Geographic Variation in Physician Visits for Uninsured Children
The Role of the Safety Net

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The State Children’s Health Insurance Program (CHIP), passed by Congress as part of the Balanced Budget Act of 1997, is intended to extend health insurance coverage to a significant proportion of the nation’s uninsured children, thereby increasing their access to health care services.1 The program provides for generous federal grants to states, which in turn have substantial latitude in designing the specifics of their programs. Targeted on uninsured children in families with incomes less than 200% of the federal poverty level, CHIP will provide either Medicaid or private insurance coverage. The latter must guarantee a benefit package consistent with state or federal employees’ benefits, but with upper limits on cost-sharing amounts to protect low-income children. Most of the states plan to use Medicaid as their CHIP mechanism, either wholly (27 states) or in combination with a private insurance program (10 states).2

There is an extensive literature comparing access to care for uninsured and insured children.3-10 Being uninsured reduces the likelihood a child has any physician contact during a time period and reduces the number of visits for a child with some contact. The full effect is about 30% to 50% fewer visits by uninsured children than those insured by either Medicaid or private insurance. Clearly, then, the evidence suggests that CHIP will lead to increased use among those who participate in the program.

A limitation of this literature, however, is that with only 1 exception, it is based on national data. In contrast, the CHIP program is to be undertaken by individual states, and policymakers care about differential impacts in their own jurisdictions. These differences may be substantial. There exist differences among states in the health status of children and their access to care, which may affect program out-
comes. In addition, diversity in state regulations and programs has produced significant interstate variation in all aspects of the health care system. Therefore, to assess the potential and limitations of new state programs targeted to the uninsured requires information about how access differs across states.

The purpose of this article is to examine variation in access to physician services for uninsured children in 10 states and to explore the role the safety net plays in this variation. Using simulation methods, we also investigate the likely improvements in access under a new public insurance program for low-income uninsured children in the 10 states. To date, all but 2 states have received approval from the Health Care Financing Administration for a CHIP plan to expand coverage of children. However, at least 20 states indicate they are still developing the fully phased-in CHIP program. Thus, it will be some years until the CHIP programs are fully implemented and several years beyond that before postimplementation empirical evidence is available on the effects of the programs. Therefore, our simulation analysis provides policymakers with current information about the potential implications of CHIP.

METHODS
Data
Data for our study come from the Robert Wood Johnson Foundation Family Health Insurance Survey conducted in 10 states between summer 1993 and spring 1994. The states were Colorado, Florida, Minnesota, New Mexico, New York, North Dakota, Oklahoma, Oregon, Vermont, and Washington. They were selected for the Foundation's State Initiatives in Health Care Reform program through a competitive application process, but the selection was designed to include both large and small states and states in all regions of the country. The states span the range of variation observed in all 50 states in important population, health system, and health policy characteristics including age, education, race, income, health maintenance organization enrollments, physicians per capita, health spending per capita, and state health care spending per capita. They also represent the range of existing state health care financing programs for children as measured by the number of Medicaid children per 1000 children (ranging from 168-341 in the 10 states vs 168-388 among all states) and Medicaid expenditures per enrolled child (ranging from $870-$1970 in the 10 states and $630-$1970 nationwide). States are an appropriate geographic unit for our analyses because they are the relevant jurisdiction for CHIP policy.

More than 2000 twenty-five-minute telephone interviews were conducted with families in each state. Families with Medicaid enrollees or uninsured persons were oversampled using a general population telephone screening interview. The Medicaid population identified in the screening interview was supplemented by sampling from program enrollment lists in 9 of the 10 states. Finally, households without telephones in a small number of geographic areas in each state were identified and interviewed in person. Response rates ranged from 61% in New York to 83% in North Dakota.

The interview unit was the family. Within families, the survey collected demographic and insurance information about all children in the family and asked about the health status and utilization of a randomly selected child. This yielded complete data for 11 857 children. We used this sample to estimate the number of low-income uninsured children in each state, which measures the potential impact of CHIP if all children eligible for public insurance enrolled in it.

To estimate access effects of providing coverage to low-income uninsured children, we modelled physician visits as described below. To fit the model, we restricted the sample to children who were uninsured for the full year prior to the survey, those who were covered by Medicaid or special state-sponsored programs (eg, MinnesotaCare) during the entire year, or those who were covered by private employer-sponsored insurance (including the Civilian Health and Medical Program of the Uniformed Services [CHAMPUS]) for the full year. We limited our sample to those whose insurance remained constant for the year because our health service utilization measures were also for the preceding year. Lack of congruence between the measure of insurance and the measure of health service use can lead to biased estimates of the effect of insurance status. Moreover, other research has shown that the relationship between health care use and insurance status does not differ for the continuously uninsured and those in insurance transitions during the period of uninsurance and so the exclusion should not bias our estimates of the relationship.

We also excluded children who were covered by more than 1 type of insurance program during the year and those covered by private, individual insurance. Finally, we excluded children who were entitled to Medicaid because they were receiving Supplemental Security Income. These children were eligible for Medicaid because they had special health problems. Including them in our model might result in selection bias in our estimates of the insurance effect, and so in our simulation of the effect of an expanded public insurance program. The sample used in fitting our analytic model included a total of 8565 children in the 10 states, of whom 1586 were uninsured, 2723 were covered by Medicaid, and 4256 were covered by employer-sponsored private insurance. Each state was given equal weight in the analysis. Within states, weights were used to account for differential sampling probabilities.

We collected secondary data on health care safety net resources by state. Each safety net quantity was then expressed as a proportion of some denominator—for example, public hospital beds divided by total hospital beds. When the safety net resource generally served a subset of the population, the chosen denominator reflects an attempt to measure the appropriate in-
come, insurance, or demographic group that is served. Some of the measures we used are indicators of capacity while others include dimensions of both capacity and service utilization. Because we compared differences between states in the measures of the safety net with differences between them in our estimates of access for uninsured children, we would have preferred pure measures of capacity. However, measures that accurately reflect capacity were not always available. For example, simple counts of physical plant (such as the number of hospital emergency and outpatient departments) do not measure the number of patients that can be served. In such case, we have used utilization as the measure to standardize differences in the number of physical plants per state. We believe the consistency of the relationships we observed for both the pure capacity measures and those that included some component of utilization supports our conclusions.

States were classified as having “high” vs “low” safety net capacity. To do so, the states were ordered from highest to lowest on each of the 5 safety net capacity measures collected and were assigned a rank from 1 to 10 consecutively. The 5 rankings for each state were then summed to create an index; the 3 states with the highest rankings (lowest index values) were deemed to have high safety net capacity, whereas the 3 with the lowest rankings (highest index values) were classified in the low-capacity group.

**Estimation of Access Effects**

We used a 2-part multivariate model to estimate the relationship between insurance status and ambulatory care visits for the children in our analytic sample. The first part was a logit model for the probability of having an ambulatory physician visit in a year; the second part was a linear regression for the logarithm of the number of visits for those who have at least one. Both models included indicator variables for the type of insurance the individual had (uninsured, private employer-sponsored coverage, or Medicaid); indicators for the state; the child’s age, sex, race, and health status; the family income expressed as a percentage of poverty; and interactions of insurance status with health status and family income. To capture state differences in utilization patterns in different programs, we also allowed for differences among the states in the effect of insurance and for differences in the insurance and income interaction by state by including terms interacting the state indicators with these other variables.

We used the model to predict or simulate the number of ambulatory care physician visits that each low-income uninsured child would have if uninsured all year and if insured for a full year. The simulated value for each child is the product of the predicted probability of use from the logistic model times the predicted number of visits. The latter is the exponential of the predicted value from the regression times a factor to retransform from the logarithmic scale to the raw quantity scale.

We first used the model to predict annual uninsured visit rates for each currently uninsured child. We used the model rather than observed values because some of these children were insured for part of the year, so observed visits will be higher than rates of use while uninsured.

We then predicted the number of visits that each of these children would make if enrolled in Medicaid to represent use under a new state insurance program for the uninsured, because most states’ CHIP plans involve Medicaid expansions and will provide Medicaid benefits. Medicaid managed care enrollments have increased rapidly—from 14.4% in 1993 to 47.8% in 1997. However, most physicians are still reimbursed on a fee-for-service basis and so their practice styles are not likely to be altered. Moreover, other research suggests that managed care alters hospital use rates, but that there are few differences in ambulatory care visit rates between the managed care and fee-for-service delivery systems. Therefore, we believe our estimates of predicted Medicaid visits based on 1993 data are still likely to be valid for the current Medicaid program.

We also predicted what each uninsured child’s use would be if covered by private employer-sponsored coverage for the year to estimate how use patterns would change if the new public program required greater patient cost sharing than Medicaid.

The tables that follow show the predictions averaged over all of the uninsured children in our sample in the state. (The regression equations on which these predictions are based are available on request to the authors.) We measured variation between the states in access rates by the coefficient of variation—the SD of the 10 state estimates divided by the unweighted mean of the state estimates. We compared differences between the states in predicted access with differences in safety net capacity. This is an indirect estimate of the effect of the safety net, rather than a direct estimate of the relationship that would be obtained by including these measures in the multivariate models. We could not include the safety net measures, which are state-specific measures, directly in our regressions because we used a fixed-effects model with state indicators and interactions of state indicators and other key variables. We chose this approach to capture the myriad of differences between states in health care policies and programs and the effect they may have on access. With only 10 states, we do not have enough df to include measures for each of the important programs and policies that vary among the states. If safety net capacity is correlated with other state policies that affect access, however, our approach may overstate the marginal contribution of the safety net.

**RESULTS**

There are substantial differences among states in the potential of a public insurance program to expand coverage of low-income uninsured children. In our survey states, the uninsured rate for low-income children ranged from 9% in Vermont to 31% in Florida (TABLE 1). As a proportion of all un-

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insured children, the low-income group ranged from 61% in Vermont to 86% in New Mexico. These disparities, which have been documented by others, suggest that there will be considerable differences in the magnitude of the coverage effects of CHIP among states. They are a reflection of past differences in private insurance coverage, in Medicaid and other public insurance programs, and in the income distribution of families with children.

We predict that expanding public insurance would substantially improve access for low-income uninsured children (Table 2). On average in the 10 states, use would rise from 2.3 visits to 4.6 visits per year (a 105% increase). We used behavior for children under Medicaid and state-only insurance programs for low-income populations to estimate the effect of a new program because few states have imposed cost sharing that exceeds Medicaid levels in their CHIP programs. Should states impose greater cost sharing, use could be significantly lower. Specifically, we predict low-income uninsured children would have about 3.5 visits with cost sharing comparable to that in existing private plans, or only about one-half the improvement predicted with benefits comparable to Medicaid.

The increases in utilization would vary substantially from state to state, however, ranging from lows of only 41% in Minnesota and 50% in New York, to highs of 135% in New Mexico and Vermont and 189% in Oregon. Access differences for the uninsured and those in public programs differed significantly between the states (χ² = 13.0 for the probability of use; χ² = 17.4 for the number of visits among users). These differences have little to do with differences in service use under public insurance programs for children—the levels of use among the states were pretty tightly distributed around the mean. Instead, they have much more to do with state-specific differences in use by uninsured children. The coefficient of variation in uninsured use was about twice that for the insured use (Table 2). The differences in the use rates by the uninsured among states are significantly different (χ² = 42.8 for the probability of use; χ² = 17.0 for the number of visits among users).

We investigated whether differences between states in the demographic and health characteristics of their uninsured children account for the variation in access by predicting values for each state using a standardized population. Results for the standardized population were essentially the same as those for the state’s own uninsured children and are not presented here. Thus, we conclude that population differences do not account for the state-to-state variation.

We explored another possible cause of the state variation—specifically, the availability of safety net services to the uninsured, which serve as a partial substitute for having insurance. Table 3 shows several measures of health safety net resources for the three states with the highest access for the uninsured (Colorado, Minnesota, and New York) and the three states with the lowest access (New Mexico, Oregon, and Vermont). The estimates shown are based on simple means of the estimates for the 3 individual states—that is, they are not weighted by each state’s population—because our objective was to use these states as observations to characterize circumstances in similarly situated states that were not studied. The high-access states, where utilization by uninsured children is 160% of that in the low-access states, had 120% to 220% more safety net capacity depending on the particular measure considered.

The results were similar when explored from another perspective. We ranked states according to their safety net capacity across the 5 measures presented in Table 3. The 3 highest-capacity states (Florida, New York, and Washington) had an average predicted use rate for uninsured children that was 129% of that for the 3 lowest safety net capacity states in our study (North Dakota, Oregon, and Vermont). Limiting the ranking to the 3 safety net measures that are independent of utilization resulted in 5 of the 6 states remaining in their respective group and a relative use rate of 126%.

**COMMENT**

Our simulations of an illustrative public insurance program for low-income uninsured children suggest that CHIP promises to have significant effects, both on the number of children who

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### Table 2. Predicted Number of Annual Physician Visits for Low-Income Uninsured Children, If Uninsured and If Covered by Public Program in 10 States*

<table>
<thead>
<tr>
<th>State</th>
<th>Uninsured</th>
<th>If covered by public program</th>
</tr>
</thead>
<tbody>
<tr>
<td>Colo</td>
<td>2.5</td>
<td>5.1</td>
</tr>
<tr>
<td>Fla</td>
<td>2.3</td>
<td>3.8</td>
</tr>
<tr>
<td>Minn</td>
<td>3.4</td>
<td>4.8</td>
</tr>
<tr>
<td>NM</td>
<td>1.7</td>
<td>4.0</td>
</tr>
<tr>
<td>NY</td>
<td>2.9</td>
<td>4.2</td>
</tr>
<tr>
<td>ND</td>
<td>2.1</td>
<td>4.5</td>
</tr>
<tr>
<td>Okla</td>
<td>2.3</td>
<td>4.5</td>
</tr>
<tr>
<td>Ore</td>
<td>1.8</td>
<td>5.2</td>
</tr>
<tr>
<td>Vt</td>
<td>2.0</td>
<td>4.7</td>
</tr>
<tr>
<td>Wash</td>
<td>2.5</td>
<td>5.4</td>
</tr>
<tr>
<td>Mean</td>
<td>2.3</td>
<td>4.6</td>
</tr>
</tbody>
</table>

*Data from 1993 Robert Wood Johnson Foundation Family Health Insurance Survey. Predicted physician visits are averaged for the population of low-income uninsured children below 200% of poverty.

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### Table 1. Potential Eligibles Under a Public Insurance Program: Percentage of Low-Income Uninsured Children in 10 States*

<table>
<thead>
<tr>
<th>State</th>
<th>As a % of all low-income children</th>
<th>As a % of all uninsured children</th>
</tr>
</thead>
<tbody>
<tr>
<td>Colo</td>
<td>26.9</td>
<td>69.0</td>
</tr>
<tr>
<td>Fla</td>
<td>31.6</td>
<td>70.0</td>
</tr>
<tr>
<td>Minn</td>
<td>16.7</td>
<td>67.0</td>
</tr>
<tr>
<td>NM</td>
<td>29.1</td>
<td>86.0</td>
</tr>
<tr>
<td>NY</td>
<td>17.6</td>
<td>60.0</td>
</tr>
<tr>
<td>ND</td>
<td>14.7</td>
<td>75.0</td>
</tr>
<tr>
<td>Okla</td>
<td>23.0</td>
<td>75.0</td>
</tr>
<tr>
<td>Ore</td>
<td>26.0</td>
<td>61.0</td>
</tr>
<tr>
<td>Vt</td>
<td>9.0</td>
<td>70.0</td>
</tr>
<tr>
<td>Wash</td>
<td>21.0</td>
<td>70.0</td>
</tr>
</tbody>
</table>

*Data from 1993 Robert Wood Johnson Foundation Family Health Insurance Survey. Low income is family income below 200% of poverty.

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will be newly insured and on their access to physician services. These effects will vary significantly among the states, however, not only because of the size and the income distribution of the pool of uninsured children, but also because of differences in baseline use of physician services. We found evidence to suggest that the states vary in their contributions from the safety net, with a resultant effect on access for the uninsured.

Our results show the potential for the CHIP program, but several factors may alter the actual outcomes. CHIP may not reach all of the targeted uninsured. Participation rates in public programs fall far short of universal, and participation rates are likely to vary among states because of differences in the implementation of CHIP. Thus, our estimates of the number of low-income uninsured will overstate the number of children the CHIP program is targeted to reach who will actually be covered. On the other hand, some families may shift children from employer plans to CHIP—the “crowd-out” effect—which would increase the number of children enrolled. But there would not be access gains for those who have substituted private insurance for public insurance, except to the extent that the public program provides more comprehensive coverage than the existing private coverage. Thus, our estimates of the average access gains for the uninsured may overstate the average access gains across all CHIP enrollees.

Several other considerations may also result in bias in our estimates of the access gains for the uninsured who enroll in CHIP. First, if those who choose to participate in CHIP differ from those who remain uninsured in ways that affect health care use, then our estimates of the access gains when the entire population of uninsured is enrolled in a public program may be a biased estimate of the access gains in CHIP. We compared the demographic and health characteristics of sample persons below the poverty level who were uninsured and those on Medicaid to see whether there is evidence that these conditions relate with participation in public programs. Except for age differences, which reflect the Medicaid eligibility expansions for young children, we did not observe differences between those who did and did not participate in public programs.

Second, our estimates of the access gains were based on comparing current use by the Medicaid population with similar individuals in the uninsured population. However, the Medicaid population is also a self-selected population. We controlled for self-selection by including important determinants of Medicaid eligibility for children in our model—especially income and the child’s age. We also controlled for self-reported health status in our estimation and excluded the Supplemental Security Income population—known to be a less healthy population—from our estimation. However, there may be other unmeasured factors related to Medicaid enrollment and use of services that could lead to selection bias.

For example, those who are entitled to Medicaid on the basis of medical need are likely to have greater use than the uninsured with otherwise similar demographic profiles. To test for selection bias, we carried out our model estimation using only sample members drawn from the Medicaid program enrollment lists. This list sample included only children who were receiving cash assistance or were enrolled in poverty-related expansions, so the selection controlled for enrollment related to health status. For the 9 states in which Medicaid lists were used to select a part of the sample, predicted average visits for uninsured children if they had been enrolled in Medicaid were 4.6 whether using the model fit on the full sample of Medicaid children or the restricted sample.

These considerations suggest that our estimates of access effects are unlikely to be biased by selection into Medicaid or by selection into CHIP. Nonetheless, there may be unmeasured

### Table 3. Relationship Between Access to Care for Uninsured Children and Safety Net Resources, 3 High-Access vs 3 Low-Access States

<table>
<thead>
<tr>
<th>Access or Safety Net Measure</th>
<th>High-Access States†</th>
<th>Low-Access States‡</th>
<th>High-Access States as a % of Low-Access States§</th>
</tr>
</thead>
<tbody>
<tr>
<td>Access</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Predicted No. of annual physician visits for low-income uninsured children, 1993</td>
<td>2.9</td>
<td>1.8</td>
<td>160</td>
</tr>
<tr>
<td>Safety net</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>State and local health and hospital expenditures, excluding Medicaid, as a % of total health spending, 1993</td>
<td>7.5</td>
<td>5.9</td>
<td>127</td>
</tr>
<tr>
<td>Public hospital beds as a % of total hospital beds, 1992</td>
<td>22</td>
<td>10</td>
<td>220</td>
</tr>
<tr>
<td>Total hospital emergency department and outpatient department visits per person with family income &lt;200% poverty, 1994</td>
<td>7.5</td>
<td>6.2</td>
<td>120</td>
</tr>
<tr>
<td>Estimated No. of uninsured children served by BPHC-supported health centers per 100 uninsured children with family incomes &lt;200% poverty, 1996</td>
<td>28</td>
<td>20</td>
<td>140</td>
</tr>
<tr>
<td>No. of NHSC providers in federal grant–funded facilities per 100,000 uninsured persons with family incomes &lt;200% poverty, 1995</td>
<td>7.2</td>
<td>5.5</td>
<td>132</td>
</tr>
</tbody>
</table>

*Data from 1993 Robert Wood Johnson Foundation Family Health Insurance Survey; Liska et al.; American Hospital Association; Bureau of Primary Health Care; McCluskey et al.; and Urban Institute. BPHC indicates Bureau of Primary Health Care; NHSC, National Health Service Corps.
†Colorado, Minnesota, and New York.
‡New Mexico, Oregon, and Vermont.
§Percentages calculated from detail underlying the rounded figures in the preceding 2 columns.
GEOGRAPHIC VARIATION IN PHYSICIAN VISITS

differences between participants and nonparticipants that could cause us to overstate or underestimate the gains. Clearly, participation in CHIP, the “crowd-out” effect, and the implications of these for access gains are prime topics for retrospective evaluations years from now, once the programs are fully implemented and data from before and after implementation become available for analysis.

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Treat the man who is sick and not a Greek name.
—Abraham Jacobi (1830-1919)