Simulated Effects of Policies to Reduce Diabetes Risk among Adults with Schizophrenia Receiving Antipsychotics

Simulation Parameters

(1) Demographic variables: Age was assessed each year, and calculated as the difference between an episode start date in each year and date of birth. Person-years were categorized into four age groups: 20 to 25 years, 26 to 34 years, 35 to 44 years, and 45 to 55 years, to facilitate the combination of Medicaid and NHANES data. Race/ethnicity classification was based on the most frequent race/ethnicity category whenever the classification was observed to change from year to year.

(2) U*ndiagnosed diabetes conditions at baseline:*

Diabetes. We imputed baseline undiagnosed diabetes using a 2-stage approach. First, we calculated the prevalence of undiagnosed diabetes rates in each ten-year age range, sex, and race/ethnicity category using NHANES data. We classified NHANES respondents as having undiagnosed diabetes if they had an A1c measure greater than 6.5%, did not report insulin use, and responded “no” to the question “Have you ever been told by a doctor or health professional that you have diabetes or sugar diabetes?” The calculated NHANES prevalence rates employed sampling weights to adjust for NHANES survey design. Second, we randomly assigned individuals without diagnosed diabetes to the undiagnosed diabetes group to match the NHANES prevalence rate.

Pre-diabetes. We identified NHANES respondents as having undiagnosed pre-diabetes if they had A1c values between 5.7 and 6.5 and if they answered “no” to the question: “Have you ever been told by a doctor or other health professional that you have any of the following: pre-diabetes, impaired fasting glucose, impaired glucose tolerance, borderline diabetes or that your blood sugar is higher than normal but not high enough to be called diabetes or sugar diabetes?” We randomly assigned

individuals without diabetes in our simulation sample to the undiagnosed pre-diabetes state to match NHANES prevalence rates.

(3) Diagnosed diabetes conditions at baseline:

Diabetes. We created a diagnosed diabetes indicator variable equal to one if the MAX data included a diagnosis for the individual in 2002.

Pre-diabetes. We calculated prevalence of pre-diabetes from the NHANES data based on A1c values and self-report. As before, we randomly assigned individuals in our simulation sample to the diagnosed pre-diabetes state to match NHANES prevalence rates.

(4) Incident diabetes conditions: We estimated year-to-year diabetes condition progression rates by calculating the marginal effects for a one-year change in age from multivariate regression of the diagnosed diabetes condition flags on linear, quadratic, and cubic age terms for each combination of sex and race/ethnicity. We inflated these rates by age and gender-specific multiplicative factors derived from the Clinical Antipsychotic Trials of Intervention Effectiveness (CATIE) study (1, 2) to account for differences between the general population included in the NHANES sample and the study cohort with schizophrenia. The factors were 1.3, 1.7, and 1 for males under age 30, between age 30 and 39, and age 40 or over, respectively, and 2.1, 1.7, 1.3, and 1 for females under age 30, between age 30 and 39, between age 40 and 49, and age 50 and over, respectively. We used the same approach to estimate year-to-year undiagnosed diabetes condition progression rates.

(5) Antipsychotic exposure and metabolic risk categories: We conservatively operationalized antipsychotic exposure as at least 90 days of drug fills of a specific

drug, not necessarily consecutive (3-5), and assigned individuals to risk-conferring categories depending on the antipsychotic drug. Thus, in the simulation model, individuals in the medium and high risk categories are 100% and 300% more likely to develop pre-diabetes and diabetes, respectively, than individuals in the low risk group. We arrived at these relative risk attributions based on a review of the extant empirical evidence (1, 3, 5-12) and expert input from one of the authors.

We used the MAX pharmacy data and metabolic risk categories to assign each person-year observation to one of three risk groups: high if the individual had filled more than a 90-day cumulative supply of clozapine, olanzapine, or a low-potency first-generation antipsychotic (e.g., chlorpromazine); medium if the individual had filled more than a 90-day cumulative supply of risperidone, quetiapine, or a medium-potency first-generation antipsychotic (e.g., perphenazine); and low, if the individual had filled fewer than a 90 cumulative days of the aforementioned antipsychotics or more than a 90-day supply of aripiprazole, ziprasidone, or a high-potency first-generation antipsychotic (e.g., haloperidol) in the 1-year period. We used the prescription fill date and days supplied variables to calculate exposure, and we partitioned individual prescriptions across calendar years where necessary.

Each patients' 2012 risk category was their starting risk category (with a distribution of 40 percent high risk, 43 percent moderate risk, 9 percent low risk, and 8 percent without any antipsychotic). Patients' subsequent risk status over the 10 simulation periods was determined using a set of transition probabilities estimated using the panel sample.

(6) Prior metabolic testing: We define metabolic testing as receipt of at least one lipid test (triglycerides, HDL, LDL, or total cholesterol; Current Procedural Terminology [CPT] codes 3048F, 3049F, 3050F, 80061, 82465, 83700, 83701, 83704, 83718, 83721, or 84478) and at least one glucose test (hemoglobin A1c, fasting plasma glucose; CPT codes 80047, 80048, 80050, 80053, 80069, 82947, 82950, 82951, 3044F, 3045F, 3046F, 83036, 83037) in a given year. Testing rates are calculated from the MAX data separately for individuals with and without a diabetes diagnosis.

(7) Prescriber decision parameters: In the base simulation model we assumed that prescribers (i) review and correctly interpret metabolic testing results 90% of the time, and (ii) switch patients to a low-risk antipsychotic upon diagnosing pre-diabetes or diabetes 90% of the time. We varied these assumptions in sensitivity analyses.

(8) Policy effectiveness: We defined policy effectiveness as the proportion of previously untested individuals who receive metabolic testing as a result of a policy. We refer to the situation absent the policy as the status quo. Policy effectiveness varies from 0% (i.e., no change from status quo testing rates) to 100% (i.e., universal testing). A policy effectiveness of 40% implies that the policy reduced the untested population by 40%. Policy effectiveness is the key parameter estimate that we vary in different simulation runs. We intentionally implemented policy effectiveness as a general concept (rather than tied to a specific policy tool or mechanism) so as to increase the generalizability of our results across different payer and policy contexts.

Medicaid Spending Outcomes

Testing-specific costs are calculated as the average payment for one lipid and one glucose test recorded in the Medicaid data. Other health care costs are predicted values using the estimated coefficients from a model predicting total log Medicaid spending as a function of age, sex, race/ethnicity, year, and a random intercept and slope for each individual. We truncated the random slope distribution at 5% and 95% to avoid extreme increases or decrease in spending within an individual over time. We fit the model on all available person-year records in the Medicaid data and calculated out-of-sample predictions for an additional ten years for each individual assuming they remained in their baseline state throughout the simulation, and separately assuming they were diagnosed with diabetes at the start of the simulation. At the end of this process, we found that annual Medicaid costs are approximately 50% higher for individuals with diabetes compared to those without.

We used the appropriate cost estimate – with or without a diabetes diagnosis – depending on the state the individual is in at each period in the simulation, discounting forward by 5% from the first simulation period. While pre-diabetes is also potentially associated with costs (including testing and other preventive services), the detection and documentation of pre-diabetes diagnoses is unreliable in Medicaid claims and we did not attempt to estimate costs associated with pre-diabetes in our cohort. We do not include implementation costs or incentive payments associated with policies aiming to increase metabolic testing rates (although we discuss these costs below). We assume patients remain in Medicaid for the full simulation time horizon.

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