Proceedings of the 2018 Winter Simulation Conference
M. Rabe, A.A. Juan, N. Mustafee, A. Skoogh, S. Jain, and B. Johansson, eds.

A SIMULATION MODEL TO ASSESS THE IMPACT OF INSURANCE EXPANSION ON COLORECTAL CANCER SCREENING AT THE POPULATION LEVEL

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ABSTRACT

Recent health care reform debates have triggered substantial discussion on how best to improve access to insurance. Colorectal cancer (CRC) is an example of a largely preventable condition, if access to and use of healthcare is increased. Early and ongoing screening and intervention can identify and remove polyps before they become cancerous. We present the development of an individual-based discrete-event simulation model to estimate the impact of insurance expansion scenarios on CRC screening, incidence, mortality, and costs. A national repeated cross-sectional survey was used to estimate which individuals obtained insurance in North Carolina (NC) after the Affordable Care Act (ACA). The potential impact of expanding the state's Medicaid program is tested and compared to no insurance reform and the ACA without Medicaid expansion. The model integrates a census-based synthetic population, national data, claims based statistical models, and a natural history module in which simulated polyps and cancer progress.

1 BACKGROUND

Colorectal cancer (CRC) is one of the leading causes of cancer and cancer-related deaths in the United States (National Cancer Institute 2014). Early and routine use of CRC screening is highly effective in reducing CRC incidence through the detection and removal of polyps before they become cancerous (Bibbins-Domingo et al. 2016) . Adherence to the recommended screening guidelines is critical to early detection of CRC, ultimately reducing morbidity and mortality associated with this disease (Bibbins-Domingo et al. 2016). Screening guidelines recommend colonoscopy every ten years, sigmoidoscopy every five years, or stool testing annually among adults ages 50 to 75 (Bibbins-Domingo et al. 2016).

Despite being largely preventable, CRC remains a prevalent condition due to relatively low screening rates (American Cancer Society 2017; National Health Interview Survey 2015; Siegel et al. 2017). In 2015, less than two-thirds (62.4%) of adults age 50 or older were up-to-date on CRC screening nationally (Siegel et al. 2017). Younger adults ages 50-64 were less likely to be up-to-date than older adults age 65 and older (57.8% vs. 68.3%, respectively) (Siegel et al. 2017). Low screening rates can be explained, in part, by disparities in access to insurance. For example, among persons aged 50-64 years, CRC screening rates for the uninsured (25.3%) were markedly lower than for the privately insured (62.1%) or publicly insured (56.9%) (NHIS). There are other predictors of low screening rates beyond insurance access, such as race, ethnicity, and geographic location (Davis et al. 2017; Wheeler et al. 2014; Wheeler et al. 2017). The relative impact of interventions and policies aiming to increase CRC screening by addressing insurance access versus other factors is not yet known. Therefore, this paper uses a modeling approach to understand the potential impact of multiple insurance expansion scenarios on CRC screening, diagnoses, mortality, and treatment costs in the future, which can be compared to the projected impact of other targeted interventions.

2 LITERATURE REVIEW

Most simulation models of CRC screening may be grouped as either Markov models or discrete event simulation (DES) models. Markov models identify the health states that an individual will experience during the course of the disease and changes in states are defined by probabilistic transitions. Several practitioners have taken a Markov approach to model CRC (Frazier et al. 2000; Ladabaum et al. 2001; Vijan et al. 2001). In contrast, DES models simulate specific events of interest during an individual's lifetime, allowing modelling of complex interactions and responses to interventions at the individual level, as we do.

Modeling, including DES, can be used to forecast the outcomes, unanticipated consequences, and magnitude of effects of health reform policies (Glied and Tilipman 2010). Examples include estimates of how various health insurance policy proposals will affect total enrollment in health plans, uninsured rates, and costs of coverage (Parente and Feldman 2013; Buettgens 2011; Auerbach et al. 2011; Eibner and Liu 2017). Specific outcomes include enrollment in private health insurance related to particular provisions of the Affordable Care Act (ACA) and Medicaid coverage as a result of states' decisions about whether to expand their Medicaid programs (Parente and Feldman 2013). The Health Insurance Policy Simulation Model (HIPSM), developed by the Urban Institute, provided opportunities to estimate the effects of policy changes related to Medicaid eligibility, health insurance exchanges, and individual and employer mandates, as compared to the status quo, at the individual, family, and employer levels (Buettgens 2011). The RAND Comprehensive Assessment of Reform Efforts (COMPARE) simulation model was used to predict state-level changes in the uninsured rate as well as healthcare spending of ACA provisions in five states (Auerbach et al. 2011). More recently, analyses using the RAND COMPARE model assessed the impact of tax credit and reinsurance policies on insurance access and associated costs (Eibner and Liu 2017). In addition to the effects of policies on insurance access, simulation has also been used to project health status and health equity outcomes of insurance expansion policies (Milstein et al. 2010).

The Cancer Intervention and Surveillance Modeling Network (CISNET) consortium focuses on using models (MISCAN-Colon (Loeve 2000; Loeve et al. 1999; Vogelaar et al. 2006), SimCRC (Frazier et al. 2000), and CRC-SPIN (Rutter and Savarino 2010)) to guide public health research and priorities. The MISCAN-Colon model is the first example of a DES model focusing on CRC. The model can be distinguished by two important parts – 1) natural history, and 2) screening. In the natural history part, life histories are generated during which colorectal polyps and cancer may develop, sometimes causing death when no screening occurs. In the second part, screening for CRC is modeled, thus changing individual life histories. Sim-CRC and CRC-SPIN also simulate colorectal disease progression in an individual from birth to death and share many characteristics with the MISCAN-Colon model, including the simulated US population, the progression of adenomas to CRC, risk factor trends and screening characteristics.

The V/NCS model (Roberts et al. 2007) is noteworthy in that it employs an object-oriented programming-based approach wherein the primary object is a person. Within each person object, secondary objects are adenomas, which are collections belonging to each person; each adenoma (several may be present) has its own development cycle and impact on survival. Further, adenoma incidence is correlated with common risk factors. Statistics may be collected either at the end point in the simulation for a cohort, which is death, or at any specified point in time for the collective population.

The NC-CRC model presented in this paper was developed to examine the health and economic impact of population-level screening strategies and rates on the development and consequences of CRC. This model is an adaptation of the model built by RTI (Subramanian et al. 2009). NC-CRC expands upon earlier models by (i) applying statistical models from administrative claims data to predict the preferred screening modality and receipt of screening of individuals; (ii) allowing insurance status to change over time; and (iv) incorporating the effects of population-level interventions to increase screening.

Several details about the NC-CRC model and its components have been published in previous work (Cornejo et al. 2014; Wheeler et al. 2014; Hassmiller Lich et al. 2017). In this paper, we provide experimental results by simulating three policy scenarios about the full implementation of the ACA in 2014

in order to understand the differential impact of these strategies on CRC screening, incidence, treatment, and mortality within the state of NC over time to inform state-level and community-level program planning.

3 SIMULATION MODEL DESCRIPTION

The NC-CRC model was developed by the University of North Carolina and North Carolina State University using AnyLogic simulation software, which is built on an object-oriented programming language, Java. A description of the structure of the model was previously published (Cornejo et al. 2014). The primary object in the simulation is the person; the simulation of the events within the lifetime of a single person determines the length of the simulation. The replication terminates when the person dies. As visualized in Figure 1, there are three distinct modules including natural history, demography, and screening and testing. Interventions, such as insurance change dynamics are then overlaid onto the model.

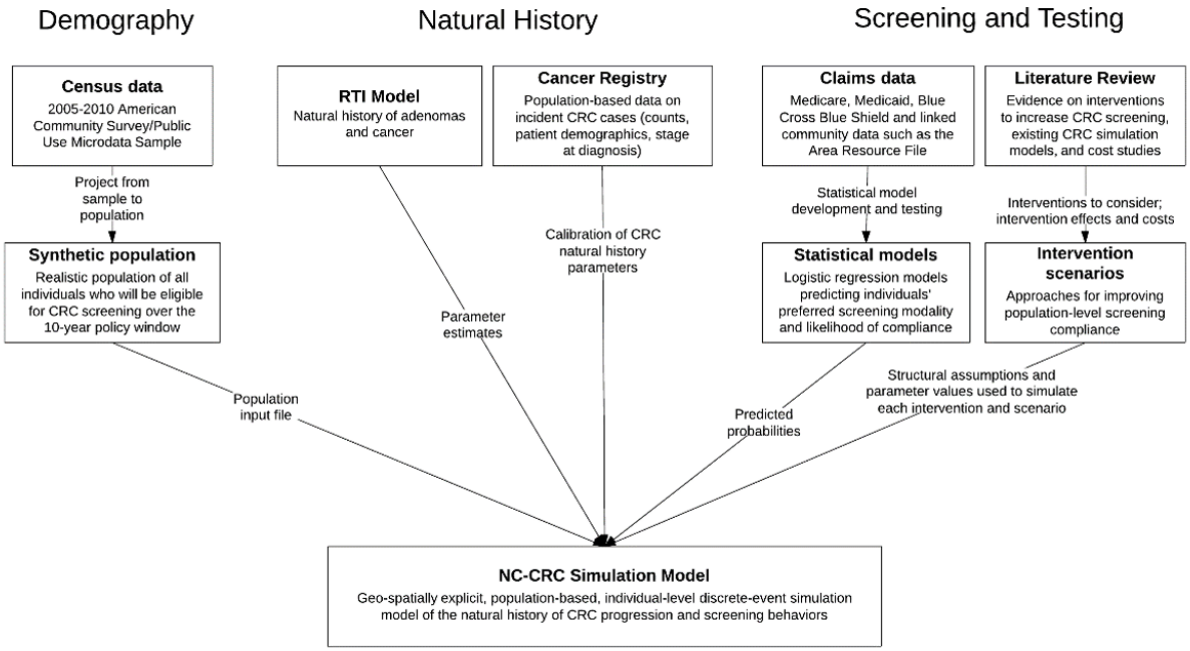

Figure 1: An overview of elements that make up the inputs to the NC-CRC model.

3.1 Demography and Synthetic Population

Details about our synthetic population have been described in previously published literature (Cornejo et al. 2014; Hassmiller Lich et al. 2017). The synthetic population was created using the American Community Survey Public Use Microdata Sample data from 2005-2010 (U.S. Census Bureau 2014). Details on how data were transformed into the synthetic population and validation of the population are published elsewhere (Wheaton et al. 2009; Hassmiller Lich et al. 2017). The model simulates the full life course of every NC resident between the ages of 50 and 75 at any time during the study's intervention window of January 1, 2014 through December 31, 2023. The full cohort of the synthetic population includes 3,918,469 people, as of January 1, 2009 when the synthetic population was created, who would be eligible for screening at some point during the 10-year intervention window. Individual-level characteristics affect the simulated events in the natural history and screening components. The population input file contains information on individual and household-level data, including age, sex, race, household income, insurance status, education, residential location, state health insurance program participation, and marital status. Table

1 presents a snapshot of a few demographic characteristics for those aged 50-75 on January 1, 2014 (though additional characteristics of the population such as income level play a role as inputs to the simulation model). Further details are provided in (Hassmiller Lich et al. 2017).

Table 1. Characteristics of North Carolina residents aged 50-75 on January 1, 2014.

Characteristic	**N**	**%**
Total	2,852,111	100.0
Sex		
Male	1,363,984	47.8
Female	1,488,127	52.2
Race		
White	2,187,959	76.7
Black	534,103	18.7
Other	130,049	4.6
Ethnicity		
Hispanic	84,217	3.0
Non-Hispanic	2,767,894	97.0
Age		
50-64	1,898,525	66.5
65-75	953,586	33.5

3.2 Natural History

The natural history of an individual is determined by all the actions that would occur in the absence of screening for cancer. This includes the development and progression of polyps and cancer, the clinical discovery of cancer through the emergence of symptoms, and death from CRC or other causes. Polyps develop progressively through three different sizes: small, medium, and large. Medium and large polyps may develop into a cancer, but small polyps cannot immediately turn into cancer. Cancerous polyps develop through four stages. In the current model we used the clinical stages defined by the American Joint Committee on Cancer (Edge and Compton 2010) that correspond to the extent of the malignancy. During the polyp's progression, symptoms may lead a provider to suspect cancer and recommend a diagnostic screening test. If the person exhibits symptoms, elects to take a diagnostic test, and the result is positive, the cancerous polyp is considered to be clinically detected. At this point, the model stops tracking its progression, and the person remains in the state represented by his or her stage at diagnosis until death, where death rates are stage-specific. If the person elects not to take the diagnostic test or the result is negative, the cancerous lesion remains undetected and eventually progresses. The state transitions in the natural history model are the same in structure as those developed by RTI (Subramanian et al. 2009). The natural history parameters determine whether polyps turn into CRC. To account for racial differences, in this model we utilize more recent information available on polyp incidence by age, race and gender (Lansdorp-Vogelaar et al. 2009). Once a polyp has developed into clinical cancer, the survival of a person is generated according to the survival parameters. The expected lifespan is based on race- and sex-specific life tables from the U.S. Census. Natural history of CRC for each simulated individual may modify his or her CRC-free lifespan. If a person dies from CRC before he or she would die from other causes, the lifespan and age at death are adjusted accordingly.

3.3 Screening and Testing

The screening and natural history components of the model run simultaneously so that screening for CRC may detect polyps or cancers at any stage in the natural history. This may adjust the life history of the individual from the existing progression of the natural history. Polyps that are detected during a diagnostic

exam (which is implemented in the model only as a colonoscopy) will be removed and polyps will be biopsied for clinical diagnosis and treatment. The effect of screening is reflected in the aggregated gains in life years as a result of screening.

In this analysis, one of the primary outcomes of interest is receipt of CRC screening, subsequently referred to as compliance. Screening compliance, as well as an individual's choice of test modality (the model currently implements colonoscopy and fecal immunochemical test (FIT)), are based on a probabilistic distribution of choices. The compliance and modality choice model in our simulation has previously been described (Cornejoet al. 2014; Wheeler et al. 2017; Wheeler et al. 2014) and is comprised of logistic regressions based on observational claims data of individuals enrolled in either a state-sponsored health plan (Medicaid and Medicare) or private health insurance through a large private insurer. The multi-level, random effects logistic regression allows for individual attributes (e.g. sex, income) to have varying impacts between county level attributes (e.g. percent below poverty line) in the state of NC. The outcomes of the regression are compliance and modality within a 6 year window. The regression outcome corresponding to the probability of compliance within the 6 year window, p. Since FIT is recommended every year and colonoscopy every 5 years we convert these from 6 year probabilities to the appropriate time interval assuming that the probability of screening in a single year is distributed as a Bernoulli random variable, thus the number of screens in a given time period are binomially distributed. For FIT, we use a 1-year probability, P_{FIT}; for colonoscopy we use a 5-year probability to account for variations from the recommended screening interval, P_{col}. These probabilities are calibrated such that the expected time between screens for a compliant person is 10 years.

3.3.1 Increase in compliance probability for first-time testers

When an individual becomes eligible for a particular screening modality for the first time, they may have an increased probability (p') of compliance (Fedewa et al. 2017). This leads to a corresponding increase in probability of being screened over a five-year-period. For individuals screening with a colonoscopy, the increase of p' can be directly applied to the adjusted probability (the output from the logistic regression) of screening since the adjusted probability of screening is computed for a period of five years. If P_{col} is the adjusted probability of screening (i.e., probability an individual is compliant with colonoscopy screening over a five-year-period), then the increased probability of screening for newly eligible individuals ($\widehat{P_{col}}$) is given by $\widehat{P_{col}} = \min(P_{col} + p', 1)$. For individuals screening with FIT, computing the desired increase in probability is more challenging. This is because of the fact that for an FIT, the adjusted probability of screening from the statistical model is computed for a period of one year. As a result p', which is the desired increase in probability for first time screeners which is over a five-year-period (to allow time for those new to insurance to adjust to new screening patterns) needs to first be converted into an increase in probability of being screened over a one-year-period. Thus, if the increase in probability of screening for newly eligible individuals over one year is x, the relationship between x and p' is computed using the formula based on the binomial distribution in the following manner.

$$P(\text{at least one screen in } 5 \text{ years } |P_{FIT} + x) = P(\text{at least one screen in } 5 \text{ years}|P_{FIT}) + p'$$
$$1 - (1 - P_{FIT} - x)^5 = 1 - (1 - P_{FIT})^5 + p'; (1 - P_{FIT})^5 - (1 - P_{FIT} - x)^5 = p'.$$

Solving for x yields $x = 1 - P_{FIT} - \sqrt[5]{(1 - P_{FIT})^5 - p'}$. Finally if P_{FIT} is the adjusted probability of screening (probability an individual is compliant with FIT over a single year), the increased probability of screening for newly eligible individuals ($\widehat{P_{FIT}}$) is given by $\widehat{P_{FIT}} = P_{FIT} + x = 1 - \sqrt[5]{(1 - P_{FIT})^5 - p'}$.

4 CALIBRATION OF % UP-TO-DATE WITH CRC TESTING

Calibration was performed by matching the percent up-to-date output of the model to the 2002-2014 Behavioral Risk Factor Surveillance (BRFSS) survey self-reported percentage up-to-date values. We used data from the BRFSS between 2002 and 2012 (conducted every 2 years) to estimate the proportion of NC

residents aged 50-75 years who reported being up-to-date with CRC screening The estimated proportions likely were overestimates of the true proportions of North Carolinians up-to-date with screening. Therefore, we adjusted the percent up-to-date by self-report using the sensitivity and specificity of self-report relative to chart reviews reported from a meta-analysis (Rauscher et al. 2008).

The objective was to determine values by which the compliance probabilities of an individual are to be increased such that the percentage up-to-date obtained from the model matched the BRFSS data after adjustment for self-report. During each of the years 2002, 2004, 2006, 2008, 2010 and 2012, a year-specific constant adjustment was made to each individual's compliance probability. If an individual's compliance probability obtained from the choice model in year x turned out to be p_x, a constant value of c_x is added to obtain an adjusted compliance probability. These year-specific constants, $c_x, \forall\, x \in \{2002, 2004, 2006, 2008, 2010, 2012\}$ were chosen such that the % up-to-date output for those years obtained from the model matched the BRFSS data described earlier. The structure of the model facilitated an iterative yearly calibration process. This is because any adjustment made to each individual's compliance probability in a particular year will reflect in a change to the % up-to-date output only during future years. Thus, c_{2002} is determined, following by c_{2004}, c_{2006}, ..., in that order. The result of this calibration exercise is that the % up-to-date obtained from the model is within 1% of the % up-to-date obtained from the BRFSS data adjusted for self-report bias for all years under consideration.

5 POLICY SCENARIOS

Insurance status, one predictor of routine compliance with screening, can change over a person's life time. One time that this may occur is at age 65, when Americans age into Medicare eligibility. Individuals ≤65 years of age in 2009 have their new insurance status assigned when they turn 65. Specifically, individuals who are privately insured or have Medicare have their new status assigned as Medicare, individuals on Medicaid have their status assigned as Dual, and uninsured low income individuals are assigned Dual while other uninsured individuals are assigned Medicare.

Insurance status may also change due to insurance expansion. Simulation of realistic scenarios around insurance expansion and reduction is critical given ongoing debates regarding health insurance reform nationally. Existing research has shown that the uninsured face greater barriers to preventive care services, including CRC screening, than insured populations (White et al. 2017) . CRC screening access also differs by type of insurance among the insured, although the differences are more muted. Due to uncertainties about the future of health insurance in the U.S., simulation provides a unique opportunity to compare the short-term and long-term effects of different strategies on population health and survival related to CRC. These projections can then be used to inform policy decisions.

We simulated three policy scenarios in order to understand the differential impact of these strategies on rates of CRC screening, polyp detection and removal, cancer diagnoses, and mortality among the population in NC. Each of the scenarios were modeled starting in 2014, reflecting policy options associated with the ACA. The first scenario, the status quo, is the development and use of the health insurance exchange under the ACA as implemented in North Carolina (i.e., without Medicaid expansion). The second scenario is the expansion of the state's Medicaid program, increasing the threshold for Medicaid eligibility for all residents to 138% of the federal poverty level (FPL). The third scenario is if insurance expansion did not happen under the ACA, i.e., insurance reduction or removal of ACA. The model has the capability to test these scenarios in other states as well. We focus on the NC population in this analysis for multiple reasons. Simulation of these scenarios in a single state allows for an understanding of the effects of insurance-related policies in a particular context in terms of population size, demographics, geography, and political climate. Additionally, there is an opportunity to project the long-term outcomes of not expanding Medicaid, which may be representative of other non-expansion states. Implementation details follow.

5.1 Scenario 1: ACA Implementation

Implementation of ACA meant that the years 2013 and 2014 led to an increase in health insurance coverage for a number of individuals which saw an increase in the population's healthcare coverage (Smith and Medalia 2015). Our goal was thus to find out whether we could observe an increase in health coverage as a result of ACA implementation and to quantify this increase. We were interested in determining the probability of having health insurance coverage for different combinations of specific respondent characteristics and the variable 'year' via a logistic regression model. State specific data was extracted from the Behavioral Risk Factor Surveillance Survey (BRFSS) (which contained year-specific survey responses of both landline and cellphone users). We modeled health insurance (yes=1, no=0) using a multivariable logistic regression with interactions. The independent variables included sex, age category (18-24, 25-34, 35-44, 45-54, 55-64, 65+), race (non-Hispanic white, non-Hispanic black, Hispanic, other), income category, marital status and year. It must be noted that the original variable for income had a total of 6 categories: five representing different income ranges and one for missing values. Since non-response rates on this question was high, we imputed the missing values using monotone logistic regression in SAS.

For all subgroups of the independent variables, we estimated the predicted probabilities of having insurance in 2013, 2014 and 2015. For each subgroup, we then calculated the conditional probability that a person will become newly insured in 2014 and 2015, given that they were not insured in 2013. The model then applies this increase to each individual (based on annual income thresholds for the federal poverty level (FPL) issued by the U.S. Department of Health and Human Services) (U.S. Department of Health & Human Services, 2018). For a single person, the FPL was $11,490 in 2013, $11,670 in 2014, and $11,770 in 2015. For a four-person household, the FPL was $23,550, $23,850, and $24,250, respectively, in these same years. Those who became newly insured either get private insurance (e.g., through the exchange) or Medicaid coverage (if they qualify).

5.2 Scenario 2: ACA + Medicaid Expansion

The second scenario relating to Medicaid expansion is implemented on top of scenario 1. Once the model performs the algorithms relating to the implementation of ACA, it performs a check to see if uninsured individuals in 2014 and 2015 are eligible for Medicaid. The eligibility condition is determined by the FPL income thresholds outlined by the U.S. Department of Health and Human Services (U.S. Department of Health & Human Services 2018). In 2014, the income eligibility limit for Medicaid was increased to 138% of the FPL in states that expanded their Medicaid program. In North Carolina, a non-expansion state, the eligibility limit for adults with dependents is 43% of the FPL, and all adults without dependents regardless of their income are ineligible for Medicaid (The Henry J. Kaiser Family Foundation 2018). To understand the potential impact of Medicaid expansion in North Carolina, all residents with incomes at or below 138% of the FPL are considered eligible for Medicaid in this scenario. If eligible, the individuals are probabilistically assigned to Medicaid enrollment based on enrollment rates in NC.

6 EXPERIMENTS AND RESULTS

We ran the model via AnyLogic on a dedicated 64-core machine, running a 64-bit Windows Server 2008 R2 Datacenter with 1TB of ram and 2 GHz Intel Xeon X7550 processors connected to 2 TB of disk storage. The life-spans of the entire synthetic population of individuals are simulated from birth to death. We run 5 replications with a total run time of approximately 150 minutes. An application of Common Random Numbers (CRN) allows for substantial computational benefits by ensuring that an individual's life courses are identical across replications and scenarios, except when the changes are induced by different interventions, as previously reported (Cornejo et al. 2014). The output statistics, compiled via the statistical software R, provide us with an insight into how different policies affect the population of individuals in terms of insurance trajectories, cancer incidence, cancer deaths and treatment costs. Table 2 presents the impact of each policy scenario on cancer incidence by stage and on deaths due to cancer. In comparison to the third scenario "No ACA", (i.e., ACA was never implemented), the number of cases of CRC is reduced

under both the health insurance exchange under the ACA and the ACA + Medicaid expansion program. Additionally, the number of deaths due to cancer is reduced by 2.3% under the implementation of the ACA + Medicaid expansion program when compared with the No ACA.

Table 2. CRC incidence by stage and CRC mortality of full cohort projected for lifetime.

	No ACA	**ACA**	**ACA + Medicaid Expansion**
CRC Cases	140,837	139,432	137,918
Stage 1	47,911	47,544	47,164
Stage 2	42,665	42,170	41,752
Stage 3	28,507	28,194	27,834
Stage 4	21,754	21,524	21,168
CRC Deaths	56,561	55,967	55,244

Table 3 presents the impact of each policy scenario, independently, on the percentage of people up-to-date with CRC screening in 2023 among all subpopulations studied. Implementation of the ACA + Medicaid expansion program saw an increase in the percentage of individuals up-to-date with recommended CRC screening across all subpopulations, except for uninsured individuals. The most substantial mechanism by which insurance expansion increases CRC screening is through offsetting the cost of health services received among those with insurance (that is, decreasing the out of pocket cost of screening among the uninsured). In NC in 2014, only 16.6% of uninsured individuals were up-to-date with screening while 66% of insured individuals were up-to-date, *before* adjusting for self-report bias (Rauscher et al. 2008), about 53% after adjusting for self-report. As such, it is illuminating to see how the insurance expansion scenarios impact the number of uninsured individuals age-eligible for screening (i.e., age 50-75) within the state over time. Figure 2 presents this number by year and gender (a) or race (b) These counts quantify the subpopulations that would need to be targeted for CRC intervention among the state's uninsured population, which require meaningfully different actions than targeting insured populations.

Table 3. Simulated age-eligible NC population up to date with CRC screening on January 1, 2023.

Variable	No ACA	Percentage-point change in percent up to date on CRC screening compared with the No ACA	
		ACA	ACA + Medicaid Expansion
Overall	48.65%	+1.03%	+1.74%
By sex			
Male	46.13%	+0.94%	+1.55%
Female	51.00%	+1.11%	+1.92%
By race			
White	49.92%	+0.73%	+1.29%
Black	45.92%	+2.01%	+2.88%
Hispanic	42.22%	+0.05%	+2.90%
Other	42.36%	+1.40%	+3.40%
By insurance			
Private	53.87%	+0.01%	+0.03%
Dual	58.02%	+0.02%	+0.99%
Medicare	59.85%	+0.09%	+0.15%
Medicaid	42.63%	+0.07%	+0.02%
Uninsured	17.84%	-0.04%	-0.04%

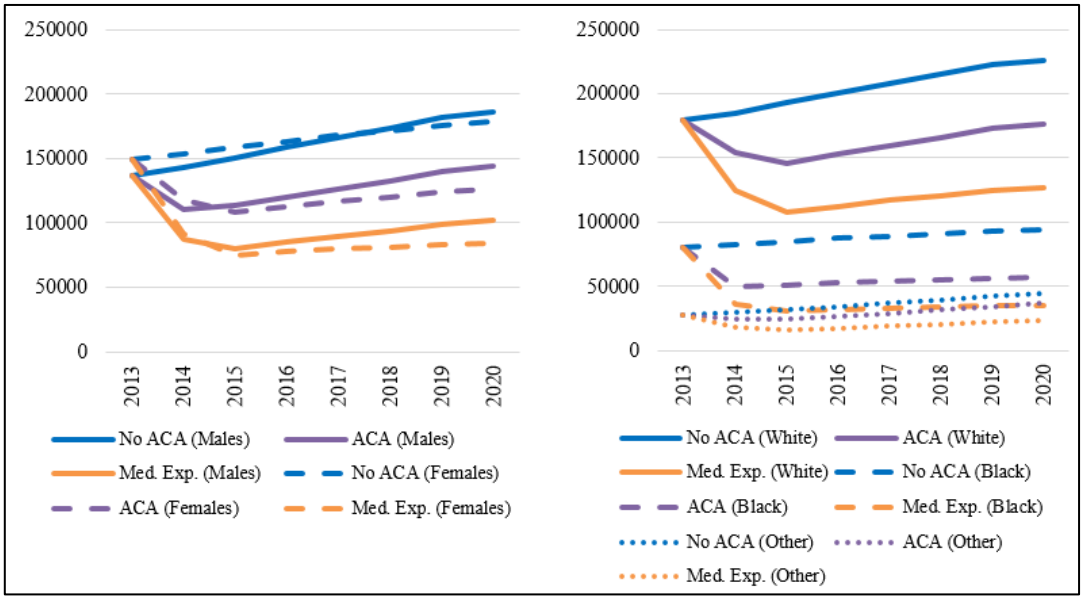

Figure 2: Number of uninsured by gender (a) and race (b), by insurance policy scenario between Jan 1, 2013 and Jan 1, 2020.

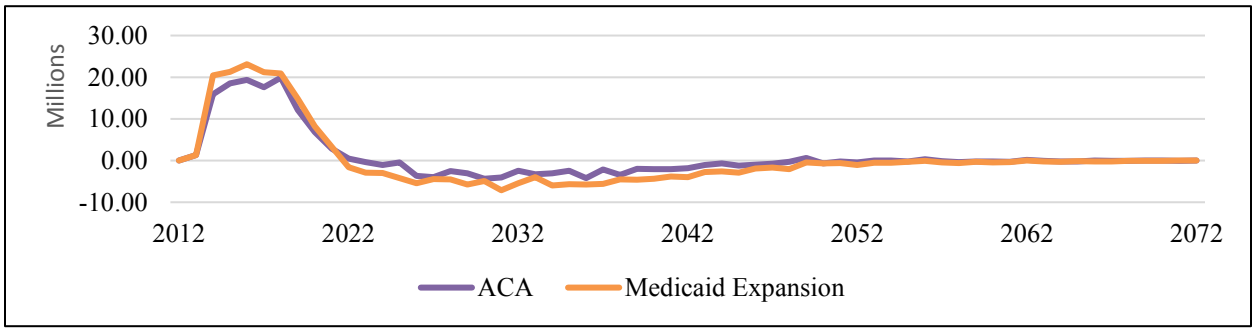

Figure 3. Difference in all CRC costs by year, compared to the No ACA scenario, 2013+.

Figure 3 presents the annual differences in the total cost of treating CRC under each insurance expansion scenario as compared to the No ACA scenario (ACA never occurred) from the state's perspective; costs include routine and diagnostic screenings, treating complications arising from a colonoscopy (bleeding and perforations), and the lifetime treatment costs from the perspective of each individual with cancer (Zauber et al. 2007). Both scenarios that we tested provided lower total CRC treatment costs when compared to the removal of ACA scenario. Overall, the results of this analysis show positive effects of the health insurance exchange under the ACA, as compared to no ACA, in terms of increasing the percentage of the NC population screened, resulting in fewer CRC cases, decreased severity of CRC cases (as shown by cancer stage), reduced mortality, and lower treatment costs. The expansion of the state's Medicaid program under the ACA would result in a greater magnitude of positive effects across all outcomes measured. Importantly, increased health care coverage was also found to reduce racial disparities in screening. For example, compared to the base-case, the increase in screening under ACA + Medicaid expansion was higher for Blacks (2.88%), Hispanics (2.90%), and Other (3.4%) than for Whites (1.29%), indicating that insurance access is one barrier affecting racial minority populations' use of recommended screening. Although the changes in outcomes are somewhat modest they are commensurate

with other state-wide interventions (Hassmiller Lich et al. 2017). Furthermore, these findings are important from a public health perspective because they highlight the potential for future insurance expansion policies to reduce CRC incidence, morbidity, mortality, and costs, as well as ensure more equitable access to efficacious cancer screenings. In conjunction with other evidence-based studies, simulation models can be used to address disparities and close gaps in screening by informing and testing strategies to efficiently meet established health targets.

7 CONCLUDING REMARKS

The NC-CRC model is intended to be used as a "virtual world" in which to simulate the effects of alternate scenarios about population demographics, disease determinants, clinical interventions, or policies on CRC screening, incidence, treatment, and mortality within the state of NC over time to inform state-level and community-level analyses. The object oriented structure of the model allows us to easily compartmentalize the components that make up the core of the model. The model can simulate realistic cohorts (e.g., for comparative effectiveness research) or the entire population of NC. While the experimental results presented in this paper examine the effects of implementing different policies in the past, the power of the model becomes more evident when estimating the impact of future policies. Additionally, the simulation need not be restricted to North Carolina's populations and policies. While the model reflects best available evidence and substantial local data, care must be taken to consider the model a representation of our current understanding of the determinants of CRC disparities across the state. Additionally, sensitivity analyses may be conducted around uncertain parameters, e.g. uptake of Medicaid among the newly eligible.

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