Acknowledgements: This study was supported by funding from the Kaiser Family Foundation Health Resources and Services Administration (HRSA). The opinions and conclusions expressed in this article are those of the authors and do not necessarily represent the views of the funder, the Urban Institute, or its sponsors or trustees. This research benefited from the helpful insights of Genevieve M. Kenney, Fredric Blavin, John Holahan, Linda Blumberg, Michael Huntress, and Habib Moody.
DOCUMENTATION ON THE URBAN INSTITUTE’S AMERICAN COMMUNITY SURVEY-HEALTH INSURANCE POLICY SIMULATION MODEL (ACS-HIPSM)

Executive Summary
We use the Urban Institute’s American Community Survey - Health Insurance Policy Simulation Model (ACS-HIPSM) to estimate the effects of the Affordable Care Act on the non-elderly at the state and local level. This model builds off of the Urban Institute’s base HIPSM, which uses the Current Population Survey (CPS) as its core data set, matched to several other data sets including the Medical Expenditure Panel Survey-Household Component (MEPS-HC), to simulate changes under ACA. To create HIPSM-ACS, we apply the core behavioral components of the base HIPSM to ACS records to exploit the much larger sample size for more precise estimates at the state and sub-state level. The modeling on the ACS-HIPSM produces projections of coverage changes related to state Medicaid expansions, new health insurance options, subsidies for the purchase of health insurance, and insurance market reforms (see Appendix 1 for more detail on HIPSM).

These estimates assume that the ACA is fully implemented with the Medicaid expansion in all states and that the same basic implementation decisions are made across the states. At the time of writing, even states such as Massachusetts which have been on the forefront of ACA implementation had not finalized their plans, so any modeling of variation in state decisions would necessarily involve a lot of guesswork. Also, it will take several years for enrollment in new programs such as the exchanges and Medicaid expansion to ramp up so the full effects that are estimated under the simulation model would not be felt until 2016 or later. Enrollment in the initial years would also be affected by state and federal decisions. For example, in the proposed rules released by HHS in January 2012, the deadline for establishing unified eligibility and enrollment between Medicaid and the exchange was pushed back to 2015.¹

¹ Federal Register Vol. 78 No. 14, pp. 4593-4724.
The American Community Survey (ACS)

Pooled American Community Survey (ACS) data from 2008, 2009, and 2010 form the core data set for this model (see Appendix 2 for more detail on ACS modeling and variable definitions). The ACS is an annual survey fielded by the United States Census Bureau. We use an augmented version of the ACS prepared by the University of Minnesota Population Center, known as the Integrated Public Use Microdata Sample (IPUMS), which uses the public use sample of the ACS and contains edits for family relationships and other variables (Ruggles et al. 2010). The 2009 ACS has a reported household response rate of 98.0 percent, which ranges from 94.9 percent in the District of Columbia to 99.4 percent in Wisconsin (U.S. Census Bureau 2009). It is a mixed-mode survey that starts with a mail-back questionnaire – 52.7 percent of the civilian non-institutionalized sample was completed by mail in 2009 (Mach and O’Hara 2011) – and is followed by telephone interviews for initial non-responders, and further followed by in-person interviews for a sub-sample of remaining non-responders (Griffin and Hughes 2010). The estimates presented here are derived from the data that were collected on approximately 2.5 million non-elderly sample people (ages 0 to 64) in the civilian non-institutionalized population per year, yielding a total sample of approximately 7,525,000.2

In 2008, a question was added to the ACS to ask the respondent about coverage of each individual in the household in any of the following types of health insurance or health coverage plans at the time of the survey:

a. Insurance through a current or former employer or union (of this person or another family member)
b. Insurance purchased directly from an insurance company (of this person or another family member): this is described as non-group coverage in our estimates
c. Medicare, for people age 65 or over, or people with certain disabilities
d. Medicaid, Medical Assistance, or any kind of government-assistance plan for those with low incomes or a disability
e. TRICARE or other military health care
f. VA [Department of Veterans Affairs] (including those who have ever enrolled in or used VA health care)
g. Indian Health Service

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2 This includes non-elderly people living in private residences as well as students in dorms and a small number of other people living in group quarters, such as outpatient treatment facilities.
h. Any other type of health insurance or health coverage plan—specify

The uninsured are identified on the survey as those not having coverage under categories a through f (including those recoded from the write-in option, category h) who are also not classified as having coverage based on other information collected on the survey. We edit the coverage data based on evidence of misclassified coverage (See Editing the ACS Coverage Data in the appendix). Since the data are collected continuously over a 12 month period, the coverage estimates represent an average day in the calendar year.

**Eligibility for Medicaid/CHIP and Subsidized Coverage in the Exchanges**

We simulate eligibility for Medicaid/CHIP and subsidies using the Urban Institute Health Policy Center’s ACS Medicaid/CHIP Eligibility Simulation Model, which builds on the model developed for the CPS ASEC by Dubay and Cook. We simulate both pre-ACA eligibility and the MAGI-based eligibility introduced by the ACA. This allows us to simulate different scenarios for Medicaid maintenance-of-eligibility under the ACA. The distinction between pre-ACA eligible and newly eligible is also important in determining the share of a beneficiary’s costs paid by the federal government.

Using the three-year pooled sample, the model simulates eligibility for comprehensive Medicaid and CHIP coverage or subsidy using available information on the regulations for implementing the ACA, including the amount and extent of income disregards for eligibility pathways that do not change under the ACA and for maintenance-of-eligibility for each program and state in place as of approximately June 2010 (Heberlein et al. 2011).

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3 Overall, results from the Urban Institute Health Policy Center’s ACS Medicaid/CHIP Eligibility Simulation Model have been shown to line up well with those from a similar model using the CPS ASEC, despite differences between the surveys (Kenney et al. 2010).


5 Based on the most recent regulations as of this analysis, we assume maintenance-of-eligibility for children and adults.

6 There is much ambiguity in what the final regulations will stipulate so this model represents our best understanding of the plan to date.
Current eligibility is determined based on state rules for 2010. State rules include income thresholds for the appropriate family\textsuperscript{7} size, asset tests, parent/family status, and the amount and extent of disregards\textsuperscript{8}, for each program and state in place as of the middle of 2010 (Heberlein et al. 2011).

New Medicaid eligibility depends on having family income less than or equal to 138 percent of the federal poverty level (FPL) as defined in US Department of Health and Human Services guidelines and subsidy eligibility depends on having family income between 138 percent and 400 percent FPL and lacking an affordable employee-sponsored coverage offer. Under the ACA income eligibility is based on the IRS tax definition of modified adjusted gross income (MAGI), which includes the following types of income for everyone who is not a tax-dependent child: wages, business income, retirement income, investment income, Social Security, alimony, unemployment compensation, and financial and educational assistance (see Modeling Unemployment Compensation in the appendix).

MAGI also includes the income of any dependent children\textsuperscript{9} required to file taxes, which for 2009 is wage income greater than $5,700 and investment income greater than $950.\textsuperscript{10} To compute family income as a ratio of the poverty level, we sum the person-level MAGI across the tax unit.\textsuperscript{11} For ACA eligibility, the tax unit includes parents and their dependent children and married people regardless of whether they file separately. In situations where a dependent child is away at school, the ACS does not contain data on the family income and other family information on the child’s

\textsuperscript{7} Family-level characteristics used in determining pre-ACA eligibility, such as income, are based on the family groupings that states define during the process of determining eligibility under pre-ACA rules. However, indicators for “family” characteristics discussed in this paper refer to the family unit that is generally eligible for the same private plan, known as the health insurance unit (HIU).

\textsuperscript{8} The model takes into account disregards for childcare expenses, work expenses, and earnings in determining eligibility, but does not take into account child support disregards because data on such amounts was not available.

\textsuperscript{9} We use the IRS definition of dependent child in cases where the ACS does not allow us to identify children residing in other households. The IRS definition includes people living with their parents if they are unmarried and less than age 19 or less than age 23 and in school.


\textsuperscript{11} We use “tax unit” and “HIU” or “health insurance unit” interchangeably in this report.
record or the presence of the dependent child on the records of family members so we assign some college students to families before computing family MAGI (See Assignment of College Students in the appendix).12

Subsidy and Medicaid eligibility, under current and new rules, also depend on immigration status. Current and new rules require that enrollees be citizens or authorized immigrants. Because the ACS does not contain sufficient information to determine whether most non-citizens are authorized immigrants according to their state’s rules, we impute documentation status for non-citizens in each year of survey data separately based on a year-specific model used in the CPS-ASEC. Documentation status is imputed to immigrants in two stages using individual and family characteristics, based on an imputation methodology that was originally developed by Passel (Passel and Cohen 2009). The approach is designed to produce imputations that match, in the aggregate, published summary estimates of the U.S. undocumented population, nationally and in California, Florida, New York, New Jersey, Illinois, and Texas. In some states, immigrant eligibility under current rules also depends on how long an immigrant has been in the country so we also determine immigration eligibility using state rules and ACS information about citizenship and date of immigration.

We model subsidy eligibility, which depends on the family (more precisely, the health insurance unit) not having an affordable offer for employer-sponsored insurance (ESI) according to the ACA rules. We impute offer status using regression models estimated from CPS data collected in 2005, the last year that the CPS included information on ESI offers in its February supplement. We first impute firm size on the ACS because offer is highly dependent on firm size. Similarly, we impute policy-holder status to people in families with ESI because the ACS does not ask whose job offered the ESI (See Imputing Affordable Offer in the Appendix).

To impute values for the cost of employees’ contributions to their insurance premium, we use results from HIPSM based on industry group and wage-level.13 We impute contributions for

12 Apparent college students living in dormitories and remaining after we attempt to put them back with families are restricted from being eligible unless they also have Medicaid/CHIP reported.

13 Summary tables from the MEPS-HC (http://meps.ahrq.gov/data_stats/quick_tables.jsp) and the Kaiser/HRET Employer Health Benefits Survey (EHBS) (http://ehbs.kff.org/pdf/2009/7937.pdf) show that
individual employee coverage because the cost of the individual contribution is what is used to
determine whether the family has an offer of ESI that is affordable (See Imputing Affordable Offer in
the appendix).

Once we have all the components required for eligibility simulation, we simulate eligibility for
adults and children for the eligibility pathways which correspond roughly to the order in which we
expect eligibility will actually be determined. For children, we check for disability (SSI or
Aged/Blind/Disabled eligibility under current rules), new Medicaid eligibility, CHIP eligibility
under current rules, and eligibility under current rules, otherwise known as maintenance-of-
eligibility (see Eligibility Under Pre-ACA Rules in the appendix). For adults, we check for disability
(SSI or Aged/Blind/Disabled eligibility under current rules), Title IV-E/foster care, new Medicaid
eligibility, and maintenance-of-eligibility (see Eligibility under Pre-ACA Rules in the appendix).
Maintenance-of-eligibility does not apply to those with partial coverage\textsuperscript{14} or 1115 waivers.

\textbf{Changes in Health Insurance Coverage Under the ACA}

Once we have modeled eligibility status for Medicaid/CHIP and subsidized coverage in the
exchanges, we use HIPSM to simulate the decisions of employers, families, and individuals to offer
and enroll in health insurance coverage and then map those results using regression modeling to
ACS to assign probabilities of take-up. HIPSM relies primarily on the CPS-ASEC for demographic and
economic characteristics, with data from several other surveys matched to provide input
information needed for the simulation that the CPS does not collect. The CPS is an employment-
focused survey containing data on approximately 185,000 interviewed non-elderly individuals, and
the ASEC is a supplement to the core CPS questions asked in March. Health care costs of surveyed
individuals are estimated using data from many sources, such as the MEPS-HC and the National
Health Expenditure Accounts.

\textsuperscript{14} Limited benefit programs are those federally- or state-funded programs that offer substantially more
limited medical services (e.g., no hospital coverage), higher cost sharing, or other limitations.
To calculate the impacts of reform options, HIPSM uses a micro-simulation approach based on the relative desirability of the health insurance options available to each individual and family under reform. The approach (known as a “utility-based framework”) allows new coverage options to be assessed without simply extrapolating from historical data. The health insurance coverage decisions of individuals and families in the model take into account a number of factors such as premiums and out-of-pocket health care costs for available insurance products, health care risk, whether or not the individual mandate would apply to them, and family disposable income. Affordability of coverage is built into the decision-making and can be greatly affected by the individual mandate for those who do not qualify for an exemption.

Our utility model takes into account people’s current choices as reported on the survey data. For example, if someone is currently eligible for Medicaid but not enrolled, they or their parents have shown a preference against Medicaid. They will be less likely to enroll in Medicaid under the ACA than a similar person who becomes newly eligible for Medicaid. We use such preferences to customize individual utility functions so that their current choices score the highest, and this affects their behavior under the ACA. The resulting health insurance decisions made by individuals, families, and employers are calibrated to findings in the empirical economics literature, such as price elasticities for employer-sponsored and non-group coverage.

Changes in health insurance coverage under the ACA are computed in six main steps (See Modeling Medicaid Take-up in the appendix for details and take-up rates):

1. *New Medicaid and CHIP Enrollment.* We begin by estimating additional enrollment in Medicaid and CHIP, both by those gaining eligibility under the ACA and those currently eligible, but not enrolled. Many characteristics are used to determine take-up, but the two most important are new eligible status and current insurance coverage, if any. For purposes of take-up, those with incomes below the 138 percent threshold who are currently eligible for limited benefit Medicaid programs are not considered newly Medicaid eligible unless their state’s program is closed to enrollment.

2. *Enrollment in the non-group exchange.* We estimate enrollment in single and family policies in the non-group exchange, both by those eligible for subsidies and those ineligible. Undocumented immigrants are barred from the exchange. First, we estimate those who would be family policy-holders based on the characteristics of their family and estimate enrollment for them and their family members who would be eligible for the same insurance plan. Then, for those not covered by family policies, we estimate enrollment in single plans.
3. **Additional enrollment of the uninsured in ESI.** There would be additional demand for ESI due to the individual mandate, small group market reforms, and small firm tax credits. We estimate additional ESI enrollment for those currently uninsured with an ESI offer in their family and who would not enroll in coverage in Steps 1 and 2 above. As with Step 2, we treat single and family policies separately. In a full HIPSM simulation, employers change their ESI offer decisions, and there is movement both into and out of ESI. We do not currently model employer behavior on the ACS, but our results are similar to results from the full simulation with the CPS for overall level of ESI post-reform as well as the characteristics of the uninsured who gain ESI coverage.

4. **Additional enrollment of the uninsured in non-group coverage.** We complete the simulation by estimating additional enrollment in non-group coverage outside the exchange by those currently uninsured with no ESI offer in the family who would not enroll in Steps 1 or 2. This would be due largely to the effect of the mandate. There would be some additional coverage for the undocumented here as well, since it would be their only option for coverage without an ESI offer.

5. **Transition from single to family ESI.** The individual mandate will provide incentives for families to obtain coverage for all members. In particular, the expected utility model in HIPSM predicts a certain number of single ESI policy-holders in families where other members are uninsured or taking non-group coverage would purchase family ESI to cover the entire family. We model such transitions on the ACS based on the behavior of single ESI policy-holders in HIPSM with mixed coverage in other members. Such families are not common, but this captures a behavioral response to the individual mandate.

6. **Transition from non-group to ESI.** In addition to the transition from ESI to the non-group exchange in Step 2, there are transitions in HIPSM from non-group coverage to ESI. These cannot be fully modeled on the ACS because we do not model changes in ESI offers, but we can model such transitions in cases where an ESI offer was present both with and without the ACA. Single and family ESI policies are considered separately. The number of people changed by this step is much lower than the number affected by most of the earlier steps, but this movement into ESI is a notable result from HIPSM.15

For these projections, we model certain implementation assumptions the same across states. For example, we assume that eligibility for waiver coverage ends beginning in 2014 for adults above 138 percent of the FPL. We assume that the non-group and small group markets are pooled separately since most states are proposing this approach. We also define small firm to be one of up

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to 100 full-time employees (FTEs) since beginning in 2016, states must use this definition. For 2014 and 2015, a state can choose to use its current definition—50 FTEs in nearly all states—instead. Earlier work examined the impact of these implementation choices.16

Comparison of HIPSM-ACS and HIPSM-CPS Findings
To evaluate the ACS model, it is useful to compare its results to those of CPS/HIPSM. However, it should be kept in mind that there are known differences between the two surveys, including differences in timing, sampling, question design, content, and editing. In particular, the CPS/HIPSM data derive from the CPS March Supplements collected in 2008 and 2009. Therefore the tabulations from this model represent an average of those years or an average as of the interview dates (March 2008 and March 2009), depending on the characteristic being tabulated. For the ACS, we used three years of data: 2008, 2009, and 2010. So even prior to adjustment, our ACS data represent conditions somewhat later in date than does our CPS data. This is exacerbated by the reweighting we applied to the ACS data. Because we wanted the ACS to as closely as possible represent conditions just prior to the implementation of ACA, we re-weighted the 2008 ACS and the 2009 ACS so that they matched the 2010 ACS demographic distributions according to the full crossing of income category, state of residence, household full-time worker status (i.e., does household include a person working full-time), and type of household structure (single person, married without children, married with children, or unmarried with children). The result of this reweighting is that data representing 2008 and 2009 are made to look demographically similar to those from 2010. Thus results from the ACS model can be considered to represent conditions about two years subsequent to those represented by the CPS data.

With these factors in mind, we compare baseline coverage:

**Table 1. Coverage of U.S. Residents under 65 at Baseline**

<table>
<thead>
<tr>
<th></th>
<th>CPS</th>
<th>ACS</th>
</tr>
</thead>
<tbody>
<tr>
<td>ESI</td>
<td>56.0%</td>
<td>56.6%</td>
</tr>
<tr>
<td>Non-Group</td>
<td>5.4%</td>
<td>4.3%</td>
</tr>
<tr>
<td>Medicaid/CHIP</td>
<td>16.8%</td>
<td>17.9%</td>
</tr>
<tr>
<td>Medicare</td>
<td>3.2%</td>
<td>3.0%</td>
</tr>
<tr>
<td>Uninsured</td>
<td>18.7%</td>
<td>18.1%</td>
</tr>
</tbody>
</table>


**Notes:** Estimates reflect an adjustment for the misreporting of Medicaid and private non-group coverage on the ACS. Estimates reflect an adjustment for the misreporting of Medicaid.

While these patterns are fairly similar, we see that for the ACS the percentage of persons estimated to be enrolled in Medicaid/CHIP is about 6.6% higher than in CPS. In percentage terms, the difference in estimated non-group enrollment is larger (about 20%) but less important due to the smaller percentage of the population with this coverage. It is likely that these differences are due in part to the different way respondents are questioned about their households’ coverage: survey research shows that responses on coverage are particular sensitive to the presentation of the query. These may be exacerbated by timing differences, edit procedures, biases engendered by response patterns, and so forth.

Turning to model projections for coverage under the ACA, we find the following CPS and ACS results:

**Table 2. Projected ACA Coverage of U.S. Residents Under 65**

<table>
<thead>
<tr>
<th></th>
<th>CPS</th>
<th>ACS</th>
</tr>
</thead>
<tbody>
<tr>
<td>ESI</td>
<td>57.5%</td>
<td>56.3%</td>
</tr>
<tr>
<td>Non-Group</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Exchange</td>
<td>5.7%</td>
<td>5.5%</td>
</tr>
<tr>
<td>Non-Exchange</td>
<td>0.9%</td>
<td>1.0%</td>
</tr>
<tr>
<td>Medicaid/CHIP</td>
<td>22.9%</td>
<td>24.6%</td>
</tr>
<tr>
<td>Medicare</td>
<td>3.2%</td>
<td>3.0%</td>
</tr>
<tr>
<td>Uninsured</td>
<td>9.8%</td>
<td>9.6%</td>
</tr>
</tbody>
</table>


**Notes:** Estimates reflect an adjustment for the misreporting of Medicaid and private non-group coverage on the ACS. Estimates reflect an adjustment for the misreporting of Medicaid on the CPS.
Overall, the projected changes in coverage under the ACA based on the ACS are fairly similar to those based on the CPS—in both instances, under the ACA, substantial increases are anticipated in Medicaid/CHIP coverage and substantial decreases are anticipated in un-insurance. By and large, the distributions are more similar under the ACA scenario than under the baseline scenario, particularly with regard to non-group coverage. Plausibly, this is because coverage under the ACA is less dependent on survey-reported coverage and more dependent on income relative to poverty, family structure, and work status variables which may be more similar across the two surveys. Even so, differences in projected Medicaid coverage rates under the ACA largely mirror those seen in the baseline. In fact, for CPS the ratio of ACA to baseline Medicaid coverage rates is 136.5%. For ACS this is almost identical at 137.4%. As expected, there is a projected increase in Medicaid coverage due to the expansion of adult Medicaid eligibility to all legal residents with an income to poverty ratio of 138 percent or less. Because ACA regulations include a maintenance-of-eligibility provision, the majority of persons reported with Medicaid coverage who were classified as eligible for Medicaid at baseline are largely projected to retain that coverage under the ACA. This likely contributes to ACS Medicaid coverage under the ACA exceeding that projected from CPS, as the proportion of people eligible for Medicaid has increased over-time which is reflected in the ACS estimates.

For reasons explained previously, the results of the ACS implementation of HIPSM described here are not strictly comparable to results from the standard (CPS) implementation of HIPSM. At the same time, it is important to note how closely the estimates from the two simulations line up on a state-by-state basis. Performing an ordinary least square regression between the CPS baseline and ACS baseline on state-by-state percentage of persons by coverage yields an R-square of 0.686 for Medicaid and 0.673 for uninsured, both of which are highly significant. Repeating this analysis for coverage under ACA increases R-square to 0.744 for Medicaid and 0.825 for uninsured. This supports our earlier contention that model agreement is greater in the ACA scenario that under the baseline which is more directly dependent on respondents’ reported coverage. What is more, if

17 Based on the most recent regulations as of this analysis, we assume maintenance-of-eligibility for children and adults.
rather than this static analysis we compare the change in percent covered going from baseline to ACA, we get an R-square of 0.836 for Medicaid and 0.842 for Uninsured. Thus, the ACS model tracks the CPS state by state estimated changes in coverage quite well. Not surprisingly, we find the greatest differences between the estimated coverage distributions in states with the smallest sample. This suggests that to some degree, misalignment between ACS and CPS state level results is a function of sample error. To the extent that this is true, it lends support to the conclusion that the ACS estimates are somewhat more reliable (due to much larger sample sizes) than the CPS estimates.

We have also looked into how the results of the ACS implementation of HIPSM described here compare to results for California produced by Lucia et al. 2013. However we are unable to determine how the results compare without going beyond the scope of this project. In part, we cannot immediately compare the results because we are unable to identify the year the authors use as their base year of comparison. In addition, their projection is for the period 2014-2019 while ours is for 2014 so we do have comparable results currently available. However, we can discern that we assume differences in take-up rates so we assume that this difference alone should lead to different results. Lucia et al assume a take-up rate of 61 percent for newly eligible uninsured adults while we assume a rate of about 72 percent (see above in Step 1. Modeling New Medicaid and CHIP Enrollment).
Appendix 1: HIPSM\textsuperscript{18}

We use multiple years of the Current Population Survey (CPS) and the Household Component of the Medical Expenditure Panel Survey (MEPS-HC) for our core model. We estimate health care expenditures for each individual in the data set in each possible coverage status, including out-of-pocket spending, spending covered by insurance, Medicaid/CHIP spending, and uncompensated care for the uninsured. We impute offers of employer-sponsored insurance, immigration status, and type of Medicaid/CHIP eligibility. We group together workers with the same employment characteristics, such as firm size and industry, into simulated firms.

The general flow of a HIPSM simulation is as follows:

- The model constructs available insurance packages and computes premiums based on current enrollment
- Simulated employers choose whether or not to offer coverage and whether to offer coverage inside or outside the exchange
- Individuals and families choose from among the coverage options available to them: employer sponsored insurance, non-group insurance, health benefit exchanges (if applicable), Medicaid/CHIP, or uninsured
- Employer, individual, and family decisions are calibrated so that overall behavior is consistent with a number of results from the health economics literature
- Premiums are updated based on the new enrollment decisions. The cycle is repeated until equilibrium—in other words, until there is little change between successive iterations of the model

Mapping the HIPSM/CPS micro-simulation approach on to the ACS to compute changes in health insurance coverage under the ACA involves six main steps:

**Step 1. Modeling New Medicaid and CHIP Enrollment**

We first estimate the probability that individuals currently eligible or newly eligible under ACA will take-up coverage under reform (see Appendix Table 1). We estimate these probabilities based on

\textsuperscript{18} For details, see Matthew Buettgens, “Health Insurance Policy Model Methodology Documentation, 2011 National Version” (Washington, DC; The Urban Institute, 2011)

results from HIPSM’s simulation of enrollment changes under ACA, mapped to the ACS. To do this, we categorize respondents eligible for Medicaid into broad categories and within these categories use regression to provide estimates of enrollment rates. The categories were made according to the cross classification of these characteristics:

- Age Group: Child (age 18 or less) or adult
- Eligibility Status: Currently eligible or newly eligible under ACA
- Current Coverage Status: private coverage (ESI or non-group) or uninsured.

Thus there were eight cells that were used for modeling, where estimation and application of modeling were distinct. For all the cells, we use probit regressions with no interaction terms.

We use the following covariates for adults and persons currently having private coverage (6 cells):

- HIU Type: Individual, Unmarried with child, Married without Child, or married with children
- Age Category: 0 – 5, 6 – 18, 19 – 44, 45 – 64.
- Health Status
- Worker Status (Individual Level)
- Worker Status (Household Level)
- Wage (Logarithmic Transformation)
- ESI Offer Status (Individual Level)
- ESI Offer Status (HIU Level)
- HIU Income to Poverty Threshold Ratio
- Educational Attainment Category
- Medicaid Eligibility Status Post-Reform (HIU Level)
- Current Coverage: ESI or non-group

For the other two cells (children without private coverage currently eligible and children without private coverage newly eligible under the ACA), the only covariate is the HIU Income to Poverty Threshold Ratio. Once the models were fitted using HIPSM output and applied to ACS records, the assigned predicted probabilities were adjusted through a raking process. Essentially, we determined a fixed odds rate adjustment within each modeling cell that rendered the aggregate take-up rate within that cell to equal to the corresponding value determined by the HIPSM process.

19 ACS does not actually collect health status. Thus this was imputed using a hot-deck assignment from MEPS according to cells defined by characteristics assumed related to it.
To impute the Medicaid take-up status for the individual respondents eligible for Medicaid, we compared the estimated probability of take-up (after the raking adjustment) to a pseudo-generated standard uniform random number. If the random number was less than the probability, we imputed Medicaid take-up to them.

The following table compares Medicaid/CHIP take-up rates for eight categories of non-elderly people eligible under the ACA, but not currently enrolled. It shows that the ACS and CPS models predict mostly similar probabilities of enrollment by category. Newly eligible adults and children with no private coverage have the highest probabilities of Medicaid take-up.

Appendix Table 2. Medicaid Take-up Rates under the ACA

<table>
<thead>
<tr>
<th>Adult Eligible</th>
<th>Newly Eligible</th>
<th>Private Coverage</th>
<th>ACS Take-Up Count</th>
<th>ACS Take-Up Rate</th>
<th>CPS/HIPSM Take-Up Count</th>
<th>CPS/HIPSM Take-Up Rate</th>
</tr>
</thead>
<tbody>
<tr>
<td>No</td>
<td>No</td>
<td>No</td>
<td>2,373,305</td>
<td>52.0%</td>
<td>2,408,497</td>
<td>50.1%</td>
</tr>
<tr>
<td>No</td>
<td>No</td>
<td>Yes</td>
<td>1,272,767</td>
<td>9.5%</td>
<td>1,086,420</td>
<td>9.0%</td>
</tr>
<tr>
<td>No</td>
<td>Yes</td>
<td>No</td>
<td>48,280</td>
<td>74.2%</td>
<td>33,501</td>
<td>76.3%</td>
</tr>
<tr>
<td>No</td>
<td>Yes</td>
<td>Yes</td>
<td>84,582</td>
<td>23.2%</td>
<td>40,533</td>
<td>32.3%</td>
</tr>
<tr>
<td>Yes</td>
<td>No</td>
<td>No</td>
<td>632,798</td>
<td>14.9%</td>
<td>647,364</td>
<td>14.1%</td>
</tr>
<tr>
<td>Yes</td>
<td>No</td>
<td>Yes</td>
<td>390,093</td>
<td>16.4%</td>
<td>593,969</td>
<td>16.0%</td>
</tr>
<tr>
<td>Yes</td>
<td>Yes</td>
<td>No</td>
<td>9,810,622</td>
<td>72.4%</td>
<td>9,203,667</td>
<td>73.0%</td>
</tr>
<tr>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>3,076,239</td>
<td>35.3%</td>
<td>2,854,343</td>
<td>38.4%</td>
</tr>
<tr>
<td><strong>Total</strong></td>
<td></td>
<td></td>
<td><strong>17,688,686</strong></td>
<td></td>
<td><strong>16,868,294</strong></td>
<td></td>
</tr>
</tbody>
</table>


**Step 2. Modeling Enrollment in the Non-group Exchange**

We construct a second set of take-up models to determine which ACS respondents are most likely to move into the non-group exchange under the ACA (see Appendix Table 2). We fit our models to HIPSM output and produce estimates of the probability that ACS respondents would move from their current coverage to the non-group exchange, either as individuals or as an HIU. Candidates for non-group exchange enrollment in our model included ACS respondent with baseline ESI, non-
group, or uninsurance who were not undocumented immigrants and not eligible for Medicaid under ACA regulations.

We design our models to select the ACS respondents who are likely to enroll in the non-group exchange as policy holders; dependent non-group exchange coverage is then assigned accordingly. In order to predict who would newly enroll in the non-group exchanges as a policy holder, we first develop an algorithm to create a pool of potential policy holders, and then predict who would actually enroll. In a two worker HIU, the highest earner is assigned to this pool. In a one worker HIU, that worker is selected as the likely policy holder. In an HIU with no workers, the highest educated member is selected. In the event of a tie within a zero or two worker HIU, the oldest member is selected. If the eligible members of the family cannot be differentiated by age, then potential policy holder status is assigned randomly to one of the tying members. For family policy holders, we restrict this algorithm to HIUs in which there was at least one potential dependent.

We estimate separate models to first select family, then single policy holders. After predicting the family policy holders, we assign eligible dependents in the HIU to non-group exchange coverage as well. The single policy model was run on the residual HIUs, that is, HIUs in which no member had taken up family coverage. We reason that ACS respondents would have differential take-up patterns according to their baseline coverage type and assign them to separate models as such. Thus to estimate take-up in the non-group exchange, we estimate six separate models: single and family policies in our three baseline coverage categories (ESI, non-group, and uninsured). For each model we use the following covariates:

- HIU Type: Individual, Unmarried with child, Married without Child, or married with children
- Age Category: 0 – 5, 6 – 18, 19 – 44, 45 – 64.
- Self-Reported Health Status
- Worker Status (Individual Level)
- Worker Status (Household Level)
- Wage (Logarithmic Transformation)
- ESI Offer Status (Individual Level)
- ESI Offer Status (HIU Level)
- HIU Income to Poverty Threshold Ratio
- Educational Attainment Category
- Subsidy Eligibility Status
- Number of Children
Presence of a Child in Public Coverage

Using a probit model with a policy-holder indicator as the dependent variable, we fit the model to HIPSM estimates and apply the predicted probabilities by characteristic to the ACS observations. To assign take-up, we compare the predicted probability to a generated standard uniform random number and assign the ACS respondent to non-group exchange coverage if their predicted probability exceeded the random number. Appendix Table 2 shows the take-up rates based on the results of our model. It shows that current non-group enrollees are the most likely to move into the non-group exchange under the ACA and ESI enrollees are the least likely to move into the exchange.

Appendix Table 3. Non-group Exchange Take-Up Rates under the ACA, by Subsidy Eligibility Status and Baseline Health Insurance Type

<table>
<thead>
<tr>
<th>Subsidy Eligible</th>
<th>Baseline Insurance</th>
<th>Child</th>
<th>Adult</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>ESI</td>
<td>13.5%</td>
<td>9.4%</td>
<td>9.9%</td>
<td></td>
</tr>
<tr>
<td>Non-Group</td>
<td>86.9%</td>
<td>77.8%</td>
<td>79.1%</td>
<td></td>
</tr>
<tr>
<td>Uninsured</td>
<td>41.0%</td>
<td>38.1%</td>
<td>38.2%</td>
<td></td>
</tr>
<tr>
<td>Total</td>
<td>41.3%</td>
<td>35.8%</td>
<td>36.3%</td>
<td></td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Not Subsidy Eligible</th>
<th>Baseline Insurance</th>
<th>Child</th>
<th>Adult</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>ESI</td>
<td>1.2%</td>
<td>1.6%</td>
<td>1.5%</td>
<td></td>
</tr>
<tr>
<td>Non-Group</td>
<td>70.8%</td>
<td>64.3%</td>
<td>65.6%</td>
<td></td>
</tr>
<tr>
<td>Uninsured</td>
<td>23.2%</td>
<td>26.4%</td>
<td>26.0%</td>
<td></td>
</tr>
<tr>
<td>Total</td>
<td>4.8%</td>
<td>6.1%</td>
<td>5.8%</td>
<td></td>
</tr>
</tbody>
</table>


1. Subset to the nonelderly who are not Medicaid eligible and not undocumented immigrants

**Step 3. Modeling Additional ESI Enrollment of the Uninsured**

Under the ACA, a sizeable number of currently uninsured persons could take-up ESI coverage. In HIPSM, employers take into account their employees’ gains or losses from having a health insurance offer and perceived offering costs to decide whether to make an offer. Employers will make an offer when they anticipate that (i) the employees’ combined value of the offer exceeds the
offering costs, and (ii) there are enough employees who gain from having the offer. The costs of offering coverage, which can change under reform, are calculated as:

- The employers’ premium contributions;
- Plus any assessments to which the employer is liable under reform based on whether or not it offers coverage deemed affordable to its workers;
- Plus a fixed administrative cost to employers of offering ESI;
- Minus any tax incentives due to employers’ tax exclusions; and
- Minus any employer tax credits under reform.

To account for this movement, we assemble an ESI take-up model that estimates the probability that ACS respondents who are currently shown as uninsured but likely to be or become eligible for ESI will take-up coverage. To estimate the probability that eligible individuals (either by themselves or as part of an HIU) take-up ESI from uninsured status, we build models of this movement from the HIPSM simulation of coverage changes under ACA. We perform the modeling in two stages: first at the individual level for respondents imputed to have offers of ESI coverage, and second at the HIU level for respondents who are in HIUs imputed to have at least one offer of ESI coverage. For the individual model we use these covariates in an uninteracted probit model:

- HIU Type
- Bad Health (Individual Level: Respondent Reported Fair or Poor Health)
- Bad Health (HIU Level: Respondent Reported Fair or Poor Health)
- MAGI Income to Poverty Threshold Ratio Category and Rate
- Wage (Logarithmic Transformation)

We estimate the model from HIPSM output, with the dependent variable being an indicator of whether the individual moved from uninsured to single-person ESI.

For uninsured persons who were not imputed to take up single-person ESI coverage, we compute an HIU-level (family-level coverage) probability of ESI take-up. Because it is possible that two adults in the HIU both may have been imputed to have an ESI offer, it is expedient to impute who would acquire the ESI coverage if the HIU were to take it up. This is done by using the ESI policyholder status probabilities that were generated in the offer status model. Essentially, all adults imputed to have an ESI offer are assigned a probability of being the policyholder proportionate to their share of the sum of the total HIU probability of being policyholders, using a Monte-Carlo imputation.
Then, for the adult in the HIU imputed to be the policy holder should a policy be taken, we use their characteristics to estimate the probability that they will take up family coverage. The covariates are

- HIU Type: Individual, Unmarried with child, Married without Child, or married with children
- Bad Health Status (Respondent-Reported as Fair or Poor)
- Age Group
- MAGI Income to Poverty Threshold Ratio, category and rate
- Wage (Logarithmic Transform)

We also interact HIU Type (Single Person Household) with the lowest MAGI Income to Poverty Threshold category.

Comparing the model’s predicted probability to a standard uniform number, we impute take-up to the putative policy holder. However, if that person is imputed to take-up family coverage, then all other members of the HIU who are currently uninsured are also imputed to take up that ESI policy. Appendix Table 3 shows family ESI take-up of the uninsured not enrolling in Medicaid/CHIP or the exchange. It shows that the predicted rates by category are similar for the ACS and CPS models and the rates are lowest for people with incomes below 138 percent of the poverty level.

Appendix Table 4. Family ESI Take-up of the Uninsured not Enrolling in Medicaid/CHIP or the Exchange.

<table>
<thead>
<tr>
<th>Income to Poverty Thresh. Ratio</th>
<th>ACS Takeup Count</th>
<th>ACS Takeup Rate</th>
<th>CPS/HIPSM Takeup Count</th>
<th>CPS/HIPSM Takeup Rate</th>
</tr>
</thead>
<tbody>
<tr>
<td>0 - 138%</td>
<td>141,017</td>
<td>19.5%</td>
<td>43,418</td>
<td>19.1%</td>
</tr>
<tr>
<td>138 - 250%</td>
<td>797,570</td>
<td>59.2%</td>
<td>345,309</td>
<td>58.1%</td>
</tr>
<tr>
<td>250 - 400%</td>
<td>544,419</td>
<td>56.0%</td>
<td>255,528</td>
<td>56.3%</td>
</tr>
<tr>
<td>400+ %</td>
<td>312,045</td>
<td>57.1%</td>
<td>314,217</td>
<td>60.5%</td>
</tr>
<tr>
<td>1,795,051</td>
<td></td>
<td></td>
<td>958,472</td>
<td></td>
</tr>
</tbody>
</table>


Appendix Table 4 shows single policy ESI take-up of the uninsured not enrolling in Medicaid/CHIP or the exchange. It shows that the predicted rates by category are mostly similar for the ACS and
similar to what we observe for family policy take-up, the rates are lowest for people with incomes below 138 percent of the poverty level.

Appendix Table 5. ESI Single Policy Take-up Rates for the Uninsured not Enrolling in Medicaid or the Exchange.

<table>
<thead>
<tr>
<th>Income to Poverty Thresh. Ratio</th>
<th>Single Person HIU Status</th>
<th>ACS Takeup Count</th>
<th>ACS Takeup Rate</th>
<th>CPS/HIPSM Takeup Count</th>
<th>CPS/HIPSM Takeup Rate</th>
</tr>
</thead>
<tbody>
<tr>
<td>0 - 138%</td>
<td>No</td>
<td>98,135</td>
<td>20.9%</td>
<td>82,568</td>
<td>19.3%</td>
</tr>
<tr>
<td>0 - 138%</td>
<td>Yes</td>
<td>50,323</td>
<td>16.1%</td>
<td>65,423</td>
<td>21.1%</td>
</tr>
<tr>
<td>138 - 250%</td>
<td>No</td>
<td>358,841</td>
<td>50.9%</td>
<td>231,108</td>
<td>50.9%</td>
</tr>
<tr>
<td>138 - 250%</td>
<td>Yes</td>
<td>768,696</td>
<td>80.4%</td>
<td>1,086,181</td>
<td>83.7%</td>
</tr>
<tr>
<td>250 - 400%</td>
<td>No</td>
<td>167,980</td>
<td>41.5%</td>
<td>120,565</td>
<td>36.3%</td>
</tr>
<tr>
<td>250 - 400%</td>
<td>Yes</td>
<td>377,700</td>
<td>74.1%</td>
<td>618,625</td>
<td>79.1%</td>
</tr>
<tr>
<td>400+ %</td>
<td>No</td>
<td>114,635</td>
<td>45.3%</td>
<td>203,043</td>
<td>58.4%</td>
</tr>
<tr>
<td>400+ %</td>
<td>Yes</td>
<td>207,565</td>
<td>79.1%</td>
<td>463,057</td>
<td>79.6%</td>
</tr>
</tbody>
</table>

**Step 4. Modeling Additional Non-group Enrollment of the Uninsured**

In addition to the creation of the exchanges, we expect to see a more limited expansion of the non-group market through the non-exchange, mainly through new enrollment of those currently uninsured. To this end, we develop an additional model to estimate the probabilities that certain ACS respondents would move from uninsurance to the non-group non-exchange. We restrict our model to include only the baseline uninsured who had not already taken up Medicaid or the exchange and did not have an ESI offer in the family. Again, we applied an algorithm to create a subsample of the most likely policy-holders, described above in Step 2. We estimate a model to determine family policy holder status, assign their eligible dependents to non-group coverage, and run a single policy holder model on the remaining HIUs. Thus we estimate two separate probit models, each with the following covariates:

- Age Category: 0 – 5, 6 – 18, 19 – 44, 45 – 64.
- Health Status
- Worker Status (Household Level)
- Wage (Logarithmic Transformation)
- HIU Income to Poverty Threshold Ratio
- Number of Children
- Presence of a child in Public Coverage
- Citizenship Status
- Number of Adults in the Family

---

20 Additionally, under the ACA, individuals will have the choice of non-group coverage through the exchange or outside it. The same benefit tiers and essential benefits are required across the exchange and non-exchange markets, and risk adjustment across them is required. Choice between non-group coverage inside and outside the exchange is governed by the difference in expected utility between the plans and a latent preference term whose distribution can be set to simulate behavior such as inertia, making individuals already purchasing coverage in the pre-exchange non-group market less likely to switch to the exchange. Subsidies for premiums are available only in the exchange and eligibility for these will change the costs facing potential purchasers. Absent subsidies, we assume administrative costs create the only difference in expected utility between the exchange and non-exchange plans. By default, we assume full risk adjustment, as that is the intent of the law. When more regulatory guidance is available on exactly which risk adjustment methodologies will be used and their effectiveness is assessed, we will implement less than full adjustment between the exchange and non-exchange plans as an option.

21 ACS does not actually collect health status. Thus this was imputed using a hot-deck assignment from MEPS according to cells defined by characteristics assumed related to it.
The dependent variable is an indicator of non-group non-exchange policy holder status. Again we compare each respondent’s predicted probability to a standard uniform random number and assign enrollment in the non-group non-exchange to those observations with probabilities that exceed the random number. Appendix Table 5 shows the overall new enrollment in the non-group non-exchange coming out of our model. It shows that the large majority of non-group enrollees outside the exchange are expected to come from single-person policyholders.
Appendix Table 6. Non-group Enrollment Outside the Exchange under the ACA

<table>
<thead>
<tr>
<th>Family</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Policy Holders</td>
<td>21,135</td>
</tr>
<tr>
<td>Dependents</td>
<td>44,742</td>
</tr>
<tr>
<td>Total</td>
<td>65,877</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Single</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Policy Holders</td>
<td>384,933</td>
</tr>
<tr>
<td>Dependents</td>
<td>0</td>
</tr>
<tr>
<td>Total</td>
<td>384,933</td>
</tr>
</tbody>
</table>


1. Subset to the baseline uninsured without and ESI offer in the family that do not take up Medicaid or non-group coverage

Step 5. Modeling the Transition from Single to Family ESI Policies

We also expect to see some single ESI policy holders extend coverage to their dependents in response to the ACA’s coverage mandate. Thus, we develop a model, again based on HIPSM output, to predict which single ESI policy holders in the ACS are likely to switch to a family plan. We restrict our model to HIUs in which there is at least one single policy holder and at least one other member of the HIU that could potentially be covered by an ESI family plan. The eligible dependents include those with baseline non-group or uninsurance that had not already taken up coverage in a previous model. Note that we only model moving from an individual plan to a family plan; we did not model adding a dependent to a current family plan. Within the eligible group of single ESI policy holders, we use the following covariates to estimate the probability that they will switch to a family ESI policy:

- HIU Type: Individual, Unmarried with child, Married without Child, or married with children
- Age Category: 0 – 5, 6 – 18, 19 – 44, 45 – 64.
• Health Status\textsuperscript{22}  
• Worker Status (Individual Level)  
• Wage (Logarithmic Transformation)  
• HIU Income to Poverty Threshold Ratio  
• HIU Income to Poverty Threshold Categories (<138\% FPL, 138\% - 200\% FPL, 200\% - 300\% FPL, 300\% - 400\% FPL, 400\%+ FPL)  
• Number of Children  
• Presence of a child in Public Coverage  
• Citizenship Status  
• Firm Size\textsuperscript{23}  
• Education Status

Again, these covariates entered into a probit model where the dependent variable is an indicator for a family ESI policy holder. Once we fit this model to HIPSM and the predicted probabilities are assigned to the ACS according their characteristics above, we assign enrollment as a family policy holder to those with probabilities higher than a generated standard uniform random number. ESI coverage is then assigned to eligible dependents, as described above.

\textit{Step 6. Modeling the Transition from Non-group to ESI}

Another expected coverage transition within the insured population is the movement from non-group coverage to ESI. The eligible non-group population includes ACS respondents with an ESI offer in the family who are not eligible for exchange subsidies. We model this by fitting a probit model to HIPSM data in order to estimate the probability that ACS respondents would move from non-group to ESI. We first model movement to family ESI coverage and then to single ESI coverage. Again, we model the movement of policy holders and assigned dependent coverage accordingly. Note that an ACS respondent does not have to be a non-group family policy holder in order to take

\textsuperscript{22} ACS does not actually collect health status. Thus this was imputed using a hot-deck assignment from MEPS according to cells defined by characteristics assumed related to it.

\textsuperscript{23} ACS does not actually collect firm size. Thus this was imputed using a hot-deck assignment from CPS according to cells defined by characteristics assumed related to it.
up family ESI coverage, but they do have to have an eligible dependent within the HIU. We estimate a model to determine family policy holder status, assign their eligible dependents to ESI coverage, and estimate a single policy holder model on the remaining HIUs. The covariates included in these models are:

- HIU Type: Individual, Unmarried with child, Married without Child, or married with children
- Age Category: 0 – 5, 6 – 18, 19 – 44, 45 – 64.
- Health Status\textsuperscript{24}
- Worker Status (Individual Level)
- Wage (Logarithmic Transformation)
- HIU Income to Poverty Threshold Ratio
- HIU Income to Poverty Threshold Categories (<138% FPL, 138% - 200% FPL, 200% - 300% FPL, 300% - 400% FPL, 400%+ FPL)
- Number of Children
- Presence of a child in Public Coverage
- Citizenship Status
- Firm Size\textsuperscript{25}
- Industry Type

We used these covariates in a probit model with an indicator for ESI policy holder as the dependent variable. Based on HIPSM output, the regression provides characteristic specific probabilities of taking up new ESI coverage. We assigned take-up of ESI coverage if the associated probabilities exceed a standard uniform random number.

**Limitations to Modeling Coverage Changes**

The current methodology does not offer the full range of transitions possible in HIPSM. Appendix Table 6 shows the transitions which are captured and those which are not. It shows that two of the

\textsuperscript{24} ACS does not actually collect health status. Thus this was imputed using a hot-deck assignment from MEPS according to cells defined by characteristics assumed related to it.

\textsuperscript{25} ACS does not actually collect firm size. Thus this was imputed using a hot-deck assignment from CPS according to cells defined by characteristics assumed related to it.
20 viable transitions are not currently simulated and five others are simulated with notable limitations, described below.

**Appendix Table 7. Coverage Transitions Modeled in ACS-HIPSM**

<table>
<thead>
<tr>
<th>Baseline Coverage</th>
<th>Post-ACA Coverage</th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Uninsured</td>
<td>Medicaid/CHIP</td>
<td>Non-Group Exchange</td>
<td>Non-Group Non-Exchange</td>
<td>ESI</td>
</tr>
<tr>
<td>Uninsured</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
</tr>
<tr>
<td>Medicaid/CHIP</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
<td>Y*</td>
</tr>
<tr>
<td>Non-Group Exchange</td>
<td>N.A.</td>
<td>N.A.</td>
<td>N.A.</td>
<td>N.A.</td>
<td>N.A.</td>
</tr>
<tr>
<td>Non-Group Non-Exchange</td>
<td>N</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
<td>Y*</td>
</tr>
<tr>
<td>ESI</td>
<td>N</td>
<td>Y</td>
<td>Y*</td>
<td>Y*</td>
<td>Y</td>
</tr>
</tbody>
</table>

* More limited than HIPSM

The Medicaid to non-group exchange transition is of minor importance, since it is available only to those not eligible for subsidies. The Medicaid to non-group or ESI transitions would occur in various maintenance-of-eligibility scenarios or in a simulation of CHIP being eliminated due to lack of federal funds. We can model such scenarios by (i) running them on HIPSM, (ii) identifying ACS observations that would lose eligibility, and (iii) imputing post-reform coverage for them using HIPSM results.

Transitions between ESI and non-group coverage involve employer behavior. Since there are no plans to attempt the construction of synthetic firms on ACS data, these transitions are limited in that we do not model changes in employer offer and the resulting coverage changes. These limitations are important for modeling options that make the non-group market notably more attractive relative to ESI than with our standard implementation of the ACA. Such options should be modeled exclusively in HIPSM.
Finally, the transitions from some form of coverage to being uninsured are all small. The transition from Medicaid to uninsured basically happens only when maintenance-of-eligibility is changed. The transition from ESI to uninsured happens almost exclusively due to loss of ESI offer. The transition from non-group to uninsured is very rare.

Also, we do not distinguish between the Small Business Health Options Program (SHOP) exchange and the rest of the small group ESI market. From the point of view of coverage and consumer affordability, there would be very little difference between small firm coverage inside and outside the exchange. The Essential Health Benefits, actuarial value tiers, medical loss ratio (MLR), and premium rating reforms would apply equally to both, and there would be risk adjustment between them. However, options involving the SHOP exchange and the small group market in general have to be done exclusively in HIPSM.

Examples of policy questions which could be addressed using HIPSM/ACS data:

- **Sensitivity analyses on Medicaid and exchange take-up.** Similar to analysis the Urban Institute has done for Washington State integrating HIPSM with the Washington State Population Survey.\(^{26}\)

- **Multi-year Medicaid enrollment and cost projections.** Similar to analysis done for Washington State. Different categories of eligibles would ramp-up enrollment at different rates, depending on the amount of new outreach necessary and their likelihood of using the no-wrong-door interface.

- **The Basic Health Program.** Similar to work done for Washington State.\(^{27}\) Estimating Basic Health Plan (BHP) eligibility and enrollment, the size of the remaining exchange, and federal payments and BHP costs.

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\(^{26}\) Matthew Buettgens, Randall R. Bovbjerg, Caitlin Carroll, and Habib Moody, “The ACA Medicaid Expansion in Washington,” (Washington, DC; The Urban Institute; 2012)

\(^{27}\) Matthew Buettgens and Caitlin Carroll, “The ACA Basic Health Program in Washington State,” (Washington, DC; The Urban Institute; 2012)
• **Maintenance-of-Eligibility Scenarios and the Future of CHIP.** Modeling loss of eligibility for the affected populations and the coverage they would have without an available public program.\textsuperscript{28}

• **Characteristics of the remaining uninsured.** Earlier work using CPS-based estimates was limited in its ability to analyze differences at the state level.\textsuperscript{29} The ACS will allow analysis by sub-state areas that would be even more useful to state health officials and safety net providers.

The following are examples of policy questions which require the full HIPSM model:

- Future trends in employer-sponsored insurance.
- SHOP (small business) exchange implementation options.
- The effects of merging the small business and non-group markets.
- Long-term health care cost trends and their effects on coverage
- Changes in non-group or ESI market rules, such as the limits on age or tobacco use rating.

\textsuperscript{28} Genevieve M. Kenney, Matthew Buettgens, Jocelyn Guyer, and Martha Heberlein, “Improving Coverage For Children Under Health Reform Will Require Maintaining Current Eligibility Standards For Medicaid And CHIP,” Health Affairs, 30, No. 12 (2011): 2371-2381

\textsuperscript{29} Matthew Buettgens and Mark Hall, “Who Will Be Uninsured after Health Insurance Reform?” (Washington, DC; The Urban Institute; 2011)
Appendix 2: ACS Modeling and Variable Construction

The appendix provides details on the simulation in the order in which it is discussed in the main body of this report, as follows:

1. Editing the ACS Coverage Data
2. Modeling Unemployment Compensation
3. Assignment of College Students
4. Imputing Affordable Offer
5. Eligibility Under Pre-ACA Rules
6. Imputing Self-Reported Health Status
7. Imputing Affordable Offer

**Editing the ACS Coverage Data**

In an effort to correct for apparent measurement errors in the ACS coverage data and to define coverage as including only comprehensive health insurance as opposed to single-service plans (e.g., dental coverage), we develop a set of logical coverage edits that are applied if other information collected in the ACS imply that coverage for a sample case likely has been misclassified in the ACS or the reported coverage is not comprehensive (Lynch et al. 2012, Lynch and Kenney 2011). We draw from approaches that have been applied to other surveys (National Center for Health Statistics 2005) and build on ACS edit rules used by the Census Bureau that add Medicare, Medicaid/CHIP, and TRICARE/military coverage to sample persons with apparent misreported coverage of those types (Lynch et al. 2010).

For adults, we believe we need to edit coverage primarily because administrative sources, other surveys, and micro-data level inconsistencies suggest there is a problem with respondents misreporting non-group or reporting single-service non-group plans in response to the ACS question on non-group coverage (Lynch and Boudreaux 2010, Mach and O'Hara 2011). We attempt to improve the validity of the adult coverage estimates by editing individual sample cases from their reported coverage status if other information collected in the ACS, including information on other household members, implies that the person with reported non-group coverage actually has Medicaid, employer-sponsored insurance (ESI) coverage, or is uninsured (i.e., has only a single service plan such as dental-only coverage) and does not have comprehensive health insurance coverage. We drew on approaches that have been applied to other surveys and developed edits that use combinations of family income, employment, program participation, Medicaid eligibility status, health insurance coverage, functional limitations, and other family- and person-level data to check
each case for the presence of a scenario implying that the ACS coverage status is incorrect. For example, our largest non-group edit for adults edits sample adults with reported ESI and non-group to ESI if their spouse has a full-time job and ESI reported (Davern et al. 2009; Jones and Cohen, 2002). In this case, the reported non-group is a likely a single-service plan or an incorrect report of the employee’s contribution to the ESI plan. We benchmark results of editing to the NHIS because that survey’s detailed questioning in face-to-face interviews and post-collection recoding (National Center for Health Statistics, 2010) suggest the coverage data should be quite valid and a record-check study on Medicaid provides evidence for that belief (Lynch and Resnick, 2009). After editing the 2009 data, our derived estimate of the number of non-elderly uninsured is 39.4 million which compares to the NHIS uninsured estimate of 39.2 million, our derived estimate of the number with Medicaid/CHIP as their primary coverage is 16.4 million compared with 16.2 million from the NHIS (authors’ tabulations), and our derived estimate of non-group is 9.9 million compared to 9.2 million from the NHIS (authors’ tabulations).

For children, edit coverage because administrative sources, other surveys and micro-data level inconsistencies suggest there is a problem with respondents underreporting Medicaid/CHIP and over-reporting comprehensive non-group. (Lynch et al. 2011, Lynch and Boudreaux, 2010). We take the same basic approach as described for the adults above. As an example, our largest edit moves Medicaid/CHIP eligible children from non-group to Medicaid/CHIP if their parent was edited from non-group to Medicaid. After editing the child data, our derived estimate of the number of uninsured is 6.7 million which compares to the NHIS uninsured estimate of 6.6 million, our derived estimate of the number with Medicaid/CHIP as their primary coverage is 16.4 million compared with 16.2 million from the NHIS (authors’ tabulations), and our derived estimate of non-group is 2.0 million compared to 2.7 million from the NHIS (authors’ tabulations). Our derived Medicaid/CHIP estimate is slightly below the administrative count, but we believe that the administrative counts could overstate the number of children enrolled in Medicaid/CHIP coverage on a given day. 30

30 While the derived administrative counts are considered to be more consistent than baseline administrative totals with respect to the Medicaid/CHIP coverage estimates from the ACS, they may still overstate this coverage on a given day because the adjustments do not take into account potential duplication in CHIP records. In addition, some people may remain on the administrative data after they have obtained another type of coverage, and families may not be aware that their child is enrolled in public coverage, due, for example, to misunderstandings about continuous eligibility periods or to automatic re-enrollment/enrollment, and thus may behave as though the child is uninsured. Finally, both retroactive and
Modeling Unemployment Compensation

The ACS collects information about unemployment compensation, alimony, financial assistance and educational assistance altogether with other income when it ask about “other income”. Of these MAGI components, our calculations suggest that only the treatment of income from unemployment compensation will affect our results. We initially intended to directly impute unemployment compensation. However, because of the considerable complexity required to do this appropriately (i.e., because we need to be able to first estimate wage rate and period of unemployment and use those in turn to estimate lost wages), as a simplification, we used “other income” in the place of unemployment compensation. In fact, in a majority of cases (as shown in CPS data), they are identical. To some degree, because of the additional types of income sources included in ACS “other income” this will cause an upward bias in the ACS MAGI computation. However, this is considerably mitigated by the infrequency of respondents reporting “other income”. Comparing this computation of MAGI (i.e., including all “other income”) distributionally to the value computed in CPS shows a high level of concordance, to the point that we consider them more or less interchangeable. When we have an opportunity to re-visit this issue we intend to attempt to further improve the precision of this computation.

Assigning College Students to Families

One challenge to simulating eligibility and enrollment in the ACS is the sample design that samples students in dormitories and other temporary residences rather than with their permanent family residence as is done in the CPS. As a result, we do not know the family incomes of students when simulating their status or know about their presence when modeling other members of their family. In an attempt to remedy this, we assign some college students to families. For this assignment, we first identify college student ACS-respondents who likely would be reported with their parents’ household in CPS. To identify ACS college students living away from home, we first look to find the ACS college students tabulated in single-person households who are as similar as possible to CPS presumptive eligibility may produce an over-count of enrollees relative to survey respondents’ beliefs regarding their coverage. Additional imprecision in the administrative totals may be introduced by the our method of accounting for duplication across states and partial coverage.
students in this situation based on statistical matching. We conduct the matching within cells formed by reported state of residence and age. Within these cells, we measure similarity according to wages, race and ethnicity, and sex. For wage similarity, the closer an ACS record is to the CPS record it is intended to match, the more likely we are to select it in a match.

It is highly unlikely that a college student surveyed at college and his or her parents would simultaneously be included in a given year’s ACS sample. Moreover, even if that were the case, it would be nearly impossible to determine to which household they belong. Therefore, our intention is to group college students on the ACS who are similar to those who would have been reported on CPS as living with their parents with a household that is likely to have such college students. We identify these households using a statistical model developed to estimate the probability that a CPS household would have a college student reported as a member based on their characteristics. We include the following characteristics in the model:

- Age and race of the oldest household member 75 years or younger
- Age difference (from previous) to person likely to be the spouse (if such a person can be identified)
- Household Income
- Household count of children aged 14 or younger
- Household count of children aged 15 to 17
- State of residence

We derive the estimates using a logistic regression model that also includes several interaction terms. Using this model, we draw a probability-proportionate-to-size systematic sample of ACS households that are designated as having college students. Because, it is frequently the case that the same household has more than one college student, we deliberately draw fewer households than college students we intended to assign. The assignment of college students on the ACS to households was random among both the students and households that had been designated in previous steps for inclusion in the assignment. We implement the assignment by changing the designated college student’s household ID to that of the target household.

**Eligibility Under Pre-ACA Rules**

Family-level characteristics used to determine pre-ACA eligibility, such as income, are based on the family groupings that states define during the process of determining eligibility under pre-ACA rules, which is slightly different from the tax unit used for ACA eligibility.
For children, the model compares family income and other characteristics to the pre-ACA Medicaid and CHIP thresholds in their state of residence for the pathways listed below.

- **SSI Recipients** – children with SSI income.
- **Section 1931** – children who meet the immigrant, asset, income and parent employment rules for 1931 eligibility in their state.
- **Poverty Expansion** – children who meet the age, immigrant, asset, and income rules for poverty expansion eligibility.
- **CHIP** – children who meet the age, immigrant, and income rules for CHIP eligibility in their state.

For adults, we consider Medicaid eligibility to be eligibility for comprehensive Medicaid or Medicaid-equivalent benefits. Limited benefit programs are those federally- or state-funded programs that offer substantially more limited medical services (e.g., no hospital coverage), higher cost sharing, or other limitations. We model the following pathways in the order shown:

- **Foster child** – 19- or 20-year-olds whose relationship to the respondent was "foster child" are automatically assigned eligibility regardless of income level (some may be aged-out foster children who are also eligible for Medicaid in most states).
- **SSI enrollee** – Individuals with SSI income, regardless of income level, unless there is evidence that the SSI income may be their child's (the ACS does not ask about income for people younger than 15).
- **Section 1931** – Adults whose (1) gross income either fell below the gross income limit or the state had no gross income test; (2) net income after subtracting disregards was below the net income limit; (3) assets fell below the asset limit; \(^{31}\) and (4) the person met the immigration qualifications. If the state applies the 100-hour rule, eligibility was limited to families meeting that condition.
- **Aged/Blind/Disabled** – Adults with a functional limitation who have countable income below the income limit for aged/blind/disabled persons, countable assets below the asset limit, and who met the immigration qualifications for aged/blind/disabled eligibility in their state.

\(^{31}\) Like the CPS and the NHIS, the ACS has only limited information on assets owned, meaning that the number of people who are not determined to be eligible due to the value of their assets is probably lower in the simulation than it would be if we had complete asset information. Thus, it is likely that we are understating the number of people who are denied eligibility because of the value of their assets.
• **Medically needy** – Adults in Medically Needy categories (disabled, parent, or dependent youth age 19 or 20) were assigned eligibility if they met the Medically Needy income and asset limits and immigration qualifications.

• **Relative caretaker** – Adults were assigned eligibility if they appeared to be "relative caretakers” (that is, living in a home with a Medicaid-enrolled child whose parents do not live in the home) and they met the immigrant requirements and income/asset thresholds to qualify for Section 1931 coverage.

• **Other.** Adults who have Medicaid reported and evidence that they were likely eligible for the any of the following pathways: disability, pregnancy, refugee, Ribicoff youth, relative caretaker, medically needy, or transitional medical assistance (TMA).

It should be noted that simulating adults’ pre-ACA eligibility is more complicated than simulating children’s eligibility. There is more variation in programs and rules across states; reports about eligibility rules generally summarize types of rules that are common across states and do not capture all the details about each state’s specific programs; and while the state manuals have more detail, each is extremely detailed, which makes it difficult to distill the relevant information for a national analysis of all 50 states.
**Imputing Self-Reported Health Status**

Health status is highly correlated with medical spending and so it affects whether individuals and households take-up health insurance and the type they choose. However, because the ACS does not include a health status indicator, we develop a process for imputing it. We use a hot deck imputation, with the donor data being the Medical Expenditure Panel Survey – Household Component (MEPS-HC) for combined year 2005 - 2007. The hot deck method randomly selects the value to be imputed to a recipient record (from the ACS file) from a donor record (from the MEPS-HC data) in the same cell (defined by a set of classification characteristics). We impute health status (which consists of this ranking: 1 - Excellent, 2 - Very good, 3 - Good, 4 - Fair, 5 - Poor) separately for children and adults. For adults, cells for the hot deck procedure were formed from these ACS variables:

- Physical Limitations
- Cognitive Limitations
- Receipt of Supplemental Security Income (SSI)
- Age Category (Less than 19, 19 – 34, 35 – 49, 50 – 59, 60 and greater)
- Sex
- Current Health Insurance Coverage Type (Medicaid, Medicare, Employee Sponsored, Other Government, Non-Group, Un-Insured)
- Health Insurance Unit Income to Poverty Threshold Ratio Category (.5 or less, 0.5 – 1, 1 – 1.5, 2.5 – 4, 4 or more)
- Education Attainment (No High School Diploma, High School Diploma, Bachelor’s Degree or higher)

For children, cells for the hot deck procedure were formed from these characteristics:

- Physical Limitations
- Cognitive Limitations
- Receipt of Supplemental Security Income (SSI)
- Health Insurance Unit Income to Poverty Threshold Ratio Category (.5 or less, 0.5 – 1, 1 – 1.5, 2.5 – 4, 4 or more)

The software used to perform the imputation collapse cells when required by dearth of sample in full crossing. Note that hot decking was performed independently for each ACS survey year according to an identical methodology, including the use of the same donor file from MEPS-HC.
**Imputing Affordable Offer**

*Policy holder.* Policyholder status is not asked in the ACS however, since it is frequently the case that within the same household there is more than one ESI policy-holder, we attempt to model policyholder status so that results are consistent with the HIPSM/CPS baseline in terms of the number of ESI policy-holders within the household. First, we model ESI policy-holder status using logistic regression on employment status, wages, and industry group. To improve the fit, for those with resulting estimated probabilities > .85, we use a second stage logistic model generating a probability based on employer type (Private, Federal, State, Local, Self-Employed, Non-Paid Employment, sex, and wages.

For households with ESI coverage, we score each employed person’s likelihood of being a policy-holder using these models. For each such household, the person most likely to be a policyholder was imputed as such. If the person with the second-highest probability of being a policy-holder was within 6.1% of the highest, they were also imputed as a policy-holder. Other working adults in the household were also flagged as policyholders if they had a probability that was at no more than 25% less than the person with the next highest probability. These cutoff percentages are derived from a manual attempt to match ESI policy holder status and ESI policy holder count by household to the training data.

*Firm size.* The probability of being offered health insurance benefits is highly dependent on firm size.\(^{32}\) We impute firm size (as categorized by number of employees: 1 - 9, 10 - 24, 25 - 99, 100 - 499, 500 - 999, or 1000+) to workers on the ACS using a Monte-Carlo simulation based on the distribution of firm sizes in the HIPSM baseline data by ESI policy-holder, geographic region (Census area, with California and Texas separate), and industry group.

*ESI Offers.* To model the probability that an employed individual is offered coverage, we perform a two-stage offer status regression. The first stage of the regression models sponsorship status for the CPS/HIPSM 2009 baseline for respondents aged 19 to 64. The following variables are used in the regression:

• Occupation (Professional; Managers; Assistants and Clerical Workers; Technicians and Repair Workers; Artists and Entertainers; Service Workers; Laborers; Salespersons; Operators; Skilled Trade Workers; Assemblers; Armed Forces)
• Industry (Agriculture; Mining; Manufacturing; Construction; Utilities: Transportation; Wholesale and Retail Trade; Info/Communications; Finance, Insurance, and Real Estate; Professional; Education; Health and Social Services; Arts/Entertainment/Recreation; Other Services; Public Administration)
• Firm Size (Count of Employees: 1 - 9; 10 - 24; 25 - 49; 50 - 99; 100 - 499; 500 - 999; 1000+)
• Full-Time Student Status
• Type of Health Insurance (Medicaid; Medicare; Employee-Sponsored (ESI); Other Public; Non-Group; Uninsured)
• Employment Status (Full Year, Full Time; Full Year, Part Time; Part Year, Full Time; Part Year, Part Time)
• Special Status (Person reported with zero wages or zero or negative household income)

The second stage of the regression models offer status for persons working for a firm that sponsored coverage, using the same covariates (shown above) for the first stage.

For each employed ACS respondent, we determine the probability of having each possible combination of firm-size and ESI policy-holder status. Then, for each of these combinations, we generate a probability of the person’s firm offering coverage and the person being eligibility for ESI, the combination of which means that the person has an insurance offer. For each respondent, these offer probabilities are summarized by taking the weighted mean offer probability among the firm-size/policy-holder-status combinations. This probability is compared to a standard uniform random number to yield an offer status imputation. Note that modeling is performed identically for each year; It used the same estimated modeling parameters derived from regression analysis of the HIPSM/CPS baseline.

Appendix Table 7 shows the results of imputing ESI offer by firm size and survey. The ACS and CPS have quite similar estimates offer rates for five of the six firm-size categories and the ACS rate is about 6.5 percentage points higher for people in firms with fewer than 10 employees.
### Appendix Table 8. ESI Offer Rates by Firm Size for Non-Elderly Employed Persons

<table>
<thead>
<tr>
<th>Firm Size (Number of Employees)</th>
<th>ACS</th>
<th>CPS/HIPSM</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Total</td>
<td>With Offer</td>
</tr>
<tr>
<td>1 - 9</td>
<td>17.8 M</td>
<td>9.2 M</td>
</tr>
<tr>
<td>10 - 24</td>
<td>12.1 M</td>
<td>7.6 M</td>
</tr>
<tr>
<td>25 - 99</td>
<td>15.9 M</td>
<td>12.2 M</td>
</tr>
<tr>
<td>100 - 499</td>
<td>16.6 M</td>
<td>13.7 M</td>
</tr>
<tr>
<td>500-999</td>
<td>7.2 M</td>
<td>6.4 M</td>
</tr>
<tr>
<td>1000+</td>
<td>52.4 M</td>
<td>46.8 M</td>
</tr>
<tr>
<td><strong>Total</strong></td>
<td><strong>122.1 M</strong></td>
<td><strong>95.9 M</strong></td>
</tr>
</tbody>
</table>


**Premium value.** To derive a value for the contribution to employer coverage, we use the CPS/HIPSM simulation output file as the source for a statistical match assignment and added employed adult CPS-sourced premiums to ACS within cells defined by industry group (DEFINE) and wage level (in increments of $5000 with a ceiling of $125,000). Within these cells the actual linking was determined by similarity (which is defined below) of these factors:

- HIU Child Count
- HIU Adult-Child Count
- Age (by year, of oldest person in household under age of 65)
- Spouse’s Age (by year, of second oldest person under age 65 in household within 14 years of age of oldest person under 65)
- Sex (of oldest person in household under age of 65)
- Firm-Size Category (of oldest person in household under age of 65)

Similarity is measured by scoring each comparison by the number of level differences by ratio of the aggregate standard deviation to the mean standard deviation with a level for each given factor. This score is then transformed by a (natural log base) exponential function. Each potential match for an ACS respondent had a probability of being selected proportional to the transformed-score and assignment is made by Monte-Carlo simulation.
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