2015

The Impact of the State Children's Health Insurance Program on Educational Outcomes in the United States: A Two-Fold Analysis

Olivia Simuoli
Oberlin College

The Impact of the State Children's Health Insurance Program on Educational Outcomes in the United States: A Two-Fold Analysis

Olivia Simuoli
Oberlin College 2015

Abstract:

This paper examines the impact of the State Children's Health Insurance Program (SCHIP) on the educational outcomes of American children as measured by fourth and eighth-grade math and reading standardized test scores from the time of the program's inception up to the year 2013. More specifically, I focus on the effects of the increases in *eligibility* for children's public health insurance coverage brought about by SCHIP on average test scores across the nation at both the state level for all 51 states and the county level for Florida's 67 counties. On the state level, I am ultimately unable to find evidence of a contemporaneous impact of increases in eligibility on average test scores; however, I discover that in a longer-term sense, cumulative increases in the proportion of life for which the cohorts of students taking the tests have been exposed to SCHIP do appear to lead to statistically significant increases in average fourth and eighth-grade math scores. On the county level, I find that increases in eligibility for SCHIP are associated with significant increases in average fourth and eighth-grade reading and math standardized test scores.

PART I

A. Introduction

The State Children's Health Insurance Program (SCHIP), put into place under the Balanced Budget Act of 1997, represented an effort by the United States federal government to expand nationwide eligibility for public health insurance and offer coverage to uninsured children in families with incomes previously too high to qualify for Medicaid. There were approximately 10 million uninsured children in the U.S. in the year 1997, many of whom belonged to families with income levels that fell above the Medicaid eligibility threshold, and it was the hope of Senators Edward Kennedy and Orrin Hatch who sponsored the program that SCHIP, with its broader criteria for eligibility, would help remedy this issue (Menfield and Fletcher, 2004). The SCHIP initiative made available $4 billion in federal funds to the 50 states and the District of Columbia each year beginning in 1998 with the requirement that each state would use the block grant funds it received to develop a public health insurance program for the children who resided there, and all states implemented the program by the year 2000 (Menfield and Fletcher, 2004). SCHIP was initially intended to run for ten years from its inception in 1997, but President Obama decided to extend and expand the program in 2009.

What especially distinguishes SCHIP from other American public health insurance initiatives like Medicaid was that in addition to funds, states were also given flexibility to tailor the program to best meet the needs of their respective populations. States were firstly able to choose their own eligibility criteria, and each state initially chose an income-poverty ratio ranging from 133% to 350% of the federal poverty level (FPL) as the cutoff for eligibility for its program (Stockley and Walter, n.d). Thirty-five states chose a threshold of at least 200% FPL, which represented a substantial increase in eligibility for public health insurance among the nation's children, who had all faced a cutoff of 185% FPL or lower to qualify for their state's Medicaid program in the time period leading up to SCHIP's implementation (Levine and Schanzenbach, 2009). By 2001, it was estimated that the percentage of children in the nation eligible for public health insurance coverage had increased to 51% from the 34% it had been in 1997 prior to SCHIP (Bansak and Raphael, 2007). States have also changed and revised their cutoffs for eligibility over the years, with many states coming to increase the income-poverty threshold up to which they offer coverage, and the percentage of children eligible for public insurance has subsequently continued to increase over time.

What further makes SCHIP unique is that the federal government also gave states the freedom to choose the type of health insurance program they wanted to pursue under the basic SCHIP parameters. The states could select among the three options of using their SCHIP funds to expand their state Medicaid program and its coverage of children, using them to establish a separate SCHIP program, or using them in a combination of the previous two ways. In allowing states to market and design their version of SCHIP as a separate health insurance program, the federal government hoped that SCHIP as a whole would be perceived more like a private program even though it was publicly funded, which would potentially free it from some of the stigma traditionally associated with Medicaid and encourage people to participate in it (Menfield and Fletcher, 2004). The actual SCHIP sign-up process itself, with a shorter application and looser requirements for face-to-face interviews, was also intended to be easier than the process of signing up for Medicaid to further encourage take-up.

In sum, SCHIP revolutionized the idea of what a public health insurance program could look like. Evidence has shown that it also ultimately proved effective in reducing uninsurance rates among American children and leading to improvements in certain measurable health outcomes, both of which will be discussed in greater detail in the following section. The program as a whole indisputably benefited many children, and it is conceivable that some of the positive effects it had on American youth likely rippled over onto other areas of their lives beyond their insurance coverage, as health status is closely related to cognitive and physical abilities, which are in turn associated with a host of other variables such as performance in school. I have therefore chosen to assess the effects of SCHIP on educational outcomes to examine its impact on the population from a wider frame of view with the aim of finding evidence of a positive association between the expanded health insurance eligibility brought about by SCHIP and improvements in educational performance across the nation.

B. Background Literature

As will be addressed in the coming paragraphs, since SCHIP's nationwide implementation in 2000, researchers have gone on to conduct numerous studies examining nearly every imaginable facet and impact of the program from its effects on the number of uninsured children to which specific features of a state's SCHIP program proved most effective in inspiring people to sign up for it. A few researchers have performed analyses similar in spirit to the one I perform here and have assessed the effects of SCHIP on educational outcomes or attainment levels, though my study differs from previous work on the topic in a few significant ways, as I will detail below. As a whole, the evidence uncovered by these myriad studies on SCHIP indicates that the program had many positive impacts on society that included but also extended beyond the narrow scope of those directly related to insurance coverage or the provision of health care services.

To begin, some of the earliest work related to SCHIP focuses on the effects of the program on reducing uninsurance. As an example, Menfield and Fletcher (2004) and Hudson, Selden, and Banthin (2005) both examine the impact of increases in eligibility for public health insurance as a result of SCHIP on children's insurance rates. Hudson, Selden, and Banthin observe a 5-percentage point increase in the number of children covered by public insurance over the 1996-2002 period and attribute this increase to SCHIP; they ultimately find that "SCHIP had a significant impact in […] increasing public insurance for both children targeted by SCHIP and those eligible for Medicaid" (p.232). Menfield and Fletcher likewise uncover evidence that SCHIP led to substantial increases in insurance coverage, reporting a decrease of 2.5 million in the number of children who were uninsured over the 2000-2004 period. Both studies affirm that SCHIP appeared particularly effective in the way of reducing uninsurance rates among its target population of children in lower-income families whose incomes, while relatively modest, were nevertheless still too high to allow them to qualify for public health insurance in the past.

There additionally exists a substantial body of literature on the effects of SCHIP on both the utilization rates of particular types of health care services and on health outcomes. Li and Baughman (2010) find that the increase in insurance coverage rates that resulted from SCHIP led to an increase in the utilization rate of well-child visits, which are generally viewed as more of a luxury good and which tend to lead to overall improvements in a child's health in the long run. Levine and Schanzenbach (2009) observe that the increases in insurance eligibility that resulted from SCHIP were associated with a reduction in the rate of occurrence of low birth weight.

Since researchers have demonstrated that SCHIP has led to increases in insurance rates and improvements in certain measurable health outcomes, the potential for there to also exist a link between SCHIP and children's academic performance seems high. Firstly, given the demonstrated correlation between access to health care and health status, if more children gain health insurance, the population of children on the whole is likely "healthier" than before. As mentioned earlier, previous works have shown that healthier children generally have better cognitive and behavioral outcomes and are thus more prone to academic success (Levine & Schanzenbach, 2009). Improvements in health status may also have a cohort effect, as the lower the chance someone in a classroom is sick, the lower the chance the other kids in the room will catch an illness at school. Finally, being healthier likely leads to missing less school days, which is also liable to improve a child's academic performance.

In keeping with this vein of thought, a few researchers have, in fact, explored this idea of the potential effects of SCHIP on educational performance. Levine and Schanzenbach (2009) perform a state-level analysis on the effects of SCHIP and general Medicaid expansions on standardized (NAEP) test scores. They hypothesize that SCHIP will lead to improvements in test scores due to its effects on health outcomes and/or by way of the crowd-out effect, through which families who previously bought private insurance because their incomes were too high to qualify for public switched to public coverage following SCHIP's implementation, allowing them to save the disposable income that they were previously spending on insurance (they cite the well-established correlation between income and educational performance as evidence as to why a link between the two would exist). Levine and Schanzenbach employ a triple-difference estimation strategy to compare test scores between fourth and eighth-grade students as a function of "exposure" to public health insurance eligibility at different moments in time, and they ultimately find that a 50% increase in public health insurance eligibility at birth is associated with an increase in reading scores of 3-scaled points (Levine and Schanzenbach, 2009, 15). They are not able to find a similar effect for math scores. They also conduct a sub-analysis to try to separate the effects of increased health insurance eligibility and those of the crowd-out effect on educational performance, and they are able to establish a direct link between infant health outcomes and reading scores independent of the crowd-out effect, indicating that increased access to health care really does appear to impact educational performance.

Finally, Cohodes, Kleiner, Lovenheim, and Grossman (2014) conduct a related empirical investigation on the effects of SCHIP on educational attainment, examining the impact of SCHIP on the long-run outcome of the level of schooling attained by lower-income American children. They ultimately discover that the expanded health insurance eligibility brought about by SCHIP led to significant increases in both high school completion and college attendance/completion rates among their population of interest.

In sum, similar studies have been done with regards to the effects of SCHIP on educational attainment and performance and have produced results indicating that the increases in eligibility for public health insurance that resulted from SCHIP generally had a positive impact on education in the nation. My study, however, differs from previous work done on the subject in a few important ways. Firstly, I focus solely on the effects of SCHIP instead of on those of both SCHIP and the Medicaid expansions of the mid 1990s, and I furthermore examine eligibility expansions for children of all ages instead of just for children from birth to age two (as Levine and Schanzenbach do). In addition, though the educational variable of standardized test scores that I focus on is short-run in nature, I observe data over a longer time frame (from the time of SCHIP's inception to the year 2013) than any previous study directly related to the topic has; Levine and Schanzenbach only observe data up to the year 2004. It is possible that the effects of increases in eligibility for health insurance on health outcomes and/or educational performance operated with a time lag or were augmented over time, and many states furthermore increased the thresholds for eligibility for their SCHIP programs well into the mid-to-late 2000s; therefore, this distinction may prove meaningful. Finally, perhaps the most marked difference is that my analysis also hones in on one state in particular and assesses the impact of the program on test scores on the smaller-grain, county/school district level.

PART II: STATE-LEVEL ANALYSIS

A. Data Description

i. Eligibility

I obtain data on the specific income-poverty ratios up to which each state offered coverage through its SCHIP program from the years 2000-2006 from Stockley and Walter (n.d.) and data on the years 2010-2013 from the Medicaid official website. I fill in the gaps for the missing years (2006-2010) with data on state-specific eligibility thresholds from the Kaiser Family Foundation and NCSL (National Conference of State Legislatures) websites.

I use data from the Current Population Survey (CPS) to determine the number of kids (aged 00-17) in each state who would have been eligible for SCHIP based on the state's eligibility criteria in that year. The CPS table generator offers data on the number of kids falling under assorted income-poverty ratios (e.g. at or below 200% FPL) in each state in each year over the 2001-2013 period. It also offers data on the total number of kids living in each state in each year over the same time frame. I use data from the 2000 Census to gather population data for the year 2000, as data from the table generator is not available this far back in time.

Finally, I obtain data from the Henry J. Kaiser Family Foundation on state-specific Medicaid thresholds in the year 1998 to serve as a point of comparison for the time period before SCHIP was put into place. I use this in conjunction with data from the Census Bureau on the number of children living at or below certain poverty thresholds in each state during this time period to estimate the proportion of children who would have been eligible for public health insurance coverage through Medicaid prior to SCHIP's implementation.

ii. Test Scores

The test score data I use in the state-level analysis comes from the National Assessment of Educational Progress (NAEP). NAEP is a nationwide standardized test carried out by the Commissioner of Education Statistics, who heads the National Center for Education Statistics (National Center for Education Statistics, 2014). NAEP tests are administered uniformly to students in grades 4 and 8 using the same test booklet across the country; thus, every kid in the same grade who takes the test takes the same test regardless of state of residence. There is no other standardized test that is uniform in content across the entire nation at the grade levels I wish to observe, so I chose NAEP because it is free from state-state variation in exam content. One drawback is that for practical reasons, NAEP does not test every child but instead selects a sample of students that it claims accurately represents students across the nation in the ways of ethnicity, school size, economic background, and gender. While scores from a uniform test administered to every student across the country would be ideal, no such test or data set exists.

I examine data on both mean reading and mathematics scores in each state for fourth and eighth-grade students over the 1996-2013 period. I look at reading scores from the years 1998, 2002, 2003, 2005, 2007, 2009, 2011, and 2013, and math scores from the years 1996, 2000, 2003, 2005, 2007, 2009, 2011, and 2013. These are the only respective years for which NAEP reading and math scores are available.

iii. Other Variables

I incorporate additional variables into the regression to try to account for other factors contributing to the variation in test scores over time besides changes in eligibility for public health insurance. For starters, although my study focuses more on changes in *eligibility* for public health insurance through SCHIP rather than changes in the percentage of kids actually enrolled in the program, I nevertheless include the take-up (participation) rate for SCHIP in each state in each year in the model; I do not anticipate finding any effect of take-up rates on test scores because enrollment rates differed so widely across states due to factors I am not directly examining (e.g. differences in state outreach efforts), but in an ideal world of near 100-percent take-up, enrollment rates would be my main variable of interest. I therefore include a take-up variable in the model, though I believe the chances of finding any effect of it on test scores to be small. Data on SCHIP take-up rates are available from the Henry Kaiser Family Foundation.

I also incorporate data on average household income in each state in each year into the model due to the established correlation between family income and academic performance (Dahl and Lochner, 2012). Similarly, I also incorporate data on the percentage of children who identified as non-white (including Hispanic) due to the correlation between socioeconomic status and race and data on the proportion of children whose parents lacked secure employment in each state in each year, as an unstable home life or source of income could likely negatively impact a child's performance in school. The data needed to construct the variables mentioned in this paragraph are available from the Annie E. Casey Foundation.

B. Methodology

I calculate the approximate number of children eligible for each state's SCHIP program in each year over the 2000-2013 period by matching the eligibility threshold in a state with data from the CPS on the number of kids who lived at or below the corresponding income-poverty ratio in that state in the given year. I then use this data in conjunction with CPS data on the total number of kids who lived in that state in that year to calculate the approximate proportion of kids in the state eligible for the state's SCHIP program, which is the final data I use in my analysis. I follow a similar procedure to estimate the proportion of children who would have been eligible for public insurance in each state through Medicaid in the time period prior to SCHIP using the data from the Henry J. Kaiser Family Foundation and the Census Bureau.

There are a few obvious potential drawbacks to this data set that are worth addressing. It is firstly necessary to state that the ideal data set including explicit information on the number of kids eligible for SCHIP in each state simply does not exist, so data on the proportion of kids eligible for the program must be constructed and are thus merely approximations. One additional problem is that kids may move between states over time, and it is impossible to track the migration of individual families using data from the CPS; thus, the same kid may have faced different eligibility criteria over time if his family moved to a different state, and there is no way to account for this with the data that are available. Finally, some states have and/or had, at some point in time, SCHIP eligibility thresholds (e.g. 235% FPL) that do not align with the rounder income-poverty ratios (e.g. 200% FPL, 250% FPL) that the CPS reports data on, so I had to round those thresholds to the nearest CPS-compatible income-poverty ratio.

C. Model

I create a fixed effects model taking the form of:

$$Score_{it} = \beta_0 + \beta_1 eligibility_{it} + B_2 income_{it} + \beta_3 insecure_{it} + \beta_4 nonwhite_{it} + \beta_5 ple_{it} + \beta_6 takeup_{it} + \varepsilon_i + u_t + u_{it}$$

Variable name	Variable description
$\boldsymbol{Score_{it}}$	Average grade-level and subject-specific NAEP test score in state *i* in year *t*
$\boldsymbol{eligibility_{it}}$	Proportion of children eligible for SCHIP in state *i* in year *t* (or proportion of children eligible for public health insurance in state *i* in year *t* if *t* is before the year 2000)
$\boldsymbol{income_{it}}$	Average household income in state *i* in year *t*
$\boldsymbol{insecure_{it}}$	Proportion of children in state *i* whose parents lacked secure employment in year *t*
$\boldsymbol{nonwhite_{it}}$	Proportion of children in state *i* who identified as non-white in year *t* (includes those identifying as Hispanic)
$\boldsymbol{ple_t}$	Maximum proportion of life for which the cohort taking the exam in year *t* could have been eligible for SCHIP, i.e. was exposed to SCHIP (e.g. in 2003, fourth-graders could have been eligible for SCHIP for at maximum 3 out of their 9 years of life; ple_{03} = 0.33)
$\boldsymbol{takeup_{it}}$	SCHIP take-up (participation) rate in state *i* in year *t*
$\boldsymbol{\varepsilon_i}$	All unobserved time-invariant factors that affect test scores in state *i*
$\boldsymbol{u_t}$	All unobserved state-invariant factors that affect test scores in year *t*
$\boldsymbol{u_{it}}$	All unobserved factors that affect test scores in state *i* in year *t* (error term)

Since I control for state-level fixed effects (instead of year fixed effects), the model in its expanded form becomes:[1]

[1] Variable key:

$\boldsymbol{d4_t}$	Binary variable which = 1 if year *t* is the fourth year for which observations exist (2005); 0 if it is not
$\boldsymbol{d5_t}$	Binary variable which = 1 if year *t* is the fifth year for which observations exist (2007); 0 if it is not
$\boldsymbol{d6_t}$	Binary variable which = 1 if year *t* is the sixth year for which observations exist (2009); 0 if it is not
$\boldsymbol{d7_t}$	Binary variable which = 1 if year *t* is the seventh year for which observations exist (2011); 0 if it is not
$\boldsymbol{d8_t}$	Binary variable which = 1 if year *t* is the eighth year for which observations exist (2013); 0 if it is not

$$Score_{it} = \beta_0 + \beta_1 eligibility_{it} + B_2 income_{it} + \beta_3 insecure_{it} + \beta_4 nonwhite_{it} + \beta_5 ple_{it} + \beta_6 takeup_{it} + \gamma_1 d4_t + \gamma_2 d5_t + \gamma_3 d6_t + \gamma_4 d7_t + \gamma_5 d8_t + \varepsilon_i + u_{it}$$

I run four separate fixed-effects regressions with each of the four score sets—fourth and eighth-grade reading and fourth and eighth-grade math—serving as the respective dependent variable. I incorporate all of the independent variables listed above including the binary year variables into each of the four regressions.

D. Summary of Data

Variable	Number of observations[2]	Mean	Standard Deviation	Min.	Max.
Fourth-grade reading scores	**390**	**218.696**	**7.695**	**179.237**	**236.774**
Fourth-grade math scores	**391**	**235.171**	**9.764**	**187.135**	**253.421**
Eighth-grade reading scores	**385**	**263.012**	**6.866**	**235.730**	**277.010**
Eighth-grade math scores	**387**	**278.699**	**9.950**	**232.832**	**300.568**
eligibility	**-**	**.414**	**.130**	**.100**	**.739**
income	**-**	**46788.810**	**8417.058**	**26704**	**71322**
insecure	**-**	**.318**	**.049**	**0.200**	**0.540**
nonwhite	**-**	**.355**	**.185**	**.054**	**.946**
takeup	**-**	**.120**	**.052**	**.001**	**.309**

Correlation matrix for independent variables:

	eligibility	income	insecure	nonwhite	takeup
eligibility	**1.000**				
income	**-0.015**	**1.000**			
insecure	**0.167**	**-0.416**	**1.000**		
nonwhite	**0.232**	**0.129**	**0.387**	**1.000**	
takeup	**-0.105**	**0.001**	**0.061**	**0.165**	**1.000**

[2] Number of observations is not the same for all four score sets due to gaps in the data available from the NAEP website (e.g. there are no math scores reported for Illinois in 1996)

E. Results

i. Fourth-grade scores

Fourth-grade	Reading scores: Coefficient (standard error)	Math scores: Coefficient (standard error)
eligibility	**-2.585 (2.292)**	**2.288 (2.262)**
income	**.00000634 (.0000583)**	**.00006 (.0000581)**
insecure	**3.354 (7.443)**	**-5.716 (7.391)**
nonwhite	**-.991 (4.791)**	**-4.854 (4.686)**
takeup	**-4.682 (5.317)**	**1.806 (5.179)**
ple	**-1.082 (1.535)**	**27.008* (1.525)**
d4	**.933 (.649)**	**-2.968* (.638)**
d5	**3.514* (.948)**	**-7.137* (.938)**
d6	**3.786* (1.227)**	**-12.991* (1.215)**
d7	**3.964* (1.225)**	**-11.940* (1.215)**
d8	**4.836* (1.264)**	**-10.662* (1.253)**
_cons	**218.889 (4.250)**	**224.623 (4.262)**

*denotes statistical significance at the 5% level
R^2: within = 0.3173 (reading), within = 0.8759 (math)

The proportions of kids in a cohort who are eligible for public health insurance, who have parents who lack secure employment, who identify as non-white, or who enroll in SCHIP do not appear to have any significant effect on average fourth-grade reading or math NAEP scores for the state in any given year.[3] Similarly, average household income in the cohort's state does not appear to have a significant effect on average reading or math NAEP scores.

For an increase of 1/9 in cumulative number of years of life for which a cohort of fourth-graders (9-year olds) have been exposed to SCHIP, there will be an increase of 3.001-scaled points (0.307 standard deviations) in average math scores. The average math scores for a cohort who have been exposed to SCHIP for their entire lives will be roughly 27.008-scaled points (2.766 SD) higher than those of a cohort taking the test before SCHIP was put into place.

[3] I will define cohort as "students in state *i* who are in fourth grade in year *t*"

Cumulative increases in the proportion of life exposed to SCHIP do not appear to have a significant effect on average fourth-grade reading scores.

Each of the year dummies in the model for average reading scores except for *d4* (2005) has a coefficient that differs significantly from zero, which suggests that these year variables absorb most of the variation in test scores over time. Since the coefficient on the PLE variable (a time-trend variable in its own right) is statistically indistinguishable from zero, the year dummy variables can be examined in isolation in order to determine the year-specific effects on reading scores independent of changes in the other variables accounted for in the model. Each of the significant coefficients is positive in sign and increasing with each subsequent year, which suggests that average fourth-grade reading scores followed an upward trend over the 2005-2013 period (i.e. all else equal, average reading scores were approximately 3.514-scaled points higher than the base score if the year was 2007, 3.786-scaled points higher than the base score if the year was 2009, etc.)

Each of the coefficients on the year dummy variables included in the math model differs significantly from zero, but unlike for the reading scores, the sign on each of these coefficients is negative. On the surface, this appears to suggest that average math scores were decreasing over the relevant time period; however, since the sign of the coefficient on the PLE variable is positive and the coefficient itself is relatively large in magnitude, it is necessary to interpret the year binary variables in conjunction with the PLE variable to discern the true year-specific effects predicted by the model. After performing some calculations, it is clear that the negative coefficients on the year dummies mitigate the PLE variable's positive effect on test scores but do not counteract it; there appears to be a persistent upward trend in average fourth-grade math scores over the sample period. All else equal, average math scores were approximately 12.036-scaled points higher than the base score if the year was 2005, 13.869-scaled points higher than the base score if the year was 2007, etc.[4]

---

[4] Looking at the significant year dummies and PLE in conjunction to predict the ultimate year-specific effects on average fourth-grade math scores:
2005: (5/9)(27.008) – 2.968 = 12.036
2007: (7/9)(27.008) – 7.137 = 13.869
2009: (9/9)(27.008) – 12.991 = 14.017
2011: (1)(27.008) – 11.940 = 15.068
2013: (1)(27.008) – 10.662 = 16.346

ii. Eighth-grade scores

Eighth-grade	Reading scores: Coefficient (standard error)	Math scores: Coefficient (standard error)
eligibility	**-1.279 (1.929)**	**1.991 (2.476)**
income	**.00000701 (.0000491)**	**.0000624 (.0000636)**
insecure	**1.500 (6.247)**	**-6.352 (8.097)**
nonwhite	**2.830 (4.020)**	**-6.817 (5.138)**
takeup	**-5.979 (4.458)**	**2.754 (5.669)**
ple	**-3.590** (1.882)**	**17.828* (2.414)**
d4	**-.228 (.546)**	**-1.935* (.700)**
d5	**.836 (.797)**	**-2.044* (1.029)**
d6	**2.615* (1.032)**	**-3.161* (1.331)**
d7	**4.568* (1.278)**	**-4.685* (1.650)**
d8	**6.810* (1.557)**	**-7.155* (2.009)**
_cons	**263.253 (3.576)**	**273.177 (4.683)**

*denotes statistical significance at the 5% level
**denotes statistical significance at the 10% level
R^2: within = 0.4752 (reading), within = 0.7568 (math)

The proportions of kids in a cohort who are eligible for public health insurance, who have parents who lack secure employment, who identify as non-white, or who enroll in SCHIP do not appear to have any significant effect on average eighth-grade reading or math NAEP scores for the state in any given year.[5] Similarly, average household income in the cohort's state in a given year does not appear to have a significant effect on average reading or math NAEP scores in the state for that year.

For an increase of 1/13 in cumulative number of years of life for which a cohort of eighth-graders (13-year olds) have been exposed to SCHIP, there will be an increase of 1.371-scaled points (0.138 SD) in average math scores. The average math scores for a cohort who have been exposed to SCHIP for their entire lives will be roughly 17.828-scaled points (1.792 SD) higher than those of a cohort taking the test before SCHIP was put into place.

[5] I will define cohort as "students in state *i* who are in eighth grade in year *t*"

As was the case for the fourth-grade math score set, each of the coefficients on the year dummy variables in the eighth-grade math model differs significantly from zero and is negative in sign. I once again interpret the year binary variables in conjunction with the PLE variable to discern the year-specific effects predicted by the model. Similarly to the fourth-grade set, there appears to be a persistent upward trend in average eighth-grade math scores over the duration of the sample period: all else equal, average math scores were approximately 4.922-scaled points higher than the base score if the year was 2005, 7.556-scaled points higher than the base score if the year was 2007, etc.[6]

The eighth-grade reading score set appears to suffer from the opposite affliction, so to speak, in that the coefficient on the PLE variable is significantly different from zero but negative in sign, and the coefficients on each of the year dummies besides the first two are significantly different from zero and positive. Interpreting the coefficients on the binary year variables in isolation would suggest an upward trend in average reading scores, but interpreting the coefficient on PLE would suggest a decrease of 0.276-scaled points (.040 SD) in average reading scores for each 1/13 increase in proportion of life for which a cohort was exposed to SCHIP. I again interpret the PLE variable and the year dummies in conjunction to discern the year-specific effects, and it appears that the PLE variable and the year dummies together predict an upward trend in test scores from the year 2009 onwards.[7]

iii. Alternate regressions

I chose to perform a few additional regressions for both the fourth and eighth-grade score sets for various reasons. Firstly, I want to determine if it is possible to isolate the effects of the PLE variable from the effects of the binary year variables. I describe two separate regressions,

---

[6] Looking at the significant year dummies and PLE in conjunction to predict the year-specific effects on average eighth-grade math scores:
2005: (5/13)(17.828) – 1.935 = 4.922
2007: (7/13)(17.828) – 2.044 = 7.556
2009: (9/13)(17.828) – 3.161 = 9.181
2011: (11/13)(17.828) – 4.685 = 10.400
2013: (13/13)(17.828) – 7.155 = 10.673

[7] Looking at the significant year dummies and PLE in conjunction to predict the year-specific effects on average eighth-grade math scores:
2009: (9/13)(-3.590) + 2.615 = 0.130
2011: (11/13)(-3.590) + 4.568 = 1.530
2013: (13/13)(-3.590) + 6.810 = 3.220

one with PLE serving as the only time-related variable in the model and one with only the year dummies, which I then compare to the original model in which they are both present. I also make a few adjustments to the model to address and deal with the potential problem of heteroskedasticity, and I lastly describe an alternate version of the model in which I include an interaction term between eligibility and take-up rates.

a. Only binary year variables

I repeat each of the four regressions detailed above but omit the PLE variable. As was the case previously, none of the variables other than the year dummies has a coefficient that differs significantly from zero in any of the four regressions.[8]

I will not elaborate too much on this as it is not the primary focus of my paper, but what is most important to note is that the year-specific effects outlined by this new model are essentially analogous to those I found above when I examined the PLE variable in conjunction with the coefficients on the year binaries.[9] The fact that the coefficient on each of these year binaries is negative in the original model for both the fourth and eighth-grade math score sets suggests that the PLE variable absorbs much of the generally-upward trends in scores but overstates the year-specific effects, so the year dummies therefore assume a negative sign to mitigate its strong positive one. Interpreting PLE and the year dummies in conjunction, however, gives a clear picture of the actual year-specific effects on average math scores. The

[8] I report the coefficients and standard errors on the year dummies when they serve as the only time-related variables in the model:

Variable	Fourth-grade reading: Coefficient (standard error)	Fourth-grade math: Coefficient (standard error)	Eighth-grade reading: Coefficient (standard error)	Eighth-grade math: Coefficient (standard error)
d3	**-.360 (.511)**	**8.994* (.508)**	**-.829** (.435)**	**4.118* (.558)**
d4	**.332 (.610)**	**12.021* (.605)**	**-1.610* (.518)**	**4.929* (.663)**
d5	**2.673* (.762)**	**13.848* (.755)**	**-1.096** (.646)**	**7.548* (.826)**
d6	**2.704* (.789)**	**14.017* (.780)**	**.131 (.671)**	**9.176* (.854)**
d7	**2.883* (.898)**	**15.068* (.887)**	**1.531* (.762)**	**10.397* (.971)**
d8	**3.754* (.971)**	**16.345* (.960)**	**3.221* (.824)**	**10.673* (1.051)**
_cons	**218.889 (4.250)**	**224.623 (4.262)**	**263.253 (3.576)**	**273.177 (4.683)**

*denotes statistical significance at the 5% level
**denotes statistical significance at the 10% level

[9] E.g. this model predicts that average fourth-grade math scores will be 12.021-scaled points higher than the base score if the year is 2005. In the original model, the coefficients on PLE and "*d4*" in conjunction predict that average fourth-grade math scores will be 12.036-scaled points higher than the base score if the year is 2005.

year-specific effects predicted by this model for both sets of reading scores are also consistent with those predicted by the PLE and binary year variables in the original model, which underscores the idea that the two variables each absorb some of the time-variant effects on scores when they are both in the model.

b. Only PLE

I repeat each of the four regressions detailed above but omit all of the binary year variables so that PLE is now the only variable in the model that accounts for time-related effects. The PLE variable now assumes a positive and statistically significant coefficient in each of the four score-set models, indicating that it absorbs much of the generally upward-trending variation in scores over the observed time period. However, the key finding here is that the year-specific effects predicted solely by the PLE variable differ from those predicted solely by the binary year variables in the previous model.[10]

It therefore seems possible to conclude the proportion of life exposed to SCHIP has an effect on average test scores that is distinguishable from just a year-specific effect. When both time-related variables are in the model, their coefficients can be interpreted in conjunction to predict essentially the same year-specific effects as are predicted by the year dummies when they are in their own model; however, PLE and the year dummies predict disparate year-specific effects when they are each in their own individual model. Thus, it appears that though the effect of the PLE variable is not completely independent from the effects of the binary year variables,

10

Year	Year-specific effects on fourth-grade reading scores:	Year-specific effects on fourth-grade math scores:	Year-specific effects on eighth-grade reading scores:	Year-specific effects on eighth-grade math scores:
Coefficient on PLE (S.E.)	**2.704*** **(.799)**	**12.784*** **(.958)**	**4.790*** **(.896)**	**9.840*** **(1.044)**
2003	**(3/9)(2.704) = 0.901**	**(3/9)(12.784) = 4.261**	**(3/13)(4.790) = 1.105**	**(3/13)(9.840) = 2.271**
2005	**(5/9)(2.704) = 1.502**	**(5/9)(12.784) = 7.102**	**(5/13)(4.790) = 1.842**	**(5/13)(9.840) = 3.785**
2007	**(7/9)(2.704) = 2.103**	**(7/9)(12.784) = 9.943**	**(7/13)(4.790) = 2.579**	**(7/13)(9.840) = 5.298**
2009	**(9/9)(2.704) = 2.704**	**(9/9)(12.784) = 12.784**	**(9/13)(4.790) = 3.316**	**(9/13)(9.840) = 6.812**
2011	**(1)(2.704) = 2.704**	**(1)(12.784) = 12.784**	**(11/13)(4.790) = 4.053**	**(11/13)(9.840) = 8.326**
2013	**(1)(2.704) = 2.704**	**(1)(12.784) = 12.784**	**(13/13)(4.790) = 4.790**	**(13/13)(9.840) = 9.840**

*denotes statistical significance at the 5% level

The year-specific effects predicted here are not analogous to those found above, e.g. the PLE variable predicts that average fourth-grade math scores will be 7.102-scaled points higher than the base score if the year is 2005, which is not equivalent to the roughly 12-scaled point increase predicted in the previous two models.

which makes sense as it is essentially a time trend variable, there is something else there to the relationship between it and average test scores since the year-specific effects it alone predicts are not identical to those that the year dummies alone predict.

c. Heteroskedasticity

There is cause for concern of heteroskedasticity in the model due to the fact that the NAEP exam is not administered to all students but rather to a select sample of students in each state. While NAEP is administered to a larger number of kids in states with larger populations, there appears to be no linear relationship between the number of kids tested in a state and the state's population, and the share of kids tested in each state therefore varies considerably. For example, in 2013, 8200 fourth-grade students took the NAEP exam in California, while only 3400 took it in North Dakota; however, due to differences in population size, approximately 1.834% of fourth-grade students in California were tested, whereas approximately 48.571% of kids in North Dakota were (National Center for Education Statistics, 2014).

For that reason, I repeat the analysis using both robust standard errors and weights, with the share of kids tested for each grade and subject-specific test in each state serving as the weight. The results of both of the robust standard error and weighted regressions are essentially analogous to the initial results. Despite small changes in magnitude of the coefficients and standard errors, there are no sign changes or changes in significance for any of the coefficients and no major alteration in the standard errors reported. I will therefore not provide a formal representation of the results.

d. Interaction term

As eligibility and take-up are essentially two alternate measures of the same thing (i.e. children gaining access to public health insurance through SCHIP), I decided to repeat the analysis including an interaction term between the *eligibility* and *takeup* variables in order to see if there was any difference in the effect of eligibility on test scores based on differences in state take-up rates (e.g. the effect of eligibility is stronger if take-up is higher). The results from estimating this new model proved consistent with the findings above in that the coefficient on the interaction term was statistically indistinguishable from zero in all four score set models.

Despite the relatively low degree of correlation between eligibility and take-up (roughly 10.5%, as per the correlation matrix), they are still basically two different measures of the same thing, so I decided to repeat the analysis omitting each of the variables—*eligible* and *takeup*—

from the model just to ensure that there would not be any major changes in either's coefficient when the other was absent. In both cases, there were not; neither variable assumes a significant coefficient when the other is not present, and there are no major changes in the standard errors reported. I again will therefore not provide a formal representation of the results.

F. Discussion

It is first necessary to express that in general, the results of the state-level analysis I describe here are not entirely satisfying; it seems there is not enough variation in the data on the aggregate (state) level to find evidence of the relationship between increases in eligibility for public health insurance and average test scores I was hoping to detect. The fact that none of the other non-binary variables apart from proportion of life exposed to SCHIP, such as average household income or demographic characteristics of the population which have been proven to be correlated with educational outcomes in previous studies, appears to have any significant impact on test scores further corroborates the notion that the state is likely just too large a unit of observation to use in this particular analysis. Any changes that occurred in these variables over the observed time frame were likely too small on the state level to contribute to changes in average test scores, so time-related variables observe all of the variation in scores in the model.

Furthermore, in a unit of observation as large as the state, it is likely that there were many other things that changed over this extended window that contributed to changes in the state's average test scores but that would have been too difficult to include in the model. For example, state-level governments could have passed initiatives that allocated more money to public schools, or there could have been curriculum changes in certain states at some point over the relevant 13-year period that better prepared students for the material appearing on the NAEP test.

However, based on what I do have here, an interesting provisional conclusion is that eligibility for health insurance may have a longer-term effect on average test scores on the state level than the one I was initially looking for. On the aggregate level, it is not possible to observe an impact of changes in eligibility for health insurance in a given year on average test scores in that year (possibly because said changes are not large enough in magnitude), but increases in the proportion of lifetime the cohorts taking the test have been exposed to and potentially eligible for SCHIP do seem to have a positive impact on scores.

Finally, the observed effect of the proportion of life exposed to SCHIP on test scores appears to be stronger for fourth-grade students than for eighth-grade students, which is potentially indicative of the importance of access to health care from an early age. My findings suggest that prolonged exposure to an expanded public health insurance program has a more substantial impact on academic performance the younger the children in question are; from a policy standpoint, this may indicate that early-on access to health care is crucial, as it can ostensibly play an important role in a young child's cognitive development.

PART III: COUNTY-LEVEL ANALYSIS

I chose to examine Florida's SCHIP program in more depth and perform an analogous analysis to the one described above, but with the county as the unit of observation rather than the state. Florida is an ideal state to use in an analysis of this type for a few reasons: firstly, each of their school districts perfectly corresponds to a county, so it is easy and feasible to match test score data on the school district level to poverty data on the county level. Secondly, Florida's income-poverty cut-off ratio for SCHIP eligibility is 200% FPL, which is a nice, round number often reported on by the Census Bureau.

To provide a brief overview of Florida's SCHIP program: Florida pursued the "combination" option discussed earlier, which means that some of its SCHIP funds went towards expanding its Medicaid program, and some went towards establishing a separate program. The separate program, Florida KidCare, covers the majority of kids in the state who are enrolled in public insurance, and as mentioned above, its income-poverty cut-off ratio for eligibility is 200% FPL. One notable feature of Florida's SCHIP program is an extremely simple application process consisting of a one-page application and no requirement for face-to-face interviews.

A. Data Description

i. Eligibility

I obtain data on the percentage of children in each of Florida's 67 counties who lived at or below 200% FPL over the 2001-2010 period from the Small Area Health Insurance Estimates (SAHIE) section of the Census Bureau website. This gives a reasonable approximation of the proportion of kids in each county who would have been eligible for SCHIP each year.

ii. Test scores

I obtain fourth and eighth-grade reading and math standardized (FCAT) test scores on the school district level from the Florida Department of Education website. The FCAT was a standardized test administered to all public school students in grades 3-11 in Florida over the 1998-2010 period; in 2011, Florida transitioned from the FCAT to the decidedly different FCAT 2.0, so I examine only FCAT scores to avoid any variation in exam content, style, or scoring method (Florida Department of Education, 2014). I look at FCAT scores from the years 2001-2010; unfortunately, no test score data for the 1998-2000 period are available on the Florida DOE website. Since the test was administered to all public school students in all counties, this score set is free from the problem of the state-level set in which the share of students tested differed across states.

iii. Other variables

I obtain data on median household income at the county-level from the Small Area Income and Poverty Estimates (SAIPE) section of the Census Bureau website. I acquire data on the proportion of kids enrolled in fourth and eighth grades (in public school) who identified as non-white in each school district in each year from the ElSi (Elementary/Secondary Information System) on the National Center for Education Statistics website. I was unable to find SCHIP take-up rates or data on the proportion of children whose parents lacked secure employment on the county level, so those variables do not appear in this model.

B. Methodology

All methods are analogous to those described previously but with the county/school district-level as the unit of observation rather than the state.

C. Model

I create a fixed-effects model taking the form of:

$$Score_{it} = \beta_0 + \beta_1 eligibility_{it} + B_2 income_{it} + \beta_3 nonwhite_{it} + \beta_4 ple_{it} + \varepsilon_i + u_t + u_{it}$$

Variable name	Variable description
Score$_{it}$	Average grade-level and subject-specific FCAT score in county *i* in year *t*
eligibility$_{it}$	Proportion of children eligible for SCHIP in county *i* in year *t*
income$_{it}$	Median household income in county *i* in year *t*

$nonwhite_{it}$	Proportion of children in county *i* who identified as non-white in year *t* (includes those identifying as Hispanic)
ple_t	Proportion of life for which the cohort taking the exam in year *t* was exposed to SCHIP
ε_i	All unobserved time-invariant factors that affect test scores in county *i*
u_t	All unobserved county-invariant factors that affect test scores in year *t*
u_{it}	All unobserved factors that affect test scores in county *i* in year *t* (error term)

Since I control for county-level fixed effects (instead of year fixed effects), the model in its expanded form becomes:[11]

$$Score_{it} = \beta_0 + \beta_1 eligibility_{it} + B_2 income_{it} + \beta_3 insecure_{it} + \beta_4 nonwhite_{it} + \beta_5 ple_{it} + \beta_6 takeup_{it} + \gamma_1 d3_t + \gamma_2 d4_t + \gamma_3 d5_t + \gamma_4 d6_t + \gamma_5 d7_t + \gamma_6 d8_t + \gamma_7 d9_t + \gamma_8 d10_t + \varepsilon_i + u_{it}$$

I run four separate fixed-effects regressions with each of the four score sets—fourth and eighth-grade reading and fourth and eighth-grade math—serving as the respective dependent variable. I incorporate all of the independent variables listed above including the binary year variables into each of the four regressions.

D. Summary of Data

Variable	Number of observations	Mean	Standard Deviation	Min	Max
Fourth-grade reading scores	**670**	**313.009**	**13.731**	**260**	**344**
Fourth-grade math scores	**603**[12]	**312.974**	**17.384**	**255**	**349**
Eighth-grade reading scores	**670**	**300.928**	**14.310**	**208**	**330**
Eighth-grade math scores	**670**	**313.658**	**13.302**	**262**	**342**
eligibility	**-**	**.462**	**.099**	**.209**	**.711**
income	**-**	**39338.540**	**7899.973**	**24031**	**67238**
nonwhite (fourth grade)	**-**	**.354**	**.205**	**.032**	**.968**
nonwhite (eighth grade)	**-**	**.342**	**.201**	**.022**	**.973**

[11] Variable key:

$d3_t$	Binary variable which = 1 if year *t* is 2003; 0 if it is not
$d4_t$	Binary variable which = 1 if year *t* is 2004; 0 if it is not
$d5_t$	Binary variable which = 1 if year *t* is 2005; 0 if it is not
$d6_t$	Binary variable which = 1 if year *t* is 2006; 0 if it is not
$d7_t$	Binary variable which = 1 if year *t* is 2007; 0 if it is not
$d8_t$	Binary variable which = 1 if year *t* is 2008; 0 if it is not
$d9_t$	Binary variable which = 1 if year *t* is 2009; 0 if it is not
$d10_t$	Binary variable which = 1 if year *t* is 2010; 0 if it is not

[12] "N" is lower for fourth-grade math scores than for the other tests because fourth-grade FCAT math scores are not available from the FDOE website for the year 2001. Thus, the sample period for that score set is 2002-2010.

Correlation matrices for independent variables

	eligibility	income	insecure
eligibility	**1.000**		
income	**-0.614**	**1.000**	
nonwhite (4th)	**0.180**	**0.006**	**1.000**

	eligibility	income	insecure
eligibility	**1.000**		
income	**-0.614**	**1.000**	
nonwhite (8th)	**0.160**	**-0.009**	**1.000**

E. Results

i. Fourth-grade

Fourth-grade	Reading scores: Coefficient (standard error)	Math scores: Coefficient (standard error)
eligibility	**13.968* (6.788)**	**22.329* (9.247)**
income	**.000212 (.000143)**	**.0000271 (.000186)**
nonwhite	**5.797 (6.621)**	**-20.467* (9.137)**
ple	**27.798* (3.658)**	**36.147* (9.415)**
d4	**9.044* (1.100)**	**9.860* (1.918)**
d5	**6.432* (1.429)**	**4.435** (2.663)**
d6	**-3.631** (1.865)**	**6.153** (3.702)**
d7	**-3.716 (2.309)**	**4.682 (4.691)**
d8	**-4.210 (2.672)**	**7.438 (5.679)**
d9	**-2.374 (3.000)**	**6.898 (6.627)**
d10	**-4.771 (3.084)**	**8.074 (6.673)**
_cons	**279.829 (6.965)**	**279.909 (9.044)**

*denotes statistical significance at the 5% level
** denotes statistical significance at the 10% level
R^2: within = 0.7840 (reading), within = 0.8465 (math)

If 50% more of the kids in a fourth-grade cohort are eligible for public health insurance, the average reading scores for the cohort will be 6.984-scaled points (0.509 standard deviations) higher and the average math scores for the cohort will be 11.165-scaled points (0.642 SD) higher.[13] For an increase of 10% in the number of kids in a cohort who are eligible for public insurance, there will be an increase in average fourth-grade reading scores of 1.397-scaled points (0.102 SD) and an increase in average math scores of 2.233-scaled points (0.128 SD).

Median household income in the cohort's county in a given year does not appear to have a significant effect on average fourth-grade reading or math scores in the county that year.

The proportion of fourth-graders in a county who identify as nonwhite in a given year does not appear to have a significant effect on average reading scores in the county that year. However, for an increase of 10% in the percentage of fourth-graders who identify as nonwhite, there will be a decrease of 2.047-scaled points (0.118 SD) in average math scores for the county.

For an increase of 1/9 in cumulative number of years of life for which a cohort of fourth-graders have been exposed to SCHIP, there will be an increase of 3.089-scaled points (0.225 SD) in average reading scores and an increase of 4.016-scaled points (0.231 SD) in average math scores for the county. The average reading scores for a cohort who have been exposed to SCHIP for their entire lives will be roughly 27.798-scaled points (2.024 SD) higher than those of a cohort taking the test before SCHIP was put into place; similarly, the average math scores for a cohort who have been exposed to SCHIP for their entire lives will be roughly 36.147-scaled points (2.079 SD) higher than those of a cohort taking the test before SCHIP was put into place.

[13] I will define cohort as "students in county *i* who are in fourth grade in year *t*"

ii. Eighth-grade

Eighth-grade	Reading scores: Coefficient (standard error)	Math scores: Coefficient (standard error)
eligibility	**19.179**** **(10.807)**	**32.367*** **(6.399)**
income	**.000322** **(.000230)**	**.000515*** **(.000136)**
nonwhite	**-11.997** **(10.938)**	**-3.311** **(6.476)**
ple	**18.639*** **(8.521)**	**-3.675** **(5.046)**
d4	**-6.458*** **(1.760)**	**1.978**** **(1.042)**
d5	**-7.662*** **(2.265)**	**.645** **(1.341)**
d6	**-9.546*** **(2.929)**	**1.097** **(1.735)**
d7	**-8.605*** **(3.631)**	**4.399*** **(2.150)**
d8	**-2.343** **(4.191)**	**9.893*** **(2.482)**
d9	**-2.517** **(4.685)**	**8.862*** **(2.774)**
d10	**-2.876** **(5.319)**	**10.696*** **(3.149)**
_cons	**279.620** **(10.903)**	**277.373** **(6.456)**

*denotes statistical significance at the 5% level
**denotes statistical significance at the 10% level
R^2: within = 0.3835 (reading), within = 0.6654 (math)

If 50% more of the kids in an eighth-grade cohort are eligible for public health insurance, the average reading scores for the cohort will be 9.590-scaled points (0.670 SD) higher and the average math scores for the cohort will be 16.184-scaled points (1.217 SD) higher.[14] For an increase of 10% in the number of kids in a cohort who are eligible for public health insurance, there will be an increase in average reading scores of 1.918-scaled points (0.134 SD) and an increase in average math scores of 3.237-scaled points (0.243 SD).

Median household income in the cohort's county in a given year does not appear to have a significant effect on average eighth-grade reading scores in the county that year. However, for an increase of $10,000 in median household income, there will be an increase of 5.150-scaled points (0.387 SD) in average eighth-grade math scores.

[14] I will define cohort as "students in county *i* who are in eighth grade in year *t*"

The proportion of kids in a county who identify as nonwhite does not appear to have a significant effect on average eighth-grade reading or math scores in the county.

For an increase of 1/13 in cumulative number of years of life for which a cohort of eighth-graders have been exposed to SCHIP, there will be an increase of 1.434-scaled points (0.100 SD) in average reading scores. The average reading scores for a cohort who have been exposed to SCHIP for their entire lives will be roughly 18.639-scaled points (1.303 SD) higher than those of a cohort taking the test before SCHIP was put into place. There is no observed significant effect of increases in the proportion of life exposed to SCHIP on average math scores.

iii. Alternate regressions

As I established in the state-level section of the paper, the effects of the PLE variable are not entirely independent from but are still distinct from just year-specific effects, so I will not repeat the alternate regressions I performed above on this data set. There are also not similar concerns of heteroskedasticity for the county-level data.

F. Discussion

The fact that other variables in the county-level model besides PLE and the binary year variables assume a coefficient that differs significantly from zero corroborates the notion that the state was simply too large a unit of observation to use for this particular study. On the county scale, changes in figures such as median household income, the demographic makeup of the population, and the proportion of kids eligible for SCHIP were sizable enough to have had an impact on average standardized test scores. The fact that fewer of the binary year variables assume a statistically significant coefficient in this model further conveys that year-specific effects do not absorb all of the changes in average test scores on the smaller-grain scale.

Now to address the primary focus of the paper: the county-level results indicate that there is evidence of the positive relationship between SCHIP eligibility and educational performance that I was hoping to detect. Changes in eligibility for SCHIP do appear have a significant effect on average fourth and eighth-grade reading and math standardized test scores on the county level in the state of Florida, as there exists a positive correlation between the proportion of kids eligible for SCHIP and average scores for all four score sets. For both the fourth grade and eighth grade sets, the effect of SCHIP eligibility is greater for average math scores than it is for average reading scores. Looking at each subject area in isolation, the effect of SCHIP eligibility is greater on eighth-grade scores than it is on fourth-grade scores (i.e. SCHIP eligibility has a greater effect on eighth-grade reading scores than fourth-grade reading scores and a greater effect on eighth-grade math scores than fourth-grade math scores).

In addition, as was the case in the state-level analysis, increases in the proportion of life for which the cohorts of kids taking the test have been exposed to SCHIP generally appears to have a positive impact on average test scores. On the fourth-grade level, the effect of the PLE variable is more pronounced for math scores than it is for reading scores, which is consistent with the theme pervading this paper of math scores appearing to be more highly correlated with factors related to health insurance eligibility than reading scores are. The effect of the PLE variable is also greater on fourth-grade scores than it is on eighth-grade scores in this analysis; at the eighth-grade level, the proportion of life for which a cohort have been exposed to SCHIP does not appear to have a significant effect on their average math scores.

An interesting aspect to the county-level results is that the effect of the proportion of kids eligible for SCHIP on test scores is greater for eighth-grade students than it is for fourth-grade students, whereas the effect of the proportion of life exposed to SCHIP on test scores is greater for the younger group. It appears that whether the cohort taking the test have been exposed to SCHIP for a longer portion of their lives affects their educational performance more strongly if the kids making up the cohort are younger. Access to heath care may therefore play a greater role in shaping cognitive development when kids are at an earlier stage in life—a nine-year old exposed to SCHIP for 50% of his life gained exposure to the program at a younger age than a thirteen-year old exposed for 50% of his life. What is curious, however, is that the proportion of the kids taking the test who are currently eligible for SCHIP has a greater effect on scores for the older kids. Not taking into account how long the kids have been exposed to and/or eligible for SCHIP, it appears that how many kids in the room are currently eligible for SCHIP has a greater impact on their average test scores if the kids are thirteen years of age rather than nine.

Finally, the sub-finding that in general, the impact of SCHIP eligibility on test scores, at least in Florida, appears to be stronger for math than for reading is noteworthy given that in Levine and Schanzenbach's analysis, they find that increases in SCHIP eligibility from birth are associated with increases in reading scores but do not find evidence of an impact of the program on math scores. While my study does find evidence of an effect on both sets of scores, the dichotomy between the two sets of results nevertheless calls for closer examination.

In their paper, Levine and Schanzenbach (2009) reference a previous study which finds that reading performance is more likely to depend on "family and non-school factors," whereas "math achievement" depends more on what goes on in school (p. 22). They suggest that improvements in health fall into the former category of factors, which is why they are able to detect an impact of SCHIP only on reading scores. While their point is interesting, the "family and non-school factors" that affect a child's reading achievement seem likely to be related to whether the child is taught to read before entering school, family attitude toward education, income, etc. The parents who are more likely to read to their kids are probably those who are both more educated and have jobs that allow them the time to read (e.g. they are not working twelve-hour shifts or nights); in other words, they are those who are less likely to be affected by SCHIP. Even if lower-income families do gain insurance through SCHIP, health care services are probably just one less expense they have to worry about, and having a child acquire health insurance is probably not going to greatly alter a parent's schedule or attitude towards education. Since prior studies have shown that access to health care impacts a child's cognitive and physical abilities, expanded eligibility for health insurance may actually fall into the "school learning" rather than "family and non-school" factor category. On the whole, healthier children are likely better able to concentrate in school and to have better attendance records, which probably affects how much and how well they are able to learn. If this is true, my findings that increases in health insurance eligibility have a stronger effect on math scores than on reading scores makes sense.

With that having been said, another possibility is that the findings of my analysis differ from Levine and Schanzenbach's because they only look at SCHIP expansions for children from age birth through age two, whereas I look at expansions for children of all ages. Many of the children I examine likely gained access to health insurance at an older age, but if the only children Levine and Schanzenbach include in their study are those who gained access to insurance during infancy or toddlerhood, it is entirely possible that the early-on access to care these children received in some way impacted their cognitive development before they even entered the classroom. If this is the case, SCHIP eligibility could be very well be taken as more of a "non-school factor," so the differences in the two sets of findings may be due to the differences in the age range of children examined. In any case, both sets of findings indicate that increased eligibility for public health insurance does appear to have a positive impact on average test scores, which, from a policy standpoint, may be what matters most.

PART IV: CONCLUSION

To summarize, I am not able to find evidence of an effect of the proportion of kids eligible for SCHIP on average scores on the state level for any score set. I do, however, detect evidence of a positive correlation between SCHIP eligibility and average test scores on the county level in Florida; the results indicate that an increase of 10% in the proportion of kids eligible for SCHIP in a given year leads to an increase on the order of 0.102-0.243 standard deviations (SD) in average scores, while an increase of 50% in the proportion of kids eligible for SCHIP is associated with increases on the order of 0.509-1.217 SD in average scores depending on the subject of the test and grade level of the students. While the impact of changes in SCHIP eligibility on average test scores I observe is consistently less than or around 1 standard deviation and is therefore obviously not monumental in size, its existence nevertheless underscores the idea that access to health care can affect a child's learning ability and/or academic performance.

On the both the county and state levels, I find that cumulative increases in the proportion of life for which the cohorts of students taking the test have been exposed to SCHIP are generally associated with increases in average scores. On the state level, the proportion of life exposed to the program has a strong positive effect on average fourth and eighth-grade math scores. On the county level, the proportion of life exposed to SCHIP has a positive impact on all test score sets with the exception of average eighth-grade math, for which it is negligible. While there was some uncertainty at first as to the ability to separate the effects on scores of the proportion of life exposed to SCHIP from the effects of the binary year variables, further analysis demonstrated that the two predict different time-related effects on test scores when they are in their own separate versions of the model and that the effect of the PLE variable is therefore distinct from just a year-specific effect. It thus appears that there is something to the relationship and that cumulative increases in the proportion of life for which the cohorts of kids taking the test were exposed to an expanded public health insurance program were generally associated with improvements in test performance.

As a final note, it is necessary to state that it is difficult to extrapolate a broad statement from these results as to the general impact of SCHIP on education across the nation. Though there is promising evidence here of a spillover impact of SCHIP on educational performance in the state of Florida, my study does only look in-depth at the effects of the program in one state. It is entirely possible that there are certain aspects to Florida's SCHIP program (e.g. potential outreach/publicity efforts or its extremely simple application process) that have contributed to its ostensible success there. In order to arrive at a broader conclusion as to the impact of SCHIP on educational performance across the U.S., it would be necessary to examine more states; this analysis thus marks just the first step in what would likely be a promising study.

ACKNOWLEDGEMENTS

Thank you to Professors Barbara Craig, Tobias Pfutze, and Martin Saavedra of Oberlin College for their guidance and feedback.

REFERENCES

Bansak, C. & Raphael, S. (2007). The effects of state policy design features on take-up and crowd-out rates for the State Children's Health Insurance Program. *Journal of Policy Analysis and Management, 26*(1), 149-175.

Benefit details: Florida KidCare (SCHIP). (n.d.). Retrieved February 23, 2015, from http://www.benefits.gov/benefits/benefit-details/1599

CHIP annual reports (n.d.). Retrieved January 18, 2015 from Medicaid official website: http://www.medicaid.gov/chip/chip-annual- reports.html

Cohodes, S., Kleiner, S., Lovenheim, M.F., & Grossman, D. (2014). The effect of child health insurance access on schooling: evidence from public insurance expansions (Working Paper No. 20178). Retrieved from National Bureau of Economic Research website: http://www.nber.org/papers/w20178

Current Population Survey (n.d). Retrieved October 1, 2014 from United States Census Bureau website: https://www.census.gov/hhes/www/cpstables/032014/pov/pov01_000.htm

Dahl, G. B. & Lochner, L. (2012). The impact of family income on child achievement: evidence from the earned income tax credit. *American Economic Review*, *102*(5)*, 1927-2956.*

ElSi (Elementary/Secondary Information System). (n.d.). Retrieved January 18, 2015, from National Center for Education Statistics website: http://nces.ed.gov/ccd/elsi/

FCAT results interactive search by school and district. (n.d.). Retrieved January 5, 2015, from Florida Department of Education website: http://fcat.fldoe.org/results/

Hudson, J.L., Selden, T.M., & Banthin, J.S. (2005). The impact of SCHIP on insurance coverage of children. *Inquiry, 42*(3), 232-254.

Income: state median income (n.d.). Retrieved November 22, 2014 from United States Census Bureau website: https://www.census.gov/hhes/www/income/data/statemedian/

Kids Count data center: Kids Count national indicators (2014). Retrieved November 23, 2014 from Annie E. Casey Foundation website: http://datacenter.kidscount.org/data#USA/1/0

Levine, P.B. & Schanzenbach, D.W. (2009). The impact of children's public health insurance expansions on educational outcomes (Working Paper No. 14671). Retrieved from National Bureau of Economic Research website: http://www.nber.org/papers/w14671.pdf

Li, M. & Baughman, R. (2010). Coverage, utilization, and health outcomes of the State Children's Health Insurance Program. *Inquiry*, *47*(4), 296-314.

Lo Sasso, A.T. & Buchmueller, T.C. (2004). The Effect of the State Children's Health Insurance Program on Health Insurance Coverage. *Journal of Health Economics, 23*(5), 1059-1082.

Medicaid eligibility for families and children. (n.d.). Retrieved November 8, 2014, from Henry J. Kaiser Family Foundation website: http://kff.org/medicaid/medicaid-eligibility-for-families-and-children/

Menfield, C.E. & Fletcher, A. (2004). The State Children's Health Insurance Program: Has it reduced the percentage of uninsured children? *Journal of Health and Human Services Administration*, *27*(2), 194-209.

NAEP overview (n.d.). Retrieved October 29, 2014 from National Center for Education Statistics website: http://nces.ed.gov/nationsreportcard/about/

NAEP state comparisons (n.d.). Retrieved October 1, 2014 from National Center for Education Statistics website: http://nces.ed.gov/nationsreportcard/statecomparisons/

Small area health insurance estimates (SAHIE) (n.d.). Retrieved January 5, 2015 from United States Census Bureau website: http://www.census.gov/did/www/sahie/data/index.html

Small area income and poverty estimates (SAIPE) (n.d.). Retrieved January 5, 2015 from United States Census Bureau website: http://www.census.gov/did/www/saipe/data/index.html

Stockley, K. & Walter A. (n.d.) State Children's Health Insurance Program (SCHIP) expansion: will increasing income eligibility limits for children increase insurance coverage? Unpublished working paper, Notre Dame, IN. Retrieved October 1, 2014, from Notre Dame Department of Economics website: https://economics.nd.edu/assets/24017/stockley_and_walter_schip.pdf

United States Census 2000: demographic profiles (n.d.). Retrieved November 8, 2014 from United States Census Bureau website: http://censtats.census.gov/pub/Profiles.shtml

APPENDIX

Table 1.1: Average NAEP fourth-grade reading scores by state

State	1998	2002	2003	2005	2007	2009	2011	2013
Alabama	211.337526	206.880029	207.083847	207.752033	216.388953	216.273355	220.273413	218.575953
Alaska			211.547153	211.061318	214.476954	211.127368	207.923695	209.347288
Arizona	206.434866	205.347275	208.872801	207.142736	209.520624	209.989269	212.395049	213.134131
Arkansas	208.741779	212.881797	213.615304	217.071528	217.027817	216.151581	216.514864	218.523885
California	202.424798	205.916587	205.632437	206.512026	208.522186	209.76240	211.358636	212.545967
Colorado	220.241012		223.660982	223.65613	223.732652	225.696640	223.433843	226.663219
Connecticut	230.004509	229.381142	228.340615	225.753019	227.203649	228.972116	227.427304	229.581599
D.C.	179.236472	190.518073	188.374478	190.787355	197.085950	201.984637	200.627987	205.613936
Delaware	207.49871	224.303558	223.928811	225.838459	225.070542	225.513086	225.130511	225.771651
Florida	205.733211	214.404597	218.014488	219.465222	223.534926	225.673407	224.528585	227.463176
Georgia	208.508599	214.818437	213.597219	214.430920	218.888171	217.848105	220.810720	221.836712
Hawaii	199.726623	207.585442	208.259567	209.578767	213.496555	210.616418	213.614571	214.843879
Idaho		220.217617	218.259885	221.859511	223.404065	221.022924	220.829770	219.302986
Illinois			216.304288	216.48972	219.386811	219.16578	219.357498	218.540183
Indiana		221.880346	220.406491	218.072533	221.673092	222.659480	220.731342	225.332340
Iowa	220.118009	223.330640	223.271129	220.809400	224.894795	221.42229	220.707447	223.815804
Kansas	221.250836	221.978331	220.143229	220.468749	224.658362	223.924213	223.565091	223.386368
Kentucky	217.500165	219.042067	219.044417	219.926817	222.432314	225.606242	225.135062	224.427540
Louisiana	200.340635	206.640449	204.729487	209.165658	207.406805	207.486137	210.410726	210.454963
Maine	224.761099	224.508278	223.859493	224.577772	225.544045	223.790428	222.037332	224.833289
Maryland	211.679094	217.211175	218.673759	220.029585	224.781265	226.047783	230.782841	232.055973
Massachusetts	222.837528	233.74841	227.604259	231.279439	235.753462	233.749463	236.778666	232.373156
Michigan	215.952294	218.613319	218.789056	218.260689	220.118452	218.235550	218.860810	217.365167
Minnesota	219.211336	225.258514	222.608962	225.226578	224.917004	223.336668	222.308672	227.030741
Mississippi	203.227700	202.793328	205.464406	204.393607	207.809518	210.506517	209.188020	208.518536
Missouri	215.551927	220.171767	222.260230	221.168622	220.776827	223.842357	220.346171	222.334185
Montana	224.791361	224.162866	222.746541	224.552179	226.666532	224.651750	225.144216	222.982749
Nebraska		221.565239	220.611802	221.377462	222.902554	222.523307	223.311726	223.252785
Nevada	205.786356	209.129161	206.959682	207.186974	210.819009	211.140589	212.575191	213.755313
New Hampshire	226.180531		227.789508	227.438324	229.017173	229.144520	230.392676	231.998366
New Jersey			225.073328	223.298393	230.646972	229.394486	231.237629	228.719744
New Mexico	204.868936	207.501170	203.185312	206.791620	211.631884	207.645730	208.014119	205.756405
New York	215.421751	222.445054	222.188207	222.6952	223.752027	224.368748	222.493810	223.813362
North Carolina	212.901159	221.634039	221.220579	217.134448	217.934042	219.296045	221.356963	222.227715
North Dakota		223.591558	221.642245	224.810846	226.325481	225.967471	225.577526	224.083385
Ohio		222.435965	221.865799	222.533253	225.666987	224.532178	223.828213	223.887746
Oklahoma	219.211313	213.328415	213.579357	213.861450	216.955654	217.190627	215.477585	216.988876
Oregon	211.556950	219.936918	217.614535	216.899980	215.017323	218.142340	216.440154	219.132674
Pennsylvania		220.636393	218.698427	222.771980	226.353658	223.679439	227.236463	226.402323
Rhode Island	217.886351	219.623505	216.494015	216.439867	218.761444	222.704885	222.481596	222.802239
South Carolina	208.833461	213.858854	214.807724	213.203507	213.836527	215.942298	214.899808	213.646543
South Dakota			222.273178	222.398692	223.398526	222.166592	219.814446	217.930744
Tennessee	211.796116	213.693917	211.947541	214.221269	215.749268	216.737811	214.640214	219.735394
Texas	214.154157	216.932241	214.808005	218.733824	219.604313	218.858272	218.320844	216.909597
Utah	216.215269	221.514180	219.270338	221.310921	221.261428	219.204130	220.416034	222.767635
Vermont		226.961227	226.121746	226.886251	228.248538	228.735783	226.771642	227.986519
Virginia	217.247970	225.009435	223.340359	225.813710	227.136724	226.527568	226.378434	228.555737
Washington	218.156518	223.655932	221.096695	223.486397	223.999336	221.330110	220.528788	225.048863
West Virginia	215.620928	218.777794	219.17952	214.767066	215.130555	214.520200	214.386024	214.663401
Wisconsin	222.389048		220.833427	221.164226	223.318009	220.135540	221.239906	220.818103
Wyoming	218.232022	221.129753	222.075166	223.262146	225.894833	222.652196	224.062278	225.848975

Table 1.2: Average NAEP fourth-grade math scores by state

State	1996	2000	2003	2005	2007	2009	2011	2013
Alabama	211.646974	217.22322	223.344643	225.071236	228.520018	227.962650	231.286019	232.861332
Alaska	223.833455		232.991654	235.510706	237.273893	237.212284	236.359658	236.122004
Arizona	217.575941	218.867620	228.911396	229.800673	231.936934	229.991105	235.157597	240.304911
Arkansas	215.846436	216.175620	229.006588	235.545467	237.670687	237.540591	237.810157	239.890522
California	209.129082	212.694133	227.454981	230.366957	230.034091	231.674927	234.164993	233.654464
Colorado	225.805857		235.193116	239.215874	240.205890	243.13244	244.456097	246.975708
Connecticut	232.026573	233.768222	240.615241	242.120732	242.755646	244.717742	242.413406	243.440297
D.C.	187.13467	191.582147	204.919850	211.122298	213.698898	219.260141	221.808283	228.567253
Delaware	215.025101		235.859424	239.716912	241.794894	239.490569	240.359832	243.107758
Florida	215.763582		233.728811	238.930649	242.02025	241.944909	239.826451	241.675809
Georgia	215.455861	218.976885	230.25497	233.635737	235.209017	236.029572	238.366542	240.047236
Hawaii	214.965561	216.319076	226.834610	230.096875	234.286135	235.679780	238.821927	243.308618
Idaho		224.471784	234.943764	241.650115	240.902843	241.042802	240.328832	240.722019
Illinois		222.975988	232.856775	233.067494	237.287041	238.285668	238.836878	239.000204
Indiana	229.394443	233.025616	237.968279	240.069098	245.144255	242.616809	243.836876	248.596777
Iowa	229.126198	231.072948	238.476694	239.880801	242.819589	242.595644	242.604872	245.793505
Kansas		232.092153	241.747365	245.782046	247.923654	245.308653	246.255334	246.185701
Kentucky	219.988195	219.380275	228.726343	231.492305	235.087920	238.835902	240.830700	241.469926
Louisiana	209.02067	218.186824	226.247729	230.231196	230.043119	229.432455	230.778869	231.366308
Maine	232.207044	229.545137	237.615710	240.691459	242.370604	244.455732	244.257016	245.847001
Maryland	220.694960	221.536541	233.079852	238.421706	240.328230	243.795041	247.106555	245.169379
Massachusetts	228.966402	233.394116	241.664527	247.337049	252.430319	252.254789	253.396455	253.033785
Michigan	226.25805	229.309575	235.686974	237.706003	237.605553	236.279719	236.402213	236.819778
Minnesota	232.193088	233.720090	241.912295	245.746191	246.997762	249.455534	249.186686	253.420961
Mississippi	208.434118	210.557603	222.890600	226.69884	227.612377	227.262260	229.86802	231.105721
Missouri	224.734461	227.801022	234.836425	235.035547	239.411102	240.684380	240.494831	239.548361
Montana	227.516236	228.471849	235.754915	240.575488	243.618811	244.400751	243.796606	243.698884
Nebraska	227.543992	225.057392	236.254108	237.706178	238.040808	238.748463	239.803268	243.157929
Nevada	217.622612	219.550787	227.513598	229.871595	231.781600	235.152273	237.031878	236.262899
New Hampshire			243.110142	245.625926	248.571526	251.071752	251.778836	252.993525
New Jersey	227.240167		238.776541	243.978931	248.621522	246.529869	248.004162	246.87090
New Mexico	213.844025	213.476353	222.518009	224.027218	228.064312	230.029589	232.840370	232.781432
New York	222.634058	225.139222	235.930075	238.173976	242.543018	240.641098	237.519942	240.349816
North Carolina	224.325124	229.901823	242.040125	241.235549	241.617994	243.778460	244.517900	244.801732
North Dakota	230.904183	229.816101	237.577386	242.736995	245.415854	245.189526	245.156416	246.424794
Ohio		230.007534	237.782067	242.105935	244.532731	243.687552	244.038621	245.549796
Oklahoma		223.729538	229.096621	233.955328	236.802194	236.780985	237.429082	238.921877
Oregon	223.476164	223.913822	236.305905	238.324930	236.039657	238.032327	236.914497	240.099252
Pennsylvania	226.212014		235.947017	240.572963	244.001273	243.587873	245.654910	244.01262
Rhode Island	220.418093	224.069811	230.297962	233.436772	235.877935	238.766859	241.624774	241.416735
South Carolina	213.194414	219.869422	235.793223	238.302675	237.107411	235.66830	237.303025	236.625899
South Dakota			237.264820	241.594186	241.213428	242.097789	240.979792	240.981099
Tennessee	219.176248	219.847110	227.755044	231.688079	232.753710	231.825486	232.901117	239.774787
Texas	228.712919	231.278328	237.305921	241.990916	242.339759	240.464623	241.101793	241.926288
Utah	226.515841	226.808786	234.782950	238.797423	239.404988	240.318712	242.537513	242.820688
Vermont	224.881060	231.563630	241.926072	243.528855	246.357405	247.767226	246.639729	247.803294
Virginia	222.643213	229.541480	239.203089	240.497568	243.521129	243.071296	245.333618	246.177456
Washington	225.053298		238.292839	241.684674	242.542232	242.257091	243.182884	246.288338
West Virginia	223.350132	223.203602	230.767748	230.843267	236.337805	232.983144	234.655806	237.440632
Wisconsin	231.411851		236.755414	240.568581	244.181214	243.585253	244.691865	244.706291
Wyoming	223.196002	228.626636	241.085700	242.955913	243.866915	242.009195	243.874435	246.522400

Table 1.3: Average NAEP eighth-grade reading scores by state

State	**1998**	**2000**	**2003**	**2005**	**2007**	**2009**	**2011**	**2013**
Alabama	255.036152	252.501705	253.172593	251.978391	251.936881	254.895246	258.421090	257.427838
Alaska			256.409625	258.721274	258.798455	259.449426	261.285252	261.256092
Arizona	259.954719	256.734911	255.320115	254.787938	254.828792	257.595275	260.148005	260.448287
Arkansas	256.002413	260.134870	257.998089	257.691731	257.960995	258.048580	259.140937	261.964490
California	252.332229	250.450803	251.007500	250.431056	251.287791	252.631380	254.935218	261.502455
Colorado	263.642216		267.592640	264.758106	266.407881	265.513119	270.636204	271.009086
Connecticut	270.467913	267.032072	267.218075	264.012759	267.055691	271.810133	274.681399	274.459542
D.C.	235.730444	239.810524	238.700733	238.203093	240.793624	242.490424	242.056368	247.739153
Delaware	253.721489	267.274190	264.532051	266.009365	264.544830	264.998966	265.839475	265.984985
Florida	254.547253	261.053655	257.301319	255.77997	259.790720	264.362040	262.121374	265.828297
Georgia	257.227061	258.005481	257.714825	256.872381	258.704992	260.244524	262.358643	264.615713
Hawaii	248.846620	251.613131	251.284801	248.505423	251.330810	254.738979	257.188010	259.960569
Idaho		266.499769	264.439775	264.301743	264.886342	264.837185	268.014671	270.224168
Illinois			266.408968	263.517029	262.826617	264.514002	265.643729	266.898721
Indiana		264.888121	264.83253	261.013686	264.095960	265.691240	264.729844	267.272974
Iowa			267.504831	267.003171	267.450719	264.888126	264.554527	269.003449
Kansas	267.647139	269.115935	266.011689	266.831233	267.413790	266.799519	267.336395	266.887523
Kentucky	262.306553	265.246740	266.191435	263.938418	261.965951	266.854019	268.833963	269.616471
Louisiana	251.503839	256.268351	253.448288	252.691593	253.238294	253.329004	254.688347	257.351242
Maine	271.414032	269.821249	268.323265	269.983443	269.920153	267.706499	269.872413	269.193764
Maryland	260.965750	263.344864	261.595731	260.782383	265.240121	267.298056	271.222896	273.801903
Massachusetts	268.769855	270.518266	272.906645	273.716062	273.284048	273.589289	275.368517	277.009559
Michigan		264.723045	264.378292	261.138472	260.317706	261.89815	265.194041	265.942963
Minnesota	265.117702		267.711358	268.356672	268.197442	269.739820	270.148960	271.019654
Mississippi	251.466846	255.021192	255.010828	250.530668	250.063570	251.305654	253.833440	253.147818
Missouri	262.336244	267.909415	267.363673	264.659368	263.442316	266.876460	266.762051	267.215011
Montana	270.924927	270.165042	269.833416	269.224129	270.93785	270.393926	272.874140	271.765782
Nebraska		269.948920	266.313690	267.455694	267.030850	267.067856	267.703865	269.22191
Nevada	257.778411	251.363201	252.309915	252.869062	252.348473	253.840954	258.193264	261.695982
New Hampshire			270.734453	269.651270	269.734588	270.74815	272.078626	274.307731
New Jersey			267.786953	269.423228	270.141550	272.802633	275.183164	276.377987
New Mexico	257.972035	253.662756	251.599156	251.033330	250.753174	254.129173	255.861634	255.870077
New York	264.794081	263.948636	265.329794	265.138561	263.545716	264.288057	265.697028	266.346063
North Carolina	262.305587	265.022858	261.711644	258.160185	259.136703	259.528486	262.928956	264.540999
North Dakota		268.090026	269.730354	270.243755	268.017670	269.239984	268.694217	267.779199
Ohio		268.315861	266.566105	266.767281	267.978979	268.678235	268.283949	269.086973
Oklahoma	265.24627	262.012003	261.719961	259.63136	259.547225	259.495771	260.121264	261.931495
Oregon	266.009065	268.144530	264.025569	263.156890	265.710210	265.089246	264.225611	268.282662
Pennsylvania		265.320558	264.267365	266.821911	267.665630	270.700536	267.750596	272.085365
Rhode Island	264.388041	261.903434	260.879572	260.968326	258.321117	259.885589	265.119556	266.677052
South Carolina	254.798881	257.640782	258.088991	257.169104	257.421202	257.274184	260.307019	261.449050
South Dakota			269.971058	268.540435	269.596763	270.060990	268.941537	268.100772
Tennessee	257.939142	260.276441	258.108364	259.072341	259.161954	260.946676	259.208370	265.359504
Texas	261.161778	262.100424	258.777258	258.191598	260.812919	260.368795	261.428390	263.684137
Utah	263.436679	263.283637	264.303442	261.870872	262.228024	265.591577	267.087406	270.041925
Vermont		271.834589	270.519439	268.772420	273.045757	272.305134	273.840765	274.368547
Virginia	266.493300	269.197450	268.004817	267.808966	266.878737	265.641981	267.272891	267.589864
Washington	263.817226	268.168154	264.494066	264.656551	264.947778	266.917617	267.577473	272.036124
West Virginia	261.783374	263.689781	259.564237	255.073379	254.998552	254.799747	256.106861	257.383509
Wisconsin	265.326199		266.468617	266.228560	264.184509	265.812615	267.167029	267.542994
Wyoming	263.19824	264.938465	267.001028	268.124234	266.225543	268.159428	269.568729	270.966172

Table 1.4: Average NAEP eighth-grade math scores by state

State	1996	2000	2003	2005	2007	2009	2011	2013
Alabama	256.594863	263.617387	261.939022	262.2111	266.000109	268.524120	269.096515	269.194280
Alaska	277.643071		279.025069	278.958709	282.557154	283.047662	283.272797	281.559572
Arizona	267.874834	268.576075	271.177350	274.30509	275.548426	277.332282	279.033501	279.722268
Arkansas	261.652745	257.415473	265.771589	271.636348	273.899862	275.9995	279.088205	277.914802
California	262.772478	259.786969	267.049500	268.558128	270.381784	270.448588	272.769803	275.901350
Colorado	275.608214		283.399858	280.824007	286.192756	287.372907	291.742672	289.681800
Connecticut	279.591244	280.785141	283.729811	281.068953	282.472790	288.608513	286.999944	285.243972
D.C.	232.831509	234.619069	243.059638	245.215780	248.198742	253.595186	260.466877	265.259365
Delaware	266.733673		277.158368	280.953542	282.992082	283.829473	282.769966	282.338298
Florida	263.639393		271.371490	274.048376	277.383497	279.335264	277.837035	280.855839
Georgia	262.466020	265.358917	269.677009	272.191564	274.778664	277.561199	278.483619	279.179110
Hawaii	262.130081	262.183948	265.728581	265.629319	268.772013	273.758606	277.836211	281.412922
Idaho		277.225284	279.939266	280.966896	283.507595	287.305215	286.675063	286.413881
Illinois		274.548708	277.160081	277.672238	280.497096	282.431417	283.228134	284.897647
Indiana	275.529036	281.319929	281.220939	281.714945	285.007210	286.809977	285.002916	287.767653
Iowa	283.986368		283.953344	283.810928	285.226903	284.170178	284.920836	285.070137
Kansas		283.008634	284.191088	284.030053	290.032599	288.596403	289.619282	289.518256
Kentucky	266.591684	269.884981	274.278472	273.983027	278.704749	279.284216	281.608809	280.645442
Louisiana	252.380394	258.560095	266.328359	267.755030	272.386299	272.379906	272.843333	272.760966
Maine	284.059857	281.353686	281.903773	281.058540	286.472253	286.361425	288.732297	288.731159
Maryland	269.681431	271.931910	277.716112	277.930794	285.734265	288.341565	287.997802	286.641381
Massachusetts	277.565642	278.949013	286.520694	291.513541	297.923344	298.854346	298.512431	300.568235
Michigan	276.866078	277.271244	276.441861	277.346682	276.830517	278.268168	280.176518	280.133597
Minnesota	284.048944	286.980219	290.680056	290.074995	291.851116	294.443320	294.946422	294.592972
Mississippi	250.215489	254.135884	260.911933	262.456242	264.890918	265.001958	269.235645	271.160967
Missouri	273.284887	270.928275	278.766250	276.449939	280.619538	285.808001	281.947646	282.988457
Montana	283.00387	285.234013	285.928022	286.432001	287.075529	291.542942	292.907804	289.228453
Nebraska	282.769606	280.015961	282.193756	283.962991	283.650598	284.259093	283.197044	285.061348
Nevada		264.944819	268.043137	269.905585	270.804024	274.148541	278.113153	278.286680
New Hampshire			286.198468	285.253357	287.557061	292.321817	292.108739	295.665123
New Jersey			281.407119	283.902604	288.583451	292.657227	294.138771	296.053351
New Mexico	261.970366	259.334121	263.272906	263.275163	267.538078	269.704253	274.454701	272.761808
New York	270.231486	271.462874	279.749257	279.716253	280.141177	282.576915	280.453026	281.807787
North Carolina	267.834560	276.241167	281.240350	281.825136	283.880668	284.332635	286.267028	285.645388
North Dakota	284.222268	281.892936	287.144640	286.960953	291.561611	292.842488	291.998404	290.515111
Ohio		280.584751	281.607295	283.251774	284.851639	285.583013	288.602596	289.528096
Oklahoma		269.734439	271.905151	271.359902	274.534989	275.711956	279.179608	275.506732
Oregon	276.341513	280.062236	280.892470	282.237325	283.826277	285.036814	282.518206	283.524589
Pennsylvania			278.537758	280.713835	286.166863	288.304168	286.102741	289.623651
Rhode Island	268.877308	268.943754	271.998694	272.345018	275.386990	277.923719	282.875659	284.092212
South Carolina	260.775447	264.584747	277.300449	281.234321	281.503601	280.380855	281.000133	279.824608
South Dakota			284.881736	287.303618	288.463925	290.619127	290.615196	287.270390
Tennessee	263.118935	261.617187	268.175728	270.524576	273.978786	274.761821	274.038710	277.720127
Texas	270.199577	273.443798	277.052649	281.102845	285.870708	286.685076	290.346709	288.198967
Utah	276.773105	273.526491	280.645369	279.156123	281.087473	284.068251	283.308332	284.331486
Vermont	279.253243	280.500388	285.645572	287.356487	291.010773	292.866096	293.882577	295.469562
Virginia	269.754404	274.765866	281.676643	284.371628	287.625905	286.069755	289.255411	288.142959
Washington	276.117119		281.151364	285.052229	284.862804	288.722375	288.107761	289.956988
West Virginia	264.865205	266.47237	270.770353	269.099492	270.084093	270.415765	273.263173	274.430134
Wisconsin	282.848741		283.915865	284.541556	285.617942	288.140726	288.665932	288.745780
Wyoming	274.778947	275.572331	283.503349	282.100609	286.98777	286.104034	287.767926	288.119137

Figure 1.1: Change in average NAEP fourth-grade reading scores over time in selected states

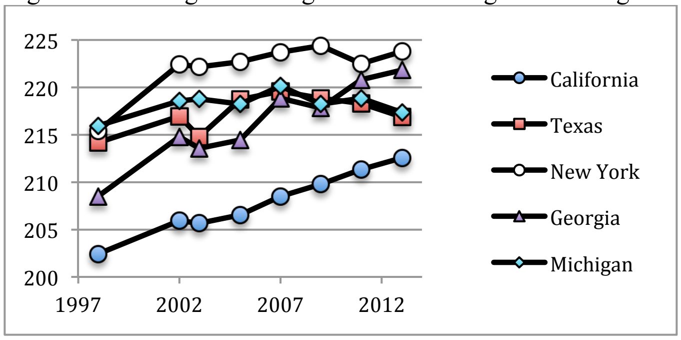

Figure 1.2: Change in average NAEP fourth-grade math scores over time in selected states

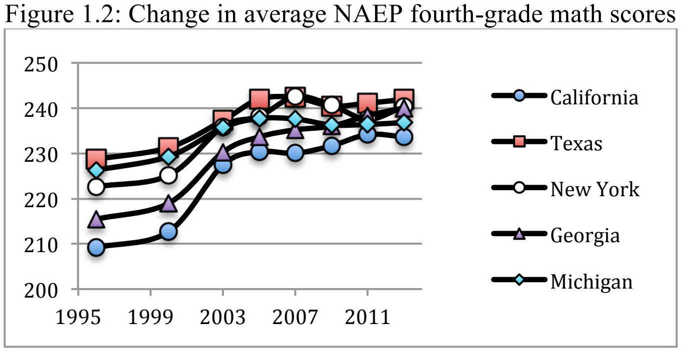

Figure 1.3: Change in average NAEP eighth-grade reading scores over time in selected states

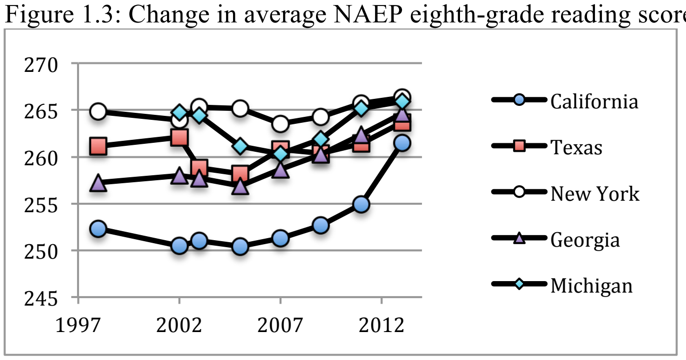

Figure 1.4: Change in average NAEP eighth-grade math scores over times in selected states

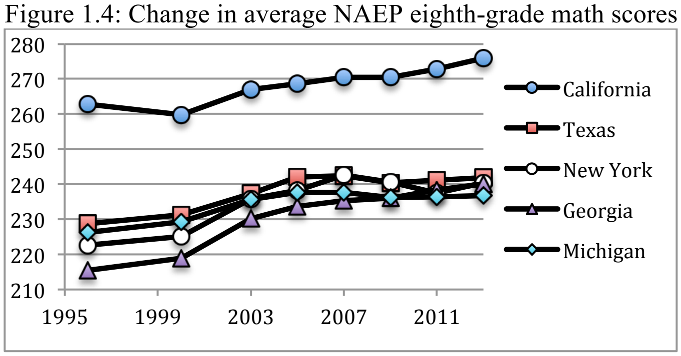

Table 2.1: Average fourth-grade FCAT reading scores by school district

School District	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010
Alachua	302	306	312	326	320	318	319	320	325	325
Baker	295	288	308	323	318	301	311	317	329	326
Bay	310	306	314	322	327	316	325	325	328	323
Bradford	294	286	293	305	309	308	307	309	310	308
Brevard	315	314	321	330	333	327	329	334	337	335
Broward	301	304	306	318	316	318	316	319	325	324
Calhoun	311	316	311	326	325	326	327	327	330	331
Charlotte	312	310	317	325	323	318	317	326	330	325
Citrus	300	304	317	322	327	325	326	330	330	329
Clay	310	314	322	329	332	323	327	333	333	335
Collier	298	295	301	321	317	312	310	316	320	322
Columbia	301	297	303	312	316	312	318	326	325	320
Dade	280	288	292	313	314	311	311	313	317	320
Desoto	268	278	293	302	316	302	304	313	321	319
Dixie	281	287	288	319	313	307	316	306	324	311
Duval	297	303	306	314	320	312	312	317	322	318
Escambia	298	296	304	314	310	310	310	313	317	314
Flagler	313	305	311	323	323	318	317	326	328	328
Franklin	306	302	309	301	313	302	304	303	325	319
Gadsden	269	277	288	290	297	284	288	293	298	299
Gilchrist	303	299	314	318	326	313	324	327	322	324
Glades	292	263	285	304	303	299	304	311	320	320
Gulf	301	304	309	308	312	306	320	324	325	330
Hamilton	272	273	283	310	298	297	303	300	304	294
Hardee	288	282	283	302	304	301	304	305	317	320
Hendry	281	286	293	307	307	301	303	308	312	314
Hernando	307	305	313	319	319	317	320	323	327	327
Highlands	294	294	298	310	314	303	309	313	317	313
Hillsborough	302	301	304	316	316	311	313	316	322	320
Holmes	316	298	313	319	315	310	319	319	324	318
Indian River	305	301	308	324	328	318	319	322	327	326
Jackson	301	302	310	321	325	318	314	322	329	326
Jefferson	260	268	274	289	284	294	300	298	296	272
Lafayette	304	316	303	315	327	302	316	332	325	323
Lake	306	301	309	317	318	313	315	319	324	321
Lee	301	304	307	318	319	314	315	320	328	326
Leon	315	321	325	330	331	326	327	326	332	332
Levy	305	295	304	311	311	304	309	310	320	310
Liberty	306	300	314	317	320	304	315	308	316	309
Madison	282	287	282	296	294	300	295	291	291	302
Manatee	304	299	308	315	316	310	312	316	322	316
Marion	300	300	300	315	316	309	315	317	320	320
Martin	310	315	319	329	334	324	328	330	332	334
Monroe	311	307	311	322	326	324	324	326	328	332
Nassau	304	306	320	325	328	321	331	328	335	332
Okaloosa	314	316	326	330	337	331	336	337	341	338
Okeechobee	297	283	297	301	310	303	301	305	315	312
Orange	287	289	298	313	315	310	312	316	321	322
Osceola	281	284	294	305	308	298	300	308	316	316
Palm Beach	298	300	303	317	318	314	318	320	325	325
Pasco	296	294	302	318	317	309	315	318	325	320
Pinellas	300	299	309	320	321	312	316	319	324	322
Polk	297	292	300	309	310	304	307	310	315	312
Putnam	283	290	298	310	313	302	304	312	319	315
Santa Rosa	323	321	330	336	341	329	338	339	339	339
Sarasota	315	317	320	333	330	321	334	333	336	338
Seminole	315	317	322	329	331	325	331	331	338	336
St. Johns	313	315	325	333	338	333	335	337	344	343
St. Lucie	297	294	299	318	316	307	307	309	314	312
Sumter	296	296	303	322	320	313	317	321	330	328
Suwannee	292	294	294	308	314	303	309	311	316	313
Taylor	294	303	301	318	321	305	313	311	312	313
Union	302	297	301	309	318	319	324	326	327	327
Volusia	304	306	313	321	322	313	315	321	325	323
Wakulla	322	324	327	324	332	320	322	330	337	334
Walton	310	302	312	326	328	318	326	323	332	331
Washington	300	302	316	312	315	321	316	318	327	324

Table 2.2: Average fourth-grade FCAT math scores by school district

School District	2002	2003	2004	2005	2006	2007	2008	2009	2010
Alachua	297	299	315	311	320	322	326	330	336
Baker	279	297	311	299	296	306	319	325	329
Bay	299	304	314	316	317	326	329	334	332
Bradford	276	283	291	289	299	306	308	312	320
Brevard	310	314	322	325	333	331	338	340	339
Broward	303	305	321	320	334	329	332	337	334
Calhoun	313	304	325	314	333	323	331	335	327
Charlotte	302	308	314	314	318	319	332	338	332
Citrus	294	299	311	313	326	327	332	338	340
Clay	304	311	319	323	326	327	332	336	335
Collier	295	297	321	316	318	318	322	324	323
Columbia	291	288	292	292	303	316	326	326	326
Dade	282	287	309	309	315	316	321	327	328
Desoto	271	290	294	308	301	309	322	324	319
Dixie	277	277	306	296	304	310	329	336	337
Duval	283	289	300	305	306	309	314	324	328
Escambia	285	295	306	301	310	311	316	322	324
Flagler	296	298	310	308	318	309	324	328	328
Franklin	290	290	294	297	311	298	306	324	335
Gadsden	261	276	287	287	287	289	301	313	313
Gilchrist	293	308	321	317	331	324	336	317	339
Glades	265	267	299	285	310	321	330	334	329
Gulf	293	303	298	310	306	335	325	334	341
Hamilton	255	284	297	292	285	289	301	298	293
Hardee	283	282	295	299	308	322	328	335	332
Hendry	277	281	299	300	307	310	319	324	323
Hernando	296	302	318	313	324	325	326	326	329
Highlands	287	289	297	305	302	311	319	323	321
Hillsborough	301	299	310	309	315	316	321	328	329
Holmes	293	299	302	300	300	313	322	326	325
Indian River	288	300	311	320	322	319	324	327	326
Jackson	291	302	317	315	330	325	339	345	340
Jefferson	266	261	278	257	284	293	306	294	285
Lafayette	305	298	333	334	313	315	333	334	330
Lake	294	300	309	310	317	318	325	326	329
Lee	293	297	312	312	316	316	320	329	328
Leon	317	319	326	326	333	330	334	339	339
Levy	284	293	295	291	306	312	312	320	315
Liberty	285	292	313	315	304	309	305	303	315
Madison	270	264	275	272	284	292	298	295	306
Manatee	291	297	303	305	309	309	316	322	319
Marion	289	297	312	312	316	320	323	329	331
Martin	311	317	326	331	329	331	337	338	339
Monroe	304	307	312	322	324	322	333	330	335
Nassau	290	304	310	317	323	329	332	337	342
Okaloosa	309	321	325	335	340	342	346	344	340
Okeechobee	286	287	298	308	305	310	314	319	315
Orange	288	291	307	305	313	315	320	326	330
Osceola	283	282	295	296	295	300	308	315	315
Palm Beach	292	296	316	315	319	325	331	335	332
Pasco	291	293	307	303	303	307	310	317	320
Pinellas	293	299	309	316	321	321	327	328	327
Polk	285	291	299	304	306	310	315	322	322
Putnam	276	285	299	300	302	311	319	327	328
Santa Rosa	313	319	327	330	330	337	340	344	346
Sarasota	312	314	327	322	325	331	338	342	341
Seminole	312	318	327	327	333	337	338	344	345
St. Johns	311	318	325	331	333	332	340	349	349
St. Lucie	289	293	312	304	310	304	311	316	320
Sumter	288	299	325	316	317	314	324	336	335
Suwannee	284	284	296	300	304	312	320	316	321
Taylor	294	288	299	297	305	315	327	319	327
Union	292	288	300	308	324	329	330	336	340
Volusia	302	305	314	314	314	317	325	327	327
Wakulla	312	314	316	325	326	316	332	334	337
Walton	290	296	308	315	323	328	325	334	332
Washington	295	314	312	315	328	324	329	343	339

Table 2.3: Average eighth-grade FCAT reading scores by school district

School District	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010
Alachua	307	300	303	301	298	300	304	315	312	312
Baker	292	289	289	282	292	295	302	310	312	307
Bay	309	305	308	303	306	308	209	317	323	318
Bradford	279	284	299	286	295	289	293	299	298	300
Brevard	311	310	315	311	314	314	316	322	326	324
Broward	297	300	305	301	301	305	306	314	316	318
Calhoun	320	311	320	309	309	306	307	320	318	323
Charlotte	312	309	313	309	308	308	313	319	316	316
Citrus	303	305	307	300	296	300	304	309	313	312
Clay	312	310	315	305	305	307	312	317	318	318
Collier	299	294	300	295	295	296	302	312	312	311
Columbia	293	294	297	290	296	293	295	302	306	303
Dade	272	275	284	281	282	289	292	304	305	306
Desoto	272	275	285	266	277	276	295	288	299	297
Dixie	282	302	297	294	294	293	293	316	315	309
Duval	292	293	296	288	297	296	301	305	308	307
Escambia	302	296	301	292	290	293	298	306	305	305
Flagler	311	313	312	307	304	300	302	309	314	312
Franklin	299	296	288	269	286	287	293	294	304	303
Gadsden	259	254	271	258	266	266	274	279	282	288
Gilchrist	300	302	314	305	305	307	315	315	323	322
Glades	284	285	294	288	283	276	290	294	296	305
Gulf	304	304	308	300	295	305	314	308	208	315
Hamilton	278	274	273	266	268	260	282	286	294	278
Hardee	288	280	277	264	279	270	281	293	289	300
Hendry	278	278	276	275	276	278	280	296	294	294
Hernando	299	301	301	291	297	296	303	312	308	312
Highlands	292	303	303	295	295	291	295	304	306	302
Hillsborough	302	306	306	301	299	298	302	307	310	312
Holmes	296	301	301	296	302	294	299	311	309	304
Indian River	298	305	305	302	303	301	304	312	314	312
Jackson	296	300	300	300	299	298	299	308	318	313
Jefferson	264	263	263	265	274	261	280	282	269	285
Lafayette	307	315	315	288	288	292	289	296	322	295
Lake	299	302	302	295	297	297	300	308	310	309
Lee	297	304	304	296	297	299	303	308	312	313
Leon	315	320	320	314	315	314	314	316	319	320
Levy	298	297	297	290	288	293	292	303	307	305
Liberty	312	291	291	308	310	294	300	302	308	319
Madison	279	289	289	264	276	280	278	294	292	294
Manatee	299	302	302	297	297	293	298	305	309	306
Marion	295	304	304	295	294	299	301	307	309	306
Martin	320	312	320	317	313	312	319	324	325	327
Monroe	313	304	311	305	301	307	309	313	318	321
Nassau	301	302	306	301	306	306	311	316	320	320
Okaloosa	313	313	324	318	327	321	325	327	330	330
Okeechobee	293	292	293	279	284	289	298	301	303	302
Orange	290	288	293	287	295	299	302	308	308	312
Osceola	285	280	288	282	286	289	289	295	301	302
Palm Beach	296	292	301	294	296	298	303	311	314	315
Pasco	301	299	302	297	296	299	303	311	313	311
Pinellas	303	304	310	302	303	301	307	314	315	312
Polk	290	285	293	282	287	288	294	300	303	302
Putnam	282	279	288	286	286	288	291	296	300	297
Santa Rosa	322	321	326	322	319	318	323	326	329	326
Sarasota	316	309	312	303	305	307	312	322	324	322
Seminole	313	315	316	312	312	314	317	322	326	327
St. Johns	313	308	321	322	320	318	323	326	329	327
St. Lucie	294	291	295	292	294	293	297	306	304	307
Sumter	288	280	294	295	294	296	309	316	315	311
Suwannee	294	281	293	289	296	297	299	304	312	303
Taylor	292	285	296	294	296	303	307	308	317	313
Union	302	289	304	288	300	295	301	306	313	312
Volusia	303	298	315	297	298	300	301	310	311	310
Wakulla	315	303	305	311	305	313	316	310	317	319
Walton	307	299	305	301	302	307	311	314	316	316
Washington	302	303	301	305	299	295	297	304	312	310

Table 2.4: Average eighth-grade FCAT math scores by school district

School District	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010
Alachua	318	312	316	316	311	313	320	328	323	325
Baker	306	307	309	308	310	308	320	330	327	322
Bay	312	311	313	313	316	318	322	328	329	329
Bradford	287	290	302	297	300	295	302	313	308	308
Brevard	319	320	324	326	329	328	332	335	334	335
Broward	313	310	316	317	320	322	323	328	328	330
Calhoun	332	318	330	326	321	319	321	333	322	332
Charlotte	324	321	322	323	326	323	325	334	327	330
Citrus	319	321	318	317	314	316	322	326	327	329
Clay	321	321	325	322	321	321	328	330	329	330
Collier	313	311	313	315	313	316	319	327	321	325
Columbia	298	301	302	300	304	303	304	309	312	313
Dade	289	286	294	298	301	304	307	319	316	318
Desoto	291	293	296	286	296	290	308	306	314	312
Dixie	291	302	294	300	307	304	310	330	327	326
Duval	301	301	302	303	308	311	318	320	320	321
Escambia	308	302	304	301	299	299	308	317	314	315
Flagler	323	318	319	318	315	313	317	322	324	325
Franklin	308	299	297	286	300	302	307	313	314	317
Gadsden	272	266	282	272	282	278	291	297	298	304
Gilchrist	325	315	331	326	324	327	328	333	329	334
Glades	302	306	294	301	296	296	310	311	314	322
Gulf	314	312	310	309	307	318	324	320	316	324
Hamilton	290	288	280	275	277	276	299	298	308	290
Hardee	308	298	302	295	298	303	302	314	310	320
Hendry	295	291	287	292	293	297	300	315	310	314
Hernando	311	308	311	304	309	309	318	326	319	324
Highlands	306	303	313	307	312	309	309	320	318	316
Hillsborough	319	317	320	322	320	317	321	324	322	325
Holmes	316	309	316	316	319	313	314	327	321	317
Indian River	305	304	311	311	316	317	321	328	326	325
Jackson	307	305	310	313	309	308	312	319	321	323
Jefferson	270	262	269	272	279	281	299	283	281	294
Lafayette	319	316	323	313	304	301	318	323	332	318
Lake	309	307	310	309	313	315	318	324	320	322
Lee	308	309	313	311	312	314	317	321	321	323
Leon	327	322	326	327	328	325	328	330	328	329
Levy	306	307	309	306	306	315	318	323	322	325
Liberty	319	294	298	313	317	307	301	314	314	327
Madison	287	262	283	280	285	287	287	297	291	300
Manatee	314	311	312	312	311	311	313	320	319	320
Marion	304	300	312	310	311	314	315	322	320	319
Martin	327	322	324	324	326	328	335	338	336	337
Monroe	319	316	319	314	317	323	325	329	328	332
Nassau	317	317	315	319	321	323	323	329	327	332
Okaloosa	324	324	331	333	342	336	340	340	339	340
Okeechobee	312	301	307	299	302	309	316	315	318	319
Orange	304	301	307	306	310	314	315	322	319	322
Osceola	297	295	299	296	299	301	304	309	310	313
Palm Beach	311	307	312	314	317	317	322	329	327	331
Pasco	311	311	311	309	309	313	315	324	323	324
Pinellas	313	311	315	313	315	317	319	325	324	323
Polk	301	296	302	299	301	302	307	312	312	314
Putnam	292	290	295	302	302	305	304	310	310	311
Santa Rosa	333	329	334	332	331	332	334	339	336	337
Sarasota	327	323	323	323	323	323	328	336	333	333
Seminole	322	324	328	327	327	329	333	335	334	336
St. Johns	320	318	324	332	334	330	337	338	338	339
St. Lucie	304	299	303	305	306	306	309	316	313	317
Sumter	302	294	303	308	302	313	322	329	322	322
Suwannee	304	294	301	302	307	313	311	316	319	313
Taylor	307	301	311	309	317	318	321	319	328	323
Union	319	304	309	301	308	313	313	318	317	323
Volusia	310	304	309	310	309	313	314	320	319	321
Wakulla	321	307	308	318	323	329	329	325	328	333
Walton	312	313	309	311	314	321	324	334	327	331
Washington	312	312	315	318	312	313	315	317	314	322

Figure 2.1: Change in average fourth-grade FCAT reading scores over time in selected counties

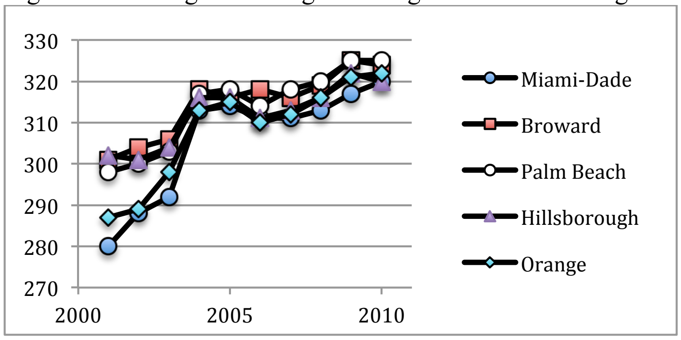

Figure 2.2: Change in average fourth-grade FCAT math scores over time in selected counties

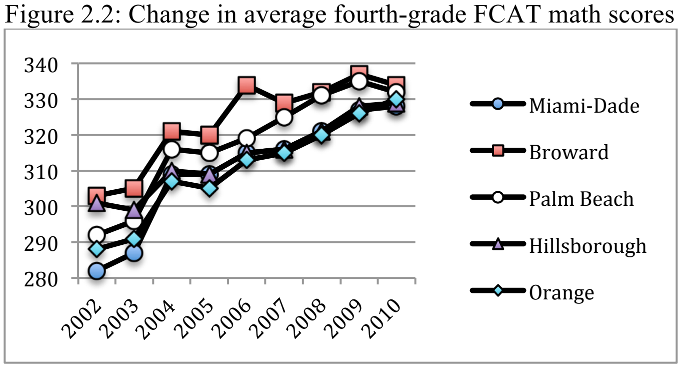

Figure 2.3: Change in average eighth-grade FCAT reading scores over time in selected counties

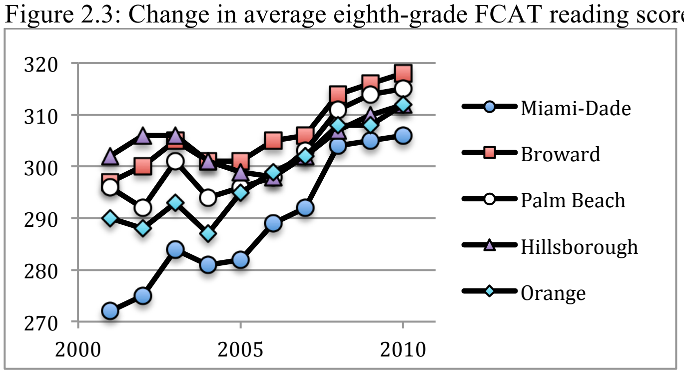

Figure 2.4: Change in average eighth-grade FCAT math scores over time in selected counties

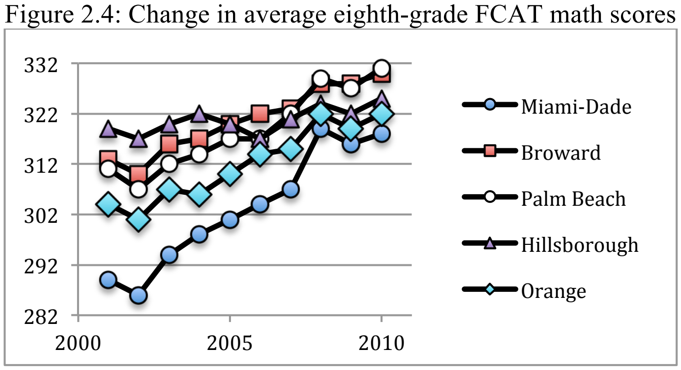

Table 1.5: SCHIP eligibility thresholds by state[15]

State	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013
AL	200	200	200	200	200	200	200	200	200	300	300	300	300	300
AK	200	200	200	175	175	175	175	175	175	175	175	175	175	175
AZ	200	200	200	200	200	200	200	200	200	200	200	200	200	200
AR	200	200	200	200	200	200	200	200	200	200	200	200	200	200
CA	250	250	250	250	250	250	250	250	250	250	250	250	250	250
CO	185	185	185	185	185	185	200	205	205	225	250	250	250	250
CT	300	300	300	300	300	300	300	300	300	300	300	300	300	300
D.C.	200	200	200	200	200	200	200	300	300	300	300	300	300	300
DE	200	200	200	200	200	200	200	200	200	200	200	200	200	200
FL	200	200	200	200	200	200	200	200	200	200	200	200	200	200
GA	235	235	235	235	235	235	235	235	235	235	235	235	235	235
HI	200	200	200	200	200	200	200	200	300	300	300	300	300	300
ID	150	150	150	150	185	185	185	185	185	185	185	185	185	185
IL	185	185	185	200	200	200	200	200	200	200	200	200	200	200
IN	200	200	200	200	200	200	200	200	250	250	250	250	250	250
IA	200	200	200	200	200	200	200	200	300	300	300	300	300	300
KS	200	200	200	200	200	200	200	200	200	200	250	238	232	232
KY	200	200	200	200	200	200	200	200	200	200	200	200	200	200
LA	150	200	200	200	200	200	200	250	250	250	250	250	250	250
ME	200	200	200	200	200	200	200	200	200	200	200	200	200	200
MD	200	300	300	300	300	300	300	300	300	300	300	200	300	300
MA	200	300	300	300	300	300	300	300	300	300	300	300	300	300
MI	200	200	200	200	200	200	200	200	200	200	200	200	200	200
MN	275	275	275	275	275	275	275	275	275	275	275	275	275	275
MS	200	200	200	200	200	200	200	200	200	200	200	200	200	200
MO	300	300	300	300	300	300	300	300	300	300	300	300	300	300
MT	150	150	150	150	150	150	150	175	250	250	250	250	250	250
NE	185	185	185	185	185	185	185	185	185	185	200	200	200	200
NV	200	200	200	200	200	200	200	200	200	200	200	200	200	200
NH	300	300	300	300	300	300	300	300	300	300	300	300	300	300
NJ	350	350	350	350	350	350	350	350	350	350	350	350	350	350
NM	235	235	235	235	235	235	235	235	235	235	235	235	235	235
NY	250	250	250	250	250	250	250	400	400	400	400	400	400	400
NC	200	200	200	200	200	200	200	200	200	200	200	200	200	200
ND	140	140	140	140	140	140	140	150	160	160	160	160	160	160
OH	200	200	200	200	200	200	200	200	300	300	300	300	200	200
OK	185	185	185	185	185	185	185	185	185	185	185	200	185	185
OR	170	170	170	185	185	185	185	185	185	200	200	200	300	300
PA	200	200	200	200	200	200	200	300	300	300	300	300	300	300
RI	250	250	250	250	250	250	250	250	250	250	250	250	250	250
SC	150	150	150	150	150	150	150	150	200	200	200	200	200	200
SD	140	200	200	200	200	200	200	200	200	200	200	200	200	200
TN	133	133	133	133	133	133	250	250	250	250	250	250	250	250
TX	200	200	200	200	200	200	200	200	200	200	200	200	200	200
UT	200	200	200	200	200	200	200	200	200	200	200	200	200	200
VT	300	300	300	300	300	300	300	300	300	300	300	300	300	300
VA	185	200	200	200	200	200	200	200	200	200	200	200	200	200
WA	250	250	250	250	250	250	250	250	250	300	300	300	300	300
WV	150	200	200	200	200	200	200	220	220	300	300	300	300	300
WI	185	200	200	200	200	200	200	200	300	300	300	300	300	300
WY	133	133	133	185	185	185	185	200	200	200	200	200	200	200

[15] Individual numbers denote percentages of the FPL

Table 1.6: Proportion of children eligible for SCHIP in each state

State	2000	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013
AL	0.411	0.4095	0.4241	0.4411	0.4429	0.3778	0.4178	0.4719	0.7241	0.6425	0.5836	0.6558	0.653
AK	0.2580	0.3142	0.2903	0.3015	0.2865	0.2670	0.2174	0.2226	0.3016	0.3219	0.3116	0.3119	0.2954
AZ	0.354	0.3928	0.4626	0.4489	0.4943	0.4789	0.4549	0.4902	0.5111	0.5137	0.5146	0.4976	0.5749
AR	0.4460	0.5183	0.4923	0.4742	0.4639	0.5546	0.5265	0.5061	0.5014	0.5455	0.5274	0.5226	0.519
CA	0.467	0.5222	0.5114	0.5335	0.5034	0.5187	0.5105	0.5209	0.5256	0.5676	0.5709	0.5514	0.5456
CO	0.2640	0.2742	0.2790	0.2595	0.2850	0.3386	0.3001	0.3282	0.4697	0.4128	0.4035	0.4107	0.4176
CT	0.3570	0.4394	0.3675	0.4003	0.4001	0.4303	0.4131	0.3847	0.3648	0.4357	0.4572	0.4098	0.4437
DC	0.275	0.3136	0.3164	0.335	0.3401	0.3291	0.3304	0.3437	0.3625	0.3967	0.4363	0.4603	0.4569
DE	0.3940	0.5387	0.5046	0.5586	0.5585	0.5184	0.6689	0.6131	0.6352	0.6232	0.5886	0.5900	0.6539
FL	0.365	0.4023	0.4148	0.4023	0.3871	0.3881	0.4000	0.4156	0.4491	0.4552	0.4572	0.4554	0.4347
GA	0.5070	0.4954	0.4766	0.5365	0.5155	0.5059	0.4935	0.5444	0.5286	0.5625	0.5625	0.5814	0.5654
HI	0.2710	0.3595	0.3176	0.2977	0.2735	0.2969	0.2977	0.5771	0.5766	0.6663	0.6236	0.6458	0.5721
ID	0.2260	0.3044	0.2460	0.3531	0.3242	0.3702	0.3100	0.4006	0.3941	0.4407	0.4684	0.4310	0.3537
IL	0.2780	0.3175	0.3791	0.3655	0.3519	0.3461	0.3622	0.3857	0.4257	0.4555	0.4389	0.4297	0.3875
IN	0.3070	0.3443	0.3363	0.4085	0.4195	0.3387	0.3811	0.5441	0.5385	0.5503	0.5473	0.5844	0.5022
IA	0.3160	0.3308	0.3045	0.3589	0.3126	0.3689	0.2936	0.5368	0.5694	0.5410	0.5709	0.5752	0.5868
KS	0.3110	0.3188	0.3371	0.3718	0.3857	0.3874	0.4014	0.4110	0.4093	0.5817	0.5531	0.5509	0.4912
KY	0.4240	0.4405	0.4530	0.4434	0.4185	0.4560	0.4316	0.4710	0.4299	0.4685	0.5179	0.4848	0.5585
LA	0.3090	0.4874	0.5022	0.4858	0.4573	0.4500	0.5223	0.5520	0.5126	0.5792	0.5723	0.5836	0.5563
ME	0.3600	0.3895	0.3869	0.3166	0.3858	0.3414	0.3391	0.3647	0.3735	0.3742	0.4038	0.3728	0.4102
MD	0.2340	0.3767	0.4272	0.4425	0.4746	0.4085	0.4113	0.4305	0.4440	0.4659	0.2921	0.4502	0.5008
MA	0.2450	0.4477	0.4412	0.3890	0.4341	0.4027	0.4373	0.4279	0.4714	0.4199	0.4592	0.4685	0.4062
MI	0.2920	0.3476	0.3611	0.3887	0.3588	0.3703	0.3821	0.3743	0.3943	0.4300	0.4107	0.3995	0.4090
MN	0.4170	0.4239	0.4209	0.3900	0.4167	0.4783	0.4748	0.5111	0.5383	0.5004	0.4837	0.4869	0.4573
MS	0.4650	0.5068	0.5161	0.5066	0.5424	0.5358	0.5395	0.5201	0.5862	0.5644	0.5009	0.4977	0.5020
MO	0.5440	0.5117	0.5507	0.5654	0.5772	0.5829	0.6083	0.6139	0.5990	0.5662	0.6194	0.5883	0.5512
MT	0.2630	0.3403	0.3793	0.3149	0.3115	0.2660	0.3221	0.5163	0.5925	0.5866	0.6149	0.5703	0.5875
NE	0.3210	0.2888	0.2474	0.3086	0.2510	0.2865	0.2921	0.3216	0.3008	0.3589	0.3266	0.3922	0.3467
NV	0.3030	0.4193	0.4039	0.3815	0.3687	0.3935	0.3745	0.3880	0.4321	0.4801	0.4812	0.5057	0.5749
NH	0.4060	0.3834	0.3942	0.3908	0.3835	0.3978	0.3541	0.3555	0.3803	0.3515	0.4116	0.4371	0.4380
NJ	0.4700	0.4747	0.4908	0.4772	0.4724	0.5031	0.5061	0.5395	0.4975	0.5068	0.5222	0.5280	0.5621
NM	0.4410	0.6154	0.6786	0.6118	0.6580	0.5441	0.5418	0.6045	0.6361	0.6274	0.6181	0.6451	0.6215
NY	0.3601	0.5000	0.5054	0.4846	0.4889	0.4793	0.7011	0.7000	0.7055	0.7163	0.7393	0.7252	0.6899
NC	0.3540	0.4210	0.4718	0.4098	0.4096	0.4484	0.4245	0.4161	0.4399	0.4816	0.4788	0.4573	0.4731
ND	0.2249	0.2528	0.2218	0.2411	0.2309	0.2512	0.2648	0.2770	0.2502	0.2558	0.2068	0.2747	0.2385
OH	0.3169	0.3294	0.3463	0.3626	0.3622	0.3863	0.3798	0.5894	0.6138	0.5899	0.6401	0.4195	0.4153
OK	0.4209	0.4072	0.4186	0.3633	0.3969	0.4424	0.4057	0.4203	0.3753	0.4456	0.4757	0.4486	0.4295
OR	0.1999	0.3251	0.3610	0.3354	0.3705	0.3132	0.2974	0.3633	0.4328	0.4503	0.4412	0.6366	0.5803
PA	0.3269	0.3471	0.3420	0.3581	0.3668	0.3695	0.5521	0.5336	0.5479	0.5561	0.5628	0.5470	0.4962
RI	0.3358	0.4357	0.4327	0.4552	0.3915	0.4210	0.4352	0.4622	0.4960	0.4622	0.4595	0.4757	0.4912
SC	0.2219	0.3156	0.3020	0.3257	0.3010	0.2781	0.3337	0.4416	0.4011	0.4759	0.5307	0.4571	0.4017
SD	0.2329	0.3557	0.3346	0.3817	0.3679	0.3823	0.3293	0.3842	0.4334	0.4383	0.4313	0.3953	0.3546
TN	0.2227	0.2667	0.2570	0.2642	0.2526	0.5443	0.5440	0.5624	0.5560	0.5705	0.5698	0.5992	0.5558
TX	0.3740	0.4874	0.5148	0.4816	0.4790	0.4690	0.4710	0.5062	0.5057	0.5275	0.5203	0.5073	0.4872
UT	0.2879	0.3494	0.3579	0.3762	0.3538	0.3885	0.3428	0.2948	0.3364	0.3705	0.4128	0.4037	0.3098
VT	0.5160	0.5511	0.5127	0.4645	0.4774	0.4755	0.5209	0.5124	0.5882	0.5245	0.5462	0.5184	0.4727
VA	0.1961	0.3202	0.2698	0.2940	0.3200	0.3203	0.3372	0.3140	0.3326	0.3064	0.3085	0.3211	0.3229
WA	0.3174	0.4505	0.4620	0.4546	0.4211	0.4118	0.3912	0.4197	0.5610	0.5859	0.6008	0.5380	0.5453
WV	0.3220	0.5136	0.4944	0.4383	0.4534	0.4727	0.4642	0.4415	0.6133	0.6522	0.6926	0.6141	0.5449
WI	0.2719	0.3051	0.3469	0.3658	0.3322	0.3338	0.3139	0.5452	0.5394	0.5478	0.5532	0.5751	0.5193
WY	0.1534	0.2209	0.3031	0.2721	0.2765	0.2572	0.3200	0.2735	0.3508	0.3697	0.3688	0.3668	0.3692

Table 2.5 Proportion of Children Eligible for SCHIP in each county (Florida)

County	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010
Alachua	0.359973	0.361460	0.412945	0.344968	0.437814	0.417296	0.426194	0.397899	0.429233	0.457139
Baker	0.394933	0.358992	0.445754	0.379304	0.430078	0.411817	0.442715	0.446342	0.497266	0.519412
Bay	0.413627	0.397540	0.433623	0.378295	0.432774	0.414792	0.428680	0.432216	0.481595	0.489686
Bradford	0.466372	0.437434	0.489191	0.410849	0.485752	0.466212	0.497060	0.514995	0.545332	0.564711
Brevard	0.337737	0.317921	0.348123	0.300447	0.343769	0.335951	0.347482	0.373952	0.406602	0.405213
Broward	0.378722	0.369071	0.425227	0.380993	0.358939	0.366077	0.374851	0.378971	0.410006	0.424968
Calhoun	0.545101	0.497981	0.528905	0.449203	0.574816	0.548767	0.542043	0.560196	0.585052	0.602722
Charlotte	0.391031	0.365091	0.377751	0.318429	0.375380	0.388099	0.411324	0.418059	0.470027	0.472001
Citrus	0.467976	0.451679	0.462935	0.384911	0.502175	0.450920	0.466605	0.505423	0.532428	0.529657
Clay	0.313663	0.258417	0.298419	0.271354	0.330841	0.301615	0.327621	0.342951	0.363634	0.380561
Collier	0.375883	0.328349	0.354138	0.321999	0.348917	0.442517	0.448065	0.353795	0.414607	0.474841
Columbia	0.512567	0.532374	0.546233	0.438092	0.583329	0.497260	0.520619	0.540934	0.570733	0.588171
Dade	0.531699	0.555067	0.593205	0.491446	0.522498	0.488289	0.509168	0.481041	0.522167	0.532542
Desoto	0.651774	0.591470	0.58244	0.487791	0.641071	0.629841	0.646054	0.658453	0.699335	0.692866
Dixie	0.56455	0.542943	0.561835	0.480667	0.635380	0.587426	0.595659	0.665770	0.662004	0.665233
Duval	0.350414	0.336281	0.389619	0.346231	0.349678	0.376254	0.402283	0.410482	0.449702	0.472658
Escambia	0.45938	0.424464	0.445324	0.385979	0.473897	0.464236	0.483689	0.483428	0.520380	0.537875
Flagler	0.527694	0.444538	0.449096	0.394688	0.478696	0.437713	0.47209	0.453734	0.506608	0.506345
Franklin	0.534898	0.435405	0.450139	0.387177	0.501591	0.554580	0.583127	0.549751	0.591052	0.631784
Gadsden	0.486389	0.468545	0.505265	0.425765	0.502494	0.581128	0.599658	0.604179	0.635516	0.667612
Gilchrist	0.538326	0.511861	0.534989	0.437192	0.538232	0.514625	0.519510	0.532997	0.570488	0.563160
Glades	0.513675	0.408387	0.420321	0.356402	0.448080	0.505644	0.501243	0.532931	0.551275	0.559710
Gulf	0.489048	0.416127	0.479803	0.389543	0.494369	0.468852	0.488880	0.489297	0.519585	0.537230
Hamilton	0.566272	0.496473	0.545540	0.461363	0.602064	0.596940	0.613924	0.625752	0.650016	0.661182
Hardee	0.651701	0.608439	0.617529	0.540297	0.694324	0.628167	0.634439	0.659606	0.692392	0.693140
Hendry	0.571762	0.509575	0.523619	0.449457	0.594664	0.579818	0.612790	0.622029	0.660365	0.699849
Hernando	0.526722	0.503675	0.529693	0.419775	0.515498	0.432649	0.446790	0.493194	0.519408	0.508330
Highlands	0.516680	0.465477	0.503115	0.422298	0.619999	0.531777	0.555450	0.577535	0.623682	0.629653
Hillsborough	0.393731	0.396064	0.441842	0.384696	0.406976	0.387314	0.405851	0.412359	0.445436	0.462680
Holmes	0.534690	0.515399	0.560166	0.484258	0.633199	0.548672	0.558077	0.600291	0.600523	0.605101
Indian River	0.361723	0.333181	0.358911	0.301428	0.395471	0.395019	0.407635	0.388443	0.434730	0.479132
Jackson	0.507870	0.463503	0.511396	0.449666	0.544486	0.497288	0.511582	0.527993	0.555512	0.541707
Jefferson	0.463266	0.440434	0.503166	0.382155	0.488962	0.496461	0.511960	0.474275	0.519661	0.554157
Lafayette	0.561818	0.550318	0.589031	0.537461	0.711394	0.567073	0.590024	0.577018	0.604114	0.608719
Lake	0.469286	0.425096	0.435123	0.356256	0.433568	0.400689	0.418355	0.430599	0.477835	0.482375
Lee	0.422454	0.379044	0.396422	0.346230	0.374850	0.381629	0.406729	0.407034	0.481216	0.494939
Leon	0.314042	0.308376	0.360337	0.303424	0.373595	0.350316	0.360700	0.351061	0.386371	0.427719
Levy	0.514123	0.483998	0.516351	0.42923	0.594751	0.555770	0.571346	0.612263	0.632686	0.629344
Liberty	0.535907	0.500624	0.536864	0.463790	0.592202	0.551577	0.569620	0.552439	0.576510	0.555681
Madison	0.474029	0.435872	0.481790	0.428727	0.562229	0.567632	0.584611	0.590063	0.618678	0.635910
Manatee	0.353124	0.347116	0.369039	0.317391	0.346854	0.390250	0.401007	0.416201	0.454667	0.488071
Marion	0.518595	0.497689	0.511360	0.402862	0.501084	0.475384	0.498582	0.530799	0.559589	0.565742
Martin	0.298875	0.262316	0.301346	0.262973	0.307950	0.344047	0.349253	0.300938	0.347016	0.385408
Monroe	0.341515	0.313059	0.354311	0.303072	0.327712	0.371481	0.365200	0.334486	0.382124	0.408010
Nassau	0.319477	0.277696	0.325363	0.293544	0.315921	0.325259	0.350420	0.337198	0.367413	0.403796
Okaloosa	0.366643	0.341604	0.379963	0.327854	0.377688	0.366318	0.374892	0.374478	0.417113	0.420096
Okeechobee	0.579134	0.501786	0.502782	0.432920	0.552496	0.539389	0.552954	0.589441	0.623981	0.646535
Orange	0.445956	0.440342	0.462076	0.419884	0.455533	0.414536	0.423030	0.444422	0.483612	0.490578
Osceola	0.542018	0.545970	0.589511	0.495960	0.575334	0.504933	0.526940	0.561986	0.606128	0.574446
Palm Beach	0.339147	0.322488	0.359038	0.330151	0.364458	0.389248	0.391510	0.368018	0.412001	0.434147
Pasco	0.404490	0.412830	0.440569	0.372696	0.377127	0.367842	0.367773	0.441930	0.465019	0.448919
Pinellas	0.353119	0.360723	0.412599	0.342587	0.386515	0.351265	0.362839	0.377224	0.407150	0.432534
Polk	0.466051	0.445309	0.487301	0.429301	0.462109	0.464032	0.484125	0.510618	0.528303	0.548045
Putnam	0.515528	0.487194	0.531021	0.457873	0.588097	0.554922	0.586524	0.624231	0.638082	0.662548
Santa Rosa	0.361154	0.333749	0.363968	0.320303	0.334534	0.335223	0.343587	0.371635	0.392962	0.398768
Sarasota	0.296808	0.267540	0.306991	0.273995	0.319406	0.350204	0.362401	0.343237	0.409216	0.424130
Seminole	0.282349	0.274333	0.330881	0.302323	0.279555	0.287826	0.291228	0.314964	0.345549	0.356779
St. Johns	0.233700	0.208933	0.258847	0.229910	0.209655	0.240436	0.243218	0.220901	0.235911	0.267612
St. Lucie	0.464222	0.425162	0.470499	0.388617	0.476186	0.461343	0.473592	0.485630	0.528694	0.535400
Sumter	0.456024	0.415056	0.423556	0.375606	0.459805	0.539917	0.487050	0.403991	0.468232	0.490182
Suwannee	0.561578	0.528607	0.556204	0.460271	0.554596	0.541251	0.566087	0.596271	0.628776	0.622905
Taylor	0.456218	0.446742	0.478500	0.401202	0.49587	0.517029	0.535616	0.540658	0.566755	0.588567
Union	0.411685	0.432225	0.477550	0.417746	0.525054	0.465479	0.491500	0.504217	0.551819	0.556829
Volusia	0.378286	0.367215	0.400204	0.341898	0.326288	0.415537	0.427241	0.450581	0.490066	0.494764
Wakulla	0.417270	0.384214	0.403132	0.351325	0.411274	0.410191	0.426672	0.416046	0.459047	0.446953
Walton	0.523670	0.489857	0.471493	0.37446	0.440331	0.471654	0.452812	0.443362	0.507609	0.524053
Washington	0.52701	0.483717	0.512709	0.42296	0.508793	0.528366	0.556892	0.579250	0.599507	0.599303

Figure 1.5: Change in proportion of children eligible for public health insurance over time in selected states

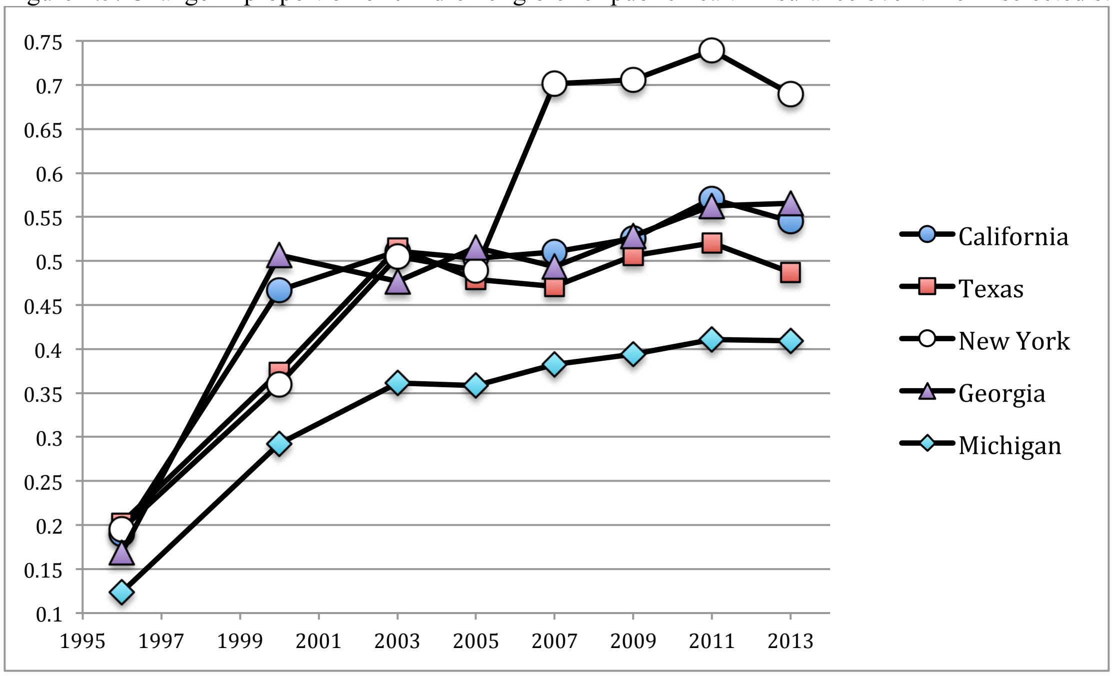

Figure 2.5: Change in proportion of kids eligible for SCHIP in selected counties over time (Florida)