promise Neighborhoods*. 10 June 2011. 2011. <http://www.unitedwaylane.org/what-we-do/community-impact/education/success-by-6/promise-neighborhoods/>

providing a comprehensive support system for families and children at risk.

Student mobility is an important topic in education and in United Way's research agenda. During preliminary discussions with United Way's Associate Director of Education Holly Mar Conte, we discovered that student mobility might become a significant topic on United Way's agenda as they continue to develop a formal strategy for the Promise Neighborhoods. Mobility has been a discussion topic in United Way meetings, but little is known about its effects on students or the surrounding community.

Mobility raises two primary concerns for United Way and its goals in the Promise Neighborhoods. First, mobility has financial impacts. United Way faces finite financial resources, and they must make decisions on how they will effectively allocate their money in order to produce efficient, effective, and positive outcomes. The movement of students in and out of the Promise Neighborhoods could threaten to reduce the effectiveness of a dollar spent in the Promise Neighborhoods relative to a dollar spent in a less mobile area. Second, mobility may affect student performance. There is evidence that student mobility has a negative effect on school performance. If there is high mobility in the Promise Neighborhoods, then students who are more mobile will be less likely to be "ready to learn" – a possible phenomenon in the Promise Neighborhoods that United Way wants to address.

Based on these concerns, we will address four main questions: What are the specific mobility rates (within, between, to, and from) the Promise Neighborhoods? Should United Way be concerned? Will our findings have a significant effect on policy and designing the Promise Neighborhood program? What kind of data should United Way collect for future studies?

Background Information:

United Way's Promise Neighborhood is a program modeled off of the Harlem Children's Zone (HCZ). The project began in the early 1990s, when HCZ organized a wide range of support services for a single block in Harlem, a neighborhood in New York City. The goal was to address typical problems facing poor families: violent crime, chronic health problems, failing schools, and inadequate housing. The single block later expanded to a 24-block area. United Way's goals with the Promise Neighborhood program are quite similar to the successes of HCZ. The Promise Neighborhoods will focus on two small neighborhoods in the Bethel and Springfield School Districts and will primarily target childhood development and education. The vision is to develop a full continuum of support for children. Currently, around 82 percent of children in the Promise Neighborhoods who are entering kindergarten do not meet the early literacy benchmark.[2] This benchmark includes simple skills such as knowing how to hold a book and being able to recognize letters of the alphabet.

Specifically, in the district lines of Fairfield and Malabon Elementary schools, which span the Bethel Promise Neighborhood, 92 and 88 percent of kindergarten students are below the benchmark, respectively. Brattain and Maple Elementary Schools in the Springfield Promise Neighborhood have 76 and 71 percent of students under the benchmark, respectively. We believe these statistics may exhibit sampling error and bias; nonetheless, they are indicators of the poor academic performance in the Promise Neighborhoods. Appendix A provides boundary maps of the Promise Neighborhoods. Figure 1 is the Springfield Promise Neighborhood, and Figure 2 is the Bethel Promise Neighborhood.

Consulting the scholarly literature on student mobility and performance, we see that the

[2] Mar Conte, Holly. Personal Interview. 13 May 2011.

relationship between mobility and testing performance is somewhat unclear. This may be due to the geographic scope of the various analyses. When studies draw from a national database, the effects of mobility and performance dissipate. That is, the more heterogeneous the sample, the harder it is to tease out the effects of mobility on student performance. For example, Lee and Burkam hypothesize that demographic characteristics of children and their family would impact mobility. They use national data to determine mobility rates by race, socioeconomic status, and gender. Lee and Burkam observe that the effects of mobility seem to be small, and that mobility seems less intrusive when considering the overall effects for the entire population. On the other hand, effects of mobility and student performance strengthen with local projects or studies that draw from more a homogeneous sample. The Chicago Longitudinal Study finds that one move costs students about two months' worth of achievement, and that students who move three or more time are five to six months behind their peers.[3] Since this study is bound to data gathered in Chicago, consequences of mobility on student performance are more evident.

When scholars do find statistically significant effects, they see that mobility has a negative impact on student performance. Highly mobile children perform worse on academic achievement tests than their peers.[4] Repeated mobility, or when a student changes schools more than once in a short time period, has a consistently negative effect and its magnitude increases with the frequency of moves.[5] Reynolds and his colleagues find a significant relationship between mobility and both lower school achievement and dropping out.[6] Additionally, he finds that both early mobility and mobility during high school have the greatest impact.

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[3] Kerbow, David. "Patterns of Urban Student Mobility and Local School Reform." *Center for Research on the Education of Students Placed at Risk* 5 (1996)

[4] Beatty, Alexandra, comp. "Student Mobility: Exploring the Impact of Frequent Moves on Achievement: Summary of a Workshop." *National Research Council and Institute of Medicine* (2010).

[5] Ibid.

[6] Ibid.

Yet, the literature is again unclear on mobility and its consequences on specific academic skills. Many scholars suggest students who move repeatedly have reading skills that often fall further behind those of their peers.[7] At conference on student mobility, Lee and Burkam present that moving had a smaller effect on mathematics performance than on reading performance. However, at the same conference, Hannaway presents there are consistently negative effects of moving within a district on mathematics scores and marginal effects on reading scores.[8]

Housing problems are the main reasons why students move. Forty-three percent of households with children had at least one significant housing problem in 2007.[9] These problems include housing that is physically inadequate or overcrowded, as well as housing that costs more than 30 percent of the resident's income. This figure is up from 40 percent in 2005, and may look even worse when considering the 2008-2009 housing crisis. Persistent housing and poverty problems can motivate populations with children to move, which translate into high rates of school mobility. Forty-two percent of fourth-grade student in poor families changed schools in the last two years, compared with 26 percent in non-poor families.[10] A change in a family's physical residence – for whatever reason – is the main reason why students change schools.[11]

Changing schools involves a complex relationship of issues that span student learning, classroom instruction, and school organization.[12] Student mobility not only affects the individual student who moves, but also alters the non-mobile children in the school. Evidence implies that when schools experience high rates of mobility, achievement levels decrease. Lash and Kirpatrick state that high student-mobility rates can also disrupt the learning environment in the

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[7] Smith, Jean Louise M., Fien, Hank, and Paine, Stan C. "When Mobility Disrupts Learning." *Educational Leadership* 65 (2008).
[8] "Student Mobility: Exploring the Impact"
[9] Ibid.
[10] "When Mobility Disrupts Learning."
[11] "Student Mobility: Exploring the Impact"
[12] "Patterns of Student Mobility"

classroom and throughout the school.[13] This suggests a negative spillover effect: the negative impacts of mobility reside in a school, even after the student has moved.[14] In other words, mobile students also influence the performance of non-mobile students. Student churning is likely to interfere with instruction, academic skills that build over time, and social networks.

Scholars reiterate that findings on mobility and performance are likely to be conservative.[15] The negative impacts of mobility are actually more pronounced than past studies have shown. Current researchers are emphasizing local studies over national studies to help examine the specific effects of mobility on student performance within a unique area. Thus, piecing together individual studies with robust findings can help shed more light on the dynamics of student mobility.

Data Organization:

We utilized two data sets to calculate and interpret the effects of mobility. The first data set was obtained from Lane County Elections and contained the entire population of registered voters in Lane County in 2006 and 2008. This data set has close to 400,000 observations and allows us to calculate the mobility rates with respect to age groups and geographical areas for the entire population of registered voters in Lane County. We also calculated mobility rates in the Promise Neighborhoods. Our second data set included withdrawal codes for each student changing classrooms in the Bethel School District. While we focused on physical moves with the Lane County voter data set, we were uncertain whether a withdrawal from a school meant that a student had physically moved and changed addressed. Therefore, we used the Bethel data set to

[13] "When Mobility Disrupts Learning"
[14] "Student Mobility: Exploring the Impact"
[15] Ibid.

calculate measures of educational disruption. This variable served as a rough proxy for mobility.

Lane County Election Data

Using Lane County voter data, we were able to calculate the mobility rates of registered voters in Lane County. The data set included 394,577 observations across two years with names, precinct numbers, full addresses, and unique voter identification numbers. Using the unique voter identification numbers, we could match observations across the two time periods with very high accuracy. We then determined three possible categories for mobility for each 2006-registered voter over the two-year period:

- Outbound Mobility: a registered voter had an observation in 2006 but no observation in 2008, and thus was presumed to have moved out of the county.
- Churning: a registered voter had an observation in 2006 at a given address and an observation in 2008 at a different address
- No Move: a registered voter had an observation in 2006 and 2008 but at the same address.

The Lane County election data had a few, yet important drawbacks that decreased the reliability of our estimates. First, there is a possibility that not every individual who moved in Lane County reregistered at his or her new address. Second, outbound mobility includes deaths. Registered voters who pass away are automatically removed from the database within two to three weeks after death. If an individual registered prior to the 2006 cutoff and died between 2006 and the 2008 cutoff, the individual is coded as outbound mobility. Our inability to distinguish between death and outbound mobility causes our calculation to have an upward bias. We decided against estimating death rates by age group and projecting them across the data to

attempt to counteract the bias of the model. Conversely, individuals who have lower incomes and more mobile are less likely to register to vote. According to U.S. Census data on elections and registration, there is a negative relationship between total family income decreases and the percentage of families registering to vote (Appendix B, Figure 1). Furthermore, there is a negative correlation between the duration of amount of time spent in a household and the percentage of families registering to vote (Appendix B, Figure 2). This results in selection bias, causing the mobility rate calculations to be understated. We assert that this downward bias is far stronger that the upward bias resulting from voters passing away.

Bethel School District Data

We received data that coded each student withdrawal from a particular school in the Bethel School District from 2002-2008. Each code had a specific reason for why the student left the classroom or school. We created four general groups of codes for the withdrawal codes: private, public, out and dropout. Observations with codes that did not fit into these categories were dropped from the data set, since they provided no ultimate insight into mobility, and thus were outside the scope of our project.

- $PRIVATE$: The student moved from a Bethel School to a private institution in the same area. Over the seven years of data, this code was never used.
- $PUBLIC$: The student changed schools within the Bethel School District.
- OUT: The student moved out of the Bethel School District.
- $DROPOUT$: The student was not reported to be attending a new school, or the student simply had stopped attending for a variety of reasons, excluding reported health-related circumstances.

Unfortunately, problems with this data set forced us to transform the data set from an individual unbalanced panel into a school-wide balanced panel. If the student withdrew from a school and was coded as a move within district, there was no new school code. Therefore, it was unclear on where a student who moved within the district actually settled. We also lacked individual demographic information attached to the individual students moves. This would have been important to tease out an argument for causality: whether mobility affected test scores, or vise versa. Finally, the panel data set was very unbalanced: some students would have multiple observations in certain years and none in other years. With such a low number of total observations, we were concerned whether we would be able to have enough degrees of freedom to pursue meaningful statistical results.

To organize the data into a balanced panel, we grouped each individual observation into school-wide percentages. For example, $PUBLIC_{i,t} = \frac{total\ PUBLIC\ observations_{i,t}}{total\ enrollment_{i,t}}$ determined the percentage of moves within the Bethel School district in school *i* at time *t*. We then used Oregon Department of Education statistics to attach demographic information to each school in each respective period. The total number of students who exhibited the trait at a specific school (*i*) was divided by the total enrollment that specific year (*t*). This produced a percent in terms of the entire student body. We included the variables:

- $BLACK_{i,t}$: Percentage of student who self-identify as Black in school *i* at time *t*.
- $INDIAN_{i,t}$: Percentage of student who self-identify as Native American/Indian in school *i* at time *t*.
- $ASIAN_{i,t}$: Percentage of student who self-identify as Asian in school *i* at time *t*.
- $HISPANIC_{i,t}$: Percentage of student who self-identify as Hispanic in school *i* at *t*.
- $RATIO_{i,t}$: Ratio of students to teachers at school *i* and time *t*.

- $MEAN_{i,t}$: Percentage of students who met or exceeded the state math benchmark at school *i* at time *t* added to the percentage of students who met or exceeded the state reading benchmark at school *i* at time *t* divided by two.
- $FREE_{i,t}$: Percentage of students who qualify for free lunch at school *i* and time *t*.

After preliminary analysis, we dropped Kalapuya High School, an alternative high school in the Bethel School District. Furthermore, we dropped the 2002 time period since not all schools had demographic data available in that year. After organization, the data were in the form of an unbalanced panel data set, with $t = 6$ and $n = 10$; thus, in total, there were 60 observations.

Empirical Analysis:

The total mobility in Lane County had a maximum of 66 percent of individuals 24-26 years of age, and a minimum of 20 percent in the 51-60 year-old age group. In the Promise Neighborhoods, mobility had a maximum at 65 percent in the 21-23 year-old category, and a minimum of 24 percent in the 51-50 year-old age group.

In all of Lane County, the outbound mobility reached a maximum at 43 percent in the 21-23 year-old age group, and a minimum of 10 percent in the 51-60 year-old age group. Outbound mobility in the Promise Neighborhoods reached a maximum at 42 percent in the 21-23 year-old age group, and a minimum of 12 percent in the 51-60 year-old age group.

Mobility within Lane County peaked at 24 percent in the 27-29 year-old age group, and reached a minimum of 8 percent in the 61+ year-old age group. Mobility within the Promise Neighborhoods had a maximum at 28 percent in the 27-29 year-old age group and a minimum of 9 percent for individuals over 61.

Appendix C provides bar graphs that display mobility rates of registered voters in Lane County (Figure 1) and in the Promise Neighborhoods (Figure 2).

We used a multi-variable regression model to determine the effects of a list of explanatory variables on a dependent variable. This mathematical technique teases out the effects of each explanatory variable and provides a unit-specific numerical estimate of how much that variable affects the dependent variable, controlling for the other explanatory variables.

Our chance of determining a casualty between mobility and student performance and failed when we transformed the data from individual data to school-wide percentages. With demographic data attached to each individual who moved, we could have known for certain which variables were having a unique affect on the dependent variable. Our variables represented percentages across each school and year. Nonetheless, we could still use the model to test the demographic variables' influence at the school-wide level.

Our final two regressions (Appendix D, Figures 1 and 2) used mobility both as a dependent variable and as an explanatory variable. Our first empirical model with the Bethel School District data had student performance as the dependent variable. The literature suggested that the casual relationship ran from student mobility to student performance, and we wanted to explore if this hypothesis was accurate in the Bethel School District. As pointed out in the background information, scholars disagree on where mobility affects reading or math scores more. Considering this disagreement, we averaged each school's reading and math test scores in the same period and used that value as the total performance variable. Our second empirical model with the Bethel School District data had student mobility as the dependent variable.

For both models, we used a linear least squares multi-variable regression with period and cross-sectional fixed effects. Since our data was non-random, we wanted to control for

unobserved heterogeneity in the data when the heterogeneity was constant over time. Furthermore, we wanted to control for differences in the data when anomalies were constant across schools. The fixed effects technique accomplishes both of these goals. Noticing a problem with heteroskedasticity, we used White's diagonal robust standard errors. It is the most general technique, and robust to all forms of heteroskedasticity, especially when *N* and *T* are small and roughly the same size. To measure goodness of fit, we referenced R-squared and minimized the Akaike Information Criterion. We gauged the significance of each explanatory variable at the 5 percent level.

Our first regression (Appendix D, Figure 1) used $PUBLIC_{i,t}$ as the dependent variable and tested the hypothesis that average test scores influenced mobility within the district. We regressed all the demographic explanatory variables on $PUBLIC_{i,t}$. To inspect if there was any non-linear relationship, we also included a non-linear term, $SQMEAN_{i,t}$ which was the square of the $MEAN_{i,t}$ variable. Apart from the constant, the only statistically significant variables ($p < 0.05$) were $SQMEAN_{i,t}$ and $MEAN_{i,t}$.

Our second regression (Appendix D, Figure 2) used $MEAN_{i,t}$ as the dependent variable and tested the hypothesis that moving within the district influenced average test scores. We regressed all the demographic explanatory variables, including $PUBLIC_{i,t}$, on a dependent variable that was one period ahead: $MEAN_{i,t}(+1)$. This was to determine if mobility ($PUBLIC_{i,t}$) and any of the other explanatory variables had an effect on mean test scores starting in the next year. We also included a contemporaneous $PUBLIC_{i,t}(+1)$ to determine if mobility had an effect on mean test scores in the same period. Apart from the constant, the only statistically significant variables ($p < 0.05$) were $PUBLIC_{i,t}$ and $PUBLIC_{i,t}(+1)$. For a full statistical output of both models, see Appendix C.

Empirical Results:

Several mobility trends are present in both the Promise Neighborhoods and in Lane County. We observe high rates of outbound mobility at younger age demographics, with that trend decreasing steadily after age 30. Additionally, outbound mobility reaches its maximum at 21-23, whereas than mobility within reaches its maximum in the 27-29 year-old age group. This data suggest that young parents, in age groups anywhere between 20-30 year-olds, may move more frequently than older parents.

Our first regression found that, across all schools and periods, a school's average test scores had a significant effect on the same school's mobility rate. The linear relationship was negative: A one percent increase a school's average test scores was associated with a .13 percent decrease in the same school's mobility rate. However, the non-linear relationship was positive: A one percent increase in the square of a school's average test scores was associated with a .07 percent increase in the mobility rate in the same school. This relationship does not make intuitive sense until it is plotted on a graph.

Appendix E contains a graph representing the change in average testing scores, holding all other variables in the regression constant.

The negative slope of the line points out that there is a negative relationship between a school's average testing scores and its mobility rate. Furthermore, this relationship exhibits decreasing marginal returns, meaning the curve's slope decreases as average test scores increase. In order words, a percentage change in average test scores is associated with a decreasing percentage change on the mobility rate as average test scores increase. At a low mean test score, mobility will change a lot; at a high mean test score, mobility will change less. Hypothetically, if

United Way were to spend money to increase test scores with the hope of decreasing the percentage of student moving within the Bethel School District, it would get the most bang for its buck by targeting schools with lower average test scores. That said, we are not implying that average test scores influences mobility, but rather that the relationship between test scores and mobility exhibits decreasing marginal returns.

Our second regression found that, across all schools and periods, mobility had a detrimental effect on a school's average test scores. Considering the lagged $PUBLIC_{i,t}$, the previous period's mobility rate turned out to have a negative effect on student performance in the following period. A one percentage change in the percentage of students moving within the district in one year at a particular school is associated with a 6.95 percent decrease in average test scores the following year at the same school. Looking at the contemporaneous variable, $PUBLIC_{i,t}(+1)$, moving in the same period had a negative effect on student performance in the same period. A one percentage change in the percentage of students moving within the district in one year at a particular school is associated with a 6.86 percent decrease in average test scores in the same year at the same school. The coefficient values are very similar (-6.95 and -6.86), suggesting the residual effects of student mobility are closely related to the contemporaneous effects of mobility at the same school.

Due to the generalization of our data, we can only infer that mobility, though significant in both regression models, is only a powerful negative relationship. In our first model, we estimated average student performance in a certain school to have a negative effect on mobility, with the relationship exhibiting decreasing marginal returns. In our second model, we estimated student mobility to have a negative effect on average student performance in a school in the previous period and in the contemporaneous period. Both of the models show that there is a

strong negative relationship between mobility and student performance. However, the panel data we used in our regressions were school-wide averages instead of individual observations; therefore, we cannot conclude that the act of a student moving causes a decrease of testing scores, or that low testing scores will cause one to move. We do not know if the student who moved belonged to a certain ethnicity, income level, or had low or high state test scores. Furthermore, if a student moved, we did not know where the student physically moved.

A perfect data set would include a data point for each mobile student, indicating his or her specific demographic data. It would also include that individual's state testing scores. One would also need to code which school the student left, and where in the district a student moved.

Conclusions:

To our disappointment, the pure effects of mobility and student performance cannot be determined, thus we finally conclude that mobility is merely a signal. We find that schools with a higher percentage of mobile students have lower average test scores, but we do not know, demographically, what kind of students these mobile students are. Furthermore, we do not know for certain why a school's average student performance would decreases. The following are a few hypotheses that might explain the relationship between mobility and student performance

- High-performing students are moving out of a school, dragging down the school's average.
- Spillover effects: mobile students are negatively affecting non-mobile students' performance at school.
- Low-performing students move to a new school, causing the new school's average to decrease faster than instances of gains in student performance.

Overall, a school's mobility rate signals that either mobile students – or an unobserved demographic group that our data could not measure within the mobile population – need attention. Our results suggest that, in the Bethel School District, there is a negative relationship between a school's mobility rate and the respective school's average student performance. United Way must address mobile populations, since they, according to our empirical results, are associated with lower student performance. Although the causal relationship will require further research, we conclude that mobility should be measured and explored to maximize outcomes generated by United Way's Promise Neighborhoods program.

Works Cited

Beatty, Alexandra, comp. "Student Mobility: Exploring the Impact of Frequent Moves on Achievement: Summary of a Workshop." *National Research Council and Institute of Medicine* (2010).

Braun, Drew. "Mobility Rate, Bethel." Message to the author. 8 Mar. 2011. E-mail.

Comey, Jennifer, Xavier De Souza, and Gretchen Weismann. "Struggling to Stay Out of High-Poverty Neighborhoods: Lessons from the Moving to Opportunity Experiment." *Metropolitan Housing and Communities Center* (2008). Mar. 2008. Web. 13 Feb. 2011.

Coulton, Claudia, Brett Theodos, and Margery Turner. "Family Mobility and Neighborhood Change: New Evidence and Implications for Community Initiatives." *The Urban Institute: Research of Record*. Nov. 2009. Web. 18 Mar. 2011. <http://www.urban.org/url.cfm?ID=411973>.

Kerbow, David. “Patterns of Urban Student Mobility and Local School Reform.” *Center for Research on the Education of Students Placed at Risk* 5 (1996).

Mar Conte, Holly. Personal Interview. 13 May 2011.

O'Donnell, Robert, and Anna Gazos. *Student Mobility in Massachusetts*. Issue brief. Office of Strategic Planning, Research, and Evlauation, 2010.

Smith, Jean Louise M., Fien, Hank, and Paine, Stan C. “When Mobility Disrupts Learning.” *Educational Leadership* 65 (2008).

Appendix A

Figure 1.

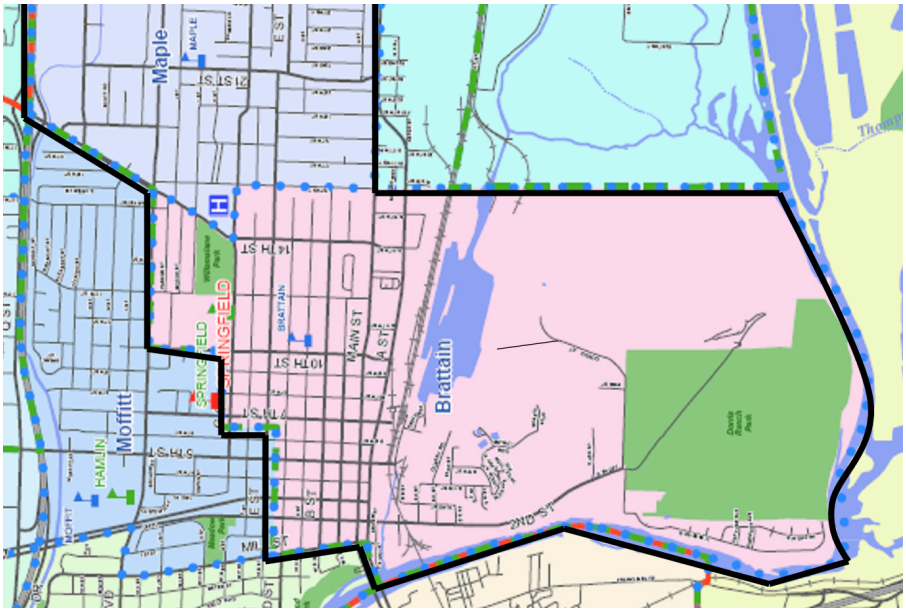
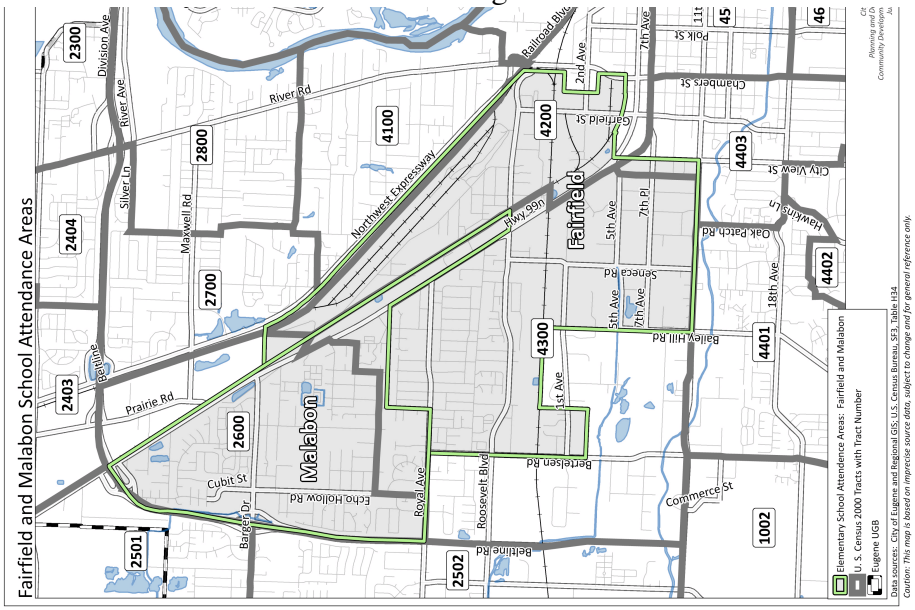


Figure 2.



Appendix B

Figure 1.

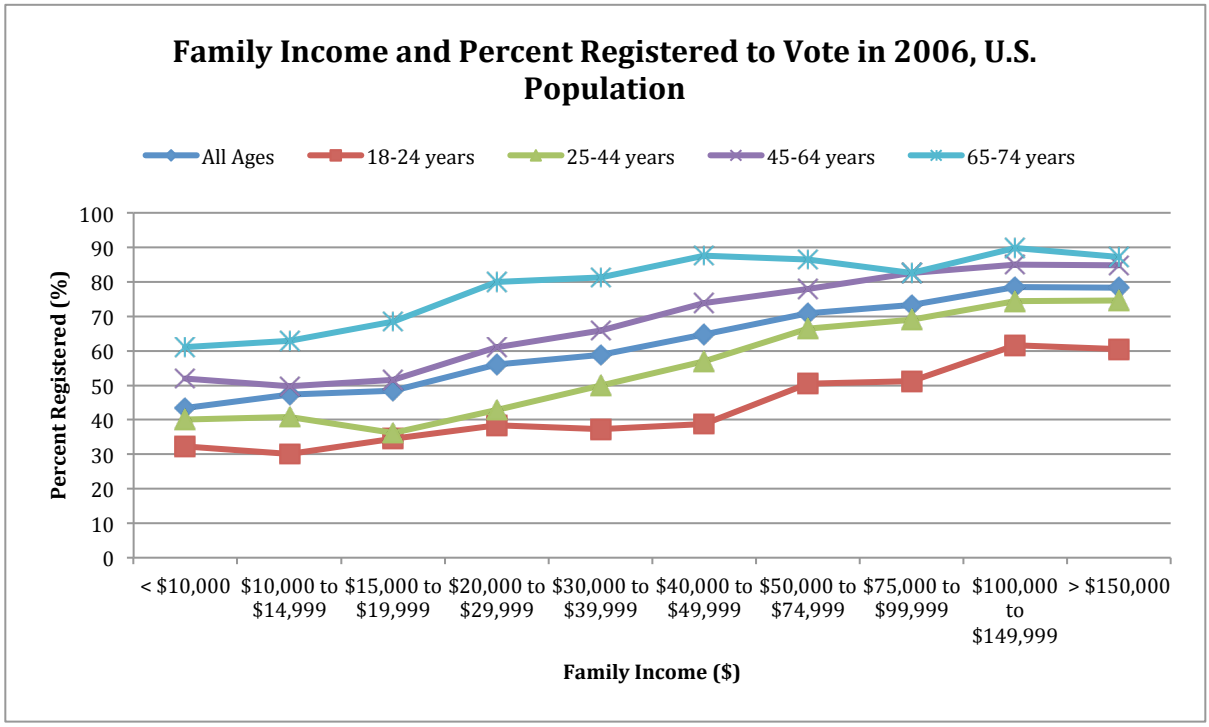
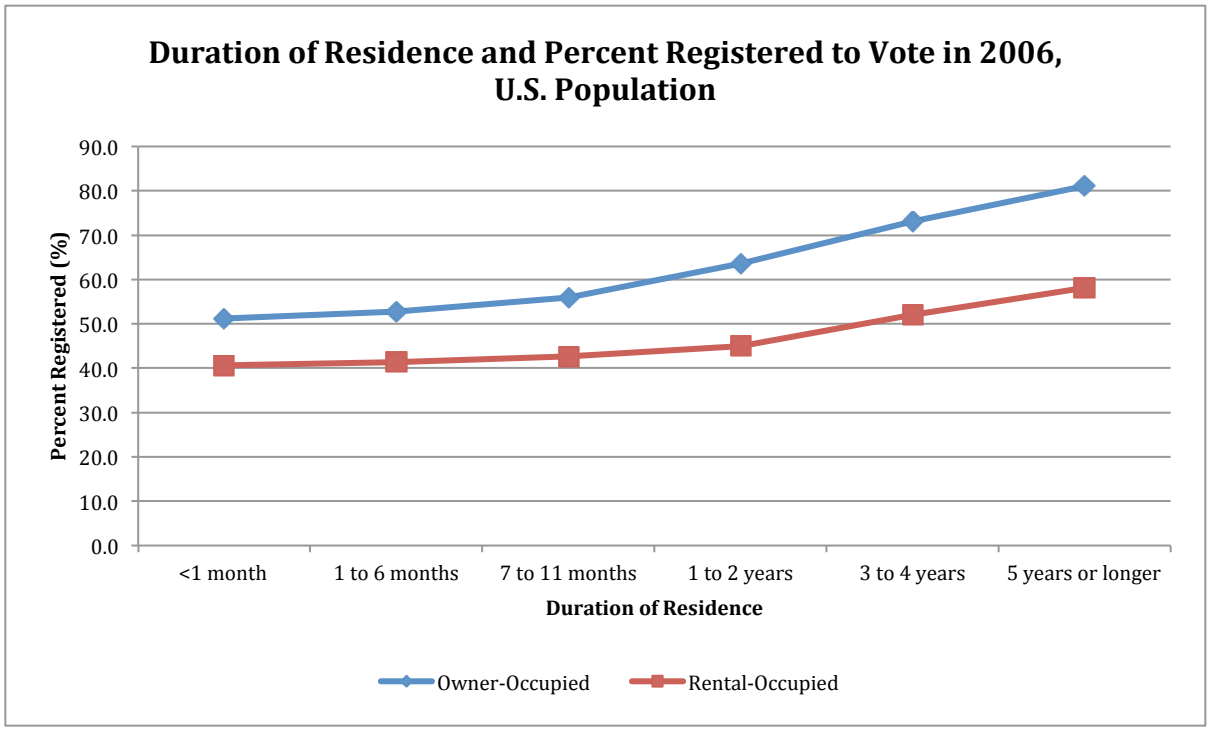


Figure 2.



Appendix C

Figure 1.

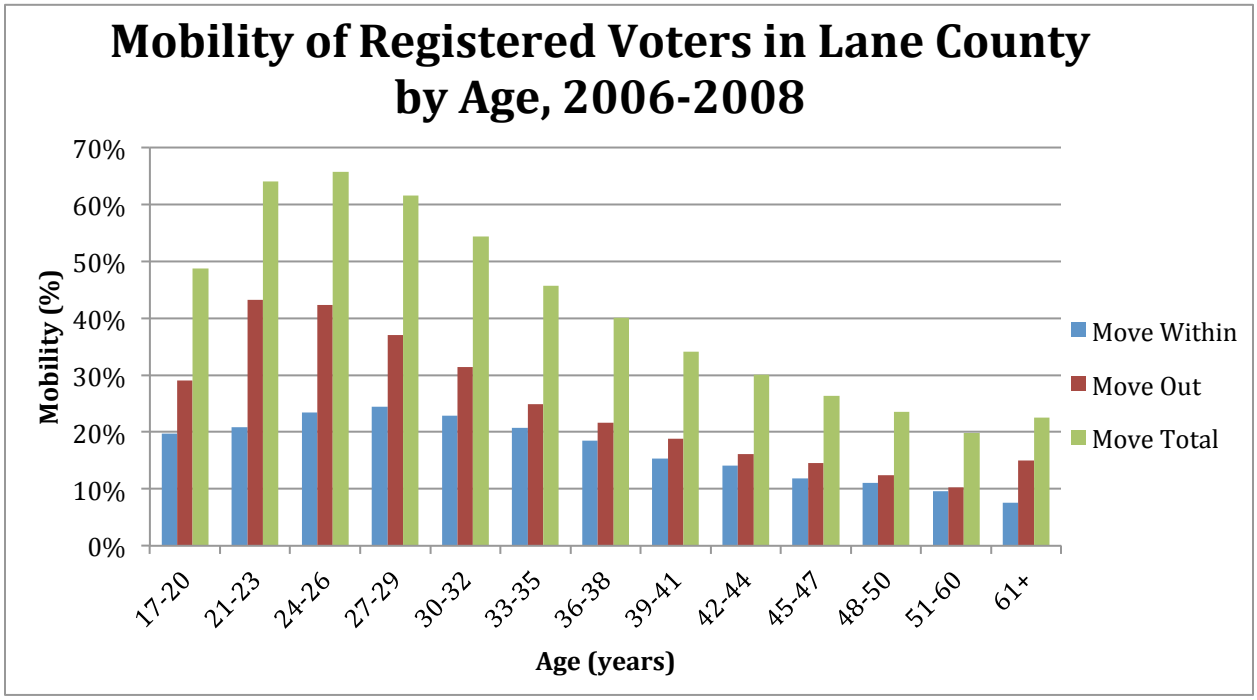
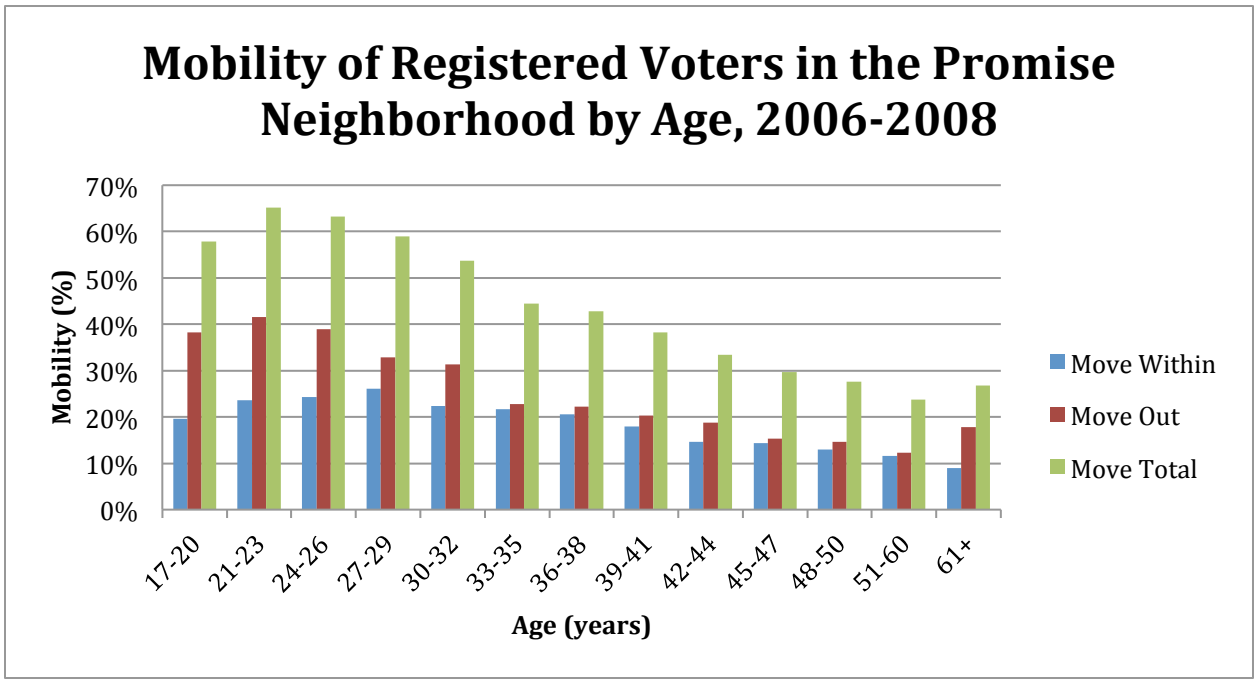


Figure 2.



Appendix D

Figure 1.

Dependent Variable: PUBLIC

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.052877	0.021617	2.446122	0.0193
RATIO	0.000127	0.000219	0.578006	0.5668
FREE	0.008063	0.008310	0.970264	0.3382
BLACK	-0.072553	0.065588	-1.106188	0.2758
HISPANIC	-0.003308	0.023157	-0.142861	0.8872
ASIAN	-0.009165	0.039450	-0.232314	0.8176
INDIAN	-0.063285	0.059769	-1.058843	0.2965
MEAN	-0.130037	0.055853	-2.328203	0.0255
SQMEAN	0.078516	0.036695	2.139685	0.0390

Cross-section fixed (dummy variables)
Period fixed (dummy variables)

R-squared	0.754803	Mean dependent var	0.002202
Adjusted R-squared	0.609010	S.D. dependent var	0.004081
S.E. of regression	0.002552	Akaike info criterion	-8.820988
Sum squared resid	0.000241	Schwarz criterion	-8.018156
Log likelihood	287.6296	Hannan-Quinn criter.	-8.506956
F-statistic	5.177221	Durbin-Watson stat	2.233768
Prob(F-statistic)	0.000006		

Figure 2.

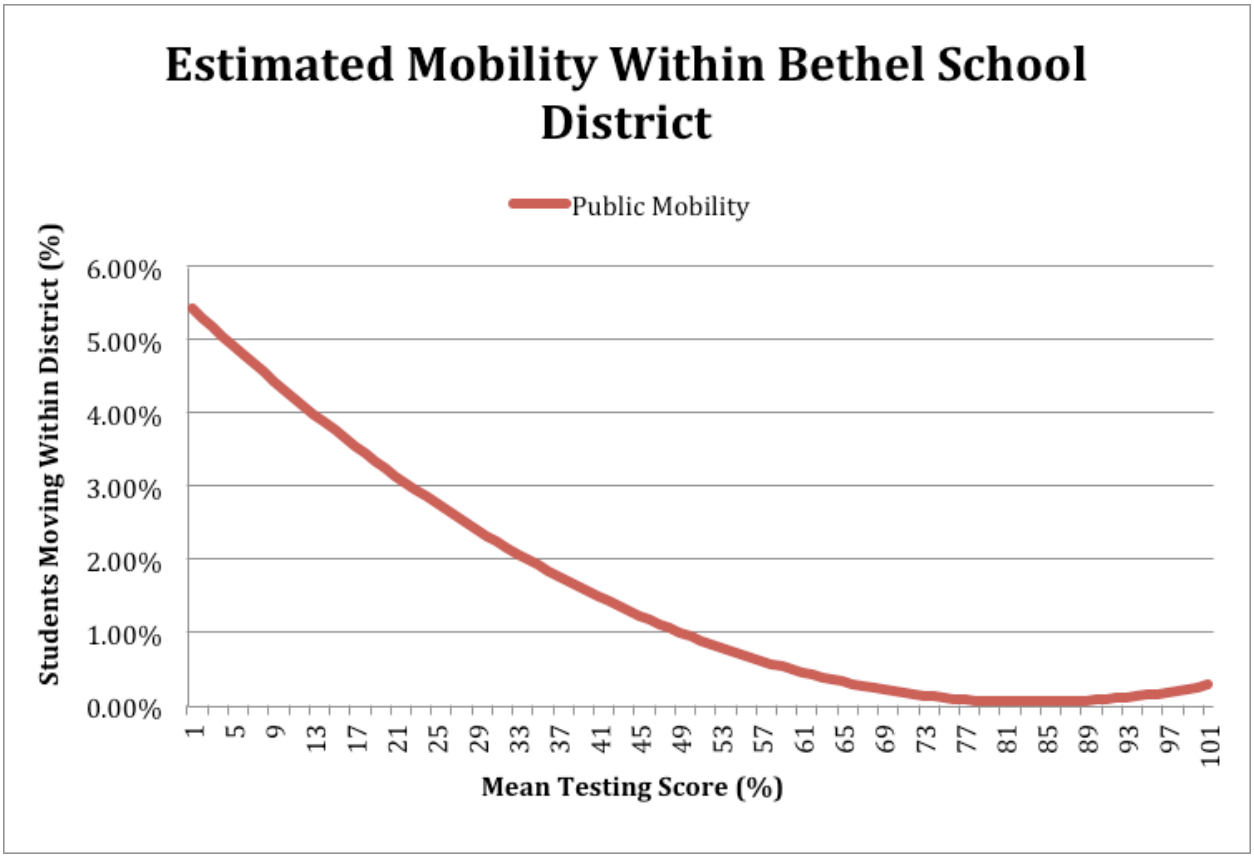
Dependent Variable: MEAN(1)

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.736662	0.134980	5.457585	0.0000
RATIO	0.007377	0.005238	1.408427	0.1700
FREE	-0.115141	0.146709	-0.784828	0.4391
BLACK	-3.068347	1.625216	-1.887963	0.0694
HISPANIC	0.452954	0.587683	0.770745	0.4473
ASIAN	0.047676	1.193381	0.039950	0.9684
INDIAN	-1.237077	1.241203	-0.996676	0.3275
PUBLIC(1)	-6.866180	3.005855	-2.284268	0.0301
PUBLIC	-6.953119	2.957995	-2.350619	0.0260

Cross-section fixed (dummy variables)
Period fixed (dummy variables)

R-squared	0.916583	Mean dependent var	0.769200
Adjusted R-squared	0.854021	S.D. dependent var	0.132432
S.E. of regression	0.050598	Akaike info criterion	-2.829610
Sum squared resid	0.071686	Schwarz criterion	-1.988319
Log likelihood	92.74024	Hannan-Quinn criter.	-2.509241
F-statistic	14.65066	Durbin-Watson stat	1.627852
Prob(F-statistic)	0.000000		

Appendix E


Estimated Mobility Within Bethel School District
Public Mobility
Students Moving Within District (%)
6.00%
5.00%
4.00%
3.00%
2.00%
1.00%
0.00%
1
5
9
13
17
21
25
29
33
37
41
45
49
53
57
61
65
69
73
77
81
85
89
93
97
101
Mean Testing Score (%)