Diabetes Outcomes-Based Credit Methodology under the Maryland Total Cost of Care Model

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EXECUTIVE SUMMARY

Improving population health is a key goal of the Maryland Total Cost of Care Model, which requires Maryland to moderate the growth of total healthcare costs for Medicare fee-for-service beneficiaries, while improving overall health and quality of care for all Marylanders. As part of the Model, the State is developing a set of proposed outcomes-based credits that can offset Total Cost of Care Model investments. The following documents delineate the State's approach to calculating an outcomes-based credit for diabetes incidence and estimating savings attributable to a reduction in incidence growth. Diabetes is a key priority for the State and a major focus area for the healthcare delivery system; therefore, Maryland has selected diabetes as one of the first outcomes-based credits to develop.

Proposal Contents

OVERVIEW

Total Cost of Care Model Introduction

Improving population health is a key goal of the Maryland Total Cost of Care Model (Maryland Model), which is governed by a contract between the Centers for Medicare and Medicaid Services (CMS) and the State of Maryland. Under the contract, Maryland is expected to progressively transform care delivery across the health care system with the objective of improving health and quality of care. At the same time, the State must meet all-payer revenue limits and confine growth in Part A and Part B Medicare spending to a rate lower than the nation's. The Total Cost of Care Model also gives the State flexibility to tailor initiatives to the Maryland health care context, and encourage providers to drive health care innovation.

Diabetes Outcomes-Based Credit Introduction

As part of Maryland's system-wide transformation, the State is developing methods to estimate savings attributable to population health improvements. The State will then request outcome credits from CMS that will be used to offset Total Cost of Care Model investments in Maryland. Through statewide focus on specific measures, Maryland aims to incentivize statewide investments, alignment, and engagement in both health system transformation and public health interventions to improve population health.

The State proposes calculating the diabetes outcome-based credit using a two-step approach. First, all-payer performance will be determined and evaluated against an appropriate comparison group. Second, we estimate annual Medicare cost reductions associated with a case of incident diabetes. Combining the results of these two steps will allow the State to estimate a potential amount of financial credit from improvement to be applied against Total Cost of Care Model investments.

Data Sources

Performance measurement data sources

The State explored using a variety of data sources to measure diabetes, including claims data, survey data, exam-based interviews, and electronic health records. In selecting a performance measure, the State considered whether potential measures met the following considerations:

- *Measure performance on all-payer basis.* In order to align with the Model's all-payer focus and emphasis on improving the health of the Maryland population, the measure must reflect the diabetes status of the state's entire adult population.
- *Annual estimates.* Yearly data updates are required to calculate the amount of credit applied to the state's annual Total Cost of Care evaluation.
- *Comparator availability.* The measure must rely on data sources that provide estimates of diabetes status for both Maryland residents and a relevant comparison group, for purposes of disentangling the effect of the TCOC model from trends in diabetes status that may affect

Maryland along with similar states.

The only data source meeting these criteria was the Behavioral Risk Factor Surveillance System (BRFSS) (See Table 1). BRFSS, administered by state health departments in cooperation with the federal Centers for Disease Control and Prevention (CDC), is a nationally representative survey that includes questions on self-reported health. The survey is fielded annually, which allows for trending of the data at a population level. From the BRFSS, the State ultimately selected diabetes incidence, defined as the number of persons per year newly diagnosed with diabetes per 1,000 residents. To identify people with incident diabetes, we relied on two BRFSS questions: "Have you ever been told you have diabetes?", and "How old were you when you were told you have diabetes?" Respondents reporting diabetes diagnosis at their current age were considered incident diabetics. Additionally, we randomly selected 50% of respondents with current age one year older than their diagnosis age for inclusion in the population of incident diabetics. The numerator for the incidence rate includes respondents reporting diabetes diagnosis at their current age and 50% of respondents age one year older than diagnosis age. The denominator includes all BRFSS respondents in the specified age group who are not prevalent diabetics. This method has been used previously by the CDC to identify incident cases of diabetes in national survey data[1].

In order to measure all-payer diabetes prevention performance, we could not use Medicare claims data to gauge diabetes incidence. However, for purposes of estimating the potential savings to Medicare for improving diabetes incidence, our methodology analyzed Medicare fee-for-service (FFS) claims paid on behalf of Maryland enrollees for calendar years 2012 2015.

Table 1. Comparisons of example data sources assessed.

Data Source	Measure all payer performance	Geographic level data availability	Annual timely reliable estimates
National Health Interview Study	✓	✗ Unavailable at state level	✓
Maryland Medicare claims	✗ Medicare only	✓	✓
Maryland All Payer Claims	✓	✗ No comparison	✗ Data delay
BRFSS incidence	✓	✓	✓

Performance Measurement

The State contracted with Mathematica Policy Research (MPR) to develop a methodology for evaluating diabetes incidence in Maryland relative to a control group. After assessing the feasibility of a number of methods, such as propensity score matching, MPR recommended a synthetic control approach, which has been used frequently in peer-reviewed literature to estimate the effects of state-level policy interventions. The goal of this approach is to identify a control group in the pre-intervention time period that closely resembles the intervention group. Each control state is weighted to create an aggregate incidence estimate for the control group that matches Maryland's pre-intervention incidence as closely as possible. The effect of the

[1] Barker, L. E., Thompson, T. J., Kirtland, K. A., Boyle, J. P., Geiss, L. S., McCauley, M. M., & Albright, A. L. (2013). Bayesian Small Area Estimates of Diabetes Incidence by United States County, 2009. *Journal of data science : JDS*, *11*(1), 269-280.

intervention may be measured as the difference between Maryland's change in incidence during the intervention period and that of the control group.

For the Maryland analysis, MPR used pre-intervention diabetes trends and demographic factors, including race/ethnicity, gender, and income, in the synthetic control matching process to determine a subset of states and weights to comprise the synthetic Maryland. The states that bear the most weight in the synthetic Maryland include Virginia (32 percent), Connecticut (30 percent), District of Columbia (19 percent), and New Jersey (16 percent). The synthetic control matches Maryland's diabetes incidence trajectory in the pre-intervention period more closely than the national mean, while achieving a much closer match on key demographic characteristics. More details on this approach are presented in the Performance Measurement Supplement.

Cost Model

The State contracted with Actuarial Research Corporation (ARC) to develop a methodology to translate changes in incidence into changes in health system costs. The attached supplement describes ARC's approach to estimating that change for Medicare enrollees. The analysis estimates that each year of incident diabetes avoided in the Medicare population would save the program about $4,100 per year in 2019. Additionally, savings for those who transition to diabetes after a delay related to the intervention are estimated at $775 per year (in 2019 dollars), which is due to reduced duration of the disease (see Table 2 for comparisons with other excess diabetes cost estimates).

Table 2. Comparisons of excess diabetes costs.

Estimate source	Annual costs
ARC Maryland estimate	$4100
CMS Office of the Actuary DPP Certification[2]	$3000
YMCA DPP annual savings[3]	$2650
American Diabetes Association[4,5]	$7800, $9600
Trogdon and Hylands [6]	$4,174

These annual numbers are used to create an aggregate estimate of savings realized during the year in which a Maryland resident would have been diagnosed with diabetes absent the TCOC Model, and also savings accrued in the following four years, when the resident may be diagnosed with diabetes but can be treated at lower cost because they have had the disease for less time. The average life expectancy of U.S. residents aging into Medicare is 19.3 years[7], and it is

[2] CMS Office of the Actuary (Mar 14, 2016). *Certification of Medicare Diabetes Prevention Program* [Memorandum] Washington, DC: Health and Human Services. Retrieved from https://www.cms.gov/Research-statistics-Data-and-Systems/Research/ActuarialStudies/Downloads/Diabetes-Prevention-Certification-2016-03-14.pdf
[3] Ibid.
[4] American Diabetes Association (2013). Economic costs of diabetes in the U.S. in 2012. *Diabetes care*, *36*(4), 1033-46.
[5] American Diabetes Association. (2018). Economic costs of diabetes in the US in 2017. Diabetes care, 41(5), 917-928.
[6] Trogdon, J. G., & Hylands, T. (2008). Nationally representative medical costs of diabetes by time since diagnosis. *Diabetes care*, *31*(12), 2307-2311.
[7] https://www.cdc.gov/nchs/data/nvsr/nvsr67/nvsr67_07-508.pdf

possible that the benefits of delayed diabetes onset would continue to accrue until the end of life. However, we used the narrower five-year cost horizon to account for uncertainty of longer-term estimates. The five-year savings estimate is $14,512, which is shown in Table 3 below. The State assumes each case of averted incidence will remain free of diabetes for 2.25 years, which is the mean onset delay observed in the Diabetes Prevention Program (DPP).[8]

Table 3. Five-Year Saving Estimates

Quarter	Year	Control	Intervention
Q1	2019	$ 1,025	$ -
Q2	2019	$ 1,025	$ -
Q3	2019	$ 1,025	$ -
Q4	2019	$ 1,025	$ -
Q1	2020	$ 1,219	$ -
Q2	2020	$ 1,219	$ -
Q3	2020	$ 1,219	$ -
Q4	2020	$ 1,219	$ -
Q1	2021	$ 1,413	$ -
Q2	2021	$ 1,413	$ 1,025
Q3	2021	$ 1,413	$ 1,025
Q4	2021	$ 1,413	$ 1,025
Q1	2022	$ 1,606	$ 1,025
Q2	2022	$ 1,606	$ 1,219
Q3	2022	$ 1,606	$ 1,219
Q4	2022	$ 1,606	$ 1,219
Q1	2023	$ 1,800	$ 1,219
Q2	2023	$ 1,800	$ 1,413
Q3	2023	$ 1,800	$ 1,413
Q4	2023	$ 1,800	$ 1,413
Total		$ 28,250	$ 13,213
Difference			**$ 15,038**
Mortality/Inflation Adjustment			$ 526
Final cost per case			***$ 14,512***

[8] Estimated from CDC DPP toolkit: https://nccd.cvc.gov/Toolkit/DiabetesImpact/Dashboard

Integrating Cost and Performance Results

Overview

In a given performance year, the difference between Maryland and the synthetic control group will be translated to the number of averted cases of diabetes and then combined with the cost model to calculate the outcomes-based credit.

Steps

1. The change in diabetes incidence from the pre-intervention period in Maryland will be compared to the change in synthetic control group incidence to calculate a difference-in-differences estimate.

2. This estimate will then be applied to the State's adult population aged 45+ to estimate the number of averted diabetes cases. The adult population will be determined based on the most recent five-year American Community Survey.

3. Because the credit accounts for costs on a five-year horizon, the methodology for determining credits in the second and subsequent years must account for the effect of prior year prevented cases that transition to diabetes in a given measurement year, as these cases can mask measurement of newly prevented cases. To accomplish this, the State relies on the predicted distribution of incident cases in each year following the intervention year as the following: 40% of prevented cases from Year 1 will become incident in Year 2, 25% of prevented cases from Year 1 will become incident in Year 3, 15% of prevented cases from Year 1 will become incident in Year 4, and 10% of prevented cases from Year 1 will become incident in Year 5.[9] The following formulas are applied, in which O represents the observed incidence difference, C represents credited incidence difference, and y is the year for which the credit is calculated:

Year 1: $C_y = O_y$

Year 2: $C_y = O_y + (O_{y-1} * .4)$

Year 3: $C_y = O_y + (O_{y-1} * .4) + (O_{y-2} * .25)$

Year 4: $C_y = O_y + (O_{y-1} * .4) + (O_{y-2} * .25) + (O_{y-3} * .15)$

Year 5: $C_y = O_y + (O_{y-1} * .4) + (O_{y-2} * .25) + (O_{y-3} * .15) + (O_{y-4} * .1)$

4. The actuarial cost estimates will then be applied to the estimated number of averted diabetes cases to calculate the outcomes-based credit.

Population Rationale

While the Medicare population is largely age 65 and above, the State believes that if Maryland can reduce or delay diabetes incidence for adults newly enrolling in Medicare, these adults will

[9] Estimated from CDC DPP toolkit: https://nccd.cvc.gov/Toolkit/DiabetesImpact/Dashboard

be healthier and cost less to Medicare. Nationally, adults aged 45 to 64 develop diabetes at a higher rate (diabetes incidence rate = 10.9 per 1000) than any other age group, including seniors (diabetes incidence rate = 9.4 per 1000).[10] Preventing these adults from transitioning to diabetes is crucial to reducing the number of adults in Medicare with complicated diabetes. Age 45 was selected as the lower bound to reflect the American Diabetes Association recommendation for diabetes screening as early as age 45.[11]

Example

In the following example, we assume that in the first year of the intervention, the synthetic control group experiences an increase of 0.5 cases per 10,000 adults, which is the mean annual incidence change among all states. We assume Maryland experiences an incidence decrease of -1.5 cases per 10,000 adults, which is one standard deviation below the mean.

Table 4. Simplified Example Performance for Year 1.

	Diabetes incidence rate per 10,000	
	Maryland	Synthetic Control
Baseline 1	112	111
Year 1	110.5	111.5
Change	-1.5 cases	+0.5 cases

For this simplified example, the estimated incidence difference between Maryland and the synthetic control group is 2 cases per 10,000 adults. This difference is then applied to the Maryland population over age 45 based on the most recent five-year American Community Survey (2,499,824). This results in an estimate of 500 averted cases. A per-case credit of $14,512 yields a one-time outcome-based credit of $7.3 million in 2019.

Application of the formulas over multiple is shown in the following table. Each band of colors represents an intervention year's prevented cases. Following a particular intervention year's prevented cases through subsequent years can be helpful to understand how the model accounts for those prevented cases later developing diabetes. The table also reflects adjustment for surveillance bias, which is discussed in more detail on page 9.

[10] Centers for Disease Control and Prevention. *National Diabetes Statistics Report, 2017*. Atlanta, GA: Centers for Disease Control and Prevention, US Department of Health and Human Services; 2017.
[11] American Diabetes Association. (2014). Standards of medical care in diabetes—2014. *Diabetes care*, *37*, S14-S80.

Table 5. Example adjustment for prior year credit.

	Base Year	Int. Year 1	Int. Year 2	Int. Year 3	Int. Year 4	Int. Year 5
Year of Observed Change	2018	2019	2020	2021	2022	2023
Control Group Incidence Rate (per 10k)	111	111.5	112	112.5	113	113.5
Observed Maryland Incidence Rate	112	110.5	110	109.5	109	108.5
Adjusted observed Maryland Incidence Rate (surveillance bias)	112	110.47	109.97	109.47	108.97	108.47
Observed difference in differences		-2.03	-3.03	-4.03	-5.03	-6.03
Observed difference in incidence in MD (DID * population)		508	758	1,008	1,258	1,508
Add: previously credited cases (Y-1) now developing the disease (assumes 40% will be delayed 1 year)			203	303	403	503
Add: previously credited cases (Y-2) now developing the disease (assumes 25% delayed 2 years)				127	190	252
Add: previously credited cases (Y-3) now developing the disease (assumes 15% delayed 3 years					76	114
Add: previously credited cases (Y-4) now developing the disease (assumes 10% delayed 4 years)						51
Equals: Current year prevented cases		508	961	1,438	1,927	2,428
Credit amount		$7,375,749	$13,953,249	$20,875,267	$27,966,510	$35,233,045
Year in which credit is applied		2020	2021	2022	2023	2024
Savings target (in millions)		156	222	267	300	336

Strengths and Limitations of the Methodology

The State's approach benefits from its reliance on BRFSS data, which are carefully collected and representative of the target population for our analysis. Similarly, the cost estimates rely on Medicare claims, which are a complete and well-characterized collection of data for the relevant population. Synthetic control modeling is a widely used approach to generating estimates of the effect of population-level interventions.

Use of the BRFSS data, however, presents some limitations. Data are self-reported and thus subject to measurement error. Survey design issues limited the number of years available for analysis to five (2013-17), which is fewer than commonly used in synthetic control analysis. The survey item regarding age of diabetes diagnosis was not uniformly administered in 2013, meaning that incident status was missing for some diabetics in that year. Incident cases of diabetes are comparatively rare. This issue, coupled with the BRFSS survey design, which selects a small sample of the population for interviewing, may lead to random variation in state incidence rates.

Additionally, changes in incidence may be obscured by surveillance bias. The interventions, including the Diabetes Prevention Program and the Maryland Primary Care Program, are likely to increase the proportion of Maryland residents screened for and diagnosed with diabetes. Similar changes in the synthetic control states are less likely. Thus, it is possible that the interventions will result in a rise in observed diabetes incidence, even if true incidence decreases in Maryland.

The State has taken several steps to address these limitations. With regard to sample size, the State has submitted an application for access to geographically identifiable data from the National Health Interview Survey, which would allow for pooling BRFSS and NHIS data to enhance the reliability of the incidence estimates. The incidence rates presented here and used to select states for inclusion in the synthetic control group were estimated using an empirical Bayes hierarchical model, a statistical approach that limits the effect of missing data and random error and has been used previously by the CDC to derive estimates of diabetes incidence from sparse data[12]. The State will employ the same model to estimate incidence during the intervention period.

Additionally, the State will address surveillance bias using information in the BRFSS pre-diabetes module, which will allow for measuring and controlling for changes in test prevalence in Maryland. To accomplish this, the State regressed state diabetes incidence against diabetes test prevalence using BRFSS data from 2013-2017. The resulting coefficient (.0003) indicates a change of 1 percent in test prevalence is associated with a rise in incidence of three cases per 10,000. The State will multiply the Maryland test rate calculated from BRFSS data for 2019 and subsequent years of intervention by this coefficient to estimate the excess cases per 10,000 associated with the increase in surveillance. The excess case rate will be subtracted from the estimated Maryland incidence rate per 10,000 in each intervention year. This surveillance-adjusted rate will then be used in the difference-in-differences analysis. The State chose to rely

[12] Barker, LE., TJ. Thompson, KA. Kirtland, J P. Boyle, LS. Geiss, MM. McCauley, and A L. Albright. 2013. "Bayesian Small Area Estimates of Diabetes Incidence by United States County, 2009." *Journal of Data Science: JDS* 11 (1): 269–80.

on pre-intervention data for this adjustment because it ensures Maryland's performance during the intervention period will not affect the coefficient, and because it allows for estimation of the surveillance coefficient using multiple years of data, which enhances reliability. We derived the coefficient from an analysis of all reporting states, rather than those in the control group, to maximize sample size and because administration of the diabetes testing question differs by state and year.

An additional limitation arises because of differing age categories in the BRFSS and U.S. Census data, which are combined for the purpose of selecting control states while matching on demographic characteristics. BRFSS censors age at 80. The Census files in question categorize age in 10-year increments, including one that spans 75-84. In order to aggregate Census and BRFSS data while maintaining comparable age categories, we restricted the analytic file to BRFSS respondents 35-74 for purposes of estimating the rate of prevented diabetes cases in Maryland. We then apply this rate to the Maryland population 45 and older to obtain a count of prevented cases. We include the 75+ population in this calculation because average life expectancy at 75 exceeds the five-year cost horizon. This process will result in an unbiased estimate if the difference in incidence in the 75+ age group between Maryland and the control group is the same as the average difference in the younger age groups.

It is important to note that the information presented here and in the appendices, including selection of control group states, may change after the State gains access to NHIS data and the BRFSS 2018 survey file, which will be released in late 2019.

Complementary Measure

As previously indicated, Maryland recognizes the potential for methodologic limitations, particularly surveillance bias, to obscure improvements in diabetes incidence. This would occur if, for example, a reduction in incidence is accompanied by enhanced diabetes surveillance in Maryland results in a shift from undiagnosed diabetes incidence to diagnosed diabetes incidence during the treatment period. To address this possibility, the State developed the obesity complementary performance measure. Because obesity is a key determinant of diabetes,[13] and the Maryland Department of Health prediabetes interventions will include a significant focus on body mass index (BMI), the State would expect improvements in obesity and diabetes to trend together. The BMI credit methodology is detailed in the Complementary Measure Supplement.

[13] Centers for Disease Control and Prevention. *National Diabetes Statistics Report, 2017*. Atlanta, GA: Centers for Disease Control and Prevention, US Department of Health and Human Services; 2017.

II. BACKGROUND AND INTERVENTIONS FOR DIABETES OUTCOMES-BASED CREDIT

BACKGROUND AND INTERVENTIONS FOR DIABETES OUTCOMES-BASED CREDIT

Component Summary

This document describes the rationale for selecting diabetes as an outcomes-based credit, examines trends in diabetes and diabetes risk factors, details existing programs and infrastructure to address diabetes in Maryland, and outlines planned interventions.

Background

Selecting a Chronic Condition for Outcomes Based Credit

Maryland analyzed prevalence and cost data to identify health conditions with the greatest burden. In terms of prevalence, the top five chronic health conditions were hypertension, depression, asthma, diabetes, and chronic obstructive pulmonary disease (COPD) (see Table 1).

Table 1. Prevalent Chronic Diseases in Maryland, 2016-2017

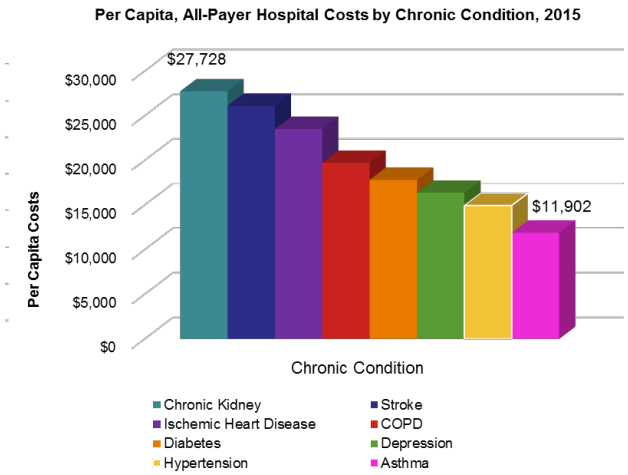
Condition	2016	2017
Hypertension[a]	34.4%	33.1%
Depression	15.4%	17.6%
Asthma	14.0%	15.1%
Diabetes[b]	10.8%	10.5%
COPD	5.4%	5.8%

Data source: 2016 and 2017 Maryland BRFSS, gestational = women told only during pregnancy
[a]Excluding gestational hypertension and borderline hypertension
[b]Excluding gestational diabetes

Maryland also analyzed its all-payer hospital claims data to assess the financial impact of chronic disease (see Figure 1). This analysis shows diabetes involves a higher hospital cost per capita when compared to hypertension, depression, and asthma, even though those conditions appear to have a higher prevalence in Maryland. While COPD, stroke, heart disease, and chronic kidney disease have higher per capita hospital costs compared to diabetes, prevalence of these conditions is lower. Maryland is projected to spend $9.6 billion annually on diabetes-associated health care by 2020 and $11.1 billion by 2025, including costs related to prediabetes and undiagnosed diabetes. Nearly 50 percent of these costs are projected to come from the senior population.[14,15] In addition, rising diabetes prevalence is an area of concern across the State, appearing in nearly all community health needs assessments and hospital community benefit reports.

[14] Institute for Alternative Futures. *Diabetes 2030 – U.S., State, and Metropolitan Trends, 2015- Maryland*. Alexandria, VA: Institute for Alternative Futures; 2017. http://www.altfutures.org/pubs/diabetes2030/MARYLANDDataSheet.pdf.
[15]Institute for Alternative Futures. *Diabetes 2025 Forecasts, 2011 – Maryland's Diabetes Crisis.*. Alexandria, VA: Institute for Alternative Futures; 2011.
http://www.altfutures.org/pubs/diabetes2025/MARYLAND_Diabetes2025_Overall_BriefingPaper_2011.pdf

Figure 1: Per Capita Costs in Maryland Associated with Chronic Disease Burden



Data Source: HSCRC/CRISP analysis of all-payer hospital claims data

Diabetes and Diabetes Risk Factor Trends

Prevalence of self-reported diabetes in adults has grown in Maryland since 2011, and is expected to continue rising, with an expected growth of 10.4% between 2017 and 2023 (Table 2). Diabetes was the state's sixth-leading cause of death in 2016, with an age-adjusted mortality rate of 19.6 per 100,000.[16]

Table 2. Maryland Diabetes Prevalence and Mortality Trends, 2011 to 2023

YEAR	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021	2022	2023
Diabetes Prevalence %													
ACTUAL	9.6	10.4	10.0	10.2	10.4	10.8	10.5	--	--	--	--	--	--
PROJECTION	*9.8*	*10.0*	*10.1*	*10.3*	*10.4*	*10.6*	*10.7*	*10.8*	*11.0*	*11.1*	*11.3*	*11.4*	*11.6*
Diabetes Mortality rate[17]													
ACTUAL	20.8	19.1	19.0	19.6	18.3	19.6	20.3	--	--	--	--	--	--
PROJECTION	*20.2*	*20.0*	*19.8*	*19.6*	*19.4*	*19.2*	*19.0*	*18.8*	*18.6*	*18.5*	*18.3*	*18.1*	*17.9*

The prevalence of diabetes differs by race/ethnicity, with higher percentages of black non-Hispanic adults reporting diabetes compared to all other race/ethnicity groups in 2017 (Table 3.)

[16] Vital Statistics Administration, Maryland Department of Health. *Maryland Vital Statistics Report, 2016*. Baltimore, MD; 2017; linear progression estimate on 4/10/2018
[17] Ibid.

Table 3. Diabetes Prevalence by race/ethnicity, Adults, Maryland, BRFSS 2017

Race/Ethnicity	% Self-reported diabetes	Estimated Total adults
All Races/Ethnicities	10.5%	488,942
White non-Hispanic	9.4%	229,005
Black non-Hispanic	13.9%	184,407
Asian	11.9%	36,049
Hispanic	4.9%	20,628

Diabetes Risk Factors

The State will focus interventions on factors that put Marylanders at higher risk for diabetes. Those risk factors include pre-diabetes, obesity, physical inactivity, and smoking (Table 4). BRFSS data provide a snapshot of the risk factor trends that can help the State tailor interventions and programs. If Maryland can slow or reverse the growth in these trends, Marylanders will be at a lower risk of developing diabetes.

Table 4. Maryland selected diabetes risk factor trends, Adults, Maryland BRFSS 2011-2017

Adults reporting (%)	2011	2012	2013	2014	2015	2016	2017
Prediabetes (told by a doctor)	-	-	-	10.5%	-	-	11.7%
Overweight/Obese (based on calculated BMI)	64.4%	63.8%	64.1%	64.9%	65.0%	64.6%	66.2%
Hypertension (told)[a]	31.3%	-	32.8%	-	32.5%	-	32.4%
No leisure time physical activity in past month	26.2%	23.1%	25.3%	21.4%	24.1%	23.1%	25.6%
Current smoking	19.1%	16.2%	16.4%	14.6%	15.1%	13.7%	13.9%

[a]Includes women told only during pregnancy and borderline hypertension in the denominator

Assessment of Infrastructure to Impact Diabetes

The Total Cost of Care Model provides opportunities for the State of Maryland to build on its existing foundation of diabetes prevention and management programs with innovative and aligned approaches. The Maryland Department of Health (MDH) has supported statewide efforts and programs to prevent and manage diabetes by engaging partners, building and sustaining evidence-based programs, developing statewide initiatives and partners, and implementing communication and awareness campaigns. However, historically, it has been difficult to bridge the gap between public health interventions and the clinical health system. With the new Total Cost of Care Model, and the outcomes-based credit in particular, the outcomes of the public health sphere directly affect the traditional health care system, and lead to higher levels of engagement and commitment throughout the state.

Prior to the Total Cost of Care Model, the State's diabetes prevention and management initiatives were largely funded through multiple CDC cooperative agreements. However, most of these agreements and investments focused on building the infrastructure and process to help enable interventions, but did not measure or reward actual changes in population health. In contrast, by pairing this existing funding and infrastructure with enthusiastic buy-in from stakeholders inside and outside the Department, and new

incentives provided by an outcomes-based credit, Maryland can implement sustainable investment in population health improvement. Maryland has a diverse health system and public health landscape, the potential of an outcomes-based credit will serve as a powerful incentive for focused collaboration and engagement. To this end, the State is developing a Diabetes Action Plan that will identify how all stakeholders can engage and collaborate to reduce the burden of diabetes in Maryland. The State expects this plan will be finalized in the fall. In the interim, the State continues its work on the diabetes prevention initiatives described below that were developed both traditionally, and in response to the TCOC Model.

Initiatives to track population health

The State will build on an already robust infrastructure for tracking and intervening on population health, including efforts such as the State Health Improvement Process (SHIP), hospital population health intervention tracking, and Local Health Improvement Coalitions. These initiatives allow the State to monitor the effect of diabetes interventions and identify successful local programs that could be expanded across Maryland. The State Health Improvement Process (SHIP)[18] tracks indicators that are not direct causes of diabetes, but are instead major social determinants of health, associated risk factors, and related health behaviors that result in poor health outcomes and drive healthcare costs.[19]

Initiatives to promote maintaining healthy weight and physical activity

The State currently addresses dietary and physical activity behaviors to prevent and control obesity and maintain healthy lifestyles; initiatives are informed by evidence-based strategies identified in the *Guide to Community Preventive Services*, recommendations from national organizations such as the Institute of Medicine and the CDC.[20] For example, through partnerships with local health departments and community partners, the State promotes and supports many activities, such as farmers markets, nutrition standards for schools and worksites, healthy food banks, walking and biking paths and safe physical activity. Nine Maryland jurisdictions are working with multiple partners to implement walking promotion plans which are intended to increase access to physical activity in the community.

Diabetes Prevention Program (DPP) Initiatives

With the onset of the Total Cost of Care Model, Maryland has a strong incentive to scale up evidence-based Diabetes Prevention Program (DPP) initiatives, which focus on preventing or delaying diabetes among those at risk for type 2 diabetes. In DPP, trained lifestyle coaches encourage participants to eat a healthy diet, increase their physical activity and to track weight loss, food intake, and physical activity.[21] Modest lifestyle changes adopted through this program, including weight loss and increased physical activity, can delay or prevent transition to diabetes.[22] Maryland plans to build on prior DPP success to ramp up participation and effectiveness of DPP by increasing payer engagement and reimbursement mechanisms, improving DPP access through recruitment of new Maryland DPP suppliers, and increasing health system and provider engagement.

[18] Under SHIP, the State monitors 39 measures of population health pegged to Healthy People 2020 goals and program performance measures to address key public health priorities.

[19]Braveman, P., Egerter, S., & Williams, D. R. (2011). The social determinants of health: coming of age. *Annual review of public health*, *32*, 381-398.

[20]The Community Guide is a website that houses the official collection of all Community Preventive Services Task Force (Task Force) findings and the systematic reviews on which they are based. https://www.thecommunityguide.org.

[21]Centers for Disease Control and Prevention, Diabetes Prevention Recognition Program, July 2016 <http://www.cdc.gov/diabetes/prevention/pdf/dprp-standards.pdf>.

[22]Knowler, W. C., Barrett-Connor, E., Fowler, S. E., Hamman, R. F., Lachin, J. M., Walker, E. A., & Nathan, D. M. (2002). Reduction in the incidence of type 2 diabetes with lifestyle intervention or metformin. *The New England journal of medicine*, *346*(6), 393-403.

Historical success and foundation:

Due to Maryland's previous success with DPP, specifically in its Medicaid program, the state is well-positioned to scale the program throughout the state. Between July 2012 and October 2017, the CDC reported 2,407 people in Maryland participated in National DPP classes; of the 2,407 participants, 532 completed at least 4 sessions and of those completers, there was an average weight loss of 4.4%.[23] In January 2019, CDC reported that 4,625 Marylanders participated in DPP since the beginning of the program, a nearly twofold increase in participation since the October 2017 report.

While the participation to date is promising, the State is committed to ensuring that more Marylanders are aware of and have access to this important service. To that end, Maryland also participated in the CDC 6|18 initiative to receive technical assistance from multiple partners to address diabetes prevention on an all-payer basis. Goals of the work included: Build a payer and health system engagement strategy; Increase provider (clinical and administrative office staff) and DPP Supplier awareness, education, and training. These goals, as well as other planned developments of DPP in Maryland, are further discussed below.

Payment mechanisms:

Maryland is committed to increasing payer engagement and reimbursement mechanisms to ensure providers can offer and be reimbursed for DPP. Through this process, the State will support existing and new Maryland DPP organizations in sustaining programs through new billing and reimbursement mechanisms. In a major policy achievement, Maryland was approved for a Section 1115 demonstration waiver amendment to expand payment for National DPP services to all eligible Medicaid Managed Care Organization enrollees. This approval builds on a successful NACDD/CDC's Medicaid Demonstration Project that enabled the state to develop and implement a reimbursement model for Medicaid beneficiaries who participate in evidence-based National DPPs. Four Medicaid Managed Care Organizations (MCOs) built systems to: 1) increase testing; and 2) assure referral of and reimbursement for beneficiaries who have prediabetes into the National DPP. The Medicaid demonstration enrolled patients through January 2018 into community and online National DPPs. The State is building custom secondary outcomes analysis to communicate the business case of the DPP to stakeholders, including a rationale for investment in preventive care in support of the Maryland Total Cost of Care Model.

In addition, Maryland is increasing coverage of medically necessary diabetes equipment, supplies, and outpatient self-management training and educational services to apply to the treatment of, elevated blood glucose levels induced by prediabetes or pregnancy. The State will also reimburse services rendered by a licensed dietician or nutritionist for the treatment of prediabetes and obesity.[24]

Supplier expansion efforts:

While the State has a significant number of DPP suppliers, increasing the number of suppliers is crucial to ensuring all eligible Marylanders can access DPP. Currently, there are 61 Diabetes Prevention Recognition Program (DPRP) organizations in Maryland; this includes local health departments,

[23]The National DPP is a CDC-recognized year-long lifestyle change program based on research led by the National Institutes of Health, showing that people with prediabetes who take part in a structured year-long lifestyle change program can reduce their risk of developing type 2 diabetes by 58% when those lifestyle changes result in a 5-7% weight loss and 150 minutes of physical activity a week .Centers for Disease Control and Prevention, Diabetes Prevention Recognition Program, October 2017, Sent from CDC to Maryland Center for Chronic Disease Prevention and Control, January 4, 2018.

[24] Maryland Legis. Heath Insurance – Coverage for Elevated or Impaired Blood Glucose Levels, Prediabetes, and Obesity Treatment. 2018. http://mgaleg.maryland.gov/webmga/frmMain.aspx?pid=billpage&stab=03&id=sb0656&tab=subject3&ys=2018RS

community organizations, and YMCAs, which are either fully recognized or have pending recognition through this program, and currently deliver the National DPP. Since 2016, the Maryland Center for Chronic Disease Prevention and Control has provided significant technical assistance to National DPPs to support the registration as a Medicare DPP. To date, only two organizations are registered as Medicare DPP suppliers in Maryland, but the State expects this number to grow with the strong statewide push on diabetes and the additional experience gained through the Medicaid demonstration and expansion. The State is committed to working with community based programs to provide the necessary knowledge, skills and tools to build internal billing systems to assure they meet the requirements of being a Medicare DPP supplier. The Maryland Diabetes Prevention Network has prioritized the increase in the number of enrolled Medicare DPP suppliers to receive reimbursement for Maryland Medicare participating beneficiaries.

In the coming years, the State plans to significantly increase the number of DPP suppliers and the number of Marylanders participating in DPP, building on Maryland's successful Medicaid demonstration experience.

Health System Engagement

The State is coordinating efforts to engage healthcare providers to screen and test for diabetes and to refer those with diabetes and prediabetes to appropriate evidence-based programs. The State plans to enhance existing referral mechanisms for bidirectional feedback and build new referral mechanisms. The Maryland Department of Health has established referral mechanisms with health care providers and built the BeHealthyMaryland.org referral site to provide referral links between providers and National DPPs. In addition, the State is looking to strengthen links between health care systems and local National DPP organizations to encourage testing and referral. For example, Care Transformation Organizations (CTOs) participating in the Maryland Primary Care Program (MDPCP) will be expected to connect participating doctors with diabetes prevention programs to increase the likelihood of DPP referrals for eligible patients. MDPCP coaches will be trained on diabetes prevention opportunities and resources to share with MDPCP practices that the Program Management Office (PMO) is working with Public Health, Medicaid, and CRISP to develop a robust e-referral tool that can be used by MDPCP practices and CTOs. The PMO is discussing with hospital and CTO stakeholders how to expand diabetes prevention services including the establishment of DPP suppliers in Medicare. For example, several CTOs already have DPPs in place, such as Bethesda NEWtrition and Wellness Solutions with the Aposle Group and Medstar CTO with Medstar practices.

To further support these referral efforts, the State is increasing awareness through media and transit campaigns to increase testing for diabetes and prediabetes and to find local programs.

III. Performance Methodology Matching Approach

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MEMORANDUM

DATE: 1/11/2019 (Updated 3/4/2019)

SUBJECT: Synthetic Control Matching Approach and Results Summary

Objective

The state of Maryland aims to determine improvements in statewide population health during the Maryland Total Cost of Care Model. To do so, we must compare the change in Maryland's diabetes incidence rate to the change in the diabetes incidence rate in a comparison group selected to match Maryland's demographic characteristics and pre-Model trends. This difference between Maryland and a comparison group measures the difference between Maryland's performance and what could have occurred absent the Model, that is, the Model's effect.

This methodology comprises two steps: selecting an appropriate comparison group and using that comparison group to calculate whether Maryland diabetes incidence is better or worse than what would be expected. Not all comparison selection methodologies are appropriate for all data types, so the methodology we use to select an appropriate comparison group depends in part on the data available for analysis. After considering individual-, county-, and state-level data, we identified the Behavioral Risk Factor Surveillance Survey (BRFSS) respondent-level data files from 2013 to 2017 as the best available data source. While the individual data provide a useful level of detail, the files contain responses from different samples in each year, which precludes the use of a traditional cohort study design. Instead, we estimate diabetes incidence for each state and year, and use those estimates to evaluate Maryland against a group of comparison states.

Although a state-level analysis is the best available option, it constrains our comparison group selection approach and introduces its own challenges. Typical approaches, like propensity score matching, are impracticable when the treatment group is very small. We will therefore select the comparison group using synthetic control matching, a technique developed for scenarios like this one where the treatment group contains only one entity.

Synthetic control matching is designed to align the pre-intervention time trends on the outcome variable in the treatment and synthetic control groups; when only a few years of data are available and outcome values fluctuate from year to year, as in the BRFSS data, matching the time trend may lead to overfitting rather than a robust counterfactual. To guard against overfitting that would undermine the comparison group, we match on annual diabetes incidence

rates estimated in each state and year using an Empirical Bayesian model, which also imputes missing values where they occur.

The Empirical Bayesian approach stabilizes the estimates by drawing on information from the overall mean when estimating incidence rates for specific states and years. In a traditional model, if the data set contained little information about, for example, North Dakota in 2013, the estimated incidence rate for that state and year would be noisy and possibly extreme because it's based on so little data. In an Empirical Bayesian model, we also incorporate information from the overall average incidence rate across all states and years when producing estimates for small cells. The weight that the overall average bears in the final estimate is proportional to the amount of data available in the cell; in the extreme case where no data is available for a given state and year, the model imputes the missing value with the overall mean.

This process is commonly called "shrinkage" because it pulls outlying estimates closer to the overall mean, making them both more credible and more precise. Crucially, estimates that are "shrunken" in this way have lower mean squared error than traditional estimates,[25] meaning that they predict future performance better. This property is very desirable for matching because we use the matched comparison group to predict what the treatment group's outcomes would have been without the intervention – the better the prediction, the better the counterfactual.

After creating a synthetic control group using Empirical Bayesian incidence estimates and other background characteristics, we will estimate the impact of Maryland's diabetes initiative using difference-in-differences regression. We elaborate on both the matching and regression steps in the sections that follow.

Step 1: Synthetic Control Matching

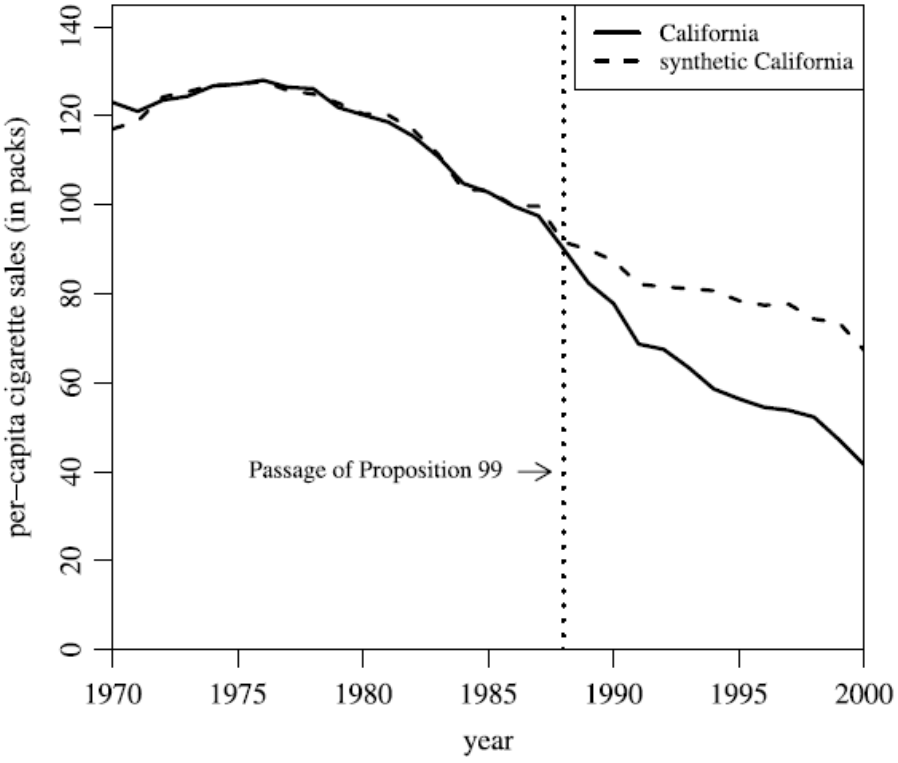
Most comparison group selection techniques, such as propensity score matching or weighting, require a large pool of treated subjects and an even larger pool of potential comparison subjects. Cases like this one, where the treatment group contains only one unit, demand an alternative approach; synthetic control matching is such an approach. This method, introduced by Abadie and Gardeazabal (2003)[26] and developed further in Abadie et al. (2010),[27] creates a control unit for a single treated unit based on the treated unit's pre-intervention time trend on the variables of interest. This synthetic control is a weighted average of several potential control units, with the weights selected to ensure that the synthetic control's pre-intervention time trend matches the treated unit's pre-intervention time trend. If we achieve a good match on the pre-intervention time trend, the post-intervention difference in outcomes between the treatment unit and the synthetic control group represents the causal effect of treatment, as Figure 1 shows.

[25] Efron, B. & C. Morris, 1977. Stein's paradox in statistics. *Scientific American 236*(5), pp. 119-127.

[26] Abadie, A. & J. Gardeazabal (2003). The economic costs of conflict: A case study of the Basque Country. *The American Economic Review 93*(1), 113-132.

[27] Abadie, A., A. Diamond, & J. Hainmueller (2010). Synthetic control methods for comparative case studies: Estimating the effect of California's tobacco control program. *Journal of the American Statistical Association 105*(490), 493-505.

Figure 1: Example of Synthetic Control Matching Result



Source: Abadie et al. (2010), Figure 1, p. 500.

Notes: This figure depicts the results of synthetic control matching to assess the effects of a cigarette control program implemented in California in 1988. The synthetic California – dashed line – is a weighted average of the other states that, up to that time, had not introduced similar tobacco control initiatives.

Although the algorithm emphasizes the pre-intervention time trend, it can also achieve balance on important background characteristics, like the demographic composition of the states in our study. In our case, given the relatively small number of states and pre-intervention time periods, we limit the number of background characteristics included in the model to avoid over-fitting.

Outcome Variable Selection

Because synthetic control matching strongly emphasizes the pre-intervention time trend, it is important to align the dependent variable for synthetic control matching with the outcome of interest in the evaluation. Earlier versions of this memo and analysis used the diabetes prevalence rate as the outcome of interest because diabetes prevalence data are readily available in BRFSS. However, the Total Cost of Care Model aims to reduce diabetes incidence, so a model based on diabetes prevalence would at best approximate the true outcome of interest. Therefore, HSCRC developed a method to determine diabetes incidence at the individual level based on other information in the BRFSS questionnaire; they then aggregated this information to the state and year using the Empirical Bayesian approach described above.

Changing the outcome from diabetes prevalence to diabetes incidence involves a trade-off between accurately matching the outcome and the availability of data. Diabetes prevalence data

are available starting in 2011, while diabetes incidence data are available starting in 2013. Although the literature does not provide a strict guideline, increasing the duration of the pre-intervention period increases the credibility of the counterfactual. Published examples of synthetic control matching we have identified use at least ten years of pre-intervention data, while for diabetes incidence, only five years are available (2013-2017). Reducing the number of years included in the synthetic control matching model increases the risk of overfitting and thus of producing a faulty counterfactual, a risk that will be reduced slightly by incorporating 2018 data when it becomes available.

We show in the results section that the approach based on incidence produces a synthetic control group comprising states with similar economic and demographic profiles to Maryland and with reasonable balance on background characteristics. The balance based on an analysis of diabetes incidence rates is comparable to balance we previously obtained using diabetes prevalence as the outcome variable. These results strengthen our confidence in the selected approach and lead us to conclude that, on balance, focusing the evaluation on the appropriate outcome is more important to the accuracy of the match than obtaining two more years of pre-intervention data.

Synthetic Control Matching

Synthetic control matching was developed for case studies like this one, where only one entity receives the treatment of interest. Conducting this analysis at the state level requires us to use state-level averages for the trends and background characteristics of interest; summarizing this information at the state level necessarily oversimplifies Maryland's diversity. Earlier versions of this memo described synthetic control matching separately by age group in order to obtain a more nuanced synthetic control with the available data. The age-stratified synthetic control estimates were then combined by taking a weighted average of the subgroup-specific controls based on the proportion of Maryland's population each subgroup represents.

However, we found that accounting for variation in age in the empirical Bayes estimation process, rather than by combining age-stratified estimates, resulted in improvements in the stability of estimates and minimized differences between incidence for Maryland and the synthetic control group. Thus, results presented here are based on a random-effects model controlling for age, rather than aggregating age-stratified estimates.

Assessing Balance

The goal of synthetic control matching is to produce a synthetic Maryland that resembles the real Maryland as closely as possible on the matching characteristics. Thus, when gauging the success of the synthetic control matching procedure, we must compare Maryland's characteristics to those of the synthetic control. This balance assessment allows us to decide whether the matching procedure has succeeded. Model fit diagnostics, like the mean squared prediction error obtained by the synthetic control matching procedure, can also help to determine which of several candidate approaches best predicts the outcome trajectory in Maryland. However, this diagnostic focuses exclusively on the time trend in the outcome variable; to gauge the match's overall quality, we must consider the mean squared prediction error statistic along with assessments of the balance on background characteristics.

The literature does not offer any guidelines or metrics for gauging the degree of balance resulting from synthetic control matching, so we will compare Maryland to the synthetic control by measuring simple differences and percentage differences in the prevalence of each characteristic. We will perform the same comparison between Maryland and the national mean to learn how the synthetic control compares to a naïve alternative.

Calculating Baseline Diabetes Incidence

To calculate the baseline diabetes incidence in the synthetic control group, we simply multiply the synthetic control weight for each state times the diabetes incidence rate for that state. The weighted average of the diabetes incidence rates in the synthetic control states in the pre-intervention period is the baseline diabetes incidence rate for the synthetic control. In practice, many potential controls receive a weight of 0, indicating that their characteristics do not contribute to the synthetic control. Weights sum to one within the synthetic control group. Analogously, the simple average of diabetes incidence rates in the pre-intervention period is the baseline diabetes incidence rate for Maryland.

Synthetic Control Matching Results: Composition of the Synthetic Maryland

The states that comprise the synthetic Maryland, and their weights, provide a face validity check on the results; if the synthetic control comprises primarily states with very different demographic characteristics and health care environments than Maryland, it loses credibility. The states that bear the most weight in the synthetic Maryland are Mid-Atlantic or New England states with similar economic profiles, including Virginia (32 percent), Connecticut (30 percent), District of Columbia (19 percent) and New Jersey (16 percent). These states are likely to resemble Maryland in their socioeconomic characteristics and health care environments, lending credence to the synthetic control. We tabulate the synthetic control states and their representation in the overall synthetic Maryland in Table 1.

Table 1. Synthetic Control Weights

State	Weight
VA	32%
CT	30%
DC	19%
NJ	16%
MA	2%
DE	0.3%

Two thirds of the weight comes from Mid-Atlantic states (Virginia, Delaware, New Jersey, and the District of Columbia), while the remaining weight comes from Massachusetts and Connecticut, nearby states with comparable economic profiles.

Synthetic Control Matching Results: Balance on Matching Characteristics

After establishing the face validity of the synthetic control, we determine its appropriateness as a counterfactual by examining the differences between Maryland and the synthetic Maryland on the characteristics used in matching. For each characteristic, we calculate the difference between Maryland and the synthetic control, as well as the percentage difference relative to Maryland's value. We provide the same calculations for the national average value as context.

In Table 2 we see that diabetes incidence rates from 2013-2017 for the synthetic control group track closely with Maryland's rates. The synthetic control resembles Maryland much more closely than the national mean on diabetes incidence and demographic characteristics used in matching, especially in its racial/ethnic and socioeconomic composition. For example, Maryland's population is 28.8 percent black, compared to 20.8 percent in the synthetic Maryland but only 10.2 percent nationally. Similarly, 33.6 percent of Maryland's 35-to-74 population holds a college degree; this proportion is 35.9 percent in the synthetic Maryland but only 29 percent nationally, for percentage differences of 27.2and 13.6percent, respectively. These disparities are similar to those observed in the initial version of this analysis, which treated diabetes prevalence as the outcome rather than diabetes incidence. Percent differences on the diabetes incidence rate are also slightly smaller on average than differences on the diabetes prevalence rate.

Thus, the synthetic control captures Maryland's diabetes incidence trajectory in the pre-intervention period as well as or better than the national mean, while achieving a much closer match on key demographic characteristics.

Table 2. Balance on Characteristics Used in Matching

Variable (%)	Maryland	Synthetic Control	National Mean[a]	MD vs Synthetic		MD vs Nation	
				Difference	% Difference	Difference	% Difference
Primary Outcome [b, c]							
Diabetes incidence (2013)	110.243	109.304	104.692	0.939	0.9	5.551	5.0
Diabetes incidence (2014)	111.220	111.219	105.515	0.001	0.0	5.705	5.1
Diabetes incidence (2015)	112.026	111.795	106.042	0.232	0.2	5.985	5.3
Diabetes incidence (2016)	113.223	113.576	106.405	-0.353	-0.3	6.818	6.0
Diabetes incidence (2017)	112.701	113.212	106.602	-0.511	-0.5	6.100	5.4
Demographic Characteristics							
Male[b]	47.74	48.03	48.80	-0.29	-0.6	-1.06	-2.2
Asian[d]	6.28	5.42	3.98	0.86	13.6	2.30	36.6
Black[d]	28.79	20.88	10.19	7.90	27.4	18.59	64.6
Hispanic[d]	6.98	10.04	8.26	-3.06	-43.8	-1.28	-18.3
White[d]	56.58	62.33	74.72	-5.75	-10.2	-18.13	-32.0
College graduates[b]	33.57	35.97	29.00	-2.40	-7.2	4.57	13.6
Urban[e]	87.15	86.72	72.50	0.43	0.5	14.65	16.8
Poor[d]	7.21	9.05	10.12	-1.84	-25.5	-2.91	-40.3
Near poor[d]	9.95	11.17	14.70	-1.23	-12.3	-4.76	-47.9
Middle income[d]	23.57	23.13	29.64	0.43	1.8	-6.08	-25.8
High income[d]	58.48	55.40	44.49	3.07	5.3	13.98	23.9
Health insurance[b]	90.20	89.97	90.32	0.23	0.3	-0.12	-0.1
Check-up in last year[b]	75.34	74.53	73.41	0.82	1.1	1.94	2.6

Notes: Values in this table represent the 35-74 population.

[a] *National values are an unweighted average across all 50 states plus the District of Columbia for the population age 35-74.

[b] Data source: 2013-2017 Behavioral Risk Factor Surveillance Survey (BRFSS) microdata

[c] Diabetes incidence is measured in cases per 10,000 population.

[d] Data source: 2016 American Community Survey (ACS) five-year rolling averages

[e] Data source: U.S. Census Summary File

Step 2: Impact Estimation

After developing a synthetic control for Maryland, we wish to use this synthetic control to estimate the change in Maryland's diabetes incidence under the Total Cost of Care Model compared to the change in a similar comparison group not under the Total Cost of Care Model. This change is a measure of the effect of the population health initiative. Of course, this measure of the effect is subject to limitations, particularly its reliance on an observational rather than a randomized design. The proposed methodology permits a causal interpretation but also requires caution in interpreting the results.

As shown in Figure 1, we could simply estimate the effect of the Total Cost of Care Model as the difference in the post-intervention period between the diabetes incidence rates in Maryland and in the synthetic control group. However, the validity of this estimate depends greatly on the exactness of the match between the synthetic control group and Maryland's pre-intervention time trends. Thus, we may wish to estimate the intervention's effects using a difference-in-differences framework. A difference-in-differences approach compares the change in Maryland's diabetes incidence rate to the change in the synthetic control's diabetes incidence rate in the same time frame. Synthetic control matching and difference-in-differences analysis pair well together because synthetic control matching is designed to align the pre-intervention outcome trends in the treatment and control groups, the central assumption of difference-in-differences.

When we estimate the effect of the Total Cost of Care Model, it is essential to acknowledge the statistical uncertainty or error in that estimate. Thus, we recommend implementing difference-in-differences in a regression framework, which facilitates error estimation.[28] Although it is possible to calculate the difference-in-differences impact estimate directly from the available weights and incidence rates, it is much less straight-forward to determine the uncertainty of the estimate obtained in this way.

A linear regression analogous to the manual difference-in-difference calculation takes the form:

$$Y_{it} = \alpha + \gamma T_i + \delta Post_t + \theta T_i * Post_t + \varepsilon_{it}$$

- Y_{it} is the outcome, diabetes incidence, measured in state i in year t
- α is an overall intercept
- γ controls for residual differences between Maryland (treatment indicator $T_i = 1$) and the matched comparison states (treatment indicator $T_i = 0$) in the pre-intervention period
- δ estimates the overall difference between pre- ($Post_t = 0$) and post-period ($Post_t = 1$) diabetes incidence rates

[28]Linear regression is a simple and straight-forward way to obtain standard errors of estimated treatment effects, but it is not always accurate. Linear regression standard error estimates do not account for all possible sources of error, including error in the covariate measurements and the weights, and depend on the regression specification. Mixed effects regression with random effects of state adjusts standard errors for these correlations. However, a mixed effects approach does not account for uncertainty in the covariate measurements and weights or ensure that the regression is correctly specified.

- θ represents the difference-in-differences between Maryland and the comparison states, pre- and post-intervention
- ε_{it} captures random error

The θ term in this model is the impact estimate – the difference-in-differences comparing the change in Maryland's diabetes incidence rate to the change in the synthetic control states.

As specified, this model does not adjust for background characteristics. If the synthetic control matching procedure does not produce adequate balance on demographic characteristics, or if we wish to implement a doubly-robust approach, we can also use the linear regression framework to adjust for residual differences between Maryland and the synthetic control states.

To include regression adjustment, we add a term to the formula from above:

$$Y_{it} = \alpha + \beta X_{it} + \gamma T_i + \delta Post_t + \theta T_i * Post_t + \varepsilon_{it}$$

Here, β controls for background characteristics X_{it} related to diabetes incidence, so that we interpret the impact estimate θ as the difference-in-differences assuming the same values of the background characteristics in the treatment and comparison states.

To incorporate information from synthetic control matching and thereby satisfy the assumptions of difference-in-differences regression, we must weight each observation in the regression. In this case, the observations are the diabetes incidence rates in each state and year, along with a treatment status indicator, post-intervention period indicator, and pre-intervention background characteristics for each state. Regression weights combine synthetic control weights, which are set equal to 1 for all Maryland observations.

IV. Cost Estimates Supplement

Estimating health system savings attributable to reductions in the incidence of diabetes in the Medicare population[29]

Summary

We estimate that each case of incident diabetes among Medicare enrollees in Maryland costs the program $4,100 in the first year, and that the annual cost of diabetes increases $775 for each additional year with the disease (both values are measured in 2019 dollars).

Because the effectiveness of an intervention at delaying the onset of diabetes varies by individual as well as by the intervention itself, the observed change in the incidence of the disease is a combination of two influences. One influence is the effect of the intervention on delaying cases that would have occurred in the present year (called "newly incident" cases for convenience. This influence is offset by previously delayed cases becoming incident (called "delayed incident" cases).

Because a diabetes prevention program is more likely to delay the onset of the disease than to prevent it, Medicare program savings are largely the product of the annual incremental cost and the average number of years by which the program delays the incidence. In addition to these savings, a diabetes prevention program produces "hidden" savings in the form of lower annual costs as a result of a delay in the onset of diabetes, even if an individual becomes an incident case. Collateral savings may also accrue to the extent that spillover effects of the intervention lead to early detection of diabetes and to reduced mortality among people with diabetes.

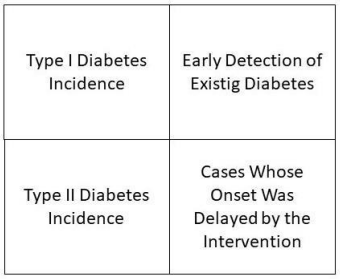
Background

As part of Maryland's Total Cost of Care Model, the State is developing a plan to track progress and estimate savings attributable to reductions in the incidence of diabetes. The State contracted with Actuarial Research Corporation (ARC) to develop a methodology to translate changes in incidence into changes in health system costs.

[29] This report was prepared for the Maryland Health Services Cost Review Commission (HSCRC) by Daniel Waldo and Rebecca Socarras, both of Actuarial Research Corporation, under Contract HSCRC-17-045. Neither ARC nor the HSCRC nor any of their employees or contractors make any representations or warranties, express, implied, or statutory, as to the validity, accuracy, completeness, or fitness for a particular purpose; nor represent that use would not infringe privately owned rights; nor assume any liability resulting from the use of such materials and shall in no way be liable for any costs, expenses, claims, or demands arising out of the use of this report. In no event shall ARC be liable to the HSCRC or to any third party for any indirect, special or consequential damages or lost profits arising out of or related to this Report, or the accuracy or correctness of the information and data in the Report, even if ARC has been advised of the possibility thereof.

Tables in Appendix A show the prevalence of diagnosed diabetes in the Medicare Fee-for-Service (FFS) population during calendar year 2015, in Maryland and in the United States, and Medicare payments made through Parts A and B on behalf of enrollees with diabetes. Generally speaking, diabetes prevalence is slightly higher in Maryland than in the rest of the United States, especially among older enrollees. Rates appear to be lower among Hispanic enrollees and among enrollees with ESRD – but these latter findings may be the result of small cell sizes. Total Medicare payments are about twice as high for enrollees with diabetes as for those without diabetes, consistent with what is observed in the rest of the USA. Mortality rates were about 2.2 percentage points higher for people with diabetes, again consistent with rates seen elsewhere in the nation.

Diabetes incidence model



Because diabetes is an irreversible condition (except for gestational diabetes, which we have excluded from this analysis), the conceptual model of diabetes incidence is fairly straightforward.

In this model the measured incidence of diabetes is directly affected by 4 factors:

- **Incidence of Type 1 diabetes** New cases of Type I diabetes, which is a clinical condition not susceptible of intervention.[30] This type of diabetes reduces the leverage of interventions on the rate of incidence of the disease.
- **Incidence of Type II diabetes** New cases of Type II diabetes are susceptible of intervention; to the extent that the intervention is successful, this incidence will be lower than otherwise expected.
- **Effectiveness of intervention at delaying onset of diabetes** Eventually, some cases affected by the intervention move from prediabetic to diabetic stages. When this happens, the observed incidence rises, all other things equal.
- **Accurate diagnosis of diabetes** The measured prevalence of diabetes differs from the clinical prevalence of the condition to the extent that cases are undiagnosed. Thus, if interventions directly or indirectly reduce the rate of undiagnosed diabetes, incidence will appear to increase, all other things equal.

Cost per incident case of diabetes in the population

Because diabetes is a progressive disease, an estimate of the average cost of the disease per person is likely to overstate the savings per case delayed due to the intervention. We estimated the cost of diabetes in the first year of the disease and re-estimated the cost per subsequent year.

[30] http://kidshealth.org/en/parents/prevention.html

Cost of the first year of diabetes

To model these costs, we used Medicare fee-for-service (FFS) claims for enrollees in Maryland.[31] We used data for calendar years 2012 through 2015.

We constructed a diabetes status measure based on claims data. A person was deemed to have incident diabetes in year *t* if there was any diagnosis of diabetes (ICD-9 250.xx) during the year and none in previous years.[32] If the person did have diabetes diagnoses in prior years, their diabetes status was set to continuing. People with no diagnoses in the current or prior years were assigned a status of none. Those people who entered the Medicare program in 2015 and had diabetes were assigned a status code of unknown.

The model itself is fairly straightforward:

(1) pr(E>0) = *f*(diabetes status, age, age squared, sex, original reason for entitlement [age, disability, or ESRD], current ESRD status, dual-eligibility status, year)

(2) E = *g*(diabetes status, age, age squared, sex, original reason for entitlement [age, disability, or ESRD], current ESRD status, dual-eligibility status, year) where E>0

The expenses in the model are limited in three respects. First, they exclude spending on outpatient drugs, because claims paid under Medicare Part D were not made available. Second, they exclude beneficiary cost sharing liability (deductible and coinsurance). Third, they exclude spending on services not covered by Medicare.

We conducted our analysis using the Stata software package, using two distinct methods. First, we regressed year-to-year change in Medicare payments using a GLM model with a gamma distribution and log transformation. Data were winsorized at the 5-percent point in each tail, to reduce the effects of extreme values, and beneficiaries with existing diabetes were excluded from the model. We performed analysis separately for inpatient expenditure and other expenditure.

After performing the regression, we predicted the probability of use and the value of expenditures for each person (the factual case) and again with the diabetes marker turned off (the counterfactual case), and compared the mean factual and counterfactual predictions. The predicted expenditure in both cases was the predicted probability of use times the predicted value of expenditure given use.

We also tabulated "diabetes-related" Medicare payments for incident cases. These payments are for claims in which an ICD-9 diagnostic code 250.xx was found in any of the first four positions on the claim. The restriction to the first 4 diagnoses was intended to separate those where diabetes was a contributing factor from those where diabetes was mentioned as a patient condition.

[31] The data exclude the Medicare Advantage population, which may affect the generalizability of the findings to the total Medicare population. Possibly, managed care could result in lower costs per incident case, but the extent of that difference cannot be determined at present.

[32] To use claims to establish that an enrollee has diabetes, we used the same approach used in the Chronic Conditions Data Warehouse: at least one inpatient, SNF, or home health claim, or at least two outpatient or physician claims.

Findings

Tables 5 summarizes our analysis of Maryland Medicare FFS claims. Using a regression approach, we estimate that the first year of diabetes is associated with an increase in Medicare payments (distinct from covered charges) of $5,500. Using an alternate approach and simply tabulating diabetes-related claim payments (defined above), the first-year cost of diabetes is $2,100.

Adjusting the figures in Table 5 to 2019 (using the Medicare Trustees Report estimates of per enrollee spending in 2014 and 2019), the range of first-year costs is $2,300 to $6,300.[33] The actual figure is likely to fall somewhere between these two estimates: the tabulated figure does not reflect the cost of comorbidities to the extent that the claims are not coded with a diabetes diagnosis, and the regression predictions are subject to the problems associated with analyzing very skewed variables. We chose $4,100 as a point estimate – slightly below the midpoint of the range.

[33] Over the 2014-2019 period, Part A spending per enrollee rose from $5,034 to $5,326; Part B spending per enrollee rose from $5,396 to $6,467.

Table 5. Analysis of 2013-2015 Maryland Medicare FFS Claims (All Dollars in Nominal Values)													
		Diabetes Status											
		All People with Diabetes			Incident			Continuing			Unknown		
Stata variable	Description	Factual	Counter-factual	Difference	Factual	Counter-factual	Difference	Factual	Counter-factual	Difference	Factual	Counter-factual	Difference
benes	Count of people	723,203			96,168			597,580			29,455		
pmt_est	Estimated Winsorized Medicare payments	$12,499	$6,693	$5,806	$11,554	$6,027	$5,527	$12,731	$6,859	$5,872	$10,874	$5,484	$5,390
w_pmt_inp	Winsorized inpatient payments				$5,286			$4,091			$4,096		
inp_est	Predicted (winsorized) inpatient payments	$4,248	$2,064	$2,184	$3,942	$1,881	$2,061	$4,326	$2,109	$2,217	$3,669	$1,741	$1,928
w_pmt_nec	Winsorized noninpatient payments				$7,684			$8,102			$6,907		
nec_est	Predicted (winsorized) noninpatient payments	$8,251	$4,629	$3,622	$7,612	$4,146	$3,466	$8,406	$4,750		$7,206	$3,744	$3,462
pmt_tot	Actual Medicare payments	$17,387			$19,480			$17,118			$16,021		
pmt_inp	Inpatient	$7,580			$10,070			$7,177			$7,625		
pmt_nec	Noninpatient	$9,808			$9,410			$9,941			$8,396		
pmt_snf	SNF	$1,431			$1,803			$1,383			$1,200		
pmt_hsp	Hospice	$250			$167			$269			$132		
pmt_hha	HHA	$575			$567			$584			$437		
pmt_opt	Outpatient	$3,241			$2,788			$3,323			$3,052		
pmt_car	Carrier (physician etc)	$3,971			$3,849			$4,023			$3,300		
pmt_dme	DME	$339			$236			$359			$276		
diab_tot_pmt	Actual Medicare payments, diabetes-related	$3,463			$2,101			$3,683			$3,453		
diab_inp_pmt	Inpatient	$1,456			$1,106			$1,505			$1,605		
diab_snf_pmt	SNF	$328			$230			$346			$290		
diab_hsp_pmt	Hospice	$12			$3			$14			$4		
diab_hha_pmt	HHA	$285			$127			$314			$225		
diab_opt_pmt	Outpatient	$655			$309			$708			$715		
diab_car_pmt	Carrier (physician etc)	$642			$308			$700			$561		
diab_dme_pmt	DME	$84			$19			$96			$53		

Cost of subsequent years of diabetes

To arrive at this cost, we re-estimated the model created by Trogdon and Hylands (2008),[34] using adjusted Medical Expenditure Panel Survey (MEPS) data (2013-2015). This MEPS adjustment took place in two steps. First, MEPS survey respondents were re-weighted to reflect the Maryland population, based on adjustment factors (race, age, sex, poverty band and insurance status) from the 2015 Current Population Survey (CPS) data.

After calibrating MEPS respondents to the Maryland population, we scaled MEPS spending figures (inpatient and all other care) to match 2019 projected state health expenditure estimates for the noninstitutionalized population in Maryland. We compared historical National Health Expenditure (NHE) per capita figures with historical state health expenditures for Maryland through 2014, and used NHE projections, modified by observed historical differences, to project the Maryland figures to 2019. We did this for Personal Health Care Expenditures, hospital care and all other care; we removed nursing home care from all other care to better reflect a noninstitutionalized population.

We subset the population by dropping respondents who reported the onset of diabetes before age 26 (these were assumed to be people with Type 1 diabetes, clinically unaffected by an intervention) and by creating an "affected" group of people who were already covered by Medicare or who were 55 years of age or older.

Using the adjusted MEPS data, we re-estimated the Trogdon model to estimate the annual increment in the cost of diabetes from the point of onset. The model consists of two equations, one for use of services (logistic regression) and the second for Medicare costs given use of service (GLM, with gamma family and log link):

Use = *p*(diabetes, number of years with diabetes, squared number of years with diabetes, age, square of age, sex, race, poverty status, education, insurance type, Census region, year)

E =*h*(diabetes, number of years with diabetes, squared number of years with diabetes, age, square of age, sex, race, poverty status, education, insurance type, Census region, year)

As with the first-year cost model, we created factual and counterfactual estimates to demonstrate the marginal effect of delayed onset. For each respondent in the combined MEPS sample, we used the regression results to predict spending. Then we increased the years-with-diabetes value by 1 year, by 5 years, and by 10 years and re-predicted spending. The difference in predicted spending represents the value of pushing back the onset of diabetes for the respondent by 1, 5, and 10 years. We averaged these effects over the population with diabetes, using survey weights to take sampling probabilities into account.

[34] Trogdon, J. G. and Hylands, T. (2008) Nationally Representative Medical Costs of Diabetes by Time Since Diagnosis. Diabetes Care 31: 2307-2311. Note: The results presented in this memo have been updated from our earlier analysis "Trogdon_revisited.docx" emailed to MD_HSCRC on January 2, 2018. Because we inflated spending differently in this estimate compared to our earlier version (20180102), the dollar savings attributable to a one-year delay in the onset of diabetes is higher.

Findings

Table 6 summarizes the results of our re-estimation of the Trogdon analysis of incremental costs of diabetes.

Table 6. Annual Increment in Medicare Costs, From Onset of Diabetes					
		Five years		Ten years	
Population with diabetes	One year	Total	Per year	Total	Per year
Full population	$722	$3,687	$737	$7,533	$753
Dropping probable Type 1 cases	$729	$3,726	$745	$7,628	$763
Medicare enrollees and people aged 55 years or older	$769	$3,928	$786	$8,025	$803
Based on 2013-2015 Medical Expenditure Panel Survey, survey weights adjusted to Maryland population and dollars scaled to reflect State Health Expenditure and National Health Expenditure estimates.					

Based on these estimates, we chose $775 as the best point estimate. This figure is closer to the lower end of the range of estimated values ($769-$803), and it is likely that interventions would more likely delay the onset of diabetes by one year than by ten years.

Savings attributable to interventions

As mentioned above, the metric for Maryland's Diabetes Outcomes Based Credit is the incidence of diabetes. Each case of reduced incidence produces savings to the Medicare program. However, these observed savings are dwarfed by "hidden" savings that result from delaying the incidence of diabetes.

Observed savings

The savings associated with an observed reduction in incidence are fairly straightforward to estimate but the calculation requires an assumption about the effectiveness of the intervention in delaying the onset of the disease.

Exhibit A. Illustrative Example of Measuring Observed Savings Attributable to a Diabetes Prevention Model				
Year	A Observed Incidence of Diabetes	B Expected Incidence of Diabetes	C Observed Difference in Incidence	G Savings ($4,100 per case) (k)
1	1,400	2,000	-600	$2,460
2	2,250	2,000	250	($1,025)
3	2,150	2,000	150	($615)
4	2,100	2,000	100	($410)
5	2,050	2,000	50	($205)
5-year total	9,950	10,000	-50	$205

Superficially, simply measuring the incidence of diabetes in each year produces savings equal to the difference between observed and expected incidence by the first-year cost of the disease. Exhibit A illustrates this superficial case with a simplified example. (In this example, there is no cost inflation and no mortality among beneficiaries, although in reality both would occur and both would be reflected in the savings estimates.) The example shows a one-time intervention that is successful in delaying the onset of the disease for different time periods for different beneficiaries. For this hypothetical example, we deploy a

model that delays by one year or more in 60 percent of the cases of prediabetes touched by the intervention. Twenty-five percent of cases are delayed by a single year, 15 percent are delayed by 2 years, 10 percent are delayed by 3 years, 5 percent are delayed by 4 years, and 5 percent are delayed by 5 years or more. As a result, in the first year of the time period – the year in which the intervention is deployed – the number of incident cases is reduced by 600. Over the next 4 years, most of these delayed cases become incident, but at the end of the 5-year window a small number of beneficiaries remain pre-diabetic.

Hidden savings

Hidden savings accrue to the model because a delay in the onset of diabetes lowers the patient's annual costs for an extended period. Therefore, even if an enrollee does eventually develop the disease and becomes an incident case, Medicare costs are lower than they would have been in the absence of the intervention. The stylized example shown in Exhibit B – which extends the hypothetical example of Exhibit A – illustrates this.

Exhibit B. Stylized Example of Savings Attributable to Intervention

		Years by Which Incidence is Delayed					
		1	2	3	4	5+	Total
Number of beneficiaries		250	150	100	50	50	600
Diabetes-related spending without intervention (in thousands)							
	Annual Cost						
2019	$4,100	$1,025	$615	$410	$205	$205	$2,460
2020	$4,875	$1,219	$731	$488	$244	$244	$2,925
2021	$5,650	$1,413	$848	$565	$283	$283	$3,390
2022	$6,425	$1,606	$964	$643	$321	$321	$3,855
2023	$7,200	$1,800	$1,080	$720	$360	$360	$4,320
All 5 years		$7,063	$4,238	$2,825	$1,413	$1,413	$16,950
Diabetes-related spending with intervention (in thousands)							
2019		$0	$0	$0	$0	$0	$0
2020		$1,025	$0	$0	$0	$0	$1,025
2021		$1,219	$615	$0	$0	$0	$1,834
2022		$1,413	$731	$410	$0	$0	$2,554
2023		$1,606	$848	$488	$205	$0	$3,146
All 5 years		$5,263	$2,194	$898	$205	$0	$8,559
Program savings from delayed incidence (in thousands)							
2019		$1,025	$615	$410	$205	$205	$2,460
2020		$194	$731	$488	$244	$244	$1,900
2021		$194	$233	$565	$283	$283	$1,556
2022		$194	$233	$233	$321	$321	$1,301
2023		$194	$233	$233	$155	$360	$1,174
All 5 years		$1,800	$2,044	$1,928	$1,208	$1,413	$8,391

The exhibit is based on the same stylized assumptions about the number of people whose diabetes has been delayed as is used in Exhibit A. The first bank in the exhibit shows what would have been diabetes-related spending in the absence of the 1-year intervention: in 2019 – when the beneficiary first became diabetic, the annual cost is $4,100 per beneficiary, and the annual cost of diabetes rises to $7,200 per beneficiary by 2023.

The second bank shows spending under the assumption that the onset of the disease is delayed. So, for example, the 250 beneficiaries whose disease was delayed by a year incurs no diabetes-related costs in 2019, and their first-year costs begin in 2020. Those whose disease was delayed by two years do not begin to incur diabetes-related costs until 2021. And those whose onset is delayed by 5 or more years do not incur diabetes-related costs during the budget window.

The third bank shows the difference in spending as a result of the delayed incidence, subtracting the second bank from the first bank. The "hidden" savings – $8.4 million in this example – include the superficial observed savings but clearly are far greater than the observed savings.

Estimating these hidden savings requires some knowledge of the effectiveness of the model at delaying the onset of diabetes. This knowledge can come from literature reviews, from experience with similar interventions elsewhere, or from observed trends in Maryland diabetes incidence.

If multiple interventions take place, or if an intervention is deployed in more than one year, the approach shown in Exhibit B is complicated a bit. The initial effectiveness of the various interventions must be weighted to derive the correct mix of delayed incidence.

Collateral savings

In addition to the direct savings from delayed onset of diabetes, there may be collateral benefits of the intervention. For example, if the intervention were to lead to behavior or treatment that reduces premature mortality among diabetic patients, the cost of a last year of life would be delayed. Similarly, if the intervention were to lead to earlier recognition of undiagnosed diabetes, the incidence rate would increase, but downstream expenditures might well be reduced.

We note that incidence delayed in populations nearing Medicare eligibility can translate into program savings in outyears of the intervention. For example, a person who would have become diabetic at age 62 but who is kept in a pre-diabetic state for 3 years would enter the program at age 65 with 2 additional years of savings, so that this person's first-year savings to Medicare would be $1,550 (in 2019 dollars) greater than a newly-incident Medicare case. Thus, it is important to measure incidence for the near-Medicare population as well as for the Medicare population itself.

Conclusions

Using Medicare fee-for-service claims data, supplemented by data from the Medical Expenditure Panel Survey, we estimate that the Medicare savings attributable to delaying an incident case of diabetes by one year is between $2,300 and $6,300 in 2019 dollars; a midpoint in that range is $4,100. To the extent that an intervention can delay incidence by more than one year, the savings rises about $775 per additional year of delay.

Appendix A. Diabetes Prevalence and Costs in Maryland and the United States

Table A1. Number of Fee-for-Service Medicare enrollees and mean Medicare payments, 2015, by State and indication of diabetes

Maryland (100%)							
	Diabetes indicated						
	No		Yes				
All services	Number of enrollees	Mean Medicare payment	Number of enrollees	Proportion	Mean Medicare payment	Payment ratio	Ratio of MD and US ratios
Total	545,119	$8,556	221,892	28.9%	$17,897	2.09	1.00
Age and sex							
Males < 45 years	12,754	$7,992	1,865	12.8%	$27,639	3.46	1.08
Males 45-64 years	41,315	$7,755	15,649	27.5%	$24,686	3.18	1.02
Males 65-69 years	61,393	$5,758	23,588	27.8%	$15,019	2.61	1.05
Males 70-74 years	44,489	$7,719	22,404	33.5%	$16,461	2.13	1.03
Males 75 years +	71,230	$11,694	36,578	33.9%	$19,076	1.63	0.96
Females < 45 years	10,847	$10,651	2,037	15.8%	$28,673	2.69	0.97
Females 45-64 years	45,273	$8,002	17,183	27.5%	$22,390	2.80	1.00
Females 65-69 years	78,043	$6,113	27,499	26.1%	$14,476	2.37	1.01
Females 70-74 years	60,040	$7,488	25,153	29.5%	$15,188	2.03	1.02
Females 75 years +	119,735	$10,918	49,936	29.4%	$17,806	1.63	1.01
Race							
White	396,843	$8,747	136,195	25.6%	$16,925	1.94	0.98
Black	113,868	$8,868	69,656	38.0%	$21,093	2.38	0.95
Hispanic	4,956	$6,345	2,591	34.3%	$14,274	2.25	0.76
Other	29,452	$5,147	13,450	31.4%	$11,876	2.31	0.92
Original reason for Medicare entitlement							
Age	436,623	$7,993	169,122	27.9%	$15,349	1.92	1.01
Disability	105,871	$10,041	49,772	32.0%	$23,631	2.35	1.03
ESRD only	1,342	$39,871	1,415	51.3%	$63,751	1.60	0.88
ESRD & DIB	1,283	$44,623	1,583	55.2%	$68,810	1.54	1.01

Table A1 continued						
Rest of the United States (5%)						
	Diabetes indicated					
	No		Yes			
All services	Number of enrollees	Mean Medicare payment	Number of enrollees	Proportion	Mean Medicare payment	Payment ratio
Total	1,190,872	$7,585	446,939	27.3%	$15,817	2.09
Age and sex						
Males < 45 years	34,277	$6,252	5,039	12.8%	$20,047	3.21
Males 45-64 years	104,512	$6,003	38,558	27.0%	$18,772	3.13
Males 65-69 years	134,594	$5,095	48,421	26.5%	$12,716	2.50
Males 70-74 years	96,116	$6,786	44,139	31.5%	$14,012	2.06
Males 75 years +	157,861	$10,499	76,699	32.7%	$17,756	1.69
Females < 45 years	27,871	$7,490	5,099	15.5%	$20,682	2.76
Females 45-64 years	104,745	$6,376	37,533	26.4%	$17,791	2.79
Females 65-69 years	156,522	$5,392	49,760	24.1%	$12,596	2.34
Females 70-74 years	119,375	$6,792	43,800	26.8%	$13,548	1.99
Females 75 years +	254,759	$10,455	97,791	27.7%	$16,910	1.62
Race						
White	1,017,564	$7,705	349,885	25.6%	$15,237	1.98
Black	95,799	$7,798	57,751	37.6%	$19,576	2.51
Hispanic	20,889	$6,304	12,621	37.7%	$18,757	2.98
Other	56,380	$5,545	26,582	32.0%	$13,905	2.51
Original reason for Medicare entitlement						
Age	904,697	$7,327	316,399	25.9%	$13,921	1.90
Disability	280,418	$7,877	122,836	30.5%	$18,031	2.29
ESRD only	2,876	$31,556	3,438	54.5%	$57,656	1.83
ESRD & DIB	2,641	$39,309	4,166	61.2%	$60,046	1.53

SOURCE: Medicare 5% Limited Data Set Standard Analytic Files for US, 100% for Maryland
NOTE: Enrollee counts reflect 5-percent sample counts for US
To be included, enrollees must be FFS A&B for all months of eligibility

Table A2. Number of Fee-for-Service Medicare enrollees and mean Medicare inpatient payments, 2015, by State and indication of diabetes						
Maryland (100%)						
Diabetes indicated	No		Yes			
Inpatient care	Number of enrollees	Mean Medicare payments	Number of enrollees	Mean Medicare payments	Payment ratio	Ratio of MD and US ratios
Total	545,119	$3,031	221,892	$7,626	2.52	1.02
Age and sex						
Males < 45 years	12,754	$3,426	1,865	$13,855	4.04	1.11
Males 45-64 years	41,315	$3,296	15,649	$11,966	3.63	1.03
Males 65-69 years	61,393	$2,126	23,588	$6,775	3.19	1.06
Males 70-74 years	44,489	$2,845	22,404	$7,089	2.49	1.03
Males 75 years +	71,230	$4,343	36,578	$8,019	1.85	0.96
Females < 45 years	10,847	$4,160	2,037	$13,011	3.13	0.96
Females 45-64 years	45,273	$2,906	17,183	$9,861	3.39	0.99
Females 65-69 years	78,043	$1,934	27,499	$5,963	3.08	1.00
Females 70-74 years	60,040	$2,362	25,153	$6,129	2.60	1.08
Females 75 years +	119,735	$3,646	49,936	$7,069	1.94	1.03
Race						
White	396,843	$3,041	136,195	$7,119	2.34	1.00
Black	113,868	$3,376	69,656	$9,214	2.73	0.97
Hispanic	4,956	$2,170	2,591	$5,670	2.61	0.79
Other	29,452	$1,705	13,450	$4,909	2.88	0.96
Original reason for Medicare entitlement						
Age	436,623	$2,705	169,122	$6,246	2.31	1.03
Disability	105,871	$4,090	49,772	$11,030	2.70	1.03
ESRD only	1,342	$13,869	1,415	$27,219	1.96	0.82
ESRD & DIB	1,283	$15,331	1,583	$30,470	1.99	0.99

Table A2 continued					
Rest of the United States (5%)					
Diabetes indicated	No		Yes		
Inpatient care	Number of enrollees	Mean Medicare payments	Number of enrollees	Mean Medicare payments	Payment ratio
Total	1,190,872	$2,484	446,939	$6,154	2.48
Age and sex					
Males < 45 years	34,277	$2,483	5,039	$9,073	3.65
Males 45-64 years	104,512	$2,317	38,558	$8,167	3.52
Males 65-69 years	134,594	$1,740	48,421	$5,228	3.00
Males 70-74 years	96,116	$2,304	44,139	$5,580	2.42
Males 75 years +	157,861	$3,628	76,699	$6,960	1.92
Females < 45 years	27,871	$2,706	5,099	$8,786	3.25
Females 45-64 years	104,745	$2,077	37,533	$7,130	3.43
Females 65-69 years	156,522	$1,542	49,760	$4,738	3.07
Females 70-74 years	119,375	$2,054	43,800	$4,919	2.40
Females 75 years +	254,759	$3,227	97,791	$6,057	1.88
Race					
White	1,017,564	$2,493	349,885	$5,863	2.35
Black	95,799	$2,805	57,751	$7,932	2.83
Hispanic	20,889	$2,211	12,621	$7,298	3.30
Other	56,380	$1,870	26,582	$5,581	2.98
Original reason for Medicare entitlement					
Age	904,697	$2,310	316,399	$5,203	2.25
Disability	280,418	$2,891	122,836	$7,577	2.62
ESRD only	2,876	$9,234	3,438	$22,185	2.40
ESRD & DIB	2,641	$11,541	4,166	$23,144	2.01

SOURCE: Medicare 5% Limited Data Set Standard Analytic Files for US, 100% for Maryland
NOTE: Enrollee counts reflect 5-percent sample counts for US
To be included, enrollees must be FFS A&B for all months of eligibility

Table A3. Number of Fee-for-Service Medicare enrollees and mean Medicare noninpatient payments, 2015, by State and indication of diabetes						
Maryland (100%)						
Diabetes indicated	No		Yes			
Other care	Number of enrollees	Mean Medicare payments	Number of enrollees	Mean Medicare payments	Payment ratio	Ratio of MD and US ratios
Total	545,119	$5,525	221,892	$10,271	1.86	0.98
Age and sex						
Males < 45 years	12,754	$4,565	1,865	$13,784	3.02	1.04
Males 45-64 years	41,315	$4,459	15,649	$12,720	2.85	0.99
Males 65-69 years	61,393	$3,631	23,588	$8,244	2.27	1.02
Males 70-74 years	44,489	$4,874	22,404	$9,372	1.92	1.02
Males 75 years +	71,230	$7,351	36,578	$11,057	1.50	0.96
Females < 45 years	10,847	$6,491	2,037	$15,662	2.41	0.97
Females 45-64 years	45,273	$5,096	17,183	$12,530	2.46	0.99
Females 65-69 years	78,043	$4,179	27,499	$8,513	2.04	1.00
Females 70-74 years	60,040	$5,126	25,153	$9,059	1.77	0.97
Females 75 years +	119,735	$7,273	49,936	$10,737	1.48	0.98
Race						
White	396,843	$5,705	136,195	$9,806	1.72	0.96
Black	113,868	$5,493	69,656	$11,879	2.16	0.93
Hispanic	4,956	$4,175	2,591	$8,604	2.06	0.74
Other	29,452	$3,441	13,450	$6,968	2.02	0.89
Original reason for Medicare entitlement						
Age	436,623	$5,288	169,122	$9,103	1.72	0.99
Disability	105,871	$5,951	49,772	$12,600	2.12	1.01
ESRD only	1,342	$26,003	1,415	$36,532	1.40	0.88
ESRD & DIB	1,283	$29,292	1,583	$38,340	1.31	0.98

Table A3 continued					
Rest of the United States (5%)					
Diabetes indicated	No		Yes		
Other care	Number of enrollees	Mean Medicare payments	Number of enrollees	Mean Medicare payments	Payment ratio
Total	1,190,872	$5,102	446,939	$9,664	1.89
Age and sex					
Males < 45 years	34,277	$3,769	5,039	$10,974	2.91
Males 45-64 years	104,512	$3,686	38,558	$10,605	2.88
Males 65-69 years	134,594	$3,355	48,421	$7,488	2.23
Males 70-74 years	96,116	$4,483	44,139	$8,432	1.88
Males 75 years +	157,861	$6,871	76,699	$10,796	1.57
Females < 45 years	27,871	$4,784	5,099	$11,896	2.49
Females 45-64 years	104,745	$4,299	37,533	$10,662	2.48
Females 65-69 years	156,522	$3,850	49,760	$7,858	2.04
Females 70-74 years	119,375	$4,739	43,800	$8,629	1.82
Females 75 years +	254,759	$7,228	97,791	$10,854	1.50
Race					
White	1,017,564	$5,212	349,885	$9,374	1.80
Black	95,799	$4,993	57,751	$11,644	2.33
Hispanic	20,889	$4,092	12,621	$11,460	2.80
Other	56,380	$3,675	26,582	$8,325	2.27
Original reason for Medicare entitlement					
Age	904,697	$5,017	316,399	$8,718	1.74
Disability	280,418	$4,986	122,836	$10,454	2.10
ESRD only	2,876	$22,322	3,438	$35,471	1.59
ESRD & DIB	2,641	$27,768	4,166	$36,902	1.33

SOURCE: Medicare 5% Limited Data Set Standard Analytic Files for US, 100% for Maryland
NOTE: Enrollee counts reflect 5-percent sample counts for US
To be included, enrollees must be FFS A&B for all months of eligibility

Table A4. Number of Fee-for-Service Medicare enrollees and mortality rate, 2015, by State and indication of diabetes						
Maryland (100%)						
Diabetes indicated	No		Yes			
Mortality	Number of enrollees	Mortality	Number of enrollees	Mortality	Mortality ratio	Ratio of MD and US ratios
Total	545,119	3.4%	221,892	5.6%	1.65	
Age and sex						
Males < 45 years	12,754	0.9%	1,865	3.0%	3.27	1.07
Males 45-64 years	41,315	2.3%	15,649	4.5%	1.99	0.94
Males 65-69 years	61,393	1.6%	23,588	3.5%	2.25	1.06
Males 70-74 years	44,489	2.3%	22,404	4.3%	1.89	1.02
Males 75 years +	71,230	7.4%	36,578	10.0%	1.35	1.00
Females < 45 years	10,847	0.8%	2,037	1.7%	2.14	0.79
Females 45-64 years	45,273	1.4%	17,183	3.1%	2.17	0.96
Females 65-69 years	78,043	0.9%	27,499	2.4%	2.58	0.94
Females 70-74 years	60,040	1.3%	25,153	3.1%	2.37	1.08
Females 75 years +	119,735	6.8%	49,936	8.7%	1.27	0.96
Race						
White	396,843	3.7%	136,195	6.1%	1.64	0.99
Black	113,868	2.9%	69,656	5.2%	1.82	0.94
Hispanic	4,956	2.1%	2,591	3.3%	1.55	0.77
Other	29,452	1.7%	13,450	3.4%	1.96	0.99
Original reason for Medicare entitlement						
Age	436,623	3.6%	169,122	5.7%	1.59	0.99
Disability	105,871	2.7%	49,772	5.2%	1.92	0.98
ESRD only	1,342	4.4%	1,415	8.8%	1.99	0.82
ESRD & DIB	1,283	6.0%	1,583	11.0%	1.83	1.00

Table A4 continued					
Rest of the United States (5%)					
Diabetes indicated	No		Yes		
Mortality	Number of enrollees	Mortality	Number of enrollees	Mortality	Mortality ratio
Total	1,190,632	3.7%	446,839	6.2%	1.68
Age and sex					
Males < 45 years	34,277	0.9%	5,039	2.6%	3.05
Males 45-64 years	104,512	2.2%	38,558	4.6%	2.11
Males 65-69 years	134,594	1.7%	48,421	3.7%	2.13
Males 70-74 years	96,116	2.5%	44,139	4.6%	1.85
Males 75 years +	157,861	8.0%	76,699	10.8%	1.34
Females < 45 years	27,871	0.8%	5,099	2.2%	2.72
Females 45-64 years	104,745	1.5%	37,533	3.3%	2.25
Females 65-69 years	156,522	1.0%	49,760	2.8%	2.74
Females 70-74 years	119,375	1.7%	43,800	3.6%	2.19
Females 75 years +	254,759	7.4%	97,791	9.8%	1.32
Race					
White	1,017,564	3.9%	349,885	6.4%	1.66
Black	95,799	3.2%	57,751	6.1%	1.93
Hispanic	20,889	2.5%	12,621	5.0%	2.02
Other	56,380	2.3%	26,582	4.4%	1.97
Original reason for Medicare entitlement					
Age	904,697	4.0%	316,399	6.4%	1.61
Disability	280,418	2.8%	122,836	5.4%	1.96
ESRD only	2,876	4.3%	3,438	10.5%	2.44
ESRD & DIB	2,641	6.2%	4,166	11.4%	1.84

V. Complementary Measure Supplement

COMPLEMENTARY MEASURE SUPPLEMENT

Objective

The State will evaluate changes in statewide diabetes incidence under the Maryland Total Cost of Care Model. However, estimating incidence trajectories for Maryland and comparison states is subject to sampling and measurement error, as well as other limitations. It is possible that Maryland could successfully intervene on diabetes incidence, and that those changes would be masked by the limitations of the synthetic control methodology. This would occur if, for example, enhanced diabetes surveillance in Maryland results in a shift from undiagnosed diabetes incidence to diagnosed diabetes incidence during the treatment period. While we plan to adjust for enhanced surveillance, the adjustments are also subject to measurement and sampling error, and thus may not eliminate surveillance bias.

To address these limitations, the State has specified body mass index (BMI) as a complementary endpoint for the diabetes outcome credit. It is important to note that the State will not uniformly apply for credit under the complementary outcome if the diabetes methodology fails to yield a credit. Rather, the State will evaluate performance under the complementary outcome during a given year of the intervention period if the diabetes outcome estimation indicates no improvement in Maryland, but diabetes test prevalence in Maryland in that year increases by more than two points over the 2017 value. This reflects a change of one standard deviation above the mean variation in year-over-year state prevalence changes observed in BRFSS.

As an outcome, BMI is less susceptible to surveillance bias than diabetes incidence. Most people are aware of their weight and height, while obtaining one's diabetes status requires access to a medical provider and lab work. The use of BMI offers enhanced statistical power, in that all BRFSS respondents may be included in state mean BMI calculations, while those with prevalent diabetes are not eligible to become incident and thus must be excluded from incidence calculations. BMI is a key determinant of Type II diabetes, meaning that changes in BMI will result in changes in diabetes incidence.

The State's approach for evaluating changes in BMI under the TCOC model closely follows the methodology developed for Type II diabetes. Specifically, we compare the change in Maryland's mean BMI to the mean BMI change in a comparison group selected to match Maryland's demographic characteristics and pre-Model trends. This difference between Maryland and a comparison group captures the effect of the TCOC model.

Criteria for selecting data sources for the complementary outcome mirror those for diabetes data and are not detailed here. The State will use the person-level BRFSS files from 2013 to 2017 to construct empirical Bayes estimates of BMI by state and year. Identification of a comparison group relies on the same synthetic control matching process used for diabetes, with identical matching covariates.

Calculating Baseline Mean BMI

To calculate the baseline mean BMI in the synthetic control group, we simply multiply the synthetic control weight for each state times the mean BMI for that state. The weighted average of the BMI means in the synthetic control states in the pre-intervention period is the baseline mean BMI for the synthetic control. Analogously, the simple average of mean BMI in the pre-intervention period is the baseline mean BMI for Maryland.

Synthetic Control Matching Results: Composition of the Synthetic Maryland

The states that comprise the synthetic Maryland, and their weights, provide a face validity check on the results; if the synthetic control comprises primarily states with very different demographic characteristics and health care environments than Maryland, it loses credibility. In comparison with the diabetes control group, the BMI control group contains fewer states, although both of those selected are in the mid-Atlantic region. These states are likely to resemble Maryland in their socioeconomic characteristics and health care environments, lending credence to the synthetic control. We tabulate the synthetic control states and their representation in the overall synthetic Maryland in Table 1.

Table 1. Synthetic Control Weights

State	Weight
NJ	85%
DC	13%
CT	2%

Synthetic Control Matching Results: Balance on Matching Characteristics

After establishing the face validity of the synthetic control, we determine its appropriateness as a counterfactual by examining the differences between Maryland and the synthetic Maryland on the characteristics used in matching. For each characteristic, we calculate the difference between Maryland and the synthetic control, as well as the percentage difference relative to Maryland's value. We provide the same calculations for the national average value as context.

In Table 2 we see that mean BMI from 2013-2017 for the Maryland and the control group are tightly matched, and that the synthetic control resembles Maryland much more closely than national estimates of both BMI and demographic characteristics. Thus, the synthetic control captures Maryland's BMI trajectory in the pre-intervention period better than the national mean, while achieving a much closer match on key demographic characteristics

Table 2. Balance on Characteristics Used in Matching

Variable (%)	Maryland	Synthetic Control	National Mean[a]	MD vs Synthetic		MD vs Nation	
				Difference	% Difference	Difference	% Difference
Primary Outcome [b, c]							
BMI (2013)	28.76	28.74	28.56	0.019	0.1	0.198	0.7
BMI (2014)	28.74	28.73	28.56	0.001	0	0.176	0.6
BMI (2015)	28.73	28.72	28.57	0.004	0	0.160	0.6
BMI (2016)	28.79	28.79	28.58	-0.003	0	0.212	0.7
BMI (2017)	28.74	28.75	28.59	-0.013	0	0.153	0.5
Demographic Characteristics							
Male[b]	47.74	47.99	48.80	-0.25	-0.5	-1.06	-2.2
Asian[d]	6.28	8.36	3.98	-2.09	-33.2	2.30	36.6
Black[d]	28.79	17.85	10.19	10.93	38	18.59	64.6
Hispanic[d]	6.98	15.06	8.26	-8.08	-115.7	-1.28	-18.3
White[d]	56.58	58.15	74.72	-1.56	-2.8	-18.13	-32.0
College graduates[b]	33.57	34.98	29.00	-1.41	-4.2	4.57	13.6
Urban[e]	87.15	95.44	72.50	-8.30	-9.5	14.65	16.8
Poor[d]	7.21	8.84	10.12	-1.62	-22.5	-2.91	-40.3
Near poor[d]	9.95	11.15	14.70	-1.20	-12.1	-4.76	-47.9
Middle income[d]	23.57	22.68	29.64	0.89	3.8	-6.08	-25.8
High income[d]	58.48	56.56	44.49	1.92	3.3	13.98	23.9
Health insurance[b]	90.20	88.22	90.32	1.98	2.2	-0.12	-0.1
Check-up in last year[b]	75.34	76.49	73.41	-1.15	-1.5	1.94	2.6

Notes: Values in this table represent the 35-74 population.

[a] *National values are an unweighted average across all 50 states plus the District of Columbia for the population age 35-74.

[b] Data source: 2013-2017 Behavioral Risk Factor Surveillance Survey (BRFSS) microdata

[c] Diabetes incidence is measured in cases per 10,000 population.

[d] Data source: 2016 American Community Survey (ACS) five-year rolling averages

[e] Data source: U.S. Census Summary File

Step 2: Impact Estimation

After developing a synthetic control for Maryland, we wish to use this synthetic control to estimate the change in Maryland's BMI under the Total Cost of Care Model compared to the change in a similar comparison group not under the Total Cost of Care Model. This change is a measure of the effect of the population health initiative. Of course, this measure of the effect is subject to limitations, particularly its reliance on an observational rather than a randomized design. The proposed methodology permits a causal interpretation but also requires caution in interpreting the results.

As shown in Figure 1, we could simply estimate the effect of the Total Cost of Care Model as the difference in the post-intervention period between the mean BMI in Maryland and in the synthetic control group. However, the validity of this estimate depends greatly on the match between the synthetic control group and Maryland's pre-intervention time trends. A more robust option is estimating the intervention's effects using a difference-in-differences framework. A difference-in-differences approach compares the change in Maryland's mean BMI to the change in the synthetic control's mean BMI in the same time frame. Synthetic control matching and difference-in-differences analysis pair well together because synthetic control matching is designed to align the pre-intervention outcome trends in the treatment and control groups, the central assumption of difference-in-differences.

When we estimate the effect of the Total Cost of Care Model, it is essential to acknowledge the statistical uncertainty or error in that estimate. Thus, we recommend implementing difference-in-differences in a regression framework, which facilitates error estimation. Although it is possible to calculate the difference-in-differences impact estimate directly from the available weights and incidence rates, it is much less straight-forward to determine the uncertainty of the estimate obtained in this way.

A linear regression analogous to the manual difference-in-difference calculation takes the form:

$$Y_{it} = \alpha + \gamma T_i + \delta Post_t + \theta T_i * Post_t + \varepsilon_{it}$$

- Y_{it} is the outcome, mean BMI, measured in state i in year t
- α is an overall intercept
- γ controls for residual differences between Maryland (treatment indicator $T_i = 1$) and the matched comparison states (treatment indicator $T_i = 0$) in the pre-intervention period
- δ estimates the overall difference between pre- ($Post_t = 0$) and post-period ($Post_t = 1$) mean BMIs
- θ represents the difference-in-differences between Maryland and the comparison states, pre- and post-intervention
- ε_{it} captures random error

The θ term in this model is the impact estimate – the difference-in-differences comparing the change in Maryland's mean BMI to the change in the synthetic control states.

As specified, this model does not adjust for background characteristics. If the synthetic control matching procedure does not produce adequate balance on demographic characteristics, or if we wish to implement a doubly-robust approach, we can also use the linear regression framework to adjust for residual differences between Maryland and the synthetic control states.

To include regression adjustment, we add a term to the formula from above:

$$Y_{it} = \alpha + \beta X_{it} + \gamma T_i + \delta Post_t + \theta T_i * Post_t + \varepsilon_{it}$$

Here, β controls for background characteristics X_{it} related to mean BMI, so that we interpret the impact estimate θ as the difference-in-differences assuming the same values of the background characteristics in the treatment and comparison states.

To incorporate information from synthetic control matching and thereby satisfy the assumptions of difference-in-differences regression, we must weight each observation in the regression. In this case, the observations are the mean BMIs in each state and year, along with a treatment status indicator, post-intervention period indicator, and pre-intervention background characteristics for each state. Regression weights reflect the synthetic control weights, which are set equal to 1 for all Maryland observations.

The difference in mean BMI is used to estimate diabetes incidence difference between Maryland and the control group by multiplying the BMI difference-in-differences estimate against a coefficient reflecting the association between BMI and age-, sex-, and race-adjusted diabetes incidence. The State derived the coefficient by regressing state diabetes incidence against mean state BMI using 2013-2017 BRFSS data for all states. The coefficient (.0023) indicates that a one-unit change in mean BMI is associated with a diabetes incidence change of 2.3 per thousand residents.

After obtaining the incidence difference using Maryland's mean BMI and the coefficient, estimation of the credit value proceeds as in the same manner as the diabetes incidence credit.