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# Technical Report on the Diabetes Prevention Impact Toolkit

RTI INTERNATIONAL

# CONTENTS

# FIGURES

# TABLES

# 1. INTRODUCTION

This document describes the methods the Diabetes Prevention Impact Toolkit used to project the health and economic effects of the National Diabetes Prevention Program (National LCP) or similar programs on a state, employer, or insurer's population at high risk for diabetes. Specifically, the Impact Toolkit allows users to estimate program costs, diabetes-related medical costs, and return on investment (ROI) among other cost and health outcome measures.

The Impact Toolkit has three modules: State, Employer, and Insurer. In general, these modules are very similar. The key difference is that in the Employer and Insurer modules, the user can choose from a set of predefined populations or enter a customized set of population characteristics. In contrast, the State module only offers state populations for estimating the health and economic effects of the National LCP or similar program. The differences between the modules are mainly reflected in the Population Characteristics section of the Input Dashboard. Sections 2.1 through 2.3 describe the Population Characteristics inputs for each module separately. All other sections of this technical report apply to all three modules, except for Section 2.5.7, Productivity Costs, which only applies to the Employer module.

The Diabetes Prevention Impact Toolkit was completed in 2017. As the information technology used in the toolkit becomes outdated, the toolkit needs to be modernized using current technology. Due to resource constraints, we are unable to update the data used in the toolkit, except for adjusting the cost parameters from 2013 U.S. dollars to 2023 U.S. dollars. While using older data is a limitation, the results generated by the model remain valid, as the logic and algorithms underlying the model are still sound. To address this data limitation, we encourage users to input their own data rather than relying on the default values in the model so that results better reflect current circumstances and their specific situations.

# 2. INPUT DASHBOARD

For each module (State, Employer, and Insurer), the Population Characteristics section has different features and functions. Skip to the Population Characteristics section corresponding to the module you are using. Section 2.1 covers the technical details of population characteristics for the State module, Section 2.2 covers the Employer module, and Section 2.3 covers the Insurer module. Sections 2.4 and 2.5 cover the technical details associated with additional sections of the Input Dashboard that are the same in each module (e.g., screening assumptions, cost assumptions).

## 2.1 State Module Population Characteristics

When a state is selected from the drop-down list (or the U.S. map), the Impact Toolkit references a table of state-level data that contains the predicted prevalence for each of the risk groups eligible to participate in the National LCP or similar program. The default risk group is set to "Persons with prediabetes," but you can also select a larger group ("Persons with prediabetes and other persons at risk for type 2 diabetes") or a smaller group ("Persons with high-risk prediabetes"). These risk groups only include persons who are eligible for the National LCP (body mass index [BMI] ≥ 24 kg/m$^2$). See Section 2.4 for more information on how these groups are defined.

State estimates of the number of people in each of these risk groups were derived using a prediction equation based on age, sex, race/ethnicity, and BMI characteristics. These risk groups were estimated in two steps. First, we estimated an ordered logistic regression model using National Health and Nutrition Examination Survey (NHANES) 2011–2014 data to predict the probability of having prediabetes. The ordered logistic regression approach allowed us to account for other diabetes-related outcomes, including normal glucose, prediabetes, undiagnosed diabetes, and diagnosed diabetes. Second, we applied this prediction equation to the sample of state residents in the Behavioral Risk Factor Surveillance System (BRFSS, 2014) for each state. In other words, based on the age, sex, race/ethnicity, and BMI characteristics observed in each state, we predicted the number of people who would have prediabetes and BMI ≥ 24 kg/m$^2$. For Asian persons, we allowed a lower BMI threshold (BMI ≥ 22 kg/m$^2$) per the Centers for Disease Control and Prevention's (CDC) Diabetes Prevention Recognition Program criteria (CDC, 2015b). People with diagnosed or undiagnosed diabetes were excluded from all risk groups (persons with diabetes are not eligible for the National LCP).

For the larger risk group, "Persons with prediabetes and other persons at risk for type 2 diabetes," we calculated the CDC Prediabetes Screening Test score for each person in BRFSS (using age, BMI, and physical activity status) to ascertain how many were at risk for diabetes (CDC, 2015a). People with a score of 9 or higher are recommended for prediabetes screening and are eligible to participate in the National LCP. From this estimate of state residents with a score of 9 or higher, we then subtracted the predicted prevalence of persons with diabetes and added the predicted prevalence of persons from the prediabetes risk group that had a risk score of less than 9. This is necessary because the group of "Persons with prediabetes and other persons at risk for type 2 diabetes" should contain everyone in the prediabetes group even if they had a score of less than 9. A step-by-step description of the algorithm for estimating the state-level predicted prevalence of "Persons with prediabetes and other persons at risk for type 2 diabetes" follows:

1. Generate indicator for high/low risk score (a score of 9 or higher qualifies as a high score).

2. Generate state predictions of "Persons with prediabetes" (BMI ≥ 24 kg/$m^2$) who have a low-risk score (i.e., "Persons with prediabetes" who are not in the "Persons with prediabetes and other persons at risk for type 2 diabetes" group except for the fact that they have prediabetes). Estimate the survey weighted means for the state.
3. Generate an indicator for people with a high BMI (BMI ≥ 24 kg/$m^2$) and low-risk score. Estimate the survey weighted means for the state.
4. Multiply (2) and (3) to get "Persons with prediabetes" (BMI ≥ 24 kg/$m^2$) who would not otherwise qualify for the "Persons with prediabetes and other persons at risk for type 2 diabetes" group.
5. Generate state predictions for total diabetes (undiagnosed and diagnosed diabetes) in persons with a high-risk score and BMI ≥ 24 kg/$m^2$.
6. Calculate the full state-level risk group, "Persons with prediabetes and other persons at risk for type 2 diabetes" as follows:
    a. "Persons with prediabetes and other persons at risk for type 2 diabetes" = {(1) – [(5)*(1)]} + (4)

Finally, the smallest group, "Persons with high-risk prediabetes," was calculated using the predicted prevalence for the "Persons with prediabetes" risk group and the fraction of persons with prediabetes that are considered high risk (34.3%). Using NHANES data (2011–2014), we estimated this fraction by defining high-risk prediabetes as an A1C of 6.0%–6.4% or a fasting plasma glucose (FPG) of 110–125 mg/dL. This fraction may have changed since 2014, which may affect the proportion and number of people in each risk category. See Section 2.4 for more information on how the high-risk prediabetes group and other risk groups are defined.

National estimates offered in the State module ("UNITED STATES" selection in the dropdown menu) do not use a prediction equation to predict the prevalence of "Persons with prediabetes" because their prediabetes status is observed in the results of the NHANES laboratory data (i.e., A1C or FPG test results). Thus, we used the NHANES data (2011–2014) directly for the U.S. population selection in the State module, whereas state-level data were based on (1) the prediabetes prediction equation estimated in NHANES (2011–2014) and (2) the state-level characteristics observed in BRFSS (2014).

Using the national data from NHANES, we demonstrate the method for parsing these risk groups in Tables 1 through 3. In Table 4, we show the predicted prevalence of each risk group, for each state. Table 4 is essentially a lookup table that is used in the State module to look up the number of people in each risk group in a particular state (i.e., people who are eligible and might participate in a National Lifestyle Change Program (LCP). The state-level predicted prevalence estimates in Table 4 are multiplied by the total adult population in the selected state (Table 5) to get the total number of people in each risk group who are eligible for the National LCP. Depending on your screening and participation assumptions (see Sections 2.5.1 and 2.5.2), only a fraction of these eligible state residents will end up participating and reducing their risk of progression to diabetes.

**Table 1. National Estimates of Prediabetes and Diabetes (NHANES 2011–2014)**

| | Normal Glucose | Prediabetes | Diabetes (No Diagnosis) | Diabetes (w/ Diagnosis) |
|---|---|---|---|---|
| Estimate | 52.5% | 35.6% | 3.1% | 8.8% |

**Table 2. National Estimates of "Persons with Prediabetes" and BMI ≥ 24 (NHANES 2011–2014)**

| Normal Glucose | Prediabetes, BMI < 24 | Prediabetes, BMI ≥ 24 | Total Type 2 Diabetes |
|---|---|---|---|
| 52.5% | 6.4% | 29.2% | 11.9% |

**Table 3. National Estimates of "Persons with Prediabetes," "Persons with Prediabetes and Other Persons at Risk for Type 2 Diabetes," and Related Estimates (NHANES 2011–2014)**

| Normal Glucose[a] | Prediabetes, BMI <24 | Prediabetes, BMI ≥ 24 | Prediabetes and Others at Risk, BMI ≥ 24[b] | Total Type 2 Diabetes |
|---|---|---|---|---|
| 40.4% | 6.4% | 29.2% | 41.3% | 11.9% |

Note: The percentages in this table do not add up to 100% because the "Persons with prediabetes, BMI ≥ 24" is subsumed in the "Persons with prediabetes and other persons at risk for type 2 diabetes, BMI ≥ 24" estimate.

[a] "Normal glucose" excludes persons eligible for the "Persons with prediabetes, BMI ≥ 24" or "Prediabetes and other persons at risk, BMI ≥ 24" (which includes persons with a CDC Prediabetes Screening Test score of 9 or higher and a BMI ≥ 24).

[b] The "Persons with prediabetes and other persons at risk for type 2 diabetes" group includes the Prediabetes group as well as persons with a CDC Prediabetes Risk Score of 9 or higher and BMI ≥24).

**Table 4. State-Level Predicted Prevalence Across Toolkit Risk Groups (Full Adult Population)**

| National or State Abbreviation | Prediabetes | Prediabetes and Others at Risk | High-Risk Prediabetes |
|---|---|---|---|
| US (National, NHANES 2011–2014) | 29.18% | 41.28% | 10.00% |
| AL (State, BRFSS 2014) | 30.23% | 44.28% | 10.36% |
| AK | 29.23% | 40.41% | 10.01% |
| AZ | 29.71% | 42.03% | 10.18% |
| AR | 30.73% | 45.60% | 10.53% |
| CA | 30.04% | 40.77% | 10.29% |
| CO | 26.21% | 37.16% | 8.98% |
| CT | 29.17% | 41.53% | 9.99% |

| National or State Abbreviation | Prediabetes | Prediabetes and Others at Risk | High-Risk Prediabetes |
|---|---|---|---|
| DE | 31.05% | 44.62% | 10.64% |
| DC | 25.49% | 34.20% | 8.73% |
| FL | 29.99% | 42.83% | 10.27% |
| GA | 30.08% | 42.49% | 10.30% |
| HI | 30.62% | 39.25% | 10.49% |
| ID | 28.48% | 41.43% | 9.76% |
| IL | 28.83% | 41.64% | 9.88% |
| IN | 29.51% | 43.92% | 10.11% |
| IA | 29.32% | 43.23% | 10.05% |
| KS | 29.53% | 43.21% | 10.12% |
| KY | 29.23% | 44.04% | 10.01% |
| LA | 30.98% | 44.87% | 10.61% |
| ME | 28.83% | 42.79% | 9.88% |
| MD | 30.65% | 42.95% | 10.50% |
| MA | 27.64% | 39.36% | 9.47% |
| MI | 29.49% | 43.55% | 10.10% |
| MN | 28.86% | 42.11% | 9.89% |
| MS | 31.64% | 46.42% | 10.84% |
| MO | 29.13% | 43.10% | 9.98% |
| MT | 28.12% | 40.77% | 9.63% |
| NE | 29.21% | 42.78% | 10.01% |
| NV | 29.80% | 42.26% | 10.21% |
| NH | 29.02% | 42.53% | 9.94% |
| NJ | 30.58% | 43.30% | 10.48% |
| NM | 30.55% | 42.89% | 10.46% |
| NY | 29.48% | 42.30% | 10.10% |
| NC | 30.22% | 43.52% | 10.35% |
| ND | 29.66% | 43.73% | 10.16% |
| OH | 29.91% | 44.16% | 10.25% |
| OK | 30.42% | 44.64% | 10.42% |
| OR | 28.40% | 39.97% | 9.73% |
| PA | 29.71% | 43.70% | 10.18% |
| RI | 28.91% | 42.16% | 9.90% |
| SC | 30.40% | 43.77% | 10.41% |
| SD | 28.99% | 42.86% | 9.93% |
| TN | 30.02% | 44.12% | 10.28% |
| TX | 31.25% | 44.83% | 10.71% |
| UT | 25.81% | 36.72% | 8.84% |
| VT | 27.29% | 40.44% | 9.35% |
| VA | 29.41% | 42.25% | 10.08% |
| WA | 29.37% | 41.77% | 10.06% |

| National or State Abbreviation | Prediabetes | Prediabetes and Others at Risk | High-Risk Prediabetes |
|---|---|---|---|
| WV | 30.50% | 46.19% | 10.45% |
| WI | 29.91% | 43.59% | 10.25% |
| WY | 28.48% | 41.81% | 9.76% |

**Table 4. State-Level Predicted Prevalence Across Toolkit Risk Groups (Full Adult Population) (continued)**

| National or State Abbreviation | Prediabetes | Prediabetes and Others at Risk | High-Risk Prediabetes |
|---|---|---|---|
| IL | 28.83% | 41.64% | 9.88% |
| IN | 29.51% | 43.92% | 10.11% |
| IA | 29.32% | 43.23% | 10.05% |
| KS | 29.53% | 43.21% | 10.12% |
| KY | 29.23% | 44.04% | 10.01% |
| LA | 30.98% | 44.87% | 10.61% |
| ME | 28.83% | 42.79% | 9.88% |
| MD | 30.65% | 42.95% | 10.50% |
| MA | 27.64% | 39.36% | 9.47% |
| MI | 29.49% | 43.55% | 10.10% |
| MN | 28.86% | 42.11% | 9.89% |
| MS | 31.64% | 46.42% | 10.84% |
| MO | 29.13% | 43.10% | 9.98% |
| MT | 28.12% | 40.77% | 9.63% |
| NE | 29.21% | 42.78% | 10.01% |
| NV | 29.80% | 42.26% | 10.21% |
| NH | 29.02% | 42.53% | 9.94% |
| NJ | 30.58% | 43.30% | 10.48% |
| NM | 30.55% | 42.89% | 10.46% |
| NY | 29.48% | 42.30% | 10.10% |
| NC | 30.22% | 43.52% | 10.35% |
| ND | 29.66% | 43.73% | 10.16% |
| OH | 29.91% | 44.16% | 10.25% |
| OK | 30.42% | 44.64% | 10.42% |
| OR | 28.40% | 39.97% | 9.73% |
| PA | 29.71% | 43.70% | 10.18% |
| RI | 28.91% | 42.16% | 9.90% |
| SC | 30.40% | 43.77% | 10.41% |
| SD | 28.99% | 42.86% | 9.93% |
| TN | 30.02% | 44.12% | 10.28% |
| TX | 31.25% | 44.83% | 10.71% |
| UT | 25.81% | 36.72% | 8.84% |
| VT | 27.29% | 40.44% | 9.35% |

| National or State Abbreviation | Prediabetes | Prediabetes and Others at Risk | High-Risk Prediabetes |
|---|---|---|---|
| VA | 29.41% | 42.25% | 10.08% |
| WA | 29.37% | 41.77% | 10.06% |
| WV | 30.50% | 46.19% | 10.45% |
| WI | 29.91% | 43.59% | 10.25% |
| WY | 28.48% | 41.81% | 9.76% |

**Table 5. National and State-Level Population Estimates for Calculating Risk Group Size**

| National or State Abbreviation | National or State Population Estimate |
|---|---|
| US (National, NHANES 2011–2014) | 245,561,099 |
| AL (State, BRFSS 2014) | 3,739,646 |
| AK | 556,360 |
| AZ | 5,091,417 |
| AR | 2,266,396 |
| CA | 29,544,655 |
| CO | 4,115,447 |
| CT | 2,832,225 |
| DE | 730,755 |
| DC | 545,460 |
| FL | 15,832,660 |
| GA | 7,623,372 |
| HI | 1,112,388 |
| ID | 1,204,877 |
| IL | 9,888,842 |
| IN | 5,030,005 |
| IA | 2,386,030 |
| KS | 2,186,730 |
| KY | 3,402,842 |
| LA | 3,537,716 |
| ME | 1,068,811 |
| MD | 4,649,776 |
| MA | 5,365,728 |
| MI | 7,693,748 |
| MN | 4,191,574 |
| MS | 2,260,730 |

| | |
|---|---|
| MO | 4,673,556 |
| MT | 802,869 |
| NE | 1,417,407 |
| NV | 2,166,196 |
| NH | 1,061,487 |
| NJ | 6,949,942 |
| NM | 1,579,709 |
| NY | 15,519,718 |
| ND | 583,766 |
| OH | 8,968,842 |
| OK | 2,944,523 |
| OR | 3,109,293 |
| PA | 10,099,122 |
| RI | 839,958 |
| SC | 3,749,025 |
| SD | 649,956 |
| TN | 5,067,014 |
| TX | 19,900,570 |
| UT | 2,068,310 |
| VT | 506,408 |
| VA | 6,499,147 |
| WA | 5,475,871 |
| WV | 1,474,021 |
| WI | 4,459,989 |
| WY | 453,235 |

In the State module, we used a table of the national and state-level adult population (noninstitutionalized, as reported in BRFSS 2014) to estimate the number of people eligible for a National LCP in each state. These population estimates are based on the survey-weighted BRFSS population counts for 2014 (see Table 5). The State module assumes that the entire eligible state population is being offered the National LCP. Thus, population estimates cannot be changed in the State module. However, in the Employer module (Section 2.2) and Insurer module (Section 2.3), you can enter smaller or larger population sizes to represent the approximate size of an employee population or insured adult population.

## 2.2 Employer Module Population Characteristics

Before selecting a radio button to designate your population's characteristics, you will first enter your population size (i.e., "Number of employees" in the Employer module). This number should include all employees, not just those participating in the National LCP or similar programs. The default number of employees is set to 1,000.

Once you have entered the total number of employees at a firm, you then will select a radio button to determine the population characteristics of your employee population. There are several predefined sets of population characteristics as well as an option to enter your own employee population characteristics (age, race/ethnicity, sex, BMI). The proportion of the population that is eligible for the National LCP will be calculated using the set of population characteristics defined here and a prediction equation estimated in NHANES (2011–2014).

When selecting one of the first four radio buttons ("Assume national average for population characteristics" or "Assume state average for population characteristics" or "Assume industry average for population characteristics" or "Assume occupation average for population characteristics") in the Employer module, the Impact Toolkit references a lookup table of predicted prevalence estimates for each of the risk groups eligible to participate in a National LCP. Sections 2.2.1 through 2.2.4 describe the data and methods underlying each set of predefined population characteristics. The default risk group is set to "Persons with prediabetes," but you can also select a larger group "Persons with prediabetes and other persons at risk for type 2 diabetes" or a smaller group "Persons with high-risk prediabetes." These risk groups only include people who are eligible for the National LCP (BMI ≥ 24 $kg/m^2$). See Section 2.4 for more information on how these groups are defined.

Unlike the first four radio button selections that use lookup tables, when you select the radio button "Enter employee characteristics," the predicted prevalence of each risk group is calculated based on a prediction equation and other assumptions. See Section 2.2.5 for the data and methods related to implementing the prediction equation when you enter your own employee population characteristics.

### *2.2.1* Assume National Average for Population Characteristics

National average population characteristics in the Employer module are survey-weighted estimates from the sample of U.S. employed persons in NHANES (2011–2014). National estimates offered in the Employer module do not use a prediction equation to predict the prevalence of "Persons with prediabetes" because their prediabetes status is observed in the results of the NHANES laboratory data (i.e., A1C or FPG test results). Thus, we used the observed NHANES data (2011–2014) directly for the national selection in the employer module, whereas state-level data are based on (1) the prediabetes prediction equation estimated in NHANES (2011–2014) and (2) the state-level characteristics observed in

BRFSS (2014). See Section 2.1 and Tables 1 through 3 to see how the risk groups were parsed from the national data.

### *2.2.2* Assume State Average for Population Characteristics

State estimates of the number of people in each risk group were estimated using a prediction equation based on age, sex, race/ethnicity, and BMI characteristics. The predicted prevalence of each risk group was estimated in two steps. First, we estimated an ordered logistic regression model NHANES (2011–2014) to predict the probability of having prediabetes. The ordered logistic regression approach allowed us to account for other diabetes-related outcomes, including normal glucose, prediabetes, undiagnosed diabetes, and diagnosed diabetes. Second, we applied this prediction equation to the sample of employed adults in BRFSS (2014) for each state. In other words, based on the age, sex, race/ethnicity, and BMI characteristics observed in each state's employed population, we predicted the number of people who would have prediabetes and BMI ≥ 24 kg/$m^2$. For Asian persons, we allowed a lower BMI threshold (BMI ≥ 22 kg/$m^2$) per CDC's Diabetes Prevention Recognized Program criteria (CDC, 2015b). People with diagnosed or undiagnosed diabetes were excluded from all risk groups (people with diabetes are not eligible for the National LCP).

For the larger risk group, "Persons with prediabetes and other persons at risk for type 2 diabetes," we calculated the CDC Prediabetes Screening Test score for each person in BRFSS (using age, BMI, and physical activity status) to ascertain how many were at risk for diabetes (CDC, 2015a). People with a score of 9 or higher are recommended for prediabetes screening and are eligible to participate in the National LCP. From this estimate of employed state residents with a score of 9 or higher, we then subtracted the predicted prevalence of persons with diabetes and added the predicted prevalence of persons from the prediabetes risk group that had a risk score of less than 9. This is necessary because the group of "Persons with prediabetes and other persons at risk for type 2 diabetes" should contain everyone in the prediabetes group even if they had a score of less than 9. A step-by-step description of the algorithm for estimating the state-level predicted prevalence of "Persons with prediabetes and other persons at risk for type 2 diabetes" follows:

1. Generate indicator for high/low risk score (a score of 9 or higher qualifies as a high score).
2. Generate state predictions of "Persons with prediabetes" (BMI ≥ 24 kg/$m^2$) who have a low-risk score (i.e., "Persons with prediabetes" who are not in the "Persons with prediabetes and other persons at risk for type 2 diabetes" group except for the fact that they have prediabetes). Estimate the survey weighted means for the state.
3. Generate an indicator for people with a high BMI (BMI ≥ 24 kg/$m^2$) and low risk score. Estimate the survey weighted means for the state.

4. Multiply (2) and (3) to get "Persons with prediabetes" (BMI ≥ 24 kg/$m^2$) who would not otherwise qualify for the "Persons with prediabetes and other persons at risk for type 2 diabetes" group.
5. Generate state predictions for total diabetes (undiagnosed and diagnosed diabetes) in persons with a high-risk score and BMI ≥ 24 kg/$m^2$.
6. Calculate the full state-level risk group, "Persons with prediabetes and other persons at risk for type 2 diabetes" as follows:
   a. "Persons with prediabetes and other persons at risk for type 2 diabetes" = {(1) − [(5)*(1)]} + (4)

Finally, the smallest group, "Persons with high-risk prediabetes," was calculated using the predicted prevalence for the "Persons with prediabetes" risk group and the fraction of persons with prediabetes that are considered high-risk (34.3%). Using NHANES data (2011–2014), we estimated this fraction by defining high-risk prediabetes as an A1C of 6.0–6.4% or an FPG of 110–125 mg/dL. See Section 2.4 for more information on how the high-risk prediabetes group and other risk groups are defined.

Table 6 presents the predicted prevalence of each risk group for each state's population of employed adults. This lookup table is used in the Employer module to estimate the number of people in each risk group in a particular state's employed population (i.e., people who are eligible and might participate in the National LCP). The state predicted prevalence estimates in Table 6 are multiplied by the "Number of Employees" (entered by the user) to get the total number of people in a given risk group that are eligible for the National LCP. Depending on your screening and participation assumptions (see Sections 2.5.1 and 2.5.2), only a fraction of these eligible employed adults will end up participating and reducing their risk of progression to type 2 diabetes.

**Table 6. State-Level Predicted Prevalence Across Toolkit Risk Groups (Adult Employed Population)**

| National or State Abbreviation | Prediabetes | Prediabetes and Others at Risk | High-Risk Prediabetes |
|---|---|---|---|
| US (National, NHANES) | 26.95% | 39.77% | 9.23% |
| AL (State, BRFSS) | 28.31% | 40.95% | 9.70% |
| AK | 28.21% | 38.50% | 9.66% |
| AZ | 27.76% | 38.78% | 9.51% |
| AR | 29.35% | 43.07% | 10.06% |
| CA | 29.26% | 39.09% | 10.02% |
| CO | 25.11% | 35.10% | 8.60% |
| CT | 28.40% | 39.98% | 9.73% |
| DE | 29.61% | 42.60% | 10.14% |
| DC | 22.27% | 29.36% | 7.63% |
| FL | 28.06% | 39.46% | 9.61% |
| GA | 28.94% | 40.44% | 9.92% |

| National or State Abbreviation | Prediabetes | Prediabetes and Others at Risk | High-Risk Prediabetes |
|---|---|---|---|
| HI | 30.55% | 38.86% | 10.47% |
| ID | 27.19% | 39.55% | 9.32% |
| IL | 27.59% | 39.43% | 9.45% |
| IN | 27.92% | 41.94% | 9.56% |
| IA | 27.63% | 41.41% | 9.47% |
| KS | 28.35% | 41.28% | 9.71% |
| KY | 26.61% | 39.47% | 9.12% |
| LA | 29.63% | 42.54% | 10.15% |
| ME | 26.99% | 40.30% | 9.25% |
| MD | 29.90% | 41.61% | 10.24% |
| MA | 26.45% | 37.62% | 9.06% |
| MI | 27.30% | 40.10% | 9.35% |
| MN | 27.32% | 40.02% | 9.36% |
| MS | 30.40% | 43.98% | 10.42% |
| MO | 27.40% | 40.64% | 9.39% |
| MT | 26.42% | 38.37% | 9.05% |
| NE | 27.91% | 41.03% | 9.56% |
| NV | 28.68% | 39.85% | 9.83% |
| NH | 27.43% | 39.41% | 9.40% |
| NJ | 30.00% | 42.33% | 10.28% |
| NM | 29.51% | 41.09% | 10.11% |
| NY | 27.65% | 39.36% | 9.47% |
| NC | 28.77% | 40.72% | 9.86% |
| ND | 28.59% | 42.61% | 9.79% |
| OH | 27.98% | 41.00% | 9.58% |
| OK | 28.74% | 41.61% | 9.85% |
| OR | 26.53% | 36.41% | 9.09% |
| PA | 27.87% | 41.18% | 9.55% |
| RI | 27.51% | 39.72% | 9.42% |
| SC | 28.84% | 41.00% | 9.88% |
| SD | 27.64% | 40.93% | 9.47% |
| TN | 28.20% | 39.83% | 9.66% |
| TX | 30.45% | 43.36% | 10.43% |
| UT | 25.01% | 35.40% | 8.57% |
| VT | 25.41% | 37.58% | 8.71% |
| VA | 28.56% | 40.58% | 9.79% |
| WA | 28.29% | 39.80% | 9.69% |
| WV | 28.32% | 42.59% | 9.70% |
| WI | 28.24% | 41.51% | 9.67% |
| WY | 26.65% | 39.02% | 9.13% |

(continued)

### *2.2.3* Assume Industry Average for Population Characteristics

Industry characteristics are based on the sample of employed persons in NHANES (2011–2014) and the relative rates of obesity across industries. Industries are defined in NHANES using the U.S. Census Bureau's 2002 Occupation and Industry coding system. To estimate the number of people in each risk group, we started by estimating a baseline employed group using the mean values of each population characteristic (age, sex, race/ethnicity, and BMI) observed in NHANES (2011–2014) for employed adults. BMI was modeled as a variable with the following categories: normal weight, overweight, and obese. Overweight was defined as a BMI = 24.0–29.9 kg/m$^2$ to match the National LCP criteria. Obesity was defined as BMI ≥ 30 kg/m$^2$.

An analysis of National Health Interview Survey (NHIS) data by Luckhaupt and colleagues (2014) provided us with obesity prevalence ratios by industry. In other words, people in some industries have a higher risk of obesity than the average across all industries, and Luckhaupt et al. quantified this in a prevalence ratio (controlling for sociodemographic factors such as age and race/ethnicity). If a particular industry has a prevalence ratio of 1.0, then people in that industry have the same risk of obesity as the average person across all industries. Prevalence ratios greater than 1.0 signal a higher risk of obesity, whereas prevalence ratios less than 1.0 signal a lower risk of obesity. We used these prevalence ratios to inflate the percentage of people who have obesity in each industry according to the prevalence ratio associated with that industry from Luckhaupt et al. (2014).

To implement this approach, we also had to assume that as the percentage of obesity increased for a given industry population, the percentage of overweight also increased, but to a smaller degree. We made this assumption because more than three-quarters of the employed population has overweight or obesity, and some prevalence ratios were large enough that allowing a one-to-one increase in the percentage overweight (as the obesity percentage increases) led to a population with more than 100% having overweight or obesity. Thus, we used NHANES data to estimate the marginal effect of the probability of obesity on the probability of having overweight in the employed population (we used an ordinary least squares approach for this estimate). We found that for every one percentage point increase in the probability of having obesity, there was a 0.63 percentage point increase in the probability of having overweight.

Using the prediction equation for prediabetes, we estimated the probability of having prediabetes for employed people with overweight and for employed people with obesity. We used the mean values for other characteristics included in the prediction equation (age, sex, and race/ethnicity). The predicted probability of prediabetes for people with overweight and people with obesity was then combined according to their relative weights. For instance, in the baseline employed group (prevalence ratio = 1.0), 33.9% of employed people had obesity and 41.6% had overweight (and 24.5% were normal weight). A prediction of the probability of prediabetes was generated for the group with obesity and the group with overweight, and then these groups received weights of 33.9% and 41.6%, respectively. We did not calculate a probability of prediabetes for 24.5% of the population that was assumed to be normal weight because they are not eligible for the National LCP. They effectively have a probability of 0.

The steps described above get us the predicted prevalence of "Persons with prediabetes" (and BMI $\geq$ 24 kg/$m^2$), but we still need a way to calculate the larger risk group "Persons with prediabetes and other persons at risk for type 2 diabetes" and the smaller risk group "Persons with high-risk prediabetes." To calculate the "Persons with prediabetes and other persons at risk for type 2 diabetes" group, we assumed that this larger group was 1.48 times as large as the "Persons with prediabetes" group that was estimated for each industry using the methods above. We assumed that this relationship was 1.48 based on a comparison of the "Persons with prediabetes" group and the "Persons with prediabetes and other persons at risk for type 2 diabetes" group as they are observed in the NHANES data (2011–2014) among employed people. Similarly, we assumed that the smaller risk group ("Persons with high-risk prediabetes") was 0.34 times the size of the "Persons with prediabetes" group based on the relationship between these groups observed in the NHANES data (2011–2014) among employed people. The resulting predicted prevalence of each risk group is shown in Table 7.

**Table 7. Industry Group Predicted Prevalence Across Toolkit Risk Groups**

| Industry Group | Prediabetes | Prediabetes and Others at Risk | High-Risk Prediabetes |
|---|---|---|---|
| Agriculture, forestry, fishing, and hunting | 29.06% | 43.01% | 9.96% |
| Mining | 31.80% | 47.07% | 10.90% |
| Utilities | 27.46% | 40.64% | 9.41% |
| Construction | 29.06% | 43.01% | 9.96% |
| Manufacturing | 29.75% | 44.02% | 10.19% |
| Wholesale trade | 26.55% | 39.29% | 9.10% |
| Retail trade | 27.69% | 40.98% | 9.49% |
| Transportation and warehousing | 30.20% | 44.70% | 10.35% |
| Information | 32.94% | 48.76% | 11.29% |
| Finance and insurance | 27.92% | 41.32% | 9.56% |
| Real estate, rental and leasing | 22.21% | 32.87% | 7.61% |
| Professional, scientific, and technical services | 26.32% | 38.95% | 9.02% |
| Management of companies and enterprises | 29.29% | 43.35% | 10.03% |
| Administrative, support, waste management, and remediation services | 29.06% | 43.01% | 9.96% |

| Industry Group | Prediabetes | Prediabetes and Others at Risk | High-Risk Prediabetes |
|---|---|---|---|
| Education services | 30.66% | 45.38% | 10.50% |
| Health care and social assistance | 33.40% | 49.43% | 11.44% |
| Arts, entertainment, and recreation | 24.04% | 35.57% | 8.23% |
| Accommodation and food services | 26.09% | 38.61% | 8.94% |
| Other services (except public administration) | 26.32% | 38.95% | 9.02% |
| Public administration | 35.46% | 52.48% | 12.15% |

### *2.2.4* Assume Occupation Average for Population Characteristics

Occupation characteristics are based on the sample of employed persons in NHANES (2011–2014) and the relative rates of obesity across occupations. Occupations are defined in NHANES using the U.S. Census Bureau's 2002 Occupation and Industry coding system.

The methods for estimating the predicted prevalence of each risk group for an occupation are identical to the methods for the industry groups described in Section 2.2.3. The prevalence ratios associated with occupation groups from Luckhaupt et al. (2014) were used to implement the same approach, and the predicted prevalence of each risk group is shown in Table 8.

**Table 8. Occupation Group Predicted Prevalence Across Toolkit Risk Groups**

| Occupation Group | Prediabetes | Prediabetes and Others at Risk | High-Risk Prediabetes |
|---|---|---|---|
| Agriculture, forestry, fishing, and hunting | 29.06% | 43.01% | 9.96% |
| Mining | 31.80% | 47.07% | 10.90% |
| Utilities | 27.46% | 40.64% | 9.41% |
| Construction | 29.06% | 43.01% | 9.96% |
| Manufacturing | 29.75% | 44.02% | 10.19% |
| Wholesale trade | 26.55% | 39.29% | 9.10% |
| Retail trade | 27.69% | 40.98% | 9.49% |
| Transportation and warehousing | 30.20% | 44.70% | 10.35% |
| Information | 32.94% | 48.76% | 11.29% |
| Finance and insurance | 27.92% | 41.32% | 9.56% |
| Real estate, rental and leasing | 22.21% | 32.87% | 7.61% |
| Professional, scientific, and technical services | 26.32% | 38.95% | 9.02% |
| Management of companies and enterprises | 29.29% | 43.35% | 10.03% |
| Administrative, support, waste management, and remediation services | 29.06% | 43.01% | 9.96% |

| Occupation Group | Prediabetes | Prediabetes and Others at Risk | High-Risk Prediabetes |
|---|---|---|---|
| Education services | 30.66% | 45.38% | 10.50% |
| Health care and social assistance | 33.40% | 49.43% | 11.44% |
| Arts, entertainment, and recreation | 24.04% | 35.57% | 8.23% |
| Accommodation and food services | 26.09% | 38.61% | 8.94% |
| Other services (except public administration) | 26.32% | 38.95% | 9.02% |
| Public administration | 35.46% | 52.48% | 12.15% |

### *2.2.5* Entering Employee Population Characteristics

For customized results based on your organization's unique population characteristics, select the "Enter employee characteristics" option. When this option is selected, you will see that the fields for each characteristic have already been filled with default values. These default values reflect national averages for the employed population in the United States. You can change these to reflect your own employee population characteristics. If you want to return to the default values at any point, click the "RESTORE DEFAULTS" link in the upper right-hand corner. This button will clear all the data that you have entered and restore the default data.

The values entered in the employee characteristics fields are used to predict the percentage of employees in each risk group (see Section 2.4 for more information on risk groups). The first step to predicting each of the risk groups is to predict the prevalence of the primary risk group, "Persons with prediabetes." The other two risk groups are predicted indirectly, using multipliers to inflate or deflate the prediction for "Persons with prediabetes" based on the relative size of the other two risk groups observed in NHANES data (2011–2014). To predict the percentage of employees with prediabetes, we estimated an ordered logistic regression model of NHANES data (2011–2014) to account for other diabetes-related outcomes, including normal glucose, prediabetes, undiagnosed diabetes, and diagnosed diabetes. The model included independent variables for age, sex, race/ethnicity, and BMI. BMI was modeled as a variable with the following categories: normal weight, overweight, and obese. Overweight was defined as a BMI = 24.0–29.9 kg/m$^2$ to match the National LCP criteria. Obesity was defined as BMI ≥ 30 kg/m$^2$.

To limit the burden of data collection and data entry on the user, we developed an ad hoc method to apply this prediction model using the set of population characteristic averages entered by the user. Instead of asking the user to provide a person-level dataset of their employee population, we generated a predicted prevalence of "Persons with prediabetes" based on the characteristic averages with special emphasis on two key predictive variables: overweight and obesity status. Using the prediction model for prediabetes, we estimated two separate predicted prevalence estimates of "Persons with prediabetes": one for persons with overweight and another for persons with obesity. These two predicted prevalence estimates are combined in a weighted average to estimate the predicted prevalence of "Persons with prediabetes" in your employee population. We did not calculate a predicted prevalence of "Persons with prediabetes" for the proportion of the population that is normal weight because they are not eligible for the National LCP. They effectively have a probability of 0.

The following example illustrates this method. Using the default employee population characteristics in the Employer module (age, sex, and race/ethnicity), we predicted the prevalence of "Persons with prediabetes" for persons with overweight and persons with obesity separately. The predicted prevalence of "Persons with prediabetes" for each BMI group was then combined according to their relative proportions in the employee population. In the default employee population characteristics, 33.9% of employed people had obesity and 41.6% had overweight (and 24.5% were normal weight, which effectively have a probability of 0). A weighted average predicted prevalence of "Persons with prediabetes" was calculated based on these weights and represents the proportion of your employee population that is predicted to have prediabetes and BMI ≥ 24 $kg/m^2$.

The steps described above get us the predicted prevalence of "Persons with prediabetes" (and BMI ≥ 24 $kg/m^2$), but we still need a way to calculate the larger risk group "Persons with prediabetes and other persons at risk for type 2 diabetes" and the smaller risk group "Persons with high-risk prediabetes." To calculate the "Persons with prediabetes and other persons at risk for type 2 diabetes" group, we assumed that this larger group was 1.48 times as large as the "Persons with prediabetes" group that was estimated for your employee population using the methods above. We assumed that this relationship was 1.48 based on a comparison of the "Persons with prediabetes" group and the "Persons with prediabetes and other persons at risk for type 2 diabetes" group as they are observed in the NHANES data (2011–2014) among employed people. Similarly, we assumed that the smaller risk group ("Persons with high-risk prediabetes") was 0.34 times the size of the "Persons with prediabetes" group based on the relationship between these groups observed in the NHANES data (2011–2014) among employed people. The resulting predicted prevalence of the risk group you select will be reported in the Output Dashboard.

## 2.3 Insurer Module Population Characteristics

To designate your population's characteristics, you will first enter your population size (i.e., "Number of Adults Insured" in the Insurer module). This number should include all privately insured adults, not just those participating in the prevention program. The default number of privately insured adults is set to 1,000.

Once you have entered the total number of privately insured adults in your population, you will then select a radio button to determine the population characteristics of your population. There are several predefined sets of population characteristics as well as an option to enter your own privately insured adult population characteristics (age, race/ethnicity, sex, BMI). The proportion of the population that is eligible for the National LCP will be calculated using the set of population characteristics defined here and a prediction equation estimated in NHANES (2011–2014).

When selecting one of the first four radio buttons ("Assume national average for population characteristics" or "Assume state average for population characteristics" or "Assume industry average for population characteristics" or "Assume occupation average for population characteristics") in the Insurer module, the Impact Toolkit references a lookup table of predicted prevalence estimates for each of the risk groups eligible to participate in the National LCP. Sections 2.3.1 through 2.3.4 describe the data and methods underlying each set of predefined population characteristics. The default risk group is set to "Persons with prediabetes," but you can also select a larger group, "Persons with prediabetes and other persons at risk for type 2 diabetes," or a smaller group, "Persons with high-risk prediabetes." These risk groups only include people who are eligible for the National LCP (BMI ≥ 24 kg/m$^2$). See Section 2.4 for more information on how these groups are defined.

Unlike the first four radio button selections that use lookup tables, when you select the radio button "Enter insured adult population characteristics," the predicted prevalence of each risk group is calculated based on a prediction equation and other assumptions. See Section 2.3.5 for the data and methods related to implementing the prediction equation when you enter your own privately insured adult population characteristics.

### *2.3.1* Assume National Average for Population Characteristics

National average population characteristics in the Insurer module are survey-weighted estimates from the sample of U.S. privately insured persons in NHANES (2011–2014). National estimates offered in the Insurer module do not use a prediction equation to predict the prevalence of "Persons with prediabetes" because their prediabetes status is observed in the results of the NHANES laboratory data (i.e., A1C or FPG test results). Thus, we used the observed NHANES data (2011–2014) directly for the national selection in the Insurer module, whereas state-level data are based on (1) the prediabetes prediction equation estimated in NHANES (2011–2014) and (2) the state-level characteristics observed in BRFSS (2014). See Section 2.1 and Tables 1 through 3 to see how the risk groups were parsed from the national data.

### *2.3.2* Assume State Average for Population Characteristics

State estimates of the number of people in each risk group were estimated using a prediction equation based on age, sex, race/ethnicity, and BMI characteristics. The predicted prevalence of each risk group was estimated in two steps. First, we estimated an ordered logistic regression model of NHANES data (2011–2014) to predict the probability of having prediabetes. The ordered logistic regression approach allowed us to account for other diabetes-related outcomes, including normal glucose, prediabetes, undiagnosed diabetes, and diagnosed diabetes. Second, we applied this prediction equation to the sample of privately insured adults in BRFSS (2014) for each state. In other words, based on the age, sex, race, and BMI characteristics observed in each state's privately insured adult population, we predicted the number of people who would have prediabetes and BMI ≥ 24 kg/$m^2$. For Asian persons, we allowed a lower BMI threshold (BMI ≥ 22 kg/$m^2$) per CDC's Diabetes Prevention Recognition Program criteria (CDC, 2015b). People with diagnosed or undiagnosed diabetes were excluded from all risk groups (persons with diabetes are not eligible for the National LCP).

For the larger risk group, "Persons with prediabetes and other persons at risk for type 2 diabetes," we calculated the CDC Prediabetes Screening Test score for each person in BRFSS (using age, BMI, and physical activity status) to ascertain how many were at risk for diabetes (CDC, 2015a). People with a score of 9 or higher are recommended for prediabetes screening and are eligible to participate in the National LCP. From this estimate of privately insured state residents with a score of 9 or higher, we then subtract the predicted prevalence of persons with diabetes and add the predicted prevalence of persons from the prediabetes risk group that had a risk score of less than 9. This is necessary because the group of "Persons with prediabetes and other persons at risk for type 2 diabetes" should contain everyone in the prediabetes group even if they had a score of less than 9. A step-by-step description of the algorithm for estimating the state-level predicted prevalence of "Persons with prediabetes and other persons at risk for type 2 diabetes" follows:

1. Generate indicator for high-/low-risk score (a score of 9 or higher qualifies as a high score).
2. Generate state predictions of "Persons with prediabetes" (BMI ≥ 24 kg/$m^2$) that have a low-risk score (i.e., "Persons with prediabetes" that are not in the "Persons with prediabetes and other persons at risk for type 2 diabetes" group except for the fact that they have prediabetes). Estimate the survey weighted means for the state.
3. Generate an indicator for people with a high BMI (BMI ≥ 24 kg/$m^2$) and low-risk score. Estimate the survey weighted means for the state.
4. Multiply (2) and (3) to get "Persons with prediabetes" (BMI ≥ 24 kg/$m^2$) that would not otherwise qualify for the "Persons with prediabetes and other persons at risk for type 2 diabetes" group.
5. Generate state predictions for total diabetes (undiagnosed and diagnosed diabetes) in persons with a high-risk score and BMI ≥ 24 kg/$m^2$.
6. Calculate the full state-level risk group, "Persons with prediabetes and other persons at risk for type 2 diabetes" as follows:
   a. "Persons with prediabetes and other persons at risk for type 2 diabetes" = {(1) – [(5)*(1)]} + (4)

Finally, the smallest group, "Persons with high-risk prediabetes," is calculated using the predicted prevalence for the "Persons with prediabetes" risk group and the fraction of persons with prediabetes that are considered high risk (34.3%). Using NHANES data (2011–2014), we estimated this fraction by defining high-risk prediabetes as an A1C of 6.0%–6.4% or an FPG of 110–125 mg/dL. See Section 2.4 for more information on how the high-risk prediabetes group and other risk groups are defined.

Table 9 presents the predicted prevalence of each risk group for each state's population of privately insured adults. This lookup table is used in the Insurer module to estimate the number of people in each risk group in a particular state's privately insured adult population (i.e., people who are eligible and might participate in the National LCP). The state predicted prevalence estimates in Table 9 are multiplied by the "Number of Adults Insured" (entered by the user) to get the total number of people in each risk group that are eligible for the National LCP. Depending on your screening and participation assumptions (see Sections 2.5.1 and 2.5.2), only a fraction of these eligible insured adults will end up participating and reducing their risk of progression to type 2 diabetes.

**Table 9. State-Level Predicted Prevalence Across Toolkit Risk Groups (Adult Privately Insured Population)**

| National or State Abbreviation | Prediabetes | Prediabetes and Others at Risk | High-Risk Prediabetes |
|---|---|---|---|
| US (National, NHANES) | 26.56% | 38.31% | 9.10% |
| AL (State, BRFSS) | 29.69% | 43.17% | 10.17% |
| AK | 28.44% | 39.78% | 9.74% |
| AZ | 28.00% | 39.49% | 9.59% |
| AR | 29.35% | 43.07% | 10.06% |
| CA | 29.26% | 39.09% | 10.02% |
| CO | 25.11% | 35.10% | 8.60% |
| CT | 28.04% | 39.71% | 9.61% |
| DE | 29.65% | 42.83% | 10.16% |
| DC | 22.30% | 28.81% | 7.64% |
| FL | 30.07% | 42.51% | 10.30% |
| GA | 28.94% | 40.44% | 9.92% |
| HI | 30.55% | 38.86% | 10.47% |
| ID | 27.09% | 39.50% | 9.28% |
| IL | 28.30% | 41.12% | 9.69% |
| IN | 27.92% | 41.94% | 9.56% |
| IA | 27.82% | 41.52% | 9.53% |
| KS | 28.35% | 41.28% | 9.71% |

| National or State Abbreviation | Prediabetes | Prediabetes and Others at Risk | High-Risk Prediabetes |
|---|---|---|---|
| KY | 27.92% | 42.08% | 9.57% |
| LA | 30.63% | 43.99% | 10.49% |
| ME | 26.99% | 40.30% | 9.25% |
| MD | 30.96% | 43.48% | 10.61% |
| MA | 25.39% | 35.87% | 8.70% |
| MI | 28.71% | 42.31% | 9.83% |
| MN | 27.71% | 40.43% | 9.49% |
| MS | 30.92% | 44.69% | 10.59% |
| MO | 27.40% | 40.64% | 9.39% |
| MT | 25.99% | 37.81% | 8.90% |
| NE | 27.62% | 41.00% | 9.46% |
| NV | 28.80% | 40.80% | 9.87% |
| NH | 27.79% | 40.52% | 9.52% |
| NJ | 29.67% | 42.05% | 10.16% |
| NM | 29.28% | 41.19% | 10.03% |
| NY | 29.25% | 42.06% | 10.02% |
| NC | 29.17% | 41.87% | 9.99% |
| ND | 28.20% | 42.21% | 9.66% |
| OH | 29.06% | 42.96% | 9.96% |
| OK | 28.74% | 41.61% | 9.85% |
| OR | 27.49% | 38.58% | 9.42% |
| PA | 28.98% | 42.91% | 9.93% |
| RI | 28.03% | 41.01% | 9.60% |
| SC | 29.86% | 42.81% | 10.23% |
| SD | 27.64% | 40.93% | 9.47% |
| TN | 30.63% | 44.24% | 10.49% |
| TX | 30.45% | 43.36% | 10.43% |
| UT | 24.65% | 34.99% | 8.44% |
| VT | 25.57% | 37.79% | 8.76% |
| VA | 28.97% | 41.11% | 9.93% |
| WA | 28.35% | 40.43% | 9.71% |
| WV | 29.84% | 45.41% | 10.22% |
| WI | 28.47% | 41.83% | 9.75% |
| WY | 26.65% | 39.02% | 9.13% |

### *2.3.3* Assume Industry Average for Population Characteristics

Industry characteristics in the Insurer module are based on the sample of employed persons in NHANES (2011–2014) and the relative rates of obesity across industries. We used the sample of employed people for this selection in the Insurer module because insured adults who work in a particular industry are employed. Industries are defined in NHANES using the U.S. Census Bureau’s 2002 Occupation and Industry coding system.

The methods for estimating the predicted prevalence of each risk group for an industry are identical to the methods described in Section 2.2.3. The predicted prevalence of each risk group by industry is shown in Table 7.

### *2.3.4* Assume Occupation Average for Population Characteristics

Occupation characteristics in the Insurer module are based on the sample of employed persons in NHANES (2011–2014) and the relative rates of obesity across occupations. We used the sample of employed people for this selection in the Insurer module because insured adults who work in a particular occupation are employed. Occupations are defined in NHANES using the U.S. Census Bureau’s 2002 Occupation and Industry coding system.

The methods for estimating the predicted prevalence of each risk group for an industry are identical to the methods described in Section 2.2.4. The predicted prevalence of each risk group by occupation is shown in Table 8.

### *2.3.5* Entering Insured Population Characteristics

For customized results based on your unique insured population’s characteristics, select the “Enter insured adult population characteristics” option. When this option is selected, you will see that the fields for each characteristic have already been filled with default values. These default values reflect national averages for the privately insured adult population in the United States. You can change these to reflect your own privately insured adult population characteristics. If you want to return to the default values at any point, click the “RESTORE DEFAULTS” link in the upper right-hand corner. This button will clear all the data that you have entered and restore the default data.

The values entered in the insured adult population characteristics fields are used to predict the percentage of insured adults in each risk group. The methods for generating the predicted prevalence of each risk group are identical to the methods described in Section 2.2.5 for the Employer module. The resulting predicted prevalence of the risk group you select will be reported in the Output Dashboard.

## 2.4 Risk Group to Participate in Program

Defining the population characteristics allowed us to predict the prevalence of each risk group in the state, employee, or privately insured adult population. Using the radio buttons under the “Risk Group to Participate in Program” heading, you can select from the three risk groups eligible for the National LCP. The annual probability of developing type 2 diabetes is different for each risk group. The default annual probability for each risk group is prepopulated in the input box. You can change this number if you would like to assume a higher or lower probability of diabetes. We recommend using the default annual probabilities of diabetes unless you have (1) read this section of the technical report and (2) generated inputs from your own data sources or identified updated data available in the scientific literature.

We determined the diabetes incidence rates for each risk group using two key sources: (1) Selvin et al.’s (2010) analysis of Atherosclerosis Risk in Communities study (ARIC) data and (2) a systematic review of annual diabetes probabilities (in the prediabetes range) by Zhang and colleagues (2010). We calculated a weighted average incidence across the A1C categories presented by Selvin et al. and Zhang et al. (Table 10, orange cells). The Zhang et al. review included studies with a combined sample size roughly 4 times larger than Selvin et al.’s ARIC sample. Thus, the Zhang et al. review received a weight of about 80%, and the Selvin et al. analysis received a weight of about 20%.

**Table 10. Annual Incidence Probability of Diabetes by A1C Category**

| Source | Total N | <5.0% | 5.0–5.5% | 5.5–5.9% | 6.0–6.4% |
|---|---|---|---|---|---|
| Selvin et al. (2010) | 11,092 | 0.0046 | 0.0087 | 0.0166 | 0.0399 |
| Zhang et al. (2010) | 44,203 | 0.0030 | 0.0105 | 0.0340 | 0.0725 |
| Weighted average | 55,295 | 0.0033 | 0.0101 | 0.0305 | 0.0660 |
| Unweighted average | 55,295 | 0.0038 | 0.0096 | 0.0253 | 0.0562 |

Note: Weighted average was calculated based on the relative sample sizes of each study (see Total N column). We calculated the midpoint of the annualized incidence probabilities presented in Zhang et al. (2010) (see Table 11).

We used the midpoint of the low and high estimates (Table 11) reported for each A1C category in the Zhang et al. (2010) review. The average age was slightly older in Selvin et al. (2010) (56.7) than in Zhang et al. (2010) (53.4), and the race/ethnicity makeup differed substantially. Several studies in Zhang et al. (2010) were from Asian and American Indian populations, which were not well represented in Selvin et al.’s ARIC sample (U.S. population: 78% white, 22% black). From the data in Selvin et al. (2010) and Zhang et al. (2010), we determined that a plausible range for annual diabetes incidence was 1% to 7% for these National LCP–eligible risk groups. Just under the “Annual Probability of Diabetes” entry field in the toolkit, we state this recommended range. Using values outside of this range may lead to results with low credibility.

**Table 11. Low, High, and Midpoint Annual Incidence Probability Estimates by A1C Level from Zhang et al. (2010)**

| Estimate from Zhang et al. (2010) | A1C <5.0% | A1C 5.0–5.5% | A1C 5.5–5.9% | A1C 6.0–6.4% |
|---|---|---|---|---|
| Zhang et al. (2010) Low | 0.0030 | 0.0030 | 0.0180 | 0.0500 |
| Zhang et al. (2010) High | 0.0030 | 0.0180 | 0.0500 | 0.0950 |
| Midpoint | 0.0030 | 0.0105 | 0.0340 | 0.0725 |

Note: We assumed that the low estimate for A1C (<5.0) was the same as the high estimate. At this low value, few studies provided data. In Table 10, we can see that Selvin et al.'s estimate is higher than Zhang et al.'s for this low A1C category (the only A1C category in which this occurs).

The accepted range for prediabetes is 5.7% to 6.4% using the A1C blood test or 100 to 125 mg/dL using the FPG blood test (CDC National Diabetes Statistics, 2014). The two highest A1C categories reported in Zhang et al. (2010) and Selvin et al. (2010) are 5.5% to 5.9% and 6.0% to 6.4%, which cover the full range of prediabetes (5.7% to 6.4%) as measured by the A1C blood test. We used the weighted average diabetes incidence probabilities from Table 10 for 5.5% to 5.9% (0.0305) and 6.0% to 6.4% (0.0660) to calculate an annual incidence probability for each risk group. The weighted average annual probabilities of diabetes from Table 10 for <5.0% (0.0033) and 5.0% to 5.5% (0.0101) were not used to determine risk group annual incidence probabilities because these A1C values do not fall in the prediabetes range (5.7% to 6.4%).

## *2.4.1* Persons With Prediabetes

This group includes persons predicted to have prediabetes (and BMI ≥ 24 kg/$m^2$). "Persons with prediabetes" have a blood sugar level higher than normal, but not high enough for a diagnosis of diabetes (FPG 100–125 mg/dL or A1C 5.7%–6.4%). The default annual probability of diabetes for persons with prediabetes is 3.8%. This was calculated as a weighted average using (1) the distribution of the risk group (persons with prediabetes) across A1C categories as the weight (see Table 12, column 2) and (2) the weighted average annual probability for persons with an A1C of 5.5% to 5.9% (0.0305) and 6.0% to 6.4% (0.0660) (see Table 10) for the annual probabilities of diabetes that are being weighted.

**Table 12. Persons With Prediabetes: Calculation of a Weighted Average Annual Probability of Diabetes by A1C Category**

| A1C Category | Distribution of Risk Group Across A1C Categories | Weighted Average Annual Probability | Annual Probabilities Weighted by A1C Category |
|---|---|---|---|
| <5.7%–5.9% | 79.8% | 3.1% | 2.5% |
| 6.0%–6.4% | 20.2% | 6.6% | 1.3% |

| A1C Category | Distribution of Risk Group Across A1C Categories | Weighted Average Annual Probability | Annual Probabilities Weighted by A1C Category |
|---|---|---|---|
| | | | Summing of Weighted Probabilities: 3.8% |

Note: The distribution of the "Persons with prediabetes" risk group across A1C categories is based on a survey-weighted estimate from NHANES (2011–2014).

### *2.4.2* Persons With Prediabetes and Other Persons at Risk for Type 2 Diabetes

This is the largest group, as it includes all "Persons with prediabetes" and "other persons at risk for type 2 diabetes." This group is generally about 1.5 times larger than the risk group of people with prediabetes. "Other persons at risk for type 2 diabetes" were defined using criteria from the CDC Prediabetes Screening Test (CDC, 2015a). A score of 9 or higher on the Prediabetes Screening Test determines whether a person is at risk for diabetes. Because this group includes a broader range of people at risk for diabetes, the default annual probability of diabetes is slightly lower at 3.6%. This probability was calculated as a weighted average using (1) the distribution of the risk group (persons with prediabetes and other persons at risk for diabetes) across A1C categories as the weight (see Table 13, column 2) and (2) the weighted average annual probability for persons with an A1C of 5.5%–5.9% (0.0305) and 6.0%–6.4% (0.0660) (see Table 10) for the annual probabilities of diabetes that are being weighted.

**Table 13. Persons With Prediabetes and Other Persons at Risk for Type 2 Diabetes: Calculation of a Weighted Average Annual Probability of Diabetes by A1C Category**

| A1C Category | Distribution of Risk Group Across A1C Categories | Weighted Average Annual Probability | Annual Probabilities Weighted by A1C Category |
|---|---|---|---|
| <5.7%–5.9% | 85.7% | 3.1% | 2.7% |
| 6.0%–6.4% | 14.3% | 6.6% | 0.9% |
| | | | Summing of Weighted Probabilities: 3.6% |

Note: The distribution of the "Persons with prediabetes and other persons at risk for type 2 diabetes" group across A1C categories is based on a survey-weighted estimate from NHANES (2011–2014).

### *2.4.3* People With High-Risk Prediabetes

This group is a subset of the group with prediabetes. This group is the smallest (about 34% of the prediabetes group), but it represents those with the highest risk of progressing to diabetes. "Persons with high-risk prediabetes" are defined as persons with an A1C between

6.0% and 6.4% or an FPG between 110 and 125 mg/dL. This risk group has the highest annual probability of diabetes with a default of 6.2%.

This annual probability was determined by taking a weighted average of two annual probabilities. In NHANES (2011–2014), we found that about 20% of persons with prediabetes would qualify as having "high-risk prediabetes" under the A1C criteria alone (6.0%–6.4%). We assumed that this group had an annual probability of diabetes equal to 6.6% (see Table 10). When we added in the FPG criteria (110–125 mg/dL), the predicted prevalence of persons with high-risk prediabetes among "Persons with prediabetes" increased from 20% to 34%. We assumed that the incremental persons qualifying as high-risk under the FPG criteria had a somewhat lower annual probability of diabetes based on the annual probability reported in Nichols et al. (2010) (5.6%) for persons with an FPG 110–125 mg/dL. The persons qualifying under the A1C criteria (with an associated annual probability of 6.6%) and the incremental persons qualifying under the FPG criteria (with an associated probability of 5.6%) were combined in a weighted average of roughly 60% and 40%, respectively. These weights are based on the proportion diagnosed with A1C criteria and the incremental proportion diagnosed with FPG criteria. The resulting annual probability for people with high-risk prediabetes was 6.2%.

## 2.5 Additional Toolkit Inputs

After selecting your population characteristics and risk group, you can customize additional inputs by clicking on the "CUSTOMIZE FURTHER" button just above the "GET RESULTS" button (Figure 1). For these additional inputs, we recommend beginning with "Screening" in the first row and ending with "Medical Costs" in the last row (your choice of screening options will affect subsequent input choice).

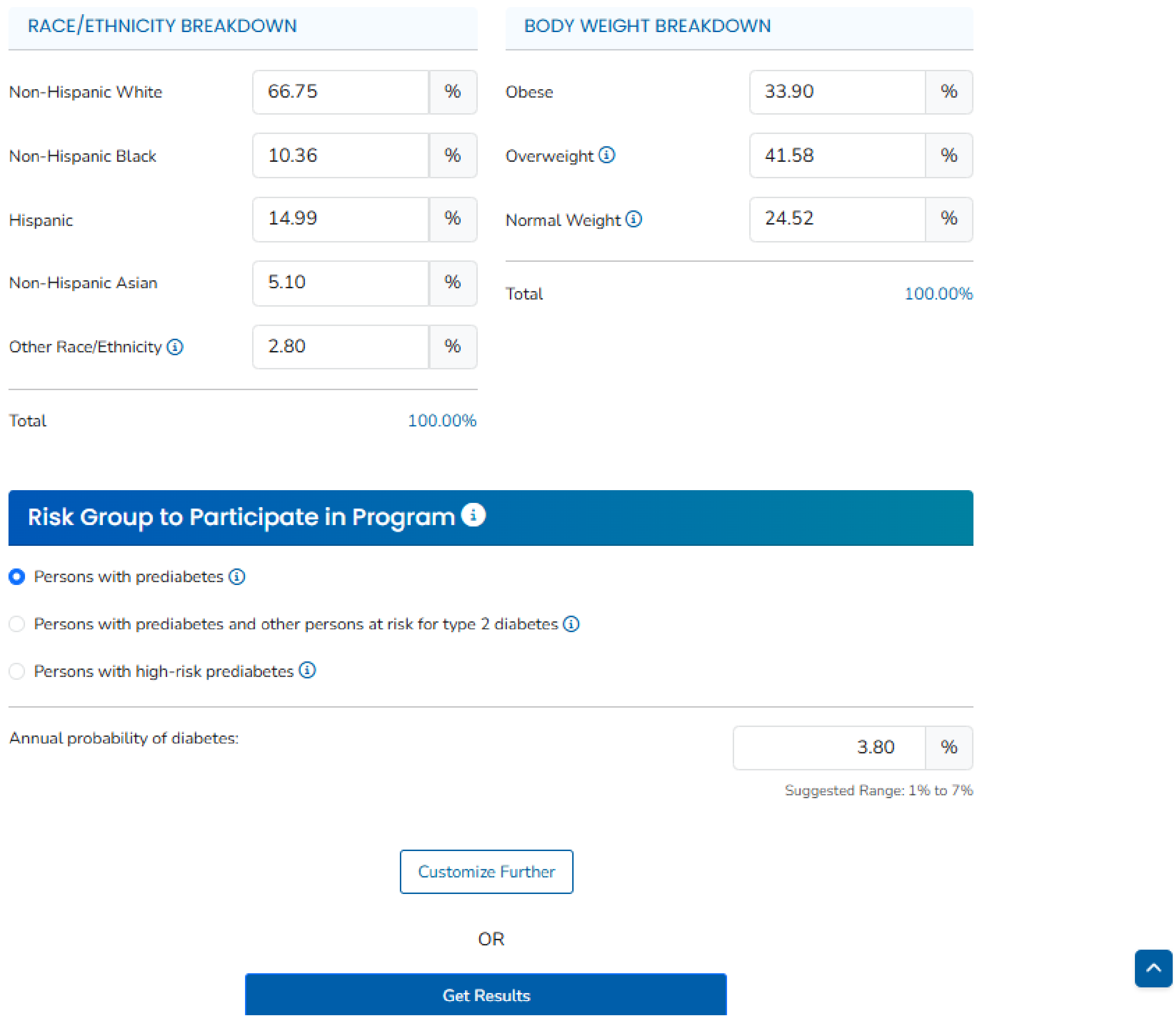
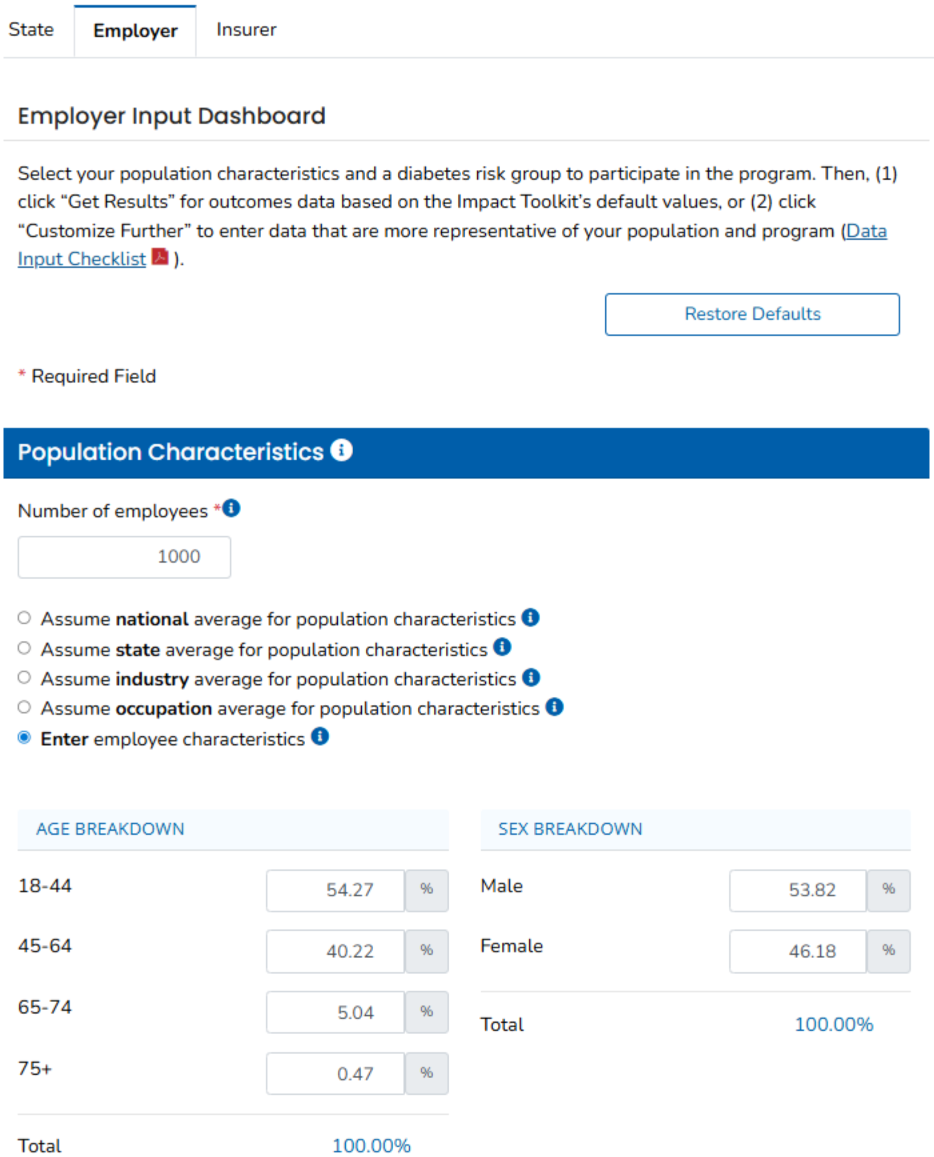

RACE/ETHNICITY BREAKDOWN
Non-Hispanic White 66.75 %
Non-Hispanic Black 10.36 %
Hispanic 14.99 %
Non-Hispanic Asian 5.10 %
Other Race/Ethnicity 2.80 %
Total 100.00%
BODY WEIGHT BREAKDOWN
Obese 33.90 %
Overweight 41.58 %
Normal Weight 24.52 %
Total 100.00%
Risk Group to Participate in Program
Persons with prediabetes
Persons with prediabetes and other persons at risk for type 2 diabetes
Persons with high-risk prediabetes
Annual probability of diabetes:
3.80 %
Suggested Range: 1% to 7%
Customize Further
OR
Get Results

**Figure 1. Employer Input Dashboard**




Although everyone in your population can be recruited and screened for the National LCP, only a minority of this target population will be eligible and willing to participate in the program. If they do participate, they may receive weight loss, diabetes risk reduction, and medical cost reduction benefits associated with the program. In Sections 2.5.1 through 2.5.7, we describe all assumptions related to conducting the National LCP in your population. In Section 3, we describe the benefits realized by conducting this program, as reported in the Output Dashboard.

### *2.5.1* Screening

In the screening section, you can choose if you would like to screen potential participants for prediabetes if they have not already been screened. The default setting for the toolkit assumes that 46% of your population has undergone screening recently (see Section 2.5.2) and knows their prediabetes status (although this assumption can be altered in the "Program Enrollment and Participation" section) (see Section 2.5.2). If you choose to conduct screening for unscreened people in your population, then screening costs will be incurred (see Section 2.5.5).

Screening costs are shown in the screening cost calculation box in the Program Costs section (the box will appear in that section if you have chosen to conduct a screening program). This box calculates the average screening cost per person as the product of the assumed screening cost ($15 in 2023 U.S. dollars in the default setting) and the average number of people screened per case detected (two in the default setting). This calculation allows us to account for the costs of negative screenings in overall program costs. For further details on program cost calculations, see Section 2.5.5 on program costs. To assume a different number of people screened for the average screening cost calculation, edit the number in the box for "Average number of people screened for each case of prediabetes detected." An increase in this number would reflect an unscreened population with a low prevalence of prediabetes, while a decrease would reflect an unscreened population with a high prevalence of diabetes. If you are not sure about the underlying prevalence in your unscreened population, then we recommend using the default setting of two people screened per case detected. This reflects the prevalence of prediabetes of about 50% among unscreened people who agree to participate in a screening program.

### *2.5.2* Program Enrollment and Participation

Here you can enter the percentage of eligible participants that have already been screened for prediabetes. The default setting is 46%, which is based on the percentage of people at risk for diabetes who have been screened in the past 3 years (Bullard et al., 2015; Kiefer et al., 2015). Persons at risk for diabetes include older adults and those who are physically inactive, have a family history of diabetes, have high blood pressure, and have other risk factors per the American Diabetes Association (ADA, 2016) and the U.S. Preventive Services Task Force (Calange et al., 2008) criteria for screening for type 2 diabetes. Other analyses have shown that only about 11% of people with prediabetes in 2010 were screened and aware of their disease status (CDC, 2013). This value of 11% can be entered into as an alternative to the default value of 46%.

If you have chosen to conduct additional screening for your program, then you can also input the "percentage of eligible, previously unscreened persons receiving screening" (the entry field for this input will only be shown if you have chosen to conduct screening in the screening section). The default value is 100%, which assumes that all persons with a BMI ≥ 24 who have not been screened will receive screening. You can adjust this value downward as appropriate for your population.

Next, you enter your assumed participation rate. The default setting for the participation rate is 35%, which is based on the participation rate in a demonstration of the National LCP with large employers (R. Li, R. Ackermann, personal communication, June 22, 2015). The participation rate might be higher or lower for your population based on the incentives offered for participating or the perceived benefits of participation.

In the final entry field shown in this section, the program enrollment and participation inputs are used to determine the total percentage of participation among eligible adults. For example, if 46% of eligible adults have previously been screened, no additional screening occurs (the default value), and the participation rate is 35%, then the total percentage of eligible adults participating will be 16% (46% * 35% = 16%). However, in a scenario where a screening program is conducted to identify additional eligible persons, the calculation is somewhat more complex (Equation 1).

**Equation 1. Percentage of Screened Population Who Participate in the Intervention**

| | | |
|---|---|---|
| Percentage of screened population who participate in the intervention | = | % of the population previously screened for prediabetes * % of screened persons participating in intervention + [(100% − % of population previously screened for prediabetes) * % of previously unscreened persons receiving screening * % of screened persons participating in intervention] |

### *2.5.3* Intervention Weight Loss and Regain Schedule

The Diabetes Prevention Program Study demonstrated that participants in intensive lifestyle intervention lost about 7.2% of their weight in the first year of the program (DPP, 2002; Hamman et al., 2002). Real-world adaptations of the DPP trial, such as the National LCP, resulted in a smaller weight loss effect—4.4% on average at the end of the first year of follow-up (R. Li, personal communication, June 24, 2015). This estimate is based on results from the National LCP, represents the first-year weight loss for program participants, and is supported by other studies.[1] A participant was defined as someone attending at least 4 of the 16 program sessions. Attending at least 9 sessions was associated with a slightly higher weight loss (5.1%) (R. Li, personal communication, June 24, 2015).

The DPP trial and studies of real-world interventions with additional years of follow-up show that the initial weight lost is regained in future years. Based on data from these studies, we assume that about 50% of the weight lost is regained in year 2, and another 20% is regained in year 3 (Barte et al., 2010). In years 4 through 10, we assume that all the weight lost has been regained (0% weight loss relative to baseline weight). These weight loss and regain assumptions are based on the group-based National LCP lifestyle change

*[1] In 2012, Ali et al. (2012) reported a 4.1% weight loss at 12 months' follow-up for translational programs conducted in the United States and modeled on the Diabetes Prevention Program (DPP) trial's lifestyle intervention.*

program or similar programs with a maximum of 16 sessions over 6 months (no maintenance program after 6 months).

The intervention weight loss and regain schedule in the toolkit shows the average percentage difference (relative to baseline body weight) for 10 years of follow-up. Data from the DPP and Diabetes Prevention Program Outcomes Study (DPPOS) trial showed that weight loss was the greatest after 1 year (7.2%; Hamman et al., 2002) and was associated with a 58% diabetes risk reduction over the 3-year study period. Based on these DPP trial data and the associated diabetes risk reductions observed in the trial, we estimated the average diabetes risk reduction from the National LCP and similar programs by discounting the DPP trial risk reduction according to Equation 2.

**Equation 2. Discount Factor for Translational DPP Program Effects for Program Participants: Weight Loss**

(NDPP weight loss) / (DPP weight loss) = (4.4%) / (7.2%) = 61.1%

Note: This discount factor is automatically recalculated in the toolkit if the user adjusts the weight-loss effect as described above.

Thus, the National LCP lifestyle change program is assumed to have 61.1% of the effect on diabetes risk that was observed in the DPP trial. This translates to a 35.4% risk reduction in the first year of participating in the National LCP. Table 14 shows the default assumptions for weight loss and the calculated diabetes risk reduction (using Equation 2) associated with each year’s weight loss estimate. The diabetes risk reduction effects in each year are automatically updated by Equation 2 when the weight loss and regained effects are changed by the user. Although these default settings are based on the best available data for the average National LCP participant, your population and program may differ from the average. You can edit this weight loss and regain assumptions according to the expectations for your program.

**Table 14. Default Intervention Weight Loss and Weight Regain Schedule**

| Year | Intervention Weight Loss (from baseline weight) | Assumed Diabetes Incidence Risk Reduction |
|---|---|---|
| 1 | 4.4% | 35.4% |
| 2 | 2.4% | 19.3% |
| 3 | 1.9% | 15.3% |
| 4 | 0.0% | 0.0% |
| 5 | 0.0% | 0.0% |
| 6 | 0.0% | 0.0% |
| 7 | 0.0% | 0.0% |
| 8 | 0.0% | 0.0% |
| 9 | 0.0% | 0.0% |
| 10 | 0.0% | 0.0% |

Note: Year 1 is the year in which the intervention is delivered to participants. All weight loss percentages are based on participants' baseline weight (before the intervention). In the default setting, weight is gradually regained with a full return to baseline weight in year 4. This regain trend is based on evidence from a review of group-based lifestyle interventions. Weight loss and regain are associated with a reduced incidence of diabetes as described in Section 2.5.3.

### *2.5.4* Program Budget

In the default setting, the toolkit assumes that a state, employer, or insurer will offer the program to all eligible people who want to participate. However, if there is a limited budget for implementing the National LCP or similar program, then you can check the box in this section to set a maximum budget. Once you have checked this box, an additional entry field will appear for you to enter your maximum budget. The budget you enter will limit the number of program participants based on the size of your eligible population, your program costs, and your screening costs (if you choose to screen previously unscreened people). Equation 3 demonstrates this calculation.

**Equation 3. Determining the Proportion Participating in the Program When There is a Limited Budget**

Proportion participating in intervention = Minimum [Proportion completing screening * Percentage of screened persons participating in intervention $\left(\frac{Total\ Program\ Budget}{Average\ program\ cost\ per\ person\ with\ screening}\right)$]

### *2.5.5* Program Costs

Here you can enter the per-person costs of your program. The default cost of $499 (2023 U.S. dollars) is the per-participant cost of the group-based National LCP or similar program without screening costs included (Li et al., 2015). We updated this cost estimate from 2013

U.S. dollars to 2023 U.S. dollars using the personal consumption expenditures price index (PCEPI) (available in the Bureau of Economic Analysis interactive data application). All costs in this section should be calculated and entered per participant. If you are conducting a screening program (i.e., selected "Screen persons for prediabetes if they have not been previously screened" in the screening section), then this section will also show an "AVERAGE SCREENING COST CALCULATION" box. Here, we assume that screening costs are $15 (inflated to 2023 U.S. dollars using PCEPI) in the default setting. Either the FPG test ($8.64) or the hemoglobin A1C test ($21.37) can be used to diagnose prediabetes, so we assume the average cost ($15) of these two tests according to the 2015 Medicare Laboratory Fee Schedule (CMS, 2016a).

If you plan to use one of these tests or believe that your screening costs differ from these estimates, then the screening test costs can be modified in this section. If you plan to use the CDC Prediabetes Screening Test (CDC, 2015a) (a questionnaire that can also be used to determine eligibility for the National LCP) instead of a blood test, then your costs may be lower than either of the blood test costs (e.g., the cost of printing and distributing self-administered questionnaires). We also assume that there are "Other screening costs," which include the cost of a brief follow-up visit to discuss the patient's screening test results and receive a referral to a program such as the National LCP. The default cost of $24 (in 2023 U.S. dollars) for "Other screening costs" only includes the cost a brief office visit and not the costs of recruitment for screening. "Other screening costs" are based on the 2015 Medicare Physician Fee Schedule (CMS, 2016b) associated with an evaluation and management visit of low complexity (HCPCS code 99211) for an established patient (about 5 minutes of face-to-face time at the cost of $20.02 in 2013 U.S. dollars). This cost can be adjusted to reflect a more intensive screening program with recruitment costs. Recruitment costs for the National LCP are not widely reported in the literature yet; however, a couple of sources suggest that recruitment costs are low,[2] ranging from about $1.20 to $16.76 (inflated to 2023 U.S. dollars).

As noted in Section 2.5.1, we also account for the costs of negative screenings by assuming that you must screen two people to detect one case of prediabetes on average. The number of people screened per case detected (which can be modified in the Screening Section) is used in this section to calculate the screening cost per participant (Equation 4).

---

[2] *Recruitment costs vary widely across studies depending on the intensity of the recruitment strategy. Recruitment costs at an employee worksite program with 1,800 employees (just 107 were found to be eligible based on blood-test confirmed prediabetes criteria) were $1,500 ($1,094 for printing/mailing and $406 for tent cards, flyers, and posters) (Taradesh et al., 2015). Thus, recruitment costs were about $14 (or $16.76 inflated to 2023 U.S. dollars) per eligible person recruited. Krukowski et al. (2013) reported recruitment costs of $1.13 (or $1.35 in 2023 U.S. dollars) per participant. This is just the cost of flyers left at senior centers to recruit participants into a lifestyle intervention. Taradesh et al.'s estimate of $14 (or $16.76 inflated to 2023 U.S. dollars) for recruiting costs is more consistent with data reported from the YMCA demonstrations (personal communication, Andrew Lanza, CDC).*

**Equation 4. Screening Cost per Participant (if conducting a screening program)**

| | | |
|---|---|---|
| Average screening cost per person detected | = | (Screening cost per person + Other screening costs per person) * Number of people screened per case detected |

Next, the average screening cost per participant is added to the base program cost ($499 in the default setting) to calculate the overall program cost per person. This calculation is shown in Equation 5 and is used as the overall program cost in calculations of net costs shown in the Output Dashboard.

**Equation 5.Average rogram Cost (With Screening)**

Average program cost per person with screening = Program cost per person +

$$\left[\frac{\text{Average screening cost per person detected} * \left(\begin{array}{l}(100\% - \%\text{ of pop previously screened for prediabetes}) * \\ \%\text{ of previously unscreened persons receiving screening}\end{array}\right)}{\%\text{ of screened persons participating in intervention}}\right]$$

## *2.5.6* Medical Costs

In the year that a person is diagnosed with diabetes, he or she will have substantial medical costs associated with diagnosing and treating their diabetes. In each subsequent year, the person will continue to have medical costs for the treatment of his or her disease, although not as great as the initial year of diagnosis. These are sometimes called diabetes-attributable medical costs, and they are defined as the excess medical costs for a person with diabetes compared with a similar person without diabetes.

The default values that are provided in the toolkit reflect the average excess medical costs for persons with diabetes based on a CDC analysis of longitudinal medical claims data from MarketScan (2001–2013) (Shrestha et al., 2016). Based on these data and a review of other cost analyses,[3] we assumed default values of $7,690 for the first year of diagnosis and $4,668 for the years after diagnosis (2023 U.S. dollars). The first year's costs are approximately 1.65 times greater than subsequent years' costs. If you believe that excess medical costs associated with diabetes differ in your population, we suggest maintaining this approximate relationship between the first year's costs and the subsequent years' costs. We also suggest staying within the suggested range of $3,950 to $11,850 for first year's costs and $2,395 to $7,185 for subsequent years' costs. Using excess medical cost estimates outside of these ranges may lead to results with low credibility.

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[3] *Studies that use cross-sectional cost data may underestimate costs in the year of diabetes onset. Previous analyses using the National Health Interview Survey and the Medical Expenditure Panel Survey linked data file have noted this limitation as well (Trogdon et al., 2008). However, in studies that use longitudinal data to follow individuals before and after the onset of diabetes, authors find a spike in medical costs in the year of onset (Nichols et al., 2000; Shrestha et al., 2016).*

We used cost equations from Zhuo et al. (2014) to account for increasing age and duration of diabetes (for persons that develop the disease) in future years. Table 15 shows how the excess medical costs increase with increasing age and duration of diabetes (for people developing diabetes). On average, the excess medical cost associated with having diabetes was about $7,690 in the year of diagnosis and $4,668 per year in the years after diagnosis. When the user enters a different value in the Input Dashboard, a cost multiplier is calculated based on these default excess costs of diabetes. Equation 6 shows how the cost multiplier is calculated for the year of diagnosis and Equation 7 shows how the cost multiplier is calculated for the years after diagnosis. All the values in Table 15 (year of diagnosis) are increased by the multiplier calculated in Equation 6, while all the values in columns 2 through 10 are increased or decreased by the multiplier calculated in Equation 7.

**Table 15. Estimated Diabetes Attributable Medical Costs by Year and Duration of Diabetes**

| Year of Follow-Up | Duration of Diabetes (years) | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | <1 | ≥1, <2 | ≥2, <3 | ≥3, <4 | ≥4, <5 | ≥5, <6 | ≥6, <7 | ≥7, <8 | ≥8, <9 | ≥9, <10 |
| 1 | 7690 | | | | | | | | | |
| 2 | 7690 | 3312 | | | | | | | | |
| 3 | 7690 | 3166 | 3701 | | | | | | | |
| 4 | 7690 | 3031 | 3566 | 4108 | | | | | | |
| 5 | 7690 | 2744 | 3279 | 3822 | 4369 | | | | | |
| 6 | 7690 | 2610 | 3146 | 3689 | 4237 | 4788 | | | | |
| 7 | 7690 | 2457 | 2992 | 3535 | 4084 | 4636 | 5190 | | | |
| 8 | 7690 | 2301 | 2836 | 3379 | 3928 | 4480 | 5035 | 5590 | | |
| 9 | 7690 | 2160 | 2695 | 3237 | 3786 | 4339 | 4895 | 5451 | 6005 | |
| 10 | 7690 | 2001 | 2535 | 3077 | 3626 | 4179 | 4735 | 5292 | 5847 | 6998 |

Note: All participants begin as people without diabetes. Cells with a longer duration of diabetes than a year of follow-up are left blank because a participant in Year 2 cannot have diabetes for more than 2 years if they did not have diabetes at year 0. All costs are stated in 2023 U.S. dollars.

**Equation 6. Calculating the Cost Multiplier for the Year of Diagnosis**

$$\text{Year of diagnosis cost multiplier} = \frac{\textit{Annual diabetes attributable cost in the year of diagnosis cost}}{\$7{,}690}$$

**Equation 7. Calculating the Cost Multiplier for the Years after the Diagnosis**

$$\text{Years after diagnosis cost multiplier} = \frac{\textit{Annual diabetes attributable cost in the year after diagnosis cost}}{\$4{,}668}$$

In the toolkit, all costs incurred in the future are discounted back to the present using a discount rate assumed in the Medical Cost section of the Input Dashboard. The discount rate input box allows us to account for the fact that the money we have today has more value than the money received in the future. This accounts for future inflation, lost investment opportunity, and risk. Applying this discount allows us to more accurately compare the money that will be spent in the future with the money that is spent today. An annual discount rate of 1.0% to 5.0% is common. Our default value is 3.0%.

### *2.5.7* Productivity Costs (Employer Module Only)

In the Employer module only, we include productivity costs associated with diabetes. We limit productivity costs to the costs of days of work missed due to diabetes and the value of these days. The value of the days of work missed (per person) is calculated by multiplying the "Days of work missed per year due to diabetes" and the "Daily earnings for persons with diabetes." Days of work missed per year due to diabetes are the excess days of work missed by someone with diabetes compared with a similar person without diabetes (e.g., similar age, sex, comorbidities).

We used NHIS to estimate the number of days of work missed attributable to diabetes. Pooling data from 2009 through 2013 NHIS, we estimated days of work missed at the national level.[4] Our final estimation used a two-part model with a logit model for the first part and a Generalized linear model for the second part. We controlled for the following comorbidities: arthritis, asthma, cancer, depression, chronic bronchitis, back problems, and pregnancy. We also included the following sociodemographic controls: age, age squared, race/ethnicity, education, family income, health insurance, and occupation.

We found that, on average, a person with diabetes will miss 3.3 more days of work each year as compared to a similar person without diabetes.[5] The default daily earnings of $330

*[4] In NHIS, people with diabetes are identified by the question "Have you ever been told that you have diabetes?" The work-loss analysis was restricted to people employed at any point during the year. Number of workdays lost was defined using the following NHIS question: "During the past 12 months, about how many days did you miss work at a job or business because of illness or injury (do not include maternity leave)?" To estimate workdays lost due to diabetes, we tested four models for best fit: one-part negative binomial model, two-part truncated negative binomial model with a logit, two-part generalized linear model with a logit, and a zero-inflated negative binomial model. Based on a comparison of the model residuals, the Akaike information criterion (AIC), and the Bayesian information criterion (BIC), our final estimation used a two-part model with a logit model for the first part and a GLM for the second part.*

*[5] This estimate of 3.3 work-loss days is the weighted average of the estimated work loss associated with diabetes for 45- to 64-year-old males (53.8% in the employed population, NHANES 2011–2014) and females (46.2% in the employed population, NHANES 2011–2014). We selected the 45–64 age group because the mean age of people with prediabetes is about 52.*

was calculated as a weighted average of daily earnings for males and females aged 45 to 64.[6] This value can be edited to reflect the average earnings for your employee population.

After filling in all the fields discussed in Sections 2.1 through 2.5, click "GET RESULTS" to view your customized results in the Output Dashboard. See Section 3 for information about calculations made in the Output Dashboard and how to interpret results.

# 3. OUTPUT DASHBOARD

The results in the Output Dashboard are unique to your data inputs. They predict the health and economic outcomes for your program participants because of implementing the National LCP or similar program.

## 3.1 Projected Participants

Figure 2 demonstrates how the projected number of participants is calculated from the total population. The total adult population being considered for the National LCP is shown in the top bar in the figure. This is determined by the total adult population in your state (State module), the number of employees at your company (Employer module), or the number of insured adults (Insurer module). In the second bar from the top, a subset of the total population is projected to be eligible for the intervention based on (1) the assumed population characteristics (Sections 2.1–2.3), and (2) the risk group selected in the Input Dashboard (Section 2.4). Next, some or all (depending on your screening inputs; see Section 2.5.1 and 2.5.2) of the eligible people have been previously or newly screened, confirming their eligibility for the intervention (shown in the third bar from the top). Among the eligible screened people, some or all (depending on your participation inputs; see Section 2.5.2) will participate in the intervention. The predicted number of participants is shown in the bottom bar of this figure. This number is calculated by multiplying the number of eligible people in second bar by the "Percentage of screened population who participate in the intervention" calculated in Equation 1 in Section 2.5.2.

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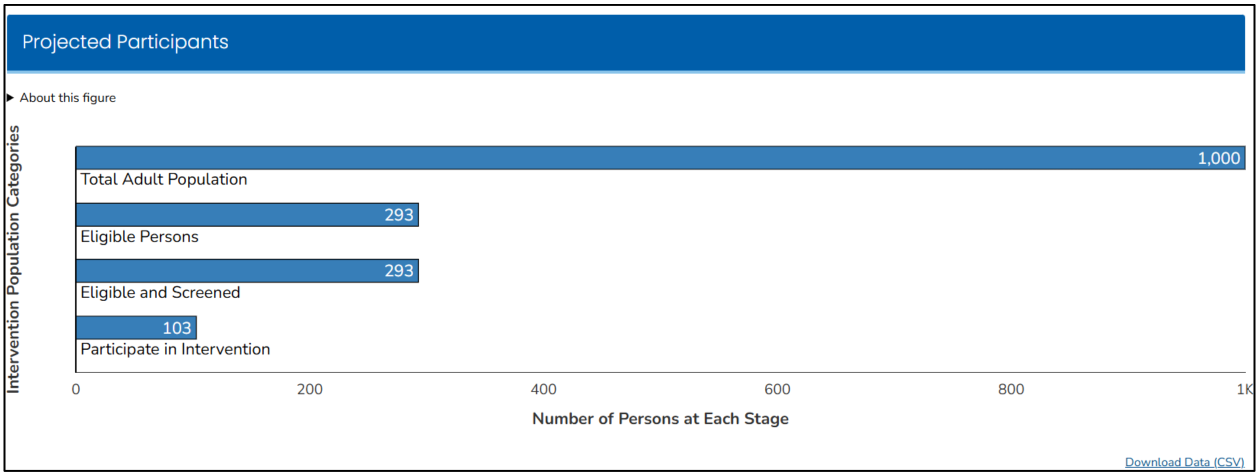
[6] *This estimate of $330 in daily earnings is a weighted average of the estimated daily earnings for 45- to 64-year-old males (53.8% in the employed population, NHANES 2011–2014) and females (46.2% in the employed population, NHANES 2011–2014). We selected the 45–64 age group because the mean age of people with prediabetes is about 52. To estimate the daily earnings, we used the Current Population Survey's (CPS) 2014 annual wage estimates by 5-year age groups, aggregated these to the 45–64 age group using 2014 population counts from the U.S. Census, and deflated to wages to 2013 U.S. dollars. We calculated daily wage as the annual wage divided by 250 workdays per year.*

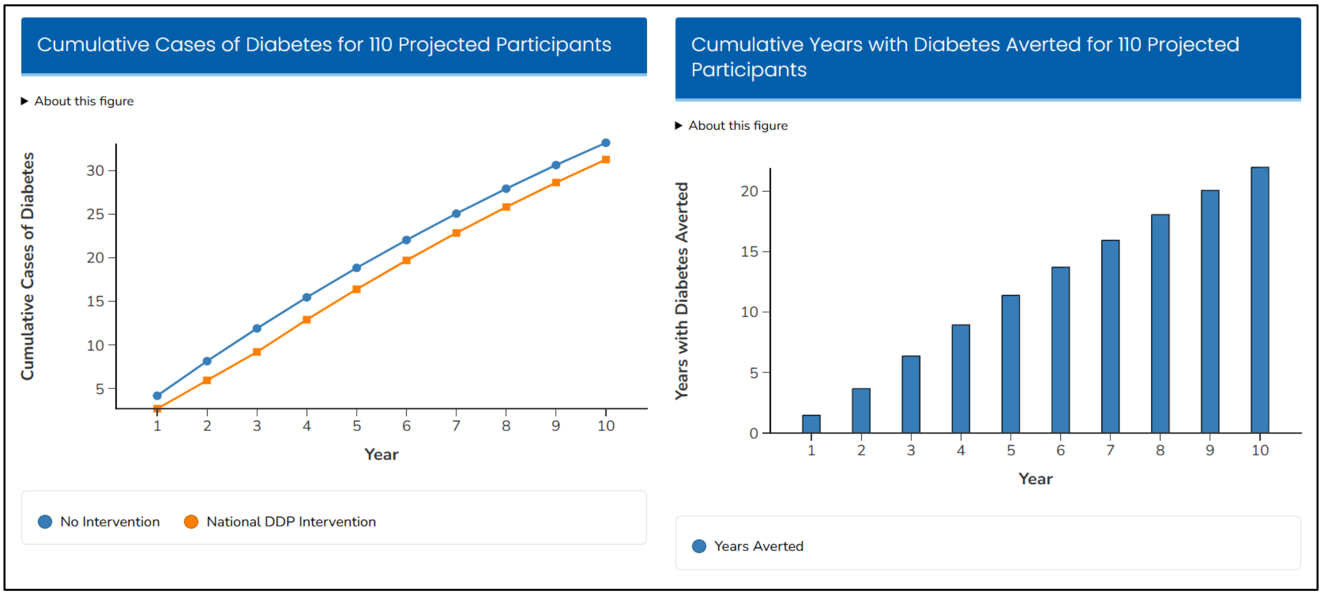
**Figure 2. Projected Participants**




## 3.2 Cumulative Projected Cases of Diabetes

Figure 3 demonstrates the effect of the National LCP or similar programs on new cases of diabetes. In the chart on the left in Figure 3, the cumulative number of diabetes cases with and without the National LCP intervention is shown for your population of participants. The blue line estimates the number of new diabetes cases without the National LCP. The orange line represents the number of new diabetes cases with the National LCP. The difference between the two lines represents the cases of diabetes averted at a given point in time. In the chart on the right in Figure 3, the cumulative years with diabetes averted are shown for your population of participants. The cumulative years with diabetes averted (by the National LCP or similar programs) is the cumulative calculation of the cases averted in each year.

**Figure 3. Projected Cases of Diabetes and Years With Diabetes Averted by Participating in the National LCP or Similar Programs**




The projected cases of diabetes were determined using a simplified Markov model and two key inputs: (1) the annual probability of diabetes (see Sections 2.4.1 through 2.4.3), and (2) the weight loss/regain assumptions, which reduce the probability of diabetes (see Section 2.5.3). The simplified Markov model was initially a spreadsheet model that mimics a Markov model with 1-year cycles and three states: No diabetes, Diabetes, and Dead. The model begins with the full sample of program participants (final bar from "Projected Participants" figure). During each annual cycle, a percentage of these participants progresses from prediabetes to diabetes according to the annual probability of diabetes set by the user (e.g., with an annual probability of diabetes of 3.8%, 38 out of 1,000 participants develop diabetes in the first cycle). People developing diabetes are removed from the sample of people without diabetes, and the number of cases in the next cycle is calculated based on this new sample (e.g., the number of cases in the next cycle is calculated based on a sample of 962 participants [1,000 − 38 = 962] without diabetes). The calculations made by the spreadsheet-based Markov model were programmed to calculate cases of diabetes over the 10-year period as well as the other outcomes described in Sections 3.3 through 3.7.

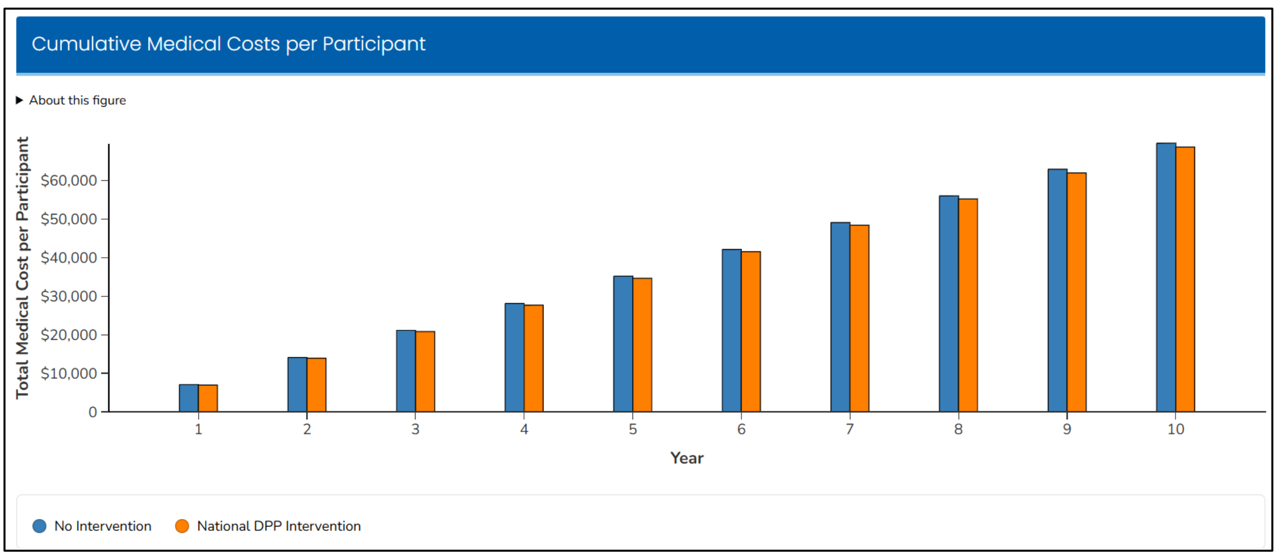
To calculate the blue line (no intervention), the model assumes no weight loss and therefore no reduction in the annual probability of diabetes. To calculate the orange (National LCP intervention) line, the model assumes some weight loss and some reduction in the annual probability of diabetes, leading to a smaller number of cases. In each annual cycle, the annual probability of diabetes is only reduced if there is a weight loss effect assumed for the applicable annual cycle. In the default setting, there are weight loss effects in the first 3 years that translate to diabetes risk reduction effects (see Table 14) in each of the first 3 years. The simplified Markov model also incorporates mortality. See Section 3.7 for details regarding the death rate and relative risk of death for persons with diabetes.

Clicking on the "DATA TABLE" button will open a table with more information. The table shows the number of "Cases Averted" in each year and the "Years with Diabetes Averted." The "Cases Averted" are calculated as the difference between the blue and orange line. The "Years with Diabetes Averted" represents the cumulative number of person-years with diabetes that are averted with intervention. The maximum number of "Cases Averted" in a single year will usually occur in the last year assumed to have some weight loss effect (Year 3 in the default setting).

## 3.3 Cumulative Medical Costs per Participant

Figure 4 shows the difference in cumulative medical costs with and without the National LCP intervention. Results are displayed per participant and can be easily scaled up by multiplying results by your number of participants. The blue bar on the left indicates the cumulative medical costs without the National LCP, and the orange bar on the right indicates the cumulative medical costs with participation in the National LCP. The cumulative medical cost savings is the difference between these amounts. Click on the "DATA TABLE" button to see more detailed information.

**Figure 4. Cumulative Medical Costs per Participant**



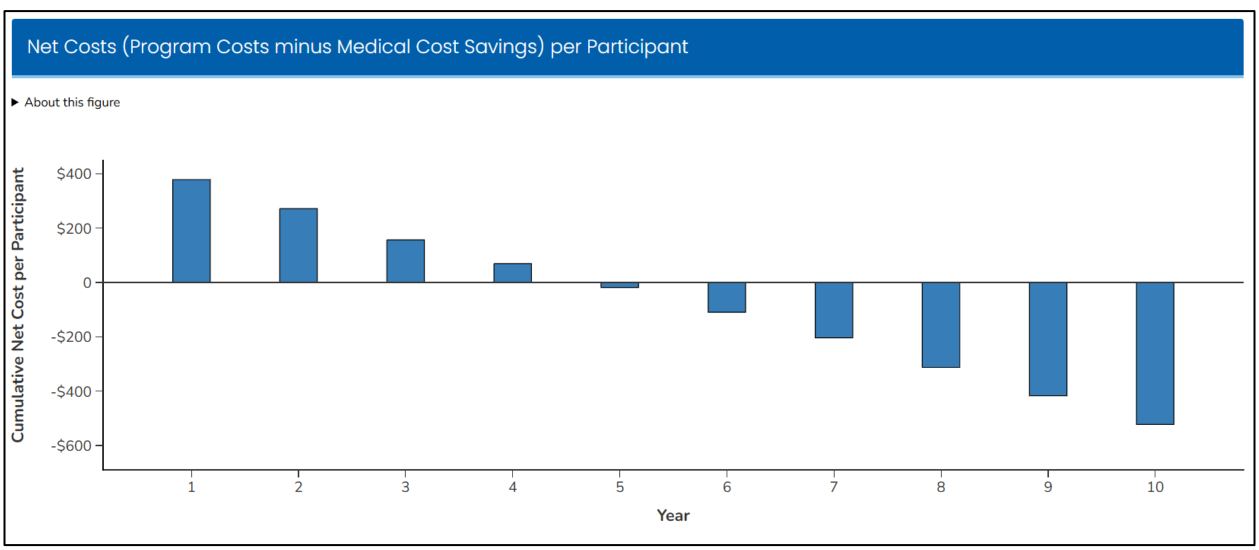

Using the simplified Markov model described in Section 3.2, medical costs are calculated for persons with diabetes and for persons without diabetes in each annual cycle using the diabetes attributable medical costs shown in Table 15. Medical costs for the full sample of participants are summed up and then divided by the number of sample participants to get the medical costs per participant. Medical costs per participant are slightly lower in the orange bars (National LCP intervention) because fewer people progress to diabetes when participating in the National LCP and thus do not incur the excess costs associated with having diabetes. We assume that diabetes onset occurs at the beginning of the period and death occurs at the end of the period for our medical cost calculations.

Results in this figure are largely affected by the medical cost assumptions (Section 2.5.6, Table 15, and Equations 6 and 7), the assumed annual probability of developing diabetes for your risk group, and the assumed weight loss effects. Even when the excess medical costs of diabetes are assumed to be large (e.g., $7,690 in the year of diagnosis and $4,668 per year in subsequent years in the default setting), the average difference in medical costs can be small. This is because (1) only a fraction of participants develops diabetes each year (e.g., 3.8% each year in the default setting for persons with prediabetes), and (2) only a fraction of the projected cases of diabetes are averted among participants (this will depend on the weight loss/regain assumptions).

## 3.4 Net Costs (Program Costs Minus Medical and Productivity Cost Savings) per Participant

Figure 5 uses the cumulative medical costs (Section 3.3) and the cumulative program costs (Section 2.5.2) to generate the cumulative net cost per participant. In each annual cycle, the cumulative medical cost savings (and productivity savings in the Employer module) is subtracted from the cumulative program cost to produce the cumulative net cost in that year. Results are displayed per participant and can be easily scaled up by multiplying results by your number of participants.

**Figure 5. Net Costs (Program Costs Minus Medical and Productivity Cost Savings) per Participant**



Note: Productivity cost savings are only included in the Employer module.

In Figure 5, program costs are represented by the “overall program cost” described in Equation 5 (see Section 2.5.5). This overall program cost (per person) includes the base cost of the program (e.g., $499 in the default setting) and the cost of screening. The cost of screening accounts for (1) the basic screening test cost ($15 in the default setting), (2) “other screening costs” ($24 in the default setting), (3) the number of screenings per case detected (two in the default setting), and (4) the number of positive screenings that do not result in a participant (only 35% of eligible, screened persons actually participate in the default setting). See Equation 5 in Section 2.5.5 for the detailed equation that calculated the overall program cost

In general, the cumulative net costs decrease over time, so that by year 10 or sooner there may be negative cumulative net costs, indicating that the program is cost-saving (all calculations account for the time value of money using the discount rate you specify—see the end of Section 2.5.6). Net costs fall because the program cost is only paid once in year 1, whereas medical cost savings because of program participation occur each year. The net cost calculation is most sensitive to your assumptions regarding program cost, weight loss/regain, and medical costs. Click on the “DATA TABLE” button to see more information. It should be noted that net costs only include medical and program costs and do not otherwise reflect the health benefits to participants.

### *3.4.1* Productivity Costs in the Employer Module

In the Employer module, productivity cost savings are calculated in addition to medical cost savings. In the net costs figure (Figure 5), these productivity cost savings are also subtracted from the overall program costs in each period to get the net costs. For each new case of diabetes, several days of work are missed each year due to diabetes (3.3 days in the default setting—see Section 2.5.6). Each day is valued by the average wages assumed for your employee population ($330 per day in the default setting). For example, in the default setting, about $1,089 in productivity costs are incurred each year for everyone who has developed diabetes in that cycle or a previous cycle.

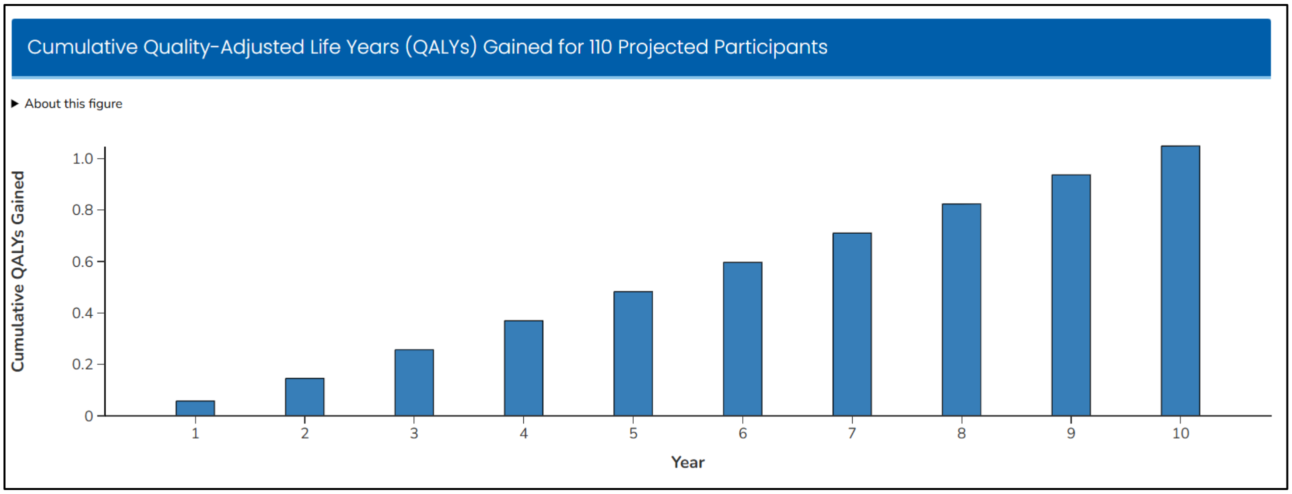
The productivity cost savings from averting cases of diabetes in the intervention scenario

are averaged across all participants. Similar to the medical costs, the productivity costs with the intervention are only slightly lower than the productivity costs without the intervention due to the fact that (1) only a fraction of participants develop diabetes each year (e.g., 3.8% each year in the default setting for persons with prediabetes), and (2) only a fraction of the projected cases of diabetes are averted among participants (this will depend on the weight loss/regain assumptions). The productivity costs with the intervention and without the intervention and the calculated cost savings (all per person) are shown in the data table associated with Figure 5. Click on the "SHOW DATA TABLE" button to see the detailed 10-year data in the toolkit.

## 3.5 Cumulative Quality-Adjusted Life Years (QALYs) Gained

Figure 6 shows the cumulative quality-adjusted life years (QALYs) gained for your population of participants. QALYs are a combined measure of health and time, allowing us to weight years lived by the health-related quality of life in those years. One QALY is equal to 1 year of life with a perfect quality of life.

**Figure 6. ☐Cumulative Quality-Adjusted Life Years (QALYs) Gained**




When a person develops diabetes, we assume that their quality of life is reduced by about 5% on average. The estimate of a 5% reduction in quality of life is based on the quality-of-life decrement associated with progressing from prediabetes to diabetes in the CDC/RTI model of diabetes.[7] This reduction in quality of life is averted or delayed with each case of diabetes that is averted or delayed (due to the National LCP or similar programs). Like the method for calculating medical costs, QALYs are calculated with and without effect of the National LCP using a simplified Markov model. Using the Markov model approach, the cumulative QALYs gained (shown in Figure 6) account for averting the reduction in quality of life associated with diabetes as well as the timing of when cases are averted. For instance, if weight losses are maintained throughout the whole 10-year period, then cases of diabetes will be delayed for a longer amount of time and QALY gains will be greater. If weight losses are quickly regained, then these cases of diabetes are not delayed as long and not as many QALYs will be gained.

[7] *A quality-of-life decrement of 0.04 relative to a baseline utility of 0.84 for persons without diabetes represents about a 5% decrease in quality of life.*

## 3.6 Incremental Cost-Effectiveness Ratios (ICERs)

Figure 7 shows the annual net costs per participant, QALYs gained per participant, incremental cost-effectiveness ratios (ICERs) (net costs divided by QALYs gained), and the cost per case averted (cumulative cases averted or “Years of Diabetes Averted” divided by the net costs).

### Figure 7. Incremental Cost-Effectiveness Ratios (ICERs)

Incremental Cost-Effectiveness Ratios (ICERs)

▶ About this figure

Download Data (CSV)

| Year | Cumulative Net Cost[1] ($) | Cumulative QALYs Gained[2] | Incremental Cost-effectiveness Ratio (ICER)[3] ($/QALY) | Cost per Case Averted ($) |
|---:|---:|---:|---|---|
| 1 | 379 | 0.0005 | 723,893 | 28,112 |
| 2 | 272 | 0.0013 | 205,208 | 13,603 |
| 3 | 157 | 0.0023 | 67,117 | 6,402 |
| 4 | 69 | 0.0034 | 20,575 | 2,961 |
| 5 | -19 | 0.0044 | Cost-saving | Cost-saving |
| 6 | -110 | 0.0054 | Cost-saving | Cost-saving |
| 7 | -203 | 0.0065 | Cost-saving | Cost-saving |
| 8 | -313 | 0.0075 | Cost-saving | Cost-saving |
| 9 | -417 | 0.0085 | Cost-saving | Cost-saving |
| 10 | -522 | 0.0095 | Cost-saving | Cost-saving |

Note: All costs and QALYs are discounted back to year 0. The default discount rate (3%) or user-entered rate is used to discount costs and QALYs.

The net costs are calculated per participant for each year by subtracting the cumulative medical cost savings from the cumulative program costs (see Section 3.4 for calculation details). This information can also be seen in Figure 5. The QALYs gained are calculated per participant in Figure 7 by dividing the cumulative QALYs gained for your population of participants (as seen in Figure 6) by the size of the population of participants.

The ICER is a measure of the cost effectiveness or “return on investment” associated with an intervention. It is calculated as the cumulative net costs divided by the cumulative QALYs gained. A lower ICER is better as it indicates that QALYs are gained from the intervention at a lower cost. A negative ICER indicates that the intervention is associated with QALY gains and reduced costs (i.e., a cost-saving intervention). Negative ICERs are shown in Figure 7 as “cost-saving.”

The Cost per Case Averted is found by dividing the cumulative cases averted (as seen in Figure 3, “Cumulative Projected Cases of Diabetes”) by the cumulative net cost. A negative cost per case averted means that the program is cost saving by that point in time. Negative costs per case averted are shown in Figure 7 as “cost-saving.”

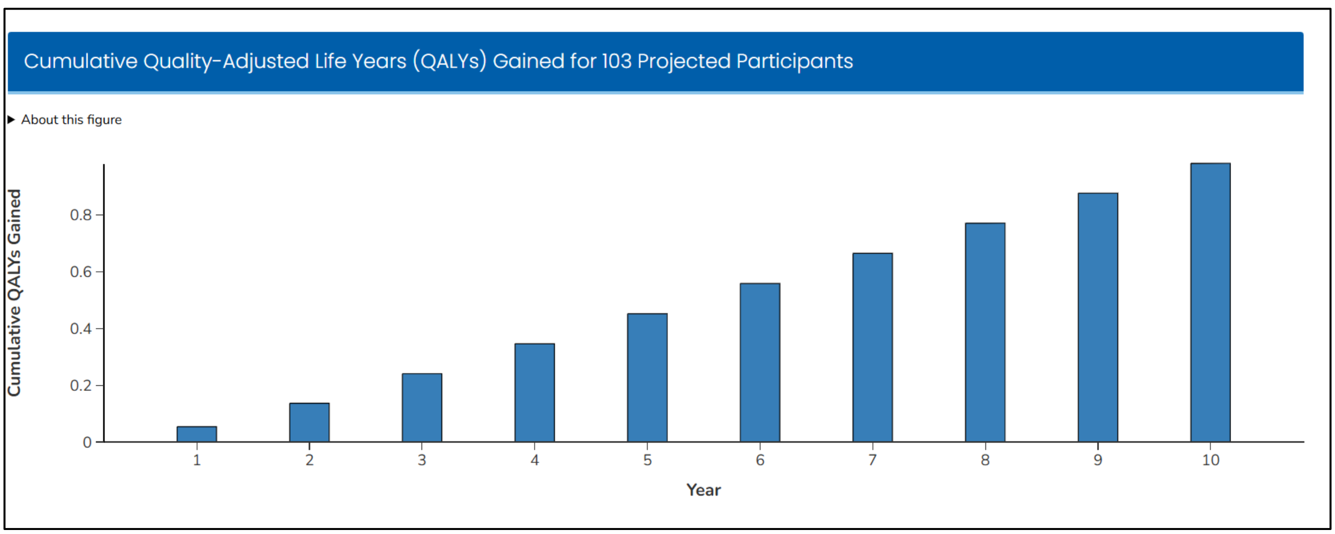
## 3.7 Cumulative Years of Life Gained

Developing diabetes is associated with an increased risk of life-threatening events, such as heart attacks and stroke. We assume that people with diabetes have twice the risk of dying each year compared with people without diabetes on average. Based on an unpublished CDC analysis, we observed a range of 2.0 to 4.0 for the relative risk of death for persons with diabetes (personal communication, Yiling Chen, April 11, 2015). These relative risk estimates varied by age and sex. We chose to use an estimate of 2.0.

When cases of diabetes are averted or delayed (due to the intervention), a small decrease in the number of diabetes-related deaths is achieved. These deaths averted are associated with a gain in the years of life lived during the 10-year period. Like other calculations discussed in Section 3, a simplified Markov model was used to calculate deaths in each annual cycle. A small percentage of people die during each cycle and are removed from the modeling sample based on an assumed mortality rate of 0.45% for persons without diabetes and 0.90% for persons with diabetes. We chose the baseline mortality rate (0.45%) from the 2010 National Vital Statistics Life Tables (Arias, 2014) based the average age (age 52) of people with prediabetes in NHANES (2011–2014).

Figure 8 shows the cumulative years of life gained for your participant population because of participation in the National LCP. These years of life gained do not account for the quality of life with diabetes as in the QALYs gained figure. Click on the "SHOW DATA TABLE" button to see more information.

**Figure 8. Cumulative Years of Life Gained**



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