THREE ESSAYS ON MICROFINANCE AND EDUCATION

by

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(Under the Direction of Glenn C.W. Ames and Michael E. Wetzstein)

ABSTRACT

This dissertation consists of three essays on microfinance and education. The first essay employs panel data from the Kyrgyzstan Household Integrated Survey from 2006 to 2010 to analyze household micro-credit allocation. A multivariate Probit model is developed and populated with borrowers' loan allocations. Key factors considered are education, gender, equipment ownership, and geographical region. Results indicate that the Naryn region has the largest impact on borrowers' likelihood to allocate loans toward food and the smallest (negative) impact on the probability of starting a new business. Mobile phone and livestock ownership are identified as two key factors, which decrease borrowers' probability of using loans to purchase food and increase the probability of agricultural investment or to start a business.

The second essay analyzes the relationship between racial diversity, school performance, and school location for elementary schools in Georgia. The results indicate that the relationship between racial diversity and school performance depends on school location. In metropolitan areas, an increase in racial diversity has a positive effect on minority students' achievement scores while there is no corresponding decline in white students' performance. In rural areas, either no significant effect was observed or it was followed by a reduction in the achievement scores of white students. The results of this study suggest that educational policy goals defined at the state level to foster school performance should be further differentiated according to the student population.

The third essay investigates the transportation cost of the voluntary inter-district school transfer program in the Atlanta Metropolitan Area (AMA). In this essay, cluster analysis was employed to recognize low and high performing schools while the distribution of the non-affluent students was realized with the centroids of the Voronoi diagram. These findings indicate that, in the Atlanta Metropolitan Area, the differences in the school performance are more clustered between school districts than within them. In addition, low-income students are less isolated from high performing schools than non-white students. This suggests that the voluntary inter-district school transfer program based on color-blind actions should be combined with policies aimed at alleviating the isolation of non-white students in the AMA.

INDEX WORDS: Kyrgyzstan, Microfinance, Educational Achievement, Racial Inequality, School Location, School Transfer, Inequality,

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1.1 Introduction

Microfinance programs are based on the concept that low-income households are affected by the lack of credit access (Petrick, 2005; Armendáriz and Labie, 2011). In general, asymmetric information reduces the lender's ability to recognize reliable borrowers and this generates credit rationing (Stiglitz, 1990). Due to the lack of borrowing history and collateral as required by banks, low-income households scattered in depressed rural areas are particularly credit constrained (Barnett et al., 2008). The relaxation of credit constraints is usually realized by microfinance through the introduction of group (joint liability) lending (Armendáriz and Labie, 2011). All members in a group are jointly responsible for a loan, which reduces a lender's risk and increases access to financial services for households (Stiglitz, 1990). Thus, microfinance has the potential to lift low-income households out of poverty (Khandker, 2005; Katsushi et al., 2010).

In Central Asia and specifically in the Kyrgyz Republic, the collapse of state directed economies produced a dramatic rise in small business and self-employment (World Bank, 2004). However, the rate of credit penetration in Kyrgyzstan is one of the lowest in Central Asia and Eastern Europe (Microfinance Center, 2011). In 2009, this penetration rate from any source among the economically active population (15-65 years old) was only11% in Kyrgyzstan (Microfinance Center, 2011). In contrast, microfinance covers more than 70% of the credit market in Kyrgyzstan, second only to Mongolia (Microfinance Center, 2011). The underdeveloped credit market in Kyrgyzstan is mainly served by microfinance. A possible reason for this dominance is that microfinance has one of the most advanced legal frameworks in Central Asia (World Bank, 2004; Brown and Jacobs, 2010). Further, Kyrgyzstan microfinance has excellent outreach capabilities to service poor households and the rural sector (World Bank, 2004).

Within the last decade the rapid growth of Kyrgyzstan microfinance has raised concerns about its economic development effectiveness. In general, if the diffusion of microfinance is associated with providing basic necessities and not for investment purposes, its effectiveness to promote economic growth is at risk. The question is: if loans are for consumption rather than for productive purposes that generate economic opportunities, this may lead to over-indebtedness (Schicks, 2012). Kyrgyzstan and Mongolia are the two countries in Central Asia and Eastern Europe with the highest level of over-indebtedness (PlaNet Finance Foundation, 2013). In May 2012 the Kyrgyzstan National Bank closed 94 microfinance lenders for charging above the industry-average interest rates due to concerns about over-indebtedness (Smith, 2013). In August 2013, the president signed a bill that sets an interest cap (price ceiling) to limit usurious practices (Youatt, 2013).

Any potential welfare improvements from these or future policies are predicated on this question of over-indebtedness. As an aid toward answering this question, the credit allocation of microfinance borrowers is analyzed. The Kyrgyzstan Integrated Household Survey (KIHS, 2010), is utilized, which provides detailed information on the socio-economic status of households from 2006 to 2010. Specifically, the survey provides information on microfinance borrowers and the purpose of their loans. This dataset supports a multivariate Probit model for analyzing the interdependence of the choices among different loan uses. The model is employed to study if households are credit constrained and if they used their loans for investment or consumption purposes. The target area is low-income households in the Naryn district (Figure 1.1), which is characterized by high rates of rural poverty. In 2011, the United National Development Program (UNDP) estimated that Naryn district had the highest poverty rate in the country, 52% of the national poverty line (Slay, 2011). In addition, the population density is the lowest with only five inhabitants per square kilometer (National Statistical Committee of the Kyrgyz Republic, NSCK, 2009). Finally, according to the KIHS (2010), the Naryn region accounts for 56% of the microfinance loans.

The essay is organized as follows: Section two provides the background on the economic transition and the microfinance sector in Kyrgyzstan; section three discusses the empirical strategy; section four describes the dataset and the variables employed; section five introduces the microeconomic model and the econometric approach for estimation; section six presents the results, while the conclusions and implications are provided in the final section.

1.2. Economic Transition and Microfinance in Kyrgyzstan

1.2.1 Economic Transition in Kyrgyzstan

The Kyrgyz Republic, located in Central Asia, received its independence in 1991 after the collapse of the Soviet Union (USSR). As with many of the former Soviet Republics, its economy was dependent on trade within the USSR, and after the collapse, it witnessed a large drop in Gross National Income (GNI) and living standards (Figure 1.2). It took 19 years to restore GNI to the pre-independence level.

The World Bank (2014a) classifies the Kyrgyzstan Republic as a low-income country. Approximately 6% of the population lives at the lowest poverty threshold of $1.25 per day. Moreover, the poverty gap increased by 37.5% from 2006 to 2011 (World Bank, 2014b).

While the country does have substantial reserves of coal, gold, uranium, antimony, and rare earth minerals, its currently mining production is only 50% of the pre-independence period (World Bank, 2005). Agricultural production, accounting for a third of the workforce, declined by 40% from 1990 to 1995 and is only now gradually recovering. In contrast, trade and the service sectors have substantially increased their share of GDP from 29.6% in 2000 to 46.6% in 2010 (National Statistical Committee of the Kyrgyz Republic, 2014).

1.2.2 Microfinance in Kyrgyzstan

According to Kyrgyz legislation, "the goal of microfinance organization activities is to provide accessible microfinance services to alleviate poverty, increase employment, and assist in the development of entrepreneurship and social mobilization of the population in the Kyrgyz Republic" (Kyrgyz Republic, 2002). In other words, microfinance in Kyrgyzstan was introduced as a poverty reduction tool, given the country's low living standards.

The first examples of microfinance organizations in Kyrgyzstan date back two decades. Since then, their presence has grown considerably. Trends in the country's microfinance sector, both in terms of size, number of loans, and interest rate, are listed in Table 1.1. From 2006 to 2011, the average loan size ranged from $391 to $597, while the real interest rate increased from 34% to 44%. In the same period, interest payments increased from $155 to $209. These figures are on the same scale with the rest of Central Asia and Eastern Europe microcredit loans (Weiss and Montgomery, 2004).

Microfinance also presents some peculiar characteristics in Kyrgyzstan. Despite a large number of microcredit institutions, the market is very concentrated: 84% of the clients are served by only five organizations - Aiyl Bank, Bai Tushum, Finca, Kompanion, and Mol Bulak Microfinance Center, 2011). Table 1.2 lists the operational self-sufficiently index and the loan portfolio at risk (over 30 days) for these institutions. From 2006 to 2010, the operational self-sufficiency index is greater than one, indicating that the costs were smaller than the revenues even when the margins of profit shrank during the world financial crisis in 2008-2009. Moreover, the level of risk is low. Table 1.2 lists the portfolio at risk for loans overdue 30 days or more, ranges from zero to 5.45%. These figures are lower than in any other Central Asian or East European country (Microfinance Center, 2011).

In recent years Kyrgyzstan has experienced an increase in competition among microfinance leaders, due to favorable legislation for their establishment (Smith, 2013). A microfinance institution (MFI) can be established with only $2,175 and no expertise in microfinance. Small MFIs are often more aggressive in attracting new clients and tend to charge higher interest rates (Smith, 2013). The growth of the interest rates and the rapid diffusion of microfinance agencies have raised some concerns about over-indebtedness, especially for low-income households in rural areas (Youatt, 2013). The higher interest rate charged to low-income borrowers scattered in remote rural areas can be motivated by a higher degree of asymmetric information suffered by the lender (Stiglitz, 1999).

Lack of property rights has also contributed to over-indebtedness (World Bank, 2009). The restricted use of agricultural assets as collateral increases the lender’s transaction costs and reduces low-income farmers’ access to credit. As in all former Soviet Union countries, the process of land reform in Kyrgyzstan moved from state owned to private ownership. Kyrgyzstan was the latest among the former Soviet republics to allow private land ownership in 1998 (Lerman and Sedik, 2009). In the last decade the number of registered properties and cadastre offices increased substantially (World Bank, 2009), but there are still constraints. Apart from the technical difficulties of mapping land characteristics, land use rights are still limited (USAID, 2005).

1.3. Empirical Strategy

There are three empirical issues to consider when modelling households' loan allocations. First, selection on the unobservables could be present (Wooldridge, 2002). Before deciding the loan allocation, a household prepares a formal application. This application is subjected to screening by microfinance officers and, if approved, the loan will be granted. Specifically, a loan allocation is observed only if the loan is approved. In this case, there are two incidental truncations: households with microfinance loans are observed conditional to the loan application and households with a specific loan purpose are observed conditional to their loan approval.
These incidental truncation problems can cause endogeneity issues (Greene, 2012; Freedman and Sekhon, 2010). Since the Kyrgyzstan Integrated Household Survey does not provide information on the loan application, the strategy is to employ a wide range of controls in the structural equation. In general, correlation between the included variables does not generate incidental truncation and bias (Wooldridge, 2002). Including relevant exogenous controls in the structural equation will remove these factors from the error term and reduce the potential correlation between equations.

In addition, even if incidental truncation were present, the model can be consistently estimated conditional to the dataset (Wooldridge, 2002). Specifically, for the households with access to microfinance, the proposed strategy produces unbiased estimates. A recent example of this empirical strategy applied to the credit market is in Huergo and Moreno (2014) and the relative literature review is provided by Cellini (2008).

The second central issue is the household's loan allocation which is an interdependent choice. In general, credit constrained households allocate scarce funds among different choices subject to their opportunity cost (Karlan and Goldberg, 2011). Some of these choices, including capital investment or financing an emergency, can have high initial costs, which precludes the use of the loan for other choices. It is then reasonable to assume that the choices are interdependent. If the choices are interdependent, the error terms will be correlated among choices. Defining univariate models for each choice provides consistent estimates of the coefficients but incorrect standard errors (Greene, 2012). Consequently, a multivariate model yielding efficient errors is preferred.

Finally, simultaneity is the third econometric issue. In general, identifying which factors affect a more productive use of microfinance can reduce food insecurity and stimulate economic growth (Schicks, 2012). In this study, the analysis of the relationship between loan allocation and durable goods will be provided. The issue is that the loan allocation is contextual to the purchase of durables goods. This is particularly true for credit constrained households, which purchase durable goods for the first time. In order to solve this problem, the independent variables that represent economic assets are lagged. In this way, it will be possible to test if the ownership of durable goods in the previous period (year) affects the probability to allocate the loan for a specific purpose in the current period.

1.4. Data

The dataset is based on the Kyrgyzstan Integrated Household Survey (KIHS, 2010) collected by the NSCK, covering the years from 2006 to 2010. The KIHS broadly consists of seven sections: general socio-economic information (age, gender, and marital status), family status (education, internal migration, and health status), consumption and expenditure composition, and employment status. Other data include purchases of non-food commodities, household income and expenditures, and housing conditions. An exhaustive description of the KIHS survey data is available in Esenaliev et al. (2011).

The survey is a rotating panel with only a maximum of one-quarter of the sample being replaced annually, leading to a non-fixed sample size of 5,016 households for 19,060 individuals per year. The sample of the KIHS is drawn using stratified two-stage random sampling based on the results of the 1999 population census. The total sample size is 25,360 observations that correspond to 7,716 households repeated by one or more times for five years.

The sample of households with access to microfinance credit consists of all the households with at least one microfinance loan during the studied period. This corresponds to 6% of the sample (608 loans, 449 households). Due to the differentiation of the durable goods variables and the off-farm income, the first year of observations is dropped from the dataset and the sample size utilized to estimate the model is 445 loans (330 households).

The socio-economic variables including age, family size, education, and off-farm income are employed along with dummy variables for gender and rural or urban residence. The socio-demographic variables were defined with respect to the household head. The exact definition of each variable is listed in Table 1.3 with summary statistics in Table 1.4.

The off-farm income is the real income calculated with the Atlas method. This method is employed to compare the living standards among countries (World Bank, 2014c), which uses the GDP deflator and the average exchange rate adjusted for the difference in the inflation rate. Due to some skewness of the distribution, the off-farm income variable was log transformed.

The dataset also provides information on the region of residence. Apart from the capital city Bishkek, there are seven districts (Oblasts): Issykul, Jalal-Abad, Naryn, Batken, Osh, Talas, and Chui. Table 1.5 indicates that the share of sampled households in the Naryn district is on the same scale with the other districts (13.4%). In contrast, the access to microfinance and share of total loans in this district is larger, 51% and 56%, respectively.

Finally, the KIHS classified the loan purposes into seven categories: Food purchase for household nutrition, starting a private business, agricultural needs, housing, education, healthcare, and other expenses. Each dependent variable was defined equal to one if the household used the loan for that purpose and zero otherwise.

1.5. Econometric Approach and Hypotheses

1.5.1 Analytical Strategy

Assume a household with access to microfinance faces M choices. Each choice consists of allocating part or the entire amount of the loan to a specific purpose. It is assumed that a household is a utility maximizer in its use of credit. A household's utility is unobservable, but household's attributes are observable. The utility function is then decomposed in the summation of a household's attributes and the error term:

$$\boldsymbol{U}_j^* = \boldsymbol{X_j}\boldsymbol{\beta}_j + \boldsymbol{\varepsilon}_j \,, \qquad j = 1 \,..\, M \,, \qquad (1.1)$$

where $\boldsymbol{U}_j^*$ is a N by 1 vector of random utilities of N households, $\boldsymbol{X_j}$ is a N by K_j matrix of household's attributes, $\boldsymbol{\beta}_j$ is a K_j by 1 vector of parameters, and $\boldsymbol{\varepsilon_j}$ is N by 1 vector of error terms. The system given in (1.1) identifies M equations, one for each choice.

System (1.1) is assumed to have a threshold value such that if the utility of the borrower i from the choice j, U_{ij}^*, is larger than the threshold, household i allocates part or the entire amount of the loan to choice j. Without loss of generality, the threshold value is assumed to be equal to zero. Utility U_{ij}^{*} is not observed, so (1.1) is empirically estimated by considering a binary variable y_{ij} equal to one if household *i* allocates the loan to choice *j* and zero otherwise:

$$y_{ij} = \begin{cases} 1\ if\ U_{ij}^{*} > 0 \\ 0\ otherwise \end{cases} \tag{1.2}$$

In particular, $\boldsymbol{\varepsilon}$ is assumed to follow a multivariate standard normal distribution $N[\mathbf{0}, \boldsymbol{\Sigma}]$ where $\boldsymbol{\Sigma}$ is the covariance matrix. This identifies the model as a multivariate Probit model, which allows for random taste variation (Train, 2009). The choice among different uses of the microfinance loan is not exclusive where more than one choice is possible. Seventy-two percent of the loans were used for one purpose, 21% for two, 6% for three, and 1% for four or five purposes. Given the normality assumption, the model is estimated with maximum likelihood estimation. The likelihood function is a multivariate distribution, which requires evaluating a multiple integral. Quadrature methods are developed for trivariate distributions, but for integrals of a level greater than three, simulation techniques are considered satisfactory in terms of speed and accuracy (Greene, 2012).

The most widely used Probit simulator is the Geweke-Hajivassiliou-Keane (GHK) smooth recursive simulator (Train, 2009). With the probability of choice *j* defined as the probability that this choice will be preferred to all the others, the GHK simulator evaluates $M-1$ integrals, where *M* is the number of choices. The integrals are evaluated by averaging over *R* draws from truncated normal distributions (Greene, 2012; Train, 2009). With a large sample size, *R* should not be smaller than the square root of the number of observations (445 observations, 22 draws) Cappellari and Jenkins (2006). With a small sample size, *R* should be at least as large as the sample size. Consequently, the estimation of the marginal effects will be based on 1000 draws.

The multivariate Probit model allows for a wide variety of marginal effects and probabilities. Interest is in the unconditional probability to choose one alternative as opposed to another. It is not possible to directly test if microfinance generates over-indebtedness, but it is possible to study how the household ranks different uses of their loan. The use of a loan for productive purposes is usually associated with a lower likelihood of over-indebtedness (Schicks, 2012). Consequently, if there is evidence loans are employed for short-run consumption and not for investment, it is determined that a risk of over-indebtedness exists. This evidence may be revealed by estimating the marginal effects of the unconditional probabilities. These estimates will identify which factors are determinant in allocating a loan to a specific choice and provide information to formulate effective policy strategies.

Greene (2012) derives analytically the partial effects, the conditional probabilities, and the unconditional probability for a bivariate Probit while Mullahy (2011) derives them for the multivariate case. Specifically, give unconditional mean functions are univariate probabilities, their partial effects are estimated likewise to the univariate case (Greene, 2012). Controlling for heteroskedasticity, the significance of the average partial effects will be estimated by the delta method from the cluster-robust standard errors with clusters defined at the household level.

1.5.2 Model Specification

Limited observations resulted in aggregating loan categories. Specifically, housing, educational, healthcare expenses, and other expenses are aggregated into a category called Other Purchases. Such aggregation does not distract from the main objective of estimating the likelihood of a household securing a loan for consumption versus investment. This defines a system of four equations:

$$
\begin{cases}
\boldsymbol{U^*_{food}} = \boldsymbol{X_0}\boldsymbol{\beta^0_{food}} + \boldsymbol{X_{food}}\boldsymbol{\beta_{food}} + \boldsymbol{\varepsilon_{food}} \\
\boldsymbol{U^*_{start}} = \boldsymbol{X_0}\boldsymbol{\beta^0_{start}} + \boldsymbol{X_{start}}\boldsymbol{\beta_{start}} + \boldsymbol{\varepsilon_{start}} \\
\boldsymbol{U^*_{farm}} = \boldsymbol{X_0}\boldsymbol{\beta^0_{farm}} + \boldsymbol{X_{farm}}\boldsymbol{\beta_{farm}} + \boldsymbol{\varepsilon_{farm}} \\
\boldsymbol{U^*_{other}} = \boldsymbol{X_0}\boldsymbol{\beta^0_{other}} + \boldsymbol{X_{other}}\boldsymbol{\beta_{other}} + \boldsymbol{\varepsilon_{other}} \quad ,
\end{cases}
\tag{1.3}
$$

where the subscript $food, start, farm,$ and $other$ identifies the loan use for Food Products, Start a Business, Agricultural Needs, and Other Purchases, respectively.

Each equation in (1.3) has a fixed group of independent socio-economic variables ($\boldsymbol{X_0}$). These socio-economic variables are gender, age, family size, education, residence, and the off-farm income. In addition, dummy variables for the Naryn district and the year were defined.

The ownership of mobile phones is also included in each equation as a measure of household's willingness to adopt new innovations. Mobile communication technology plays a strategic role in improving access to labor markets and reducing vulnerability to unpredictable shocks (World Bank, 2007). In 2006, the share of households with access to microfinance and a mobile phone was 12%. In 2010, the share was 91% (KIHS, 2010).

Explanatory variables specific to each equation represent the household's resource endowment. For (1.3), this corresponds to

$$
\begin{cases}
\boldsymbol{X_{food}} = (livestock, land, food\ storage) \\
\boldsymbol{X_{start}} = (textile, food\ storage, transportation) \\
\boldsymbol{X_{farm}} = (livestock, land, food\ storage, transportation) \\
\boldsymbol{X_{other}} = (transportation, sanitation, hot\ water)\ .
\end{cases}
\tag{1.4}
$$

The choice of the independent variables in each equation is based on the loan purpose. Dummy variables for the ownership of textile machinery and food storage equipment were included in the Start a Business equation, given the leading retail sectors in Kyrgyzstan are still food products and clothing (Huang, 2014; EurasiaNet, 2014). Similarly, the ownership of sanitation and the hot water supply were considered as a proxy of the housing conditions and they were included in the Other Purchases equation (Parkinson and Talipova, 2005; and United Nations Economic Commission for Europe, UNECE, 2009). Note that all the variables in (4), as well as the off-farm income and the ownership of mobile phone in $\boldsymbol{X_0}$, were lagged by one year to avoid endogeneity issues.

1.6. Results

The results of the multivariate Probit model for (1.3) are listed in Table 1.6. At the bottom of Table 1.6, the likelihood ratio rejects the null hypothesis of no correlation among equations at the 1% level. This indicates that loan choices are interdependent. The estimated correlation matrix is given in the lower half of Table 1.6. All the correlation coefficients are negative and significant at the 1% level, apart from the Food Products and the Start a Business allocation of the loan. This supports the hypothesis that different loan choices are considered substitutes by households. This also suggests households are substantially credit constrained given the loan allocation for one choice reduces the financial resources for other choices (Karlan and Goldberg, 2011). It is interesting to notice the absence of statistically significant correlation between buying food and starting a new business. Further, the Wald test does not reject the hypothesis of zero correlation between the Food Products choice and the Start Business choice with a p-value equal to 0.39 (Jenkins et al., 2005). A possible explanation is that the first alternative is related to the autonomous consumption, the fixed spending necessary to satisfy basic needs, which is independent from the disposable income originating from the second alternative (Aitymbetov, 2006). Note that the model also indicates numerical stability with robust results for a small number of draws, as small as 25.

The estimated probabilities and the marginal effects are listed in Table 1.7. The highest unconditional probability is Food Products (48%), followed by Agricultural Needs (32%), Other Purchases (29%), and Start a Business (25%). This relatively large household allocation of credit to food purchases and the low allocation for small business and agricultural investment generate some concerns about the borrowers' perception of risk in use of microfinance in Kyrgyzstan.

In general, microfinance loans are directed to small businesses and residually to agricultural purposes and food products as noted in other studies (Raghunathan et al., 2011). This is due to microfinance agencies providing loans with respect to several factors, mainly risk considerations. Trade and manufacturing activities are usually considered less risky given they can generate more income growth than consumption activates (Raghunathan et al., 2011). If borrowers are not able to transform their loan into a future income stream at the expiration date, they may be worse off, given that they have to repay the principal and high interest rates. Since buying food has the highest probability of loan allocation while productive uses have the lowest probability, the risk that microfinance in Kyrgyzstan could increase over-indebtedness is a very real possibility (Microfinance Center, 2011).

The analysis of marginal effects allows identifying key factors in the loan allocation. For instance, in the Agricultural Needs equation, the ownership of livestock has a positive effect (0.23) while it has a negative effect in the Food Products equation (-0.17). This suggests livestock is a strategic asset for agricultural investment and it represents a substantial food source for small farmers (Lerman and Sedik, 2009). The Kyrgyz territory is mainly mountainous and the arable land has low productivity. Gazing cattle does not require ownership of land while the employment of fertilizer and the irrigation system are still quite limited for small farmers

(Lerman and Sedik, 2009). This can explain the lack of significant effect of the ownership of arable land in the Food Products equation and the Agricultural Needs Equation.

The ownership of mobile phones also indicates an interesting pattern. If the household has a mobile phone in the previous period, the probability to use the loan to Start a Business in the current period increases by 0.12. In contrast, the ownership of mobile phone decreases the probability to allocate the credit for Food Products by 0.11. The strategic role played by mobile technology to foster the economic development in Kyrgyzstan suggests that if households improve their communication capabilities, this may reduce their vulnerability to unpredictable shocks and stimulate their access to market and job opportunities (World Bank, 2007).

The probability of using the loan to Start a Business is also positively affected by the ownership of textile and food storage equipment. If the household owns textile and food storage equipment, the probability to allocate the loan for starting a business increases by 0.07 and 0.08, respectively (10% significance). Note that the magnitude of the average partial effects of the two independent variables is basically the same. This is supported by the F-test on equal coefficients, which does not reject the null with a p-value equal to 0.82.

The off-farm income increases the probability to use the loan for Other Purchases by 0.07 and it decreases the probability to allocate credit for Agricultural Needs by 0.09. The effect of the off-farm income on loan allocation purposes is basically opposite that of the residence variable. Dwelling in a rural area increases the probability to use the loan for Agricultural Needs by 0.23 and it decreases the probability to use the loan for Other Purchases by 0.10. Labor migratory trends in Kyrgyzstan in the last two decades are in line with these results. The Kyrgyz population, especially the young, is migrating from the countryside in order to find better economic opportunities in urban areas and abroad (Thieme, 2008). Off-farm income is mainly characterized by labor income, in particular more skilled jobs present in urban areas. In addition, remittances are another substantial source of the off-farm income that may further stimulate the abandonment of the countryside.

The Naryn region is positively associated with the probability to use the loan for Food Products (0.38) and negatively with the probability to use the loan to Start a Business (-0.08). Naryn presents the highest poverty rate, at 52% (Slay, 2011), and the largest share of small microfinance loans in Kyrgyzstan (Microfinance Center, 2011). This suggests that microfinance in this region targets low-income households with substantial credit constraints. The results indicating microfinance loans are mainly used to satisfy basic needs confirms the previous analysis. Low-income households located in rural areas employ microfinance to relax their credit constraint, but the extra liquidity is mostly used for short-run purposes rather than for investment uses.

Other factors have an isolated effect only on specific choices. The gender variable confirms the use of microfinance for nutritional purposes in households headed by women, especially for the care of children (Khandker, 2005). If the head of the household is female, the probability of purchasing food increases by 11% at the 5% significance level. Similarly, the educational level of the head of the family positively affects the probability to use the loan for Agricultural Needs at the 1% significance level. If the educational level increases by one year, the probability to invest in Agricultural Needs increases by 0.03 at the 1% significance level. In general, education can improve the farmer's understanding of agricultural processes and this may stimulate expenditures in farming activities (Muhongayire et al., 2013). Finally, the Other Purchases are positively associated with family size at the 1% significance level. The average partial effect is 0.06. This may be due to the high share of young people in urban areas in Kyrgyzstan that require income for educational and healthcare expenditures (NSCK, 2009).

1.7. Conclusions and Policy Implications

An economic assessment is presented for microfinance loan allocations in Kyrgyzstan from 2006 to 2010. Results indicate that buying food for consumption has the highest loan use probability while starting a new business has the lowest probability. The study also identified a geographical component of the loan allocation. The Naryn region has the largest impact on the loan use probability to buy food and the smallest (negative) impact on the probability to start a new business. The study suggests that microfinance was able to relax low-income borrowers' substantial credit constraints, but the risk of over-indebtedness for low-income rural households was likely in Kyrgyzstan in the 2006-2010 period (Schicks, 2012; PlaNet Finance Foundation, 2013).

This study identifies two key drivers of loan allocation: mobile phone and livestock ownership. Mobile phone ownership reduces the probability to allocate the loan for food needs and increases the probability to use the loan for starting a business. Policy strategies that increase the signal coverage, improve the affordability, and the speed of the mobile phone service can be an effective tool for poverty alleviation and economic growth (Driesbach et al., 2009). In addition, other information and communication technologies such as Internet access can reduce their vulnerability to unpredictable shocks and make low-income households more informed about market conditions and borrowing costs (World Bank, 2007).

Similarly, the ownership of livestock is a strategic asset for agricultural investments and the food supply of small farmers. The poor development of crop activities for small scale farmers in the Kyrgyz Republic seems due to several factors, namely poor soil productivity, limited private land rights, and low levels of technology adoption (Lerman and Sedik, 2009). From this point of view, subsidies that address the livestock sector could be combined with policies that stimulate education and farmers' training including schooling and extension services. This can substantially contribute to rural poverty alleviation through a more productive use of microfinance for the diffusion and the adoption of farming technologies (Muhongayire et al., 2013). In addition, seed and fertilizer distribution schemes may stimulate the agricultural productivity and provide spillover benefits for the entire rural sector (Jayne et al., 2004; Tilekeyev, 2013).

Finally, regardless of microfinance, the under-development of the traditional credit channel represents one of the most difficult challenges in the Kyrgyz Republic (Microfinance Center, 2011). Policies that support financial literacy, increase the market competition, and conclude the reform of property rights can be effective, but they should be mated to other market and political liberalizations. Otherwise, the transition from a centrally planned economy to a market economy will leave the country mired in poverty.

References

Aitymbetov, S. 2006. "Emigrant Remittances: Impact on Economic Development of Kyrgyzstan." Working Paper 31, The Economic Policy Institute, Bishkek. Kyrgyzstan.

Armendariz, B. and M. Labie. 2011. *The Handbook of Microfinance*. Hackensack, NJ. World Scientific Publishing Co. Inc.

Barnett, J. B., C. B. Barnett, and J. R. Skees. 2008. "Poverty Trap and Index-Based Risk Transfer Products." *World Development* 36(10): 1766-1785.

Brown, M. and R. Jacobs. 2010. *Comparative Analysis of Microfinance Policy Frameworks and Legislation in Selected Countries*. International Financial Corporation. World Bank Group. Washington D.C.

Cappellari, L. and P. Jenkins. 2006. "Calculation of Multivariate Normal Probabilities by Simulation, with Application to Maximum Simulated Likelihood Estimation." *The Stata Journal* 6(2): 156-189.

Cellini, S. R. 2008. "Causal Inference and Omitted Variable Bias in Financial Aid Research: Assessing Solutions." *Review of Higher Education* 31(3): 329-354.

Driesbach, C., R. Walton, B. Kolko, and A. Seidakmatova. 2009. "Asking Internet Users to Explain Non-Use in Kyrgyzstan." *IEEE International Professional Communication Conference.* Available at: https://www.deepdyve.com/lp/institute-of-electrical-and-electronics-engineers/asking-internet-users-to-explain-non-use-in-kyrgyzstan-Anrucjh2ei (accessed December 8, 2014).

Esenaliev, D., A. Kroeger, and S. Steiner. 2011. "The Kyrgyz Integrated Household Survey." Working paper 62, German Institute for Economic Research. Berlin, Germany.

EurasiaNet. 2014. “Kyrgyzstan: Teachers Quitting to Take Better Paying, Unskilled Jobs.” Available at: http://www.eurasianet.org/node/70636 (accessed November 4 2014).

Freedman, D. A. and J. S. Sekhon. 2010. “Endogeneity in Probit Response Models”. *Political Analysis* 18(2): 138-150.

Greene, W. H. 2012 *Econometric Analysis*, Harlow Essex, UK: Pearson Education Limited.

Harper, M. 2005. “Farm Credit and Microfinance, Is There a Critical Mismatch?” *Small Enterprise Development Journal* 6(3): 1-11.

Huang, N. 2014. “Market Fever at Osh Bazaar in Bishkek, Kyrgyzstan.” Available at: http://www.wildjunket.com/2014/09/11/osh-bazaar-bishkek-kyrgyzstan/ (accessed November 5, 2014).

Huergo, E. and L. Moreno. 2014. “National or International Public Funding? Subsidies or Loans? Evaluating the Innovation Impact of R&D Support Programs.” Working paper 54218. Munich Personal RePEc Archive (MPRA), Munch, Germany.

Jayne, T. S., T. Yamano, and J. Nyoro. 2004. “Interlinked Credit and Farm Intensification: Evidecne From Kenya.” *Agricultural Economics* 31: 209-218.

Jenkins, P., L. Cappellari, P. Lynn, A. Jackle, and E. Sala. 2005. “Patterns of Consent: Evidence From a General Household Survey.” Working paper 490. German Institute for Economic Research, Berlin, Germany.

Kyrgyz Republic. 2002. *The Kyrgyz Republic Law on Micro-finance organization in the Kyrgyz Republic*. House of Government, 124, Bishkek. Kyrgyzstan.

Karlan, D. and N. Goldberg eds. 2011. “Microfinance Evaluation Strategies: Notes on Methodology and Findings.” In *The Handbook of Microfinance*. Hackensack, NJ: World Scientific Publishing Co. Inc.

Katsushi, S. I., A. Thankom, and S. K. Annim. 2010. “Microfinance and Household Poverty Reduction: New Evidence from India.” *World Development* 38(12):1760-1774.

Khandker, S. R. 2005. “Microfinance and Poverty: Evidence Using Panel Data from Bangladesh.” *The World Bank Economic Review* 19(2):263 286.

Lerman, Z. and D. Sedik. 2009. *Agrarian Reform in Kyrgyzstan: Achievement and Unfinished Agenda*. Food and Agricultural Organization, Rome. Italy.

Microfinance Center. 2011. “Research on the Level of Indebtedness and Repayment Performance of Individual Borrowers in Kyrgyzstan.” Available at: http://www.mfc.org.pl/sites/mfc.org.pl/files/Indebtedness%20report%20Kyrgyzstan_ENG.pdf (accessed August 24, 2014).

MixMarket Microfinance Information Exchange. 2014. “Kyrgyzstan Market Profile. Audit Files 2006-2010: Aiyl Bank, Bai Tushum, FMCC, Kompanion, and Mol Bulak Finance.” Available at: http://www.mixmarket.org/mfi/country/Kyrgyzstan (accessed December 2013).

Muhongayire, W., P. Hitayezub,O. L. Mbatiac, and S. M. Mukoya-Wangiad. 2013. “Determinants of Farmers’ Participation in Formal Credit Markets in Rural Rwanda.” *Journal of Agricultural Science* 4(2): 87-94.

Mullahy, J. 2011. “Marginal Effects in Multivariate Probit and Kindred Discrete and Count Outcome Models with Applications in Health Economics.” Working Paper 17588. National Bureau of Economic Research. Cambridge, MA.

National Statistical Committee of the Kyrgyz Republic. 2014. Available at: http://www.stat.kg/ (accessed June 11, 2014).

—. 2010. Kirgizstan Integrated Household Survey year 2006, 2007, 2008, 2009, 2010.

—. 2009. *Population and Housing Census of the Kyrgyz Republic of 2009*. Book I 2009, Bishkek. Kyrgyzstan.

Parkinson, J. and L. Talipova. 2005. *Kyrgyz Republic: Sanitation Assessment and Recommendations for Urban Upgrading in Bishkek and Osh*. World Bank. Washington D. C.

Petrick, M. 2005. Empirical Measurement of Credit Rationing in Agriculture: A Methodological Survey. *Agricultural Economics* 33: 191-203.

PlaNet Finance Foundation. 2013. *Microfinance Index of Market Outreach and Saturation.* Part 1, 13-03, Paris. France.

Raghunathan, U. K., C. L. Escalante, J. H. Dorfman, G. C. W. Ames, and J. E. Houston. 2011. "The Effect of Agriculture on Repayment Efficiency: A Look at the MFI Borrowing Groups." *Agricultural Economics* 42: 465-474.

Schicks, J. 2012. "Over-Indebtedness in Microfinance, an Empirical Analysis of Related Factors on the Borrower Level." Working paper 12(17), Centre Emile Bernheim, Brussel. Belgium.

Slay, B. 2011. *Energy and Communal Services in Kyrgyzstan and Tajikistan: A Poverty and Social Impact Assessment.* United Nations Development Program. Bratislava Regional Center, Bratislava. Slovakia.

Smith, M. G. 2013. EurasiaNet. "Kyrgyzstan could microfinance bubble burst?" Available at: http://www.eurasianet.org/node/65527 (accessed January 23, 2014).

Stiglitz, J. E. 1990. Peer Monitoring and Credit Markets. *The World Bank Economic Review* 4(3): 351-366.

Thieme S. 2008. Social Research Center American University of Central Asia. "Where to Return to? Rural Urban Inter-linkages in Times of Internal and International Labor Migration."

Available at: https://www.auca.kg/uploads/Migration_Database/susan_paper_2.pdf (accessed January 19, 2015).

Tilekeyev, K. 2013. "Seed and Fertilizers Policy Development in Kyrgyz Republic." University of Central Asia. Available at: http://www.slideshare.net/resakssasia/kanat-tilekeyev-input-policy-kyrgyzstan (accessed February 3, 2015).

Train, K. 2009. *Discrete Choice Methods with Simulation.* Cambridge, MA: Cambridge University Press.

United Nations Economic Commission for Europe. 2009. *Country Profile Kyrgyzstan, Chapter 4 Housing Conditions and New Constructions.* Institute for Real Estate, Construction and Housing. Vienna, Austria

USAID. 2005. *Land Tenure and Property Rights Assessment for Kyrgyzstan.* United States Agency for International Development. Washington D. C.

Weiss, J. and H. Montgomery. 2004. "Great Expectations: Microfinance and Poverty Reduction in Asia and Latin America." Working Paper 33142 (3), Munch Personal RePEc Archive, Munch. Germany.

Wooldridge, J. M. 2002. *Econometric Analysis of Cross Sectional and Panel Data*. Cambridge, Massachusetts: The MIT Press.

World Bank. 2014a. "Country and Lending Group." Available at: http://data.worldbank.org/about/country-and-lending-groups#Lower_middle_income (accessed September 8, 2014).

—. 2014b. "Poverty Gap at $1.25 a Day." Available at: http://data.worldbank.org/indicator/SI.POV.GAPS (accessed September 8, 2014).

——. 2014c. “What is the World Bank Atlas Method?” Available at: http://data.worldbank.org/indicator/SI.POV.GAPS (accessed July 15, 2014).

——. 2011. *The Kyrgyz Republic: Poverty Profile and Overview of Living Conditions*. Poverty Reduction and Economic Management Unit, Europe and Central Asia Region. Washington D. C.

——. 2009. “Land Registration Spurs Incentives and Growth. International Development Agency at Work: Kyrgyz Republic.” Available at: http://web.worldbank.org/WBSITE/EXTERNAL/EXTABOUTUS/IDA/0,,contentMDK:22303407~menuPK:4754051~pagePK:51236175~piPK:437394~theSitePK:73154,00.html (accessed October 9, 2014).

——. 2007. “Mobile Cell Phones and Poverty Reduction: Technology Spending Patterns and Poverty Level Change Among Households in Uganda.” Available at: http://microdata.worldbank.org/index.php/citations/1273?collection=central (accessed December 5, 2014).

——. 2005. *Mining Industry as a Source of Economic growth in Kyrgyzstan.* Project Implementation Unit of the World Bank. Washington D. C.

——. 2004. *Microfinance and The Poor in Central Asia*. Agricultural and Rural Development. Discussion Paper 6. Washington D. C.

Youatt, E. 2013. “Microfinance in Crosshair: Will Kyrgyzstan’s usury bill backfire?” Next Billion Development Through Enterprise. Available at: http://www.nextbillion.net (accessed February 12, 2014).

CHAPTER 2

RACIAL DIVERSITY AND SCHOOL PERFORMANCE: A SCHOOL LOCATION APPROACH

2.1. INTRODUCTION

Parents, educators, and policymakers are concerned about the effects of racial diversity on the educational environment and academic achievement in K-12 schools. Racial disparity is a major cause of U.S. school inequality (National Center for Education Statistics 2014). While the racial achievement gap has declined over the last 40 years, the literature still indicates a consistent difference in favor of whites. Moreover, while the achievement gap between fourth grade white and black students in the mathematics standardized test fell from 18% in 1973 to 12% in 2013, the gap still exists (National Center for Education Statistics 2014).

Within the U. S., the traditional academic approach has highlighted how racial peer-effects improve students' school performance (Jencks et al., 1972). Hoxby (2000) indicates African-American third graders perform substantially better in primarily white student classes. Similarly, Hanushek, Kain, and Rivkin (2009) determined having a higher share of non-white classmates lowers African-American student academic achievement.

Racial peer-effects, if present, are externalities. Thus, they may create opportunities for social welfare-enhancing interventions. For instance, a school financial system that encourages an efficient distribution of peers will experience improved efficiencies in human capital investments (Hoxby 2000). However, racial diversity can also be a negative externality, which reduces academic performance. For satisfying greater heterogeneous students' demands, an increase in the per pupil spending may be required or the educational outcome could decrease

(Hall and Leeson 2010). Easterly and Levine (1997) indicate the degree of ethno-linguistic fractionalization affects negatively on the number of years of schooling in the U. S. Recently, Hall and Leeson (2010) determine that racial fractionalization decreases the educational achievement of ninth grade students in Ohio school districts by 7% to 17.5%.

In general, the perception of race is affected by institutional factors of the school and its community (Akerlof 1997; Tyson et al., 2005). These factors affect students, parents, and teachers and so their idea of race. Morris and Monroe (2009) in the southeastern U.S. investigate the interaction between racial diversity and school performance. They indicate that within rural and urban areas characterized by stark disparities, racial diversity can be negatively perceived by students and it may contribute to the academic disengagement (Morris and Monroe 2009). In addition, Ely, Padavic, and Thomas (2012) determine that only when white and non-white groups consider the learning environment supportive, does the relationship between racial diversity and performance becomes positive.

Socio-economic traits usually have a spatial pattern (Anselin 2002). In general, more wealthy neighborhoods are characterized by better infrastructures and higher quality of services, in particular education (Naidoo and Munch 2014; Feitosa et al., 2008; Gordon and Monastiriotis 2007). Given that these characteristics affect the learning environment and the learning environment affects the relationship, it is expected that the interaction between racial diversity and educational outcome depends on the school location.

Consequently, the goal of this study is to empirically investigate the relationships among racial diversity, school performance, and school location. This study utilizes school-level data on race and educational achievement for Georgia fifth grade public schools for the 2008 - 2009 academic year. With Georgia one of the most racially differentiated states in the United States, it represents an interesting case to analyze racial diversity and educational achievement (U. S. Census Bureau 2012).

Moreover, the study of racial diversity, school performance, and location is also fundamental to formulating appropriate educational strategies. Traditional policies to increase the educational supply are more effective where the relationship between racial diversity and school performance is absent or negative. In contrast, in schools where the relationship is positive, investing in alternative strategies to stimulate racial diversity may be the most productive choice.

The essay is organized as follows: section two provides the empirical strategy; section three describes the dataset and the variables employed; section four presents the econometric approach for the analytical estimation; section five presents the results; while the conclusions and implications are drawn in section six.

2.2. Empirical Strategy and Background

In general, there are three central issues in estimating the relationship among racial diversity, educational achievement, and school location. First, it is reasonable to assume there are unobserved variables associated with a student's presence in a particular classroom within a school, for instance the quality of the school (Hoxby 2000; LeSage and Pace 2009). Researchers usually observe only some of these variables, but they affect the educational outcome. Several strategies are available to handle this issue. The most commonly cited remedy is the inclusion of fixed effects in the regression specification, in particular at the spatial level (Anselin and Arribas-Bel 2011). A spatial fixed effects model is a model with intercepts/dummy variables defined at some spatial level of aggregation. One approach is to define fixed effects at the school district level. Schools within the same school district share common characteristics and this can generate unobserved heterogeneity.

There are, however, several concerns associated with this model. First, to have reliable estimates, it is necessary for the number of school districts to be small relative to the number of observations and the number of observations with a district relatively large (Anselin and Arribas-Bel 2011; Wooldridge 2002). In this study, for Georgia school districts, the number of schools per school district ranges from 1 to 92. This large variability makes the applicability of a spatial fixed effects model questionable. Second, if the unit of observation is a school, defining fixed effects on the basis of school districts will remove all the variables at this level. Many socio-economic indicators are available only at the school district level, but not at individual schools. Finally, if there is within group heteroskedasticity or interaction, this will be relegated to the error term, resulting in heteroskedasticity and/or spatially correlated disturbances (Anselin and Arribas-Bel 2011).

A suitable approach for estimating the effect of racial diversity on the educational outcome is spatial regression. A spatial error model (SER) with neighborhood structure defined at school district level can address all the estimation issues (Anselin and Arribas-Bel 2011). The SER model assumes the error term is not correlated to the included variables, which may not hold. If the SER model is the true model, OLS estimates will be consistent even if inefficient (Anselin and Bera 1998). This issue may be accounted for by considering other spatial regression models. In particular, the spatial lag model (SLAG), the spatial Durbin model (SDM), and the general spatial model. These models define directly the omitted variables as spatial lag of the dependent and/or independent variables. If the learning environment affects the relationship between racial diversity and school performance, it is reasonable to assume that it also is affected by socio-economic characteristics that vary across space (Anselin and Arribas-Bel 2011). These models allow for a wide range of global and local effects, so they should adequately represent the underlying educational environment.

The second central problem with estimating the relationship between racial diversity and achievement scores is self-selection (Hoxby 2000). Parents can choose which school their children attend on the basis of different factors, primarily related to the school performance (Reback 2008; Georgia Public Policy Foundation 2010). Since school choice affects the racial composition of the school, this feedback generates endogeneity and possible unreliable estimates (Wooldridge 2002).

In general, the school choice is realized through two channels. One channel is school transfer. A student is assigned to a school with respect to the family's residence, but parents can request a different school. While school transfer is allowed in Georgia, its impact is extremely limited. In Georgia, there are two types of school transfers, intra-district and inter-district. Before 2012, less than 5% of the student population in Georgia was involved intra-district transfers. After 2012, its incidence decreased. In 2012-2014, Georgia, together with 42 other states, received an amendment to federal legislation that increased the flexibility (*No Child Left Behind* Act, Georgia Department of Education 2014b). In terms of intra-district school transfer, the new legislation abolished public support for the transportation cost, and thus it further decreases the incidence of this program in Georgia (Georgia Department of Education 2014b).

The inter-district school transfer programs also have a limited impact on the racial composition of schools in Georgia. These programs allow students to attend schools outside their own district. In order to realize the inter-district school transfer, it is necessary that a space is available in the receiving school. Furthermore, the sending district and the receiving district must agree on the funding allocation to support the transfer. Finally, inter-district school transfers are allowed by the Georgia legislation under the condition that they do not change the racial integration plans (Georgia Department of Education 2014b).

In contrast, the second channel through which the school choice is realized can have a substantial impact on the racial composition of schools. Household mobility may happen in response to the educational achievement (Lareau and Goyette 2014). Families decide where to live with respect to several socio-economic factors: job opportunities, quality of the neighborhood, availability of transportation, and the ranking of schools for their children. This problem is more serious considering that the school report card provides data on the achievement scores in reading and math, the dependent variable used in this analysis, which allows parents to make informed decisions on their school choice option (Georgia Public Policy Foundation 2010)[1].

Consequently, given the risk of endogeneity of racial diversity, it will be necessary to test if this is the case and then employ specific estimation techniques, spatial general method of moments and spatial instrumental variable/two-stage least square regression (Anselin and Bera 1998; Monchuk et al., 2011).

The third estimation problem is the learning environment. In the analysis, two racial groups are considered: white majority schools and non-white majority schools. The idea is to study how the effect of racial diversity on the educational outcome changes between a racially segregated environment and a non-racially segregated environment. We also consider three different geographical areas: the Atlanta Metropolitan Area (AMA) schools, urban schools

[1] Charter schools do not affect the racial composition due to the fact that they locate to attract more students with a specific demand and thus they can increase racial segregation (Zimmer et al. 2009). Magnet schools may increase the racial diversity, but they are very few to satisfy the huge school choice demand. For instance, the Atlanta Metropolitan Area represents 48% of the sample of 537 elementary schools, but only six elementary magnet schools are located in its territory (Georgia Department of Education 2014a).

different from AMA, and rural schools. The rural-urban location is considered as one of the primary factors that affect the school environment (National Center for Education Statistics 2008)[2].The Atlanta Metropolitan Area was also evaluated separately from all the other urban schools given it is considered a specific tract to collect statistical data (U.S. Office of Management and Budget 2013) and also to assess the educational outcome (Nation's Report Card 2013).

In general, if the relationship between racial diversity and school performance changes with respect to the location and the racial composition of the school, it should be sufficient to employ an interaction term between racial diversity and dummy variables to detect the school characteristics. However, the previous argument holds if the learning environment does not change with respect to the school characteristics. Rural areas can be characterized by high poverty and low levels of family education, but also low crime rates relative to urban areas (Singh and Siahpush 2014). At the same time, non-white communities can be characterized by a high share of single-parent families, low racial diversity, and poorer living conditions than their white counterparts (Chatty et al., 2014; Cheng and Kindig 2012). From an empirical point of view, a different learning environment can imply structural breaks in the estimation equation and so different coefficients among sub-groups of the sample (Greene 2012). For instance, say y the achievement score, x_k a set of independent variables with k from 1 to K, G different equations are defined as:

$$y^g = \beta_0^g + \beta_1^g x_1^g + \beta_2^g x_2^g + \ldots + \beta_K^g x_K^g + \epsilon^g; \qquad g = 1 \ldots G, \qquad (2.1)$$

[2] Factors that are considered peculiar of the learning environment are disciplinary issues, lack of parental involvement, and access to school facilities, primarily computers (National Center for Education Statistics 2008).

where the supercript g represents the sub-group. The empirical strategy requires testing if structural breaks are present. If this is the case, different regressions for each sub-group should be estimated. Otherwise, a dummy variable approach can be employed.

2.3. DATA

Achievement data were collected from the Georgia Department of Education and Governor's Office of Student Achievement (Georgia Public Policy Foundation 2009). The data provides information to help parents make informed decisions about the quality of public education in Georgia, based on data for the 2008-2009 school year. Student achievement data are employed by school systems to evaluate student learning outcomes, teacher effectiveness, and overall school performances (Georgia Public Policy Foundation 2009). The analysis was performed at the school level employing fifth grade data. Due to some skewness, the dependent variable was log-transformed.

The data on the racial composition are also from the 2008 Georgia Department of Education, which identifies six ethnic groups: White, Black, Hispanic, Asian, Native-American, and multiracial. Four racial groups are employed: White, Black, Hispanic, and other, where White, Black, and Hispanic groups represent 94% of the student population.

Two definitions of racial fractionalization are employed. The first is the racial fractionalization index, rf_j (Hall and Leeson 2010), which measures the probability two randomly drawn individuals from the overall population belong to different ethnic groups:

$$rf_j = 1 - \sum_{k=1}^{K} \pi_{jk}^2 \quad , \tag{2.2}$$

where π_{jk} is the share of the racial group k in the school j. The index is bounded between zero and one and it increases with racial diversity.

For sensitivity analysis, Theil's racial diversity index is employed (Theil, 1971):

$$rf_j^{Theil} = \sum_{k=1}^{K} \pi_{jk} \cdot \ln(1/\pi_{jk}) \quad , \tag{2.3}$$

where if $\pi_{jk} = 0$, then $\pi_{jk} \cdot \ln(1/\pi_{jk})$ is set to zero.

The poverty rate is defined as the share of students in the fifth grade who are eligible for a reduced price or a free school lunch. Eligibility is based on family income. Data on the eligibility are provided by the National School Lunch Program (NSLP) as reported in the United States Department of Agriculture Economic Research Service (USDA-ERS) *Food Environment Atlas* (2011).

The school spending per pupil and the centralized spending per pupil were determined by dividing the funds expended at the school site by the number of full-time equivalent students. The centralized spending per pupil is the residual public spending not allocated to a particular school activity as reported by the Georgia Department of Education (2009) divided by the number of students in each school.

County-level variables were collected from the U.S. Census Bureau for year 2009 (U.S. Census Bureau 2009) and they were utilized as a measure of human capital in the school district. They are: the share of teachers with thirty or more years of experience, the unemployment rate, the percent of single-parent families, and the share of population who have a high school diploma or higher.

The urban-rural definition is from the United States Office of Management and Budget (OMB). An urban area is a city with population of 50,000 or more. The Atlanta Metropolitan Area is defined as the "Atlanta-Sandy Springs-Marietta, GA Metropolitan Statistical Area" according to the U. S. Office of Management and Budget (2013).

Data on spatial coordinates were taken from the physical address of the schools. The dataset contains 1,112 elementary schools. The descriptive statistics are presented in Table 2.1.

2.4. Estimation Approach

A spatial regression model is developed by the following equations (Anselin and Bera 1998; LeSage and Pace 2009; Anselin and Arribas-Bel 2011).

The general spatial regression model is defined as:

$$y = \rho W_1 y + X\beta + \varepsilon \quad ; \qquad \varepsilon = \lambda W_2 \varepsilon + u \quad , \tag{2.4}$$

where W_1 and W_2 are two weighting matrices and u is assumed i. i. d.

If $\lambda = 0$ the model becomes the spatial lagged model (SLAG):

$$y = \rho W_1 y + X\beta + \varepsilon \ , \tag{2.5}$$

where ε is assumed i. i. d.

If $\rho = 0$ the model becomes the spatial error model (SER):

$$y = X\beta + \varepsilon \quad ; \qquad \varepsilon = \lambda W_2 \varepsilon + u \ . \tag{2.6}$$

One alternative formulation of the model given in (2.5) is the spatial Durbin model (SDM):

$$y = \rho W_2 y + X\beta + W_2 X\theta + u \quad . \tag{2.7}$$

Notice if $\theta = -\lambda\beta$ the spatial Durbin model yields the spatial error model (Anselin and Bera 1998). Thus, we will test equations (2.4)-(2.7).

Binary contiguity matrices, which are row-standardized, were employed. Two contiguity matrices, one based on the cut-off distance and one based on the school district definition, were employed.

The cut-off contiguity matrix was built such that each observation has at least five neighbors. The distances were calculated with the Haversine formula to count for the earth curvature (Liao and Wang 2012). Figure 2.1.A indicates the details[3].

The second weighting matrix is based on the school district definition. Two schools are neighbors if they belong to the same school district. Notice that the school district definition almost corresponds to the County definition. In Georgia there are 159 counties for as many school districts plus another 21 city level school districts. These districts are illustrated in Figure 2.1.B.

The spatial regression models were estimated by maximum likelihood estimation based on the concentrated log likelihood function (Anselin and Bera 1998). The bootstrapped standard errors will be shown for all the models. The bootstrapping methodology is the paired bootstrapping from Monchuk et al., (2011). The authors analyzed three bootstrapping methods for spatial regression models: non-parametric bootstrapping, parametric bootstrapping, and paired bootstrapping. In the presence of heteroskedasticity, the paired bootstrapping is the only one that produces consistent estimates (Monchuk et al., 2011).

Specification tests for the model choice require performing robust tests if more spatial dependences are detected (Anselin and Florax 1995). After robust Lagrange multiplier (LM) tests, if the diagnostics are still not able to indicate a specific form of spatial dependence, the model with the highest robust LM test will be chosen (Anselin and Florax 1995).

The analysis of endogeneity of racial diversity requires performing the Hausman test. To control for heteroskedasticity, the significance of the test will be calculated with bootstrapped standard errors (Monchuk et al., 2011). If endogeneity is present, the model will be estimated by

[3] Preliminary diagnostics shows that the presence of spatial interaction from one neighbor to five neighbors is detected, but for ten neighbors the Moran's I is not able to distinguish the sign of the spatial autocorrelation and the Geary's C does not reject the null of no spatial feedback. This is due to the high presence of spatial clusters.

spatial general method of moments (GMM) or spatial instrumental variables/two-stage least square regression (Anselin and Bera 1998; Monchuk et al., 2011).

The analysis of structural stability requires performing the spatial Chow test (Anselin 1990). In the presence of spatial dependence, there are four versions of the test: equal spatial parameter, but equal/unequal variance; unequal spatial parameter and independent/dependent equations (Anselin 1990). If no structural break is detected, the model will be estimated defining interaction terms between the racial fractionalization index and dummy variables that identify the location (rural, urban, and metropolitan) and the racial composition (white and non-white) of schools. Otherwise, different regressions will be estimated for the sub-groups that present structural instability, that is, different coefficients.

2.5. RESULTS

The diagnostics for the model choice are presented in Table 2.2. The robust Lagrange multiplier (LM) test of the SER model is significant for any weighting matrix while the test of the SLAG model with cut-off weighting matrix does not reject the null of spatial lag equal to zero (*p-value* 0.21). Notice also that the LM test is always higher for the SER model than for the SLAG model. This suggests that the SER model performs better than the SLAG model (Anselin and Florax 1995).

The diagnostics also indicate the school district weighting matrix performs better than the cut-off distance weighting matrix. Notice the likelihood ratio test (LeSage and Pace 2009) to constrain the spatial Durbin model to the SER model does not reject the null for the school district weighting matrix (*p-value* 0.28). Consequently, we will focus on the SER model based on the school district weighting matrix.

Before estimating the models, two aspects were analyzed. First, it was necessary to check if racial diversity is endogenous. Following Monchuk et al. (2011), the spatially lagged racial diversity index with one and two lags was employed. The racial fractionalization index defined at the district level in 2000 was also used (U. S. Census Bureau 2000). To check if the diagnostics change with respect to the model specification, the Hausman endogeneity test was performed employing the SER model and OLS in the second stage. The resulting tests indicate a value of 0.73 and 0.91 with the OLS model and the SER model in the second stage, respectively (p-values 0.46 and 0.36). The test never rejects the null hypothesis of exogeneity of the racial fractionalization index. This suggests the endogeneity of racial fractionalization index is not an issue for the fifth grade schools in Georgia. The statistical insignificance of feedback between achievement score and racial diversity can be explained by the low incidence of school transfers in Georgia's public schools (Georgia Department of Education 2014b). In addition, household mobility may be only partially affected by the school choice since several other factors are involved (Lareau and Goyette 2014).

Second, it is also important to consider structural instability. The Chow test results in the spatial error model are listed at the bottom of Tables 2.3 and 2.4 (Anselin 1990). The tests were estimated by assuming different variance and spatial structure for each subgroup (Anselin 1990). The tests were also performed by assuming the independence between sub-groups. Notice that only the racial definition splits the school district correlation. School districts present in both the racial sub-groups represent less than 21% of the sample and this can indicate a quite limited dependence. To check the magnitude of the correlation between white and non-white schools, the Breush-Pagan test on independent equations was calculated. The Chi-square statistics is 0.19 (1 degree of freedom) and it does not reject the null hypothesis of no correlation (p-value 0.66).

The test indicates there is substantial structural instability, in particular due to the racial composition of the school. The Chow test is equal to 727 for two racial groups (white and non-white schools), 163 for three geographical zones (AMA, urban, and rural), and 710 for all the six subgroups. All the *p-values* are equal to zero and the tests always reject the null hypothesis of no structural break. These results indicate that the learning environment changes considerably with respect to the racial composition and the location of a school. School facilities, teaching methods, and neighborhood characteristics shape the educational experience of students. The presence of structural breaks for different learning environments is also confirmed by the magnitude of the spatial parameter. Notice the lambda parameter is 0.37 in the AMA, 0.30 in urban areas different from AMA, and 0.22 in rural zones. In addition, the spatial parameter is 0.40 for non-white student majority schools and 0.27 for white student majority schools. This suggests that the noise due to the spatial interaction increases with the population density.

Tables 2.3-2.7 indicate the maximum likelihood estimates for the SER model with the school district weighting matrix. With the dependent variable specified as a log transform, the coefficients indicate that the percent change of the achievement score ($\frac{\partial lny}{\partial x_k} = \frac{\partial y/y}{\partial x_k} = \beta_k$). For comparison purposes, the estimates for the entire sample are listed in Table 2.3 column six. At the aggregate level, the racial fractionalization index is significant at the 1% level and its coefficient is equal to 5%. The positive effect of racial diversity on the achievement score is present in non-white majority schools (estimated coefficient 0.07, 1% significant) as listed in Table 2.3, columns one and two. This is offset by the negative effect of racial diversity on the achievement score in white student majority schools (estimated coefficient -0.03, 10% significant).

Table 2.4 provides further insight on the relationship between racial diversity and achievement score for the fifth grade schools in Georgia. The negative effect of racial diversity on the achievement score in white majority schools is located in urban areas (estimated coefficient -0.08, 1% significant) as listed in Table 2.4, columns one, two, and three. Similarly, the positive effect of racial diversity on the achievement score in non-white majority schools is located in metropolitan areas and urban areas, but not in rural areas. The estimated parameters are 0.06 (1% significant) and 0.09 (10% significant) in the AMA schools and urban schools, respectively.

These results indicate that Atlanta Metropolitan Area is the only region where the positive effect of racial diversity for non-white student majority schools is not followed by a reduction in the educational outcome for white majority schools located in the same region. This suggests stimulating the racial composition in the Georgia public schools could be ineffective, especially in rural areas where its positive effect on achievement scores is barely significant. In addition, increasing the racial composition in urban centers outside the Atlanta Metropolitan Area in white majority schools may be counter-productive and decrease the achievement score. Moreover, results suggest that increasing racial diversity is particularly effective in the Atlanta Metropolitan Area where the educational outcome on minority students is positive and there is no significant reduction of the white students'achievement score.

The poverty rate has a negative effect on the achievement scores. The estimated coefficient is -0.21 and -0.31 (1% significant) for white majority schools and non-white majority schools, respectively. In addition, the negative effect of poverty has the largest impact on schools located in urban areas (estimated coefficient -0.35, 1% significant). This is particularly evident for non-white student majority schools where the estimated parameter is -0.43 (1% significant,

Table 2.4). These results support previous studies, which indicated that students who are hungry are less likely to be ready to learn and more apt to exhibit behavioral problems, than children who arrive at school with adequate nutrition (Alaimo, Olson, and Frongillo 2001; Hinrichs, 2010).

The share of teachers with more than 30 years of experience has a positive effect on the achievement score in white student majority schools. The estimated coefficients are 0.45 and 0.41 (10% significant) in schools located in the AMA and in urban areas, respectively (Table 2.4). Similarly, the share of single-parent households has a negative impact on the achievement scores for non-white student majority schools. In urban areas the estimated coefficient is -0.16, 1% significant, with a similar result in rural non-white majority schools (Table 2.4).

As expected, the unemployment rate also has a negative effect on the achievement score for all racial groups and in all locations, except the Atlanta Metropolitan Area (Table 2.3). The impact is the largest in schools located in urban areas where the coefficient ranges from -0.06 (10% significant) to -0.15 (10% significant) for white majority schools and non-white majority schools, respectively (Table 2.4).

The share of population who are high school graduates or higher has a positive effect on the achievement scores for white majority schools located in the AMA and in rural areas. The estimated coefficients are 0.18 (10% significant) and 0.31 (5% significant) for white majority schools located in the AMA and in rural areas, respectively (Table 2.4). Out of six analyzed groups, only one of the two coefficients for school spending was significant. Table 2.4, fifth column, indicates the estimated coefficient is 2.12E-05 for non-white schools located in urban areas (10% significant). A $1,000 increase in the school spending per pupil FTE stimulates the achievement score by 2%. This provides additional evidence that the relationship between per pupil spending and the educational outcome in Georgia's public schools is weak or absent which is supported in other studies (Hanushek 1997; Hoxby 2002; Wenglinsky 1997).

Further evidence of the robustness on the relationship between racial diversity and achievement scores for the Georgia's fifth grade students is listed in Table 2.5-2.7. Table 2.5 lists the results of employing the racial fractionalization index (2.3) instead of (2.2). The primary difference is the coefficient magnitudes are different with the pattern of significant coefficients remaining unchanged. The estimated coefficient of the racial fractionalization index is negative for white majority schools located in urban areas (-0.04, 5% significant) and positive for non-white majority schools located in the AMA and in urban areas.

Similarly, Table 2.6 lists the estimates by defining the racial fractionalization index according to three racial groups (white, black, and other) instead of four (white, black, Hispanic, and other) as in Table 2.4. In this case, the relationship between racial diversity and achievement score is not significant in non-white student majority schools located in urban areas, but all the other results and implications do not change. In particular, the Atlanta Metropolitan Area is the only region where a positive effect of an increase of the racial diversity on the achievement score for minority students is not follow by a decrease of the school performance of the white majority schools.

Finally, the estimates of adding a dummy variable to the model to identify black student majority schools among the non-white student majority schools are listed in Table 2.7. This variable was considered to check if racial diversity is a proxy for African-American majority schools (Hall and Leeson 2010). The estimated coefficients of the racial fractionalization index are the same as in Table 2.4, fourth-sixth column. The only difference is that the single-parent family share is no longer significant. This suggests that the variable is a proxy for the African-American student majority schools.

In general, the major implication of this analysis is that an increase of the racial diversity can be considered a policy tool to positively enhance achievement scores in Georgia's public schools. However, at the disaggregate level, the study indicates different results. The results suggest policy strategies designed to increase racial diversity in the public schools should carefully consider the learning environment where they will be applied. As Akerlof (1997) pointed out, the policy implications of programs aimed at reducing social inequalities should be combined with initiatives that carefully demonstrate to students, families, and teaching staff the importance of school spirit and cohesion. If racial diversity has a negative impact on the achievement scores of some student group, then probably investing in other factors such as the teaching faculty or school facilities may produce better results.

2.6. Conclusions and Implications

Results indicate that the relationship between racial diversity and school performance depends on the learning environment. The effect is positive and larger for the non-white majority schools (7%) and negative for the white majority schools (-3%). The negative effect of racial diversity on the achievement score in the white majority schools is present in urban areas outside the Atlanta Metropolitan Area (-8%). In contrast, the positive impact on the achievement score in the black and Hispanic majority schools is found in all urban areas in general. No significant effect was determined in rural schools for any racial group whether they are white or non-white majority schools.

There are several educational strategies to stimulate racial diversity. The voluntary inter-district school desegregation programs are choice-oriented programs that allow families and students to choose a public school outside the school district boundaries of their residence (Darling 2007). In the U. S., there are eight programs of this kind involving students in elementary, middle, and high schools (Boston, MA; East Palo Alto, CA; Indianapolis, IN; Hartford, MD; Milwaukee, WI; Minneapolis, MN; Rochester NY; and St. Louis, MO (Wells et al., 2009). These programs have shown a positive impact on achievement scores, reduced drop-out rates, reduced inequality, and increased career opportunities for the enrolled students (Wells et al., 2009).

Another educational policy designed to efficiently foster racial diversity is based on the racial peer-effect externality. Public support for fees and tuition for transferring students to increase racial diversity can make human capital investments more efficient and so stimulate the economic growth through increased educational outcomes (Hoxby 2000).

Finally, increasing school spending can still be effective in some contexts, but it presents two possible downsides. First, it may compound the pressure on the already limited public funds for education. Second, there are effectiveness concerns, given the limited statistical relationship between school achievement and per student expenditure (Hanushek 1997; Hoxby 2002; Wenglinsky, 1997). Policies designed to stimulate educational achievment and social equality may represent the most effective strategy in many metropolitan areas (Barron 2009).

References

Akerlof, G. A. 1997. “Social Distance and Social Decision.” *Econometrica* 65(5): 1005-1027.

Alaimo, K., R. R. Briefel, E. A. Frongillo, and C. M. Olson. 2001. “Food insufficiency, family income, and health in U.S. preschool and school-aged children.” *American Journal of Public Health* 91:781-786.

Anselin, L. 2002. “Under the Hood Issues in the Specification and Interpretation of Spatial Regression Models.” *Agricultural Economics* 27(2): 247-267.

—. 1990. “Spatial Dependence and Spatial Structural Instability in Applied Regression Analysis.” *Journal of Regional Science* 30(2): 185-207.

Anselin, L., and D. Arribas-Bel. 2011. “Spatial Fixed Effects and Spatial Dependence.” Working paper 2011-04. GeoDa Center for Spatial Analysis and Computation, Arizona State University.

Anselin, L., and A. Bera. 1998. "Spatial dependence in linear regression models with an introduction to spatial econometrics.” In Ullah, A. and D. E. Giles, eds. *Handbook of Applied Economic Statistics*. New York NY: Marcel Dekker Press, pp 237-289.

Anselin, L., and R. J. Florax, eds. 1995. *New directions in spatial econometrics.* Berlin, Germany: Springer-Verlag.

Baltagi, B. H., and Z. Yang. 2013.” Non-normality and Heteroskedasticity Robust LM Test of Spatial Dependence.” *Regional Science and Urban Economics* 43(5): 725-739.

Barron, J. 2009. “Amending No Child Left Behind to Prevent School Rezoning and Re-segregation: A Response to the Tuscaloosa City Schools.” *Columbia Journal of Law and Social Problems*. 42(3): 374-414.

Born, B., and J. Breitung. 2011. “Simple Regression Based Tests for Spatial Dependence.” *Econometrics Journal* 14(2): 330-342.

Cheng, E. R., and D. A. Kindig. 2012. “Disparities in Premature Mortality Between High- and Low-Income US Counties.” *Center for Disease Control and Prevention – Preventing Chronical Disease* 9(11): 1-11.

Chetty, R., N. Hendren, P. Kline, and E. Saez. 2014. “Where is the Land of Opportunity? The Geography of Intergenerational Mobility in the United States.” Working paper 19843, National Bureau of Economic Research.

Darling, H. L. 2007. “Third Annual Brown Lecture in Education Research – The flat earth and education: How America’s commitment to equity will determine our future.” *Educational Researcher* 36(6): 218-344.

Easterly, W., and R. Levine. 1997. “Africa’s Growth Tragedy: Policies and Ethnic Divisions.” *Quarterly Journal of Economics.* 62(4): 1203–1250.

Ely, R. J., I. Padavic, and D. A. Thomas. 2012. “Racial Diversity, Racial Asymmetries, and Team Learning Environment: Effects on Performance.” *Organization Studies* 33(3): 341-362.

Federal Reserve Bank of St. Louis. 2015. “Economic Data.” Available at: http://research.stlouisfed.org/fred2/ (accessed January 18, 2015).

Feitosa, F. F., J. Reyes, and W. Zesk. 2008. “Spatial Pattern of Residential Segregation: A Generative Model.” in Marcelo Gattass and Lúbia Vinhas, eds., *GeoInfo 2008*. Rio De Janeiro, Brazil: INPE Press, pp 157-162.

Georgia Department of Education. 2014a. “Existing magnet schools in Georgia”. Available at: http://archives.doe.k12.ga.us/ci_iap_magnet.aspx (accessed September 8, 2014).

—. 2014b. "Intra-district school transfers". Available at: http://www.gadoe.org/School Improvement/Federal-Programs/Pages/Intra-District-Transfers.aspx (accessed August 29, 2014).

—. 2011. "School Districts in Georgia 2010-2011." Available at: http://archives.gadoe.org/ReportingFW.aspx?PageReq=211&StateId=ALL&PID=61&PTID=67&CTID=215&T=0 (accessed March 14, 2014).

Georgia Public Policy Foundation. 2009. "2008 Georgia Report Card for Parents. "Available at: http://www.gppf.org (accessed February 19, 2011).

—. 2010."2010 Georgia Report Card for Parents." Available at: hhttp://www.gppf.org (accessed July 5, 2011).

Gordon, I., and V. Monastiriotis. 2006. "Education, location, education: a spatial analysis of English secondary school public examination." *Urban Studies* 44(7): 1203-1228.

Greene, W. H. 2012. *Econometric Analysis*, Harlow Essex, UK: Pearson Education Limited.

Hall, J. C., and P. T. Leeson. 2010. "Racial Fractionalization and School Performance." *The American Journal of Economics and Sociology* 69(2): 736-758.

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

Hinrichs, Peter. 2010. "The effects of the National School Lunch Program on Education and Health." *Journal of Policy Analysis and Management* 29(3): 479.

Hoxby, C. M. 2000. "Peer Effects in the Classroom: Learning from Gender and Race Variation." Working paper 7867. National Bureau of Economic Research, Cambridge.

—— 2002. "School Choice and School Productivity." Working paper 8873. National Bureau of Economic Research, Cambridge.

Jencks, C., M. Smith, H. Acland, M. J. Bane, D. Cohen, B. Heyns, and S. Michelson. 1972. *Inequality: A re-Assessment of the Effects of Family and Schooling in America.* New York: Basic Books.

Lareau, A., and K. A. Goyette, eds. 2014. *Choosing Homes, Choosing Schools*. New York, NY: Russell Sage Foundation.

LeSage, J. P., and R. K. Pace 2009. *Introduction to spatial econometrics*. Boca Raton, FL: CRC Press.

Liao, W., and X. Wang. 2012. "Hedonic House Prices and Spatial Quantile Regression." *Journal of Housing Economics* 21(1): 16-27.

Monchuk, D. C., D. J. Hayes, J. A. Miranowski, and D. M. Lambert. 2011. "Inference Based on Alternative Bootstrapping Methods in Spatial Models with an Application to County Income Growth in the United States." *Journal of Regional Science* 51(5): 880-896.

Morris, J. R., and C. R. Monroe. 2009."Why Study the U.S. South? The Nexus of Race and Place in Investigating Black Student Achievement." *Educational Researcher* 38(21): 20-36.

National Center for Education Statistics. 2014. "Which students are making gains? Subject-grade: mathematics – fourth grade. Student group: Race-Ethnicity." Available at: http://www.nationsreportcard.gov/reading_math_2013/#/gains-by-group (accessed: May 7, 2014).

—— 2008. "Data on School Environment." Available at: http://nces.ed.gov/surveys/ruraled/environment.asp (accessed September 18, 2014).

Nation's Report Card. 2013. "Trial Urban District Assessments (TUDA) 2013." Available at: http://www.nationsreportcard.gov (accessed: September 16, 2014).

Naidoo, A. G. V., A. Van Eeden, and Z. Munch. 2014. “Spatial Variation in School Performance, a Local Analysis of Socio-economic Factors in Cape Town.” *South African Journal of Geomatics* 3(1): 78-94.

Reback, R. 2008. “Demand (and Supply) in an Inter-District Public School Choice Program.” *Economics of Education Review* 27(4): 402-416.

Singh, G. K., and M. Siahpush. 2014. “Widening Rural–Urban Disparities in Life Expectancy, U.S., 1969–2009.” *American Journal of Preventive Medicine* 46(2): 19-29.

Theil, H., and A. J. Finezza.1971. “A note on the measurement of the racial integration of schools by means of information concepts.” *Journal of Mathematical Sociology* 1(2): 187-194.

Tyson K, W. J. Darity, and D. Castellino. 2005.”It’s not a Black thing: Understanding the burden of acting White and other dilemmas of high achievement.” *American Sociological Review* 70(4):582–605.

U. S. Office of Management and Budget. 2013. *Revised Delineations of Metropolitan Statistical Areas, Micropolitan Statistical Areas, and Combined Statistical Areas.* Bulletin 13-01. Washington DC.

U.S. Census Bureau. 2012. “America Community Survey 2007-2011: ACS Demographic and Housing Estimates.” Available at: http://www.census.gov/acs/www/(accessed May 19, 2014).

—.“Census 2000 Gateway.” Available at: http://www.census.gov/main/www/cen2000.html (accessed: May 19, 2014).

U.S. Department of Agriculture, Economic Research Service 2009. “Food Environment Atlas.” Available at: http://www.ers.usda.gov/foodatlas (accessed July 14, 2011).

Wells, A. S., B. J. Baldridge, J. Duran, C. Grzesikowski , R. Lofton, A. Roda, M. Warner, and Terrenda White. 2009. *Boundary Crossing for Diversity, Equity and Achievement.* Charles Hamilton Houston Institute for Race and Justice. Cambridge, MA. http://www.charleshamiltonhouston.org.

Wenglinsky, H. 1997. "How Money Matters: The Effect of School District Spending on Academic Achievement." *Sociology of Education* 70(3): 221-237.

Wooldridge, J. M. 2002. *Econometric Analysis of Cross Sectional and Panel Data*. Cambridge, Massachusetts: The MIT Press.

Zimmer, R., B. Gill, K., Booker, S. Lavertu, and J. White 2009. *Do charter schools "cream skim" students and increase racial-ethnic segregation?* Nashville TN: Vanderbilt University for National Center for School Choice. 25-27 October.

CHAPTER 3

TRANSPORTATION COST OF THE INTER-DISTRICT SCHOOL TRANSFER PROGRAMS

3.1. INTRODUCTION

Voluntary inter-district school transfer programs are choice-oriented programs, which allow families and students to choose a public school outside the school district boundaries of their residence (Darling, 2007). Voluntary inter-district school transfer programs aim to simulate educational outcome through the classroom peer-effects. In general, increasing students' diversity in classroom may increase or decrease a student's performance while substantially depends on the learning environment (Akerlof, 1997). Previous studies indicated that classroom peer-effects are positive externalities: bad students gain more by being exposed to good students than good students lose by being exposed to bad peers (Hoxby, 2000). If this asymmetry is strong, then investments in human capital are maximized when students attend schools with a broad array of economic and social backgrounds (Angrist and Lang, 2004).

The voluntary inter-district desegregation programs also aim to reduce racial segregation and income inequality in public schools (Holme and Wells, 2008; Wells et al., 2009). Income and racial disparities comprise the two main causes of school inequality in the U.S. While the racial achievement gap has decreased in the last 30 to 40 years, studies still indicate a consistent difference in favor of whites (National Center for Education Statistics, 2014). Meanwhile, the achievement gap between high- and low-income students has widened (Reardon, 2011).

Voluntary inter-district desegregation programs provide free transportation in contrast to many state open enrollment plans. Students involved in the programs travel on the bus several miles before reaching their school of destination. This implies high transportation costs. Low-income and racially segregated families generally cannot afford this expense, and thus, their participation in the program becomes impossible without free or subsidized transportation (Aspen Associates, 2007).

The transportation cost of the voluntary inter-district school transfer programs is supported by state and local funds. In some cases, the program administrators receive funds directly from the state to cover the transportation cost (Voluntary Inter-District Choice Corporation, VICC, 2014). Alternatively, the receiving school districts support the transportation cost and then they are reimbursed by the state, based on the number of served students and the traveled distance (METCO Program, 2014). The reimbursement does not necessarily cover the entire amount of the transportation cost, and thus, a fraction of the cost falls on the involved school districts.

Funding the transportation cost reduces the allocation of resources to alternative purposes, namely institutional activities. In many public school systems, if a school is relegated to the low performing category, it has to allocate a share of its budget between tutoring activities and transportation costs for transferring students to high performing schools (Rich, 2014). In addition, local taxpayers may contest school transfers. In general, families decide where to live with respect to several socio-economic factors: job opportunities, characteristics of the neighborhood, availability of transportation, and the quality of schools for their children (Lareau and Goyette, 2014). Local taxpayers can take positions against voluntary inter-district desegregation programs if this reduces the availability of school capacity for their children. Moreover, negative reactions can undermine the community spirit necessary for the effectiveness of the program (Finnigan and Stewart, 2009).

This study develops a model to estimate ex-ante the transportation cost of voluntary inter-district desegregation programs. The model is applied to Atlanta Metropolitan Area (AMA) schools. The Atlanta Metropolitan Area is one of six urban districts in the U.S. where the inter-district school transfer program can be the most effective (Barron, 2009). In addition, the Atlanta Metropolitan Area is also one of 21 metro areas in the U. S. for which the Department of Education provides a specific assessment of the achievement scores (Nation's Report Card, 2013).

The assessment of the transportation cost is realized for the income inequality reduction strategy and the racial segregation reduction strategy (METCO Program, 2014; Minneapolis Public Schools, 2014). Given the same transportation expenditure, the analysis identifies which strategy maximizes the number of transferred students. In addition, the assessment provides an evaluation of racial and income segregation in the AMA public schools. The analysis is realized in terms of accessibility to high performing schools for students from low-income family and non-white students.

The essay is organized as follows: Section 2 provides the background on the voluntary inter-district school transfer programs, Section 3 presents the microeconomic model, Section 4 describes the data, Section 5 discusses the methodology, Section 6 presents the results, while the conclusions and implications are drawn in Section 7.

3.2. The Voluntary Inter-District School Transfer Programs

In the U. S., there are eight inter-district school transfer programs involving students in elementary, middle, and high schools. Previous studies suggested that for the students who transfer out of poor urban schools into more affluent suburban schools, the results demonstrate an improvement in educational achievement. More than half of Project Choice students in

Hartford, MD showed higher proficiency rates in test scores than their non-participant peers (Frankenberg, 2007). Similarly, the 3rd, 6th, and 10th grade students involved in METCO program in Boston in 2006-2010 outperformed their counterparts (Eaton and Chirichigno, 2011).

The improvement of the educational outcome is generally more substantial in the long term. In St. Louis, MO the students involved in the Voluntary Inter-District Choice Corporation program performed 10% better in reading and math tests than their non-participant peers by middle and high school (Freivogel, 2002). In addition, lower dropout rates, higher graduation rates, and better career opportunities are observed for those students involved in the program (Frankenberg, 2007).

The positive impact on the students' performance is not limited to the purpose of the program. In Minneapolis, MN the Choice is Yours program is aimed at low income family members regardless of their race (Minneapolis Public Schools, 2014). In comparison with the eligible non-participants, students enrolled in the program showed a 33% higher achievement score (Orfield and Gumus-Dawes, 2008).

Many choice programs started in the 1960s and they are still operative with waiting lists by far exceeding their capacity. In the 2007-2008 school year, the number of accepted students in Boston, St. Louis, and Milwaukee were 460, 1163, and 370, respectively, while the number of students in waiting list was 13000, 2499, and 1630, respectively (Wells et al., 2009).

The primary costs of the school transfers are the transportation costs and the funding for the receiving school districts (Wells et al., 2009). Funding to support the student transfer has a consistent impact on the budget of the receiving school and it depends on how much the transfer is funded. Nevertheless, the magnitude of school funds is limited at the aggregate level. At the district level, a student is already funded in his/her school of origin and only the difference in the per-pupil spending between sending and receiving schools affects the public resources (Johnson, 2012). The per-pupil spending in public schools in the U S. for white students exceeded the spending for non-white students by $334 per year (Spatig-Amerikaner, 2012).

In contrast, school transfers imply a long bus ride outside the boundaries of the school district of residence and a high cost. In metropolitan areas, the transportation cost of the voluntary inter-district school transfer programs can be more than $2,000 per student per year (Wells et al., 2009). In addition, before and after school activities make the availability of free transportation fundamental for families with a difficult work schedule (Aspen Associates, 2007). Finally, non-affluent families may find it difficult to drive their children in suburban districts outside of their communities and this reduces their participation in the program (Finnigan and Stewart, 2009).

3.3. Transportation Cost of the Inter-district Transfer Program

We assume that the transferred students come from n different locations and that each location, i, has a_i expected transferred students. Similarly, we assume that there are m receiving schools and that each school, j, has b_j expected available places for the transferred students.

The selection process starts when the student's parents complete the transfer application. Parents do not incur any particular cost apart from gathering information (Reback, 2008).There are also no requirements in terms of average grade to be eligible for the program, apart from the legal residence of the parents in the boundaries of the town and the absence of disciplinary sanctions for the student (METCO Program, 2014). Parents generally cannot rank their preferences for the destination school, which is left to the program administrators (Minneapolis Public Schools, 2012). Since the demand exceeds the supply, the student selection is usually made by lotteries for open slots to guarantee equal treatment (Wells et al., 2009). Thus, we assume that there is a random variable that follows a Bernoulli distribution and it takes value one with probability p if an applicant student is chosen and zero otherwise with probability $(1-p)$. Say E_i the number of eligible students at the location i, the number of selected students at that location will follow a binomial distribution with expected value equal to $a_i = p \cdot E_i$.

Although the participation of the receiving school districts is voluntary, their involvement is strongly encouraged by the state educational agencies (Holme and Wells, 2008). In general, only a small share of suburban school districts is not involved in the program (METCO Program, 2014; VICC, 2014). In addition, once a school district decides to participate in the program, low drop outs are observed (Wells et al., 2009). Without loss of generality, in the following analysis we assume that all the receiving schools adhere to the program.

In some programs, the selection process gives the receiving schools the opportunity to choose which students will be considered for the lotteries (Wells et al., 2009; Minneapolis Public Schools, 2014; Reback, 2008). In these cases, some choices are biased in favor of some groups. For instance, the Minneapolis program is aimed at low income students regardless of their race; subsequently, the share of white students enrolled in the program is 40% even though the share of white students in the school population is only 27% (Wells et al., 2009). In the following analysis, we assume that the receiving schools do not affect the selection process (VICC, 2014). Thus, a student transfer is only possible if there is available space in the receiving school.

In general, the availability of a transfer place depends on the number of enrolled students, the dropout rates in the receiving schools, and the residential inflows and outflows in the nearby areas of the receiving schools. It is not rare that there is only one student transferred in one receiving class (METCO Program, 2014). Similarly, we assume that there is a probability q that a transfer is available. Thus, the expected number of available transfers in the school j is equal to $b_j = q \cdot S_j$ where S_j is the number of enrolled students in that school.

In all the programs, once the transferred students are selected, the assignment of a student to a receiving school is based on proximity (Voluntary Inter-District Choice Corporation, 2014; Milwaukee Public Schools, 2013). This minimizes the transportation cost supported by public funds and it permits students to spend less time on the bus. The minimization cost problem is said to be a balanced transportation problem (Vanderbei, 2001; Berkelaar, 2014) and it is written as:

$$\min_{x_{ij}} c \cdot \sum_{i=1}^{n} \sum_{j=1}^{m} d_{ij} \cdot x_{ij} \quad , \tag{3.1}$$

subject to:

$$\sum_{j=1}^{m} x_{ij} = a_i;\ i = 1 \ldots. n$$

$$\sum_{i=1}^{n} x_{ij} = b_j;\ j = 1 \ldots. m \tag{3.2}$$

$$x_{ij} \geq 0\ \forall\ i\ and\ j$$

$$district_i \neq district_j;\ \forall\ i\ \neq\ j\ \ ,$$

where in (3.1) the transportation cost is assumed to be proportional to the distance d_{ij}, c is the per mile cost to transport one student, x_{ij} is the expected number of students transported from the location i to the school j, and $district$ is a categorical variable to specify that the school transfer is between districts.

Since the number of total trips is constant ($\sum_{i=1}^{n} a_i = \sum_{j=1}^{m} b_j = \sum_{i}^{n} \sum_{j}^{m} x_{ij}$), if we divide equation (3.1) and the constraints in (3.2) by this number, the minimization problem is equivalent to minimizing the average home school distance:

$$\min_{x_{ij}} c \cdot \sum_{i=1}^{n} \sum_{j=1}^{m} d_{ij} \cdot x'_{ij} \quad , \tag{3.3}$$

subject to:

$$\sum_{j=1}^{m} x'_{ij} = a_i / \sum_{i=1}^{n} a_i = a'_i; \quad i = 1 \ldots . n$$

$$\sum_{i=1}^{n} x'_{ij} = b_j / \sum_{j=1}^{m} b_j = b'_j; \quad j = 1 \ldots . m \qquad (3.4)$$

$$x'_{ij} \geq 0 \; \forall \; i \; and \; j$$

$$district_i \neq district_j; \; \forall \; i \; \neq \; j \; ,$$

where x'_{ij} is the share of transferred students from the location i to the school j, $a'_i = E_i / \sum_{i=1}^{n} E_i$, and $b'_j = S_j / \sum_{j=1}^{m} S_j$.

Inter-district school transfer programs differ by their eligibility criteria. This affects the vector a'_i in constraints (3.4). If the program is addressed to reduce racial segregation, all non-white students in low performing schools are considered in the vector a'_i (METCO Program, 2014). Similarly, if the program focuses on income inequality, all the students qualified for the National School Lunch Program are eligible for transfer programs (Milwaukee Public Schools, 2013).

Note that with minor modifications of the model, the transportation cost can be estimated for different school transfer programs. For instance, if the last constraint in (3.4) is removed and the vector a'_i interests all the students in low performing schools, the model reduces to the mandatory school transfer programs (Rich, 2014). Alternatively, if the last constraint in (3.4) is defined as equality, the school transfers are at the intra-district school level (Education Commission of the State, 2013).

In general, if the transportation cost is supported by public resources, the demand for transfer exceeds the supply. In these cases, the number of eligible persons will be sufficiently high and it is reasonable to assume that the representative agent (student) has a fixed probability to participate to the program. Since the availability of the service is limited by the supply of available places, the transportation cost can always be solved by shares of students.

3.4. DATA

Achievement data were taken from the Georgia Department of Education and Governor's Office of Student Achievement, as reported in the "2008 Georgia Report Card for Parents" (Georgia Public Policy Foundation, 2009). Student achievement data are used by school systems to evaluate school performance under the criteria of adequate yearly progress (Georgia Public Policy Foundation, 2009). The two most commonly used measurements of school performance are the achievement score and the exceeding standard score. The achievement score variable is the share of students per school who passed the mathematics and reading exam of the Criterion Referenced Competency Test (CRCT). The exceeding standard variable is the share of students per school who exceeded the mathematics and reading exam of the CRCT. The analysis is performed at the school level using fifth grade data. Due to some skewness, these variables are log-transformed.

Data on the eligibility based on the racial composition are also taken from the 2008 Report Card by the Georgia Department of Education and Governor's Office of Student Achievement (METCO Program, 2014; VICC, 2014). The report card identifies six ethnic groups: white, black, Hispanic, Asian, Native-American, and multiracial.

The racial fractionalization index is from Hall and Leeson (2010) and it measures the probability that two randomly drawn individuals from the overall population belong to different ethnic groups:

$$rf_j = 1 - \sum_{k=1}^{K} \pi_{jk}^2 \quad , \tag{3.5}$$

where π_{jk} is the share of the racial group k in the school j. The index is bounded between zero and one and it increases with racial diversity.

Similarly, data on the eligibility based on the student's family income are provided by the National School Lunch Program (NSLP) as reported in the USDA-ERS *Food Environment Atlas* (2011).

The Atlanta Metropolitan Area definition is the "Atlanta-Sandy Springs-Marietta, GA Metropolitan Statistical Area" as defined by the U. S. Office of Management and Budget (2013).

To estimate the annual transportation cost, the number of school days in a year is 180 (National Center for Education Statistics, 2004). Similarly, the constant *c* in equation (3.3) is the annual per student transportation cost divided by the annual per student bus miles (National Center for Education Statistics, 2013; American School Bus Council, 2010).

Data on spatial coordinates were taken from the physical address of the schools. The dataset contains 537 elementary schools. To count for differences in measurement units, all the data were also standardized. The descriptive statistics are presented in Table 3.1.

3.5. METHODOLOGY

To estimate the transportation cost of the inter-district school transfer program there are two problems. First, high performing schools have to be recognizable from low performing schools. Second, it is necessary to know the distribution of the student population. The next sections present the estimation methodology.

3.5.1 CLASSIFICATION OF HIGH PERFORMING SCHOOLS AND LOW PERFORMING SCHOOLS

The vectors $a'$and b' in the constraints (3.4) are the shares of students in the sending schools and the receiving schools, respectively. To estimate these shares, it is necessary to recognize high performing schools from low performing schools. This can be done with cluster analysis.

Cluster analysis is a statistical technique that allows identifying groups of observations cohesive and separated from other groups when the true classification is unknown (Agresti, 2013). Cluster analysis is realized with the expected-maximization algorithm (EM algorithm, Fraley and Raftery, 2002; Fraley and Raftery, 2007; Fraley et al., 2014). The EM algorithm is superior to classical approaches for cluster analysis, given the statistical properties of the model are generally known. Moreover, the EM algorithm gave good results in many applications of cluster analysis, even when the regularity conditions do not hold.

Under the normality assumption, the EM algorithm can be summarized as follows:

- Choosing a maximum number of clusters, *M*, and a set of mixture models. The choice of the mixture models is made by specifying the covariance matrix Σ_k for $k = 1 \ldots M$ through the eigenvalue decomposition:

  $$\Sigma_k = \lambda_k D_k A_k D_k^T \quad , \tag{3.6}$$

  where λ_k is a scalar, D_k is the matrix of eigenvectors, and $A_k$is a diagonal matrix proportional to the eigenvalues.

- For each number of clusters from two to *M* and for each model, the initial values of the parameters of the model $\hat{\theta}_k$ and the probabilities $\hat{\tau}_k$to belong to the *k*th cluster are estimated through hierarchical agglomeration.

- For each number of clusters from two to *M* and for each model, the E-step calculates the conditional probability z_{ik} to belong to the *k*th cluster for the observation *i*:

  $$\hat{z}_{ik} = \frac{\hat{\tau}_k \phi_k(\boldsymbol{y}_i | \hat{\theta}_k)}{\sum_{k=1}^{G} \hat{\tau}_k \phi_k(\boldsymbol{y}_i | \hat{\theta}_k)} \quad , \tag{3.7}$$

  where ϕ_k indicates the multivariate normal density function. Then, the M-step maximizes the complete-data log likelihood function:

$$\mathcal{L}(\theta_1, \dots, \theta_G; \tau_1, \dots, \tau_k | \boldsymbol{y}, \hat{\boldsymbol{z}}) = \sum_{i=1}^{n} \sum_{k=1}^{G} \hat{z}_{ik} \log [\tau_k \phi_k(\boldsymbol{y}_i | \theta_k)] \quad , \tag{3.8}$$

The E-step and M-step are iterated until convergence, after which an observations is assigned to the group or cluster corresponding to the highest conditional probability.

- For each number of clusters from two to *M* and for each model, the Bayes Information Criterion (BIC) is computed. The optimal classification corresponds to the number of clusters of the model with the highest BIC:

$$BIC = 2\mathcal{L}(\hat{\theta}_1^*, \dots, \hat{\theta}_G^*; \hat{\tau}_1^*, \dots, \hat{\tau}_k^* | \boldsymbol{y}, \hat{\boldsymbol{z}}^*) - v_k \log(n) \quad , \tag{3.9}$$

where the asterisk denotes that the log likelihood function is evaluated at its maximum, v_k is the number of parameter of the model, and n is the number of observations.

The attributes considered in the analysis are the exceeding standard variable and the achievement score variable. These attributes are considered separately in the analysis to reduce the linear dependence (Fraley and Raftery, 2007). In addition, the distance from the center of the Atlanta Metropolitan Area is considered.

In general, socio-economic factors, and in particular educational outcomes, have a precise spatial pattern. The Atlanta Metropolitan Area is characterized by low performing schools located in the inner city and high performing schools in suburban zones. In the 2012-2013 school year, Atlanta and the DeKalb County district reported the worst elementary school performance data. In contrast, Decatur city, Fayette, and Gwinnet County district reported the best elementary school performance of the entire region (Atlanta Regional Commission, 2014). Thus, the distance from the center of the Atlanta Metropolitan Area can be considered a proxy for the flow of the student transfers. Note that the center of the AMA is estimated as the arithmetic average of the coordinates of the schools since definitions based on centroids did not provide any improvement (Okabe et al., 2000).

3.5.2 Estimation of the Distribution of the Student Population.

The estimation of the transportation cost also requires knowing the distances d_{ij} in equation (3.3). The destination points are known once the school classification is estimated, given they are the locations of the receiving/high performing schools. We need to know n representative points from where students will be transferred.

In the following part we assume that the school population is a proxy for the student population in the area nearby the school. In general, this varies from state to state. In Georgia, less than 5% of the student population attends school outside the attendance area of their residence (Berge, 2012). In addition, the voluntary inter-district school transfers are allowed under the condition that they do not change the racial integration plans (Georgia Department of Education, 2014). Under this assumption, the estimation of n representative points from where students will be transferred is realized with the Voronoi diagram (Okabe et al., 2000).

The Voronoi diagram, also called Voronoi tessellation, is a geometrical technique employed to solve the closest-point problem. Given *n* sites, the Voronoi diagram divides the space into disjoint cells, one for each site, such that all the points inside a cell are the closet points to that site. If the sites are schools, the edges of the cells identify univocally the district boundaries, given that they represent the shortest distance to the school (Mumm, 2004). Moreover, each cell has also a center point inside itself. The center points are said to be centers of mass or centroids and they represent the population center of the school district.

Formally, let $P \coloneqq \{p_1, p_2, \ldots, p_n\}$ be a set of *n* distinct sites in the plane, the Voronoi diagram of *P* is the subdivision of the pane into *n* cells, one for each site in *P*, such that a point q lies in the cell corresponding to a site p_i if and only if $distance(q, p_i) < distance(q, p_j)$ for each $p_j \in P$ with $j \neq i$ and the distance is Euclidean. In addition, for each cell with e edges, the x-axis of the centroids is defined as:

$$C_x = \frac{1}{6}\sum_{v=1}^{e}(x_v + x_{v+1})\,(x_v y_{v+1} - x_{v+1} y_v) / \, \frac{1}{2}\sum_{v=1}^{e}(x_v y_{v+1} - x_{v+1} y_v)\ , \quad (3.10)$$

where x_v and y_v are the Cartesian coordinates of the vertexes which are supposed to be arranged counter-clock wise with $x_{e+1} = x_1$.The definition of C_y is similar (Okabe et al. 2000).

The Voronoi diagram is realized on a rectangular window over the boundaries of the Atlanta Metropolitan Area with the iteration algorithm (Turner, 2014; Lee and Schatcher, 1980). Figure 3.1 shows the maps of the DeKalb County in the AMA and its tessellation. DeKalb County has 84 public elementary schools, which correspond to 84 small Voronoi cells (DeKalb County School Districts, 2015). Each cell has a center from where students are hypothesized to be transferred. Thus, the distance d_{ij} in (3.3) measures how far the centroid of the sending school i is from the receiving school j.

3.6. Results

Figure 2 shows the Bayesian information criterion for the model selection. Cluster analysis with the exceeding standard variable identifies two groups for the mixture model with covariance matrix $\Sigma_k = \lambda D_k A D_k^T$ (Figure 3.2.a). Figure 3.2.b shows the results with the achievement score variable. In this case, three clusters are selected for the mixture model with covariance matrix $\Sigma_k = \lambda_k A_k$.

For each cluster, Table 3.2 lists the mean and the standard deviation of the socio-economic characteristics of the schools and Figure 3.3 maps the school distribution in the Atlanta Metropolitan Area. Both models identify a group of schools located in the inner city (red circles). These schools are characterized by poor educational outcome, low share of white students, and limited racial diversity. In addition, high poverty levels and elevated concentration of racial minority students are observed for these schools. These results confirm previous studies indicating that the largest share of the low performing schools in Georgia is located in metro Atlanta (Baron, 2009). Moreover, these results highlight structural characteristics of the region that do not depend on the studied year (Atlanta Regional Commission, 2014).

Cluster analysis also indicates that high performing schools in the Atlanta Metropolitan Area are located in suburban zones. The model based on the exceeding standards data detects one group of schools outside the inner city (blue circles, Classification 1). In contrast, the model based on the achievement score identifies two groups of schools located in suburban zones (blue and green circles, Classification 2).

Note that, for Classification 2, group 2 presents higher values of factors positively associated with high performing schools (achievement score, exceeding standards, and white student share) and lower values of factors negatively associated with high performing schools (poverty rate, African-American and Hispanic student shares) than group 3. Note also that group 3 is, on average, closer to the outer boundaries of the Atlanta Metropolitan Area. The average distance from the center of the AMA is 24 miles and 30 miles for group 2 and group 3, respectively. This result is contrary to previous studies indicating that the peripheral regions of the Atlanta Metropolitan Area show better socio-economic status than the suburban counties (Kruse, 2007). In contrast, our results indicate clearly that socio-economic characteristics of the most affluent schools reach a maximum in the suburban regions and then they decrease closer to rural regions.

Table 3.3 shows the optimal home-school distance. The one-way, home-school distance ranges from 21.77 miles to 25.01 miles. It is interesting to note that the effect of the last constraint in (3.4) is almost absent. In fact, less than 7% of the school transfers would occur inside the same school district. This suggests that the school performance is strongly associated with the school district and that segregation in the Atlanta Metropolitan Area is more present among school districts than within them (Clotfelter, 2006).

The estimated transportation cost of the voluntary inter-district school transfer program ranges from $1189 to $1373 per student. Compared with a regular bus route, the annual per student transportation cost is $386 and $394 in Atlanta and DeKalb County, respectively, in 2011-2012 constant dollars (Georgia Department of Education, 2014).

In addition, Table 3.3 indicates that the income inequality reduction policy (first strategy) is less expensive than the racial segregation reduction policy (second strategy). In the Atlanta Metropolitan Area, the annual transportation cost ranges between $1189-$1280 and $1325-$1373 for the first and second strategies, respectively. This means that the income inequality reduction strategy allows transferring 10% more student than the racial segregation reduction policy. In addition, this implies that low-income students are less isolated from high performing schools than non-white students in the AMA (Reardon and Sullivan, 2004). This result is quite surprising if compared with other studies.

In 2012, Atlanta reported the most unequal income distribution over the fifty largest cities in the U.S. (Berube, 2014). In addition, although racial segregation is still severe in the region, integration for the African-American population showed a substantial improvement since the 1970s (U.S. 2010 Census Project, 2015).

The presence of alternative educational institutions, in particular charter schools, can explain this result. Evidence indicates that charter schools do not decrease the racial segregation in U.S. public schools and in several cases they may actually increase it (Bifulco and Ladd, 2007). Charter schools may increase the racial segregation due to the fact that they select their location to attract more demand, that is, the more racially segregated students, and this does not help them respond to opportunities outside their immediate neighborhood (Zimmer et al., 2009).

3.7. Conclusions and Policy Implications

An economic assessment of the educational outcome for the fifth grade public schools in the Atlanta Metropolitan Area is presented. Results confirm that the school performance is clustered in this region (Atlanta Regional Commission, 2014). High performing schools are located in suburban areas while low performing schools are in the inner city. In addition, the school performance is strongly related to the school districts (Clotfelter, 2006). At the aggregate level, high performing schools tend to gather in high performing school districts and vice versa. The analysis of the transportation cost also suggests that, in the Atlanta Metropolitan Area, low-income students are more exposed to high performing schools than non-white students.

This study suggests that, to stimulate the educational outcome and equal opportunities in the Atlanta public schools, it is necessary to focus more at the inter-district level and less at the intra-district level (Holme and Wells, 2008). In general, housing programs intended to provide affordable dwellings can reduce racial and income disparities between suburban and urban neighborhoods and thus educational performance among school districts. Examples are the mixed-income housing program and the tenant-based rental assistance program (DeLuca and Rosenblatt, 2010; Joseph, 2006).

In addition, educational policies based on the strategic site selection for new schools and attendance zones that carefully consider the neighborhood demographics can stimulate the school diversity and thus the student performance (Rich, 2014). Moreover, faculty recruitment policies that allow low performing schools to be endowed with a more qualified teaching body can remove one of the primary causes of the achievement gap in urban areas (Foody, 2015).

Finally, the voluntary inter-district school transfer program represents an effective educational strategy in the Atlanta Metropolitan Area, especially for the limited transportation cost. This study suggests that the voluntary inter-district school transfer program aimed at reducing income inequality allows school districts to transport 10% more students than the racial segregation reduction policy in the AMA. To maximize the effect on educational outcome and stimulate equal opportunities, this strategy can be combined with policies aimed at alleviating the isolation of non-white students in the Atlanta Metropolitan Area.

References

Agresti, A. 2013. *Categorical Data Analysis*. Hoboken, New Jersey: John Wiley & Sons Inc.

Akerlof, G. A. 1997. “Social Distance and Social Decision.” *Econometrica* 65(5): 1005-1027.

American School Bus Council. 2010. “Environmental benefits.” Available at: http://www.americanschoolbuscouncil.org/issues/environmental-benefits (accessed March 25, 2013).

Angrist, J. D. and K. Lang. 2004. “Does School Integration Generate Peer Effects? Evidence from Boston’s Metco Program.” *American Economic Review* 94:1613-1634.

Aspen Associates. 2007. “Minnesota voluntary public school choice. 2005-2006. “ Prepared for *Minnesota Department of Education,* Minneapolis, MN.

Atlanta Regional Commission. 2014. “Does Economic Disadvantage Matters for Student Achievment?” Available at: http://documents.atlantaregional.com/regional-snapshot/2014/july/edu-k12.pdf (accessed February 10, 2015).

Barge, J. 2012. “Frequently asked questions for parents and families on Georgia’s ESEA flexibility waiver.” Available at: http://www.cobbk12.org/Hayes/georgias_esea_flexibility_waiver_q__a.pdf (accessed March 18, 2014).

Barron, J. 2009. “Amending No Child Left Behind to Prevent School Rezoning and Re-segregation: A Response to the Tuscaloosa City Schools.” *Columbia Journal of Law and Social Problems*. 42(3):374-414.

Berkelaar, M. 2014. “lpSolve: Interface to Lp_solve v.5.5 to solve linear/integer programs.” R package version 5.6.10. Available at: http://CRAN.R-project.org/package=lpSolve (accessed August 14, 2014).

Berube, A. 2014. “All Cities Are Not Created Equal.” Brookings Institution. Available at: http://www.brookings.edu/research/papers/2014/02/cities-unequal-berube (accessed: February 22, 2015).

Bifulco, R., and H.F.Ladd, (2007). “School Choice, Racial Segregation, and Test-Score Gaps: Evidence from North Carolina's Charter School Program.” *Journal of Policy Analysis and Management* 26(1): 31-56.

Chetty, R., N. Hendren, P. Kline, and E. Saez. 2014. “Where is the Land of Opportunity? The Geography of Intergenerational Mobility in the United States.” Working paper 19843, National Bureau of Economic Research, Cambridge.

Clotfelter, C. T. 2006. *The Rise and the Retreat of School Desegregation*. Princeton, NJ: Princeton University Press.

Darling, H. L. 2007. “Third Annual Brown Lecture in Education Research – The flat earth and education: How America’s commitment to equity will determine our future.” *Educational Researcher* 36(6):218-344.

DeKalb County School Districts. 2015. “Elementary School Attendance Areas”. Available at: http://www.dekalb.k12.ga.us/planning (accessed February 9, 2015).

DeLuca, S. and P. Rosenblatt. 2010. “Does Moving to Better Neighborhoods Lead to Better Schooling Opportunities? Parental School Choice in an Experimental Housing Voucher Program.” *Teachers College Record* 112(5):1443,1491.

Eaton, S. and G. Chirichigno. 2011. “The History and Status of METECO.” A *Pioneer Institute Public Policy Research.* White Paper 74, Harvard Law School, Boston.

Education Commission of the State. 2013. “Open Enrolment 50-States Report.” Available at: http://ecs.force.com/mbdata/mbtab8OE?sid=a0i70000006fu14&rep=OE132T (accessed January 4, 2015).

Finnigan, K. S. and T. J Stewart. 2009. “Inter-district Choice as Policy Solution: Examining Rochester’s Urban-Suburban Inter-district Transfer Program.” Prepared for *School Choice and School Improvement: Research in State, District and Community Contexts* Vanderbilt University., Nashville, TN.

Foody, K. 2015. “Gov. Deal Takes on Failing Schools.” *Athens Banner-Herald*. February, 16:A1-A4.

Fraley, C., and A. E. Raftery. 2002. “Model-Based Clustering, Discriminant Analysis, and Density Estimation.” *Journal of the American Statistical Association* 97(458):611-631.

—. 2007. “Bayesian Regularization for Normal Mixture Estimation and Model-Based Clustering.” *Journal of Classification* 24:155-181.

Fraley, C., A. E. Raftery, and L. Scrucca. 2014. “Mclust: Normal Mixture Modelling for Model-Based Clustering, Classification, and Density Estimation.” R package version 4.4. Available at: http://cran.r-project.org/web/packages/mclust/index.html (accessed October 16, 2014)

Frankenberg, E. 2007. “Improving and Expanding Hartford’s Project Choice Program.” Poverty and Race Research Council. Washington D.C.

Freivogel, W. 2002. “St. Louis: The nation’s largest voluntary school choice plan. “ In R. Kahlenberg, (ed.), *Divided We Fail: Coming Together Through Public School Choice*. New York: Century Foundation Press.

Georgia Department of Education. 2014. “Intra and Inter-district school transfers”. Available at: http://www.gadoe.org/SchoolImprovement/Federal-Programs/Pages/Intra-District-Transfers.aspx (accessed August 29, 2014).

Georgia Public Policy Foundation. 2009. “2008 Georgia Report Card for Parents. “Available at: http://www.gppf.org (accessed February 19, 2011).

—. 2010.“2010 Georgia Report Card for Parents.” Available at: hhtp://www.gppf.org (accessed July 5, 2011).

Hall, J. C., and P. T. Leeson. 2010. “Racial Fractionalization and School Performance.” *The American Journal of Economics and Sociology* 69(2):736-758.

Holme, J. J. and A. S. Wells. 2008. “School Choice Beyond District Borders: Lessons for the Reauthorization of the No Child Left Beyond from inter-district Desegregation Open Enrollment Plans.” In R. Kahlenber, (eds.), *Improving on No Child Left Behind*. New York: Century Foundation.

Hoxby, C. M. 2000. “Peer Effects in the Classroom: Learning from Gender and Race Variation.” Working paper 7867. National Bureau of Economic Research, Cambridge.

Johnson, C. D. 2012. *Fiscal year 2013 Budget Analysis PK-12 Education*. Atlanta: Georgia Budget and Policy Institute, May.

Joseph, M. L. 2006. “Is Mixed-Income Development an Antidote to Urban Poverty?” *Housing Policy Debate* 17(2):209-234.

Kruse, K. M. 2007. *White Flight: Atlanta and the Making of Modern Conservatism (Politics and Society in Twentieth-Century America).* Princeton, NJ: Princeton University Press.

Lareau, A., and K. A. Goyette, ed. 2014. *Choosing Homes, Choosing Schools*. New York, NY: Russell Sage Foundation.

Lee, D. T., and B. J. Schatcher. 1980. “Two algorithms for Constructing a Delaunay Triangulation.” *International Journal of Computer and Information Sciences* 9(3):219-242.

Morris, J. E. and C. R. Monroe. 2008. “Why Study the U.S. South? The Nexus of Race and Place in Investigating Black Student Achievement.” *Educational Research* 38(1):21-36.

METCO Program. 2014. “Metropolitan Council of Educational Opportunity Inc.” Available at: http://www.doe.mass.edu/metco (accessed September 8, 2014).

Milwaukee Public Schools. 2013. “Suburban Schools Opportunities.” Available at: http://www2.milwaukee.k12.wi.us/extra/docs/Chapter-220-Suburban-2013.pdf (accessed May 28, 2014).

Minneapolis Public Schools. 2014. “Choice is Yours program.” Available at: https://schoolrequest.mpls.k12.mn.us (accessed June 25, 2014).

Mumm, M. 2004. “Voronoi Diagrams.” *The Montana Mathematics Enthusiast* 1(2):29-65.

National Center for Education Statistics. 2004 “Average length of school year and average length of school day, by selected characteristics: United States, 2003–04.” Available at: http://nces.ed.gov/surveys/pss/tables/table_2004_06.asp (accessed: May 7, 2014).

—. 2013. “Students transported at public expense and current expenditures for transportation: Selected years, 1980–81 to 2009–10.” http://nces.ed.gov/fastfacts/display.asp?id=67 (accessed: February 7, 2015).

—. 2014. “Which students are making gains? Subject-grade: mathematics – fourth grade. Student group: Race-Ethnicity.” Available at: http://www.nationsreportcard.gov/reading_math_2013/#/gains-by-group (accessed: May 7, 2014).

Nation’s Report Card. 2013. “Trial Urban District Assessments (TUDA) 2013.” Available at: http://www.nationsreportcard.gov (accessed: September 16, 2014).

Okabe, A., B. Boots, K. Sugihara, and S. N. Chiu. 2000. *Spatial Tessellations. Concepts and Applications of Voronoi Diagrams*. Chichester, West Sussex, England: Wiley.

Reardon, S. F., and D. O'Sullivan. 2004. “Measures of spatial segregation.” *Sociological Methodology* 34:121-162.

Reardon, S. F. 2011. *The Widening Academic Achievement Gap Between the Rich and the Poor: New Evidence and Possible Explanations*. New York: Russell Sage Foundation Press.

Reback, R. 2008. “Demand (and Supply) in an Inter-District Public School Choice Program.” *Economics of Education Review* 27(4):402-416.

Rich, M. 2014. “In Washington State, Political Stand Puts Schools in a Bind.” *The New York Times*, 5 October.

Spatig-Amerikaner, A. 2012. *Unequal Education*. Washington DC: Center for American Progress, August.

Turner, R. 2014. “deldir: Delaunay Triangulation and Dirichlet (Voronoi) Tessellation.” R package version 0.1-6. Available at: http://CRAN.R-project.org/package=deldir (accessed August 3, 2014).

U. S. Office of Management and Budget. 2013. *Revised Delineations of Metropolitan Statistical Areas, Micropolitan Statistical Areas, and Combined Statistical Areas.* Bulletin 13-01, February. Washington DC.

U. S. 2010 Census Project. 2015. “Residential Segregation.” Available at: http://www.s4.brown.edu/us2010/segregation2010/Default.aspx?msa=12060 (accessed February2, 2015).

Vanderbei, R. J. 2001. *Linear Programming: Foundations and Extensions*. New York: Springer Science.

Voluntary Inter-District Choice Corporation. 2014. “Volunatary Inter-District Choice Corporation.” Available at: http://www.choicecorp.org (accessed September 10, 2014).

Wells, A. S., B. J. Baldridge, J. Duran, C. Grzesikowski , R. Lofton, A. Roda, M. Warner, and T. White. 2009. *Boundary Crossing for Diversity, Equity and Achievement.* Charles Hamilton Houston Institute for Race and Justice. Cambridge, MA. http://www.charleshamiltonhouston.org (accessed November 14, 2014).

Zimmer, R., B. Gill, K., Booker, S. Lavertu, and J. White. 2009. *Do charter schools “cream skim” students and increase racial-ethnic segregation?* Nashville TN: Vanderbilt University for National Center for School Choice. 25-27 October.

Table 1.1. Microfinance Loans in Kyrgyzstan, 2006-2011

	2006	2007	2008	2009	2010	2011
Loan Volume (million dollar)[a]	78.9	112.4	148.8	161.2	195.4	274.8
Number of Loans	172,702	188,166	311,126	412,302	484,953	579,714
Loan Amount (dollar)[a]	457	597	478	391	403	474
Annual Real Interest Rate (%)[b]	34	36	36	40	36	44
Interest Payment (dollar)[c]	155	215	172	156	145	209

[a] Monetary values are in real terms deflated by the CPI (2005 = 100).
[b] The interest rate is the arithmetic average of interest rate for different loan sizes ($200, $500, and $1,000).
[c] The average interest payment is the product of the average annual real interest rate multiplied by the average loan amount.
Source: National Statistical Committee of the Kyrgyz Republic, 2014.

Table 1.2. Performance and Portfolio Risk of the Largest Microfinance Institutions in Kyrgyzstan, 2006-2010

Microfinance Institution	Aiyl Bank	Bai Tushum	FMCC	Kompanion	Mol Bulak Finance
		Portfolio at Risk > 30 days[a]			
2006	3.94%	3.65%	1.68%	0.57%	0.00%
2007	5.16%	0.00%	0.92%	0.11%	0.52%
2008	5.45%	1.08%	0.56%	0.36%	0.14%
2009	1.36%	2.72%	0.58%	0.01%	0.71%
2010	3.63%	2.53%	3.89%	2.33%	2.23%

Microfinance Institution	Aiyl Bank	Bai Tushum	FMCC	Kompanion	Mol Bulak Finance
		Operational Self-sufficiency Index[b]			
2006	164%	140%	148%	132%	213%
2007	168%	164%	132%	135%	166%
2008	106%	133%	125%	125%	108%
2009	111%	130%	129%	114%	110%
2010	135%	128%	111%	116%	115%

[a] The portfolio at risk more than 30 days indicates the portfolio share of loans overdue from 30 days or more.
[b] Financial revenue / (financial expenses + operating expenses + net impairment loss).
The operational self-sufficiently index is defined as the financial revenues divided by the summation of the financial expenses, operational expenses, and net impairment loss.
Source: Mix Market Microfinance Information Exchange, 2014.

Table 1.3. Variable Definition

Variable Name	Unity	Description
Food Products	Dummy (0,1)	1 if microfinance loan is used to buy food products
Start a Business	Dummy (0,1)	1 if microfinance loan is used to start a new business
Agricultural Needs	Dummy (0,1)	1 if microfinance loan is used to invest in agricultural equipment
House Expenses	Dummy (0,1)	1 if microfinance loan is used to invest for housing expenses
Healthcare Expenses	Dummy (0,1)	1 if microfinance loan is used for healthcare expenses
Educational Expenses	Dummy (0,1)	1 if microfinance loan is used for educational expenses
Other Expenses	Dummy (0,1)	1 if microfinance loan is used for other expenses
Gender	Dummy (0,1)	1 if household head is female
Age	Years	Household head age
Family Size	Members	Number of family members
Education	Years	Years of school attendance of the household head (World Bank 2011): 0 (illiterate), 2 (incomplete elementary degree), 4 (elementary degree, 4th grade), 7 (incomplete basic secondary degree), 9 (basic secondary degree, 9th grade), 11 (professional and special secondary school, 10th-11th grades), 13 (incomplete university degree), and 15 (complete university degree, 14th-16th grades).
Residence	Dummy (0,1)	1 if household head dwells in rural area
Off-farm Income[a]	Real dollars	Income from wages, self-employment, pension, scholarship, alimony, unemployment benefit, social benefit, subsidies, leasing, remittances, financial activities, and other.
Livestock	Dummy (0,1)	1 if ownership of livestock
Land	Dummy (0,1)	1 if ownership of arable land
Refrigerator	Dummy (0,1)	1 if ownership of refrigerator
Textile	Dummy (0,1)	1 if ownership of sewing machine and/or knitting machine.
Mobile Phone	Dummy (0,1)	1 if ownership of mobile phone
Transportation	Dummy (0,1)	1 if ownership of truck, car, and/or minivan
Hot Water	Dummy (0,1)	1 if hot water supply is present in the house
Sanitation	Dummy (0,1)	1 if sanitation system is present in the house
2008	Dummy (0,1)	1 if year 2008
2009	Dummy (0,1)	1 if year 2009
2010	Dummy (0,1)	1 if year 2010

[a] Off-farm income estimated with the Atlas method (World Bank 2014c).

Table 1.4. Household Characteristics of Microfinance Borrowers in Kyrgyzstan, 2006-2010

Variable Name[a]	Mean	Standard Deviation
Food Products	0.46	0.50
Start a Business	0.26	0.44
Agricultural Needs	0.29	0.46
House Expenses	0.08	0.27
Healthcare Expenses	0.04	0.19
Educational Expenses	0.05	0.22
Other Expenses	0.17	0.38
Gender (1=female)	0.28	0.45
Age (years)	48.18	10.62
Family Members	4.40	1.56
Education (years)	10.60	2.64
Residence (1 = rural)	0.73	0.44
Off-farm Income (real dollar)	528	602
Livestock (1= if own livestock)	0.58	0.49
Land (1 = if own arable Land)	0.55	0.50
Food Storage (1 = if own refrigerator)	0.61	0.49
Textile (1 = if own textile durables)	0.61	0.49
Mobile Phone (1 = if own mobile phone)	0.63	0.48
Transportation (1 = if own transportation)	0.28	0.45
Hot Water (1 = if house has hot water supply)	0.14	0.34
Sanitation (1 = if house has sanitation facilities)	0.33	0.47
Naryn (1 = if Naryn district)	0.56	0.50

[a] For the variable definition, see Table 1. Statistics based on 608 households.
Source: Kyrgyzstan Integrated Household Survey (KIHS 2010).

Table 1.5. Regional Access to Microfinance in Kyrgyzstan, 2006-2010

Oblast (Region)	Number of Households with Microfinance Access	Share	Number of Microfinance Loans	Share	Share of Households in the Sample
Issykul	41	9.1%	55	9.0%	13.3%
Jalal-Abad	23	5.1%	35	5.8%	13.3%
Naryn	231	51.4%	342	56.3%	10.6%
Batken	51	11.4%	53	8.7%	10.3%
Osh	29	6.5%	31	5.1%	13.4%
Talas	40	8.9%	49	8.1%	10.7%
Chui	31	6.9%	37	6.1%	13.1%
Bishkek	3	0.7%	6	1.0%	15.2%
Total	449	100.0%	608	100.0%	100.0%

Source: Kyrgyzstan Integrated Household Survey (KIHS 2010).

Table 1.6. Multivariate Probit Model SMLE Results (multiplied by 100)

	Loan Purpose[a]			
Independent Variable	Food Products	Start a Business	Agricultural Needs	Other Purchases
Gender (1 = Female)	**32.75****	5.13	−8.09	−13.44
	(15.73)	(15.62)	(19.19)	(16.12)
Age	−0.52	0.11	0.85	−0.50
	(0.73)	(0.67)	(0.74)	(0.67)
Family Size	6.10	7.71	0.81	**16.29*****
	(4.90)	(5.26)	(5.23)	(4.72)
Education	0.71	2.09	**9.71*****	−2.30
	(2.93)	(2.70)	(3.30)	(3.01)
Residence (1 = Rural)	−5.22	−17.21	**76.26*****	**−29.76***
	(18.63)	(15.40)	(18.16)	(15.63)
Region (1 = Naryn)	**108.46*****	**−27.16***	−2.41	−21.60
	(15.88)	(14.46)	(16.29)	(14.65)
Lag Livestock (1 = Livestock in $t-1$)	**−49.84*****	---	**77.74*****	---
	(17.84)	---	(19.39)	---
Lag Land (1 = Arable Land in $t-1$)	6.59	---	14.62	---
	(19.92)	---	(18.53)	---
Lag Mobile Phone (1 = Mobile Phone in $t-1$)	**−32.51***	**42.48****	7.72	−21.50
	(16.74)	(17.42)	(19.18)	(16.78)
Lag Off-farm Income (ln(income) in $t-1$)	10.31	−2.57	**−31.28*****	**20.60****
	(9.67)	(9.77)	(10.18)	(9.19)
Lag Textile (1 = Textile Machinery in $t-1$)	---	**24.27***	---	---
	---	(13.36)	---	---
Lag Food Storage (1 = Refrigerator in $t-1$)	12.99	**28.58***	10.21	---
	(14.66)	(15.24)	(16.54)	---
Lag Transportation (1 = Vehicles in $t-1$)	---	−1.02	2.14	−5.60
	---	(16.99)	(17.67)	(15.99)
Lag Sanitation (1 = Sanitation System in $t-1$)	---	---	---	8.27
	---	---	---	(15.93)

Table 1.6. Continued

Independent Variable	Loan Purposes[a] Food Products	Start a Business	Agricultural Needs	Other Purchases
Lag Hot Water (1 = Hot Water Supply in *t−1*)	---	---	---	2.35
	---	---	---	(55.78)
2008 (1 = 2008)	−3.74	−17.88	−7.39	3.74
	(19.53)	(20.02)	(23.00)	(21.11)
2009 (1 = 2009)	**57.52*** **	−5.63	−22.50	10.19
	(21.26)	(23.94)	(24.85)	(22.92)
2010 (1 = 2010)	4.99	**−92.84*** **	23.86	−1.60
	(23.06)	(25.24)	(24.28)	(23.57)
Intercept	−113.50	−66.99	−82.04	**−158.58** **
	(78.33)	(75.69)	(85.75)	(78.70)
Correlation Matrix	Food Products	Start a Business	Agricultural Needs	Other Purchases
		ρ_{12}	ρ_{13}	ρ_{14}
Food Products	---	−6.90	**−42.39*** **	**−33.13*** **
	---	(7.93)	(7.46)	(7.25)
			ρ_{23}	ρ_{24}
Start a Business	---	---	**−34.73*** **	**−29.45*** **
	---	---	(7.34)	(7.51)
				ρ_{34}
Agricultural Needs	---	---	---	**−41.98*** **
	---	---	---	(7.39)
Observations	445			
Number of Draws	1000			
Log Likelihood Function	−862.61			
Deviance test Chi2*(1,713)* Goodness of Fit (*p-value*)	1,725.22 (0.41)			
Likelihood Ratio test Chi2*(6)* (*p-value*) $(H_0{:}\, no\ correlation)$	142.12 (0.00)			
Wald test Chi2*(1)* (*p-value*) $(H_0{:}\, \rho_{12} = 0)$	0.75 (0.39)			

[a] Cluster-robust standard errors defined at the household level (330 clusters).
The symbols *, **, and *** represent significance at the 10%, 5%, and 1%, respectively.
Source: Kyrgyzstan Integrated Household Survey (KIHS 2010).

Table 1.7. Average Partial Effects and Predicted Probabilities (multiplied by 100)[a]

Independent Variable	Loan Purpose[b] Food Products	Start a Business	Agricultural Needs	Other Purchases
Gender (1 = Female)	**10.96****	1.48	−2.24	−4.46
	(5.38)	(4.54)	(5.31)	(5.31)
Age	−0.17	0.03	0.23	−0.17
	(0.25)	(0.19)	(0.21)	(0.23)
Family Size	2.04	2.21	0.23	**5.48*****
	(1.65)	(1.55)	(1.45)	(1.74)
Education	0.24	0.60	**2.70*****	−0.77
	(0.98)	(0.78)	(1.03)	(1.02)
Residence (1 = Rural)	−1.75	−4.91	**23.50*****	**−9.90***
	(6.26)	(4.47)	(6.79)	(5.20)
Region (1 = Naryn)	**37.99*****	**−7.94***	−0.67	−7.35
	(5.85)	(4.52)	(4.54)	(5.11)
Lag Livestock (1 = Livestock in $t-1$)	**−16.69*****	---	**22.74*****	---
	(6.18)	---	(6.88)	---
Lag Land (1 = Arable Land in $t-1$)	2.19	---	3.99	---
	(6.59)	---	(5.06)	---
Lag Mobile Phone (1 = Mobile Phone in $t-1$)	**−10.70***	**11.99****	2.14	−7.24
	(5.55)	(5.21)	(5.29)	(5.75)
Lag Off-farm Income (ln(income) in $t-1$)	3.44	−0.74	**−8.69*****	**6.93****
	(3.27)	(2.80)	(3.22)	(3.20)
Lag Textile (1 = Textile Machinery in $t-1$)	---	**7.10***	---	---
	---	(4.11)	---	---
Lag Food Storage (1 = Refrigerator in $t-1$)	4.36	**8.10***	2.88	---
	(4.96)	(4.44)	(4.98)	---
Lag Transportation (1 = Vehicles in $t-1$)	---	−0.29	0.60	−1.87
	---	(4.85)	(4.93)	(5.30)
Lag Sanitation (1 = Sanitation System in $t-1$)	---	---	---	2.74
	---	---	---	(5.37)
Lag Hot Water (1 = Hot Water Supply in $t-1$)	---	---	---	0.79
	---	---	---	(18.95)
Predicted Unconditional Probability	47.84	24.6	32.48	29.29

[a] Average partial effects and standard errors averaged over all the observations.
[b] Cluster-robust standard errors in parenthesis. Clusters defined at the household level (330 clusters).Standard errors calculated with the delta method.
The symbols *, **, and *** represent significance at the 10%, 5%, and 1%, respectively.
Source: Kyrgyzstan Integrated Household Survey (KIHS 2010).

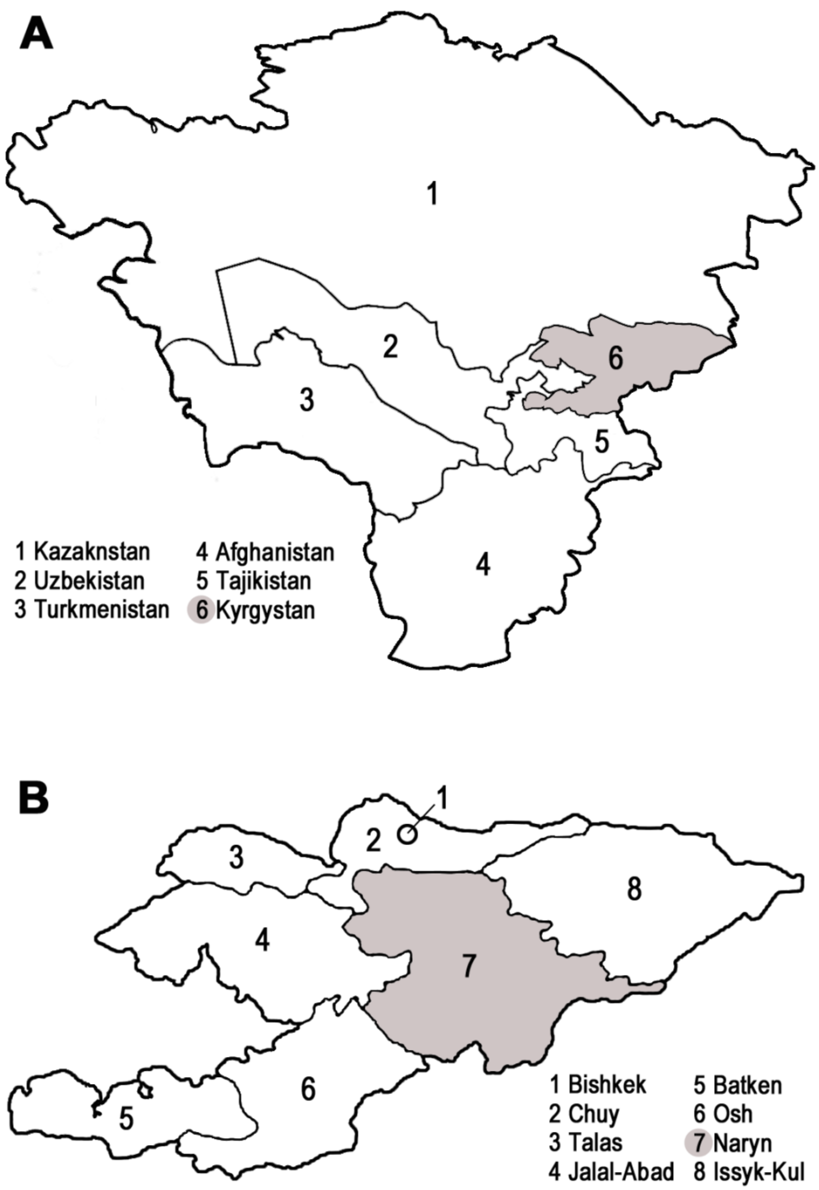


Figure 1.1. Central Asia and Regions of Kyrgyzstan. A: Central Asia Map; B: Kyrgyzstan Map.

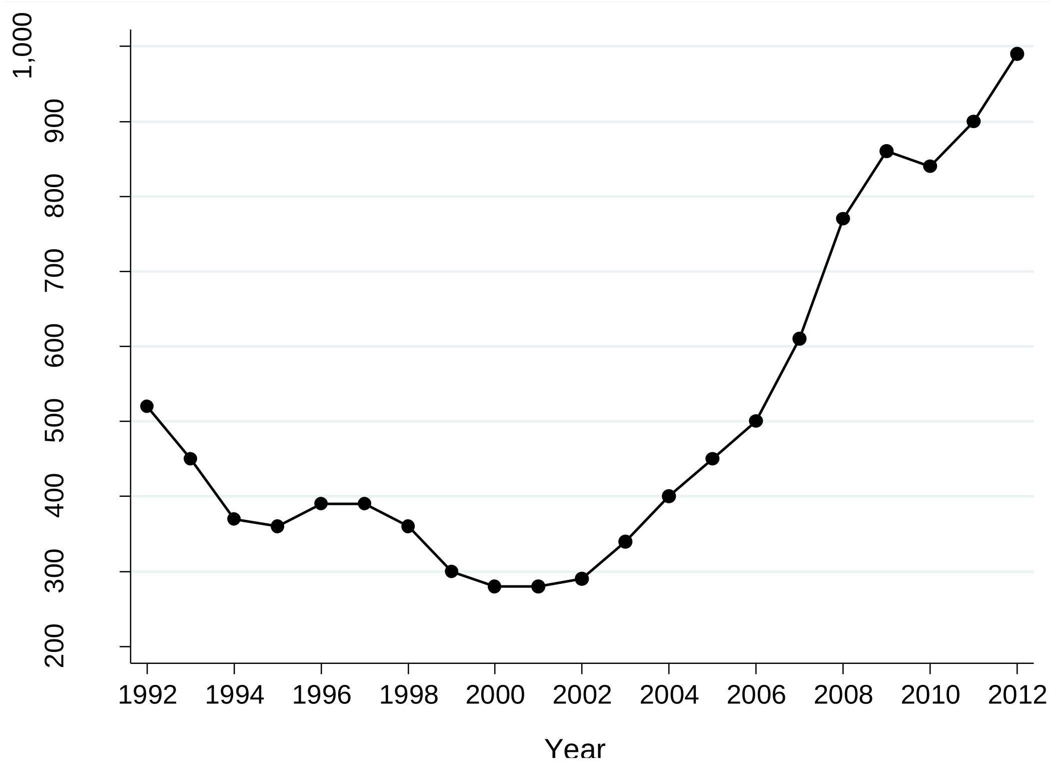


Figure 1.2. Kyrgyzstan Gross National Income Per Capita in constant 2005 U. S. dollar (World Bank, 2014a).

Table 2.1. Descriptive Statistics on Georgia's Public Elementary Schools[a]

	Average	Standard Deviation	Variable Level
Achievement Score[b]	0.86	0.09	School
Poverty Rate[c]	0.57	0.27	School
School Spending Per Pupil (real dollars)[d]	7,305	1,191	School
Centralized Spending Per Pupil (real dollars)[d]	1,890	1,104	School
Teachers With More Than 30 Years Experience %	0.05	0.02	County
Single Parent Families %	0.36	0.11	County
Unemployment Rate	0.10	0.02	County
Population With High School Degree or More %	0.83	0.07	County
Racial Fractionalization Index[e]	0.41	0.20	School
Black (= 1 if African-American Majority School)	0.37	0.48	School
AMA (=1 if Atlanta Metropolitan Area School)	0.48	0.50	County
Rural (=1 if Rural School)	0.21	0.41	County

[a] Georgia's 5th grade public schools.
[b] Share of students per school who passed the fifth grade math and reading exam on CRCT.
[c] Share of students per school who are eligible for reduced price or free meals, (NSLP).
[d] GDP Implicit price deflator, 2009 base year = 100. Source Federal Reserve Bank of St. Louis (2015).
[e] Racial fractionalization index as defined in equation (2.2) based on four racial groups (white, black, Hispanic, and other).

Table 2.2. Diagnostics for the Model Choice

Weighting Matrix	School District	Cut-off Distance
LM test H_0: $\rho = \lambda = 0$ in General *(2 DF)* (General *vs. OLS)* [a]	68.44	22.77
	(0.00)	(0.00)
LM test H_0: $\rho = 0$ in SLAG *(1 DF) (SLAG vs. OLS)* [a]	8.86	3.81
	(0.00)	(0.05)
LM test H_0: $\lambda = 0$ in SER *(1 DF) (SER vs. OLS)* [a]	63.41	20.89
	(0.00)	(0.00)
Robust LM test H_0: $\rho = 0$ in SLAG *(1 DF) (SLAG vs. OLS)* [b]	6.36	1.56
	(0.01)	(0.21)
Robust LM test H_0: $\lambda = 0$ in SER *(1 DF) (SER vs. OLS)* [b]	49.52	9.76
	(0.00)	(0.00)
LR test H_0: $\theta = -\lambda\beta$ *(8 DF) (SDM vs. SER)* [c]	9.84	17.38
	(0.28)	(0.03)

[a] Anselin and Bera, 1998.
[b] Born and Beritung, 2011; Baltagi and Yang, 2013.
[c] LeSage and Pace, 2009.

Table 2.3. SER Model MLE Results - Separate Regressions of the Achievement Score by Racial Group and Geographical Zone in Georgia[a]

Dependent Variable	In(Achievement Score)					
	Racial Group		Geographic Zone			Total Sample
Independent Variables	White Majority Schools	Non-White Majority Schools	AMA[b] Schools	Urban Schools	Rural Schools	
Poverty Rate (% NSLP)	**-0.21***** (0.01)	**-0.31***** (0.03)	**-0.26***** (0.01)	**-0.35***** (0.03)	**-0.25***** (0.03)	**-0.28***** (0.01)
School Spending Per Pupil (real dollar)	1.50E-06 (2.20E-06)	1.60E-06 (3.50E-06)	-1.10E-06 (2.60E-06)	**1.51E-05*** (8.33E-06)	-6.60E-06 (5.40E-06)	1.70E-06 (2.30E-06)
Centralized Spending Per Pupil (real dollar)	-2.00E-06 (3.30E-06)	1.30E-06 (5.20E-06)	3.70E-06 (3.60E-06)	-1.83E-05 (1.60E-05)	-4.40E-06 (4.20E-06)	7.00E-07 (3.40E-06)
Teachers with more than 30 years Exp. (%)	**0.37***** (0.13)	-0.19 (0.38)	0.16 (0.45)	0.13 (0.28)	0.07 (0.23)	0.17 (0.15)
Single Parent Families (%)	-0.01 (0.03)	-0.10 (0.08)	**-0.16**** (0.08)	0.01 (0.08)	**-0.14*** (0.08)	**-0.13***** (0.04)
Unemployment Rate (%)	**-0.04***** (0.02)	**-0.12***** (0.02)	-0.01 (0.02)	**-0.13***** (0.02)	**-0.07***** (0.02)	**-0.09***** (0.02)
Pop. With High School Degree or more (%)	**0.13*** (0.07)	0.22 (0.22)	**0.16*** (0.09)	0.20 (0.19)	**0.36**** (0.13)	**0.15*** (0.08)
Racial Fractionalization Index	**-0.03*** (0.01)	**0.07***** (0.03)	**0.06***** (0.02)	**0.04**** (0.02)	**0.05*** (0.03)	**0.05***** (0.01)
Constant	**-0.15**** (0.06)	-0.28 (0.20)	0.43 (0.26)	**-0.33**** (0.16)	**-0.28**** (0.11)	**-0.19**** (0.08)
Lambda	**0.27***** (0.06)	**0.40***** (0.09)	**0.37**** (0.15)	**0.30***** (0.11)	**0.22***** (0.08)	**0.36***** (0.04)
Sigma	0.05	0.10	0.07	0.09	0.07	0.08
Observations	618	494	537	340	235	1,112
R^2	0.56	0.46	0.67	0.62	0.64	0.56
Wald Test Overall Fit (8 DF)	444.31	216.20	572.55	300.02	778.36	861.49
p-value Wald Test	0.00	0.00	0.00	0.00	0.00	0.00
Chow Test Structural Stability[c]	727.07		162.80			---
p-value Chow Test	0.00		0.00			---

[a] Racial fractionalization index as defined in equation (2.2) based on four racial groups (white, black, Hispanic, and other).

[b] Atlanta Metropolitan Area (AMA) defined by the US Office of Management and Budget (2013) as “Atlanta-Sandy Springs-Marietta, GA Metropolitan Statistical Area.”

[c] Chow test for structural stability in the error term with unequal variance and unequal spatial structure for each group (Anselin 1990).
The symbols *, **, and *** represent significance at the 10%, 5%, and 1%, respectively.

Table 2.4. SER Model MLE Results - Separate Regressions of the Achievement Score by Racial Group and Geographical Zone in Georgia[a]

Dependent Variable	In(Achievement Score)					
	White Majority Schools			Non-White Majority Schools		
Independent Variables	AMA[b]	Urban Area	Rural Area	AMA[b]	Urban Area	Rural Area
Poverty Rate	**-0.20*** **	**-0.23*** **	**-0.22*** **	**-0.30*** **	**-0.43*** **	**-0.12***
(% NSLP)	(0.02)	(0.02)	(0.04)	(0.03)	(0.07)	(0.07)
School Spending Per Pupil	2.50E-06	1.30E-06	1.04E-06	-3.00E-07	**2.12E-05***	-2.96E-06
(real dollar)	(4.90E-06)	(4.60E-06)	(4.90E-06)	(4.50E-06)	(1.25E-05)	(8.50E-06)
Centralized Spending Per Pupil	5.30E-06	1.90E-06	-3.30E-06	3.90E-06	-2.54E-05	-2.43E-05
(real dollar)	(5.50E-06)	(1.56E-05)	(3.80E-06)	(5.30E-06)	(2.71E-05)	(2.10E-05)
Teachers with more	**0.45***	**0.41***	0.20	-0.14	-0.49	0.05
than 30 years Exp. (%)	(0.27)	(0.24)	(0.23)	(0.12)	(0.50)	(0.40)
Single Parent Families	-0.11	-0.02	0.07	-0.02	**-0.16*** **	**-0.10***
(%)	(0.11)	(0.06)	(0.09)	(0.18)	(0.06)	(0.06)
Unemployment Rate	-0.05	**-0.06***	-0.04	-0.03	**-0.15***	**-0.10***
(%)	(0.09)	(0.04)	(0.03)	(0.02)	(0.09)	(0.06)
Pop. With High School Degree	**0.18***	-0.05	**0.31** **	0.20	0.09	0.35
or more (%)	(0.09)	(0.13)	(0.14)	(0.19)	(0.37)	(0.27)
Racial Fractionalization Index	-0.02	**-0.08*** **	0.02	**0.06** **	**0.09***	0.06
	(0.02)	(0.03)	(0.04)	(0.03)	(0.05)	(0.07)
Constant	0.14	-0.06	**-0.41*** **	**1.40** **	-0.27	-0.22
	(0.16)	(0.11)	(0.11)	(0.64)	(0.42)	(0.24)
Lambda	**0.34** **	**0.20***	0.14	**0.42***	0.13	**0.30** **
	(0.16)	(0.12)	(0.12)	(0.15)	(0.26)	(0.13)
Sigma	0.04	0.05	0.06	0.09	0.11	0.07
Observations	263	181	174	274	159	61
R^2	0.64	0.58	0.39	0.48	0.49	0.63
Wald Test Overall Fit (8 DF)	247.94	169.16	66.03	135.04	89.93	57.70
p-value Wald Test	0.00	0.00	0.00	0.00	0.00	0.00
Chow Test Structural Stability[c]	710.36					
p-value Chow Test	0.00					

[a] Racial fractionalization index as defined in equation (2.2) based on four racial groups (white, black, Hispanic, and other).
[b] Atlanta Metropolitan Area (AMA) defined by the US Office of Management and Budget (2013) as "Atlanta-Sandy Springs-Marietta, GA Metropolitan Statistical Area."
[c] Chow test for structural stability in the error term with unequal variance and unequal spatial structure for each group (Anselin 1990).
The symbols *, **, and *** represent significance at the 10%, 5%, and 1%, respectively.

Table 2.5. SER Model MLE Results - Separate Regressions of the Achievement Score by Racial Group and Geographical Zone in Georgia[a]

Dependent Variable	In(Achievement Score)					
	White Majority Schools			Non-White Majority Schools		
Independent Variables	AMA[b]	Urban Area	Rural Area	AMA[b]	Urban Area	Rural Area
Poverty Rate (% NSLP)	**-0.20***** (0.02)	**-0.23***** (0.02)	**-0.22***** (0.04)	**-0.30***** (0.03)	**-0.42***** (0.07)	**-0.13*** (0.07)
School Spending Per Pupil (real dollar)	2.80E-06 (4.80E-06)	1.40E-06 (4.70E-06)	1.05E-06 (5.10E-06)	-2.00E-07 (4.40E-06)	**2.14E-05*** (1.20E-05)	-3.00E-06 (9.00E-06)
Centralized Spending Per Pupil (real dollar)	5.30E-06 (5.90E-06)	1.90E-06 (1.39E-05)	-3.40E-06 (3.50E-06)	3.90E-06 (5.30E-06)	-2.48E-05 (2.79E-05)	-3.00E-05 (2.00E-05)
Teachers with more than 30 years Exp. (%)	**0.46*** (0.27)	**0.43**** (0.22)	0.21 (0.22)	-0.14 (0.11)	-0.50 (0.52)	0.03 (0.36)
Single Parent Families (%)	-0.11 (0.10)	-0.03 (0.05)	0.08 (0.09)	-0.03 (0.18)	**-0.17***** (0.06)	**-0.10*** (0.06)
Unemployment Rate (%)	**-0.06** (0.10)	**-0.06*** (0.03)	-0.03 (0.03)	-0.02 (0.02)	**-0.16*** (0.09)	**-0.10*** (0.06)
Pop. With High School Degree or more (%)	**0.18**** (0.08)	-0.05 (0.14)	**0.31**** (0.15)	0.20 (0.20)	0.08 (0.42)	0.37 (0.26)
Racial Fractionalization Index	-0.01 (0.01)	**-0.04**** (0.02)	0.02 (0.02)	**0.03**** (0.02)	**0.06*** (0.03)	0.03 (0.05)
Constant	0.15 (0.21)	-0.04 (0.13)	**-0.41***** (0.12)	1.40 (0.61)	-0.28 (0.45)	-0.22 (0.26)
Lambda	**0.33**** (0.17)	**0.21***** (0.10)	0.13 (0.10)	**0.42***** (0.14)	0.10 (0.30)	**0.29**** (0.15)
Sigma	0.04	0.05	0.06	0.09	0.11	0.07
Observations	263	181	174	274	159	61
R^2	0.64	0.58	0.38	0.47	0.48	0.63
Wald Test Overall Fit (8 DF)	247.35	165.60	66.64	135.01	92.13	57.23
p-value Wald Test	0.00	0.00	0.00	0.00	0.00	0.00

[a] Racial fractionalization index as defined in equation (2.3) based on four racial groups (white, black, Hispanic, and other).
[b] Atlanta Metropolitan Area.
The symbols *, **, and *** represent significance at the 10%, 5%, and 1%, respectively.

Table 2.6. SER Model MLE Results - Separate Regressions of the Achievement Score by Racial Group and Geographical Zone in Georgia[a]

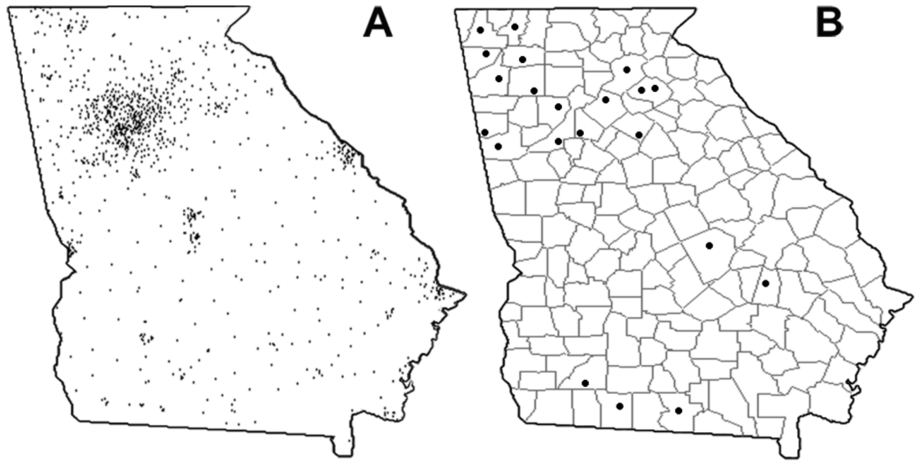
Dependent Variable	ln(Achievement Score)					
	White Majority Schools			Non-White Majority Schools		
Independent Variables	AMA[b]	Urban Area	Rural Area	AMA[b]	Urban Area	Rural Area
Poverty Rate	**-0.19*****	**-0.23*****	**-0.22*****	**-0.30*****	**-0.43*****	-0.12
(% NSLP)	(0.02)	(0.02)	(0.04)	(0.03)	(0.08)	(0.08)
School Spending Per Pupil	2.50E-06	1.50E-06	1.03E-06	-2.00E-07	**2.09E-05***	-3.00E-06
(real dollar)	(5.00E-06)	(4.40E-06)	(5.70E-06)	(4.30E-06)	(1.22E-05)	(1.13E-05)
Centralized Spending Per Pupil	5.40E-06	1.70E-06	-3.30E-06	3.70E-06	-2.61E-05	-2.44E-05
(real dollar)	(5.80E-06)	(1.47E-05)	(3.80E-06)	(4.70E-06)	(3.04E-05)	(2.01E-05)
Teachers with more	0.45	**0.41***	0.20	-0.14	-0.50	0.04
than 30 years Exp. (%)	(0.29)	(0.22)	(0.24)	(0.14)	(0.65)	(0.40)
Single Parent Families	-0.11	-0.02	0.08	-0.02	**-0.16****	-0.10
(%)	(0.10)	(0.06)	(0.09)	(0.19)	(0.06)	(0.06)
Unemployment Rate	-0.05	-0.06	-0.04	-0.03	**-0.15***	-0.09
(%)	(0.10)	(0.04)	(0.03)	(0.02)	(0.09)	(0.07)
Pop. With High School Degree	**0.18****	-0.04	**0.31****	0.20	0.08	0.33
or more (%)	(0.08)	(0.13)	(0.14)	(0.19)	(0.44)	(0.32)
Racial Fractionalization Index	-0.03	**-0.08*****	0.01	**0.06****	0.09	0.06
	(0.02)	(0.03)	(0.04)	(0.03)	(0.06)	(0.08)
Constant	0.14	-0.06	**-0.41*****	**1.50****	-0.25	-0.20
	(0.21)	(0.12)	(0.12)	(0.65)	(0.50)	(0.27)
Lambda	**0.34***	**0.20***	0.14	**0.42*****	0.13	**0.29****
	(0.18)	(0.12)	(0.12)	(0.14)	(0.27)	(0.15)
Sigma	0.04	0.05	0.06	0.09	0.11	0.07
Observations	263	181	174	274	159	61
R^2	0.64	0.58	0.38	0.47	0.48	0.55
Wald Test Overall Fit (8 DF)	249.10	168.69	65.95	134.54	90.06	57.21
p-value Wald Test	0.00	0.00	0.00	0.00	0.00	0.00

[a] Racial fractionalization index as defined in equation (2.2) based on three racial groups (white, black, and other).
[b] Atlanta Metropolitan Area.
The symbols *, **, and *** represent significance at the 10%, 5%, and 1%, respectively.

Table 2.7. SER Model MLE Results - Separate Regressions of the Achievement Score By Geographical Zone for Non-White Majority Schools in Georgia[a]

Dependent Variable	ln(Achievement Score)		
	Non-White Majority Schools		
Independent Variables	AMA[b]	Urban Area	Rural Area
Poverty Rate (% NSLP)	**-0.30***** (0.03)	**-0.42***** (0.06)	**-0.13**** (0.06)
School Spending Per Pupil (real dollar)	-2.00E-07 (4.10E-06)	**1.90E-05*** (1.02E-05)	-2.98E-06 (9.10E-06)
Centralized Spending Per Pupil (real dollar)	4.00E-06 (5.20E-06)	-2.64E-05 (3.32E-05)	-2.89E-05 (2.11E-05)
Teachers more than 30 years Exp. (%)	-0.13 (0.11)	-0.61 (0.61)	0.03 (0.34)
Single Parent Families (%)	-0.02 (0.18)	0.03 (0.31)	-0.02 (0.13)
Unemployment Rate (%)	-0.03 (0.02)	-0.18 (0.23)	**-0.12**** (0.05)
Pop. High School Degree or more (%)	0.20 (0.18)	-0.11 (0.24)	0.56 (0.27)
Racial Fractionalization Index	**0.06**** (0.03)	**0.10*** (0.05)	0.03 (0.08)
Black (= 1 if African American Majority School)	-0.01 (0.02)	**-0.05*** (0.03)	**-0.07*** (0.04)
Constant	**1.50***** (0.57)	**-0.21** (0.54)	**-0.33** (0.25)
Lambda	**0.36***** (0.14)	0.11 (0.16)	**0.29***** (0.11)
Sigma	0.09	0.11	0.07
Observations	274	159	61
R^2	0.47	0.49	0.65
Wald Test Overall Fit (9 DF)	136.03	93.94	63.17
p-value Wald Test	0.00	0.00	0.00

[a] Racial fractionalization index as defined in equation (2) based on four racial groups (white, black, Hispanic, and other).
[b] Atlanta Metropolitan Area.
The symbols *, **, and *** represent significance at the 10%, 5%, and 1%, respectively.



Binary Contiguity Matrix	A	B
	Cut-off Distance Five Neighbors[a]	School District[b]
Number of Schools	1,112	1,112
Average Number of Neighbors	208.8	30.3
Maximum Number of Neighbors	475	89
Minimum Number of Neighbors	5	0
Standard Deviation of the Number of Neighbors	176.94	30.47
Density[c]	0.19	0.03

[a] The cut-off distance is equal to 34.42 miles and it corresponds to at least five neighbors for each school.

[b] Based on 180 school districts in Georgia. Two schools are neighbors if they belong to the same school district. The bullet point in the map represents a city district in a County (Georgia Department of Education, 2011).

[c] $density = \sum_{i=1}^{n}\sum_{j=1}^{n} c_{ij}/(n(n-1)/2)$ where c_{ij} is 1 if the schools i and j are neighbors and otherwise.

Figure 2.1. Georgia Public Elementary Schools.

Table 3.1. Descriptive Statistics of the 5th Grade Public Schools in the Atlanta Metropolitan Area in the 2008-2009 School Year

Variable	Average	Standard Deviation
Achievement score[a]	0.87	0.09
Exceeding standard[b]	0.29	0.15
Poverty rate[c]	0.52	0.29
White students (%)	0.38	0.32
African-American students (%)	0.42	0.33
Hispanic Students (%)	0.13	0.17
Other race students (%)	0.08	0.06
Racial fractionalization index[d]	0.43	0.22
Observations	537	---

[a] Share of students per school who passed the fifth grade mathematics and reading exam of the Criterion Referenced Competency Test (CRCT).
[b] Share of students per school who exceeded the Georgia standard for the fifth grade mathematics and reading exam of the CRCT.
[c] Share of students per school who are eligible for reduced price or free meals (NSLP).
[d] Racial fractionalization index defined in equation (4).

Table 3.2. Clustering Analysis for the 5th Grade Student in the Atlanta Metropolitan Area[a]

	Classification 1[b]		Classification 2[c]		
	Group 1	Group 2	Group 1	Group 2	Group 3
Achievement score	0.80 (0.08)	0.92 (0.05)	0.80 (0.08)	0.95 (0.02)	0.87 (0.04)
Exceeding standard	0.18 (0.08)	0.37 (0.14)	0.19 (0.12)	0.44 (0.12)	0.24 (0.07)
Poverty rate	0.75 (0.18)	0.34 (0.22)	0.76 (0.20)	0.24 (0.17)	0.53 (0.19)
White student %	0.11 (0.17)	0.59 (0.24)	0.11 (0.18)	0.59 (0.25)	0.48 (0.28)
African-American Student (%)	0.65 (0.30)	0.23 (0.22)	0.64 (0.31)	0.22 (0.24)	0.34 (0.25)
Hispanic students (%)	0.18 (0.22)	0.09 (0.08)	0.18 (0.23)	0.08 (0.08)	0.11 (0.12)
Other race students (%)	0.07 (0.05)	0.09 (0.07)	0.07 (0.05)	0.11 (0.08)	0.07 (0.04)
Racial fractionalization index	0.37 (0.25)	0.47 (0.18)	0.36 (0.25)	0.46 (0.19)	0.49 (0.17)
Distance from AMA center (miles)	12.08 (5.20)	27.35 (9.56)	10.65 (4.29)	23.59 (7.77)	30.49 (9.40)
Number of schools	239	298	206	181	150

[a] Mean and standard deviation in parenthesis.
[b] Classification 1 based on the exceeding standard variable and the distance variable.
[c] Classification 2 based on the achievement score variable and the distance variable.

Table 3.3. Transportation Cost of the Inter-district School Transfer Program in the Atlanta Metropolitan Area

Policy Reduction Strategy		Income Inequality	Racial Segregation	Income Inequality	Racial Segregation
	Receiving Schools	Home-school distance (miles)		Annual Per Student Transportation Cost	
Classification 1[a]	Group 2	22.19	25.01	$1218	$1373
Classification 2[b]	Group 2	21.77	24.13	$1189	$1325
Classification 2[b]	Group 3	23.31	24.96	$1280	$1370

[a] Classification 1 based on the exceeding standard variable and the distance variable.
[b] Classification 2 based on the achievement score variable and the distance variable.

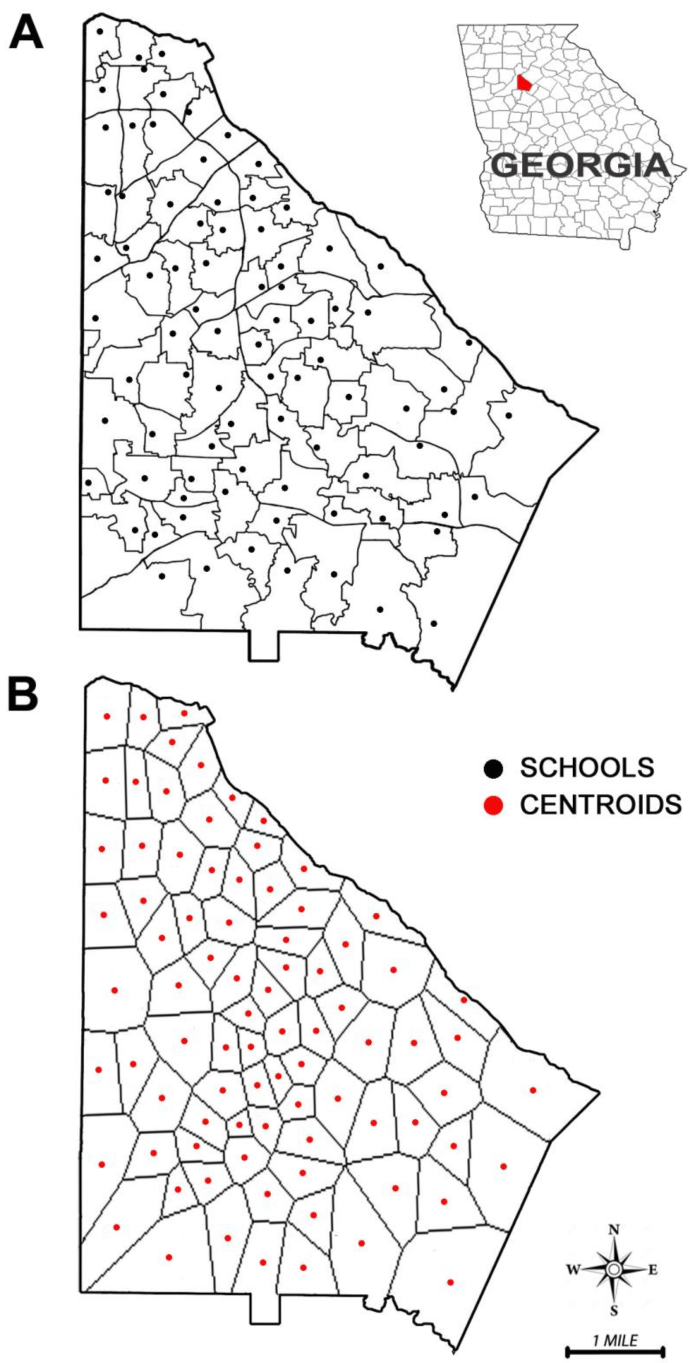


Figure 3.1. Elementary School Attendance Area in DeKalb County (GA) and Extract of Voronoi Diagram.

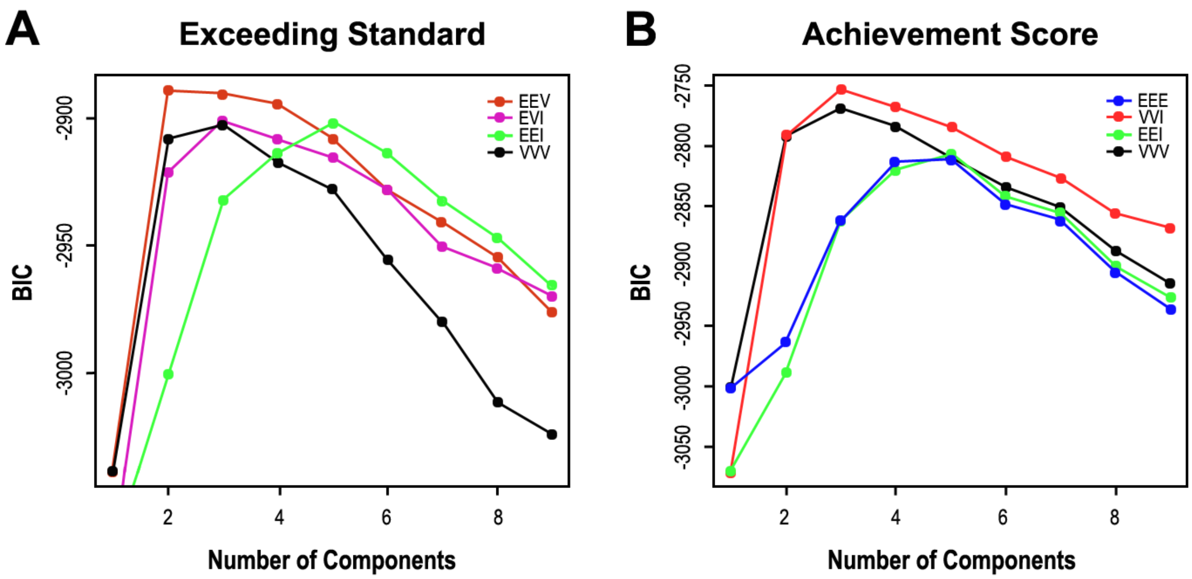


Figure 3.2. Bayes Information Criterion (BIC) for Model Selection. Covariance decomposition: $EEV = \lambda_k D_k A D_k^T$, $EVI = \lambda A_k$, $EEI = \lambda A$, $EEE = \lambda D A D^T$, $VVI = \lambda_k A_k$, $VVV = \lambda_k D_k A_k D_k^T$.

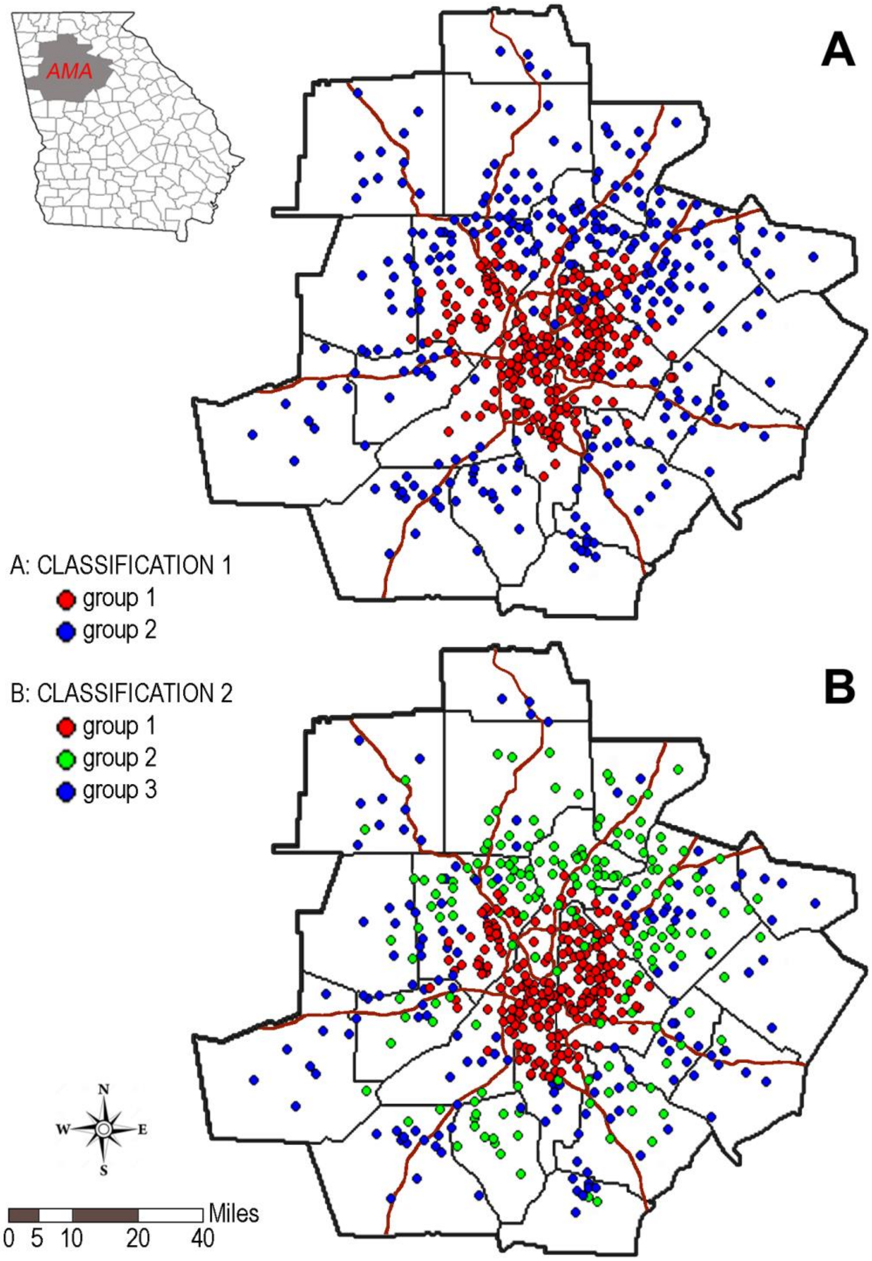


Figure 3.3. Cluster Analysis for the 5th Grade Public Schools in the Atlanta Metropolitan Area.