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IMPACT OF INPUT VARIANCE ON POPULATION-BASED MICROSIMULATION RESULTS

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ABSTRACT

Population-based microsimulations often incorporate multiple data sources and modeling techniques. Results from these complex models should include uncertainty from model inputs. This work examines the confidence of reported results from population-based microsimulations using the Future Elderly Model, a dynamic microsimulation that forecasts health and economic outcomes for middle age and older adults. The primary objective is to determine whether systematic inclusion of uncertainty will disrupt the policy conclusions obtained from population-based microsimulation results.

1 INTRODUCTION

Population-based microsimulations (PBMS) are used to aid health policy decisions worldwide (Astolfi, Lorenzoni, and Oderkirk 2012). However, reported results rarely include an assessment of uncertainty. Computationally burdensome sensitivity analysis can benefit decision-analytic health care modeling even after accounting for the trade off between report detail and computational resources (Griffin et al. 2006). Similarly, uncertainty analysis should be a significant part of PBMS validation (Kopec et al. 2010). Sharif et al. (2012) investigated the contribution of Monte Carlo (MC) error and parameter uncertainty to PBMS. However, additional sources of uncertainty are still unaccounted for. This study contributes to the current PBMS validation literature by adapting previously discussed methods to the Future Elderly Model (FEM) (Goldman et al. 2013) and suggesting methods to account for additional sources of uncertainty. Policy relevance is analyzed by assessing the contribution of each source of uncertainty to the confidence of reported results.

2 SOURCES OF UNCERTAINTY

Sources of uncertainty common in PBMS include sampling variability from input databases, sampling variability from other inputs, model misspecification, and stochastic error (Citro and Hanushek 1991). The Health and Retirement Study (HRS), a biennial survey of the US population ages 51 and older, is the primary data source of the FEM and is a contributing factor to the sampling variability from input databases. The FEM uses a single wave from the HRS as the population that starts the simulation. Simulated cohorts enter the simulation each period to replenish the population and are also based on the characteristics of the HRS. In this work, sampling variability from the HRS is considered under the conditions of a resampled HRS. The data is randomly sampled with replacement (Yeo, Mantel, and Liu 1999) taking into account HRS survey methodology. Simulated cohorts that enter each period are adjusted to the characteristics of the resampled HRS before trends are applied. Other inputs affected by sampling variability include transition probabilities and trends in health and economic characteristics applied to the simulated cohorts. Transition probabilities in the FEM are predicted for each individual using regression models estimated from the HRS. In this work, regression models for transition probabilities are estimated using the bootstrap samples of the HRS which implicitly allow for correlation between parameters. Trends used to alter the health and economic characteristics of future cohorts before they enter the simulation are estimated or pulled from the literature. Distributions of the trend parameters in each year are not available from all sources, so this work uses bootstrap samples of each cohort after applying the baseline trends in order to achieve variation in the parameters. Stochastic variability in the form of MC error is accounted for by running a large number of repetitions.

3 EFFECT OF REDUCTION IN DIABETES ON HEALTHCARE SPENIDNG

The FEM models the incidence of six chronic conditions (cancer, diabetes, heart disease, hypertension, lung disease, and stroke). Higher prevalence of chronic disease is a leading contributor to increasing healthcare expenditures. Medicare, Medicaid, out-of-pocket, and total medical spending are modeled by the FEM using data from the Medicare Current Beneficiary Survey (MCBS) and Medical Expenditure Panel Survey (MEPS). In this example, two scenarios are run through the FEM to test the confidence of reported results. The first scenario uses the status quo FEM assumptions. The second scenario assumes that the incidence of diabetes in the overweight and obese population is reduced by half. The FEM was run with 1000 bootstrap samples, each corresponding to a replicate of the simulation. The variance of the prevalence of diabetes in the population settles down by 800 replicates. Ninety-five percent confidence intervals are reported as percentiles from the distribution of simulated population-level point estimates. Total medical spending is reported in 2009 USD. If input database, transition probability, and trend sources of uncertainty are included, per capita medical spending of US adults 51 and older in 2020 is $15,549 ($15,203, $15,917) under the status quo assumptions. In the reduced diabetes incidence scenario, the per capita medical spending is $14,964 ($14,646, $15,299). The contributions of each source to total uncertainty can be examined independently by combining baseline and sampled inputs when running the simulation. Future steps include analysis of age, cohort, and period effects to test the uncertainty of model specifications. Additional work will investigate methods to reduce the computational burden of the analysis.

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