1 Introduction

This section is drawn from an existing working paper ("The Optimal Design of Prospective Subsidies for Health Insurance Under the Patient Protection and Affordable Care Act"; portions under review) and outlines the details of a microsimulation model that allows for consideration of income dynamics and advance subsidy determinations. The simulation model employed here has two principal innovations. The first is that initial estimates are benchmarked against current CBO projections of the absolute impact of the PPACA among the uninsured and individuals with non-group coverage. However, by adopting a modeling framework that incorporates endogenous take-up decisions based on errors in subsidy awards, my model can estimate the relative impact of alternative advance subsidy designs on population movements, federal and (soon) state costs. The second innovation is that I embed a social welfare model to examine the welfare implications of subsidy design. By incorporating a welfare analysis component I am able to distill the complex trade-offs of subsidy design into a scalar and transparently estimated measure of welfare that can guide recommendations for policy.

1.1 Data

The base data set for my microsimulation model is the 2001 Survey of Income and Program Participation (SIPP). The SIPP is a longitudinal survey of U.S. households administered by the Census
Bureau. Responding households are interviewed in person at baseline and then again every four months for up to three years (U.S. Census Bureau 2001). At each interview the SIPP administers a core survey instrument encompassing a number of domains, including sources of employment and income, participation in social programs, and enrollment in health insurance. The SIPP also administers a topical survey in each interview round, which yields periodic information on taxes and tax filing status, offers of health insurance, and health status.

It is important to note that I have chosen to use the 2001 SIPP over the more recently available 2004 panel for several reasons. First, as of this writing the 2001 panel serves as the basis for the CBO health reform simulation model, as well as other models such as RAND-COMPARE (Congressional Budget Office 2007, RAND Corporation 2009). Using the 2001 panel allows me to easily benchmark my model against current outside estimates of the absolute impact of reform. Second, due to budget cuts at the Census Bureau in 2006, the 2004 SIPP dramatically reduced its sample by 58 percent for the final four interview rounds. Combined with a cumulative survey attrition rate of 32 percent, the overall sample loss in the 2004 SIPP cohort is nearly 80 percent by the end of 2007 (U.S. Census Bureau 2009). Given the need to measure income over a three year period to model subsidies under the PPACA, it is important that I use measures of income that are more stable than what is available in the small three year sample of the 2004 SIPP.

1.2 Base Case and Population Calibration

Data on demographics, employment, health insurance, unemployment benefits and family composition are drawn from responses of non-elderly U.S. citizens in November 2002. Within this sample, the model selects tax units from rotation groups with data observed between January 2001 and December 2003. As noted above, this sample restriction is necessary since I need annual income measures for at least three calendar years to fully model subsidies under the PPACA. These income values are inflated by projections of the Consumer Price Index (CPI) to reflect income between 2014 and 2016.

\[\text{\footnotesize 1}\] Each monthly rotation group is a separate national sample, and SIPP interviews are designed to cover information over the preceding 4 months (including the interview month). I therefore choose the subset of rotation groups whose reference months span the period between January 2001 to December 2003.
To account for survey attrition over the three-year panel I utilize longitudinal weights provided in the public release of the 2001 SIPP. These weights are then calibrated to reflect November 2015 Census Bureau population projections of the non-institutionalized U.S. population by age, gender and state (U.S. Census Bureau 2004). Base weights are further calibrated to match benchmark CBO projections of health insurance coverage in the absence of the PPACA (CBO 2010). The reference month of November 2015 therefore serves as the annual enrollment period for the 2016 plan year.\(^2\) The final sample includes data on 10,347 nonelderly individuals.

1.3 Exchange Premiums

Since the CBO has not released detailed tabulations of projected exchange premiums, I rely on estimated national average exchange premiums by age and family/single status from the Gruber Microsimulation Model (GMSIM). The GMSIM is a microsimulation model of the U.S. health care economy that was widely employed during the recent health care reform debate. Exchange subsidies in the GMSIM are calculated endogenously as the result of individual and firm decisions in response to the PPACA. Importantly, the GMSIM yields cost and coverage estimates under the PPACA that are similar to the CBO (Table 1). A more detailed description of the model is available in Gruber (2005).

1.4 Income Measures

One advantage of using SIPP data is that I can draw upon income data based on an extensive tax model designed by the Census Bureau (U.S. Census Bureau 2001). Combined with topical survey data on tax filing status and dependents, this allows me to identify tax units and estimate MAGI in each year for units that file an income tax return. Since some lower-income households do not file a return, my model also uses the TAXSIM algorithm at the National Bureau of Economic Research (NBER) to impute MAGI and filing status using self-reported SIPP income and family relationship data (Feenberg and Coutts 1993).

\(^2\)2016 is chosen as the enrollment term since it is a year in which all aspects of the PPACA are operational.
1.5 Modeling Exchange Credits and Advance Subsidies

For each SIPP tax unit I apply the PPACA premium credit schedule using imputed Silver premiums. I do so using several measures of income. First, I calculate the final credit value using the unit’s MAGI during the plan year (2016). I then determine the initial value of prospective subsidies based on MAGI from two calendar years prior to the enrollment term (2014). Depending on the unit’s eligibility for an additional income test (which depends on the specific policy being modeled), I also estimate alternative prospective subsidy values based on income lookback windows of 1, 3, 6 and 12 months relative to the annual enrollment period.

Cost-sharing subsidies are estimated by normalizing the benchmark Silver premium to an actuarial value of 1, and then multiplying this premium by the actuarial value of the subsidized plan. The difference between this premium and the benchmark premium provides an estimate of the extra amount each plan would need to increase the generosity of plans to the benefit levels detailed in Table 1.3 For example, if the Silver premium is $5000 and the individual is eligible for an 0.87 AV plan, the value of the cost-sharing subsidy is $1,214.4

1.6 Modeling Take-Up Decisions

Take-up decisions are estimated using an elasticity-based approach. This method models behavioral reactions in a continuous fashion by converting the subsidized cost of coverage into a percentage price change relative to the price of the next-best insurance option (Gruber 2005, CBO 2007). The percentage change is then multiplied by an elasticity to estimate the base probability of take-up.

I estimate percentage price changes by comparing the total value of premium and cost sharing subsidies to the cost of the benchmark premium. The inclusion of cost-sharing payments here is important since subsidized plans provide more generous benefits, yet there is no reconciliation for excess cost-sharing payments. For example, suppose an individual is awarded $1,000 in premium assistance for a $5,000 benchmark plan, plus cost-sharing subsidies that raise the actuarial value of

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3 Notably, this estimate does not incorporate the extra spending that could be induced by moral hazard once individuals are given a more generous plan (with lower cost-sharing levels). Future work on this topic will incorporate this extra source of costs.

4 $1,214 = 5,000 \times (0.87/0.70) - 5,000$
the plan from 0.7 to 0.8. The percentage price change is larger (in absolute value) than 20% because the beneficiary receives up to $714 in extra benefits due to a higher AV. When determining the overall attractiveness of subsidies, individuals in my model consider the total value of subsidies relative to the Silver premium, not just the value of premium assistance. In other words, the percentage price reduction in this example is 34% (1714/5000).

The exchange take-up elasticity (\(\epsilon\)) measures how sensitive individuals are to changes in the price of exchange coverage. In my implementation, I adopt the CBO take-up elasticity of \(\epsilon = -0.3\), which is based off of estimates of the demand for non-group health insurance coverage among the uninsured in Marquis and Long (1995) (CBO 2007). Additional adjustments to this parameter are described in the section below.

### 1.6.1 Further Take-Up Adjustments

Since liquidity concerns may constrain the ability of lower-income people from purchasing coverage – even if that coverage is partially subsidized – I adopt an income effect term based on CBO (2007). This term acts multiplicatively on take-up and is based on the net cost of premiums (\(P_{\text{net}}\)) and income during the reference month (\(Y_{i0}\)). The income effect term is defined in the following way:

\[
IE = (1 - P_{\text{net}}/Y_{i0})^{1.5}
\]

Combining the percentage price change (\(\%\Delta P\)), the elasticity (\(\epsilon\)) and the income effect term (\(IE\)), I estimate the base probability of take-up as follows:

\[
\epsilon \cdot \%\Delta P \cdot IE
\]

What little evidence we have on coverage take-up among the uninsured is based on estimation strategies that exploit relatively small variation in non-group premiums in different geographical areas (Marquis and Long 2005). This evidence may not be informative in cases where credits and cost-sharing subsidies cover a large portion of the premium. To address this issue, when the percent subsidy is greater than 50% I adopt the approach taken by the CBO and estimate the following
take-up equation:

\[0.15 + (\%\Delta P - 0.50)^2 \ast 2.6 \ast IE\]

As explained in CBO (2007), this equation is based on a response function linking the Marquis and Long (2005) elasticity results for small price changes to observed enrollment participation rates to the 100% subsidy offered by public programs.

1.6.2 Mandate Effectiveness and CBO Benchmarking

An important unanswered question is how decisions to take up coverage will be influenced by the requirement that all U.S. citizens obtain health insurance. To my knowledge, the CBO has not released detailed assumptions on how its model adjusts take-up rates under policies that include a mandate with a penalty for non-compliance.

Since my model shares a common data source and utilizes the same take-up equations as the CBO, I address this issue by benchmarking voluntary take-up estimates under a perfect-information advance subsidy scenario against the reported take-up of subsidized exchange coverage in the CBO’s final score of the PPACA, which includes the impact of the mandate (CBO 2010). Specifically, I calibrate a mandate effectiveness parameter to match a target of 14 million subsidized exchange enrollees in 2016. The 14 million enrollee target is the result of taking the total projected exchange enrollment figure (21 million) and subtracting out CBO projections for unsubsidized exchange enrollees (4 million), the total number of subsidized exchange enrollees with an unaffordable ESI offer (1 million) and the number of subsidized exchange enrollees who no longer have an offer of ESI (2 million). Based on this benchmarking exercise, I adopt a constant mandate effectiveness parameter that raises overall take up rates by up to 0.2 for each tax unit.\(^6\)

\(^5\)The CBO has not publicly released an estimate of the number of firm dropped subsidized exchange enrollees so I rely on estimates from the GMSIM, which matches the CBO on overall reductions in ESI offers (-8.5m).

\(^6\)Since the probability of take up can never exceed 1, the mandate effectiveness parameter is less than 0.2 for units whose base probability of take up is >0.8.
1.6.3 Myopic Purchasing Behavior

When modeling the impact of advance subsidy errors, an important consideration is whether individuals are forward-looking in their purchasing decisions. To address this issue, my model includes a myopic purchasing parameter designed to capture the extent to which units take up coverage based on the prospective subsidy or the net cost after reconciliation. When this parameter is set to 0, units make coverage decisions based on perfect foresight of the net cost of premiums. Alternatively, when this parameter is set to 1, take up decisions are based purely on the size of the prospective subsidy. For the results reported here I present bounded estimates by estimating take-up with this value set at 0 and 1.

1.7 Subsidy Population

The primary target of subsidies under the PPACA is the uninsured. Individuals already covered by a non-group plan will also be eligible for subsidies. With few exceptions, individuals eligible for Medicaid (e.g. those with income under 133 percent of FPL) or with access to an ESI plan are ineligible for exchange coverage. Given these subsidy “firewalls,” the primary population of interest here is individuals above 133 percent of the FPL who are identified as uninsured or covered under a non-group policy in the reference month (November 2015).

One key group I do not currently consider is individuals who lose coverage due to firm decisions to stop offering ESI. Both the CBO and the GMSIM estimate that between 8 and 9 million workers will lose access employer-based coverage under the PPACA. While the CBO has not released detailed estimates of where these individuals will end up, the GMSIM estimates that 2.5 million will take-up subsidized coverage in the exchanges in 2016. This figure represents about 15 percent of total subsidized exchange take-up.

Another group I do not consider is individuals eligible for exchange subsidies because their employer plan has an actuarial value of less than 0.60, or because the employee share of the ESI premium exceeds 9.5 percent of income.\(^7\) Again, modeling this population would require firm decisions in response to employer provisions in the PPACA (on the overall generosity of ESI plans and on the

\(^7\) The income basis for ESI affordability determinations is the prospectively determined MAGI amount.
the employee share of the premium). The CBO estimates that about 1 million individuals would receive exchange subsidies due to unaffordable ESI offers in 2016.

Given the population restriction to non-ESI-crossovers it is important to emphasize that the primary goal of my model is to estimate the relative impact of advance subsidy policies compared to a benchmark in which subsidies are determined under perfect information. The exclusion of individuals dropped from ESI or who do not have access to an affordable ESI plan presents a problem if firm decisions respond endogenously to the advance subsidy policy. This is a concern, but is unfortunately an area with no empirical evidence to date. Future research on this topic will engage more directly with potential interactions between firm behavior and advance subsidy policy.

2 Microsimulation Results

2.1 Comparison of Baseline Results to Other Models

Table 1 compares estimates of subsidized exchange take-up and costs in my model (ACAMM) to similar estimates from the CBO and Joint Committee on Taxation (JCT), the GMSIM, and the RAND-COMPARE model (Congressional Budget Office 2010, RAND Corporation 2010). To my knowledge, no other microsimulation model explicitly builds in subsidy errors in behavioral reactions, so the relevant comparison is a simulation based on perfect income information.

I estimate total subsidized exchange take-up among non-ESI-crossovers at 14.4 million people, for a total federal cost of $60 billion in 2016. Scaling my enrollment figures linearly to match overall CBO and JCT enrollment figures that include ESI-crossovers (∼ 3 million) puts my overall cost estimate at $75 billion. This compares favorably to the fiscal 2016 $77 billion figure estimated by CBO and JCT.\(^8\)

\(^8\)It is not necessarily the case that modeling ESI crossovers in the ACAMM would lead to nearly identical take-up and enrollment compared to CBO. Rather, I include these estimates to show that the ratio of costs to coverage is similar between my model and the CBO.
References

Congressional Budget Office, *CBO’s Health Insurance Simulation Model: A Technical Description*
Congressional Budget Office 2007.


## Tables and Figures

### Table 1: Comparison of Projected Subsidized Exchange Enrollment and Costs, 2016

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<thead>
<tr>
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<th>ACAMM</th>
<th>CBO-JCT</th>
<th>GMSIM</th>
<th>RAND</th>
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<td><strong>Enrollment</strong></td>
<td>14†[17]</td>
<td>17</td>
<td>18</td>
<td>15</td>
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<td>(Millions of nonelderly people)</td>
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<tr>
<td><strong>Total Subsidies</strong></td>
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<td>77</td>
<td>81</td>
<td>68</td>
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<tr>
<td>(Billions of dollars)</td>
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**Notes:** †Excludes subsidized exchange enrollees due to ESI dropping and unaffordable ESI offers; figures in brackets estimated using linear extrapolation to match CBO enrollment totals that include ESI crossovers. ACAMM = Affordable Care Act Microsimulation Model CBO-JCT = Congressional Budget Office and Joint Committee on Taxation; GMSIM = Gruber Microsimulation Model RAND = RAND Comprehensive Assessment of Reform Efforts model