MARYLAND HEALTH CARE COMMISSION
PROCUREMENT ID NUMBER: MHCC 18-013

Population Health Benchmark Feasibility Study on Cost of Diabetes Care
FINAL REPORT

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Introduction: This is the final report for project MHCC 18-013, "Population Health Benchmark Feasibility Study on Cost of Diabetes Care". The purpose of the project was to make recommendations about ways to use the Medical Care Data Base (MCDB) and the ACG System from Johns Hopkins to produce metrics in support of the MHCC's mission and in particular the Maryland Total Cost of Care Model. The project focused on the population with Type 2 Diabetes (DM2) as one example of population health monitoring and assessment.

This report consists of 5 sections:

I. Description of analytic process
II. Cost benchmarks and other measure results
III. Discussion of results
IV. Suggestions for next steps
V. Technical appendices – (referenced only; not attached)

Section I: Analytic Process

The goal of the project was to assess the use of the ACG System on the MCDB to produce cost benchmarks for the Maryland population with DM2. The project started with an analytic plan, consisting of multiple table shells that defined the analyses needed. Before measures could be calculated, the MCDB had to be prepared and ACG software applied. The output of the ACG software was then used to calculate costs for several different groupings within the population.

Analytic Plan: The Analytic Plan consisted of a series of table shells (precise row and column definitions) that, when populated, would display all the calculations required by the project. This gave the project sponsors a concrete understanding of what to expect upon completion. It also helped focus discussion during team meetings to review emerging results.

Prepare the MCDB: The MCDB includes eligibility and claims information from multiple public and private payers. To produce accurate measures, the data from all sources must be consistent and comparable. For a separate project studying the cost of health care, MHCC had contracted with Social and Scientific Systems, Inc. (SSS) to clean the data and identify the useable portions. This project leveraged the work they had done for both 2015 and 2016 calendar years. Technical Appendix A contains the SAS programs used to create extracts of the MCDB for use with the ACG software, which expects flat files in a prescribed format.

Run the ACG software: The ACG software has a point-and-click front end that allows the user to select the settings appropriate for the population and data being analyzed. For this project, the following settings were used (screen shots from ACG software are shown in the Technical Appendix B):

1) Custom file settings for all 3 input files to match the layout of each file
    a. Patient Data
    b. Medical Services Data
    c. Pharmacy Data
2) Risk Assessment Variables = US Non-Elderly
3) Observation Period Begin Date = 2016-01-01 (for 2016) / 2015-01-01 (for 2015)
4) Observation Period End Date = 2016-12-31 (for 2016) / 2015-12-31 (for 2015)
5) Diagnostic Certainty = Stringent Diagnostic Certainty
6) Calculate Prior Cost = Calculate prior cost using observation period

The ACG software took several hours to execute on the volume of data used in this project. Full results were saved [see Technical Appendix for location], which allows the use of the ACG software's built-in reporting at a later date without having to rerun the entire process.

In addition to saving the file necessary for ACG reporting, the patient level results were exported as flat files to enable additional analysis using SAS. Technical Appendix C displays the program used to read the output into SAS datasets.

Calculate selected measures: An advisory team met every two weeks for several months to review and revise the initial analytic plan. At each meeting, the team assessed new results, recommended possible changes to methodology, and refined the categories for additional analyses.

The advisory team made several decisions to direct the analysis:

1) Rather than truncate individual costs at any particular level, which would mitigate the effect of a few extreme cases on mean values, display both mean and median cost, as well as maximum cost, for each selected subgroup to get a more complete understanding of costs associated with various characteristics.
2) Display the medians for populations with and without pharmacy claims information separately.
3) To calculate the mean total cost, impute the expected cost of pharmacy claims for the portion of the population that is missing pharmacy information from the mean cost of pharmacy for the portion that does have that information, combined with the relative risk of the two populations.

In addition, a physician on the advisory team recommended the specific conditions to measure for Table 6 (Complications of Diabetes) and Table 7 (Conditions which Diabetes May Exacerbate).

Technical Appendix D contains the programs used to produce the results displayed in the tables.

Section II: Cost benchmarks and other measure results

The completed Table Shells from the Analytic Plan for 2016 are in this Excel book:

MHCC 18_013_analytic_plan

Some tables were also produced for 2015 and can be seen in this Excel book:

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18_013_analytic_plar

Section III: Discussion of results

The results show the value of using the MCDB and ACG software to produce metrics on the health and healthcare of the Maryland population.

Tables 1 and 2 measure prevalence: what portion of the population are identified as having DM2? Where are the largest concentrations of these patients found?

Table 1 displays the prevalence of DM2 in various subpopulations. Overall, about 6% of the adult population receiving healthcare have DM2. Looking at the breakdowns by age, sex, and geography, rates are consistent with general research: prevalence increases with age and, as can be seen in the rates by county, is correlated with other sociodemographic factors. The rate for men is slightly higher than the rate for women.

Table 2 shows the distribution of the population with DM2 across these subpopulations, focusing on identifying the largest cohorts. Montgomery County, despite its low rate of diabetes, contains the second largest number of people with diabetes because of its large overall population.

Table 3 presents cost information for the population with DM2 compared with the overall population. Overall, the median cost for a patient with DM2 is about 4 times as high as the median for the overall population ($582 per member per month (PMPM) compared with $139). The mean cost is only 2.5 times ($1,426 compared with $555). This attests to the increased cost for every patient with DM2, rather than a very high increase for only a few patients. The marginal increase in cost due to DM2 diminishes with increasing age, as the prevalence of other conditions increases.

Table 4 adds the risk score to the analysis. As expected, the population with DM2 have higher risk scores than average. The cost relative to that risk, however, is slightly lower in the population with DM2 than in the overall population. Adjusting the cost to the risk level of the population removes the impact of morbidity and reveals other potential drivers of cost, such as sociodemographics. For example, the population of Queen Anne's County with DM2 costs more than their risk score would predict, whereas the population of Baltimore City with DM2 costs much less.

Table 5 was used to examine the distribution of cost in the population as part of the process of deciding whether or how to truncate individual cost as part of the study. Ultimately, it was decided not to truncate but, instead, to display both median and mean to help understand whether costs are a result of a few extreme cases or a general difference in cost level throughout the population.

Table 6 attempts to measure the cost impact of various complications of DM2. Combining the relative frequency of each complication with its increase in cost supports calculations of expected return on investments proposed to prevent that complication.

Table 7 looks at DM2 through another lens: given that person already has a particular condition, how does DM2 add to the burden of that condition? For example, for a person with hypertension, DM2 adds 75% to the median cost (from $401 to $700 PMPM).

These tables were constructed as examples of the type of information that can be produced using the ACG software on the MCDB. They can be used to assess current conditions, monitor progress over time, direct interventions, and measure impact.

Comparison with other sources

One way to calibrate the information produced by this study is to compare it to similar information from other sources. The Behavioral Risk Factor Surveillance System (BRFSS[1]), run by the Centers for Disease Control and Prevention (CDC), is a well-respected national survey of individuals used to track the prevalence of certain self-reported chronic conditions, such as diabetes. The Medicare Current Beneficiary Survey (MCBS) is another source, although it is limited to populations covered by Medicare. It should be noted that we did not specifically examine MCBS data, as the Medicare population is excluded from our analysis.

The BRFSS prevalence for diabetes statewide in Maryland in 2016 was 10.8%[2]. This compares with 6% of the non-elderly, commercially-insured adult population with DM2 calculated in this study, using the MCDB and ACG software.[3] Several key differences between the BRFSS methodology and this study account for the discrepancy in the calculated prevalence.

The BRFSS question used to measure diabetes prevalence is, *"Have you ever been told by a doctor that you have diabetes?"* This phrasing includes both Type 1 and Type 2 Diabetes, and is not limited to patients who had a medical claim in a particular year. The BRFSS also includes adults over age 65, whereas this study focused on non-elderly adults. For this study, the ACG definition of DM2 was set to "stringent" which requires that a patient have two separate medical services, on two separate dates, with a diagnosis of diabetes in order to identify the patient as having diabetes. Diagnoses associated with claims for Durable Medical Equipment (DME), lab tests, and radiology are considered provisional and are disregarded for the purpose of chronic disease identification.

Considering the differences in methods and in population, we are not surprised that the Maryland BRFSS estimates a higher prevalence. An important consideration in any study of change over time or difference among subpopulations is using a consistent definition for all groups.

Section IV: Suggestions for Next Steps

<u>MCDB Preparation</u>

The MCDB contains a vast amount of data, which must be understood and managed carefully to isolate data that accurately reflect reality. This project leveraged the work done by Social and Scientific

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[1] The Behavioral Risk Factor Surveillance System (BRFSS) is the nation's premier system of health-related telephone surveys that collect state data about U.S. residents regarding their health-related risk behaviors, chronic health conditions, and use of preventive services. Established in 1984 with 15 states, BRFSS now collects data in all 50 states as well as the District of Columbia and three U.S. territories. BRFSS completes more than 400,000 adult interviews each year, making it the largest continuously conducted health survey system in the world. https://www.cdc.gov/brfss/index.html accessed 1/17/2019

[2] URL: https://www.cdc.gov/brfss/brfssprevalence/, select Maryland, select Chronic Health Indicators, select Diabetes, select 2016. accessed 1/17/2019

[3] The MCBS for 2015 found that about 30% of Medicare beneficiaries age 65 or over and 32% of beneficiaries under age 65 reported being diagnosed with diabetes.

Systems, Inc. to identify the useable portion for 2015 and 2016 data. Going forward, plans to use the MCDB should take into account the necessity of cleaning the data and selecting the appropriate subset.

Risk Scoring

Understanding morbidity and associated costs is fundamental to population health analysis. The ACG software assigns a risk score to each member of the population, as one of a large number of informational markers. Other risk scoring systems exist, and some may be more suitable to certain populations. CMS relies on their Hierarchical Condition Categories (HCC) model for the Medicare population. The Chronic Illness and Disability Payment System (CDPS) from the University of California, San Diego (http://cdps.ucsd.edu/) is often used for Medicaid populations.

Identification of conditions

The ACG software produces markers for a number of conditions, including diabetes. Many of the conditions are subdivided by whether there is evidence of complications. Some conditions have related markers that address whether the patient is getting appropriate care for that condition. These markers are very useful for identifying populations for study. Because the software is updated regularly to include new codes as well as new conditions, it is a convenient way to get started on population health analysis.

One downside that came to light during this project was a lack of clarity around the specifics of the methodology. There were records for patients identified as having diabetes that had no indicator as to whether the patient had the correct pharmacy use. Several conversations with an ACG representative failed to bring any clarity to the difference between being identified as having diabetes and being identified as eligible to be evaluated for diabetes pharmacy use (pharmacy eligibility or lack thereof was not the explanation). It may be simply an issue of finding the right person to talk to, or Johns Hopkins may be protective of their proprietary methodology. For uses where algorithms or methodology must be documented specifically, it should be clarified whether that will be possible using ACG software.