

# **Maternal Education: The Key to Unlocking The Issue of Child Immunization and Health**

This study analyzes the effect of maternal education on child immunization status in the United States utilizing data from the National Immunization Survey produced by the Center for Disease Control (CDC). This study differs from previous work in that it examines the effect of actively induced postnatal child health outcomes as opposed to outcomes that result from prenatal maternal care. To account for the possible endogeneity of maternal education in relation to child immunizations, an instrument is constructed using number of colleges per state by potential year of maternal college initiation. This study uses a two-stage least squares model of analysis to generate results, which provide some evidence to support a positive correlation between maternal education and child immunization status. However, further work, including finding a better instrument for maternal education, is necessary for more conclusive and robust results.

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## **Introduction**

Do maternal education levels play a critical role in child health and survival? Is maternal education the key to increasing child health and decreasing child mortality? Through econometric and statistical analysis, this empirical study explores the relationship between maternal education and child immunization status in the United States. Both deductive reasoning and inductive generalization are used throughout the study in order to fully develop comprehensive results. Through inductive generalization, this study analyzes specific, individual level data from multiple states throughout the country to generate the broad conclusion that some statistical evidence supports the theory that maternal education improves child health and decreases the risk of child mortality. Deductive reasoning is used in this study in exploring the reasons behind the resulting association. In this way, both positive and normative analyses are generated. Positive analysis is used in examining the statistical and econometric results of the study. By exploring possible reasons behind the correlation between maternal education and child immunization status, normative analysis is used in formulating important policy suggestions.

This study generates some evidence to support the hypothesis that maternal education increases the likelihood of child immunization. Accordingly, as seen in recent research, these results support the general hypothesis that maternal education improves child health and decreases the likelihood of child mortality. Most recent studies, however, have explored only specific developing countries. In addition, those few studies that examine multiple countries, also focus solely on developing or low income nations. As Sandiford, Morales, Gorter, Coyle and Smith (1991) point out, today, there

are several relatively high per capita GNP countries with fairly poor levels of child health. Likewise, there are several low per capita GNP countries with surprisingly low mortality figures. Therefore, in order to achieve robust and conclusive results, this study analyzes data from the United States, a high GDP producing country that has been largely ignored in the literature. Given that this study finds the linkage to be somewhat evident in such a country, important global implications can be made and worldwide policy changes suggested, regardless of income and wealth. In addition, unlike most studies examined, this study utilizes child immunization status as a determinant of child health. In other countries, where immunization is more infrequently practiced, weight, height, and other indicators of malnutrition determine child health at birth. In these studies, the effect of maternal education on birth outcome is mostly determined through pregnancy behavior or how well a mother cares for herself during pregnancy. However, in a country such as the United States, where child malnutrition is generally lower, immunization provides a good indication of actively induced and promoted child health post pregnancy. In analyzing actual steps taken by the mother to increase the health of her child, rather than herself, the channels through which maternal education affects child health is more accurately explored. Finally, there has not been substantial research conducted using data from the late twentieth and early twenty-first century. Therefore, given that the link between maternal education and child health/survival is found to be somewhat evident using current data, this research provides further incentive for policymakers around the world, to invest in female human capital as a means to lowering child mortality and improving child health.

## **Economic Theory and Literature Review**

### ***Education and Stock of Health***

Health economists have done extensive analysis regarding the correlation between education and stock of health. However, researchers have found that education itself is very difficult to measure and quantify. This is due to the fact that education can be obtained in many ways, both conventionally and informally. Therefore, as in this study, health economists use formal schooling as a measure of educational attainment. The effect of years of schooling in terms of the production of health model can be easily studied through statistical analysis. In using this approach, economists have developed two basic theories regarding the correlation between schooling and stock of health.

One theory, developed by economist Michael Grossman, focuses on education and schooling as a central factor in the demand for health (Grossman, 1972a, 1972b). The Grossman theory asserts that those who have obtained higher levels of education (schooling) are more efficient producers of health. Given that health is a function of medical care, environment, and lifestyle, the health production function shifts up and becomes steeper with more education because people can produce it more efficiently. For example, those who are educated have acquired the understanding of technology and knowledge of medical and other market inputs that are necessary in producing positive health outcomes. Thus, the demand for health of those obtaining higher levels of education is greater.

Another theory, developed by Victor Fuchs (1982), focuses on time discounting as a method in which people choose to invest in both education and health. Those who possess high discount rates favor investments that produce immediate returns, while those with low discount rates prefer investments with long-term benefits. Given that

investments in both education (schooling) and health require substantial immediate costs, including time, money, etc, and possess long-term pay-offs, those with high discount rates will tend to not invest in both education (schooling) and health. In this way, Fuchs directly correlates obtainment of education (schooling) and health. However, his theory also suggests that increases in one will not causally affect the other. Although high discount rates will tend to produce investments in both education (schooling) and health, one will not dictate the extent of the investment in the other. This is a situation in which the correlation between schooling and health is due to the mutual relationship of such variables to an outside factor. Many health economists have studied and hypothesized that such a problem exists due to various other linking characteristics or factors.

Economists refer to this problem as an issue of self-selection. Those who choose to obtain higher levels of education (schooling) possess other characteristics that increase their likelihood of being healthier. Thus, this outside factor confounds the attainment of the direct causation of education (schooling) on health.

Many economists have produced research that examines the effect of third variables or outside factors on the education-health link. Berger and Leigh produced a study that provides evidence that refutes the theory that unobservable self-selection factors affect the health-education link (Berger and Leigh, 1989). Within this study, two separate samples of individuals were observed using two different indicators of health: blood pressure and functional disabilities or limitations. After controlling for such observable factors as race, ethnic background, family characteristics, and IQ, and finding means of measuring some unobservable factors such as personal time preference, both sample results showed that there was a direct positive correlation between schooling and

health. The unobservable factors had no significant effect on the results, thus refuting the theory of self-selection in the case of schooling and health. In another study, Behrman and Wolf analyze the effect of schooling on women's health in Nicaragua (Behrman and Wolf, 1989). This study accounts for factors affecting both schooling and health by incorporating the effect of women's childhood background factors. The study found that such factors had little to no effect on the women's health outcome and thus on the education-health link.

Another study by Behrman and Wolf provides evidence to the contrary, however (Behrman and Wolf, 1987). In this study, comparing the effect of maternal schooling on child health status, Behrman and Wolf tightly control for child background factors by studying sisters possessing varying degrees of education. The results showed that after controlling for such factors, there is no resulting correlation between maternal schooling and child health. In this way, the study provides evidence to support the theory that other outside factors, such as childhood background factors, confound or even negate the effect of schooling on health. In this way, this study provides evidence that third variables or outside factor do pose a problem in determining the education-health link.

A method of controlling for problems of self-selection or third variables in the case of the education-health relationship is the use of instruments or instrumental variables within research. An instrument is a variable that is highly correlated with the independent variable but uncorrelated with the dependent variable. Lleras-Muney (2002) conducted such a study in which she used compulsory education laws as an instrument for education. The study analyzed the health and survival patterns of people who were both affected and unaffected by the laws. In this way, information was obtained from

people with varying levels of education. Through statistical analysis, the study determined that the correlation between education and health was pure, causal and positive.

### ***The Maternal Education-Child Health Correlation***

Although substantial research has documented the intriguing link between maternal education and child health and survival, the association has still yet to be fully examined and comprehended. In fact, according to Bicego and Boerma (1993), of all of the child survival research studied, the effect of maternal education is the still the least understood. This problem is due, in part, to the fact that there exist several studies of individual countries of low income, providing situational analysis of the maternal education-child health/survival link. However, very little high-income or multi-country research exists. Thus, despite numerous studies, the connection of maternal education and child health and survival as well as the reasoning behind such correlation is under considerable debate.

Several theories have been developed through substantial research and investigation in exploring the maternal education-child health and survival link. In hypothesizing the reasoning behind the maternal education- child health and survival association, Bicego and Boerma (1993) suggest three possible explanations. First, the study offers the theory that the link is merely a result of the strong correlation between education and economic status. It is reasonable to assume that within a wealthier family, children are apt to attend school for longer periods of time, thus achieving higher levels of education, receive greater quantities of food having greater nutritional value, and have better access to health service facilities. Only a few studies have incorporated varying degrees of household wealth in their statistical analyses to account for this problem. One

such study performed by the United Nations (1985), found that approximately half of the link between maternal education and child health/survival can be explained by corresponding levels of household income. Subsequently, it appears as though income can significantly impact correlation studies of this link.

A second theory, proposed by Bicego and Boerma (1993), hypothesizes that particular education-induced behaviors are the underlying factors of the maternal education-child survival link. For instance, it is hypothesized that mothers with higher levels of education are more inclined to utilize health services (1993). One study done in the Philippines shows that for every one-year increase in maternal education, the likelihood of mothers seeking services for child health care increases by four percent (Cebu Study Team, 1991). Combinations of family culture and education can also produce behaviors that can affect the maternal education-child survival link. Cleland and van Ginneken (1988) suggest that particular cultural and social factors can influence the parental decision to educate daughters. These factors subsequently affect the educational level of the next generation of mothers. From this analysis, Sandiford, Cassel, Montenegro, and Sanchez (1995) make the postulation that parents who choose to educate their children place more value on their children's survival. Thus, this cycle of cultural parental behaviors could account for the correlation between maternal education and child survival. Similar to this theory, Caldwell (1979) claims that it is education that generates behaviors in women, by increasing their knowledge, thus prompting them to take care of their children's health at a higher level and to a greater extent. This theory coincides with Bicego and Boerma's (1993) hypothesis that mothers with an education seek out health services more than uneducated mothers. A third behavioral factor

underlying this link could be family formation patterns, including maternal age of initiation, pace, and size of family (Bicego and Boerma 1993). Through research conducted by Cleland and van Ginneken (1988), analyzing and combining the results of works of various studies, including that of Hobcraft, McDonald, and Rutstein (1984 and 1985), considerable evidence suggests that these factors in fact do not explain the maternal education-child survival link. However, given the few number of studies on these factors, overall results are still inconclusive.

A third general theory presented by Bicego and Boerma (1993) is that greater physical access to health services can explain the relationship between maternal education and child survival. If health care were accessible to both educated and uneducated mothers, it would be assumed from the prior research discussed that the educated mothers would take advantage of these services. Therefore, the difference in child health and survival between educated and uneducated mothers would be larger in comparison to an area in which there is not access to health care services. A research study performed by Orubuloye and Caldwell (1975) in Nigeria affirms this hypothesis. However, another train of thought would suggest that greater access would make health care more visible and would encourage uneducated women to utilize health services. In this way, the difference in child health and survival of educated versus uneducated mothers in areas of easy health care access would be small. According to this theory, in areas where health services are not available, educated mothers put forth the effort to seek out health care, while uneducated mothers remain unaware. Therefore, differentials would, subsequently, be greater in areas of less access to health services. Studies done by

Rozenzweig and Schultz (1982) in Colombia, and Bicego (1990) in Haiti provide statistical support for this hypothesis.

The issue of less access to health services can also be related to rural versus urban living, where greater access to health care is more likely in an urban environment rather than in a rural. From such a theory, it follows that, all else equal, urban life fosters better health and lower child mortality. However, Sastry's (1997) study of rural and urban differentials in child mortality in Brazil points to the fact that maternal education more profoundly affects community characteristics and thus child mortality. In the Mellington and Cameron (1999) comparison of rural and urban residents of Indonesia, the authors conclude that primary and secondary education significantly reduces child mortality rates in both environments. The evidence that these two studies provide thus refutes the theory that urban life is the sole factor in reducing child mortality. Instead, the evidence supports the theory that maternal education itself has a direct effect on child health and survival. As a result of the inconclusiveness of such studies, evidence of the effects of greater access to health services remains inconclusive.

The vast majority of the studies that focus on the maternal education and child health/survival correlation, several of which have already been mentioned, analyze data from specific, singular, developing countries. One of the strongest studies of this nature, exploring the three previously mentioned theories (presented by Bicego and Boerma, 1993) is reported in Sandiford, Cassel, Montenegro, and Sanchez (1995).

Through examining the Nicaraguan National Literacy Movement (the Cruzada Nacional de Alfabetización or the CNA) during the period 1980 through 1985, this study uses a fairly controlled experimental environment in which to test their study. Through the use

of the literacy movement, this study examined child health and survival of three categories of mothers: mothers who acquired literacy via primary education (prior to the CNA), mothers who remained illiterate throughout the movement, and mothers who acquired literacy via adult education through the CNA. Unlike most other studies, Sandiford, Cassel, Montenegro, and Sanchez (1995) were able to study women of similar socioeconomic status who were both literate and illiterate. In this way, the authors were able to resolve the problem presented by Biego and Boerma (1993) of separating education and socio-economic status. To ensure this control, socioeconomic status was measured through housing characteristics and ownership of assets, and literate women were matched with illiterate women of similar economic status. In addition, through extensive field work and survey administration, the study also took into account several other potential confounders such as number of children within the family, socioeconomic status, access to health services, type of water supply, presence of sanitation facilities, mother's marital status, employment outside of the home, and child care arrangement. Survey work also allowed for the collection of data for the main variables tested in the study, infant mortality rates and child health statistics. Child health statistics were measured in terms of anthropometric indicators including low-height-for-age statistics (for the presence of growth stunting), low-weight-for-age (for malnutrition), as well as mid-upper arm circumference or MUAC (for general health). Through the creation of aggregate indices, the study found that infant mortality rates of women who achieved literacy through the CNA movement fell to the same level as that of the women who achieved literacy via primary education. The study also reported that CNA literate women's children's low MUAC-for-age rates were sixty percent lower than those of

illiterate women's children. Low-weight-for-age figures for children of CNA literate women were the same as those of women who acquired education via primary schooling. Lastly, children of CNA literate mothers were at sixty-six percent lower risk for low height-for-age in comparison to illiterate mothers. Through the use of logistic regression and controlling for socio-economic factors, the study found that all correlation results excluding low-height-for age were significant. In addition, such analysis provided evidence of substantially larger differences in health of children of CNA literate mothers and children of illiterate mothers. Subsequently, Sandiford, Cassel, Montenegro, and Sanchez's (1995) study was able to provide evidence that maternal literacy positively affects the nutrition of children and decreased mortality rates.

One of the strongest multi-country studies exploring the correlation between maternal education and child health and survival in developing countries is the 1993 Bicego and Boerma study, previously mentioned in this paper. This study examined seventeen developing countries using Demographic and Health Surveys (DHS surveys) from 1987 to 1990 in an attempt to analyze the three theories previously mentioned. Through multivariate logistic regression, this study found that significantly elevated risks of neonatal mortality are associated with low levels of maternal education (Bicego and Boerma, 1993). However, after controlling for economic status, only five of the seventeen countries were statistically significant. In contrast, post neonatal mortality figures were found to be twice as sensitive to maternal education as neonatal mortality rates. Stunting and under-weight status were found to be even more highly correlated with maternal education than mortality rates. However, economic status is again reported as playing a fairly significant role in such statistics, where economic status indicators

explain fifty-six percent of the correlation. In terms of non-use of health services, namely non-use of tetanus toxoid during pregnancy and non-use of antenatal services, this study found that even after controlling for economic status, the link between low levels of maternal education and non-use of health services remained strong. For instance, non-use of tetanus toxoid during pregnancy is roughly twice as likely in children of non-educated mothers as those possessing secondary education levels. Through these results, it appears as though economic status, as a confounder of maternal education-child health and survival link, requires further study. In terms of family formation patterns, a second confounding variable in the maternal education-child health and survival link, the study found little to no evidence to support any indication of significant effects. The third confounding theory of greater access to health services was found to be inconclusive and, thus, further analysis is required.

Few studies of the maternal education – child health relationship have been conducted using data from the United States or an instrument-variables technique. However, one recent study by Currie and Moretti (2003) has penetrated this important subject matter. Within the study, Currie and Moretti reinforce the importance of incorporating analysis of high-income countries in determining the correlation between maternal education and child health: “If higher maternal education does indeed improve child health outcomes, even in a rich country such as the United States, then conventional estimates of the returns to education that focus only on wages may understate the social benefits” ( p. 1496). This study analyzes four main means through which maternal education can affect child health, or in this case, birth outcomes: prenatal care, smoking, marriage, and fertility. According to the study’s results, increases in maternal education

increase the likelihood of prenatal care usage, abstinence from smoking, marriage, and fewer children with more attention for each, or what the study calls “parity”(p.1495). As in the aforementioned research by Lleras-Muney (2002), Currie and Moretti use an instrument-variable estimator in order to account for the endogeneity of educational acquisition. The study recognizes other omitted factors that may confound the pure relationship between maternal education and child health such as family background or “forward looking behavior”, as explained by Fuch’s theory (1982). Therefore, the study uses opening of two and four-year colleges from 1940 to 1996 as an instrument for maternal education. Throughout these years different counties opened colleges for women at different times, providing additional opportunities for women’s educational attainment. In this way, the study analyzes increases in women’s education (at age 17) in comparison to future birth outcomes. Through regression analysis the study’s results indicate that increases in maternal education significantly and positively affect birth outcomes. In fact, the study shows that each “additional year of education reduces the incidence of low birth weight by approximately 10 percent” (p.1525). When added to the vast body of work focused on developing countries, this study provides an even stronger and more comprehensive testimony of the existence of a positive correlation between maternal education and child health. Thus, in adding future research involving countries of high income, the positive maternal education – child health relationship can be further cemented and important global policy suggestions can be made.

### ***Immunization***

Immunization is a vital key to the health and survival of infants and children in the United States and around the world. According to the Global Alliance for Vaccines

and Immunization (GAVI) “of the over 10 million deaths among children under five in 2002, about one-quarter were attributable to diseases that are already or soon will be vaccine preventable” (GAVI, 2004). Research conducted by Diamond, Singarimbun, and Streatfield (1990) studying the maternal education – child health link in Indonesia, supports the theory that knowledge of immunization is positively related to maternal education. However, such results in such an impoverished country still appear weak. In a country such as the United States, where poverty levels are low and vaccination services are more readily available, immunization status is a good indicator of proactively induced health of children (versus innate health). Four of the major vaccines needed to reduce the risk of poor health in children include: Diphtheria-Tetanus Toxoids-Acellular Pertussis vaccine (DTP), Inactivated Polio virus vaccine (IPV), Measles, Mumps and Rubella vaccine (MMR), and Haemophilus Influenzae type B vaccine (Hib). DTP, sometimes denoted DTaP, protects against Diphtheria, Tetanus and Pertussis. Diphtheria is a life threatening disease that can cause airway obstruction, pneumonia, heart failure and paralysis. The National Network for Immunization Information reports that the likelihood of contracting the disease and becoming violently ill is thirty times greater if not immunized. Similarly, thirty percent of all those infected with Tetanus will die each year. Moderately less fatal, the third disease protected against in the DTP vaccine is Pertussis or Whooping Cough. Today, approximately 7000 cases of Pertussis are recorded each year in the United States, with ten deaths annually. Polio immunization is crucial for infants today. Before the IPV vaccine was developed, 13,000 – 20,000 were paralyzed and nearly 1,000 died each year from the virus, most of whom were children. The MMR vaccine protects against three diseases, Measles, Mumps, and Rubella.

Measles is a highly contagious disease that can be spread through the simple touch of a hand or even through breathing. Likewise, both Mumps and Rubella can be spread through mucus from sneezes or coughs. Twenty to thirty deaths due to Mumps and nearly 1000 cases of Rubella are reported each year. The fourth vaccine, Hib, prevents the contraction of severe meningitis as well as other serious infections caused by Haemophilus Influenzae.

The following chart depicts all of the vaccines and appropriate ages of immunization recommended by the Center for Disease Control (CDC):

**Table I**

**Recommended Childhood and Adolescent Immunization Schedule  
United States · July–December 2004**

Vaccine ▼	Age ▶	Range of Recommended Ages								Catch-up Immunization		Preadolescent Assessment	
		Birth	1 mo	2 mo	4 mo	6 mo	12 mo	15 mo	18 mo	24 mo	4-6 y	11-12 y	13-18 y
Hepatitis B <sup>1</sup>		HepB #1	only if mother HBsAg (-)	HepB #2		HepB #3			HepB series				
Diphtheria, Tetanus, Pertussis <sup>2</sup>			DTaP	DTaP	DTaP		DTaP			DTaP	Td	Td	
Haemophilus influenzae Type b <sup>3</sup>			Hib	Hib	Hib	Hib							
Inactivated Poliovirus			IPV	IPV	IPV				IPV				
Measles, Mumps, Rubella <sup>4</sup>						MMR #1			MMR #2		MMR #2		
Varicella <sup>5</sup>						Varicella			Varicella				
Pneumococcal <sup>6</sup>			PCV	PCV	PCV	PCV			PCV	PPV	PPV		
Influenza <sup>7</sup>					Influenza (Yearly)				Influenza (Yearly)				
Hepatitis A <sup>8</sup>									Hepatitis A Series				

*Vaccines below red line are for selected populations*

As seen in the above chart, four doses of DTP, three doses of IPV, one dose of MMR and three doses of Hib are recommended, all of which should be obtained by 19 months of age.

## **Method**

### *Data*

The primary data used in this study is acquired through the National Immunization Survey (NIS) conducted by the National Center for Health Statistics, a branch of the Center for Disease Control (CDC). This telephone survey uses a list-assisted random-digit-dialing technique to acquire data from a random sample of mothers across the country. Given that the group began data collection in April of 1994, this study utilizes the 1995 through 2003 surveys. In this way, the study uses cross sectional data over a span of nine years, thus achieving experimental conditions that are broad in terms of geographics and comprehensive in terms of time. Through the use of this data, key factors potentially impacting immunization status are formulated and assessed. These factors include maternal age, race, maternal education, income, marital status, number of children within the household, state of residence, and year of survey. As seen in Table II, given all of the data is categorical, these variables are, thus, converted into dummy variables. The state dummies used in the study control for omitted variables that are constant in a single state across time. The year dummies control for omitted variables that are constant across the entire country in a given year.

Table III highlights the descriptive statistics of these variables, illustrating the distribution and relative strengths of each dummy variable within its own category as well as the study as a whole. The sample shows that the majority of the data participants are white females with two children. In this way, the study is slightly skewed in terms of reporting accurate results for the whole population regardless of race and family size. However, the other variables are fairly evenly distributed across the sample population,

including the key variable, maternal education. In this way, the sample provides a good data set for the study.

In addition to the dummies generated in Table II, immunization dummy variables, the primary child health outcomes in this study, are also created. The four key vaccinations aforementioned, DTP, IPV, MMR and Hib, represent the immunization factors analyzed in this study. Incorporating all four of these primary vaccinations, the 4:3:1:3 series is appropriately labeled “all4shot” in this study. The 4:3:1:3 series indicates if a child has received all recommended doses for each of the four key vaccinations, DTP (4 doses), IPV (3 doses), MMR (1 dose), and Hib (3 doses). This series represents the best possible measure of child immunization. Table IV lists the “all4shot” dummy setup. In addition, the following table (Table V) displays the descriptive statistics of this immunization variable. This shows that slightly more than half of the sample population immunized their children with the 4:3:1:3 series. In addition, within each category of maternal education studied, slightly over half of each sub-sample population immunized their children with the 4:3:1:3 series. In this way, the sample provides a good and evenly distributed data set for the study. It should also be noted that the age range of the children used in this study, as surveyed by the NIS, is 19 months through 35 months; the recommended age in which every child should be immunized is 19 months. Therefore, each child included in this study should already have these immunizations.

A second source of data, used to create instrumental variables in this study, is a data set of two-year and four-year college openings per state per year in the United States, formulated by Currie and Moretti (2003). Currie and Moretti constructed this data

set using the National Center for Education Statistic's Integrated Postsecondary Education Data System (IPEDS) for two-year colleges and the Peterson's Guide to Four-Year Colleges (1999) and the Barron's Profiles of American Colleges (1996) for four-year colleges. In analyzing the histories of these colleges, the Currie and Moretti (2003) study compiles a large data set of openings of two-year and four-year college per state, using public opening dates as opening years (as opposed to date of acquisition of land, etc.). Excluded from the data set are schools of psychology, law schools, seminaries, bible colleges and other such religious schools, internet-based schools, medical schools, graduate schools and research institutions, and foreign universities residing in the US.

Given that this study analyzes the effects of college openings at the time in which women surveyed in 1995-2003 were deciding to go to school, data for the number of colleges available per maternal state of residence by year of college initiation for mother needs to be generated. In this study, the age at which the mother is most likely to begin college (maternal age of college initiation) is approximated at 17 years old.

Unfortunately, this is one limitation of the CDC dataset which does not report the year a woman began college. Some women may be older or younger at the time they begin college. Therefore, this is strictly an estimation. An even greater limitation is that the CDC reports maternal age as a categorical variable. Therefore, it is impossible to determine the precise year of which a woman turned 17. Given that survey recorded ages are categorical variables, ages for each category are approximated as follows:

MatAge1  $\leq$  19  $\Rightarrow$  MatAge1 = 19  
MatAge2 = 20-29  $\Rightarrow$  MatAge2 = 25  
MatAge3  $\geq$  30  $\Rightarrow$  MatAge3 = 31

These approximations are one of the greatest sources of limitation in this study. Due to the fact that the data is categorical and must be approximated by only one age per category, many of the women's ages are misclassified. They are approximated by the women who are 19, 25, and 31 at the time of the survey.<sup>1</sup> In addition, the Currie and Morreti data on college openings is only collected through 2000. Therefore, the few people turning 17 in 2001-2003 are dropped. Through this methodology, for each year of NIS data used, 1995 to 2003, three years of maternal age at 17 years old are generated. Through this process, it is determined that the youngest mother in this approximated study, surveyed in 2003, would have been 17 in 2001. Likewise, the oldest mother in this approximated study, surveyed in 1995, would have been 17 in 1983.

The following are the variable names generated for the number of four-year and two-year colleges per state by year of college initiation (age 17):

Number of Four-Year Colleges in a particular state and year = count4  
 Number of Two-Year Colleges in a particular state and year = count2

### ***Preliminary Findings/Model Development***

This study's main model examines the relationship between immunization and maternal education, taking into account other confounding factors such as race, income, marital status, and number of children within the family. Preliminary tests were conducted on the following model for the immunization variable used in this study, all4shot (containing DTP, Polio, Hib, and MMR):

$$\text{all4shot} = B_1 + B_2 * \text{Race Dummies} + B_3 * \text{Maternal Education Dummies} + B_4 * \text{Income Dummies} + B_5 * \text{Marital Status Dummies} + B_6 * \text{Number of Children Dummies} + B_7 * \text{State Dummies} + B_8 * \text{Year Dummies} + e$$

where  $B_2$  through  $B_8$  represent vectors of coefficients and the dummy variables are defined as in Tables II and IV.

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<sup>1</sup> Through the same methodology, age approximations of 19, 29, and 39 are also tested in this study.

Given that the dependent variable in the model is a dummy variable, ordinary least squares regression will produce biased results. Therefore, in order to eliminate such bias, a probit model is used. The probit model is associated with the cumulative standard normal probability function. It produces probabilities between 0 and 1 and is used for non-linear or S-shaped relationships between independent variables and their subsequent probabilities. Given that the data set this study analyzes is large, the maximum likelihood estimator produced by the probit model is normally distributed, consistent, and best (meaning, no competing estimator has smaller variances). For these reasons, the probit model is used in this preliminary testing. More specifically, the `dprobit` command, available in STATA, which is the econometrics software used in this study, provides results that are not in coefficient form, but express results in terms of the change in probability for a small change in the independent variable.

Through the preliminary results shown in Table VI, the probability that a child is fully immunized with the 4:3:1:3 series (`all4shot`) is greater with every increase in maternal education. For example, a mother with a high school degree is 6.2% more likely to immunize her child relative to a high school dropout, while a college graduate is 9.7% more likely. Given that these probabilities are significant at the 1% level, they can be analyzed as reliable results. Other results from this preliminary testing provide evidence for some predictable and logical outcomes. As seen in Table VI, the race variables show stark differences in results with regard to immunization. According to the results, whites are the most likely to immunize their children, while blacks have the lowest likelihood of immunizing their children. Specifically, white mothers are approximately 5% more likely than hispanic mothers to immunize their children. In

contrast, black mothers are 3% less likely to immunize their children in comparison to hispanic mothers. In terms of income, children of lower income families are less likely to immunize their children than those of higher incomes. For instance, families with an annual income of less than or equal to \$12,500 are .2% less likely to immunize their children in comparison to those with an annual income of greater than or equal to \$20,000. Likewise, children of divorced, separated, or widowed mothers are 4.1% less likely to be immunized in comparison to married mothers. Mothers who have never been married are also unlikely to immunize their children. They are 3.2% less likely to immunize their children in comparison to married mothers. Lastly, in terms of number of children within the family, the results show that the greater the number of children, the lower the probability of immunizing such children. Those mothers with four or more children are 4% less likely to immunize their children in comparison to those mothers with only one child. In this way, preliminary results show the disadvantaged, minority, encumbered sections of the population are less likely to immunize their children. Therefore, they prove to be valid confounders in terms of the maternal education-immunization link.

A key independent variable in this study, maternal education, is also tested in order to ensure its reliability as a source of acceptable results. In this case, the various sub-categories of maternal education, MatEduc1-MatEduc4 are tested for statistical independence or difference using Wald Tests. This is accomplished through the following hypothesis tests:

$$\begin{array}{l} \text{I} \quad H_0: B_5 = B_6 \\ \quad \quad H_1: B_5 \neq B_6 \end{array}$$

$$\text{II} \quad \begin{aligned} H_0: B_6 &= B_7 \\ H_1: B_6 &\neq B_7 \end{aligned}$$

$$\text{III} \quad \begin{aligned} H_0: B_5 &= B_6 = B_7 \\ H_1: B_5 &\neq B_6 \neq B_7 \end{aligned}$$

$$\text{using, } \text{all4shot} = B_1 + B_2(\text{RaceW}) + B_3(\text{RaceB}) + B_4(\text{RaceO}) + B_5(\text{MatEduc2}) + B_6(\text{MatEduc3}) + B_7(\text{MatEduc4}) + B_8(\text{inc1}) + B_9(\text{inc2}) + B_{10}(\text{MaritalWDS}) + B_{11}(\text{MaritalNM}) + B_{12}(\text{NumChildren2}) + B_{13}(\text{NumChildren3}) + B_{14} - B_{63}(\text{statedum}) + B_{64} - B_{71}(\text{yrdum}) + e$$

where  $B_5$  is the coefficient for *MatEduc2*,  $B_6$  is the coefficient for *MatEduc3* and  $B_7$  is the coefficient for *MatEduc4*.

In hypothesis test I, the study analyzes the statistical difference between *MatEduc2* and *MatEduc3*, high school graduates versus those with some college experience. Through the use of STATA, the Wald test for hypothesis test I produces the following results:

$$\begin{aligned} \text{chi}^2 &= 16.06 \\ \text{Prob} > \text{chi}^2 &= 0.0001 \end{aligned}$$

As seen above, the probability that the cut-off statistic is not greater than the  $\text{chi}^2$  statistic is extremely low. Therefore, the null hypothesis that the coefficients for *MatEduc2* and *MatEduc3* are equal can be rejected at the 1% significance level. Having determined that high school graduate data is statistically different from some college experience data, hypothesis test II analyzes the relationship between *MatEduc3* and *MatEduc4*, some college experience versus college graduate status. The following results are produced from this Wald Test:

$$\begin{aligned} \text{chi}^2 &= 41.98 \\ \text{Prob} > \text{chi}^2 &= 0.000 \end{aligned}$$

Through this test, it can be seen that the probability cut-off is not greater than the  $\text{chi}^2$  statistic and, thus, the null hypothesis that the coefficients on *MatEduc3* and *MatEduc4* are equal can be rejected. Given that the maternal education coefficients are statistically

different in pairs, the last hypothesis test (III) examines all three maternal education variable coefficients used in the dprobit regression model in total. It tests to see if  $B_5$ ,  $B_6$ , and  $B_7$  are all statistically different from each other. The following results are generated:

$$\begin{aligned} \text{chi}^2 &= 129.94 \\ \text{Prob} > \text{chi}^2 &= 0.000 \end{aligned}$$

Given that the probability cut-off is not greater than the  $\text{chi}^2$  statistic, the null hypothesis of equality of all three coefficients can be rejected. Therefore, the sub-categories of MatEduc can be rendered significantly statistically independent or different.

### ***Final Research Model/Two-Stage Model***

As seen in recent research and economic theory, maternal education may be endogenously linked to child health inputs and, thus, immunization. This is an omitted variable problem where other unknown factors, previously discussed, affect immunization status. In this way, maternal education is random but correlated with the random error or disturbance  $e$ . Therefore,  $E(\text{MatEduc} * e) \neq 0$  (expected value of the product of maternal education and the error term does not equal zero).

In order to correct for such possible endogeneity, an instrumental variable is substituted for the potentially endogenous independent variable, maternal education (MatEduc). In this study two instrumental variables are used, the number of four-year colleges per state by year of maternal age at 17 (count4) and the number of two-year colleges per state by year of maternal age at 17(count5). Such instruments are constructed through the use of Currie and Moretti's (2003) data on college openings by state and year, as previously mentioned. The instrument variables that are created are linear and include an integer number of colleges. Given that increased numbers of four and two year colleges promote acquisition of and access to education for women, these

two instruments are likely to be highly correlated with education. In addition, one would expect that the numbers of four and two year colleges to be uncorrelated with immunization and thus the error term. In this way, these instruments satisfy the following:  $E(\text{count4} * e) = 0$  and  $E(\text{count2} * e) = 0$ . They are efficient instruments to use within this study.

By incorporating instrumental variables within the study, a two-stage probit regression model is required. The first stage regresses maternal education, the endogenous variable, on all appropriate independent variables used in the preliminary testing in addition to the two instrumental variables. Given that maternal education is a dummy variable, each sub-category is used as a dependent variable regressor. The following model produces four regressions:

$$\text{dependent variable} = B_1 + B_2(\text{RaceW}) + B_3(\text{RaceB}) + B_4(\text{RaceO}) + B_5(\text{inc1}) + B_6(\text{inc2}) + B_7(\text{MaritalWDS}) + B_8(\text{MaritalNM}) + B_9(\text{NumChildren2}) + B_{10}(\text{NumChildren3}) + B_{11}-B_{60}(\text{statedum}) + B_{61}-B_{68}(\text{yr dum}) + B_{69}(\text{count4}) + B_{70}(\text{count2}) + e$$

*where the dependent variable is each of the maternal education dummy variables (MatEduc1, MatEduc2, MatEduc3, or MatEduc4) run in turn.*

From these four regressions, predicted values of maternal education are collected to form four new variables labeled MatEducHat1-MatEducHat4. In stage two of this model, the predicted values of maternal education, created through the inclusion of the instrumental variables, are used as an independent variable. Within this stage, immunization status, or more specifically, all4shot status is regressed on all of the independent variables used in stage one (excluding the instrument variables) as well as MatEducHat2-MatEducHat4.

The following formula is thus created:

$$\text{all4shot} = B_1 + B_2(\text{RaceW}) + B_3(\text{RaceB}) + B_4(\text{RaceO}) + B_5(\text{inc1}) + B_6(\text{inc2}) + B_7(\text{MaritalWDS}) + B_8(\text{MaritalNM}) + B_9(\text{NumChildren2}) +$$

$$B_{10}(\text{NumChildren3}) + B_{11}-B_{60}(\text{statedum}) + B_{61}-B_{68}(\text{yrdum}) + \\ B_{69}(\text{MatEducHat2}) + B_{70}(\text{MatEducHat3}) + B_{71}(\text{MatEducHat4}) + e$$

In STATA, the command “robust” is added to both stages of this model. The term “robust” stands for robust standard errors, which allows for results that account for problems of heteroskedasticity.

Through this two-stage model of regression, this study analyzes six different variations/manipulations of the data. The first uses the data as is mapped out in this paper thus far. The second test changes the maternal age approximations, leaving all else the same. The third and fourth tests change the maternal education categories into two different groupings, leaving all else constant. The fifth and six tests explore changing both the maternal age approximations and maternal education groupings. In this way, this study produces comprehensive results, possessing interesting implications.

## **Analysis of Results**

### ***Standard Test I***

The first two-stage model explored in this study uses all of the variables as they are classified in the methodology section of this paper. Table VII shows each of the four regression results from stage one. Table VIII illustrates the final regression in stage two. In comparing the results from Table VIII with those of the dprobit test that does not use instruments (Table VI), the coefficients on maternal education in relation to immunization status drastically change in comparison to the initial results. In the stage two regression, there is no specific trend describing the maternal education-child immunization relationship. The results show that those mothers with only a high school diploma are most likely to immunize their children, while those with some college education are highly unlikely to immunize their children in comparison to those with less

than a high school education. Lastly, those mothers possessing a college degree are likely to immunize their children, but not to the extent that those with only a high school degree are. All of these results are significant at the 5% level and lower. Therefore, they can be considered reliable.

One possible reason why this outcome is achieved could be due to the fact that some moderate to highly educated people believe that immunization of children involves great risk. Some feel that children can suffer ill effects from vaccinations. Therefore, some parents choose not to immunize their children. This could possibly account for the fact that those with some college education are less likely to immunize their child and those with a college degree have a smaller likelihood of immunizing their children in comparison to high school educated mothers.

Another more plausible reason why this outcome is achieved could be due to the fact that the instruments used in this study may be faulty. Given that the resultant coefficients on maternal education change to such a large degree from the non-use to use of the instruments, it does not appear that the instruments correlate or approximate maternal education well. This could be due in large part to the problem of approximation of maternal age dummies. The selected estimated ages per category may not effectively represent each age grouping.

### ***Test II: Maternal Age Approximation Change***

The second two-stage model tests all of the same forms of the variables explained thus far, with the exception of the maternal age approximation used in creating the instrumental variable. This test attempts to improve on the standard test by changing the maternal age category approximation to the following:

MatAge1  $\leq$  19  $\Rightarrow$  MatAge1 = 19  
MatAge2 = 20-29  $\Rightarrow$  MatAge2 = 29  
MatAge3  $\geq$  30  $\Rightarrow$  MatAge3 = 39

Table IX displays the stage two regression findings. As seen in these results, again, high school graduate mothers are most likely to immunize their children, while those with some college experience are highly unlikely to vaccinate. The statistical results for those mothers with a college degree were rendered insignificant given the p-value is .193.

This test further points to a problem involving the instrument. Even with a change in the maternal age approximation, such estimations could fail to successfully represent all of the women within each category. Non-categorical data regarding maternal age may be required in order to obtain an accurate instrument output.

### ***Test III: Maternal Education Category Change A***

Another method of altering the variables within the model is to change the maternal age dummy groupings. Although each dummy coefficient is proven to be statistically different, a change in grouping could generate different regression results and weights; this could provide more insight into the maternal education-child immunization relationship. In this test, the following maternal education dummies are grouped:

MatEduc1 and MatEduc2  $\Rightarrow$  MatEduc12  
MatEduc3 and MatEduc4  $\Rightarrow$  MatEduc34

Through this transformation, MatEduc12 represents those mothers with partial or complete high school education, and MatEduc34 represents those mothers with partial or complete college education. After running a two-stage model of regression for these new dummy categories, results show that those women with partial or complete high school education are less likely to obtain immunization for their children. Unfortunately,

however, as seen in Table X, the p-value of this outcome is .822, rendering the result insignificant.

***Test IV: Maternal Education Category Change B***

Another way to isolate the lower levels of maternal education is to analyze the lowest level in comparison to all of the rest. In this case, MatEduc1, less than high school educated mothers, is tested against all other higher education levels. In this test, the maternal education dummy variables have been changed as follows:

$$\begin{aligned} & \text{MatEduc1} \Rightarrow \text{MatEduc1} \\ & \text{MatEduc2, MatEduc3, and MatEduc4} \Rightarrow \text{MatEduc234} \end{aligned}$$

Table XI shows the outcome of this second stage regression. As seen in these results, less than high school level maternal education in comparison to all other higher levels of maternal education is negatively correlated with positive immunization status. Given that the p-value is .0000, this finding is rendered significant at all percentage levels.

Subsequently, this test shows some minor evidence to support the theory that maternal education is positively correlated with immunization status.

***Test V: Change in Maternal Age and Education A***

The fifth test in this series changes both the maternal age approximations and the maternal education dummy groupings in order to allow for the consideration of multiple complicating factors. In this test the age approximations are set at 19, 29, and 39, as in Test II. The maternal education dummies are grouped as they are in test III: MatEduc12 and MatEduc34. Through this joint methodology of change, the results seen in Table XII show a negative correlation between lower levels of maternal education and immunization status. Mothers with partial or complete high school backgrounds are less likely to immunize their children. However, this result is rendered insignificant for all

levels below 15.6%. This result, although insignificant, is not as insignificant as the result determined by test III. In this way, test V provides incentive for test VI.

### ***Test VI: Maternal Age and Education Change B***

The sixth test in this series combines a change in maternal age approximations with a change in maternal education dummies. As in tests II and V, the maternal age approximations are set to be 19, 29, and 39. The maternal education dummies are grouped as they are in test IV, the less than high school level of education versus all higher levels of education. In testing under these conditions, the lowest level of education appears to have a negative correlation with regard to positive immunization status (see Table XIII). Mothers possessing less than a high school education are less likely to immunize their children. Given that the p-value is .0000, this result is proven to be statistically significant at the 1% level. In this way, further evidence is generated to support the theory that maternal education is positively correlated with child immunization. Or, more specifically, this provides support for the theory that low maternal education is correlated with failure to immunize.

### ***General Assessment of Six Tests***

Through this progression of six tests, this study attempts to improve upon itself by analyzing possible reasons for failure within the first standard regression model and performing subsequent tests to explore such options. In this way, the study provides a comprehensive look at the relationship between maternal education and child immunization status using the instruments of number of four and two-year colleges per state by year of maternal age 17. Through this process, both maternal age approximations and maternal education dummy groups are redefined and analyzed.

Although the majority of results generated by these changes are inconclusive, an underlying positive correlation between maternal education and child immunization status is reported. Through test VI, valid and significant results show a negative correlation between low maternal education and positive child immunization status. Such a finding can be loosely restated to say that an underlying positive correlation exists between increased maternal education levels and positive child immunization status. Further testing is required in order to eliminate such confounding problems as the categorical nature of the maternal age variable. However, these tests generate evidence that provides incentive to perform such research.

## **Conclusion**

Like many pieces of literature regarding the maternal education-child health link, this study produces somewhat inconclusive results. Although certain variations of the data produce results showing a positive correlation between maternal education and child immunization status, such findings are limited and specific. Many results showing trendless outcomes, and coefficients that vary greatly with the initial non-instrumental results, point to potential problems with the instrument created. This could be due in part to the fact that data regarding maternal age, used to construct the instrument in the study, is categorical in nature. The approximations generated allow for some problems in accurately representing all women surveyed in the study. In this way, future research should acquire data that is non-categorical in nature in order to achieve more effective and robust results. In addition, changes in maternal education groupings have a significant effect on the regression output. Future research development should include

the collection of non-categorical data on maternal education in order to obtain more effective results.

In terms of improving the instrument for future research, several other concepts or data sources exist that could potentially achieve conclusive and robust results. One potential source of instrumental data is financial aid given by state. Since financial aid is distributed differently across all fifty states, it results in varying incentives and degrees to which women obtain education. Specifically, future research could utilize total state grant aid by state and year at maternal age 17. Such data can be found through the National Association of State Student Grant Aid Programs or NASSGAP. Annual reports showing total grant allotment per state and estimated grant dollars per resident college-age population are available dating back to 1969. Such data could produce an instrument highly correlated with maternal education and uncorrelated with immunization.

Another source of instrumental data that could be used in future research is affirmative action, which affected such minority groups as women. In the late 1990s, there was a public backlash against such policies, citing them as reverse discrimination. As a result, several states such as California banned the use of sex/race preferences in admissions at state and local colleges. A study could be conducted using increases in female enrollment by state and year at maternal age 17 during the period of complete acceptance of affirmative action through the late 1990s. Such data would be used to construct a valid instrument, correlated with maternal education yet uncorrelated with immunization.

Similar to affirmative action, the results of Title IX could be used to create an instrument. Title IX of the Education Amendments Act of 1972 prohibited discrimination on the basis of sex by universities and colleges receiving federal funding. Subsequently, the number of women attending colleges and universities rose substantially in the period following this act. Future research could use such increases across states by year at which maternal age is 17 in constructing a valid instrument.

With many options available for further future research this study generates increased incentive to fully confirm and generate stronger evidence for the existence of a positive correlation between maternal education and child immunization. If such support were created, important policy implications could be made both in the United States and across the globe. Federal governments could focus health initiatives on increasing maternal education. Through the implementation of policies directed toward the promotion of female education, governments could increase the likelihood of having the next generation healthy and immunized.

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## Tables

**Table II Dummy Variable Construction: Independent Variables**

<b>Race Dummies</b>	
raceH=1 if Hispanic raceH=0 if otherwise	raceB=1 if black raceB=0 if otherwise
raceW=1 if white raceW=0 if otherwise	raceO=1 if other raceO=0 if otherwise
<b>Maternal Age Dummies</b>	
MatAge1=1 if maternal age $\leq$ 19 MatAge1=0 if otherwise	MatAge3=1 if maternal age 30+ MatAge3=0 if otherwise
MatAge2=1 if maternal age 20-29 MatAge2=0 if otherwise	
<b>Maternal Education Dummies</b>	
MatEduc1=1 if maternal education <12yr MatEduc1=0 if otherwise	MatEduc3=1 if maternal education >12yr MatEduc3=0 if otherwise
MatEduc2=1 if maternal education =12yr MatEduc2=0 if otherwise	MatEduc4=1 if maternal education=college graduate MatEduc4=0 if otherwise
<b>Income Dummies</b>	
inc1=1 if income of $\leq$ \$12,500 inc1=0 if otherwise	inc3=1 if income of $\geq$ \$20,001 inc3=0 if otherwise
inc2=1 if income of \$12,5001-20,000 inc2=0 if otherwise	
<b>Marital Status Dummies</b>	
MaritalWDS=1 if widowed, divorced or separated MaritalWDS=0 if otherwise	MaritalM=1 if married MaritalM=0 if otherwise
MaritalNM=1 if never married MaritalNM=0 if otherwise	
<b>Number of Children Dummies</b>	
NumChildren1=1 if 1 child NumChildren1=0 if otherwise	NumChildren3=1 if 4+ children NumChildren3=0 if otherwise
NumChildren2=1 if 2-3 children NumChildren2=0 if otherwise	
<b>State Dummies</b>	
stdum1-stdum51 representing 51 states/major territories	
<b>Year Dummies</b>	
yr dum1-yr dum9 representing 1995-2003	

**Table III Descriptive Statistics: Independent Variables**

	<b>Observations</b>	<b>Mean</b>	<b>Standard Deviation</b>	<b>Variance</b>
<b>raceW</b>	183094	.6442265	.4787483	.2292
<b>raceB</b>	183094	.1452205	.352324	.1241322
<b>raceO</b>	183094	.058642	.2349541	.0552034
<b>inc1</b>	183094	.1407856	.3478012	.1209657
<b>inc2</b>	183094	.1288518	.3350368	.1122497
<b>MatEduc2</b>	183094	.2989448	.4577968	.209578
<b>MatEduc3</b>	183094	.2111484	.4081245	.1665656
<b>MatEduc4</b>	183094	.3783084	.4849664	.2351924
<b>MaritalWDS</b>	183094	.0800299	.2713403	.0736255
<b>MaritalNM</b>	183094	.1707866	.3763234	.1416193
<b>NumberChildren2</b>	183094	.5984467	.4902138	.2403096
<b>NumberChildren3</b>	183094	.1199002	.3248456	.1055247

**Table IV Immunization Dummy Variable Construction**

<b>all4shot Dummy</b>
all4shot1=1 if received 4:3:1:3
all4shot1=0 if otherwise

**Table V Descriptive Statistics: Immunization Variable**

	<b>Observations</b>	<b>Mean</b>	<b>Standard Deviation</b>	<b>Variance</b>
<b>all4shot</b>	183094	.5984467	.4902138	.2403096
<b>all4shot if MatEduc2=1</b>	54735	.5340459	.4988441	.2488454
<b>all4shot if MatEduc3=1</b>	38660	.5567253	.4967782	.2467886
<b>all4shot if MatEduc4=1</b>	69266	.5876043	.4922692	.242329

**Table VI Preliminary Findings: Output in Detail**

<b>all4shot</b>	<b>dF/dx</b>	<b>Robust Std. Err.</b>	<b>z</b>	<b>P&gt; z </b>	<b>95% Confidence Interval</b>	
<b>MatEduc2</b>	.0624802**	.0042693	14.53	.000	.054113	.070848
<b>MatEduc3</b>	.0755653**	.0045828	16.27	.000	.066583	.084547
<b>MatEduc4</b>	.0967811**	.0045184	21.21	.000	.087925	.105637
<b>raceW</b>	.0462647**	.0040062	11.56	.000	.038413	.054117
<b>raceB</b>	-.0316466**	.0049449	-6.41	.000	-.041338	-.021955
<b>raceO</b>	-.0169036**	.0060556	-2.80	.005	-.028772	-.005035
<b>inc1</b>	-.0018167	.0040581	-.45	.654	-.00977	.006137
<b>inc2</b>	-.004365	.0038425	-.11	.910	-.007968	.007095
<b>MaritalWDS</b>	-.0405181**	.0045692	-8.89	.000	-.049474	-.031563
<b>MaritalNM</b>	-.0318207**	.0037945	-8.40	.000	-.039258	-.024384
<b>NumChildren2</b>	-.0001382	.0027011	-.05	.959	-.005432	.005156
<b>NumChildren3</b>	-.0404687**	.0041424	-9.79	.000	-.048588	-.03235

(Stdum and yrdum results are produced but not shown)

\* significant at 5%, \*\*significant at 1%

**Table VII Standard Test I: Stage One Output (correlation matrix)**

	<b>MatEduc1</b>	<b>MatEduc2</b>	<b>MatEdu3</b>	<b>MatEduc4</b>
<b>raceW</b>	-.8920784	-.0173981	.1375805	.5474006
<b>raceB</b>	-1.018982	.0812143	.3289748	.4063751
<b>raceO</b>	-.6524221	-.0433044	.0220837	.60942
<b>inc1</b>	.88524221	.301524	-.32981	-.8251509
<b>inc2</b>	.6824857	.3654393	-.1021902	-.7749711
<b>MaritalWDS</b>	.1316843	.2096062	-.2194009	-.417862
<b>MaritalNM</b>	.365693	.2898398	.0590259	-.6615816
<b>NumChildren2</b>	.2541306	.0767871	-.0083291	-.1939519
<b>NumChildren3</b>	.6372966	.1228776	-.0024863	-.5162133
<b>count4</b>	.0752675	.0767346	.0149398	-.1376663
<b>count2</b>	.0340850	.0548866	.0288502	-.0861303

**Table VIII Standard Test I: Stage Two Output**

<b>all4Shot</b>	<b>dF/dx</b>	<b>Robust Std. Err.</b>	<b>z</b>	<b>P&gt; z </b>	<b>95% Confidence Interval</b>	
<b>MatEducHat2</b>	.270547**	.071969	3.76	0.000	.12949	.411604
<b>MatEducHat3</b>	-.5995542**	.2137301	-2.81	0.005	-1.01846	-.180651
<b>MatEducHat4</b>	.0620996*	.0309274	2.01	0.045	.001483	.122716
<b>raceW</b>	0786798**	.0115344	6.81	0.000	.056073	.101287
<b>raceB</b>	.0230568	.0205363	1.12	0.263	-.017194	.063307
<b>raceO</b>	-.0021281	.0088838	-0.24	0.811	-.01954	.015284
<b>inc1</b>	-.0949516**	.0271623	-3.49	0.000	-.148189	-.041714
<b>inc2</b>	-.0506168**	.016364	-3.10	0.002	-.08269	-.018544
<b>MaritalWDS</b>	-.0159141	.0109658	-1.45	0.146	-.037407	.005578
<b>MaritalNM</b>	-.0512456**	.0071534	-7.17	0.000	-.065266	-.037225
<b>NumChildren2</b>	-.0045803	.0040392	-1.13	0.257	-.012497	.003336
<b>NumChildren3</b>	-.0508195**	.006761	-7.53	0.000	-.064071	-.037568

(Stdum and yrdum results are produced but not shown)

\* significant at 5%, \*\*significant at 1%

**Table IX Test II: Stage Two Output**

*Using Instrument*

*Without Instrument*

<b>all4shot</b>	<b>dF/dx</b>	<b>P&gt; z </b>		<b>all4shot</b>	<b>DF/dx</b>	<b>P&gt; z </b>
<b>MatEducHat2</b>	.288765**	0.000		<b>MatEduc2</b>	.0629203**	.000
<b>MatEducHat3</b>	-.838393**	0.000		<b>MatEduc3</b>	.0775709**	.000
<b>MatEducHat4</b>	.0399212	0.193		<b>MatEduc4</b>	.1012975**	.000
<b>raceW</b>	.0907202**	0.000		<b>raceW</b>	.0469447**	.000
<b>raceB</b>	.0464499*	0.031		<b>raceB</b>	-.0370999**	.000
<b>raceO</b>	.0027165	0.762		<b>raceO</b>	-.015069*	.025
<b>inc1</b>	-.1228566**	0.000		<b>inc1</b>	-.0028401	.544
<b>inc2</b>	.06505**	.000		<b>inc2</b>	.0060762	.174
<b>MaritalWDS</b>	-.0047469	0.662		<b>MaritalWDS</b>	-.0392445**	.000
<b>MaritalNM</b>	-.052904**	0.000		<b>MaritalNM</b>	-.032406**	.000
<b>NumChildren2</b>	-.0069805	0.099		<b>NumChildren2</b>	.0044076	.157
<b>NumChildren3</b>	-.0552803**	0.000		<b>NumChildren3</b>	-.362796**	.000

(Stdum and yrdum results are produced but not shown)

\* significant at 5%, \*\*significant at 1%

**Table X Test III: Stage Two Output**

<i>Using Instrument</i>			<i>Without Instrument</i>			
<b>all4shot</b>	<b>dF/dx</b>	<b>P&gt; z </b>		<b>all4shot</b>	<b>DF/dx</b>	<b>P&gt; z </b>
<b>MatEducHat12</b>	-.0064834	0.822		<b>MatEduc12</b>	-.041894**	.000
<b>raceW</b>	.0658432**	0.000		<b>raceW</b>	.0584569**	.000
<b>raceB</b>	-.0172685*	0.032		<b>raceB</b>	-.0246567**	.000
<b>raceO</b>	.002752	0.752		<b>raceO</b>	-.0042209	.526
<b>inc1</b>	-.024094*	0.019		<b>inc1</b>	-.0127488**	.006
<b>inc2</b>	-.0105487	0.238		<b>inc2</b>	-.0009418	.832
<b>MaritalWDS</b>	-.0437424**	0.000		<b>MaritalWDS</b>	-.0410023**	.000
<b>MaritalNM</b>	-.0430942**	0.000		<b>MaritalNM</b>	-.0365597**	.000
<b>NumChildren2</b>	.0004227	0.904		<b>NumChildren2</b>	.002427	.435
<b>NumChildren3</b>	-.0478538**	0.000		<b>NumChildren3</b>	-.042785**	.000

(Stdum and yrdum results are produced but not shown)

\* significant at 5%, \*\*significant at 1%

**Table XI Test IV: Stage Two Output**

<i>Using Instrument</i>			<i>Without Instrument</i>			
<b>all4shot</b>	<b>dF/dx</b>	<b>P&gt; z </b>		<b>all4shot</b>	<b>DF/dx</b>	<b>P&gt; z </b>
<b>MatEducHat1</b>	-.112307**	0.000		<b>MatEduc1</b>	-.0766989**	.000
<b>raceW</b>	.0440566**	0.000		<b>raceW</b>	.0515209**	.000
<b>raceB</b>	-.0430532**	0.000		<b>raceB</b>	-.0343715**	.000
<b>raceO</b>	-.0163798	0.062		<b>raceO</b>	-.0098708	.414
<b>inc1</b>	-.003269	0.677		<b>inc1</b>	-.010474*	.024
<b>inc2</b>	.0026227	0.664		<b>inc2</b>	-.0019904	.652
<b>MaritalWDS</b>	-.042661**	0.000		<b>MaritalWDS</b>	-.436729**	.000
<b>MaritalNM</b>	-.0358568**	0.000		<b>MaritalNM</b>	-.0391375**	.000
<b>NumChildren2</b>	.0038876	0.237		<b>NumChildren2</b>	.0027653	.374
<b>NumChildren3</b>	-.0365112**	0.000		<b>NumChildren3</b>	-.040301**	.000

(Stdum and yrdum results are produced but not shown)

\* significant at 5%, \*\*significant at 1%

**Table XII Test V: Stage Two Output**

<i>Using Instrument</i>			<i>Without Instrument</i>			
<b>all4shot</b>	<b>dF/dx</b>	<b>P&gt; z </b>		<b>all4shot</b>	<b>DF/dx</b>	<b>P&gt; z </b>
<b>MatEducHat12</b>	-.0397363	0.156		<b>MatEduc12</b>	-.041894**	.000
<b>raceW</b>	.0588771**	0.000		<b>raceW</b>	.0584569**	.000
<b>raceB</b>	-.0240999**	0.002		<b>raceB</b>	-.0246567**	.000
<b>raceO</b>	-.00376	0.663		<b>raceO</b>	-.0042209	.526
<b>inc1</b>	-.0134395	0.181		<b>inc1</b>	-.0217488**	.000
<b>inc2</b>	-.0015433	0.860		<b>inc2</b>	-.0009418	.832
<b>MaritalWDS</b>	-.0411432**	0.000		<b>MaritalWDS</b>	-.04100023**	.000
<b>MaritalNM</b>	-.0369989**	0.000		<b>MaritalNM</b>	-.0365597**	.000
<b>NumChildren2</b>	.0022836	0.512		<b>NumChildren2</b>	.002427	.435
<b>NumChildren3</b>	-.0430612**	0.000		<b>NumChildren3</b>	-.0427805**	.000

(Stdum and yrdum results are produced but not shown)

\* significant at 5%, \*\*significant at 1%

**Table XIII Test VI: Stage Two Output**

<i>Using Instrument</i>			<i>Without Instrument</i>			
<b>all4shot</b>	<b>dF/dx</b>	<b>P&gt; z </b>		<b>all4shot</b>	<b>DF/dx</b>	<b>P&gt; z </b>
<b>MatEducHat1</b>	-.1225602**	0.000		<b>MatEduc1</b>	-.076689**	.000
<b>raceW</b>	.0419393**	0.000		<b>raceW</b>	.0525209**	.000
<b>raceB</b>	-.0455547**	0.000		<b>raceB</b>	-.0343715**	.000
<b>raceO</b>	-.0182396*	0.038		<b>raceO</b>	-.0098708	.141
<b>inc1</b>	-.0011846	0.880		<b>inc1</b>	-.010474*	.024
<b>inc2</b>	.0039876	0.510		<b>inc2</b>	-.0019904	.652
<b>MaritalWDS</b>	-.0425252**	0.000		<b>MaritalWDS</b>	-.436729**	.000
<b>MaritalNM</b>	-.0350801**	0.000		<b>MaritalNM</b>	-.0391375**	.000
<b>NumChildren2</b>	.0042272	0.198		<b>NumChildren2</b>	.0027653	.374
<b>NumChildren3</b>	-.0354051**	0.000		<b>NumChildren3</b>	-.040301**	.000

(Stdum and yrdum results are produced but not shown)

\* significant at 5%, \*\*significant at 1%