Taking Up, Getting Better and Crowding Out: Evaluating Local Effects of the California Healthy Kids Insurance Program

Kyle Pubols

Prof. Jay Bhattacharya, Advisor
Honors Program
Department of Economics
Stanford University
Stanford, CA 94305
June 2009

Abstract

In this paper I use county level data from California to estimate the effects of the California Healthy Kids Insurance Program (CHKIP), an optional state county partnership that expands child eligibility for publicly provided health insurance. The paper is split into three sections: the first on the Political Economy of county selection into the program, the second on the program’s effect on child health outcomes, and the third on estimating the degree to which the program “crowds out” private insurance among children eligible for coverage. In the political economy section I find that the most important predictor of county selection into the program is the percentage of the population who are non-citizens. In the health outcomes section I find that CHKIP increases insurance coverage rates and decreases the likelihood that a child will delay medical care. In the crowd out section, I find no evidence for crowding out among children from families with incomes between %250 and %300 of the Federal Poverty Level, but do find evidence for small levels of crowding out among all children from families with incomes less than %300 of the Federal Poverty Level.
Introduction

The number of children without health insurance is a major concern for American policy makers. While the causal relationship between health insurance and actual health outcomes is still uncertain, there is evidence to suggest that higher coverage rates may lead to better health outcomes. If voters are concerned about the well-being of those around them, it follows that health insurance for children is likely a major concern. Unsatisfied with federal efforts to improve coverage, many states have decided to address the issue on their own. One of the first examples of this is a program created by the state of California. The California Healthy Kids Insurance Program (CHKIP or simply “Healthy Kids”) is a program administered by county governments with state oversight, constructed with the intent of providing or finding coverage for every child in California.

The purpose of this paper is to provide a county level evaluation of the California Healthy Kids Program from three economic angles. After a brief introduction to the program and my main data source in Section I, in Section II I address the political economics of a county’s choice to establish a program or not. The problem that I am concerned with in this regard is the issue of “community take-up.” This refers to the collective choice faced by citizens of a county over whether they will accept state funding and the requirements that come with it, or reject funding to maintain independence. In other words, I try to estimate which conditions make it more or less likely that state and local governments will collaborate in public health partnerships. Analyzing county level data for California, I find that the wealth, racial/ethnic composition, fiscal ability and health care need of a county do a relatively poor job in predicting which counties establish Healthy Kids programs. Instead, the most important factor in my model seems to be the percentage of children in a county who are not United States citizens. Though this result
may seem strange since non-citizens cannot exercise direct political power through the ballot, it makes more sense when one considers that other public insurance programs are prohibited from providing services to most non-citizens, while CHKIP is prohibited from *discriminating* based citizenship status.

In Section III, I examine the program from the perspective of Health Economics, specifically the health outcome effects of the program on children. Does CA Healthy Kids actually lead to better health outcomes for children? Does it meet its stated goals, and if so which ones? Which groups of children, if any, are most affected by its establishment? How might it affect children in ways that were not anticipated?

I find that CHKIP has a negligible effect on its target demographic, which consists of the uninsured children in families with incomes between %250 and %300 of the Federal Poverty Level. However, I do find that it has a significant positive effect on insurance rates of its “broader target” demographic, which consists of all uninsured children in families who earn less than %300 of the Federal Poverty Level. I also find that among this latter group, the CA Healthy Kids Program increases the probability that a child will visit a health care provider over the course of a year, increases self-reported health status, and decreases the chance that a child will be forced to delay medical care for a significant health issue. I conclude that although the program is not significantly impacting its target demographic, it is significantly improving the direct and indirect health outcomes of children with family incomes of less than %300 of the Federal Poverty Level.

In Section IV I evaluate the program in the realm of Public Economics. I am interested in measuring the extent to which provision of subsidized health insurance “crowds out” the level of
private health insurance among eligible children. Estimating crowd-out rates is essential in
determining whether a program is increasing coverage among the target demographic or simply
enrolling children whose parents are voluntarily dropping private health insurance, leading to no
net increase in child insurance rates. I find no evidence of crowding out among the specific target
demographic. However, I find strong evidence for a small amount of crowd-out caused by the
CA Healthy Kids Program among those children with family incomes less than 300% of the
Federal Poverty Level. I also show why my results are probably not biased by endogeneity errors
in measurement. Lastly, I present evidence that this crowd out does not seem to be caused by
firms cutting back on benefits offered to workers.

I intend for each section to read like a miniature paper, starting with a brief introduction
to the topic and a review of the relevant literature and then moving on to methodology and
results before offering conclusions about findings. Lastly, in Section V I offer some implications
for policy makers in California and elsewhere, discuss possibilities for future research and offer
some concluding remarks.
Section I: The CA Healthy Kids Insurance Program and the Data Used to Evaluate It

California’s public health insurance infrastructure is similar to the programs in other American states. MediCal, California’s version of the federal Medicaid program, provides free or heavily subsidized health insurance through a combination of federal and state funding for children from households with annual incomes less than 200% of the Federal Poverty Level (hereafter “FPL”; this equates to $41,300 for a family of four). Healthy Families, California’s version of the federal State Children’s Health Insurance Program (SCHIP), has a similar structure but extends this coverage to children with household incomes less than 250% of the FPL ($51,625 for a family of four, see US Department of Health and Human Services Guidelines for further detail).

In addition to these larger programs, counties have also had access to significant funding through Proposition 10. Passed as a ballot initiative in 1998, Prop. 10 imposed a $.50 per pack tax on cigarette sales and dispersed the revenues to each county in California. Funds were distributed based on a simple count of births per county. In order to receive funds, a county must set up a Children and Families Council (known as a CFC or “First 5 Commission” due to Prop. 10’s emphasis on children age five and younger) and follow certain guidelines on program structure, one of which was a prohibition on inquiring about “residency status”.

Other than these simple restrictions, counties were given wide leeway in the use of their funds and were encouraged to “customize to meet local needs.” This could include almost anything that could be justified as “children’s healthcare,” from providing nutrition education for parents to immunization shots for toddlers (First 5 California). Beginning in 2001, several counties used this funding to establish Children’s Health Initiatives (CHIs), locally run
organizations designed to increase child insurance rates by promoting risk awareness, increasing take-up rates of MediCal and Healthy Families, and providing subsidized coverage for uninsured children who did not qualify for the above programs. By 2005, 14 counties had established CHIs, and state lawmakers began working on a plan to encourage the creation of these programs throughout the rest of the state.

**CHKIP**

In September of 2006, Governor Schwarzenegger signed the California Healthy Kids Insurance Act into law. Roughly modeled after the early CHIs, CHKIP allows counties to establish and run their own programs subject to state oversight, and explicitly states legislative intent “that all Children in the state have health insurance by December 1st, 2010” (Senate Rules Committee). Logistics, financing and actual healthcare delivery are handled at the county level. Counties can then apply for state funding (no federal funds are used) of up to 40% of their operating costs subject to the following conditions: 1) if an applicant qualifies for MediCal or Healthy Families, the county will refer them to the that program, 2) children must come from households with incomes less than 300% of the FPL ($61,950 for a family of four), and 3) counties must not ask about immigration or citizenship status in the application process (see Figure B for a further explanation of program structure).

Many policy consultants involved with the legislation process, such as Peter Harbage of Harbage Consulting, refer to two distinct “target demographics” of the 2006 legislative session. First, there are uninsured children of families with incomes between %250 and %300 of the FPL. 

---

1 Many policy makers at the time believed this to be the most important factor of CHKIP. In independent interviews with Sacramento healthcare consultants Almis Udrys and Peter Harbage, both emphasized that providing health benefits for undocumented immigrants was the “primary motivation” for the passage of the Healthy Kids Insurance Act. Udrys believes that this decision was largely done at the Legislative level, while Harbage believes it was more a result of local lobbying. As he puts it, “the uninsured are viewed at the local level as neighbors instead of ‘illegals,’ so there is more political motivation there.”
These are referred to as families in the “expansion range” because CHKIP expanded the previous eligibility income threshold of %250 of the FPL to %300 of the FPL. “Expansion range” families are a subset of the secondary target demographic, all those children from families that earn less than %300 of the FPL. As stated above, this “Broader Target” group is considered less of a priority because so many of the children in it are already covered by Medicaid and/or SCHIP. However, a secondary goal of CHKIP is to increase take-up rates and awareness of children already eligible for Medicaid or SCHIP. For simplicity’s sake, hereafter I will use “Expansion Range” to refer to families with incomes between %250 and %300 of the FPL and “Broad Target” range to refer to families with incomes less than %300 of the FPL.

Overall the CHKIP program essentially means that the state has expanded FPL eligibility for public health insurance by 50 percentage points and cut the requirement of proof of legal residency. Since counties must pay at least 60% of operating costs, local governments face a tradeoff between program enrollment and cost. As of December 2007, 26 of California’s 58 counties had active or soon-to-be active Healthy Kids Programs. See Figure A for a map and list of these counties.

Data

In all sections I rely primarily on the 2007 and 2005 editions of the California Health Interview Survey (CHIS) conducted by the UCLA Center for Health Policy Research. CHIS was constructed by performing a random-digit-dial phone survey of households in each county, and then recording responses of a randomly selected adult in the household (Lee, et al 2). This data set provides an excellent and detailed source of county level household information on insurance rates, citizenship status, and racial composition. CHIS primarily produces output in percentage terms, which is both a blessing and curse for researchers. On one hand this allows data to be
restricted and separated by specific age groups and income levels, a feature that is especially helpful in studying programs aimed at children. The disadvantage is that all outputs must be considered in percentage terms, leading to awkward econometric interpretations.

Although CHIS does have individual level data, its use is largely restricted by researchers at the Center due to strict confidentiality agreements required to gather personalized data over the phone. The closest I can currently get to individual level data is a description of the number of observations for each county. Instead of trying to mix data types, I proceed with only the publicly available data at the county level.

In a final note, CHIS combines results from Glenn, Colusa and Tehama counties and presents them in a single cell. This was presumably done because of the rural nature of the area and the probable difficulty in obtaining a sufficient number of observations. The main problem with this is that by the end of 2007 Colusa County had established a CHKIP while Glenn and Tehama counties had not. In order to avoid measurement error of the main explanatory variable in my regressions, I have dropped these counties from my data, leaving me with 55 total observations.

In Section II I supplement the data from CHIS with information on population density, median income and local revenue, which were obtained from the California Department of Finance County Profiles Archive. I use the California Secretary of State’s online county election archives for all political data, except the measure of child citizenship status, which again is obtained from CHIS. Financial data on Prop. 10 funding of county CFCs was obtained from the Fiscal Year 2005-2006 Annual Report from the California State First 5 Commission, the parent agency of the county CFCs.
Section II: Communal Take-Up and the Political Economy of Establishing CHKIP

As many policy makers have discovered, the benefits of new government programs often miss the demographic at which they are targeted. This means that if policy makers are unsure of which areas or social classes are likely to adopt a program, the benefits of CHKIP and programs like it may be inefficiently distributed. Specifically for California, this means that the counties which could benefit most from public provision of children’s health insurance may not establish a program. As the cost of healthcare occupies a larger and larger portion of the state and national budget, it is vital that economists and policy makers understand the factors that will make a county, and by extrapolation other political entities, more or less likely to “take up” a public program. In this section I estimate the factors that determine whether a county in California will choose to create a Healthy Kids Program.

Literature Review on Local Choice

Previous literature on rational choice between differing levels of government is limited. Brown and Cousineau (1984) find that state mandates on local governments to provide health benefits for the poor are largely ineffective unless coupled with strict regulatory enforcement and significant funding incentives. Holly, et al. (1998) find that allowing local governments in Switzerland to customize payment and treatment policies result in greater take-up rates. Regarding local choice vs. state control in general, Strumpf and Oberholzer-Gee (2002) find that diversity in a local population leads to increased level of local control over alcohol regulation. This literature suggests that state governments should not expect high take up rates of their policies unless local governments are either coerced or given broad control over their institutions.
Methodology

Throughout this section I assume utility maximizing local government officials. By this I mean political leaders who perform a cost/benefit analysis of a certain political action based on the wishes of their constituents and their own personal beliefs about policy, as well as the implications for their political careers. Although this assumption is at best tenuous, a more nuanced approach is beyond the scope of this paper.

I model the choice of a county to adopt the California Healthy Kids expansion program in Equation 1, where $\text{CHKIP}_i$ is a binary dependent variable equal to 1 if the county had a Healthy Kids program in 2007 and 0 if it did not. I use a probit regression to estimate the marginal effect of each variable. See Appendix I for a detailed description and discussion of each variable.

$$\text{CHKIP}_i = \alpha A_i + \pi \Pi_i + \tau \tau_i + \varepsilon_i \quad \text{(Equation 1)}$$

$A$ contains basic demographic traits of each county that are included in Equation 1A. This includes measures of race and ethnicity (Black, Hispanic, Asian, Pacific Islander and Other/Multiple) designed to capture variance in insurance rates and variance in attitudes towards public insurance due to cultural differences. Also included are PopDensity, a measure of residents per square mile and MedInc, a measure of median family income in county $i$. These are included on the rationale that more populated counties should be easier to organize administratively, and wealthier counties can better afford to create programs, although they also might also not need them as much.

$\Pi$ contains political factors for each county that are added in Equation 1B. The first of these is the dummy variable PriorCHI, equal to 1 if a county had an existing CHI before state funding was made available and equaling 0 if it did not. HealthCareIndex is a measure of
political ideology towards public healthcare, with positive values being indicative of a political climate in favor of using tax revenue for publicly-provided healthcare and negative values indicative of general opposition to this policy. It was constructed using county vote totals on previous state-wide ballot initiatives. I use this as proxy to control for variations in “political demand” or “political pressure” for public health coverage, holding the level of coverage and other demographic factors constant.

*CoChairDem* is a dummy variable equal to 1 if the Chair of the Board of Supervisors in county *i* is a Democrat and equal to 0 if the Chair is a Republican or does not state a party affiliation. *%ChildrenNonCitizen* is a measure of the percent of total children in a county who are not citizens of the United States. If a county is concerned about lack of health insurance among all children, this variable is important because CHKIP is the only practical way to provide public insurance for many non-citizens, because for the most part only documented immigrants on permanent visas who have been in the country for over 5 years are eligible for Medicaid and SCHIP (Kaiser Commission).

*T* contains factors that would directly affect a cost-benefit analysis of providing health insurance to children in each county. These are added in Equation 1C. A utility maximizing voter or politician who is considering a CHKIP program would perform a cost benefit analysis based on the percentage of children who are eligible for the program (meaning the relative number of children who are uninsured, have family incomes below 300% of FPL, and are ineligible for Medicaid and Healthy Families) and the funding available per eligible child. *%TotalChildElig* is an estimate of the percentage of children in a county who would be affected by the program. *AssetsCFCPerEligChild* is the total funding held by the Children and Families Commission in county *i* per CHKIP eligible child. *PrivateRevEligChild* is the annual revenue each county CFC
receives from private sources per eligible child. $LocalRevPerEligChild$ is the county revenue available from local taxes and fees per eligible child.

As I mentioned, since the bulk of operating costs for a county CHKIP come from providing insurance premiums to eligible children, a utility maximizing voter and county supervisor would base the decision to establish CHKIP on the cost/benefit per eligible child. However, there is strong evidence that neither voters nor politicians make such nuanced analysis when taking political action (Congleton 40). Instead, voters may consider CHKIP as a way of achieving full youth insurance rather than the providing healthcare to the target demographic. In other words, it is possible that voters and local politicians in a given California county perceive CHKIP as a solution to the general problem of “kids without health insurance,” rather than the problem of “middle-class kids who are ineligible for MediCal and Healthy Families without insurance.” In order to proxy for this alternate political reality, in Equation 1D I replace the above $T$ variables with measurements that use total children uninsured instead of children eligible for CHKIP. These are $%TotalChildUnis$, $AssetsCFCPerUnisChild$, $PrivateRevCFCUnisChild$, $LocalRevPerUnisChild$. These alternative variables are used in exactly the same fashion as their Equation 1C counterparts.

*Assumptions in Methodology and Limitation of Data*

Of the variables used in this model, demographic and financial factors are easiest to quantify, and are perhaps of greater interest to economists and policy makers. However, it may be that the more difficult measures of political influence are actually the most important in a county’s decision to adopt the program or not.
Like the “ability” factor in labor economics, the “political will” factor is largely unobservable. The best proxy for this is opinion polling data among probable voters immediately preceding a political decision. Unfortunately, I was unable to find such county level poll data for California. My proxy for “political will,” *HealthCareIndex*, is admittedly flawed because it uses election results from two ballot initiatives which are politically different than CHKIP. See Appendix I for further discussion of this variable.

This model treats the passage of the CA Healthy Kids Insurance Act as an exogenous shock to the local health care network in each county. I do not fully control for the fact that county representatives themselves may have lobbied the legislature for policy features that would be advantageous for their particular county. This would introduce an endogeneity problem because county governments with greater political power at the State Capitol in Sacramento would be more likely to join a program they helped design. I believe that *CoChairDem* and *HealthcareIndex* control for part of this self-selection, but detailed analyses of lobbying power, individual political connections and policy preferences are beyond my resources at this time.

The estimate provided by CHIS of the percentage of children in a county who are non-citizens is also problematic. *%ChildrenNonCitizen* was obtained through an interview process, and it is likely that a significant portion of undocumented immigrants would have reservations about revealing the fact that they are in the United States without permission for fear of deportation. This suggests that the measure is biased downward.

Furthermore, there is reason to suspect that the error caused by this bias is heteroskedastic. Consider two counties that have the same estimated percentage of non-citizens, but the populations of non-citizens in each county have different traits. For example, an estimated 8% of children in both Santa Clara County and Imperial County are non-citizens.
Santa Clara County is in the heart of Silicon Valley, and has a high population of relatively wealthy foreign workers in the United States on visas for hi-tech jobs. Imperial County is on the Mexican border and is mostly desert and irrigated farmland. The majority of non-citizens here are likely undocumented immigrant workers from Mexico. When asked about residency status, workers in Santa Clara County may be more willing to report being non-citizens than their counterparts in Imperial County, because they are here legally. If this were the case then the bias would be correlated with certain county traits. I was unable to find county level data that distinguished between non-citizens in such a way.

Although there are issues with my methodology and the data that goes into it, I believe Equation 1 provides a reasonable tool for analyzing the choice of establishing CHKIP by a utility maximizing county government. My model takes into account a wide variety of factors. These include those that might affect “demand” for a program like median family income, political pressure and portion of children uninsured, as well as constraining factors like assets available and portion of children eligible for the program. There are other important factors that should be included, but this represents the best model given data constraints.

Results

Overall, this model does not appear to offer much guidance in determining which factors are most important to a county government in its decision to establish a Healthy Kids program or not. The results from Equations 1A-1D are presented in Table I. The most striking finding is how few of the variables appear to be significant in predicting county choice of CHKIP. None of the A or T variables are even close to significant in any of the regressions. CoChairDem and HealthCareIndex are also not significant predictors. In fact, the marginal effect of HealthCareIndex on county choice appears to be negative, the opposite of what I expected. In
Equation 1C, the marginal effect of a county having an established Children’s Health Initiative, \( \text{Prior CHI} \), appears to be quite large at .504, but is only borderline significant with a P-value of .102. On examining Equations 1A, 1B, and 1D this effect loses its statistical significance.

The variable that stands out among the others is \( \% \text{Children NonCitizen} \). The estimate of \( \pi_4 \) is .130 in Equation 1C and .119 in Equation 1D, with P-Values of .048 and .043 respectively. This coefficient, which can be interpreted as the marginal effect of a one percentage point increase in the portion of children who are non-citizens on the likelihood that a county establishes a CHKIP, is both large and statistically significant at the 5% level. The results from Equation 1C imply, for example, that a one percentage point increase in the fraction of non-citizens in county \( i \) is associated with a .13 increase in the probability that county \( i \) establishes a CHKIP.

**Conclusion**

These results suggest that the most important factor in predicting whether a county will adopt a Healthy Kids Program is the estimated percentage of children who are non-citizens. This may seem strange until one considers that the federal guidelines, on which MediCal and Healthy Families depend, prohibit providing benefits to the children of undocumented residents and most other non-citizens. In contrast, since Healthy Kids is run entirely by the state and local governments of California, counties are prohibited from rejecting applicants based on citizenship status. It appears that county governments take this policy into account when deciding whether to establish a Healthy Kids program or not. This provides reasonable evidence in support of the theory that a large motivation behind the creation of the California Healthy Kids insurance program was to create a mechanism through which the state could provide health insurance to uninsured non-citizen children.
Section II: The Effect of CHKIP on Health Outcomes

The next step in this analysis is to evaluate exactly how effective CHKIP is at increasing health outcomes among residents. It may be the case that we can perfectly predict which counties will create programs and fully understand how much CHKIP will crowd out private insurance, but this information means little without a thorough understanding of how effective the program is at improving health outcomes for children. In this section I measure the effect of CHKIP on several measures of health outcomes.

Literature Review on Health Outcomes

The causal relationship between health insurance and actual health outcomes is still uncertain. Increased levels of health insurance, whether in quantity or quality, does not imply that health outcomes will necessarily improve. With children, it may be the case that demand for treatment is so inelastic that the only time parents avoid treatment is when they literally cannot come up with the funds to pay for it. Under this conception of health markets, insurance does not buy better health outcomes, but rather peace of mind and protection from financial ruin.

Despite this, there is a large body of evidence to suggest that higher coverage rates among children probably do lead to better health outcomes. Lurie (1986) finds that those without insurance, controlling for other factors, are significantly more likely to develop cardio-vascular problems than those with health insurance. Curie and Gruber (1996) find that children who have insurance are %5.7 more likely to visit a hospital, and %2.7 more likely to see a doctor than those who are uninsured, although again this is a measure of healthcare utilization rather than an actual health outcome.
In a stronger case for the health benefits of insurance coverage, Stoddard, St. Peter and Newacheck (1994) find that uninsured children are 72% more likely than insured children to receive no care for pharyngitis; 11% more likely to receive no care for an acute earache; 72% more likely to receive no care for recurrent ear infections; and 87% more likely to receive no care for asthma.

Evidence on the effectiveness of local children’s insurance programs is scarce, but there are two studies that suggest they can be helpful. Lave, Keane and Lin, et. al (1998) find that previously uninsured children who we enrolled in a Pennsylvania local health initiative for at least 6 months were 3.1 percentage points less likely than their uninsured counterparts to have an unmet health need. Specifically regarding the efficacy of a Children’s Health Initiative (a locally funded predecessor to CHKIP), Cohen (2005) finds that expansions in youth coverage directly attributable to the Los Angeles CHI reduced the number of children with unmet medical needs by 18 percentage points. The literature, as limited as it is, suggests that increasing insurance rates among children seems to increase health outcomes by removing barriers to access to care. In the rest of this section I will test the effect CHKIP on coverage rates, self-reported health status and delays in medical care.

**Health Outcome Results**

As I mentioned above, CHKIP has two main goals. The first aim is to offer public health insurance coverage to children in “Expansion Range” families who are not eligible for coverage under Medicaid and/or SCHIP. The secondary goal is to increase take-up rates of families who are eligible for Medicaid or SCHIP but have not yet enrolled, as well as promoting “health and health insurance awareness, education and information,” (%100 Campaign). This means we must
examine outcomes among all “Broad Target” children in families with incomes less than %300 of the FPL, as well as the “Expansion Range” outcomes.

The first way to judge this program is by estimating the effect of a CHKIP program on the percentage of children in the expansion range who have some kind of health insurance. Since there were no state funded CHKIP programs in 2005 and all county CHKIPs were fully operational by 2007, I can compare the change in children insurance rates controlling for changes in other factors. In Equation 2, I regress the change in the percentage of Expansion Range children who were covered by some kind of insurance on the change in Median Income, the change in employment among households in the Expansion Range, change in demographic characteristics such as ethnicity in county $i$, the change in employment among parents in the expansion range, and on a binary variable equal to 1 if a county established a CHKIP program and equal to 0 otherwise.$^2$

(Equation 2)

$$\Delta \%\text{ChildInsuredIER}_i = \alpha + \beta_1 \Delta \text{MedInc}_i + \beta_2 \Delta \text{CHKIP}_i + \beta_3 \Delta \%\text{EmpIER}_i + \beta \Delta \%X_i + \epsilon_i$$

If a Healthy Kids program actually caused an increase in health insurance coverage for children in the expansion range, I would expect a positive estimate for $\beta_2$, which would be interpreted as the estimated percentage point increase in insurance rates among children in the Expansion Range caused by the creation of a CHKIP program.

$^2$ In this regression, as with all following regressions that measure changes over time, the constant $\alpha$ represents the baseline change in the dependent variable when all other variables take values of 0. In this particular regression, we could interpret this as the “natural” change in insurance rates among children due to a time trend. I would expect $\alpha$ to be statistically insignificant in most regressions in this paper.
The results from this regression are presented in Table II. Estimated co-efficients are listed first with standard errors in parentheses and P-values listed on bottom. None of the variables are statistically significant. In particular the coefficient on CHKIP is only .389 with a Standard Error of 5.444. This is probably due to the low number of observations in the CHIS data when I restrict the population to children who fall within the relatively narrow Expansion Range.

The results change when we expand the population to the “Broad Target” range of children from families who earn less than %300 of the FPL. In Equation 3, I run a similar regression to Equation 2, but expand the population size from families in the expansion range to all families earning less than 300% of the FPL. In this regression, $\beta_2$ is interpreted as the estimated percentage point increase in the insurance coverage rates of children in the Broad Target population caused by the establishment of a CHKIP program in county $i$.

(Equation 3)

$$\Delta \% \text{ ChildInsured}<300\text{FPL}_i = \alpha + \beta_1 \Delta \text{ MedInc}_i + \beta_2 \Delta \text{ CHKIP}_i + \beta_3 \Delta \% \text{ Emp}<300\text{FPL}_i + \beta \Delta \% X_i + \epsilon_i$$

As we can see in Table II, the co-efficient on $\Delta \text{ CHKIP}_i$ is 5.99 and is statistically significant with a p-value of approximately .05. This implies that if any given county establishes a CHKIP program we could expect a 5.99 percentage point increase in the fraction of insured children in families earning less than %300 of the FPL. Given that most California counties already have relatively high children coverage rates (the average value of $\% \text{ ChildInsured}<300\text{FPL}_i$ in 2005 was 90.39), this represents a significant step towards universal health coverage for children. Given that none of the other variables are significant, this is evidence that in the short-term (year to year) analysis, establishing a CHKIP program is likely
the most effective method of increasing health insurance coverage for all children at the middle to lower range of the income distribution.

However, it may be the case that policy makers feel that children lack direct access to care, and are thus more concerned with actually increasing healthcare utilization and outcomes rather than simply increasing insurance coverage. In fact, one of the stated goals of the Healthy Kids Program is to, “increase participation with local health providers,” among parents of young children (100 Percent Campaign).

In Equation 4, I regress the percentage change in children among the Broad Target group who made any kind of visit to a health care worker in the preceding 12 months on the same change in regressors from Equations 2 and 3. Although one might assume that nearly all children receive at least an annual checkup, in 2005 %14.8 of children in the Broad Target group had not seen a doctor or nurse practitioner in the previous 12 months. In this regression, the co-efficient on $\Delta \text{CHKIP}_i$ can be interpreted as the percentage point increase in the fraction of Broad Target group children who have seen a health care professional in the previous year that is associated with the creation of a CHKIP in county $i$.

(Equation 4)

$$\Delta \% \text{VisitHealthWorker}<300\text{FPL}_i = \alpha + \beta_1 \Delta \text{MedInc}_i + \beta_2 \Delta \text{CHKIP}_i + \beta_3 \Delta\%\text{Emp}<300\text{FPL}_i + \beta \Delta\%X_i + \varepsilon_i$$

This co-efficient is also relatively large and statistically significant, with a value of 7.645 and a P-value of 0.053. This suggests that the creation of a CHKIP program, holding all else constant, leads to a 7.645 percentage point increase in the percentage of children who receive professional medical attention at least once a year, among families in the Broad Target
group. Interestingly, the percentage of children in this group who see physicians at least once a year does not seem to vary with income, race, or employment status. This suggests that the largest factor in increasing rates of health care utilization among lower children might be community outreach, one of the central focuses of the CHKIP structure.

Another metric we can use for judging the effectiveness of CHKIP is a patient’s own reported health outcomes. Although by no means comprehensive or medically rigorous, self-reporting does give us a glimpse into changes in a community’s perception of its health quality, which could be interpreted as a proxy for actual quality improvements as well as a measurement of changes in health knowledge. For example, a CHKIP might educate families on the health risks of eating certain foods or smoking, which might actually make respondents consider themselves to be in worse health than before, even though they are now better informed.

In Equation 5 I regress the percentage of children in the Broad Target range who describe themselves as being in good health on the same regressors as Equation 4. Specifically, it is the percentage of respondents who say their health is “Excellent,” “Very Good” or “Good.” Parents gave their evaluation for children 5 and under, while children 6 and older were interviewed if available. The co-efficient $\beta_2$ estimates the percentage point change in the fraction of Broad Target group children who respond that they are in good health that is caused by the establishment of a CHKIP program in county $i$. 
\( \Delta \% \text{SelfEval}^{<300FPL}_{i} = \alpha + \beta_1 \Delta \text{MedInc}_i + \beta_2 \Delta \text{CHKIP}_i + \beta_3 \Delta \%\text{Emp}^{<300FPL}_{i} + \beta \Delta \%X_i + \varepsilon_i \)

Unlike previous regressions, the co-efficient on \( \Delta \% \text{MedInc}_i \) (the percentage point change in the median income in county \( i \) between 2005 and 2007) is statistically significant in this regression. The co-efficient is .0016625 with a P-value of 0.055, meaning that an increase of $1000 in the median income of county \( i \) is associated with a 1.6 percentage point increase in the percentage of children who report good health. There are several ways we could interpret this.

First, it could be that increasing incomes actually do lead to better outcomes for children, as higher incomes might allow families to eat better diets, engage in more leisure time and purchase more/better medical care. It could also be that wealthier populations tend to think of themselves as being in better health, even if by objective standards they are not. Finally, it could be the case that counties with high median incomes also tend to have better existing public health infrastructures, and that increases in individuals’ family wealth do not directly impact self-perception of health; high family incomes are simply correlated with a certain type of county infrastructure such as proximity to hospitals or local sanitation codes. The true cause of the increase in perceived health could be any one of these issues, or a combination thereof.

The co-efficient on \( \Delta \text{CHKIP}_i \) is again relatively large and statistically significant, with a value of 9.463 and a P-Value of 0.043. This suggests that establishment of a CHKIP program in county \( i \) is associated with a 9.463 percentage point increase in the fraction of children in the Broad Target group who report being in good health. Again, because this is a subjective measure and I do not have individual data, there are several ways we could interpret this finding. The straightforward explanation is that the establishment of a CHKIP program actually increases
health insurance coverage and utilization rates (evidence for which I’ve shown already) and that people perceive a real increase in their health due to these increases.

An equally likely explanation is that simply knowing that there is an active community health care organization leads people to believe they live in a healthy community, and that they themselves are in relatively good health, even if their objective health outcomes did not actually increase. In other words, it could be the case that community health makes a person feel healthy, holding their objective measurements of health constant. Lastly, there could be an omitted variable that is correlated with perceptions of health and the decision of a community to enact a CHKIP program. However, this is unlikely because as I pointed out in Table I, political, cultural and fiscal attitudes towards health care do a poor job of predicting which counties will choose to establish CHKIP programs. Again, the true explanation for the co-efficient on this variable could be any one of these explanations, or any combination thereof.

The point remains that counties that establish CHKIP programs do tend to experience an increase in the level of health reported by their own children. In simpler terms, more children tend to feel healthier after a CHKIP is established in a community. This claim is made stronger by the fact that Equation 5 measures an annual change, which means that any county level fixed effects would cancel out, so a bias inducing omitted variable would have to vary across time as well as individual counties.

The final set of health outcomes I measure are delays in receiving medical care. In Equation 6 and Equation 7 the dependent variable is the change in the percentage of children who had to delay medical care for a week or more, regardless of the reason for the delay. In Equation 6 the population is restricted to children in the Expansion Range and in Equation 7 it is
the Broad Target population. In each equation, the co-efficient on $\Delta \text{CHKIP}_i$ can be interpreted as the percentage point change in the fraction of children who had to delay medical attention associated with the creation of a CHKIP program in county $i$. This co-efficient should provide a rough estimate of CHKIP’s effectiveness at “increasing preventative care and expanding treatment for critical childhood issues that have lasting consequences,” (Udrys).

*(Equation 6)*

$$\Delta \% \text{DelayCareIER}_i = \alpha + \beta_1 \Delta \text{MedInc}_i + \beta_2 \Delta \text{CHKIP}_i + \beta_3 \Delta \%\text{EmpIER}_i + \beta \Delta \%X_i + \varepsilon_i$$

*(Equation 7)*

$$\Delta \% \text{DelayCare<300FPL}_i = \alpha + \beta_1 \Delta \text{MedInc}_i + \beta_2 \Delta \text{CHKIP}_i + \beta_3 \Delta \%\text{Emp<300FPL}_i + \beta \Delta \%X_i + \varepsilon_i$$

Among children in the Expansion Range (Eq. 6), CHKIP does not seem to have an effect on the delay of care. However, the percentage change in employment among households in the Expansion Range population does seem to lead to a decrease in the percentage of children who had to delay medical care. The estimated co-efficient on $\Delta \%\text{EmpIER}_i$ is -.0933 with a P-Value of 0.025, indicating that a one percentage point increase in employment among Expansion Range households is associated with a decrease of .09 percentage points in the fraction of children who are forced to delay medical care for more than a week in county $i$. This suggests that one of the main reasons children might be forced to delay important medical care is loss of insurance caused by unemployment, which is supported by findings in Dooley, Fielding and Levi (1996). I find a similar effect on $\Delta \%\text{Emp<300FPL}_i$ in Equation 7 among children in the Broad Target group, although the effect is an order of magnitude smaller at -.0039 with a P-value of .015.
CHKIP does seem to have an effect on delayed care among the Broad Target group. In Equation 7 I estimate $\beta_2$ as -.0680128, which is highly significant with a P-value of less than .01. We can interpret this to mean that establishing a CHKIP program in county $i$ is associated with a decrease of .068 percentage points in the fraction of children in the Broad Target group who had to delay important medical care for more than a week. This represents a significant decrease in what most would consider a vital area of children’s health. The coefficient on $\Delta \% \text{MedInc}_i$ is also significant, meaning that a $1000 increase in Median Income in county $i$ is associated with a 1.7 percentage point decrease in the fraction of children in the Broad Target Group who had to delay care.

**Conclusions on Child Health Outcomes**

Overall, the California Healthy Kids Insurance Program does seem to positively impact several measures of health outcomes for children, although it seems to have little or no effect on the population at which it was specifically targeted, the uninsured children in the Expansion Range between %250 and %300 of the FPL. Equation 2 showed that CHKIP has no statistically significant effect on coverage rates for children in Expansion Range either. However, Equation 3 shows that CHKIP likely does increase overall health insurance coverage rates for Broad Target children. This suggests that the “Medicaid take-up,” “community outreach” and “awareness” efforts of CHKIP are the most effective aspects of the program, rather than the efforts to offer publicly funded health insurance to higher income ranges.

The results from Equation 4 suggest that CHKIP has a significant impact on the likelihood that poorer children will see a doctor over the course of a year, possibly preventing many more complicating health problems later in life. Equation 5 suggests that the presence of a local CHKIP makes a significant portion of children in the Broader Target range feel better about
their health, even though this may be due to reasons other than direct healthcare provision and disease prevention. Finally, Equation 7 suggests that a CHKIP program, along with rising incomes and employment, decreases the proportion of children who delay medical care for significant health issues.

Although it may be possible to offer alternative explanations for each result, some of which I have pointed out, when all of these results are considered together it seems very likely that CHKIP has real, positive impacts on the health outcomes of children in California. Rather than conducting a full fiscal cost benefit analysis, what I have intended to do here is simply show that the programs are having positive effects, even if they seem to be missing the main objective of increasing coverage rates among the children in the Expansion Range.
Section III: Measuring Crowd Out

Crowd out of private health insurance is a vexing issue for policy makers. Quite simply it means that the government may invest large sums of money and resources with little to no improvement in child insurance rates. The crowd out rate associated with CHKIP is especially important to understand because it is a vital factor in predicting the future fiscal health of the program and its effect on local health care markets.

Literature Review on Crowding Out

The seminal paper on this topic is “Does Public Insurance Crowd Out Private Insurance?” by Cutler and Gruber (1996). In this paper the authors propose a theoretical framework similar to the one pictured in Figure C. Individuals A, B and C all make decisions about how much health insurance (measured on the horizontal axis) to purchase given their incomes and consumption of all other goods, which is measured on the vertical axis. Suppose the state offers M units of health coverage for free. Many policy makers design their policies for individuals like A and C. C is uninsured because coverage is relatively expensive for him, represented by the steeper budget constraint, which could possibly be due to a pre-existing medical condition. C also enjoys consumption much more than insurance coverage, so he is uninsured and spends all of his income on F amount of goods. Once the state makes it’s offer, C is now able to enjoy M units and continue consuming other goods at level F. Individual A places a high value on personal health insurance, and so he continues to purchase D units of coverage even after the government offers M units free of charge because he desires a greater quantity of insurance.

The problem is that most public programs have no mechanism for controlling the enrollment of individual B, who places a relatively low value on health insurance and therefore
consumes E units. By dropping all E units of privately purchased coverage and enrolling in the
public program, B can maximize utility by consuming F units of other goods, while enjoying M
units of coverage at the taxpayer’s expense. Thus even though policy makers might claim that a
new public insurance program like CHKIP is increasing the number of insured because of high
enrollment, many parents may simply be dropping private coverage for their child and enrolling
him in CHKIP, freeing up extra income to consume other goods.

Using individual level data from the March supplement of the CPS, Cutler and Gruber
use the changing eligibility requirements for children in the 1980s and 1990s to compare the
change in incidence of private insurance in states that increased eligibility in a given year with
those that did not. They find a crowd out rate of roughly %50, meaning that for every 2
individuals who enrolled in Medicaid after the expansion, one gave up some sort of private
health insurance.

While Cutler and Gruber (1996) show very convincing results, it could be the case that
crowd out rates among children are different since their parents make healthcare decisions for
them. Lo Sasso and Buchmueller (2004) focus on the SCHIP expansion on children using
individual level data and again find crowd out rates of approximately %50. They also find that
anti-crowd out clauses in certain state statutes are fairly effective, although they negatively
impact take up rates as well.

Yazici and Kaestner (2000) use longitudinal individual data to estimate crowding out
among children due to Medicaid expansion over a period of several years, on the hypothesis that
consumers may not react immediately to eligibility shifts, but are more likely to become aware of
them over a longer course of time as information becomes more available. They find a crowd out
rate of %14.5, significantly below other estimates at the time.
Ham and Shore-Sheppard (2005) use a Linear Probability model and a Two-Stage Least Squares method to estimate crowd out rates using SIPP data immediately following an SCHIP expansion. They find no evidence of crowding out, but do find that take up rates increase when those immediately surrounding a child are also eligible.

Perhaps the paper that is most applicable to CHKIP expansion is Card and Shore-Sheppard (2004), in which the authors use a regression discontinuity to compare insurance coverage of children who just missed being eligible for public insurance to children who barely qualified. They find little to no evidence of crowding out. Although more recent figures such as these tend to be lower, Gruber and Simon (2007) conduct a meta-analysis of the topic in order to clarify the issue 10 years after Cutler and Gruber (1996). They come up with a result of %60, even larger than the 1996 estimate, even while using methods used by those who estimate low levels of crowd out.

Finally it should be noted that public insurance may also crowd out the supply of private insurance, as opposed to the level demanded by consumers. If firms understand that some of their employees could qualify for new expansions in public health insurance, they might drop coverage in order to control costs, at least in the short run. Shore-Sheppard, Buchmueller and Jensen (2000) use firm and individual data to estimate the change in benefits offered by employers after expansions in Medicaid income eligibility thresholds. They find no evidence that firms reduce their offers of health care benefits because of expansions in public insurance.

**Crowd Out Results**

The main difference between my analysis and those of the above authors is that I do not have access to individual data that would allow me to measure individual decisions to drop
private coverage and substitute with CHKIP. Instead, I use methods similar to my previous regressions and estimate the effect of CHKIP on the change in Private Insurance rates of children between 2005 and 2007. My general strategy is to identify any change in private insurance that can be econometrically attributed to the establishment of a Healthy Kids program.

A statistically significant negative coefficient on the CHKIP variable would indicate that establishing a CHKIP program in a county decreases the percentage of children covered by private insurance. In Equation 8 I regress the change in the fraction of children in the Expansion Range who are covered by private insurance (either provided by the parent’s employer or purchased privately by the parents themselves) on the change in Median Income, percentage change in employment among adults in the Expansion Range, the percentage change in demographic information and a binary variable equal to 1 if county $i$ established a CHKIP by 2007.

(Equation 8)

$$\Delta \% \text{PrivateInsIER}_i = \alpha + \beta_1 \Delta \text{MedInc}_i + \beta_2 \Delta \text{CHKIP}_i + \beta_3 \Delta\%\text{EmpIER}_i + \beta \Delta\%X_i + \epsilon_i$$

As with previous regressions that limited the population to the Expansion Range, neither change in Median Income, percentage changes in demographic factors or establishment of CHKIP have any significant effect on the change in percentage of children with private insurance. However, the co-efficient of .447 on $\Delta\%\text{EmpIER}_i$ is significant with a P-value of .012, implying that a one percentage point change in the employment rate among adults in the Expansion Range is associated with a .447 percent increase in the fraction of children who are covered by private health insurance. This result is largely anticipated, as we would expect that as
more workers are hired more family members will be covered by employer-provided health benefits.

What this regression also shows is that at the county level, very few, if any, parents who earn between %250 and %300 of the FPL are substituting CHKIP for their employers’ health plans or their own family plans. If anything, the existence of CHKIP in Equation 8 seems to encourage enrollment in private coverage, possibly by raising awareness of the benefits of having insurance.

Like my previous strategy in estimating the health outcome effects of CHKIP, I run a similar regression but expand the population to all children in the Broad Target group. Again, a statistically significant negative co-efficient on $\Delta \text{CHKIP}_i$ would indicate that CHKIP is crowding out private provision of health insurance, while a statistically significant positive co-efficient would indicate that CHKIP some how encourages parents to obtain private health insurance for their children, possibly by raising awareness of the risks of remaining uninsured.

(Equation 9)

$\Delta \% \text{PrivateIns}<300\text{FPL}_i = \alpha + \beta_1 \Delta \text{MedInc}_i + \beta_2 \Delta \text{CHKIP}_i + \beta_3 \Delta \%\text{Emp}<300\text{FPL}_i$ 

$+ \beta \Delta \%X_i + \varepsilon_i$

As in Equation 8, percentage changes in employment appear to have the largest effect, with increasing levels of employment having a statistically significant positive effect on the percentage of children in the Broad Target group covered by private insurance.

Most importantly, it does seem that among the Broad Target group, CHKIP has a small but statistically significant crowd out effect in private health insurance coverage. The co-efficient on $\Delta \text{CHKIP}_i$ is -1.92998 with a P-Value of 0.042, which implies that establishing a CHKIP program, holding other factors constant, leads to an estimated 1.929 percentage point decrease in
the fraction of children who are covered by private insurance. It is important to note that this metric is not similar to those used by Cutler and Gruber (1996), Ham and Shore-Sheppard (2001), Yazici and Kaestner (1998) or any of the other authors reviewed thus far. As previously mentioned, nearly all other studies have used individual data, and were therefore able to come up with a “crowd out rate,” or the percentage of people enrolling in public insurance who were substituting for private insurance. The metric I have found is simply the estimated percentage decrease in private insurance caused by the introduction of CHKIP.

However, this metric is still useful. Even though CHIS does not provide direct data on the percentage of children enrolled in Healthy Kids, since Equation 3 showed that CHKIP had a positive effect on overall insurance rates, we can infer that much of the decrease in private coverage is transferred to public coverage. This represents direct evidence that CHKIP does in fact crowd out private health care provision, even though I cannot estimate the percentage of the children who leave private insurance and then enroll directly into CHKIP.

Finally, I test the crowd out effect of CHKIP on the supply of private insurance offered by employers. CHIS provides very limited data on firm resources, so unfortunately I cannot include variables for changes in the cost of supplying healthcare. However, CHIS does provide estimates of the percentage of citizens who were eligible for benefits from their employer. In Equation 10 I regress the change in the percent of children in the Broad Target group eligible for employer provided health insurance on the change in Median Income, percent change in demographic traits, the percentage change in employment and a binary variable representing the establishment of CHKIP. It is important to stress that the dependent variable in this case is the change in the percentage of children *eligible* for employer provided health benefits, not the percentage who
actually received benefits. This allows for a more accurate picture by isolating firms’ decisions, rather than allowing “noise” caused by parents who are eligible for benefits but for some reason do not accept them. As mentioned at the beginning of Part IV, it might be the case that in order to control costs firms may cut benefits to workers who they knew were eligible for public insurance. This also represents a crowd out of insurance on the firm’s side, and would be revealed by a statistically significant negative co-efficient on $\Delta CHKIP_i$. This would be interpreted as the estimated percentage point decrease in benefits offered by an employer caused by the establishment of CHKIP in county $i$.

\[(Equation\ 10)\]

$$\Delta \% \ ChildEligBenefits<300FPL_i = \alpha + \beta_1 \Delta MedInc_i + \beta_2 \Delta CHKIP_i +$$

$$\beta_3 \Delta %Emp<300FPL_i + \beta \Delta %X_i + \varepsilon_i$$

As the regression results show, I find no significant effect of CHKIP on the provision of health insurance for dependents by employers. The percentage change in employment has a large and statistically significant effect on the percentage change in children eligible for benefits, which we should expect because an increase in employment among adults most likely leads to an increase in the percentage of children who have access to employer provided care. Still, the most important part of this regression is that it suggests that CHKIP does not crowd out employer provision of health benefits. This is important because it suggests that at the respective income eligibility thresholds and economic conditions, few to no workers lose employer provided health benefits due to CHKIP, a major concern of many policy makers.
The Endogeneity Problem

As with nearly every paper that estimates issues of crowding out, there is the problem of endogeneity in measuring the percentage change in private health insurance. Basically, this presents a problem for the estimate of crowding out from Equation 9. It could be the case that no families with private health insurance actually substitute for public health insurance, but instead that families who lack health insurance for their children move to counties with a CHKIP, so that the change in the percentage of children with private health insurance appears to decrease even though no one has actually substituted coverage.

The traditional way of dealing with this issue would be an instrumental variable. This would be a factor that is correlated with the percentage of people with health insurance but uncorrelated with the individual decision to move to a county with a CHKIP program. Again, since I do not have individual data, I cannot proxy for a factor among families that is exogenous to their decision to change counties for a CHKIP program. Instead I will use a more basic, method to present evidence that endogeneity does not significantly threaten my estimate for crowding out.

Endogeneity biases the accuracy of this estimate when people move between counties, changing populations that I am basically treating as static. This means that for the endogeneity to cause a problem two conditions must be met. First, a county must establish a CHKIP, because it is the variable from which I get the co-efficient in question. Second, the population that is treated by CHKIP, namely children in the Broad Target group who live in families earning less than 300% of the FPL, must change by a significant amount in order to bias my estimate for the percentage of the population that substitutes private insurance for public insurance.
In Table IV I list all of the counties in California with a CHKIP, besides Colusa, which as previously mentioned was dropped from consideration. I then list the percentage of children in each county that are in the Broad Target range for 2007 and 2005, along with the Standard Error for each year in parenthesis. I treat each county observation in 2005 as an estimate for the true value of the proportion of children in the Broad Target Group in 2005. With a large number of observations, these 2005 county estimates are distributed approximately normally, and thus I can conduct a Differences in Proportions test, where \( H_0 : \%<300FPL_{07} = \%<300FPL_{05} \) and \( H_A : \%<300FPL_{07} \neq \%<300FPL_{05} \). The results from these tests are shown in the last column of Table IV.

As the table shows, among counties that established CHKIP programs, the estimated percentage of children in the Broad Target range actually appeared to decrease from 2005 to 2007, although only 2 of these results are statistically significant. Of the few that did appear to increase, only Merced county, denoted with ***, experienced a statistically significant increase in the percentage of children from families who earn less than \%300 of the FPL. So, judging by simple summary statistics and difference in means test, it does not appear that any county besides Merced saw a statistically significant increase in its Broad Target population.

I use a slightly more sophisticated method in Equation 11. In this model, I regress the percentage change in the fraction of children who are in the Broad Target range on change in Median Income, percentage change in demographic factors, percentage change in employment among Broad Target range households and a binary variable representing the creation of CHKIP. The co-efficient on \( \Delta CHKIP_i \) can be interpreted as the estimated percentage point change in the fraction of children who belong to the Broad Target group caused by the creation of a CHKIP in county \( i \). In other words, if uninsured families in the Broad Target group really are “voting with
their feet” by moving into counties with a CHKIP in order to get health insurance, then we would expect a positive and statistically significant co-efficient on $\Delta CHKIP_i$.

(Equation 11)

$$\Delta \% Child<300FPL_i = \alpha + \beta_1 \Delta MedInc_i + \beta_2 \Delta CHKIP_i + \beta_3 \Delta % Emp<300FPL_i + \beta \Delta \% X_i + \epsilon_i$$

As we can see in the last column of Table II, not only is the co-efficient on $\Delta CHKIP_i$ not statistically significant, but it is negative. This means that, if anything, families in the Broad Target group are actually moving away from counties that establish a CHKIP program.

What this all means is that there is absolutely no evidence that families in the Broad Target range are attracted towards counties with CHKIP programs, which is a necessary condition for endogeneity to be an issue. The need for Instrumental Variables and other complex methods of dealing with endogeneity arise from the fact that we usually do not study static populations. However, because a child must live in a county to enroll in a program and there is evidence that the income demographics of nearly all counties changed very little between 2005 and 2007, it is unlikely that my estimate for the crowd out effect of CHKIP among children in the Broad Target range is biased by endogeneity.

Conclusions

I have tried to show fours things in Section IV. First I presented evidence that there was little or no effect of CHKIP on the private insurance coverage rates among children in the Expansion Range, as shown in Equation 8. Next I presented evidence that CHKIP does seem to crowd out Private insurance rates of children in the Broad Target group. The estimate is that a county which establishes a CHKIP program can expect a 1.92 percentage point decrease in the
fraction of children covered by private insurance in the Broad Target group. I also showed that although the overall fraction covered by private health insurance decreased, firms do not decrease their offers of health benefits to children in the Broad Target group after the establishment of CHKIP. Finally, I presented evidence that the problem of endogeneity and self-selection into counties probably does not threaten the estimate in Equation 9, at least not in 2007.
Section V: Findings, Policy Implications, Suggestions for Future Research and Closing Remarks

In this paper I have attempted to give a comprehensive evaluation of the economic effects of the California Healthy Kids Insurance Program. CHKIP was started in 2006 and fully established in 26 counties by 2007. In addition to community healthcare outreach, it allows locally run health initiatives to apply for state reimbursement of funds used in providing health insurance to children in the “Expansion Range” of families earning between %250 and %300 of the Federal Poverty Level, provided that they adhere to certain conditions.

One of these conditions is that CHKIP representatives refrain from inquiring about an applicant’s citizenship status. Many people involved in the legislative process of CHKIP viewed the program as being at least partially designed to provide public insurance for undocumented children and other non-citizens without insurance who are prohibited from receiving federal funding. In fact, the percentage of a county that is made up of non-citizens is the only variable that significantly increases the probability that a county establishes a Healthy Kids Program. From a political economy perspective, this suggests that voters are much more attentive to perceived social issues than fiscal considerations when voting for local healthcare projects.

I then conducted several examinations of how CHKIP impacts health outcomes of children. I find that establishing a CHKIP program in a county has little effect on the insurance rates of children in the “Expansion Range,” but it does increase the overall coverage rates of children who have household incomes less than %300 of the FPL. Although insurance coverage is not an actual health outcome, the literature suggests that children with insurance experience better health outcomes than uninsured children.
In a related area, I find that establishment of a CHKIP also significantly increases self-reported health outcomes and significantly decreases the proportion of a county’s children who delay needed medical care. Though none of these statistics are empirical “homeruns,” they do support the claim that local CA Healthy Kids programs increase child health outcomes.

Lastly, I attempt to measure the extent to which establishment of a CHKIP crowds out the private insurance in a county. Although I do not find evidence of crowding out where I would most expect it, among the “Expansion Range” population, I do find evidence that CHKIP has a small crowd out effect on the fraction of children in the “Broad Target” range who are covered by private insurance. I also showed significant circumstantial evidence that this effect was not biased by endogenous movement of families into counties with CHKIP programs. I also presented evidence that firms do not decrease health benefits offered in response to expansion of public health insurance income eligibility thresholds. This is consistent with findings by Shore-Sheppard and Buchmueller (2000).

**Policy Implications**

There are several implications this research has for policy makers, especially those in California. The first is that community take-up rates, just like individual take up rates, can be lower than anticipated and might not be affected by the “right” reasons. As Section II implies, California residents are more likely to establish a local health awareness program based on the citizenship status of their neighbors than based on the actual percentage of kids without insurance. In a similar manner, fiscal ability and/or need often do not impact the decisions of voters when faced with public healthcare decisions.

The results from Section III suggest that policy makers should not expect local health initiatives to significantly increase coverage rates among children who are just above existing
eligibility thresholds for Medicaid and SCHIP, but they can expect a locally based children’s health program to increase overall insurance rates and health care utilization by lower income children. This suggests that the “community outreach” and “awareness” missions of CHKIP are more effective than the expansion of eligibility thresholds for public insurance, although further research into this area is definitely needed. Of course, more research is needed to evaluate whether these implications change over a longer course of time.

Finally, Section IV suggests that establishing a local health program and expanding eligibility will probably not crowd out large amounts of private insurance, but local policy makers should be prepared for a small percentage of those children who apply for the program to be substituting public insurance for private coverage. Perhaps more importantly, Section IV suggests that policy makers can be confident that expanding provision of public insurance will not cause employers to slash health benefits for workers, nor will it lead to a large influx of uninsured citizens from other counties, at least in the short term. Politicians, policy makers, government administrators and voters should at least take these findings into consideration before taking significant action on these issues.

**Suggestions for Future Research**

There are many opportunities for expansive research in all of these areas. First, although there is a vast literature in Political Science and Political Economics on the dynamics between the National government and the states, we need more work on take-up rates of communities, as opposed to individuals, as well as research on policy interactions between the states and local governments. Several interesting topics just in the realm of healthcare might include the following questions. Which lead to better health outcomes, programs run by state governments or local governments? Which increases take-up rates of public services more, top-down
advertising by the state government or grass roots organizing by local governments? Do local ordinances regarding health care that differ from state policy have an effect on health outcomes of local citizens? Do high differentials in health outcomes among neighboring counties induce people to “vote with their feet?”

More research is needed into the long term health outcome effects of the CHKIP program on children. This would require panel data, but could likely be done using county level observations and using counties without CHKIP programs as controls. Finally, there is much work that can be done to improve the local measures of crowding out. What percentage of enrollees in CHKIP are giving up private insurance, especially over a span of several years? Do crowd out rates increase as insurance is offered to higher ranges of the income distribution? What is the effect of reputation community effects on crowding out? In other words, are people less likely to substitute public insurance for private insurance if the source of their funding is local, and they are more likely to know the administrators? A more general way of asking this question might be: “Holding all benefits, eligibility thresholds and other program details constant, is there a significant difference in crowd out rates between local, state and/or federally administered programs?” Finally, we need more research at the firm level that explains why firms do not choose to cut coverage when eligibility limits increase or, if firms do cut benefits, why they do so and under which conditions. All of these areas could be undertaken in the near future and would provide vital knowledge of policy makers and economists.

**Concluding Remarks**

The best way to estimate the questions I posed in Sections III and IV would clearly have been to use individual level data. However, to quote Prof. Jonathon Meer of Texas A&M, “you
go to war with the data you have, not the data you want,” and I feel that the data at the county level are sufficient to answer some basic questions about the effect of CHKIP in California, as well as provide some insight into which parts of CHKIP are effective and which are not.

I have attempted to look at the California Healthy Kids Program from three different angles. My finding that citizenship status is the most important factor in establishment of a program most likely has significant implications for the future of public finance in the State of California. It also seems that CHKIP does have large, positive impacts on poorer children in the counties where it exists. Lastly, I find that though small, there is a crowd out effect caused by public provision of health insurance and local organizing designed to increase take up rates. It is important for policy makers to consider these findings as California and the rest of the county continue the policy debate over public vs. private health care.
Counties With CHKIP:
- Alameda
- Colusa
- El Dorado
- Fresno
- Kern
- Kings
- Los Angeles
- Merced
- Napa
- Orange
- Placer
- Riverside
- Sacramento
- San Bernardino
- San Francisco
- San Joaquin
- San Luis Obispo
- San Mateo
- Santa Barbara
- Santa Clara
- Santa Cruz
- Solano
- Sonoma
- Tulare
- Yolo
- Yuba

Counties Without CHKIP:
- Alpine
- Amador
- Butte
- Calaveras
- Contra Costa
- Del Norte
- Humboldt
- Imperial
- Inyo
- Lake
- Lassen
- Madera
- Marin
- Mariposa
- Mendocino
- Modoc
- Mono
- Monterey
- Nevada
- Plumas
- San Benito
- San Diego
- Sierra
- Shasta
- Stanislaus
- Sutter
- Siskiyou,
- Trinity
- Tuolumne
- Ventura

Figure A
Proposed California Healthy Kids Insurance Program (SB 437/AB 772)

**Legend**
- Path
- Process
- Significant Issue
- Program Integration Issue
- Company/Health
- Gap in Coverage
- Child has Health Coverage
- Directed to another map

**Doors to Health Coverage**
- Certified Application Assistors (CAAs)*
- Community-Based Orgs.
- Schools
- Food Stamps
- Women, Infants and Children (WIC)
- County Offices
- State/Single Point of Entry

**Doors to Renewal**
- Family is sent pre-populated renewal form.

**End of Renewal**
- Family phone in renewal information or return renewal form?
- Child still eligible for CHK?

**End of Process**
- Applicant denied due to age, other health insurance or no longer in California.
- Case is forwarded to CHK for follow-up and eligibility determination.

**End of Process**
- Did family pay premium?

**End of Process**
- Healthy Families Program will follow up.

**End of Process**
- Enrolled in Healthy Families; Family sent health card and billing statement.

**End of Process**
- Enrolled in Medi-Cal; Family sent health card.

**End of Process**
- Coverage continues.

**End of Process**
- If still no, then
- GAP

**End of Process**
- Did family pay premium?

**End of Process**
- Healthy Families Program will follow up.

**End of Process**
- Enrolled in Healthy Families; Family sent health card and billing statement.

Developed by The Children’s Partnership for the 100 Percent Campaign

August 2005

*Certified Application Assistors (CAAs) are often available at many of the other doors.
Figure C

Three Individual Models of Crowding Out
<table>
<thead>
<tr>
<th>Variable</th>
<th>df/dx</th>
<th>P &gt;</th>
<th>Z</th>
<th>df/dx</th>
<th>P &gt;</th>
<th>Z</th>
<th>df/dx</th>
<th>P &gt;</th>
<th>Z</th>
<th>df/dx</th>
<th>P &gt;</th>
<th>Z</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\sigma_1$ hispanic</td>
<td>0.007</td>
<td>0.252</td>
<td>-0.007</td>
<td>0.507</td>
<td>-0.013</td>
<td>0.250</td>
<td>-0.012</td>
<td>0.300</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\sigma_2$ black</td>
<td>0.029</td>
<td>0.312</td>
<td>0.047</td>
<td>0.177</td>
<td>0.050</td>
<td>0.216</td>
<td>0.036</td>
<td>0.229</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\sigma_3$ asian</td>
<td>0.026</td>
<td>0.303</td>
<td>0.012</td>
<td>0.694</td>
<td>-0.003</td>
<td>0.937</td>
<td>0.027</td>
<td>0.412</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\sigma_4$ PacificIslander</td>
<td>-0.149</td>
<td>0.462</td>
<td>-0.411</td>
<td>0.130</td>
<td>-0.480</td>
<td>0.117</td>
<td>-0.355</td>
<td>0.117</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\sigma_5$ Other/Multiple</td>
<td>-0.050</td>
<td>0.451</td>
<td>-0.104</td>
<td>0.196</td>
<td>-0.154</td>
<td>0.089</td>
<td>-0.127</td>
<td>0.118</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\sigma_6$ PopDensity</td>
<td>0.000</td>
<td>0.799</td>
<td>0.000</td>
<td>0.884</td>
<td>0.000</td>
<td>0.966</td>
<td>0.000</td>
<td>0.952</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\sigma_7$ MedInc</td>
<td>0.000</td>
<td>0.738</td>
<td>0.000</td>
<td>0.904</td>
<td>0.000</td>
<td>0.680</td>
<td>0.000</td>
<td>0.616</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\pi_1$ Prior CHI</td>
<td>0.280</td>
<td>0.250</td>
<td>0.504*</td>
<td>0.102</td>
<td>0.340</td>
<td>0.164</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\pi_2$ HealthCareIndex</td>
<td>-0.010</td>
<td>0.291</td>
<td>-0.010</td>
<td>0.299</td>
<td>-0.008</td>
<td>0.336</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\pi_3$ CoChairDem</td>
<td>0.176</td>
<td>0.353</td>
<td>0.264</td>
<td>0.183</td>
<td>0.140</td>
<td>0.426</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\pi_4$ %ChildrenNonCitizen</td>
<td>0.103</td>
<td>0.087</td>
<td>0.1305*</td>
<td>0.048</td>
<td>0.11948*</td>
<td>0.043</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\tau_1$ %TotalChildElig</td>
<td>0.012</td>
<td>0.769</td>
<td>-</td>
<td>0.012</td>
<td>0.769</td>
<td>-</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\tau_2$ AssetsCFCPerEligChild</td>
<td>0.000</td>
<td>0.242</td>
<td>-</td>
<td>0.000</td>
<td>0.242</td>
<td>-</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\tau_3$ PrivateRevEligChild</td>
<td>0.000</td>
<td>0.824</td>
<td>-</td>
<td>0.000</td>
<td>0.824</td>
<td>-</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\tau_4$ LocalRevPerEligchild</td>
<td>0.000</td>
<td>0.122</td>
<td>-</td>
<td>0.000</td>
<td>0.122</td>
<td>-</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\tau_5$ %TotalChildUnis</td>
<td>-0.047</td>
<td>0.156</td>
<td>-</td>
<td>-0.047</td>
<td>0.156</td>
<td>-</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\tau_6$ AssetsCFCPerUnisChild</td>
<td>0.000</td>
<td>0.190</td>
<td>-</td>
<td>0.000</td>
<td>0.190</td>
<td>-</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\tau_7$ PrivateRevUnisChild</td>
<td>0.000</td>
<td>0.893</td>
<td>-</td>
<td>0.000</td>
<td>0.893</td>
<td>-</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\tau_8$ LocalRevPerUnisChild</td>
<td>0.000</td>
<td>0.992</td>
<td>-</td>
<td>0.000</td>
<td>0.992</td>
<td>-</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
### Table II

<table>
<thead>
<tr>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
<th>(5)</th>
<th>(6)</th>
<th>(7)</th>
</tr>
</thead>
<tbody>
<tr>
<td>% of Child Population with Health Insurance In Expand Range (250-300% FPL)</td>
<td>% of Child Population with Health Insurance Broad Target Range (0-300% FPL)</td>
<td>% of Child Population in Broad Target Range With At Least One Doctor Visit In Prior Year (0-300% FPL)</td>
<td>% of Child Population in Broad Target Range in Reporting at least “Good” Health (0-300% FPL)</td>
<td>% of Child Population In Expand Range Who Had to Delay Care in Last Year (250-300% FPL)</td>
<td>% of Child Population in Broad Target Range Who Had to Delay Care in Last Year (0-300% FPL)</td>
</tr>
<tr>
<td><strong>Constant</strong></td>
<td>1.35309</td>
<td>2.886422</td>
<td>-1.362019</td>
<td>1.062372</td>
<td>0.0445938</td>
</tr>
<tr>
<td></td>
<td>(6.575626)</td>
<td>(3.495591)</td>
<td>(4.98268)</td>
<td>(5.313526)</td>
<td>(8.884758)</td>
</tr>
<tr>
<td></td>
<td>-0.001402</td>
<td>-0.0005508</td>
<td>-0.005508</td>
<td>-0.016625*</td>
<td>-0.0010783</td>
</tr>
<tr>
<td></td>
<td>(0.0010203)</td>
<td>(0.0005519)</td>
<td>(0.0007102)</td>
<td>(0.0008389)</td>
<td>(0.0013023)</td>
</tr>
<tr>
<td><strong>Δ Median Income</strong></td>
<td>-0.0001402</td>
<td>0.0016625*</td>
<td>-0.005508</td>
<td>-0.0010783</td>
<td>-0.001779*</td>
</tr>
<tr>
<td></td>
<td>(0.0001402)</td>
<td>(0.0005519)</td>
<td>(0.0007102)</td>
<td>(0.0008389)</td>
<td>(0.0013023)</td>
</tr>
<tr>
<td><strong>Δ CHKIP</strong></td>
<td>0.3897035</td>
<td>5.995572**</td>
<td>7.64548*</td>
<td>9.463085**</td>
<td>-6.456137</td>
</tr>
<tr>
<td></td>
<td>(5.444579)</td>
<td>(2.963328)</td>
<td>(3.81333)</td>
<td>(4.504452)</td>
<td>(6.992699)</td>
</tr>
<tr>
<td><strong>Δ %Latino</strong></td>
<td>-0.6130095</td>
<td>-0.0001402</td>
<td>-0.005508</td>
<td>-0.016625*</td>
<td>-0.0010783</td>
</tr>
<tr>
<td></td>
<td>(2.540068)</td>
<td>(0.0010203)</td>
<td>(0.0005519)</td>
<td>(0.0008389)</td>
<td>(0.0013023)</td>
</tr>
<tr>
<td><strong>Δ %African-American</strong></td>
<td>-0.6130095</td>
<td>-0.0001402</td>
<td>-0.005508</td>
<td>-0.016625*</td>
<td>-0.0010783</td>
</tr>
<tr>
<td></td>
<td>(2.540068)</td>
<td>(0.0010203)</td>
<td>(0.0005519)</td>
<td>(0.0008389)</td>
<td>(0.0013023)</td>
</tr>
<tr>
<td><strong>Δ %Asian</strong></td>
<td>0.5479283</td>
<td>-0.538068</td>
<td>-0.3315153</td>
<td>0.9781911</td>
<td>-2.443695</td>
</tr>
<tr>
<td></td>
<td>(2.656672)</td>
<td>(1.429128)</td>
<td>(1.839059)</td>
<td>(2.159977)</td>
<td>(3.353143)</td>
</tr>
<tr>
<td><strong>Δ %Other</strong></td>
<td>0.5479283</td>
<td>-0.538068</td>
<td>-0.3315153</td>
<td>0.9781911</td>
<td>-2.443695</td>
</tr>
<tr>
<td></td>
<td>(2.656672)</td>
<td>(1.429128)</td>
<td>(1.839059)</td>
<td>(2.159977)</td>
<td>(3.353143)</td>
</tr>
<tr>
<td><strong>Δ % IER Household Employment</strong></td>
<td>0.0655874</td>
<td>--</td>
<td>--</td>
<td>--</td>
<td>-0.09332375**</td>
</tr>
<tr>
<td></td>
<td>(0.1154127)</td>
<td>(0.001220226)</td>
<td>(0.001220226)</td>
<td>(0.001220226)</td>
<td>(0.001220226)</td>
</tr>
<tr>
<td><strong>Δ % &lt;300FPL Household Employment</strong></td>
<td>--</td>
<td>0.1292265</td>
<td>0.0538172</td>
<td>0.1938786</td>
<td>--</td>
</tr>
<tr>
<td></td>
<td>(0.1693148)</td>
<td>(0.2178811)</td>
<td>(0.2573695)</td>
<td>(0.2573695)</td>
<td>(0.2573695)</td>
</tr>
</tbody>
</table>
### Table III

<table>
<thead>
<tr>
<th></th>
<th>(8)</th>
<th>(9)</th>
<th>(10)</th>
<th>(11)</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Constant</strong></td>
<td>18.37981 (9.572875)</td>
<td>-.8402246 (5.332894)</td>
<td>1.169421 (5.091618)</td>
<td>2.995815 (3.56806)</td>
</tr>
<tr>
<td><strong>Δ Median Income</strong></td>
<td>-0.0017633 (.0014854)</td>
<td>0.0000788 (.000842)</td>
<td>0.000347 (.0008039)</td>
<td>-0.0007969 (.0005633)</td>
</tr>
<tr>
<td><strong>Δ CHKIP</strong></td>
<td>.3420903 (7.926283)</td>
<td>-1.92998** (.821)</td>
<td>-2.824345 (4.316333)</td>
<td>-2.865839 (3.024763)</td>
</tr>
<tr>
<td><strong>Δ %Latino</strong></td>
<td>-5.653738 (3.697862)</td>
<td>.0401179 (2.180286)</td>
<td>-0.0409374 (2.081643)</td>
<td>1.212158 (1.458756)</td>
</tr>
<tr>
<td><strong>Δ %African-American</strong></td>
<td>-6.663893 (4.249712)</td>
<td>.4415822 (2.43199)</td>
<td>2.330064 (2.32196)</td>
<td>.935549 (1.627163)</td>
</tr>
<tr>
<td><strong>Δ %Other</strong></td>
<td>.0856327 (3.867615)</td>
<td>-.704444 (2.16785)</td>
<td>-1.366317 (2.06977)</td>
<td>-2.199479 (1.450436)</td>
</tr>
<tr>
<td><strong>Δ %Asian</strong></td>
<td>-3.233996 (3.807279)</td>
<td>-1.1338571 (2.150154)</td>
<td>.420571 (2.052875)</td>
<td>1.180536 (1.438596)</td>
</tr>
<tr>
<td><strong>Δ % IER Household Employment</strong></td>
<td>.447635 ** (.1680192)</td>
<td>--</td>
<td>--</td>
<td>--</td>
</tr>
<tr>
<td><strong>Δ &lt;300FPL Household Employment</strong></td>
<td>-.1856396** (.0883076)</td>
<td>1.23732** (.546621)</td>
<td>-.0938807 (.1728249)</td>
<td>-0.590</td>
</tr>
<tr>
<td>County</td>
<td>% of Children in Broad Target Group (%0-300) 2007</td>
<td>% of Children in Broad Target Group (%0-300) 2005</td>
<td>Δ % of Children Broad Target Group (%0-300)</td>
<td>Test of Diff in Proportions, Z = (%i07 - %i05) / (%i07 (1-%i07)/N07 + (%i07 (1-%i07)/N05)^0.5</td>
</tr>
<tr>
<td>---------------</td>
<td>-------------------------------------------------</td>
<td>-------------------------------------------------</td>
<td>------------------------------------------</td>
<td>--------------------------------------------------------------------------------------------------</td>
</tr>
<tr>
<td>Alameda</td>
<td>38.3 (5.19)</td>
<td>47.2 (3.37)</td>
<td>-8.9</td>
<td>-1.277</td>
</tr>
<tr>
<td>El Dorado</td>
<td>30.9 (5.25)</td>
<td>41.8 (5.33)</td>
<td>-10.9</td>
<td>-1.613</td>
</tr>
<tr>
<td>Fresno</td>
<td>63.6 (5.84)</td>
<td>69.1 (3.51)</td>
<td>-5.5</td>
<td>-0.824</td>
</tr>
<tr>
<td>Kern</td>
<td>72.2 (5.94)</td>
<td>71.3 (3.54)</td>
<td>0.9</td>
<td>0.141</td>
</tr>
<tr>
<td>Kings</td>
<td>71.1 (6.71)</td>
<td>67.4 (3.98)</td>
<td>3.7</td>
<td>0.567</td>
</tr>
<tr>
<td>Los Angeles</td>
<td>61.7 (3.35)</td>
<td>64.5 (1.17)</td>
<td>-2.8</td>
<td>-0.410</td>
</tr>
<tr>
<td>Merced</td>
<td>81 (5.22)</td>
<td>66.3 (4.36)</td>
<td>14.7</td>
<td>2.393***</td>
</tr>
<tr>
<td>Napa</td>
<td>44.2 (5.14)</td>
<td>43 (5.15)</td>
<td>1.2</td>
<td>0.171</td>
</tr>
<tr>
<td>Orange</td>
<td>45.6 (3.37)</td>
<td>47.5 (2.55)</td>
<td>-1.9</td>
<td>-0.269</td>
</tr>
<tr>
<td>Placer</td>
<td>32.4 (4.93)</td>
<td>30.8 (4.89)</td>
<td>1.6</td>
<td>0.243</td>
</tr>
<tr>
<td>Riverside</td>
<td>55.1 (4.96)</td>
<td>58.2 (2.8)</td>
<td>-3.1</td>
<td>-0.443</td>
</tr>
<tr>
<td>Sacramento</td>
<td>48.7 (4.41)</td>
<td>51 (3.35)</td>
<td>-2.3</td>
<td>-0.325</td>
</tr>
<tr>
<td>San Bernardino</td>
<td>63.3 (3.76)</td>
<td>63.5 (2.61)</td>
<td>-0.2</td>
<td>-0.029</td>
</tr>
<tr>
<td>San Francisco</td>
<td>40.9 (4.36)</td>
<td>47 (5.4)</td>
<td>-6.1</td>
<td>-0.871</td>
</tr>
<tr>
<td>San Joaquin</td>
<td>60.8 (3.43)</td>
<td>61.9 (4.6)</td>
<td>-1.1</td>
<td>-0.160</td>
</tr>
<tr>
<td>S.L. Obispo</td>
<td>40 (3.28)</td>
<td>52.1 (4.99)</td>
<td>-12.1</td>
<td>-1.729</td>
</tr>
<tr>
<td>San Mateo</td>
<td>23.5 (3.85)</td>
<td>36.5 (5.37)</td>
<td>-13</td>
<td>-2.026</td>
</tr>
<tr>
<td>Santa Barbara</td>
<td>61 (3.36)</td>
<td>58.3 (4.83)</td>
<td>2.7</td>
<td>0.389</td>
</tr>
<tr>
<td>Santa Clara</td>
<td>36.4 (4.39)</td>
<td>37.4 (2.96)</td>
<td>-1</td>
<td>-0.147</td>
</tr>
<tr>
<td>Santa Cruz</td>
<td>47.3 (4.95)</td>
<td>48.1 (5)</td>
<td>-0.8</td>
<td>-0.113</td>
</tr>
<tr>
<td>Solano</td>
<td>47.5 (5.95)</td>
<td>46 (3.38)</td>
<td>1.5</td>
<td>0.213</td>
</tr>
<tr>
<td>Sonoma</td>
<td>46 (3.95)</td>
<td>41.4 (5.33)</td>
<td>4.6</td>
<td>0.656</td>
</tr>
<tr>
<td>Tulare</td>
<td>75.9 (2.47)</td>
<td>76.4 (3.51)</td>
<td>-0.5</td>
<td>-0.083</td>
</tr>
<tr>
<td>Yolo</td>
<td>43.6 (2.94)</td>
<td>50 (4.4)</td>
<td>-6.4</td>
<td>-0.909</td>
</tr>
<tr>
<td>Yuba</td>
<td>73.8 (3.33)</td>
<td>68.7 (4.47)</td>
<td>5.1</td>
<td>0.798</td>
</tr>
</tbody>
</table>
**Appendix I: Description of Variables for Equations 1A, 1B, 1C and 1D**

### A Variables

These variables are included in Equation 1A and are meant to capture the effects of basic demographic characteristics in county $i$.

1-5) **Race/Ethnicity** contains capture the percentage of people in each county who primarily describe themselves in CHIS as a given race or ethnicity. They are *Hispanic, Black, Asian, Pacific Islander*, and *Other/Multiple*, respectively.

6) **PopDensity** is a simple measure of people per square mile in 2005 as reported by the Department of finance. I would expect the co-efficient on this variable to be positive because it should be easier to organize and operate a community organization among a geographically concentrated community. Because of the significant logistical costs of setting up a program, CHKIP may not be cost effective for residents if the target population is spread over a wide geographic area.

7) **MedInc** is a simple measure of median family income in county $i$. I use family income because decisions concerning children’s health is usually made at a family level. The expected sign of **MedInc** is ambiguous, as wealthier counties should be better able to create a program, but are also less likely to need (or perceive to need) the program in the first place.

### B Variables

These variables are added in Equation 1B and are designed to capture the influence of political opinion towards public provision of healthcare.

1) **Prior CHI** is a dummy variable equal to 1 if a county had a county run Children’s Health Initiative prior to the passage of SB 437. Because CHKIP was modeled after these early county programs and very little additional infrastructure is needed to gain state funding, having an established CHI would significantly reduce the fixed-costs associated with establishing a program. I would therefore expect a large, positive co-efficient on this variable.

2) **HealthCareIndex** is a simple index of voter attitudes towards healthcare. I used two previous election results to obtain this index. The first is a California ballot initiative Proposition 28 from 2000. This initiative was a measure that would have completely repealed the Prop. 10 funding mentioned in the body of the paper. The second is also a California ballot initiative, Proposition 72 from the 2004 ballot. This measure would have imposed a mandate on all employers to provide health insurance for all employees and their families. I take the percentage of each county voting “No” on Prop. 28 and the percentage voting “Yes” on Prop. 72, subtract 50 percentage points from each, and then add the two together to get a measure of a county’s general political attitude towards government intervention in the healthcare sector. Positive values are indicative of counties more amenable to government provision of health insurance, while negative values suggest voters in a county are generally opposed to public provision of healthcare.

This measure is certainly imperfect. For example, many voters may be strongly opposed to government regulation of businesses and the labor market, but would be willing to pay higher taxes in order to provide health coverage for children. I also do not take into account political factors that may have been unique to each election such as the strength of each initiative’s political backers. However, in absence of county-by-
county polling data, these measures should give a good approximation of the general political attitude towards publicly provided insurance. As support of this, consider that the correlation of **HealthCareIndex** and the percentage of voters in county \( i \) registered as Democrats is 0.86, and -0.92 for those registered as Republicans.

3) **CoChairDem** is a dummy variable equal to 1 if the County Chair the Board of Supervisors is a Democrat. The Democrats have enjoyed a relatively safe majority status in the California legislature since 1996. A Democratic County Chair would be more likely to share a political philosophy with the creators of CHKIP and are also more likely to enjoy public support for participation in the program. For these reasons I would expect the co-efficient to be positive.

4) **%ChildrenNonCitizen** is a measure of the percentage of total children in a county who are not United States citizens. This variable is important because the only other sources of publicly provided insurance, MediCal and Healthy Families, use federal funds and therefore are off limits for many non-citizens. CHKIP uses only state and local funds, and counties are prohibited by the legislature from asking applicants about citizenship status. Because this provides a way for counties to provide insurance for a demographic that is largely without insurance, I would expect the coefficient to be positive. This measure is also likely biased downwards, because many undocumented immigrants might have reservations about revealing the fact that they are in American without permission of the government.

**T Variables**

These variables are added in Equation 1C and are designed to capture factors that could influence a cost/benefit analysis of starting a CHKIP program in county \( i \). The bulk of costs associated with a CHKIP program are in two areas. The first is the fixed cost associated with establishing a program staff and infrastructure. The second is providing annual insurance for those children who sign up for the program. The program’s secondary goal, increasing take-up rates for MediCaid and Healthy Families, is relatively costless for local governments. This suggests that the most appropriate measures of program efficacy are ratios of funding to eligible children.

1) **%TotalChildElig** is the estimated percentage of children in county \( i \) who are eligible for CHKIP. This roughly represents the “need” for a CHKIP program in county, because it measures the portion of children who would directly benefit from the program.

2) **AssetsCFCPerEligChild** is a measure of the total assets held by each county Children and Family Council in county at the end \( i \) in the Fiscal Year 2005-2006, which almost perfectly corresponds with the passage of CHKIP. Counties with more funding per eligible child should be more capable of starting and maintaining a program, so I would expect this co-efficient to be positive.

3) **PrivateRevEligChild** is a measure of the revenue in FY 2005-2006 from private sources, usually health care corporations and non-profit foundations. A higher level of private funding (and future expected private funding) would significantly decrease the burden of creating and maintaining a local CHKIP, so I would expect this coefficient to be positive.

4) **LocalRevPerEligChild** is a measure of total county tax revenue in FY2005-2006 per eligible child. Counties may be able to compensate for lower funding of CFCs by raising their own revenue, so I would expect this coefficient to be positive. Of course, counties have other expenses, so surplus per eligible child would be a more appropriate measure. Unfortunately, county fiscal surplus data was unavailable.

The above variables assume that the political will in a given county is focused on providing insurance for the target demographic. However, it is entirely possible that voters in a county simply perceive a general
problem of “uninsured children” and do not fully understand the eligibility requirements. In addition, they might favor the establishment of a CHKIP program simply as a means of increasing coverage through MediCal and Healthy Families. In either case, it would be more appropriate to consider a ratio of funding to the number of total uninsured children. I substitute the following $T$ variables for the above variables in Regression 4. They serve the same purpose as the first $T$ variables, except that they divide funding by the total number of uninsured children in county $i$. I would expect the signs and interpretation of $\tau_5$, $\tau_6$, $\tau_7$, and $\tau_8$ to be roughly similar to their counterparts $\tau_1$, $\tau_2$, $\tau_3$ and $\tau_4$.

5) $\%\text{TotalChildUnis}$ is a measure of the percentage of children in county $i$ who are uninsured. This might represent a more politically salient measure of the “need” in a particular county.

6) $\text{AssetsCFCPerUnisChild}$ is a measure of total assets available to a CFC in county $i$ in FY 2005-2006 per uninsured child.

7) $\text{PrivateRevCFCUnisChild}$ is a measure of the revenue in FY 2005-2006 from private sources per uninsured child.

8) $\text{LocalRevPerUnisChild}$ is a measure of total county tax revenue in FY2005-2006 per uninsured child in county $i$. 
Works Cited


California Health Interview Survey. UCLA Center for Health Policy Research.
http://www.chis.ucla.edu/main/default.asp?timeout=1

California Department of Finance 2005 County Profiles
http://www.dof.ca.gov/Research/Research.php


Institute for Health Policy Solutions. “Pioneers for Coverage: Local Solutions for Insuring All Children in California.”

http://www.kff.org/medicaid/upload/7492.pdf


http://www.leginfo.ca.gov/cgi-bin/postquery?bill_number=sb_437&sess=PREV&house=B&author=escutia


http://aspe.hhs.gov/POVERTY/07poverty.shtml


Yazici, Ezel and Robert Kaestner. 2000. “Medicaid Expansions and the Crowding Out of Private Health Insurance Among Children.” Inquiry 37(1), Spring,