MILLIMAN REPORT

Methodological Review of Cigna's Value of Integrated Benefits Study

Commissioned by Cigna, Inc.

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Executive Summary

Cigna, Inc. (“Cigna”) engaged Milliman, Inc. (“Milliman”) to perform an independent third party evaluation of the process and methodology underlying its 2020 Integrated Benefits Study (“Cigna Study”). The objective of the Cigna Study is to compare healthcare costs between members enrolled in integrated benefit plans and those enrolled in plans which carve out pharmacy coverage or comprehensive behavioral coverage (or both) among Cigna’s employer block. Cigna’s hypothesis in the context of this study is that employer groups that integrate their coverage through Cigna will experience lower healthcare costs than those that carve out either pharmacy or comprehensive behavioral coverage (or both) to another vendor. Cigna uses enrollment in integrated or carve-out plans of benefits to define test and control groups per Figure 1 below.

FIGURE 1: DEFINITION OF TEST AND CONTROL GROUPS

		BENEFITS		
STUDY POPULATION	**TEST OR CONTROL GROUP**	**MEDICAL**	**BEHAVIORIAL HEALTH**	**PHARMACY**
Triple Integration	Test	Covered	Comprehensive Covered	Covered
	Control	Covered	Basic Covered	Not Covered
Double Integration	Test	Covered	Any Level Covered	Covered
	Control	Covered	Any Level Covered	Not Covered

This report describes Milliman’s independent review of the Cigna Study. Milliman did not set out to either confirm or deny Cigna’s hypothesis. Instead, we focused on an evaluation of the matching method used by Cigna to determine whether factors that can influence the outcome are adequately accounted for in the analysis. This is generally accomplished by either matching the test and control groups, or through a normalization process. Cigna used coarsened exact matching (CEM) to account for the impact of factors that could influence the outcome in the analysis. The selection of these influencing factors was supplemented with Cigna’s subject matter expertise, gained from several years of conducting similar studies on this same population.

Cigna provided us with documentation of the study hypothesis, design elements, selection criteria, summarized results, and other relevant data. We reviewed and discussed with Cigna’s Data Science team, in detail, the data dictionary, matching algorithm, programming code, and other information necessary to evaluate the reasonableness of the Cigna Study methodology. Based on our assessment of the Cigna Study design and methodology, we believe that Cigna’s approach is reasonable and likely to generate credible results. Cigna’s approach utilizes accepted scientific principles for the measurement of treatments among comparable populations, as well as years of experience gained from relevant previous work and subject matter expertise from various contributors at Cigna. We provide herein an overview of the methods employed, along with a discussion of our approach and observations that we discussed with Cigna, and which Cigna could take into consideration for future iterations of the Cigna Study.

Milliman Review of Cigna Study

BACKGROUND

Cigna evaluates the impact of medical, pharmacy and comprehensive behavioral benefit integration on healthcare costs annually, for which its 2020 Integrated Benefits Study ("Cigna Study") is the most recent. Cigna's hypothesis in the context of the Cigna Study is that employer groups that integrate their coverage through Cigna will experience lower healthcare costs than those that carve out either pharmacy or comprehensive behavioral coverage (or both) and purchase this coverage from another vendor. Cigna believes that integration of services through the payer allows for leveraging of customer information, preferences, conditions, and medications through utilization and case management programs to identify and engage members, particularly those at higher risk for adverse outcomes. The active management and engagement of these integrated patients is then believed to lead to lower costs.

The objective of Milliman's review was to assess the Cigna Study's process and methodology for reasonableness and soundness, but not to either confirm or deny Cigna's hypothesis or opine on Cigna's findings.

MILLIMAN PROCEDURES

To perform our independent evaluation, Cigna first shared documents on the Cigna Study hypotheses, design, data elements, group, member, period and claim selection criteria; summary results in Excel and PowerPoint; interim adjustments based on preliminary findings and any other changes pertinent to the analysis. A list of the files shared by Cigna can be found in the Caveats and Limitations section of this report.

Cigna provided an overview of all provided documents through screen-sharing during scheduled conference calls (held August 19, September 8, 15, and 29, and October 13, 2020), and email correspondence. Cigna also provided ongoing support throughout the engagement to clarify details as questions arose. Milliman reviewed, in detail, the data dictionary, matching algorithm, programming code, output, and other information necessary to evaluate the reasonableness of the Cigna Study methodology.

Cigna also reviewed and provided input for Milliman's consideration drafts of this report.

SOURCE DATA

The analytical dataset for the Cigna Study is comprised of eligibility and medical claims data from Cigna's data warehouse. Receiving and performing an audit of the data was outside the scope of this review. Our analysis was based on summaries of the data, as well as on programming code, and descriptions (verbal and written) about the process provided by Cigna.

STUDY POPULATION

The retrospective analysis looks to control for the level of coverage with respect to the behavioral benefit in order to evaluate the effect of either including or excluding pharmacy coverage. Cigna used enrollment in integrated or carve-out plans of benefits to define test and control groups per Figure 1 in the Executive Summary.

The study period reviewed was calendar year 2019, although calendar year 2018 was used for the calculation of prospective risk scores. Additionally, in order to qualify for inclusion in the study, continuous enrollment in medical benefits during 2018 and 2019 and in a medical management product during 2019 was required. Figures 2A and 2B below serve to present an overview of the study's organization.

Subpopulations of interest were defined as follows:

- Health Improvement: members identified through Cigna's Utilization Management program to fill gaps in care or engage in actions related to their condition.
- Engaged Health Improvement: members who agreed to participate in Utilization Management programs to either fill gaps in care or engage in actions related to their condition.
- Identified Diabetes: members of the Health Improvement population with a diagnosis of diabetes.
- Identified Specialty Condition: members of the Health Improvement population with a prescription for a specialty medication related to serious medical conditions such as oncology.

FIGURE 2A: INCLUSION DIAGRAM FOR TRIPLE INTEGRATION STUDY POPULATION

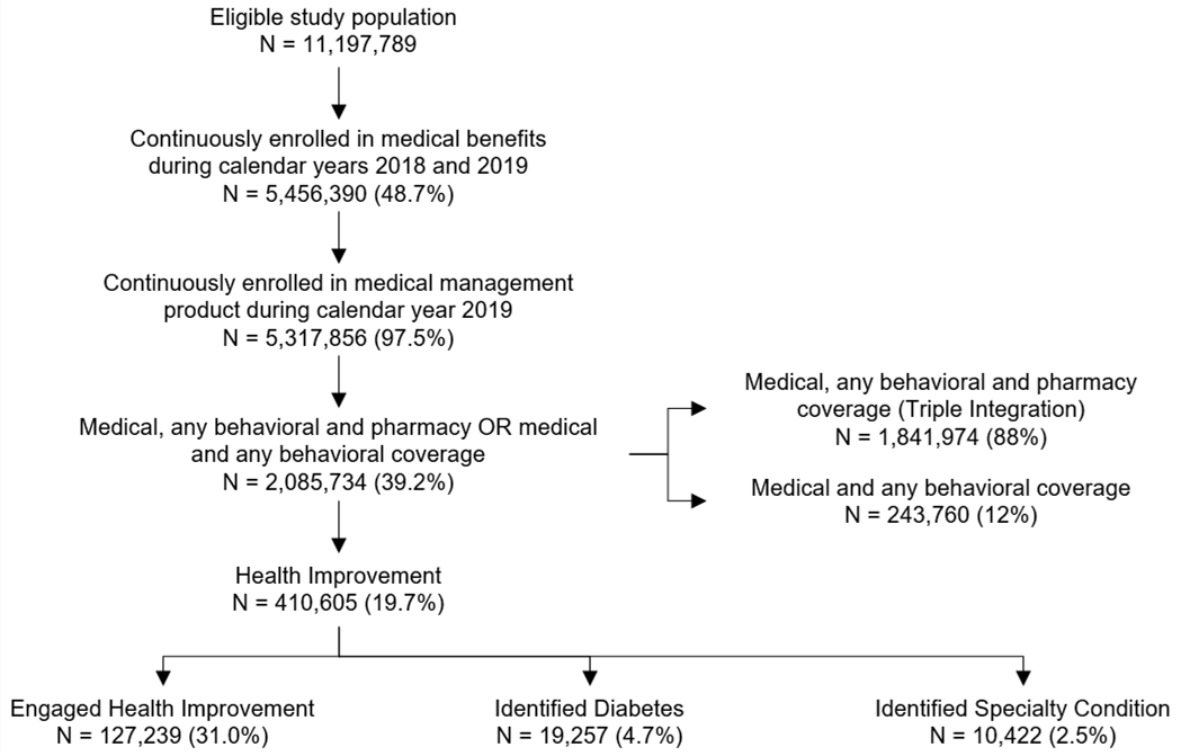
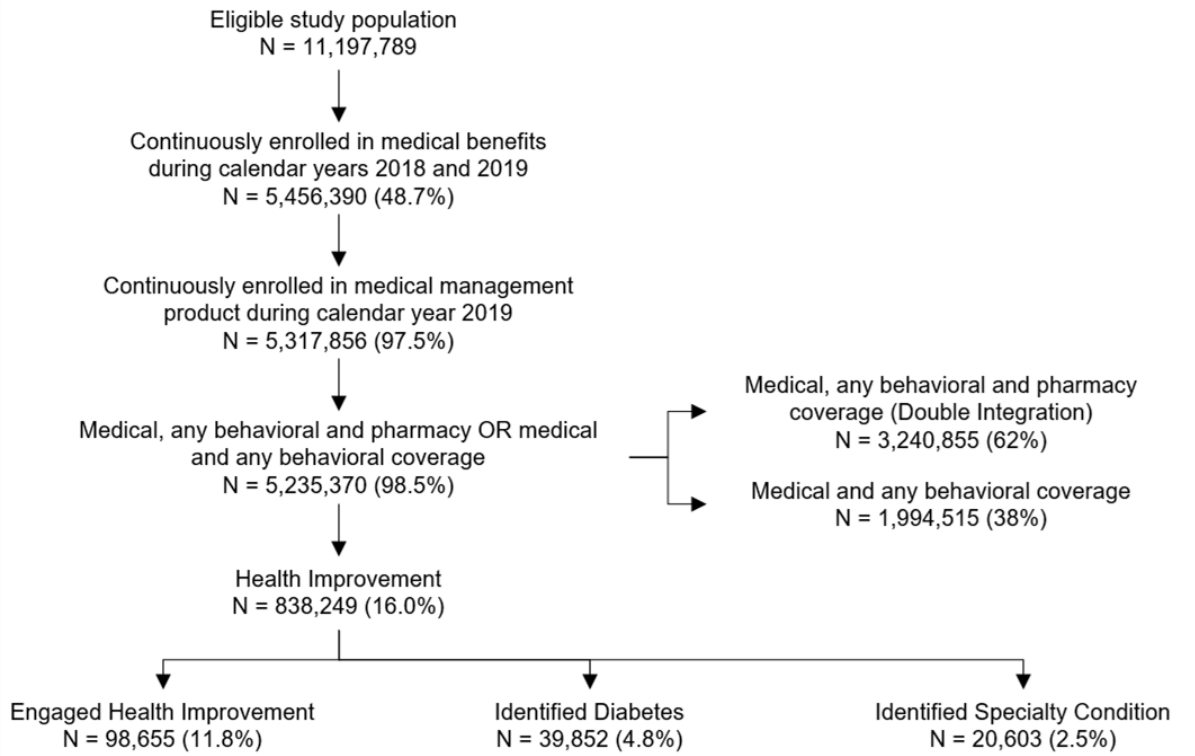


FIGURE 2B: INCLUSION DIAGRAM FOR THE DOUBLE INTEGRATION STUDY POPULATION



As described to us by Cigna, the choice of subpopulations for the Cigna Study is consistent with Cigna's medical management processes and the general way it analyzes its block of commercial large groups. Our review of the methods does not vary by subpopulation, as the methodology is consistent across all the above groupings.

METHODOLOGY OVERVIEW

In order to properly test a hypothesis of interest, factors that can influence the outcome and are also the independent variable must be adequately accounted for in the analytical methods. This is generally accomplished through either normalization techniques or a matching algorithm. Cigna employed coarsened exact matching (CEM) to account for the impact of confounding factors in the analysis. Below we provide a discussion of how matching techniques are used to account for the impact of confounding variables between test and control populations in the evaluation of a treatment.

Exact Matching

Similar to normalization or covariate adjustment, the purpose of employing a matching technique is to reduce or remove the influence of confounding variables. The most direct way to do so is to match individuals from the test group with those from the control group with the exact same value for each confounding variable in order to reach similar distributions among the groups for a set of confounding variables identified by the experimenter.

For example, suppose we have a study population where only three variables could affect the outcome: age, biological gender, and treatment. To remove the effect of the confounding variables in the evaluation of the treatment, we would form bins based on age and gender assigned at birth, such as 48-year-old females. These bins are then matched across the test and control populations. In this way, if we look at the difference in means for any bin across the test and control groups, we have eliminated the influence of any of the confounding variables on the outcome, and can, therefore, say with more confidence that any remaining difference is due to the treatment. This is exact matching, which removes imbalance (see the Considerations section for a discussion of imbalance in the context of Cigna's analysis) between the confounding variables in the test and control groups. This has the effect of ensuring that the confounding variables have no effect on any inferences made.[1]

In practice and depending on the nature of the data being used, performing exact matching may not be feasible due to the number of possible confounding variables and volume / type of data. First, there is the difficult task associated with the proper identification of all possible confounding variables. This is not always possible in practice. Then, there is the issue of dimensionality, or the number of attributes, in the analytical dataset, which can be more complicated than a simple count of the variables given that some may be inter-related. The more dimensions in the data, the more difficult it is to find exact matches across all dimensions simultaneously. Because of the challenges associated with exact matching, CEM can be employed as a reasonable alternative approach that intends to lead to a similar reduction in imbalance.

Coarsened Exact Matching

CEM works much the same as exact matching with one main difference: before matching is performed, a coarsened version of the confounding variables is made in which a copy of each is put into discrete strata, or bins. Such coarseness places bounds on the maximum imbalance.[1] For example, the continuous variable age could be coarsened into levels of 0 to 21, 22 to 50, 50 to 65, and 65 years and up. Exact matching is then performed on the coarsened variables, and any bins with either no treatment or no control members are pruned.[2] Decisions surrounding the coarsening applied to the continuous variables are often informed by subject matter expertise, as in the case of Cigna's refinement to the Cigna Study over time.

[1] Imai K, King G, Stuart E. Misunderstandings Between Experimentalists and Observationalists About Causal Inference. J Royal Statistical Society 2008:Series A,171(2);481-502.

[2] King G, Nielsen R. Why Propensity Scores Should Not Be Used for Matching. Political Analysis 2019:27(4):435-54.

Matching results in data that have been segmented into bins, such that a member in bin 1 of the control group, for example, has the same coarsened confounding variable values as a member in bin 1 of the test group, but not necessarily the exact same confounding variable values. To confirm that the matching has reduced imbalance, the empirical cumulative distribution of the data for a given set of coarsened confounding variables should be compared between the test and control groups. In the case of this project, or any with highly dimensional data, imbalance scoring is impractical. As such, a (paired and weighted) t-test was performed for each variable to test the equivalence of the means across the groups. While this does not definitely demonstrate that the data is no longer imbalanced, it does provide some evidence of more balanced means.[1]

RESULTS SUMMARY

Study results as provided by Cigna are presented in Figure 3. The average cost per member per year ("PMPY") for those with integrated benefits (test group) was subtracted from those without (control group), for which positive values indicated savings. Differences were evaluated by Cigna using a difference of means t-test.

Milliman does not opine on the validity, adequacy, or realism of these results as this is outside the scope of our review.

FIGURE 3: ALLOWED COST PER MEMBER PER YEAR (PMPY) BY BENEFIT GROUP AND STUDY POPULATION FOR 2019

POPULATION	CONTROL GROUP PMPY	TEST GROUP PMPY	PMPY DIFFERENCE	PERCENT OF CONTROL PMPY	P-VALUE
Triple Integration					
Total	$ 3,943	$ 3,716	$ 227	5.8%	<0.0001
Health Improvement	$ 9,734	$ 8,699	$1,035	10.6%	0.0012
Engaged Health Improvement	$20,671	$15,930	$4,741	22.9%	<0.0001
Identified Diabetes	$20,631	$17,854	$2,777	13.5%	<0.0001
Identified Specialty Condition	$79,063	$72,625	$6,438	8.1%	0.1598
Double Integration					
Total	$ 3,861	$ 3,769	$ 92	2.4%	<0.0001
Health Improvement	$ 9,268	$ 8,920	$ 348	3.8%	<0.0001
Engaged Health Improvement	$19,582	$16,376	$3,206	16.4%	<0.0001
Identified Diabetes	$20,304	$18,060	$2,244	11.1%	<0.0001
Identified Specialty Condition	$74,447	$69,803	$4,644	6.2%	0.0407

Discussion and Considerations

Based on our independent review, Cigna's rationale, processes and methodology are reasonable in the context of achieving comparable cohorts for measuring cost differences. The use of CEM as a means to normalize for the effects of confounding variables is appropriate. Furthermore, Cigna's approach follows generally accepted principles of matching. In addition to the analysis of the CEM approach, we confirmed that other aspects of the Cigna Study were also appropriate and reasonable, including:

1) The use of a prospective risk score methodology for the calculation of risk scores. Cigna extracted the risk score from its licensed Symmetry Product based on Episode Treatment Groups. This model uses medical claims to predict medical risk in a general population, consistent with the Cigna Study's purpose of classifying members based on their risk composition. Pharmacy claims are appropriately not used.

2) The subject matter expertise engaged by Cigna to aid in the selection of confounding factors, and the coarsening levels for those confounding factors. Cigna drew on many years of experience conducting this study when setting the coarsening levels of risk scores. Additionally, Cigna data scientists have discussed the adequacy of the approach used in the Cigna Study with Dr. Gary King, a professor at the Institute for Quantitative Social Science at Harvard University and co-author of Iacus on the discussion and statistical programming for CEM.[3]

3) The criteria used for member inclusion in the Cigna Study. Cigna's requirement for continuous enrollment ensures a certain level of maturity in the population studied and helps eliminate potential extraneous factors brought about by newly enrolled membership.

4) The identification of members across the various subpopulations using medical codes, and the adequacy of the selected codes. The use of International Classification of Diseases, Tenth Revision, Clinical Modification (ICD-10-CM) codes to identify certain diagnoses is a generally accepted standard when using claims data. We also confirmed that the specific ICD-10-CM codes used in the identification of specific subgroups were appropriate and correct.

Further discussion of our analysis, including considerations for Cigna to take into account for future iterations of the Cigna Study, is included below. As previously indicated, our review focused on the adequacy of Cigna's methodology for comparing groups that either carve in or carve out pharmacy and total behavioral benefits. We did not review either Cigna's processes for gathering the data for the study, or the actual study results.

COARSENING LEVELS AND RISK SCORE BINS

Our understanding of Cigna's general guiding principle in the selection of coarsening for any given confounder is that Cigna wanted to secure a proper balance between statistically suggested coarsening and a reasonably high "post matching percentage" in order to ensure that granularity did not overtake the CEM's ability to identify matches between the test and control populations.

Use of CEM relies on the experimenter's subject matter expertise to create bins that are large enough to enable a reasonable match rate, and hence evaluation of the average treatment effect, and small enough so as not to introduce significant bias. In consultation with Cigna's Data Science team, we learned that internal testing on customer risk score led to the conclusion that, to fully capture all differences, upwards of 150 bins would have to be created. Since this would be significantly difficult to implement, Cigna, relying on subject matter expertise gained over many years of iterations of this study, used six bins to categorize risk scores.

In order to determine if the selection of bins for risk scores was reasonable, we examined the statistical means of the test and control populations in each grouping. We performed a similar examination of mean values between the test and control populations for other groupings of continuous confounder variables, including age, comorbidity counts and levels of coverage. Although as explained in the next consideration, the general use of population statistics may not provide a direct assessment of any potential model imbalance (i.e., researcher discretion), our analysis indicated that, in general, the resulting means across test and control populations, particularly for risk scores, were very similar. This would generally mean that, at the very least, there is no significant discrepancy on the average risk composition

[3] Iacus SM, King G, Porro G. Causal Inference Without Balance Checking: Coarsened Exact Matching. Political Analysis 2012:20(1);1-24.

between test and control populations in each of the six Cigna Study risk score bins. In short, Cigna's choice of bins, while obviously not the only possible coarsening, appears reasonable and we do not believe that it introduced significant bias into the findings. Cigna should continue monitoring the adequacy of the coarsening levels selected for this Cigna Study and adjust as necessary in future iterations.

POPULATION STATISTICS

Coarsened exact matching, as all matching algorithms, attempts to remove any influence the confounding variables have on the outcome of a study; in this way, any difference in outcome between test and control groups can be attributed to the test variable alone. To that end, it is crucial that the matching produces balanced bins. That is, after an ideal exact matching, the empirical distributions of the covariates should be equal for the test and control groups for each given bin. Since coarsened exact matching is not exact, the imbalance should be tested. One example of an imbalance measure is a score proposed by Iacus and colleagues.[3] The score uses the Manhattan norm to measure the distance between the frequencies in the empirical test and control distributions for the coarsened covariates.[4] However, depending on the dimensionality of the data, application of this score can be challenging. In addition, given the use of confounders such as gender and medical management product that are not easily mapped to numbers, calculation of a distance metric may have been inadvisable in this instance.

One common alternate method used is to perform hypothesis testing of the difference of the means for each covariate for the matched test and control groups. The theory is that if the imbalance has been removed, then the means for each covariate will be equal across the test and control groups. This was the method used by Cigna. However, as pointed out by Imai and colleagues, this method can be misused.[1] Ostensibly, a given factor may have very different treatment and control empirical distributions and yet have nearly identical population means. Also, since the t-test measures differences in population statistics, and imbalance is an issue with the empirical distribution, population statistics may not fully capture the imbalance. Because of this, we examined the post matched distribution of the continuous variables and found that, in this instance, there was no significant imbalance. Furthermore, we understand that the use of population statistics to evaluate significance is common practice. Therefore, Cigna appears to be following generally accepted practices in this regard. Here, too, Cigna should ensure continual monitoring of both the means and post-match distributions of the continuous variables in order to assess any potential imbalance in future iterations of the Cigna Study.

ELIXHAUSER COMORBIDITIES COUNT

In addition to prospective risk score, an Elixhauser Comorbidity Index score was used to capture member morbidity with more precision. We believe, at a high level, that including this additional confounder which quantifies comorbidities in addition to the morbidity level captured by the risk score itself is an appropriate and valuable choice for matching purposes. The Elixhauser Comorbidity Index categorizes 31 individual comorbidities based on ICD-10-CM[5] codes into categories such as congestive heart failure, obesity, paralysis, lymphoma, depression, renal failure, drug abuse, and more. These categories range widely in terms of severity of illness and possibly in terms of the cost of care. Therefore, a weighting mechanism may be advisable.

However, there is no commonly agreed-upon weighting mechanism for the Elixhauser Index to calculate overall patient health or an outcome like annual costs. As a result, Cigna decided to use a simple count of comorbidities and then coarsen this count into four categories (0, 1, 2, and 3+ conditions). Because the risk score confounder already adequately captures a member's morbidity, the addition of a comorbidity count as a confounder serves to further differentiate members who may have similar risk scores. Therefore, the approach used for this iteration of the Cigna Study appears reasonable and acceptable. However, because each condition is weighted equally under the current approach, future iterations of the study should explore weighting mechanisms that could take into account the different effects on health of different comorbidities and more precisely reflect the actual health of a member.

[4] The Manhattan, or L^1, norm refers to the sum of the absolute values, or absolute difference of the components, of the vectors, weighing each component of the vector equally; see Gradshteyn, I. S. and Ryzhik, I. M. Tables of Integrals, Series, and Products, 6th ed. San Diego, CA: Academic Press, pp. 1114-1125, 2000., and Horn, R. A. and Johnson, C. R. "Norms for Vectors and Matrices." Ch. 5 in Matrix Analysis. Cambridge, England: Cambridge University Press, 1990. for additional detail.

[5] "The ICD-10-CM (International Classification of Diseases, Tenth Revision, Clinical Modification) is a system used by physicians and other healthcare providers to classify and code all diagnoses, symptoms and procedures recorded in conjunction with hospital care in the United States." https://searchhealthit.techtarget.com/definition/ICD-10-CM#:~:text=The%20ICD%2D10%2DCM%20(,care%20in%20the%20United%20States.

INCLUSION OF NON-ASO GROUPS IN THE TEST POPULATION

It is our understanding that approximately 25% of the test population in this analysis was enrolled in either fully insured or other types of funding arrangements that integrate pharmacy and total behavioral benefits, and which do not have the option of carving out coverage. Fully insured groups, for instance, generally are only offered policies that are all inclusive of medical, pharmacy and behavioral benefits.

However, the underlying hypothesis of this study was that the integration of medical, pharmacy and behavioral benefits results in significant cost savings for customers compared to those who do not integrate. As such, client level options and decisions were not incorporated into the study and have no direct bearing on the hypothesis. Still, future iterations of the study may want to determine if client level plan options do result in differences at the customer level and hence warrant limitations such as excluding non-ASO (Administrative Services Only) accounts.

FINAL RESULTS T-TEST

We observed that the formula used for the weights in the final calculation of savings could produce inordinately large values in situations where the test group in a given bin is large and the control group for the same bin is small. To test whether or not this was relevant to this study, we examined the bivariate distribution of bins by size of control group and test group. After analyzing these distributions, the aforementioned possible scenario does not occur in the Cigna Study, and therefore the methodology used by Cigna appears to be appropriate for the Cigna Study. However, Cigna should perform a similar analysis of the bivariate distributions by bin size in future Cigna Study iterations in order to determine whether bin definitions by confounder are reasonable.

Furthermore, in the evaluation of final results, Cigna performed t-tests for statistical significance. This is a broadly accepted and reasonable methodology for confirming the significance of results. Moreover, an evaluation of the P-values from t-tests performed on the final results of this analysis shows that most differences reached statistical significance, at less than 0.0001. Thus, both in the choice of method (CEM) and in the evaluation of outcomes, Cigna's methodology appears reasonable and appropriate.

Caveats and Limitations

This Milliman report has been prepared for the specific purpose of assessing the design and process of Cigna's 2020 Integrated Benefits Study. This information may not be appropriate, and should not be used, for any other purpose. This work has been prepared for Cigna to share with third party stakeholders. Milliman does not intend to benefit or create a legal duty to any third party recipient of this work. Our analysis was performed under the Consulting Services Agreement with Cigna. Furthermore, the terms of Milliman's Statement of Work with Cigna signed on September 4, 2020 apply to this report and its use.

In performing this analysis, we relied on data and other information, including verbal and written correspondence, as well as prepared files containing methodology documentation, provided by Cigna. Files were received on August 24, September 3, and October 2, 6, and 28, 2020. Relevant conference calls were held on August 19, September 8, 15, and 29, and October 13, 2020. We have not audited or verified this data and other information but reviewed it for general reasonableness. If the underlying data or information is inaccurate or incomplete, the results of our analysis may likewise be inaccurate or incomplete. If there are material defects in the data, it is possible that they would be uncovered by a detailed, systematic review and comparison of the data to search for data values that are questionable or for relationships that are materially inconsistent. Such a review was beyond the scope of our assignment.

Our analysis was limited to assessing the reasonability of the current methodology as of October 2020 employed by Cigna, and no commentary regarding the validity of Cigna Study results has been provided. No attempts to replicate the Cigna Study, recalculate results, test for potential omissions, weakness, or biases, or employ an alternative approach were made. Furthermore, we did not review Cigna's specific integration activities and/or whether those activities would produce results to demonstrate a causal relationship between integration activities and resulting cost differentials.

Differences between Cigna Study findings and actual amounts depend on the extent to which future experience conforms to the assumptions made for Cigna's analysis. It is certain that actual experience will not conform exactly to the assumptions used in their analysis. Actual amounts will differ from projected amounts to the extent that actual experience deviates from expected experience.

Milliman has reviewed certain models developed by Cigna for the Cigna Study. The intent of the models was to estimate cost differences between groups that either carve in or carve out pharmacy and total behavioral benefits. We have reviewed the models, including their inputs and calculations for consistency, reasonableness, and appropriateness to the intended purpose and in compliance with generally accepted actuarial practice and relevant actuarial standards of practice (ASOP).

The models rely on data and information as input to the models. We have relied upon certain data and information provided by Cigna for this purpose and accepted it without audit. To the extent that the data and information provided is not accurate, or is not complete, the analysis provided in this report may likewise be inaccurate or incomplete.

Milliman's data and information reliance includes:

- "Instructions-Population Flowcharts.xlsx", received August 24, 2020
  - Overview of accompanying programming files, study population definitions and inclusion/exclusion diagram, high-level description of coarsened exact matching (CEM), results for 2018, 2019, and 2020 studies.
- "VOI 2020 TI Run $227.egp"; "VOI 2020 TI Run Health Improvement $1035.egp"; "VOI 2020 TI Run Health Improvement Engaged $4741.egp"; "VOI 2020 TI Run Diabetes Health Improvement $2777.egp"; "VOI 2020 TI Run Specialty Health Improvement $6438.egp", received August 24, 2020
  - SAS programming for each of the five study populations of interest including (1) CEM macro for assigning weights based on input confounding variables; (2) deriving of variable binning for confounders prior to running CEM macro; (3) invocation of CEM macro and results, and (4) post-matching statistical tests for confounder variables between groups.
- "Data Dictionary for Milliman.xlsx", received September 3, 2020
  - Description of variables included in analytical datasets used in SAS programming.

- Frequency of plan funding via email on September 15, 2020
- "Cigna VOI Template with Figures.xlsx", received from Cigna October 2, 2020
  - Frequencies of confounding variables by CEM bins and size of bin signatures and P-values for 2020 results reported in "Instructions-Population Flowcharts.xlsx".
- Study population eligibility details via email on October 6, 2020
- "Pre and Post Matching Confounder Statistics TI and DI.xlsx", received October 28, 2020
  - Summary statistics of confounding variables pre- and post-matching.

ACKNOWLEDGMENT OF QUALIFICATION

I, Pedro Alcocer, FSA, MAAA, am a Consulting Actuary for Milliman. I am a member of the American Academy of Actuaries and I meet the Qualification Standards of the American Academy of Actuaries to render the actuarial opinion contained herein.

A publicly available version of this report can be found at:

https://www.milliman.com/cigna-integrated-benefits

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