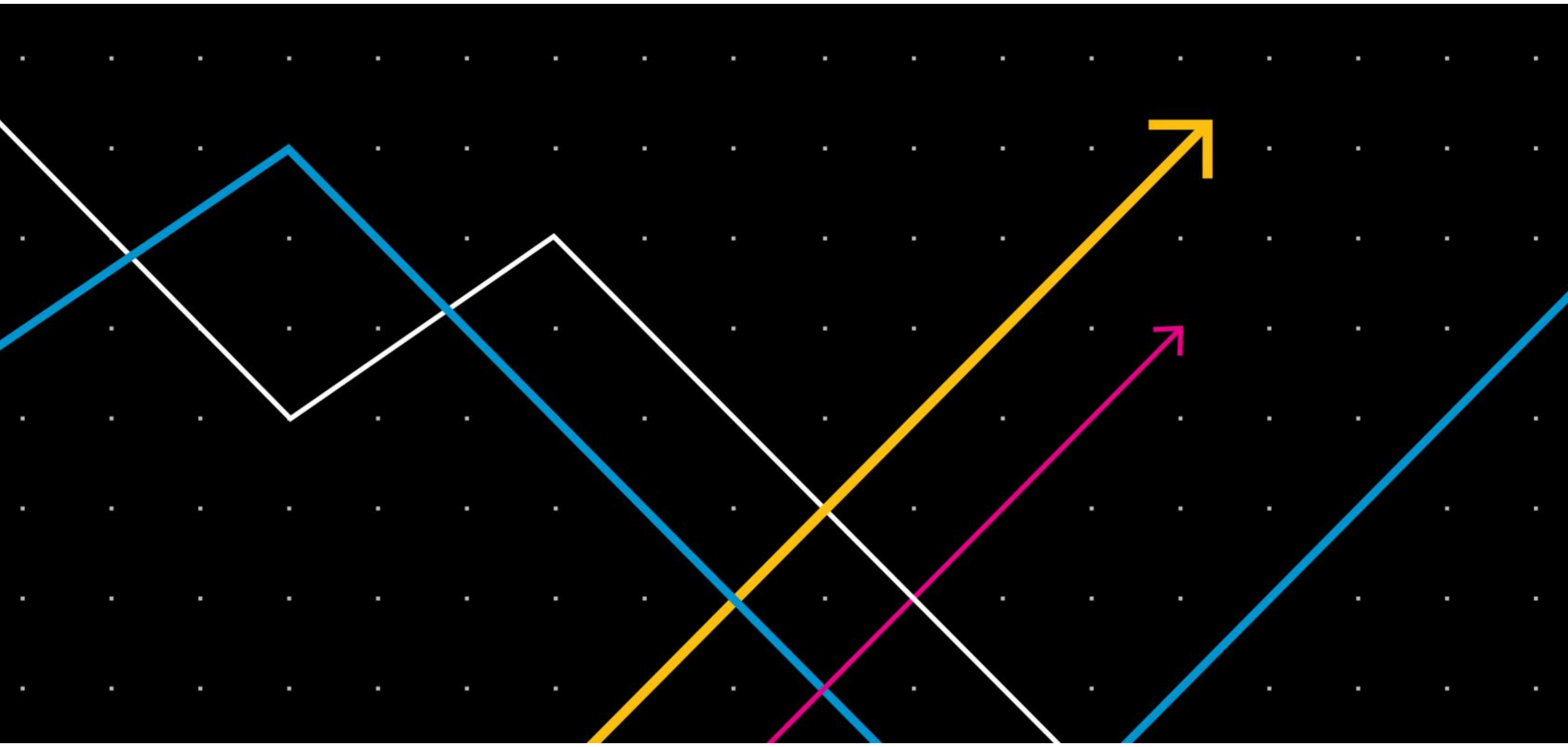

RESEARCH REPORT

The Health Insurance Policy Simulation Model for 2020

Current-Law Baseline and Methodology

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The Health Insurance Policy Simulation Model for 2020

The Health Insurance Policy Simulation Model (HIPSM) is a detailed microsimulation model of the health care system designed to estimate the cost and coverage effects of proposed health care policy options. The model simulates household and employer decisions and models the way changes in one insurance market interact with changes in other markets. HIPSM is designed for quick-turnaround analysis of policy proposals. It can be rapidly adapted to analyze a wide variety of new scenarios—from novel health insurance offerings and strategies for increasing affordability to state-specific proposals—and can describe the effects of a policy option over several years.

HIPSM is based on two years of the American Community Survey (ACS), which provides a representative sample of families large enough for us to produce estimates for individual states and smaller regions, such as cities. The model is designed to incorporate timely, real-world data to the extent they are available. In particular, we regularly update the model to reflect published Medicaid and Marketplace enrollment and costs in each state.

Results from HIPSM simulations have been favorably compared with actual policy outcomes and other respected microsimulation models, as assessed by outside experts (Glied, Arora, and Solís-Román 2015). Findings from the model were cited in the majority opinion in the Supreme Court case *King v. Burwell* and in many amicus briefs submitted to the court in that case and are broadly cited in top media, including the *New York Times*, *Washington Post*, *Wall Street Journal*, *Vox*, CNN, and *Los Angeles Times*. HIPSM results have also been displayed on the floor of the US Senate during debate and are widely distributed among legislative staff.

How HIPSM Has Been Used

The Health Policy Center at the Urban Institute has a long history of health insurance simulation work, including extensive experience working with state and national policymakers to examine the coverage effects, costs, and financing of alternative strategies to cover the uninsured. In a notable example of our early work, we simulated health reform policies that yielded a road map for the landmark 2006 health care reform legislation in Massachusetts that expanded coverage and created a subsidized private insurance market for low-income residents, among other policies. That research garnered the prestigious Health Services Research Impact Award in 2007, and the success of the Massachusetts programs influenced the design of the Affordable Care Act (ACA).

Since 2010, HIPSM has been used in analyses of the impact of the ACA and proposed alternatives. HIPSM has had a notable impact on the following:

- **ACA implementation.** Beginning in 2009, we published analyses of wide-ranging issues related to ACA implementation, including premium age rating, the role of the individual and employer mandates, nongroup market regulation, a Basic Health Program (BHP), self-insured group health coverage, and the impact of loosening restrictions on unregulated short-term, limited-duration plans (Blumberg, Buettgens, and Wang 2018). We also used HIPSM to provide technical assistance to several states, as we note below.
- **Medicaid expansion.** We regularly publish estimates of the impact on health coverage and state and federal costs if the remaining states that have not expanded Medicaid under the ACA were to do so. These estimates have played an important role in informing the policy debate about ACA Medicaid expansion in many states (Buettgens 2018). We have also conducted more detailed analyses of Medicaid expansion in some states, such as Alaska and Ohio.
- ***King v. Burwell.*** HIPSM has had an impact at the national level, most notably in a series of analyses about the impact of *King v. Burwell;* the chief justice in the Supreme Court's 2015 opinion cited HIPSM results.[1]
- **ACA repeal and replace efforts.** Congressional efforts to repeal and replace the ACA were numerous in 2017. We have published state-level analyses of the impact of these bills as they evolved (Blumberg, Buettgens, and Holahan 2016). Our research received tens of thousands of media citations in 2020 alone.
- **Single-payer and other approaches toward universal coverage.** In 2016, we published an often-cited estimate of the costs of Senator Sanders's single-payer health coverage proposal (Holahan et al. 2016). In 2019, we followed this up with a report presenting detailed cost and coverage estimates for health reforms ranging from modest expansions of the ACA to replacing the ACA with a single-payer system (Blumberg, Holahan, et al. 2019).
- ***California v. Texas.*** This is the latest legal challenge to the ACA, which was known as *Texas v. US* until the Trump administration declined to defend the law. We have published a series of frequently quoted studies of what would happen if the ACA were overturned by a finding for

the plaintiff (Blumberg, Buettgens, et al. 2019). The Supreme Court heard oral arguments in November 2020.

In addition, HIPSM is or has been used for the following state-level technical assistance efforts:

- **New York (2009–present).** We have been providing microsimulation work and technical assistance to the New York State Department of Health since 2009 on issues related to Medicaid, the Children's Health Insurance Program (CHIP), private nongroup and small-group markets, and the BHP.
- **Massachusetts (2010–present).** With funding from the Blue Cross Blue Shield of Massachusetts Foundation that was coordinated with state agencies, we have been providing technical assistance in analyzing ACA Marketplace and regulatory design choices since 2010. This year, we presented an analysis of the impact on health coverage and costs should the latest legal challenge to the ACA, *Texas v. California*, be found for the plaintiffs (Banthin, Buettgens, and Blumberg 2019).
- **Missouri (2010–11).** Following passage of the ACA, we provided broad technical assistance to the state through a 2010 grant funded by the Missouri Foundation for Health.
- **Virginia (2011)**. We presented Virginia-specific simulation estimates of the impact of the ACA to the Virginia Health Reform Initiative, convened by the governor. The presentation focused on important state decisions for ACA Marketplace implementation, such as the definition of small firms and whether to merge the small-firm and individual health insurance markets. This work was funded by the Virginia Health Care Foundation.
- **Washington (2011–12).** We provided technical assistance for ACA implementation to Washington State. In addition to this state-funded research, we published a feasibility analysis of the BHP for Washington, funded by the Empire Health Foundation.
- **Alaska (2013 and 2019)**. With funding from the Alaska Native Tribal Health Consortium, we analyzed the impact of Medicaid expansion in Alaska, estimating enrollment changes, characteristics of those gaining coverage, and Medicaid spending by both state and federal governments.
- **Oregon (2014, 2016, 2018).** In partnership with actuaries at Wakely and with funding from the state government, we prepared detailed analyses of the feasibility of the ACA's BHP in Oregon in 2014 and 2016. In 2018, we completed a detailed analysis of the characteristics of the state's uninsured and the implications of a state individual mandate.

- **Texas (2018).** With funding from the Episcopal Health Foundation, we conducted an analysis of the uninsured, providing estimates by county or group of counties and by detailed demographic and economic characteristics (Buettgens, Blumberg, and Pan 2018).
- **New Mexico (2019–2020).** In 2019, we conducted a detailed analysis of the uninsured in New Mexico for the state government (Banthin et al. 2019). In 2020, we estimated the impacts of 2020 enrollment changes and job changes related to the COVID-19 pandemic on the uninsured in New Mexico. We also simulated a range of state policy options to make health coverage more affordable (Buettgens et al. 2020).

HIPSM's Strengths Relative to Other Models

HIPSM is similar to other microsimulation models of insurance coverage and costs for the population under age 65, but it has some strengths relative to those models:

- HIPSM is based on data from the ACS and can produce reliable, state-specific estimates, and it can often produce estimates for substate areas. The simulation of any policy alternative automatically includes state variation in demographics, economics, or relevant laws and regulations and shows differences in the impact of the resulting policy change.
- HIPSM is updated annually to the most recently available state-level data on Marketplace premiums and enrollment and Medicaid enrollment and spending. This means the model produces an accurate and timely baseline against which the impact of proposed policies can be measured.
- HIPSM parameters are estimated using a series of probit estimations, each of which is a decision between two options. More complicated decisions are built from these binary decisions. This approach simplifies some of the decisions of actors in the model and yields faster run times and easier adaptations to new policies that add new health coverage choices.

Overview of the Model

HIPSM is similar to other microsimulation models of health coverage and costs in that individual and family decisions are based on an expected-utility framework.[2] Such models define an expected-utility function that accounts for expected out-of-pocket spending, health needs, risk of high health costs, and income. Each family unit chooses the option with the highest expected utility. This approach allows for evaluation of novel policies in the same framework.

Though HIPSM decisionmaking follows an expected-utility framework, we add a latent preference term for each observation that represents factors involved in a person's or family's choice that we could not capture in the available data. These terms are set so each observation makes the choice it reported, and the distribution of latent preference terms is set so the model replicates elasticity targets from the literature if premiums rise or fall. This approach makes it easier to consistently simulate novel policies while calibrating the model to a wide range of real-world data, such as Medicaid and Marketplace enrollment and estimates of price responsiveness from the literature.

Below, we summarize the construction of HIPSM's baseline under current law. Part 2 of this report, on methodology, provides greater detail, including a detailed description of the flow of a simulation.

- As the core data, we use the US Census Bureau's 2012 and 2013 ACS, which we combine to increase sample size (more than 6 million observations). The combined file is reweighted to reflect the distribution of demographic, economic, and health coverage characteristics of the 2013 ACS.
- Each year, the model is calibrated to reproduce the latest available Medicaid and Marketplace enrollment numbers in each state.
- Population weights for current and future years are based on more recent ACS data. For future years, we use projections for the 2030 population from the Urban Institute's Mapping America's Futures program. These projections match Census Bureau national population projections but include greater detail and state-level projections.
- Using the Medical Expenditure Panel Survey Household Component (MEPS-HC) and other data sources, we estimate health care expenditures for each individual in the dataset in each possible coverage status, including out-of-pocket spending, spending covered by private insurance, Medicaid/CHIP spending, and uncompensated care for the uninsured.
- We impute offers of employer-sponsored insurance (ESI), immigration status, and eligibility for Medicaid, CHIP, and subsidized qualified health plan coverage.
- We group workers with the same employment characteristics, such as firm size and industry, into simulated firms. The distribution of these firms matches the characteristics of employers in each census division provided in the Statistics of US Businesses.

Output Capabilities

Like most microsimulation models incorporating various microdata, HIPSM can output a range of coverage and spending variables. The model's outputs can be designed to meet the specific needs of a project, but, in general, are intended to compare a situation under current law versus under a policy change. This highlights changes in coverage, the impact on state and federal spending, and the detailed characteristics of those who would gain or lose coverage. We frequently use HIPSM to estimate the following:

- eligibility for Medicaid, CHIP, a BHP, Marketplace premium tax credits (PTCs), cost-sharing reductions (CSRs), and exemptions from the individual mandate
- type of coverage: employer, Marketplace (with PTCs and CSRs, with PTCs only, and full-pay), other nongroup, BHP, Medicaid (for children, children with disabilities, nonparents, parents, and adults with disabilities), CHIP, other public (including Medicare), and uninsurance
- socioeconomic characteristics: income group, age, race/ethnicity (including Asians/Pacific Islanders and American Indians/Alaska Natives, which are often unavailable because of small sample size), educational attainment, employment status, family structure, immigration status, English proficiency, and language spoken at home
- tabulations by state and substate regions
- state and federal shares of Medicaid-related costs (per capita or total)
- BHP-related costs (per capita or total): out-of-pocket premiums and cost sharing and costs to federal and state governments
- Marketplace qualified health plan costs (per capita or total): out-of-pocket premiums and cost sharing, federal PTCs and CSRs, and total premiums
- other costs: uncompensated care, employer premium contributions, and total premiums for employer health coverage
- health cost risk scores for any group of nonelderly people
- health care spending by hospital, physician, prescription-drug, and other categories

Part 1. 2020 Open Enrollment Period Baseline and Methodology

In part 1 of this report, we present detailed estimates of health care coverage and costs in early 2020 from our model, using a baseline that incorporates data from the 2020 open enrollment period (OEP). In part 2, we describe the broad methodology of our model in detail, from the data used as input to the mechanics of how families choose between available health coverage options.

We update HIPSM's baseline coverage estimates under current law every year. As mentioned, we incorporate the latest available data on enrollment and premiums and make various other adjustments. Nearly every year sees important federal and state policy changes related to the ACA and differences in enrollment driven by both these changes and other factors affecting premiums and eligibility. In addition, there is always a lag between the collection and public release of survey data on coverage. Also, survey data do not always match administrative data on enrollment in the Marketplaces, Medicaid, CHIP, or a BHP. As we incorporate those data, we make adjustments to align coverage distributions with administrative data and population totals.

The coverage estimates presented in this section assume an economy at full employment and incorporate enrollment data from the 2020 OEP, reflecting the US in January and February 2020. Since then, economic disruption from the COVID-19 pandemic and related shutdowns has led to substantial job losses that can affect health coverage. The 2020 OEP baseline served as our starting point for estimating the impact of pandemic-related job losses on health insurance coverage. Our recent work describes those estimates for 2020 (Banthin et al. 2020) and estimates for 2022 (Blumberg et al. 2020).

The HIPSM 2020 OEP Current-Law Baseline

In this section, we present estimates of health coverage and costs from our 2020 current-law baseline, based on data from the 2020 open enrollment period.

Health Insurance Coverage of the Nonelderly

In table 1, we show the detailed distribution of health coverage among the nonelderly based on 2020 OEP data. The estimates represent average monthly enrollment for 2020. However, job losses due to the pandemic have changed health coverage noticeably. We have updated the model to reflect these changes, but they are not included here.

The model estimates about 55 percent of the nonelderly (151.1 million) have health coverage provided through an employer in 2020. About 5.5 percent (15.1 million) have health coverage provided through the nongroup market or the ACA's BHP, which operates in only New York and Minnesota. Among people enrolled in the Marketplaces, 8.5 million get premium tax credits and 1.3 million others pay the full premium. Finally, we estimate 4.4 million people are enrolled in ACA-compliant nongroup coverage outside the Marketplaces. The Centers for Medicare & Medicaid Services (CMS) releases data on Marketplace enrollment, which we use to calibrate our model, but no complete data on national off-Marketplace enrollment exist; this is simulated by the model.

Based on enrollment data provided by CMS and state Medicaid agencies, we estimate 69.5 million nonelderly people are enrolled in Medicaid or CHIP in 2020. About 8.6 million nonelderly people are enrolled in other public programs, such as Medicare. That means 28.6 million people are uninsured (10.4 percent of the nonelderly), and, in an average month, 2.5 million people are enrolled in non-ACA-compliant plans (i.e., that do not provide minimum essential coverage).

TABLE 1

Health Insurance Coverage Distribution of the Nonelderly under Current Law, 2020

	Thousands of people	Percent
Insured (minimum essential coverage)	**244,346**	**88.7**
Employer	*151,117*	*54.9*
Private nongroup	*15,131*	*5.5*
Basic Health Program	890	0.3
Marketplace with PTCs	8,546	3.1
Full-pay Marketplace	1,310	0.5
Other nongroup	4,386	1.6
Medicaid/CHIP	*69,478*	*25.2*
People with disabilities	9,387	3.4
Medicaid expansion	13,965	5.1
Nondisabled adults	12,361	4.5
Nondisabled children	33,729	12.2
State-funded program	36	0.0
Other public	*8,619*	*3.1*
Uninsured (no minimum essential coverage)	**31,128**	**11.3**
Uninsured	28,596	10.4
Noncompliant nongroup	2,532	0.9
Total	**275,474**	**100.0**

Source: Urban Institute Health Insurance Policy Simulation Model, 2020 open enrollment period baseline (before the COVID-19 pandemic).

Notes: PTCs = premium tax credits. CHIP = Children's Health Insurance Program.

In table 2, we show our projected enrollment in ACA-compliant nongroup health coverage by state, based on reported plan choices after the 2020 open enrollment period. Data on how many of those plans were effectuated (i.e., how many started paying their premiums) were unavailable, so we applied effectuation rates from 2019. We estimate 890,000 people are enrolled in BHPs in New York and Minnesota, called Essential Plan and MinnesotaCare, in 2020.

TABLE 2

Types of Nongroup Coverage under Current Law, by State, 2020

Thousands of people

	Basic Health Program	Marketplace with PTCs	Full-pay Marketplace	Other nongroup	Total
Alabama	0	130	7	53	190
Alaska	0	13	2	5	20
Arizona	0	108	22	124	253
Arkansas	0	48	6	38	92
California	0	1,206	173	806	2,186
Colorado	0	110	28	143	282
Connecticut	0	68	29	45	142
Delaware	0	18	2	11	32
District of Columbia	0	1	16	0	17
Florida	0	1,570	77	334	1,982
Georgia	0	343	34	128	505
Hawaii	0	14	3	16	33
Idaho	0	66	8	24	98
Illinois	0	215	33	219	467
Indiana	0	84	39	75	197
Iowa	0	45	4	58	107
Kansas	0	67	7	40	114
Kentucky	0	58	13	46	117
Louisiana	0	66	7	76	149
Maine	0	48	6	9	63
Maryland	0	115	20	91	225
Massachusetts	0	255	75	57	387
Michigan	0	196	30	147	373
Minnesota	93	59	39	91	282
Mississippi	0	81	1	34	117
Missouri	0	146	21	64	232
Montana	0	33	5	22	60
Nebraska	0	80	3	40	123
Nevada	0	55	8	51	113
New Hampshire	0	29	10	14	53
New Jersey	0	159	46	75	279
New Mexico	0	33	10	22	64
New York	797	142	102	72	1,112
North Carolina	0	405	24	140	569
North Dakota	0	17	3	24	44
Ohio	0	128	37	134	299
Oklahoma	0	140	7	43	190
Oregon	0	94	31	53	178
Pennsylvania	0	248	32	188	469

	Basic Health Program	Marketplace with PTCs	Full-pay Marketplace	Other nongroup	Total
Rhode Island	0	27	6	11	44
South Carolina	0	169	12	50	231
South Dakota	0	25	2	17	44
Tennessee	0	146	16	84	246
Texas	0	843	80	342	1,264
Utah	0	126	56	0	182
Vermont	0	21	4	9	35
Virginia	0	185	24	91	300
Washington	0	122	69	91	282
West Virginia	0	15	2	13	29
Wisconsin	0	152	20	53	225
Wyoming	0	21	1	12	34
Total	**890**	**8,546**	**1,310**	**4,386**	**15,131**

Source: Urban Institute Health Insurance Policy Simulation Model, 2020 open enrollment period baseline (before COVID-19 pandemic).
Note: PTCs = premium tax credits.

Medicaid/CHIP Coverage by State

In table 3, we summarize our simulated Medicaid and CHIP enrollment of the nonelderly in each state by broad eligibility types. Our enrollment is based on CMS monthly enrollment snapshots, supplemented with data from certain state Medicaid agencies. In these counts, we exclude people enrolled in waiver programs (e.g., family planning) with very limited benefits.

We estimate 69.5 million people younger than 65 are enrolled in either Medicaid or CHIP in 2020. Of these, about 9.4 million are eligible because of disabilities and 14.0 million are eligible through the ACA's Medicaid expansion. For the latter group, we include all people who qualify for the federal government to cover 90 percent of their health care costs, most of whom would be ineligible for Medicaid without the ACA. Another 12.4 million Medicaid enrollees are nonelderly adults without disabilities, most of whom are parents. Lastly, about 33.7 million Medicaid/CHIP enrollees are children without disabilities. In our model, we distinguish those who are in Medicaid, CHIP-funded Medicaid programs, or separate CHIP programs, but we do not show that here. Finally, we track a small number of people enrolled in state-funded coverage providing Medicaid-like benefits.

TABLE 3

Types of Medicaid/CHIP Coverage under Current Law, by State, 2020

Thousands of people

	People with disabilities	Medicaid expansion	Nondisabled adults	Nondisabled children	State-funded program	Total
Alabama	191	0	205	576	0	972
Alaska	15	30	52	98	0	195
Arizona	195	480	313	758	0	1,746
Arkansas	123	269	76	411	0	880
California	1,054	3,210	1,777	5,126	0	11,166
Colorado	102	377	160	582	0	1,221
Connecticut	80	205	187	324	0	797
Delaware	27	43	38	81	0	189
District of Columbia	30	39	35	59	16	180
Florida	567	0	913	1,993	0	3,473
Georgia	295	0	399	1,251	0	1,945
Hawaii	29	71	48	111	0	259
Idaho	46	95	55	178	0	374
Illinois	308	539	486	1,155	0	2,489
Indiana	186	435	140	609	0	1,370
Iowa	77	172	88	341	0	678
Kansas	60	0	76	232	0	367
Kentucky	204	472	115	534	0	1,324
Louisiana	197	455	133	628	0	1,414
Maine	56	45	93	112	0	307
Maryland	145	288	244	626	0	1,304
Massachusetts	297	265	426	662	0	1,648
Michigan	371	632	286	909	0	2,198
Minnesota	140	206	201	401	0	947
Mississippi	124	0	137	360	0	621
Missouri	195	0	207	505	0	907
Montana	27	85	24	127	0	263
Nebraska	37	0	49	140	0	226
Nevada	69	206	61	299	0	636
New Hampshire	33	65	19	88	0	204
New Jersey	194	459	221	703	0	1,578
New Mexico	71	264	69	316	0	720
New York	601	1,628	1,087	2,299	20	5,635
North Carolina	363	0	483	1,251	0	2,097
North Dakota	10	24	13	28	0	75
Ohio	360	624	425	1,032	0	2,442
Oklahoma	132	0	134	375	0	641
Oregon	111	310	108	472	0	1,000
Pennsylvania	460	707	288	1,048	0	2,502
Rhode Island	40	81	46	103	0	269
South Carolina	176	0	230	535	0	942
South Dakota	18	0	24	71	0	113
Tennessee	235	0	388	742	0	1,365
Texas	669	0	927	3,120	0	4,716
Utah	50	104	85	228	0	467
Vermont	22	20	37	51	0	130
Virginia	177	450	131	602	0	1,361
Washington	178	448	180	809	0	1,615

	People with disabilities	Medicaid expansion	Nondisabled adults	Nondisabled children	State-funded program	Total
West Virginia	94	160	46	195	0	495
Wisconsin	136	0	387	443	0	965
Wyoming	9	0	12	30	0	51
Total	**9,387**	**13,965**	**12,361**	**33,729**	**36**	**69,478**

Source: Urban Institute Health Insurance Policy Simulation Model, 2020 open enrollment period baseline (before COVID-19 pandemic).
Note: CHIP = Children's Health Insurance Program.

The Uninsured by State

In table 4, we decompose the uninsured population in each state based on eligibility for public programs and immigration status. Nationally, about 20 percent of the uninsured are eligible for Medicaid or CHIP but not enrolled, and about 19 percent are eligible for premium tax credits in the Marketplaces. Just over a quarter are undocumented immigrants. The remaining 36 percent are ineligible for assistance and legally present.

Eligibility for assistance among the uninsured depends largely on whether a state has expanded Medicaid eligibility. For example, North Dakota has expanded Medicaid, whereas South Dakota has not. In North Dakota, almost 39 percent of the uninsured are eligible for Medicaid or CHIP, compared with only about 14 percent of the uninsured in South Dakota. Overall, nearly two-thirds of the uninsured in North Dakota are eligible for assistance, compared with just over 40 percent of the uninsured in South Dakota.

TABLE 4

Composition of the Uninsured under Current Law, by State, 2020

	Medicaid/CHIP-Eligible		Tax Credit–Eligible		Undocumented Immigrants		Other	
	1,000s of people	% of total uninsured	1,000s of people	% of total uninsured	1,000s of people	% of total uninsured	1,000s of people	% of total uninsured
AL	31	7.0	95	21.0	46	10.1	280	61.9
AK	26	29.2	35	39.3	4	4.5	24	27.0
AZ	143	20.5	201	28.8	213	30.5	141	20.2
AR	63	30.0	53	25.4	38	18.2	56	26.4
CA	725	21.1	558	16.3	1,381	40.2	768	22.4
CO	90	20.0	113	25.0	122	27.2	125	27.8
CT	35	19.3	30	16.2	70	38.1	48	26.4
DE	26	41.3	10	16.5	11	18.4	15	24.0
DC	20	48.5	6	14.7	4	8.7	11	28.2
FL	190	7.7	202	8.2	687	27.8	1,394	56.4
GA	74	5.7	247	19.0	285	21.9	694	53.4
HI	28	27.3	41	40.3	7	7.2	26	25.0
ID	51	34.4	24	16.0	26	17.5	47	32.0
IL	391	39.0	135	13.5	275	27.5	200	20.0
IN	179	38.7	105	22.7	70	15.0	109	23.6
IA	37	29.0	33	25.7	19	14.6	40	30.7
KS	57	17.8	67	21.1	50	15.6	146	45.6
KY	96	35.4	74	27.4	30	11.0	71	26.1
LA	118	33.2	88	24.7	52	14.6	98	27.5
ME	15	30.9	9	18.4	2	3.8	23	46.8
MD	76	20.2	52	13.8	141	37.6	106	28.4
MA	100	46.0	16	7.4	46	21.2	60	27.8
MI	215	42.3	97	19.0	58	11.4	139	27.2
MN	71	28.2	52	20.5	49	19.5	81	31.9
MS	69	19.4	76	21.5	13	3.7	197	55.5
MO	109	17.1	156	24.6	41	6.5	329	51.8
MT	23	32.3	20	27.9	2	2.2	27	37.7
NE	25	15.8	20	13.0	27	17.4	84	53.9
NV	85	24.0	76	21.6	123	34.9	69	19.6
NH	19	28.9	14	21.2	4	6.7	29	43.2
NJ	128	18.9	99	14.7	274	40.4	177	26.1
NM	47	22.9	48	23.5	61	29.9	48	23.7
NY	258	23.5	187	17.0	436	39.5	138	12.5
NC	58	5.3	221	20.2	247	22.6	565	51.8
ND	27	38.6	18	26.0	4	5.9	20	29.4
OH	236	35.7	192	29.1	53	8.0	180	27.3
Ok	162	28.3	97	17.0	66	11.5	248	43.3
OR	81	25.6	78	24.7	66	20.8	92	28.9
PA	271	43.1	115	18.3	84	13.3	159	25.3
RI	5	8.6	9	16.9	16	30.8	23	43.6
SC	49	9.3	121	22.9	66	12.4	293	55.4
SD	13	14.3	23	26.4	6	6.5	46	52.8
TN	45	6.6	190	27.9	100	14.6	347	50.9
TX	446	9.5	852	18.1	1,444	30.7	1,960	41.7
UT	98	35.5	25	9.1	76	27.4	77	28.0
VT	27	61.7	5	11.7	1	2.8	10	23.9
VA	168	24.2	153	22.0	165	23.7	210	30.1
WA	126	22.9	131	23.8	146	26.4	148	26.9

	Medicaid/CHIP-Eligible		Tax Credit–Eligible		Undocumented Immigrants		Other	
	1,000s of people	% of total uninsured	1,000s of people	% of total uninsured	1,000s of people	% of total uninsured	1,000s of people	% of total uninsured
WV	43	42.4	32	31.8	2	1.6	24	24.1
WI	121	36.5	60	18.1	49	14.8	102	30.6
WY	29	35.6	15	19.3	6	7.6	30	37.6
Total	**5,623**	**19.6**	**5,378**	**18.8**	**7,261**	**25.3**	**10,334**	**36.0**

Source: Urban Institute Health Insurance Policy Simulation Model, 2020 open enrollment period baseline (before COVID-19 pandemic).
Note: CHIP = Children's Health Insurance Program.

Health Coverage by Income

In table 5, we show the distribution of health coverage for the nonelderly at different income levels in 2020. Nearly two-thirds of those with incomes below 138 percent of the federal poverty level (FPL), the eligibility threshold for the ACA's Medicaid expansion, are enrolled in Medicaid. The share enrolled in Medicaid or CHIP drops off sharply at higher incomes. Uninsurance rates are also higher among those with lower incomes: such rates are 15.7 percent for those with incomes below 138 percent of FPL and 4.3 percent for those with incomes above 400 percent of FPL.

ESI shows the opposite pattern; about 86 percent of those with incomes above 400 percent of FPL have such coverage. This share declines to less than 12 percent among those with incomes below 138 percent of FPL. Private nongroup coverage is most common among those with incomes between 138 and 400 percent of FPL.

TABLE 5

Health Insurance Coverage Distribution of the Nonelderly under Current Law, by Income Group, 2020

	Thousands of people	Percent
Below 138% of FPL		
Insured (minimum essential coverage)	*65,909*	*83.9*
Employer	9,087	11.6
Private nongroup	2,385	3.0
Basic Health Program	327	0.4
Marketplace with PTCs	1,554	2.0
Full-pay Marketplace	97	0.1
Other nongroup	407	0.5
Medicaid/CHIP	51,981	66.2
People with disabilities	7,302	9.3
Medicaid expansion	13,958	17.8
Nondisabled adults	8,235	10.5
Nondisabled children	22,467	28.6
State-funded program	19	0.0
Other public	2,456	3.1
Uninsured (no minimum essential coverage)	*12,656*	*16.1*
Uninsured	12,333	15.7
Noncompliant nongroup	324	0.4
Total	*78,565*	*100.0*
Between 138% and 200% of FPL		
Insured (minimum essential coverage)	*26,006*	*84.5*
Employer	11,901	38.7
Private nongroup	4,313	14.0
Basic Health Program	563	1.8
Marketplace with PTCs	3,463	11.3
Full-pay Marketplace	59	0.2
Other nongroup	228	0.7
Medicaid/CHIP	8,514	27.7
People with disabilities	657	2.1
Medicaid expansion	2	0.0
Nondisabled adults	1,908	6.2
Nondisabled children	5,940	19.3
State-funded program	6	0.0
Other public	1,278	4.2
Uninsured (no minimum essential coverage)	*4,762*	*15.5*
Uninsured	4,675	15.2
Noncompliant nongroup	87	0.3
Total	*30,768*	*100.0*
Between 200% and 400% of FPL		
Insured (minimum essential coverage)	*64,972*	*88.3*
Employer	50,462	68.6
Private nongroup	4,695	6.4
Marketplace with PTCs	3,482	4.7
Full-pay Marketplace	379	0.5
Other nongroup	834	1.1
Medicaid/CHIP	7,169	9.7
People with disabilities	910	1.2
Medicaid expansion	2	0.0
Nondisabled adults	1,682	2.3

	Thousands of people	Percent
Nondisabled children	4,568	6.2
State-funded program	7	0.0
Other public	2,645	3.6
Uninsured (no minimum essential coverage)	*8,583*	*11.7*
Uninsured	7,644	10.4
Noncompliant nongroup	939	1.3
Total	*73,555*	*100.0*
Above 400% of FPL		
Insured (minimum essential coverage)	*87,458*	*94.5*
Employer	79,667	86.0
Private nongroup	3,738	4.0
Marketplace with PTCs	46	0.0
Full-pay Marketplace	774	0.8
Other nongroup	2,917	3.2
Medicaid/CHIP	1,814	2.0
People with disabilities	518	0.6
Medicaid expansion	2	0.0
Nondisabled adults	536	0.6
Nondisabled children	754	0.8
State-funded program	4	0.0
Other public	2,240	2.4
Uninsured (no minimum essential coverage)	*5,127*	*5.5*
Uninsured	3,944	4.3
Noncompliant nongroup	1,183	1.3
Total	*92,585*	*100.0*

Source: Urban Institute Health Insurance Policy Simulation Model, 2020 open enrollment period baseline (before COVID-19 pandemic).

Notes: FPL = federal poverty level. PTCs = premium tax credits. CHIP = Children's Health Insurance Program.

Health Coverage by Age

In table 6, we show the distribution of types of health coverage for different age groups in 2020. Children have the lowest uninsurance rate, just over 4 percent, largely because of high eligibility thresholds for Medicaid and CHIP. For adults, uninsurance rates drop with increasing age, from 16.7 percent of those ages 19 to 34 to 7.4 percent of those ages 55 to 64.

TABLE 6

Health Insurance Coverage Distribution among the Nonelderly under Current Law, by Age Group, 2020

	Thousands of people	Percent
Birth to age 18		
Insured (minimum essential coverage)	*74,767*	*94.9*
Employer	36,727	46.6
Private nongroup	1,391	1.8
Basic Health Program	0	0.0
Marketplace with PTCs	421	0.5
Full-pay Marketplace	221	0.3
Other nongroup	749	1.0
Medicaid/CHIP	35,223	44.7
Children with disabilities	1,494	1.9
Nondisabled children	33,729	42.8
Other public	1,426	1.8
Uninsured (no minimum essential coverage)	*3,984*	*5.1*
Uninsured	3,331	4.2
Noncompliant nongroup	652	0.8
Total	*78,751*	*100.0*
Ages 19–34		
Insured (minimum essential coverage)	*57,218*	*81.9*
Employer	36,293	51.9
Private nongroup	3,932	5.6
Basic Health Program	422	0.6
Marketplace with PTCs	2,267	3.2
Full-pay Marketplace	335	0.5
Other nongroup	908	1.3
Medicaid/CHIP	15,574	22.3
People with disabilities	2,301	3.3%
Medicaid expansion	7,223	10.3
Nondisabled adults	6,030	8.6
State-funded program	21	0.0
Other public	1,419	2.0
Uninsured (no minimum essential coverage)	*12,677*	*18.1*
Uninsured	11,698	16.7
Noncompliant nongroup	979	1.4
Total	*69,895*	*100.0*
Ages 34–54		
Insured (minimum essential coverage)	*75,891*	*86.9*
Employer	54,433	62.3
Private nongroup	5,658	6.5
Basic Health Program	317	0.4
Marketplace with PTCs	3,324	3.8
Full-pay Marketplace	468	0.5
Other nongroup	1,549	1.8
Medicaid/CHIP	13,282	15.2
People with disabilities	3,497	4.0
Medicaid expansion	4,402	5.0
Nondisabled adults	5,370	6.1
State-funded program	13	0.0
Other public	2,518	2.9
Uninsured (no minimum essential coverage)	*11,433*	*13.1*

	Thousands of people	Percent
Uninsured	10,640	12.2
Noncompliant nongroup	794	0.9
Total	*87,325*	*100.0*
Ages 55–64		
Insured (minimum essential coverage)	*36,470*	*92.3*
Employer	23,663	59.9
Private nongroup	4,150	10.5
Basic Health Program	151	0.4
Marketplace with PTCs	2,534	6.4
Full-pay Marketplace	286	0.7
Other nongroup	1,180	3.0
Medicaid/CHIP	5,399	13.7
People with disabilities	2,095	5.3
Medicaid expansion	2,340	5.9
Nondisabled adults	962	2.4
State-funded program	2	0.0
Other public	3,257	8.2
Uninsured (no minimum essential coverage)	*3,034*	*7.7*
Uninsured	2,927	7.4
Noncompliant nongroup	107	0.3
Total	*39,504*	*100.0*

Source: Urban Institute Health Insurance Policy Simulation Model, 2020 open enrollment period baseline (before COVID-19 pandemic).

Notes: PTCs = premium tax credits. CHIP = Children's Health Insurance Program.

Overall Health Care Spending

Table 7 summarizes total health care spending by payer. We chose these income groups because of their relevance to ACA programs. However, they do not contain the same number of people. For example, total household out-of-pocket health care spending is very similar between those with incomes below 138 percent of FPL and those with incomes between 138 and 200 percent of FPL. However, 78.6 million people have incomes below 138 percent of FPL, and only 30.8 million people have incomes between 138 percent and 200 percent of FPL (table 5). Thus, per capita out-of-pocket health care spending is much lower for those with incomes below 138 percent of FPL. Household spending increases with rising income, because Medicaid and the most generous Marketplace subsidies are available at lower incomes, and lower-income populations include more uninsured people.

Unsurprisingly, state and federal Medicaid spending is heavily concentrated on those with the lowest incomes; 71 percent of total Medicaid spending on acute care for the nonelderly is for those with incomes below 138 percent of FPL. Marketplace premium tax credits are for people with incomes below 400 percent of FPL, except for enhanced, state-funded premium tax credits available in California. Lastly, uncompensated care spending is generally proportional to the number of uninsured people in each income group (tables 5 and 7).

TABLE 7

Total Spending on Acute Care for the Nonelderly under Current Law, by Income Group, 2020

	Income Group				
	Below 138% of FPL	Between 138% and 200% of FPL	Between 200% and 400% of FPL	At or above 400% of FPL	Total
Household					
Premiums	15,897	22,331	85,558	149,062	272,849
Other health care spending	21,624	21,437	86,278	143,688	273,027
Subtotal	*37,522*	*43,768*	*171,836*	*292,751*	*545,876*
Federal government					
Medicaid	249,199	41,382	45,051	17,010	352,642
Marketplace PTCs	13,215	24,797	16,955	0	54,967
Marketplace CSRs	0	0	0	0	0
Additional	44	334	461	424	1,263
Uncompensated care	10,013	2,401	7,072	6,771	26,257
Subtotal	*272,471*	*68,915*	*69,539*	*24,204*	*435,130*
State government					
Medicaid	129,472	18,330	22,888	10,757	181,446
Marketplace PTCs	10	56	191	119	376
Marketplace CSRs	1	20	27	0	47
Additional	8	95	118	122	343
Uncompensated care	6,258	1,501	4,420	4,232	16,411
Subtotal	*135,748*	*20,003*	*27,643*	*15,230*	*198,624*
Employers					
Premium contributions	45,927	55,580	228,857	390,562	720,926
Providers					
Uncompensated care	8,762	2,101	6,188	5,925	22,975
Total	**500,431**	**190,366**	**504,063**	**728,671**	**1,923,531**

Source: Urban Institute Health Insurance Policy Simulation Model, 2020 open enrollment period baseline (before COVID-19 pandemic).

Notes: FPL = federal poverty level. PTCs = premium tax credits. CSRs = cost-sharing reductions.

Federal Government Spending

In table 8, we summarize state-by-state federal spending on Medicaid acute care for the nonelderly, Marketplace premium tax credits, and state reinsurance waivers. Federal BHP payments for Minnesota and New York are counted in the premium tax credit column. Tables 2 and 3 provide corresponding enrollment numbers by state.

TABLE 8

Federal Spending under Current Law, by State, 2020

Millions of dollars

	Medicaid/CHIP	Tax credits	Reinsurance	Total
Alabama	4,404	1,109	0	5,513
Alaska	1,194	110	77	1,381
Arizona	10,832	646	0	11,478
Arkansas	5,091	224	0	5,315
California	45,129	5,510	0	50,639
Colorado	5,310	481	169	5,961
Connecticut	4,489	463	0	4,952
Delaware	1,295	125	22	1,441
District of Columbia	1,471	5	0	1,475
Florida	14,935	9,273	0	24,208
Georgia	8,658	2,109	0	10,767
Hawaii	1,042	87	0	1,129
Idaho	2,128	416	0	2,543
Illinois	7,935	1,182	0	9,116
Indiana	8,066	406	0	8,472
Iowa	3,455	443	0	3,898
Kansas	1,611	476	0	2,087
Kentucky	8,494	347	0	8,841
Louisiana	7,754	426	0	8,180
Maine	1,723	324	26	2,073
Maryland	6,694	504	447	7,645
Massachusetts	7,883	821	0	8,704
Michigan	13,357	729	86	14,172
Minnesota	6,183	616	0	6,799
Mississippi	4,133	614	0	4,747
Missouri	6,761	1,077	0	7,838
Montana	1,924	196	23	2,142
Nebraska	981	743	0	1,724
Nevada	2,859	251	0	3,110
New Hampshire	870	137	0	1,007
New Jersey	6,364	602	190	7,156
New Mexico	5,266	146	0	5,412
New York	26,651	6,090	0	32,741
North Carolina	12,282	3,215	0	15,498
North Dakota	448	53	21	523
Ohio	13,836	563	0	14,399
Oklahoma	3,719	1,103	0	4,822
Oregon	5,634	512	54	6,200
Pennsylvania	14,572	1,375	0	15,947
Rhode Island	1,236	89	5	1,330
South Carolina	4,344	1,248	0	5,592
South Dakota	630	213	0	843
Tennessee	7,386	1,226	0	8,612
Texas	27,241	4,880	0	32,120
Utah	3,119	624	0	3,743
Vermont	1,100	119	0	1,219
Virginia	7,490	1,177	0	8,666
Washington	7,375	571	0	7,945
West Virginia	2,943	145	0	3,088
Wisconsin	4,042	895	142	5,079
Wyoming	303	275	0	578
Total	**352,642**	**54,967**	**1,263**	**408,872**

Source: Urban Institute Health Insurance Policy Simulation Model, 2020 open enrollment period baseline (before COVID-19 pandemic).
Note: CHIP = Children's Health Insurance Program.

In table 9, we show the distribution of the 9.4 million people getting financial assistance for enrolling in coverage either in the Marketplaces (8.5 million) or BHP (900,000) by income group. We also show total federal premium tax credit spending for each group and spending on state-funded enhanced premium tax credits and reinsurance. Reinsurance programs, where available, affect everyone enrolled in the nongroup market, not just those getting premium tax credits.

TABLE 9
Distribution of Tax Credits by Income Group and Coverage Type and Federal and State Spending on Tax Credits under Current Law, 2020

	Thousands of people with tax credits	Spending on Tax Credits (Millions of Dollars)					
		Federal			State		
		APTC	CSR	Other	APTC	CSR	Other
Basic Health Program							
< 138% of FPL	449	3,290	0	0	0	0	0
>= 138% of FPL	441	2,535	0	0	0	0	0
Marketplace with PTCs							
< 150% of FPL	2,421	16,156	0	114	24	3	25
150% to < 200% of FPL	2,596	16,031	0	231	42	18	67
200% to < 250% of FPL	1,126	6,451	0	106	63	18	26
250% to < 300% of FPL	963	4,661	0	93	79	9	23
300% to 400% of FPL	1,394	5,844	0	150	48	0	37
> 400% of FPL	46	0	0	0	119	0	0
Full-pay Marketplace	**0**	**0**	**0**	**0**	**0**	**0**	**0**
Other nongroup	**0**	**0**	**0**	**0**	**0**	**0**	**0**
Total	**9,436**	**54,968**	**0**	**694**	**376**	**47**	**178**

Source: Urban Institute Health Insurance Policy Simulation Model, 2020 open enrollment period baseline (before COVID-19 pandemic).
Notes: Other includes reinsurance and a few special programs. APTC = advanced premium tax credit. CSR = cost-sharing reduction.

State Government Spending

In table 10, we summarize state spending on Medicaid acute care for the nonelderly, supplemental state-funded premium tax credits, and state reinsurance waivers. Tables 2 and 3 provide the corresponding enrollment numbers by state.

TABLE 10

State Government Health Spending on Acute Care for the Nonelderly under Current Law, 2020

Millions of dollars

	Medicaid and CHIP	Supplemental premium tax credits and reinsurance	Total
Alabama	1,535	0	1,535
Alaska	495	0	495
Arizona	3,317	0	3,317
Arkansas	1,441	0	1,441
California	26,530	225	26,755
Colorado	2,974	81	3,055
Connecticut	3,097	0	3,097
Delaware	694	5	699
District of Columbia	574	0	574
Florida	8,742	0	8,742
Georgia	3,796	0	3,796
Hawaii	569	0	569
Idaho	626	0	626
Illinois	5,648	0	5,648
Indiana	2,885	0	2,885
Iowa	1,525	0	1,525
Kansas	987	0	987
Kentucky	2,168	0	2,168
Louisiana	2,491	0	2,491
Maine	824	0	824
Maryland	4,261	15	4,275
Massachusetts	5,669	193	5,862
Michigan	5,108	91	5,199
Minnesota	4,871	0	4,871
Mississippi	1,149	0	1,149
Missouri	3,288	0	3,288
Montana	567	12	579
Nebraska	756	0	756
Nevada	1,160	0	1,160
New Hampshire	608	0	608
New Jersey	3,937	77	4,014
New Mexico	1,219	0	1,219
New York	16,969	0	16,969
North Carolina	5,414	0	5,414
North Dakota	295	26	321
Ohio	6,111	0	6,111
Oklahoma	1,754	0	1,754
Oregon	2,228	16	2,244
Pennsylvania	9,158	0	9,158
Rhode Island	746	10	755
South Carolina	1,674	0	1,674
South Dakota	397	0	397
Tennessee	3,608	0	3,608
Texas	15,698	0	15,698
Utah	1,047	0	1,047
Vermont	776	6	782
Virginia	4,285	0	4,285
Washington	4,204	0	4,204
West Virginia	733	0	733

	Medicaid and CHIP	Supplemental premium tax credits and reinsurance	Total
Wisconsin	2,557	12	2,569
Wyoming	279	0	279
Total	**181,446**	**767**	**182,213**

Source: Urban Institute Health Insurance Policy Simulation Model, 2020 open enrollment period baseline (before COVID-19 pandemic).
Note: CHIP = Children's Health Insurance Program.

The Impact of the COVID-19 Pandemic

Shortly after we completed the annual model update based on OEP data, the COVID-19 pandemic resulted in historic job losses. This has undoubtedly had substantial impacts on health insurance coverage. Though definitive data will not be available until 2021, we have published two estimates of how the pandemic has affected health coverage and costs. Given shifts in coverage owing to pandemic-related job losses, the first analysis estimated 3 million people would be uninsured in the last three quarters of 2020 (Banthin et al. 2020). In addition, the number of people in ESI would decline by more than 7 million, while Medicaid/CHIP enrollment would increase by more than 4 million people. Nongroup enrollment would increase slightly on net; new nongroup enrollees would be largely offset by current enrollees becoming eligible for Medicaid because of lost income.

In our second analysis, we estimated distribution of current-law health coverage for 2022 (Blumberg et al. 2020). We assumed the pandemic would still have a residual impact on employment; the number of lost jobs would be lower than in 2020, but recovery would not be the same for all groups of workers. According to data from the US Bureau of Labor Statistics, employment for those with a college degree had returned to nearly prepandemic levels by September 2020, while employment for those with less educational attainment lagged substantially.[3] In our 2022 baseline estimates, roughly 2 million more people are uninsured than in our 2020 OEP baseline. And 2022 Medicaid/CHIP enrollment is higher than, ESI coverage is lower than, and net nongroup coverage is similar to those in the 2020 OEP baseline.

Part 2. HIPSM Methodology

The Underlying Population of Households and Synthetic Firms

As noted, the core data used in HIPSM are from the 2012 and 2013 American Community Surveys, an annual survey fielded by the US Census Bureau that represents the US-resident population. We use an augmented version of the ACS, the Integrated Public Use Microdata Series, which uses the public-use sample of the ACS and contains edits for family relationships and other variables. The 2012 ACS had a household response rate of 97.3 percent.[4]

We pool the 2012 and 2013 ACS data. By combining the two years of survey data, the HIPSM sample increases to just over 6 million observations. We adjust the weights associated with each observation to reflect the distribution of demographic, economic, and health coverage characteristics of the 2013 ACS population. Later, while producing each annual baseline, these weights are adjusted to match the weights of the most recent ACS. The high response rate and the large sample size of the ACS substantially increase HIPSM's power to produce estimates by state and even substate regions. HIPSM is well positioned to analyze the distributional impacts of policies that may differ in their effects on subgroups, and the model's large sample size means it is more likely to contain representative observations of small but policy-relevant subgroups.

We use these years of data for our model baseline because they predate the ACA. Later years reflect either the ACA's transitional period, during the first years of implementation, or substantial uncertainty over the ACA's future, especially given the Trump administration's executive actions beginning in 2017. Starting from pre-ACA data also makes it easier for the model to simulate both the full repeal of the ACA and the eventual full impact of the ACA under a stable administration. We incorporate demographic and economic changes between the base data year and current year by periodically reweighting the pre-ACA data, as we describe below.

Variable Editing and Imputations

Edits to pre-ACA coverage variables. We conduct edits and imputations for some key variables missing from the ACS. The Urban Institute has developed a set of health coverage edits to the ACS (Lynch, Boudreaux, and Davern 2010), and they result in health coverage that closely aligns with data from the National Health Insurance Survey and the National Association of Insurance Commissioners, which are considered two of the best measures of national health coverage. We also impute the following to individuals on the ACS: detailed firm size, insurance policyholder and dependent status, unemployment compensation, offers of ESI among those not covered by such plans, and immigration status.

Adding firm size, policyholder status, and unemployment compensation. The firm size, policyholder status, and unemployment compensation imputations build on analyses we conducted with the pre-ACA Annual Social and Economic Supplement to the Current Population Survey. We use individual-level data from the ACS and similar data from the Annual Social and Economic Supplement to impute these missing data elements to the ACS. We impute firm size on the ACS because ESI offers are highly dependent on firm size, and we need to match individuals to simulated, or "synthetic," firms based on firm size. Also, many policies under current law and various proposals are or would be implemented differently by firm size. Similarly, we impute policyholder status to people in families with ESI (absent on the ACS) because we need to match workers who take up coverage to synthetic firms that offer that coverage. We also impute unemployment compensation, which is missing from the ACS but used in computing modified adjusted gross income (MAGI).

Adding ESI offer. The ACS does not ask workers without ESI whether they are eligible for ESI or if their firm offers coverage to any of its workers. We impute offers of and eligibility for ESI by firm size and industry on our base data to match the corresponding years' Medical Expenditure Panel Survey Insurance Component (MEPS-IC) summary tables. The MEPS is a survey of individuals and families, employers, and medical providers across the United States that provides information about health care expenditures and health insurance coverage. It has two major components: The Household Component (MEPS-HC), used to estimate HIPSM health care costs as described below, collects data from individuals, families, and their health care providers. The other component, MEPS-IC, collects ESI information from employers. We begin by predicting initial probabilities of whether a worker is in a firm offering coverage and whether the worker is eligible, based on worker and employer characteristics. The data used to build the regression models come from the Contingent Worker Supplement to the February Current Population Survey collected in 2005, the last year including information on ESI offers in that supplement.[5] We then adjust the model so the probabilities of offer by firm size and industry match the latest available MEPS-IC data.

Adding immigration status. The ACS does not contain sufficient information to determine whether noncitizens are authorized immigrants. We therefore impute documentation status for noncitizens using a year-specific model, because eligibility for Medicaid/CHIP and Marketplace tax credits depends on immigration status and requires that enrollees be citizens or authorized immigrants. Moreover, in some states, immigrants' eligibility also depends on how long they have been in the country. We impute documentation status to immigrants in two stages, using individual and family characteristics based on methodology from Passel and Cohn (2009). The approach is designed to produce imputations that match, in aggregate, published summary estimates of the US undocumented population, nationally and in California, Florida, Illinois, New Jersey, New York, and Texas. To determine whether certain immigrants are eligible for public programs, we use state eligibility rules and ACS information about citizenship, imputed documentation status, and date of immigration.

Population Weights for Current and Future Years

We reweight our base data for 2020–30 using two sources: a recent source of data on the current population and state-level population projections for 2030. For the first, we reweight the base data to match the distributions of age, gender, and income in each state on the 2017 ACS. We also match Pew Research Center's 2017 estimates of the number of undocumented immigrants nationwide and in each of the large states for which they provided estimates (Passel and Cohn 2018). Our starting point was different for Alaska, Massachusetts, New Mexico, and New York; for these states, we had already developed more detailed current-law weights for other technical assistance work, and we used those instead of the standard 2017 ACS distributions.

The Census Bureau does not provide state-level population projections, so we use 2030 projections from the Urban Institute's Mapping America's Futures program. These projections match Census Bureau population projections nationally but provide greater detail and state-level projections. For years between 2020 and 2030, we extrapolate between the recent ACS and Mapping America's Future projections.

Synthetic Firms

An important step in building HIPSM is grouping workers into synthetic firms. Because ACS household survey data lack detailed information on where respondents work, we build synthetic firms to represent employers. Constructing synthetic firms allows us to model firms' decisions to offer ESI to their workers. If a synthetic firm is estimated to offer insurance, we also model the type of plan offered and compute premiums for that firm.

By grouping workers into synthetic firms within HIPSM, we can model firm decisions about ESI in response to policy changes, reflecting the combined preferences and characteristics of the workers in each firm as well as their dependents, who might also obtain coverage through the employer. The distribution of synthetic firms mimics the known distribution of employers by size, industry, region, and baseline offer status, and workers assigned to each synthetic firm are matched to firms by their reported employment characteristics.

We designed and implemented a procedure to create synthetic firms that records the distribution of workers within and across firms while minimizing computational burden. The optimal number of synthetic firms must be relatively large to analyze the distribution of firms' outcomes, and we performed experiments over an optimal number of firms. We began with a representative population of workers and their families from two years of pooled ACS data. From there, we constructed synthetic firms based on four employer characteristics:

1. Firm size (100–499 employees versus 500–999 employees)
2. Major industry group
3. Region
4. Whether the firm currently offers health coverage

We obtain information on how many actual firms and workers are in each combination of these characteristics from the latest information available in the Statistics of US Businesses. Health coverage offer rates are not available in the Statistics of US Businesses, so we use published rates from the MEPS-IC summary tables. Each firm worker in our two-year ACS file becomes the nucleus of a synthetic firm. Replicates of other workers in firms with the same combination of employer characteristics are added to each synthetic firm to make a full complement of workers. Each synthetic firm is assigned an analytic weight so weighted sums match the total number of firms in both groups of employee sizes (100–499 versus 500–999), regions, and industries from the latest Statistics of US Businesses, trended to 2016.

We then classify synthetic firms according to three other characteristics the literature has identified as particularly important in the provision of health benefits:

- **Low-wage firms versus other firms.** We use the same definition of low-wage firms as the Kaiser–Health Research and Educational Trust Employer Health Benefits survey (Kaiser-HRET survey): 35 percent or more of the workforce earns $25,000 or less annually in 2018. Synthetic firms were marked as either low wage or not low wage.

- **Plan deductible type.** Some firms offer only high-deductible coverage to their workers, and distinguishing them from firms offering comprehensive options is important. Also, our analysis of plan cost-sharing parameters (deductibles, coinsurance rates, out-of-pocket maximums) in the Kaiser-HRET survey data showed the biggest difference between various comprehensive plans was whether the plans had a deductible; plans without a deductible tended to be around 90 percent actuarial value, and plans with a deductible tended to be around 80 percent actuarial value. We classified firms into (1) those offering only a high-deductible plan, (2) those offering comprehensive coverage with deductibles, and (3) those offering comprehensive plans without a deductible. We take the shares of firms that should fall in each category, based on firm characteristics, from the Kaiser-HRET survey microdata. We use the Kaiser-HRET survey data to estimate the number of firms in each deductible group by industry, region, and low wage. Because workers' preferences factor into an employer's health benefit choices, we ensure each firm's deductible group assignment matches the preferred plan of a majority of workers taking up coverage.
- **Employer premium contribution rates.** The next section explains how we set contribution rates for single and dependent coverage.

Very few data are available regarding how the distribution of wages varies among firms of similar size and industry. Because our algorithm is based on a representative population of workers, it approximates actual distributions, on average. However, if firms of a particular size and industry employ very different mixes of workers, our synthetic firms may have less extreme wage distributions than do actual firms.

Imputation of Dependent Coverage Options and Contribution Rates

HIPSM has been enhanced to better model issues around the so-called "family affordability glitch." Under the ACA, if one family member is offered single coverage that is deemed affordable, the entire family is barred from premium tax credits. The cost of family coverage is not considered and, in some cases, may require an employee contribution that is not affordable. More generally, ESI is the leading source of coverage for children, and the availability and affordability of such coverage is crucial to many policy questions about children's coverage. We collaborated with the Agency for Healthcare Research and Quality to obtain details on dependent coverage and premiums for different types of firms from the 2013 MEPS-IC, information that was previously unavailable to outside researchers. This resulted in two main advances over our previous modeling. First, we imputed the types of dependent coverage offered by firms: no coverage, single-plus-one coverage, family coverage, or both single-plus-one and family coverage. Second, we used information about the joint distribution of required worker contributions for single, employee-plus-one, and family coverage. This allowed us to model, for example, the extent to which firms require small contributions to single coverage but large contributions to dependent coverage, which is critical for modeling the extent of the family glitch.

To assign dependent coverage options and worker contribution rates to our synthetic firms, we use the coefficients of a set of regression models run by the Agency for Healthcare Research and Quality on MEPS-IC data.[6] The regressions, based on computations in the marginal cost of dependent coverage paper, make up three sets of models: single to family coverage, single to plus-one coverage, and plus-one to family coverage. Single to family coverage gave the probability that a firm offered family coverage. Single to plus-one gave the probability that a firm offered employee-plus-one coverage. Plus-one to family gave the probability that firms offering plus-one coverage also offered family coverage. We use these to compute the probabilities that a firm offering single coverage offers one of four dependent coverage options:

- no dependent coverage
- plus-one and family coverage
- family coverage but not plus-one coverage
- plus-one coverage but not family coverage

An option was assigned to each firm using a Monte Carlo model.

Zero worker contributions for all options. In the next step, we imputed the probability that a firm would not require worker premium contributions for either single or dependent coverage, using regression models provided by the Agency for Healthcare Research and Quality.

The joint distribution of single and dependent contributions. For firms that require nonzero contributions for some coverage options, we assign each to a cell in the following matrix (table 11). We compute the quartiles over all firms with nonzero contributions and for those with employee-plus-one and family policies.

TABLE 11

Matrix for Distribution of Single and Dependent Contributions

<table>
<tr><td rowspan="2">Dependent coverage (family or plus-one)</td><td colspan="5">Single coverage</td></tr>
<tr><td>Zero contribution</td><td>1st quartile</td><td>2nd quartile</td><td>3rd quartile</td><td>4th quartile</td></tr>
<tr><td>1st quartile</td><td></td><td></td><td></td><td></td><td></td></tr>
<tr><td>2nd quartile</td><td></td><td></td><td></td><td></td><td></td></tr>
<tr><td>3rd quartile</td><td rowspan="2">Collapsed</td><td></td><td></td><td></td><td></td></tr>
<tr><td>4th quartile</td><td></td><td></td><td></td><td></td></tr>
</table>

Source: Urban Institute.

Because of sample size, two cells with zero single contributions had to be collapsed. The first set of models computed the probability that a firm was in the collapsed cell.

We impute all other cells in two stages. The first is a regression model for the probability of being in each single worker contribution group (no single contribution and the contribution quartiles columns in the table above). By design, the probabilities for the five single coverage options sum to 100 percent, so we assign a single coverage option to each firm by a Monte Carlo model.

The second stage is a regression model of the probability of being in each of the four dependent coverage contribution groups (rows in the table above). The models contain dependent variables for single coverage. Based on the resulting probabilities, we imputed the availability of plus-one and family coverage in each firm. Assignment to a dependent coverage group accounted for the imputed single coverage group, meaning each firm was assigned to only one cell in the matrix.

For each coverage type, we compute the average contribution rate in each quartile among firms with nonzero worker contributions, based on survey data. We assign single, family, and plus-one contribution rates to each firm offering such options based on the average rate for the imputed quartile.

Underlying Health Care Expenditures

Understanding heath expenditures by individuals and families is central to computing health insurance premiums, evaluating the health insurance options facing families, and assessing the costs of the components of the ACA. The ACS does not collect data on health care expenditures, so we statistically match health care expenditure data from individuals in the MEPS-HC to individuals in the ACS. We make several adjustments to the MEPS data, as we describe below.

We statistically match health care expenditures, unique health insurance variables, and health conditions from multiple years of pooled MEPS-HC datasets to our core ACS file, matching MEPS and ACS individuals by insurance coverage and demographic and other common characteristics in the two datasets. The 2020 version of HIPSM incorporates MEPS-HC data from 2002 to 2012. We chose these years because the data have been supplemented with diagnosis-based risk scores, which we use for several purposes. More recent years of MEPS data exclude risk scores.

All MEPS expenditures are adjusted to be comparable with estimates from the National Health Expenditure Accounts, following the procedure developed by the Agency for Healthcare Research and Quality, and further scaled by an inflation factor to represent dollars as of the HIPSM baseline year. Using a propensity-weighting approach, we assign a MEPS observation to each ACS observation, and we then append the health expenditure data and information on health status and health conditions from the matched MEPS individuals to their matched ACS individuals. Variables used in the match include age, sex, health status, disability/functional limitation, income group, health coverage, race, and ethnicity. We then confirm that health expenditures in the appended ACS file maintain the statistical distributions of and relationships with other variables existing in the original MEPS data.

For each observation, we include expenditure data for seven service categories: hospital, physician, dental, other professional care, home health care, prescription drugs, and other medical equipment. We created these categories to be consistent with the National Health Accounts personal health care expenditures data, which are maintained by federal actuaries. Compared with the National Health Accounts, the MEPS underestimates the aggregate insured costs associated with Medicaid and privately insured individuals (Selden and Sing 2008; Sing et al. 2006). To correct this discrepancy, we use adjustment factors to boost Medicaid and privately insured dollars; the factors are consistent with the relative differences in the two datasets identified in Sing and colleagues (2006). We apply these factors to each observation in our dataset that reported positive Medicaid and/or privately insured expenditures. We then inflate our expenditures to the current year using the National Health Accounts' per capita growth in each expenditure category.

The MEPS also misses some of the very high–cost cases in the tail of the distribution of health care expenditures. To adjust for that underreporting, we looked to the Society of Actuaries' Health Care Cost Institute database.[7] This comprehensive survey examined seven insurers and their claimants and was designed to represent the national distribution of all claims to private insurers. We found that the 97th to 99th percentiles of private expenditures among the nonelderly in MEPS data fell below the same percentiles in the Health Care Cost Institute database. The discrepancy ranged from less than 1 percent (97th percentile) to 13 percent (99th percentile). We use these discrepancies as adjustment factors for all privately insured individuals with private expenditures above the 97th percentile. Following this adjustment, we decrease the private expenditures of the privately insured individuals in the lower portion of the distribution by a fixed percentage. This keeps total health expenditures in our MEPS-appended ACS files consistent with the National Health Accounts totals.

Spending under Different Coverage Types.

Once we have assigned expenditures to each person in our matched ACS-MEPS analytic file by matching them to a similar person in the MEPS-HC, we next estimate how each individual would alter their spending under different types of insurance. This step is necessary for us to model how individuals' expected utility might change under policy proposals. Total spending on health care varies by the generosity of a health insurance plan's benefits. The same individual would spend more in total (including both out-of-pocket and insured costs) under a health insurance plan with generous benefits than under a health insurance plan with less generous benefits. Different types of health insurance vary in their covered services and cost-sharing requirements (e.g., deductibles, copayments, and out-of-pocket maximums). These plan characteristics alter the out-of-pocket price faced by an individual when consuming medical care. The higher the out-of-pocket price, the less care the individual is likely to consume.

HIPSM assumes individuals value the amount of health care they consume, and this value is included in the utility function. Thus, to understand the value of health care an individual will obtain under various coverage options, we compute health care spending under four alternate "states" of health coverage:

- uninsured
- insured by Medicaid/CHIP
- insured under a typical comprehensive employer plan
- insured under a typical nongroup plan

For the uninsured, we divide total spending into out-of-pocket and uncompensated care costs. For the other states, we divide spending into out-of-pocket and insured costs.

To predict spending for each individual in our matched ACS-MEPS files under each insurance state, we estimate four separate models (one for each insurance state). We first estimate total health care spending for each insurance state in two parts. The first part estimates the probability of having any health expenditures, and the second part estimates the amount of health expenditures conditional on having positive expenditures. In the second part, the dependent variable is the log of total health expenditures. The independent variables in both parts of the model are sociodemographic and health characteristics: age, sex, race/ethnicity, poverty category, health status, disability status, and health conditions. We estimate the coefficients of the four separate models by restricting the sample to individuals who report coverage under each of the insurance states. In the final step, we use the four sets of coefficients resulting from the four models to predict the total spending for each individual in our sample under the four insurance states, using an individual's sociodemographic and health characteristics.

Uncompensated Care

In the previous step, we estimated total health care spending for each individual in our sample under four possible insurance states, including being uninsured. Importantly, HIPSM can estimate the these individuals' demand for uncompensated care, or the amount of health care costs beyond what a person can pay on their own.

To more accurately capture the uncompensated care associated with the uninsured, we adjust MEPS expenditure data. After the previous step, we have estimates of out-of-pocket health care expenditures and total expenditures for each person were a person covered by private insurance. We first reduce total expenditures to capture the moral-hazard effect of the additional out-of-pocket spending resulting from being uninsured. The result is an estimate of the total expenditures of the uninsured person. We then calculate the difference between these expected costs and the original out-of-pocket costs for each uninsured person. This difference is a person's uncompensated care.

Using health coverage from the 2013 ACS, we calibrate individual uncompensated care values to replicate the total amount of 2013 uncompensated care, consistent with findings in Coughlin and colleagues (2014). Coughlin and colleagues estimated the federal government funds about 39 percent of uncompensated care through programs such as Medicaid and Medicare disproportionate share hospital payments, state and local governments fund 24 percent, and health care providers fund 37 percent. For future years, we inflate uncompensated care by the growth in per capita out-of-pocket health care spending in the National Health Expenditure Accounts.

Uncompensated care is currently funded by

- Medicaid disproportionate share hospital and upper payment limit programs;
- Medicare disproportionate share hospital payments;
- the Veterans Health Administration;
- other federal programs;
- state and local government programs;
- private programs, such as the patient assistance programs providing free or reduced-cost prescription drugs to qualifying individuals; and
- charity care and bad debt absorbed by health care providers.

HIPSM estimates of uncompensated care should be considered measures of the demand for uncompensated care, rather than the amount of uncompensated care actually provided. The model does not estimate the specific ways in which uncompensated care is funded, which are diverse and vary considerably between states. When simulating policy alternatives, we make no assumptions about how the sources and levels of uncompensated care funding would change, unless the policy contains specific changes to federal programs funding uncompensated care. For example, when simulating the repeal of the ACA, the demand for uncompensated care increases substantially. However, it is unclear whether funding of uncompensated care by federal, state, and local governments would automatically increase proportionally.

Construction of Insurance Packages

EMPLOYER COVERAGE

At this point in a simulation, each individual in the file has been assigned health expenditures consistent with having private coverage. These total health expenditures, however, reflect the particular benefit package the matched MEPS individual had at the time of the survey. For example, if two identical people were given two different health insurance policies, one with a high deductible and one with a low deductible, the person with the low deductible would have higher total health expenditures than the person with the high deductible. Higher out-of-pocket liability lowers expected spending (called the moral-hazard effect).

We want HIPSM to be able to model changes in benefit packages and compute the health spending of each individual under any given package. As a first step, we standardize individual spending to align with enrolling everyone in either (1) a typical benefit package for the ESI market or (2) the pre-ACA nongroup market. These adjustments are based on data with information on deductibles and out-of-pocket maximums from the Kaiser-HRET and America's Health Insurance Plan surveys, respectively. (See below for ACA packages.) Private health expenditures are adjusted to be consistent with each of the defined typical benefit packages.[8]

Induction factors provided by actuaries[9] are used to incorporate a behavioral response by individuals and families facing different levels of out-of-pocket spending under the standardized policies than they were assumed to face at the time of the MEPS. We assume those facing lower out-of-pocket expenses respond by increasing use and total expenditures, whereas those facing higher out-of-pocket expenses decrease use and total expenditures. Individuals with high spending levels, who are assumed to have more serious health conditions, respond less to changes in out-of-pocket expenses than those with lower spending levels.

Once such packages are created, they can be modified to achieve a given actuarial value, defined as the average share of spending on covered benefits paid for by the insurer over a group of insured people.

NONGROUP MARKETS, INCLUDING MARKETPLACES

Under the ACA, packages in the small-group and nongroup markets include the same essential benefits but differ in actuarial value because of different cost-sharing requirements. For the nongroup market, including the Marketplaces, we construct plans at each of the legally defined actuarial values and cost-sharing reduction levels by varying parameters, such as deductibles, maximum out-of-pocket levels, and coinsurance rates. To do so, we use the Center for Consumer Information and Insurance Oversight actuarial value calculator, as an insurer would.

Every year, we calibrate private health insurance packages and health expenditures to replicate actual Marketplace data for the coming plan year. These data are on (1) plan design (deductibles and out-of-pocket maximums) offered in state Marketplaces and (2) premiums at various metal levels for each state premium rating region, particularly the second-lowest silver plans, on which federal premium tax credits are based.

It is difficult to extract an overall coinsurance rate from available plan data. So, we take the median deductible and out-of-pocket maximum and use the current year's Center for Consumer

Information and Insurance Oversight actuarial value calculator to determine the coinsurance rate with the correct actuarial value. Various plan designs can have the same actuarial value, but they all have about the same expected value for insured costs, by definition. We simplify the plan choices people make; HIPSM decisions are based on expected values and variances of health costs (see below), because people do not have perfect information about their costs for the coming year. This means different plans with same actuarial value would have similar take-up patterns.[10] We model just one plan per metal tier.

In HIPSM, each state is a separate risk pool, as under current law. However, actual premiums can vary by rating region within a state. Our model is based on the ACS, so we use substate regions called census public use microdata areas (PUMAs) when determining premiums. Mapping Marketplace premium rating regions to PUMAs is complex: If a PUMA is entirely contained in a rating region, we use that premium. However, many PUMAs contain multiple rating regions. For these, we take an average of the premiums in each rating region, weighted by the share of a PUMA's population in each region. In this way, HIPSM can reproduce local premium variation.

Another step in constructing the baseline is to adjust health care costs in each state and region to align with the insurance packages and premiums for the coming plan year. We begin with a preliminary simulation of people covered by nongroup insurance during the current plan year, based on current enrollment data and the simulated impact of any policy changes taking effect in the next plan year. Insurers must do similarly to estimate the rates they will charge in the coming year. The difference is that we must take their premiums as fixed. We adjust health care costs, both insured and out of pocket, so the insured costs of covered lives in each state align with the state's premiums.

Expenditures in HIPSM cannot generally be disaggregated into spending on individual benefits, but we can separate spending by four provider types, based on MEPS-HC data: hospital, physician, prescription drugs, and other.

HIPSM does not explicitly model other characteristics of an insurance plan that may affect the amount of medical care a person consumes, such as the size of the provider network and the presence of utilization management and prescription drug formularies. To the extent consumers value network size or other characteristics, those effects are measured in the latent error terms and included with other unmeasured variables when the model is estimated. In our estimates of spending under different insurance sources, those effects are implicitly incorporated. For example, our estimates of what people would spend if enrolled in Medicaid incorporates the effect on utilization of the limited networks of providers accepting Medicaid.

Eligibility for Medicaid, CHIP, and Marketplace Tax Credits

Under the ACA, income eligibility for both Marketplace subsidies and Medicaid coverage is based on the Internal Revenue Service's tax definition of MAGI, which includes the following types of income for everyone, except tax-dependent children: wages, net business income, retirement income, Social Security, investment income, alimony, unemployment compensation, and financial and educational assistance.

To compute family income as a ratio of the poverty level, we sum person-level MAGI across the tax unit (Kenney et al. 2013). Current regulations define certain exceptions to using the tax unit for Medicaid eligibility determination. Also, such regulations define a formula used to determine how the income of undocumented family members, who are not considered part of the unit, is counted. In situations where a dependent lives outside the home to attend college, the ACS does not include data on family income or other family information in the child's record, nor does it include the child's presence in the records of family members. So, we assign some college students to families before beginning the simulation. In addition, we account for immigration status in determining eligibility for Medicaid, CHIP, and Marketplace tax credits, using the documentation-status imputations described above.

We model Medicaid mandatory disability-related eligibility by identifying adults with functional limitations[11] and comparing their incomes with thresholds for aged, blind, disabled Medicaid coverage. Though functional limitation is not directly comparable with disability status, as used in program eligibility determination, we find it is the best approximation available from this data source. Though some adults with functional limitations gain income-based coverage under the ACA's higher income thresholds, the ACA did not affect income thresholds and eligibility determination procedures for disability-related coverage. All states are required to continue providing Medicaid coverage to individuals receiving Supplemental Security Income benefits, and some states cover additional people with disabilities with higher incomes (Musumeci 2014). For other types of Medicaid and CHIP eligibility, we apply published MAGI eligibility thresholds for each state. Though we can distinguish finer Medicaid eligibility types in some states, we distinguish the following types of Medicaid eligibility in all states:

- people with disabilities
- Medicaid expansion

- nondisabled adults
- nondisabled children
- state-funded programs

For the rare cases in which we need eligibility rules in effect before 2014, we use the Urban Institute Health Policy Center's Medicaid/CHIP Eligibility Simulation Model. The model estimates pre-ACA eligibility for Medicaid/CHIP using available information on eligibility guidelines, including the amount and extent of income disregards and asset tests,[12] for each program and state as of mid-2013 (Lynch, Haley, and Kenney 2014).

Medicaid Eligibility under ACA Repeal

The ACA fundamentally changed how states count income for Medicaid and CHIP eligibility, with most eligibility types defined by MAGI. ACA implementation required every state to overhaul their eligibility systems; even if requirements of a Medicaid eligibility type did not change, the eligibility threshold had to be changed to reflect the ACA eligibility rules. None of the attempts to repeal the ACA would require states to go back to their old definitions and replace their eligibility systems again.

We cannot simply revert to pre-ACA income thresholds when simulating ACA repeal. Instead, we use MAGI-converted thresholds from each state's state Medicaid plan amendments submitted to CMS. If the ACA were repealed, the MAGI thresholds used to determine which enrollees qualify for the ACA's new eligible federal matching rate (in states that expanded Medicaid under the ACA) would become the maximum eligibility thresholds.

Marketplace Tax Credit Eligibility

Under the ACA, eligibility for Marketplace tax credits depends on four main variables HIPSM must compute:

1. **Eligibility for other programs.** Eligibility for Medicaid (described above) and other public health programs makes an individual ineligible for tax credits.
2. **Immigration status.** HIPSM imputes immigration status for each individual in our data. Undocumented immigrants may not purchase coverage in the Marketplaces, even without tax credits. Also, legally present immigrants ineligible for Medicaid because they have been

residents for fewer than five years may be eligible for Marketplace tax credits, even if their incomes are below the FPL.

3. **MAGI.** We construct tax units and MAGI for each unit. The importance of MAGI goes beyond premium tax credit eligibility; it is also used to determine the level of tax credits and cost-sharing reductions for which a family is eligible. For families including undocumented immigrants, we compute MAGI for the legally present family members, as specified in federal regulations, which count a portion of the income of undocumented family members without counting them in family size.
4. **Affordable offers of ESI coverage.** Under current law, a family is barred from tax credit eligibility if any member is offered single coverage deemed affordable. The maximum percentage of income considered affordable is defined each year. For each worker in a family with an offer of coverage through an employer, we look at the worker's share of the cheapest available offer of single coverage (HIPSM models which employers offer a choice of multiple plans) and compare it with family MAGI to determine whether the worker's offer is affordable.

The model also computes eligibility for state-specific programs to make health coverage more affordable: BHPs in Minnesota and New York; supplemental tax credits and cost-sharing reductions in California, Massachusetts, and Vermont; and the DC Health Alliance. We account for state and federal government financing of these programs. For BHPs, we compute federal payments according to the current formula defined by CMS. Federal BHP payments are paid into a trust fund used only to provide health coverage to beneficiaries, and we are not aware of any data that suggest these payments are insufficient to pay program costs in either New York or Minnesota. Some state supplemental subsidy programs, notably Massachusetts's ConnectorCare health plans, are financed through long-standing Medicaid waivers. Others, such as California's new program, are state-funded.

The Flow of a Policy Simulation

HIPSM coordinates behavior by iterating a sequence of four stages. In the first, the health insurance industry sets premiums for all available health insurance plans, given information observed in the last period and any policy changes that become effective for the current period. In the second stage, employers decide whether to offer an ESI plan, based on these premiums and information about their employees. If they choose to offer coverage, the employer then decides the plan to be offered and may adjust the employees' cash wages as a result. In the third stage, individuals choose their optimal health insurance option given their available alternatives and associated premiums, income, and relevant tax incentives. In the fourth stage, employer, individual, and family decisions are calibrated so overall behavior aligns with research from the health economics literature. Premiums are also updated based on the new enrollment decisions. Iterations continue until the changes in coverage fall below a specified threshold, meaning an equilibrium has been reached. Under the equilibrium, premiums and coverage distributions of individuals and families are aligned. In the following sections, we detail these stages.

Stage 1: Calculate Health Insurance Packages and Premiums

HIPSM calculates health insurance premiums using information on the health risks of enrollees, also called the risk pool, in a similar way to health insurers. For example, to calculate nongroup premiums in the current period, we use data on the health risks of people who bought a nongroup health insurance plan in the last period, accompanied by information on any policy changes that may affect the risk pool in the current period.[13] The model aims to reflect the health care costs of individuals who select into specific coverage types in the premiums for that option. Any policy change that affects individuals' health insurance decisions could affect premiums of *all* available coverage types. For example, a policy to expand public health insurance coverage will, in general, cause some people who formerly chose other types of coverage, such as nongroup health insurance, to switch to the public program. Given the change in nongroup risk pools, nongroup premiums will change accordingly.[14]

Calculation of premiums from ESI risk pools. We compute single and family ESI premiums faced by each employee and each firm for both standard and high-deductible ESI packages. We base our premium computations on the expenses of the covered lives within each synthetic firm. Premiums are calculated based on the weighted average of actual and expected insured costs, reflecting that firms are generally experience rated by insurers. From these blended costs, we calculate expected values for the individual firm and for ESI groups defined by firm size, industry, and self-insured status. This gives an average insured cost that blends the firm's and ESI group's average costs. We then apply an administrative load that varies by firm size and industry. The worker's share of premiums is then computed based on the previously calculated firm contribution rates.

Our baseline national ESI premium estimates are calibrated to be compatible with premiums in the most recent MEPS-IC and Kaiser-HRET survey. We compare the average and variance of premiums for HIPSM single, worker-plus-one, and family coverage with the latest available MEPS-IC summary tables. Premiums by firm size are calibrated by adjusting the actuarial value of ESI plans and the extent to which risk is pooled beyond a firm's workers.

We compute premiums for self-insured firms by applying a stop-loss insurance plan to a firm's health claims, which protects the firm from unexpectedly high costs. The firm is responsible for paying the remaining claims and the stop-loss premium. Stop-loss parameters vary by firm size and are based on data from the Kaiser-HRET survey and the available literature on self-insured health benefits.

Calculation of nongroup premiums. We compute single and family nongroup premiums in each iteration. The initial premiums are based on insured expenditures of those in the nongroup market at the baseline. In the following iterations, the pool is adjusted to include only those individuals simulated to enroll in nongroup coverage in the immediately preceding iteration. HIPSM follows the ACA's requirement that covered lives in each state form a single risk pool, but premium pricing can vary between regions in each state. We calibrate our model each year so nongroup premiums in each ACA premium rating region match posted premiums for the current year. (See the Construction of Insurance Plans section above.) We account for state-specific policies that affect premiums, particularly state-specific premium-rating age curves and reinsurance waivers. Premiums for policy alternatives change as the risk profile of enrollees in each state changes. To simulate alternatives to the ACA that would eliminate its nongroup market reforms, such as guaranteed issue, we can simulate individual underwriting and denials of coverage calibrated to results from pre-ACA America's Health Insurance Plans surveys.[15]

Medicaid spending. We use the latest Medicaid Statistical Information System (2012 to 2016, depending on state) to benchmark Medicaid spending in each state. We compute per capita spending for each of three groups: people with disabilities, nondisabled adults, and nondisabled children. We then age this spending to the current year using estimates from the National Health Expenditure Accounts. In computing each person's Medicaid costs, we account for differences in health risk between the pre-ACA Medicaid population and the current Medicaid population under the ACA. To ensure consistency, we then compare the per capita national federal spending for people with disabilities, nondisabled adults, and nondisabled children with the current Congressional Budget Office Medicaid baseline.

Stage 2: Employer Health Benefit Decisions

In HIPSM, synthetic firms are constructed to model employer decisions. In the model, employers account for their employees' gains or losses from having a health insurance offer and the perceived offering costs when deciding whether to make an offer. The costs of offering coverage are calculated as the cost of employers' premium contributions plus any assessments or penalties for which the employer is liable, plus a fixed administrative cost, minus any tax incentives due to the tax exclusion of ESI, and minus any employer tax-credits under reform.

Employers will make an offer when they anticipate that (1) the employees' aggregate value of the insurance offer exceeds the costs of offering and (2) enough employees gain from having the offer.[16] Workers' values of ESI offers can be summed over all workers in a firm when determining that firm's decision. We assume employers distribute the costs of offering coverage back to their employees in the form of lower wages. That is, employees' cash wages are lower when they have an employer-provided health insurance offer than they would be without an insurance offer. This wage reduction is not realized at the individual level; rather, employer costs and savings are distributed across the wages of all workers (Gruber 1994).

Stage 3: Individuals' Optimal Health Insurance Decisions

We adopted an expected utility–based approach to modeling individual and family demand for health insurance coverage. With this approach, workers value different insurance options based on premiums, expected out-of-pocket payments, risk of high out-of-pocket expenditures, and the value they place on health care. Workers convey their valuation to employers, who decide whether and what to offer their workers based on whether the sum of the workers' valuations for an insurance option is greater than its cost. Individual insurance coverage states generally fall into four categories: ESI, nongroup coverage, public coverage, or uninsurance. However, nongroup, and less commonly ESI, decisions may involve additional decisions between coverage options within each type: Under current law, families can choose between actuarial value metal tiers in the nongroup market. They can also choose between ACA-compliant and non-ACA-compliant nongroup coverage, such as short-term, limited-duration policies. Policy alternatives may add further options.

UTILITY FUNCTIONS

The utility functions are the metric for valuing different insurance options available to individuals and health insurance units. The value of each type of coverage accounts for (1) out-of-pocket health care expenses, (2) premiums, (3) the uncertainty of out-of-pocket health care expenses, (4) the value of differences in the amount of health care consumed when insured versus when uninsured, and (5) the comprehensiveness of coverage a plan provides. The utility functions also capture other aspects of family preferences, including aversion to public program participation (e.g., due to welfare stigma) and unmeasured preferences associated with sociodemographic characteristics. Key inputs to the utility calculations include (1) the expected total and out-of-pocket health care spending individuals and health insurance units would incur under each health insurance option and (2) the variance of expenditures under each option. We chose our utility function because it has the following mathematical and economic properties.

First, utility is additively separable into a function of disposable income (*C*) and a function of health care spending, whether out of pocket (*m*) or paid for by insurers, the government, or uncompensated care (*s*).

Second, both individuals and firms exhibit constant relative risk aversion (CRRA). Whereas several papers in the literature use absolute risk aversion (Feldman and Dowd 1991; Glied 2003; Zabinski et al. 1999), or ARA, HIPSM uses CRRA to achieve decreasing absolute risk aversion (DARA). We chose this for the following reasons:

- DARA incorporates two theoretically desirable behaviors: First, not only does the marginal utility of income decrease with income, but the percent decrease also decreases. Second, willingness to tolerate risk varies directly with income.
- Many studies using constant ARA were based on data from a limited income range (e.g., the RAND Health Insurance Experiment). In its utility computations, HIPSM uses income and wages adjusted to match Statistics of Income data from tax returns. The resulting amounts are not top coded. We therefore model a much larger range of income than other studies.
- The utility function in HIPSM is not used only for individual health insurance units. Sums of health insurance unit utility are the basis of firms' utility functions. With constant ARA, pooling risks has no benefits. This is why DARA utility functions are generally chosen for modeling *insurer* behavior (Venter 1983).
- Beyond DARA, empirical evidence supports CRRA (Chiappori and Paiella 2011; Szpiro 1986).

Third, we use the standard form of a CRRA utility function for risk aversion constant $\sigma \neq 1$, which is generally set to 2. For example:

$$u(C) = \frac{C^{1-\sigma}}{1-\sigma} u(C) = \frac{C^{1-\sigma}}{1-\sigma}$$

The following elasticities are constant:

$$\frac{\partial u}{\partial C} \bigg/ \frac{\partial u}{\partial m} \equiv \gamma_m \qquad \frac{\partial u}{\partial C} \bigg/ \frac{\partial u}{\partial s} \equiv \gamma_s$$

Further, the elasticities do not depend on the health insurance option under consideration, a standard assumption in the literature.

Fourth, out-of-pocket and insured costs are valued differently, (i.e. $\gamma_m \neq \gamma_s$). This is an important component of some models in the literature (Glied 2003) but absent from others (Zabinsky et al. 1999). We believe the difference in valuation between costs paid directly by the health insurance unit and those paid on its behalf is important. Based on a review of the literature, we set the out-of-pocket elasticity to 1 and the insured cost elasticity to 0.5.

Fifth, the coefficients of relative risk aversion are the same for *C*, *m*, and *s*. Various papers have estimated this coefficient for different types of risk with comparable results (Friend and Blume 1975; Szpiro 1986). Our choice of coefficient is within the ranges estimated. Empirical estimates of the coefficients for *m* and *s* would be very difficult to generate, and there is no *a priori* reason why they would differ substantially from the coefficient for *S*.

And lastly, to compute the best available option for health insurance units and employer groups, we must be able to aggregate measures of individuals' utility to a group utility. In particular, the utility of a firm can be represented by either the mean or median of the utilities of its workers, modified by the overall costs of offering coverage. The resulting individual utility function is as follows:

$$u(C,m,s) = \frac{(C_0^{\sigma}C^{1-\sigma} + (\gamma_m m_0 + \gamma_s s_0)^{\sigma}(\gamma_m m + \gamma_s s)^{1-\sigma})}{1-\sigma} \qquad (1)$$

Or, for the default CRRA coefficient of 2:

$$u(C,m,s) = -\left(\frac{C_0^2}{C} + \frac{(\gamma_m m_0 + \gamma_s s_0)^2}{\gamma_m m + \gamma_s s}\right) \qquad (2)$$

We then decompose nonhealth consumption into $C_j = Y - m_j - \pi_j + \tau_j$, where τ_j is the tax incentive for option *j*, and π_j is the out-of-pocket premium for that option. We thus consider *U* a function of m_j and s_j:

$$U(m_j, s_j) = Y_0 - \pi_0 + \tau_0 + (\gamma_m - 1)m_0 + \gamma_s s_0 - \left(\frac{C_0^2}{\mathrm{Y} - m_j - \pi_j + \tau_j} + \frac{(\gamma_m m_0 + \gamma_s s_0)^2}{\gamma_m m_j + \gamma_s s_j}\right) \qquad (3)$$

This defines a deterministic utility function, but a unit cannot know its exact out-of-pocket expenditures and insured costs for the coming year. Given a policy option *j*, the premium and tax incentives will be known, whereas the out-of-pocket expenditures and insured costs will be random variables. To find a unit's expected utility, given these variables' distribution, we consider utility a function of *m* and *s* and expand the utility function around the point $(E[m_j], E[s_j])$ to the second order:

$$E[U(m_j, s_j)] \approx U(E[m_j], E[s_j]) - \frac{E[C_0]^2 V[m_j]}{(\mathrm{Y} - E[m_j] - \pi_j + \tau_j)^3} - \frac{E[\gamma_m m_0 + \gamma_s s_0]^2 \gamma_m^2 V[m_j]}{(\gamma_m E[m_j] + \gamma_s E[s_j])^3} + \frac{V[m_0]}{E[C_0]} + \frac{\gamma_m^2 V[m_0]}{E[\gamma_m m_0 + \gamma_s s_0]} \qquad (4)$$

Given a choice between two options, *i* and *j*, a unit will choose *i* if the following is greater than zero, where ε is a latent preference term set when calibrating the model:

$$E[U(m_i, s_i)] - E\left[U\left(m_j, s_j\right)\right] + \varepsilon$$

As mentioned above, latent preference terms are set so each unit in our underlying data facing a choice between coverage options makes the choice reported in the data. We adjust the distribution of latent preference terms across populations to replicate benchmarks from the literature, particularly premium-elasticity estimates.

Stage 4. Benchmarking to the Literature

As noted earlier, after the first three stages, premiums are updated based on the new enrollment decisions. Iterations continue until the changes in coverage fall below a specified threshold, meaning an equilibrium has been reached. Before the equilibrium is deemed final, however, we review employer, individual, and family decisions and calibrate them so overall behavior aligns with research from the health economics literature.

Refinement of utility measures and benchmarking to behavioral parameters from the literature. Because our method converts utilities to dollar values, we can examine whether families' valuations for various insurance options are reasonable. We adjust the utility values for individuals by adding a latent preference term so the baseline insurance coverage choice they make in a HIPSM simulation aligns with what they are observed to have chosen in the core data. This adjustment captures unobserved reasons why people might not choose the coverage type that appears to be their best option, given what we can observe. We continue to refine our utility parameters and components so the model will reflect what is known about the sensitivity of workers' behavior to different incentives, such as price responsiveness to changes in premiums.

Choices between available options are implemented as a series of binary choices. Consider, under the ACA, a family in which the children are eligible for CHIP, the parents are eligible for Marketplace tax credits, and one parent is offered employer coverage with a premium for single coverage high enough that the family is not disqualified for tax credits. The choices are implemented as follows:

1. Do the eligible children enroll in CHIP or go uninsured?
2. Do the parents enroll in subsidized Marketplace coverage or go uninsured?

3. Would the worker enroll self or family in employer coverage rather than the CHIP/Marketplace/uninsured choices made earlier?

Each choice is made using a regression model built from reported data on comparable choices. The right side of the regression includes the difference in expected utility and a latent preference term, and some additional demographic variables not correlated with utility may be added. The latent preference terms ensure an observation used in building the model makes its reported choice. In addition, the variance and mean of the preference terms are calibrated to reproduce price responsiveness or take-up rate targets from the literature, as described below. Additional demographic variables are rarely used because of the lack of generally accepted pre-ACA elasticity estimates for specific demographic groups. Instead, the simulated take-up of ACA options is calibrated to enrollment data with demographic characteristics, where available. See below.

ESI price elasticity. Table 12 shows our elasticity targets by firm size, drawn from the literature (Blumberg, Nichols, and Banthin 2001; Gruber and Lettau 2004; Nichols et al. 2001).

TABLE 12

Employer-Sponsored Insurance Price Elasticity Targets, by Firm Size

Firm size	Elasticity
<10	-1.16
10–25	-0.45
25–50	-0.4
50–100	-0.3
100–500	-0.21
500–1,000	-0.047
1,000+	Not available from the literature but assumed to be very small given historical offer rates for such firms

Source: Authors' review of Blumberg, Nichols, and Banthin (2001), Gruber and Lettau (2004), and Nichols and colleagues (2001).

Nongroup price elasticity. For the price responsiveness of nongroup coverage, we use calculations and targets introduced by the Congressional Budget Office (CBO 2005). We separately calibrate single and family coverage by income group.

Public coverage expansions. HIPSM models the effects on Medicaid and CHIP enrollment of additional outreach and the stigma of public coverage. Expansions of public programs have often led to additional enrollment from people who were already eligible. Large expansions, such as CHIP or health reform in Massachusetts, are often accompanied by major outreach efforts that alter societal attitudes toward public coverage. Before enrollment data were available under the ACA, we used the literature on pre-ACA Medicaid expansions to calibrate Medicaid expansion take-up rates in our model.[17] These baseline take-up rates for the uninsured were between 60 and 70 percent, depending on a person's age, eligibility category, and income group. The ACA contains important provisions that increase take-up, however: States are required to establish a website capable of determining eligibility for Medicaid and automatically enrolling those eligible. Hospitals can make presumptive eligibility determinations. And new requirements simplify Medicaid and CHIP enrollment and renewal. We estimated a take-up rate of about 73 percent for the uninsured who become newly eligible under the ACA. This rate is higher than the pre-ACA rate because of outreach and enrollment simplification provisions in the law, as well as a modest indirect effect of the individual mandate, as observed in health reform in Massachusetts.

However, when estimating the impact of new Medicaid expansions, we can now use take-up rates from recent ACA Medicaid expansions, dividing actual enrollment gains by the estimated number of people gaining eligibility. The resulting overall take-up rate for the uninsured newly becoming eligible for Medicaid is close to our initial 73 percent estimate, though some states have achieved notably higher take-up rates.

Crowd-out. To ensure reasonable levels of displacement of private coverage by expanded public insurance, or crowd-out, we calibrate the decrease in private coverage as a share of the total increase in Medicaid enrollment (22 percent), following the literature (Cutler and Gruber 1996).

Individual mandates. To model the individual mandate before actual enrollment data were available, we began with the baseline HIPSM, in which behavior is calibrated to agree with results from the empirical health economics literature. The resulting model behavior is applicable for a voluntary health insurance regime. To model behavior under an individual requirement to obtain insurance, we rely heavily on empirical evidence from the only similar requirement already implemented, the Massachusetts reforms (Long and Stockley 2010). Our simulation of how behavior would change under the mandate has three components:

1. **The applicable financial penalty.** This is a computation of both whether the penalty is applicable and the amount of the penalty as defined by the law (i.e., the fully phased-in amount discounted to present dollars).
2. **An additional "disutility" of not complying with the mandate.** The mandate is more than a dollar amount; it is a legal requirement. Desire to comply with the law, or at least avoid enforcement and the stigma of noncompliance, can lead to behavioral responses much stronger than what the nominal penalty would suggest, as appears to be the case in Massachusetts. The mandate has the effect of making being uninsured less desirable. We

operationalize this in the model by applying an additional "psychic penalty" to being uninsured.[18]

3. **A relatively small spillover disutility of being uninsured on populations not bound by the mandate.** The mandate in Massachusetts was also associated with an increase in coverage among those not bound by the mandate (i.e., those who would not face a penalty for noncompliance). We assume this association was driven, in part, by a spillover effect of the mandate onto those who either mistakenly assumed they were subject to a penalty or reacted to a new social norm to have coverage. People may make judgments about whether they will lose their mandate exemption in the future because their incomes rise during the course of a year. However, for those exempt from the mandate, the amount of additional disutility of being uninsured is far smaller than for those bound by the mandate.

In the years where enrollment data were available for the ACA with an individual mandate, we take the actual increase in the nongroup market under the ACA as a given (see the next section) and set the parameters described above to achieve that enrollment level. This allows us to simulate the full impact of removing the mandate by eliminating the effect of these parameters. At present, no federal individual mandate penalty exists, but California, the District of Columbia, Massachusetts, New Jersey, and Rhode Island each have their own. We calibrate the nongroup markets in these states to 2020 target enrollment with the mandate parameters described above, and we calibrate enrollment in other states without setting any individual mandate effect.

BENCHMARKING TO REPORTED ACA ENROLLMENT

As described above, we incorporate administrative data on plan design and premiums by state and premium rating region every plan year.

For Marketplace enrollment, we use the effectuated enrollment snapshots annually reported by CMS, which list enrollment with advanced premium tax credits for each state.[19] We have done so for every year in which the Marketplace has operated. We adjust the HIPSM take-up model to achieve the reported enrollment levels for each state. We also reproduce Marketplace take-up rates by income and age group from the CMS open enrollment reports.[20] HIPSM enrolls in the Marketplace people who are eligible for advanced premium tax credits and have the highest expected utility for Marketplace coverage versus for alternative coverage types (uninsurance or ESI). The individual mandate also led to a modest increase in nongroup enrollment (inside and outside the Marketplace) among those not eligible for advanced premium tax credits.

We incorporate CMS data on overall metal-level choices. However, these are limited in two crucial ways. First, CMS only publishes metal-level choices for plan selections, not effectuated enrollment. Second, plan selections for the nongroup market outside the Marketplace are unavailable.

For Medicaid enrollment, we generally use the June enrollment report from CMS for each year since 2014.[21] We chose to use a point-in-time snapshot for all states compatible with our Marketplace targets, rather than an annual average. For each state, we compute the difference in Medicaid/CHIP enrollment between June of the target year (e.g., 2019) and 2013. We then add that difference to the simulated Medicaid enrollment in 2015 without the ACA to produce an overall June 2019 Medicaid enrollment target for each state. We cannot use the CMS totals as targets because they include the elderly. Also, the CMS reports do not separate different groups of enrollees by state, so there is no way to know how much new enrollment owes to new eligibles versus old eligibles, or even adults versus children. We use the HIPSM expected-utility model to decide which eligible people newly enroll.

Integration with the Tax Policy Center's Microsimulation Model

Health policy and tax policy are closely connected, and premium subsidies under the ACA are administered as advanceable, refundable tax credits. Some proposed tax changes, such as limiting the tax exclusion for health insurance premiums financed through an employer, have important consequences for health coverage and costs. Conversely, health reforms that improve the affordability of coverage often result in additional government spending that must be financed. Though HIPSM and the Urban-Brookings Tax Policy Center's microsimulation model cannot be completely integrated, we have developed fine-grained statistical matching procedures that allow the models to pass results back and forth to each other. This methodology and some examples are described separately (Mermin and Buettgens 2020; Mermin et al. 2020).

Limitations

HIPSM has several limitations. First, it does not model state variation in some state insurance market regulations, such as benefit mandates and requirements for health plans inside and outside the Marketplace. For example, a state may require that a plan offered outside the Marketplace also be offered in the Marketplace.

Nongroup insurance. The nongroup insurance market before the ACA had so many different plans (roughly 16,000 in New York alone) with such varied designs that no comprehensive source of what was offered before the ACA exists. Even basic statistics, such as average premiums, may not be meaningful. Thus, it would be extremely difficult to capture the extreme variation possible in the nongroup market when modeling policy changes involving repealing the ACA's insurance market reforms.

In addition, HIPSM does not model choice between different plan designs at the same actuarial value. This is of relatively small importance because different plan designs scoring the same in the actuarial value calculator have the same expected insured and out-of-pocket costs, by definition.

HIPSM also does not directly model insurer competition. However, it does account for differences in actual premiums in each state and rating region that partly owe to differences in competition. Our model has one premium per metal tier in each rating region, so any average of total premiums from our model will differ from any averages taken over the range of premiums actually offered. However, such averages are rarely reported in HIPSM, because sufficient data are seldom available to make such averages outside a model.

ESI coverage. There are no comprehensive data available on the distribution of wages within different types of firms. This has potential implications for employers' offer decisions in response to various policies. HIPSM synthetic firms are based on the characteristics of workers employed in each combination of firm size, industry, census division, and ESI offered. Millions of synthetic firms are created and the number of workers in each aligns with actual firm size. Thus, the model constructs the best approximation of within-firm wage distribution given available data.

Data on the design of ESI plans are available from the MEPS-IC and Kaiser-HRET survey. However, the available data limit HIPSM's ability to quantify the variation in plans offered by different firms of a certain type. For self-insured firms, only very limited data are available on stop-loss attachment points for firms of different types.

Limited data on Medicaid and Marketplace enrollees under the ACA. Survey data are limited in their ability to provide timely estimates of Medicaid and Marketplace enrollment. The time lag inherent in releasing survey data means data are one year old when we update the model for a new open enrollment period. The National Health Interview Survey is the most timely survey and gives the best estimates of enrollment in different types of coverage but cannot provide state-specific estimates. The Current Population Survey and ACS both differ substantially from administrative data in estimates of enrollment across coverage types. Coverage edits developed by Urban Institute researchers improve the ACS and align the uninsured with National Health Interview Survey estimates (Lynch, Boudreaux, and Davern 2010), but important differences in other types of coverage remain.

Medicaid administrative data were particularly sparse. CMS enrollment snapshots allowed us to estimate the increase in Medicaid enrollment by state from 2013 to the present but provided no further information about enrollees by state. For example, the data do not show how many new enrollees in each state were adults versus children. Publicly available Medicaid cost data are also very limited, particularly by state. As noted, we depend on data that are many years old and can only benchmark our results to recent national estimates.

Marketplace enrollment data based on enrollee plan selections were available in great detail, including enrollee characteristics such as income, age, and metal-tier selections. For effectuated enrollment, however, only state totals were available.

Lastly, HIPSM does not model differences in how state and local governments fund uncompensated care; estimates of how uncompensated care is financed are based on national analysis. See the section on uncompensated care above for more details on how these estimates should be interpreted.

Notes

1 King v. Burwell, No. 14-114, slip op. (S. Ct. Jun. 25, 2015).

2 Some models are based on elasticities from the literature. An earlier version of the Congressional Budget Office model and a model by Jonathan Gruber used that approach. The Congressional Budget Office has updated its model to be based on an expected-utility approach.

3 US Bureau of Labor Statistics, "The Employment Situation – September 2020," news release, October 2, 2020, https://www.bls.gov/news.release/archives/empsit_10022020.htm.

4 "American Community Survey Response Rates," US Census Bureau, accessed November 30, 2020, http://www.census.gov/acs/www/methodology/sample-size-and-data-quality/response-rates/.

5 Questions about employer offers were recently added to the Current Population Survey, beginning with the 2014 data year. However, offer rates by firm size differ notably from other sources, such as the MEPS-IC. For this reason, we are still investigating how more recent Current Population Survey data should be incorporated into HIPSM.

6 Detailed documentation of these regressions is found in Miller and colleagues (2017).

7 Society of Actuaries, "Group Medical Insurance Large Claims Database Collection and Analysis," July 1, 2002. https://www.soa.org/resources/essays-monographs/group-med-large-claims-coll-analysis/.

8 Our computation of moral hazard throughout the model is based on private consultation with experts at the Actuarial Research Corporation.

9 Private consultation with experts at the Actuarial Research Corporation.

10 Extreme individual plan designs, such as those with zero deductibles, may result in somewhat different expected health costs among different groups (e.g., people with low health care costs versus those with high health care costs) than the median plan design we construct here.

11 Functional-limitation status is identified by responses to questions on serious difficulty walking or climbing stairs; difficulty dressing or bathing; serious difficulty hearing or seeing when not wearing glasses; and serious difficulty concentrating, remembering, or making decisions because of a physical, mental, or emotional condition. Adults with affirmative responses to one or more of these questions are classified as having a functional limitation.

12 Pre-ACA income disregard policies varied considerably across states. In Florida, the average threshold for nonworking parents was 19 percent of FPL, compared with 56 percent of FPL for working parents (incorporating work disregards). In South Dakota, the thresholds for working and nonworking parents were the same at 50 percent of FPL.

13 To be specific, we predict who should have bought nongroup health insurance last period had the policies effective this period been in effect last period.

14 If the expansion results in people with higher-than-average health care costs leaving the nongroup market, the updated premiums will be lower. Lower premiums then induce more people into the nongroup market, and the premiums may increase if the new enrollees have higher-than-average costs. The adjustment process continues until an equilibrium is reached.

15 America's Health Insurance Plans, 2009 Individual Market Survey.

16 By an individual worker's "value of the offer," we mean the difference in his or her family's expected utility with and without an offer.

[17] See, for example, Garrett and colleagues (2009).

[18] Behavior in HIPSM is modeled using an expected-utility framework. This "penalty" is thus the disutility of not complying with the law.

[19] "June 30, 2015 Effectuated Enrollment Snapshot," Centers for Medicare & Medicaid Services, September 8, 2015, https://www.cms.gov/newsroom/fact-sheets/june-30-2015-effectuated-enrollment-snapshot.

[20] These reports are based on plan selections, not effectuated enrollment. CMS does not report effectuated enrollment by these characteristics. See ASPE (2015).

[21] Retrieved from https://www.medicaid.gov/medicaid/program-information/medicaid-and-chip-enrollment-data/report-highlights/index.html.

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About the Authors

Matthew Buettgens is a senior fellow in the Health Policy Center at the Urban Institute, where he is the mathematician leading the development of Urban's Health Insurance Policy Simulation Model (HIPSM). The model is currently being used to provide technical assistance for health reform implementation in Massachusetts, Missouri, New York, Virginia, and Washington as well as to the federal government. His recent work includes a number of research papers analyzing various aspects of national health insurance reform, both nationally and state-by-state. Research topics have included the costs and coverage implications of Medicaid expansion for both federal and state governments; small firm self-insurance under the Affordable Care Act and its effect on the fully insured market; state-by-state analysis of changes in health insurance coverage and the remaining uninsured; the effect of reform on employers; the affordability of coverage under health insurance exchanges; and the implications of age rating for the affordability of coverage.

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Jessica Banthin is a senior fellow in the Health Policy Center, where she studies the effects of health insurance reform policies on coverage and costs. Before joining the Urban Institute, she served more than 25 years in the federal government, most recently as deputy assistant director for health at the Congressional Budget Office. During her eight-year term at the Congressional Budget Office, Banthin directed the production of numerous major cost estimates of legislative proposals to modify the Affordable Care Act. Banthin has contributed to Congressional Budget Office reports and written about how reform proposals affect individuals' and families' incentives to enroll in coverage, influence employers' decisions to offer coverage to their employees, and affect insurance market competitiveness. In her recent work, Banthin has written on competition in insurer markets and the accuracy of various data sources used in modeling health reforms. She has special expertise in the design of microsimulation models for analyzing health insurance coverage and a deep background in the design and use of household and employer survey data.

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