MILLIMAN WHITE PAPER

What is the minimum number of members required to take downside risk in a payment model for children with complex medical conditions?

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This paper explores the number of members required to take downside risk in a payment model for children with complex medical conditions. The level of volatility in a cohort's claims per member per month (PMPM) decreases as the number of members in the cohort increases. High volatility in a cohort makes taking downside risk on the cohort undesirable. How many members are required to sufficiently mitigate volatility? The minimum number of members can be estimated using the statistical concept of confidence intervals. Ultimately, the minimum number of members needed depends on the risk tolerance of the entity taking the risk.

Background

The authors provide actuarial support for the Children's Hospital Association (CHA) on behalf of 10 of its Coordinating All Resources Effectively (CARE) Award hospitals, as part of the CARE Award. The CARE Award is a Health Care Innovation Award from the Center for Medicare and Medicaid Innovation (CMMI) to test the coordination of care for children with complex medical conditions.[2] One of the goals of the CARE Award is to assist CARE Award hospitals (sites) with the design of new payment models for the care of these children.

Children with complex medical conditions are defined as children with significant chronic conditions in two or more body systems or those with a single dominant chronic condition.[3] Complex medical conditions are identified in the claims data using the 3M Clinical Risk Groups (CRG) algorithm, which stratifies members into a hierarchy of risk groups. For the purposes of the CARE Award, children with complex medical conditions are defined as those with CRGs 5b to 9. Other pediatric CMMI awardees have defined the term "children with complex medical conditions" differently. Figure 1 gives a brief definition of each of the CRGs. In the Appendix, we provide a summary of claims experience used in this analysis, by site and by CRG.

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[2] For more information on the CARE Award, see https://www.childrenshospitals.org.

[3] CHA (October 11, 2013). Defining Children With Medical Complexities. Issue Brief. Retrieved December 7, 2016, from https://www.childrenshospitals.org/Issues-and-Advocacy/Children-With-Medical-Complexity/Fact-Sheets/Defining-Children-With-Medical-Complexities.

FIGURE 1: CRG DEFINITIONS

CRG	ABBREVIATED DEFINITION
5B	SIGNIFICANT LIFELONG CHRONIC DISEASE
6	SIGNIFICANT CHRONIC DISEASES IN MULTIPLE ORGAN SYSTEMS
7	DOMINANT CHRONIC DISEASES IN THREE OR MORE ORGAN SYSTEMS
8	DOMINANT / METASTATIC MALIGNANCY
9	CATASTROPHIC

According to CHA, approximately two-thirds of children with complex medical conditions are covered by Medicaid.[4] CHA estimates that, while children with complex medical conditions make up only 6% of pediatric Medicaid beneficiaries, they represent 40% of the total Medicaid and Children's Health Insurance Program (CHIP) expenditure for children.

Each site has its own program that enrolls children with medical complexity (CMC) in the CARE Award in order to better coordinate their care. These children are typically enrolled in Medicaid. As part of the CARE Award, IBM Watson processed Medicaid claims data for children eligible for the CARE Award.

A common question when discussing the potential for a payment model specifically for this population is, "What is the minimum number of members required to take downside risk?" The number of attributed members is an important question to consider in the development of any payment model. Two important, and related, considerations when developing a payment model are:

1. Does appropriate and reliable claims and enrollment experience data exist for the membership? One aspect of appropriateness and reliability of data is the volume of data. If there are too few exposures (i.e., member months) in the experience period, analysis of the experience data will not produce meaningful results.
2. How many members will be attributed to the payment model in the base period and the performance period? If too few members are attributed, the average claims PMPM for the members will be unpredictable and not suitable for downside risk.

Both these considerations relate to what actuaries call the "credibility" of a set of members, which applies to both base period experience and the performance period. In this paper, we show how we can develop credibility thresholds for the medically complex pediatric population using examples from the data of four different CARE Award sites. Please note that our analysis excludes risk adjustment and other financial protections, which are important considerations when entering into an arrangement with downside risk. The impact of stop-loss is examined in the "Alternate scenarios" section of this paper.

Providers will potentially need to enroll an entire state's population of CMC to achieve membership thresholds discussed in this paper. Substantial work may be required to build a care management infrastructure, create a network, and contract with states and / or managed care organizations (MCOs) in order to achieve the membership levels discussed in this paper. In addition, an organization should consider expenses and economies of scale when considering appropriate membership levels.

Background: Credibility theory

Actuarial Standard of Practice (ASOP) No. 25 defines credibility as "a measure of the predictive value in a given application that the actuary attaches to a particular set of data," and it defines full credibility as "the level at which the subject experience is assigned full predictive value, often based on a selected confidence interval."[5] If a data set is too small, the conclusions drawn will not be meaningful. Therefore, one of the key drivers of credibility is the number of claims the data set contains, which is a function of the number of exposures (i.e., member months) it contains. In this paper, as a simplification, we define the number of claims as the number of member months with a claim.

Credibility is a concept for describing both the reliability of past experience data and the predictability of future experience data. The future average claims PMPM for a cohort will be more predictable the larger the cohort is, all else being equal. For example, if there are 50 members and one member has a $1 million claim, this will have a much bigger effect on the claims PMPM for the cohort than if there are 5,000 members and one member has a $1 million claim.

The credibility of a data set is defined by selecting a confidence interval. A credibility threshold is generally set using two parameters, α and ε. We can calculate the number of claims required in the sample data such that the estimated claims PMPM is within ε% of the true mean claims PMPM with probability (1 - α). For example, an entity taking risk on a population's claims may desire that the estimated mean claims PMPM will be within 10% of the mean claims PMPM 95% of the time. In this example, α is 5% and ε is 10%. The number of claims n_F required, such that the probability that expected claims

[4] CHA (2016). CARE Award. Programs and Services. Retrieved December 7, 2016, from https://www.childrenshospitals.org/careaward.

[5] ASOP No. 25 is available online at http://www.actuarialstandardsboard.org/wp-content/uploads/2014/02/asop025_174.pdf.

PMPM are within ε% of the true mean claims PMPM with probability (1 - α), can be calculated as follows:

$$n_F = \left(\frac{z_{\alpha/2}}{\varepsilon}\right)^2 \left(1 + \left(\frac{\sigma}{\mu}\right)^2\right)$$

In this equation, $z_{\alpha/2}$ denotes a quantile of the standard normal distribution.[6] Use of this equation relies on some key assumptions:

- Claims amounts are independent and identically distributed with a mean μ and standard deviation σ.[7]
- The total claims PMPM is approximately normally distributed.[8]
- The frequency of claims is Poisson distributed.

If we further assume that the frequency of member months with a claim is constant, with frequency λ, then the number of exposures (i.e., member months) required for full credibility is e_F, which can be calculated as follows:

$$e_F = \frac{\left(\frac{z_{\alpha/2}}{\varepsilon}\right)^2 \left(1 + \left(\frac{\sigma}{\mu}\right)^2\right)}{\boldsymbol{\lambda}}$$

Therefore, the number of member months required depends on:

- The entity's tolerance for variation in average claims PMPM, or in other words the risk tolerance, expressed using α and ε.
- The characteristics of the data set: the coefficient of variation (σ / μ) and the frequency of claims λ.

Analysis and results

We use Medicaid claims and enrollment data for children eligible for the CARE Award (eligible data) to estimate parameters for the mean (μ) and standard deviation (σ) of claims PMPM. Using these parameters, we calculate thresholds for full credibility (e_F) in terms of member months. We use four different data sets from four different states, which are discussed in more detail below. Figures 2 to 5 show our estimates of full credibility (e_F), varying the parameters (1-α) and ε, for each site.

In Figures 2 through 5, we can see the highest credibility thresholds are for Site B. This conclusion is not immediately obvious from a visual review of the histogram shown in Figure 10 in the Appendix. This demonstrates that in-depth actuarial analysis of experience data can reveal much more than is available through cursory and high-level review of experience data.

FIGURE 2: FULL CREDIBILITY THRESHOLDS IN AVERAGE ANNUAL MEMBERS, SITE A

	1-α			
ε	99.5%	99.0%	95.0%	90.0%
0.5%	544,800	458,700	265,600	187,100
1.0%	136,200	114,700	66,400	46,800
5.0%	5,500	4,600	2,700	1,900
10.0%	1,400	1,200	700	500

FIGURE 3: FULL CREDIBILITY THRESHOLDS IN AVERAGE ANNUAL MEMBERS, SITE B

	1-α			
ε	99.5%	99.0%	95.0%	90.0%
0.5%	2,074,300	1,746,700	1,011,300	712,300
1.0%	518,600	436,700	252,900	178,100
5.0%	20,800	17,500	10,200	7,200
10.0%	5,200	4,400	2,600	1,800

FIGURE 4: FULL CREDIBILITY THRESHOLDS IN AVERAGE ANNUAL MEMBERS, SITE C

	1-α			
ε	99.5%	99.0%	95.0%	90.0%
0.5%	1,408,800	1,186,300	686,800	483,800
1.0%	352,200	296,600	171,700	121,000
5.0%	14,100	11,900	6,900	4,900
10.0%	3,600	3,000	1,800	1,300

FIGURE 5: FULL CREDIBILITY THRESHOLDS IN AVERAGE ANNUAL MEMBERS, SITE D

	1-α			
ε	99.5%	99.0%	95.0%	90.0%
0.5%	446,500	375,900	217,700	153,300
1.0%	111,700	94,000	54,500	38,400
5.0%	4,500	3,800	2,200	1,600
10.0%	1,200	1,000	600	400

The numbers in Figures 2 through 5 are all in terms of average annual members. Numbers highlighted in green are the numbers shown in Figure 6.

[6] This equation relies on the theory of limited fluctuation credibility. For more background on this theory, see the American Academy of Actuaries' Long-Term Care Credibility Monograph at http://actuary.org/files/imce/LTC_Credibility_Monograph_08172016.pdf.

[7] This is a commonly used simplifying assumption. Claims may not be independent due to factors such as comorbidities.

[8] This is a commonly used simplifying assumption. Claims PMPM may not be normally distributed.

While it is possible to establish full credibility using multiple years of experience, a payment model is often adjudicated on an annual basis, which does not allow for the aggregation of multiple years of experience. In the performance period of a payment model, the number of members needs to be sufficient to establish full credibility in light of the entity's risk tolerance. The alternative is a membership cohort with too much volatility, which poses too much potential downside risk. Therefore, when developing a payment model, it is important to consider not only how many member months of experience data are available for analysis, but also how many members will be present on average per year in the performance period.

In Figures 2 through 5, we assume 10 annual months per member. This assumption will vary depending on Medicaid eligibility in a given state. Figures 2 through 5 show that, even holding constant values of (1-α) = 99.5% and ε = 5.0%, differing levels of volatility in the underlying data as well as differing average durations of membership mean the threshold for full credibility can vary from around 5,000 members to around 21,000, approximately a fourfold difference. We note that the number of members required for CMS's Next Generation ACO (NGACO) program is 10,000, which is within the range of the membership thresholds in Figures 2 through 5 using (1-α) = 99.5% and ε = 5.0%.[9] The level of variance for Medicare beneficiaries will differ from the level of variance for Medicaid eligible pediatric patients with complex medical conditions, so the two thresholds are not necessarily comparable.

We also examine the potential annual dollar impact if each site were to use 10,000 members rather than the minimum thresholds from Figures 2 through 5. We define dollars at risk as the number of additional dollars of claims that could be incurred by the population beyond the maximum number of dollars at risk, using (1 - α) = 99.5%, ε = 5.0%, and 10 average months enrolled per member per year. For sites A and D, whose minimum thresholds are lower than 10,000, using 10,000 members results in fewer dollars at risk.

Figure 6 shows that the dollars at risk from using 10,000 members may be as much as $28.6 million for Site B, or $286 PMPM. On the other hand, if Site D uses 10,000 members, which is 5,000 members more than its minimum threshold for the specified risk tolerance, its potential downside risk is reduced by $33.4 million, or $334 PMPM.

FIGURE 6: ADDITIONAL OR (FEWER) DOLLARS AT RISK FROM ENROLLING 10,000 MEMBERS INSTEAD OF THE MINIMUM REQUIRED

(1-α) = 99.5%, ε = 5.0%
Average Annual Months Per Member = 10

SITE	MINIMUM MEMBERS REQUIRED	MEMBERS USED	ADDITIONAL (FEWER) ANNUAL DOLLARS AT RISK	ADDITIONAL (FEWER) DOLLARS AT RISK PMPM
A	5,000	10,000	$(26,635,000)	$ (266)
B	21,000	10,000	28,600,000	286
C	14,000	10,000	9,204,000	92
D	5,000	10,000	$(33,373,000)	$ (334)

Note: Numbers may not tie exactly due to rounding.

Depending on the amount of claims volatility as measured by the coefficient of variation, the number of members required for down side risk can be reduced substantially when a stop loss is present. The appendices contain summaries of our analyses using an individual stop loss with a $250,000 threshold. A $250,000 threshold may not be appropriate for all stop loss arrangements. Health care providers taking downside risk with stop loss should carefully weigh the cost of the stop loss premiums against the value the stop loss provides. The return on investment for stop loss may not be positive. Actuarial analysis of experience data can help health care providers select the appropriate threshold for stop loss.

Data sources and drivers of variance

The data used in this analysis consists of claims and enrollment experience for children eligible for each site's program (i.e., children in CRGs 5b through 9) for four different sites. Each of the sites is in a different state. The eligible data for a given site typically consists of 50,000 to 300,000 member months, which varies significantly by site. The eligible population may be distributed across the entire state or only a portion of the state, and it may also be limited to the membership in a single payer, for example a Medicaid managed care organization. Therefore, the eligible data we received may not represent the entire eligible population in a given state or region.

As can be seen in Figures 2 through 5 above, the number of average annual members required for full credibility for a given level of risk tolerance (as represented by α and ε) varies significantly. Why are the thresholds for full credibility so different when using different data sets? The two main drivers of different results between the data sets are the level of variance and the frequency of claims. The coefficient of variation, σ / μ, is affected by both the amount of volatility in the data set and the frequency of claims, so it serves as a metric for comparing the data sets.

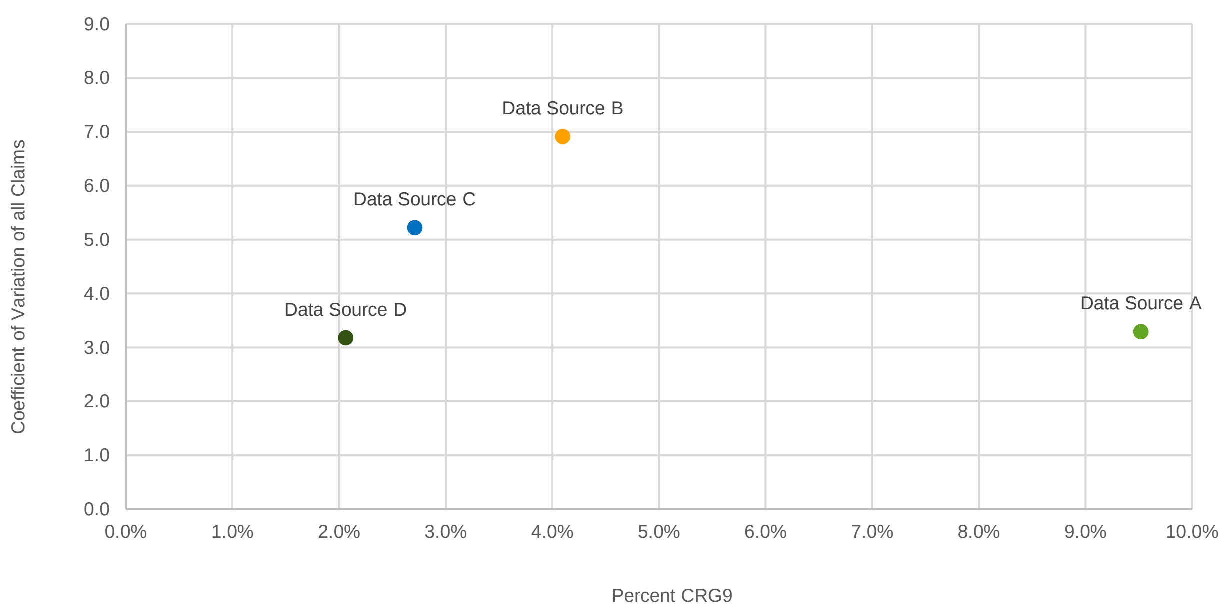
[9] See NGACO Request for Applications, January 18, 2017, at https://innovation.cms.gov/Files/x/nextgenaco-rfa2018.pdf.

The acuity of the members present in the data set is a driver of the volatility and the frequency of claims.[10] We use CRG as a proxy measurement for acuity. Although the distribution of members by CRG is not a perfect measure of acuity, much of the acuity is explained by CRG. Higher-acuity members will produce more frequent high-dollar claims. CRG 9 (Catastrophic) often contains the CARE-eligible members with the costliest claims in the experience data. Figure 7 shows how the coefficient of variation (i.e., σ / μ) relates to the percentage of eligible members in each data set who are in CRG 9 (Catastrophic).

As can be seen in Figure 7, the percentage of members in CRG 9 is not perfectly correlated with the coefficient of variation. Data points for sites B, C, and D suggest a linear relationship between coefficient of variation and CRG. But the exception to the rule is Site A, where a relatively high percentage of CRG 9 members is associated with a relatively low coefficient of variation, relative to the other three sites. While the percentage of members in CRG 9 is a driver of variance, we note that it doesn't explain all of the differences in acuity or variance. We do not recommend relying solely on distribution of members by CRG when estimating how volatile a population's claims per member per year (PMPY) will be.

Not only do the data sets contain different levels of acuity, they also represent data from different states' Medicaid organizations. Therefore, differences in results using the various data sets are also caused by differences in Medicaid reimbursement structures, covered services, and the presence of managed care, among other things. Sites looking to implement payment models should therefore use data from their own states when analyzing a payment model, because using data from different states can produce results that are very different, even when all other variables are equal.

FIGURE 7: COEFFICIENT OF VARIATION BY PERCENTAGE OF CRG 9 IN ALL FOUR DATA SOURCES



[10] For more information on the acuity of the CARE Award population, please see our white paper "CARE Award Patient Acuity: Analysis of Selection Effects" at https://www.childrenshospitals.org. Note that the data used in this white paper differs from the data used in previous white papers.

FIGURE 8: CREDIBILITY THRESHOLDS, ALTERNATE SCENARIOS: (1 - α) = 99.5%, ε = 5.0%, AVG. ANNUAL MONTHS / MEMBER = 10

	Average Annual Members Required				Change Relative to Baseline Scenario			
SCENARIO	SITE A	SITE B	SITE C	SITE D	SITE A	SITE B	SITE C	SITE D
BASELINE, NO SL	5,500	20,800	14,100	4,500	BASE	BASE	BASE	BASE
BASELINE, $250K SL	4,500	8,500	13,500	3,600	-18%	-59%	-4%	-20%
EXCLUDE CRG 8 AND NO SL	5,500	20,200	14,200	4,500	0%	-3%	1%	0%
EXCLUDE CRG 8 AND $250K SL	4,600	7,900	13,400	3,600	-16%	-62%	-5%	-20%
EXCLUDE CRG 7, 8, 9 (CRG 5B-6 ONLY) AND NO SL	6,400	19,500	11,900	4,700	16%	-6%	-16%	4%
EXCLUDE CRG 7, 8, 9 (CRG 5B-6 ONLY) AND $250 SL	5,900	8,400	11,600	3,700	7%	-60%	-18%	-18%
EXCLUDE CRG 5B, 6 (CRG 7, 8, 9 ONLY) AND NO SL	2,200	8,000	N/A*	N/A*	-60%	-62%	N/A*	N/A*
EXCLUDE CRG 5B, 6 (CRG 7, 8, 9 ONLY) AND $250 SL	1,700	3,400	N/A*	N/A*	-69%	-84%	N/A*	N/A*
EXCLUDE HOME HEALTH AND NO SL	7,200	21,400	14,300	4,500	31%	3%	1%	0%
EXCLUDE HOME HEALTH AND $250K SL	5,700	8,700	13,700	3,700	4%	-58%	-3%	-18%
EXCLUDE RX AND NO SL	6,800	31,000	21,200	8,000	24%	49%	50%	78%
EXCLUDE RX AND $250K SL	5,900	13,300	20,700	7,600	7%	-36%	47%	69%
EXCLUDE COAGULATION DEFECTS AND NO SL	5,200	19,000	13,500	3,200	-5%	-9%	-4%	-29%
EXCLUDE COAGULATION DEFECTS AND $250K SL	4,400	8,200	12,800	3,100	-20%	-61%	-9%	-31%
EXCLUDE RX AND COAGULATION DEFECTS AND NO SL	6,800	30,300	20,000	7,100	24%	46%	42%	58%
EXCLUDE RX AND COAGULATION DEFECTS AND $250K SL	5,800	12,800	19,400	6,800	5%	-38%	38%	51%

*Results excluded because there is insufficient data remaining after exclusions.

Alternate scenarios

We investigated thresholds for full credibility under a number of different scenarios. These scenarios represent potential “carve-outs” that may exist within a payment model. In general, we find the minimum membership thresholds decrease when the exclusion of claims decreases average claims volatility. The results are summarized in the table in Figure 8 as average annual members needed for full credibility, assuming (1 - α) = 99.5%, ε = 5.0%, and 10 average months enrolled per member per year. The first scenario listed in Figure 8 is the baseline scenario, which is identical to the results summarized in Figures 2 through 5 above and is presented again for comparison purposes. On the right side of Figure 8, results by site and scenario are compared to the baseline results. For each alternate scenario, we show results after an individual annual stop loss (SL) with a $250,000 threshold applied. In these scenarios, we removed claims amounts beyond the threshold for each individual whose claims exceeded the threshold during the plan year analyzed. The effect of this stop-loss varies significantly by site, and is related to both the average claims level and the amount of volatility in the site’s experience data.

The scenarios we examined are as follows:

- Exclude CRG 8: We exclude members and claims for members who are in CRG 8. This effectively represents carving out payments for members with cancer. The effect of this is minimal, because the number of members in CRG 8 is relatively small.
- Exclude CRGs 7, 8, and 9: We exclude members and claims for members who are in CRG 7, CRG 8, or CRG 9. This effectively represents carving out payments for the higher-acuity members. The results are mixed. For sites A and D, the credibility threshold increases. For sites B and C, the credibility threshold decreases. Members with CRGs 7, 8, and 9 are neither uniformly more volatile nor uniformly less volatile than members with CRGs 5b and 6. This demonstrates that the distribution of members by CRG is not enough information to determine the potential for volatility of claims.
- Exclude CRGs 5b and 6: We exclude members and claims for members who are in CRG 5b or CRG 6. CRGs 5b and 6 are considered lower acuity than CRGs 7, 8, and 9, so this scenario represents only including higher-acuity members. For sites A and B, this scenario has a lower credibility threshold than the baseline, which, at first glance, may be perceived as a counter-intuitive result. Excluding CRGs 5b and 6 increases the mean claims substantially, and the volatility relative to the mean claims is reduced. This causes the credibility threshold to decrease. For sites C and D, the number of members remaining after excluding CRGs 5b and 6 is insufficient for analysis. This demonstrates that for some sites a payment model for members in CRGs 7, 8, and 9 only is likely not a viable option. But this would need to be considered on a site-specific basis.

- Exclude home health: In this scenario, we excluded claims data for home health. Only Site A had a significant volume of home health claims in the experience data. The absence of home health claims for Site A removed a large number of small claims, which increased the average volatility relative to the mean. This increases the credibility threshold for Site A. Sites B, C, and D did not have a significant volume of home health claims in the experience data.
- Exclude Rx: In this scenario we excluded prescription drug claims. We found this substantially increases thresholds for full credibility. The reason for this is the high frequency and low average amount of prescription drug claims in the experience data we analyzed. While the credibility thresholds increase for all sites, the magnitude of the increase varies greatly by site. This demonstrates that an accurate ballpark estimate of the effect of carving out drug claims may be difficult to derive without a more in-depth analysis of claims experience.
- Exclude coagulation defects: In this scenario we excluded members with coagulation defects (e.g., hemophilia). These members often have the highest claims per year in the experience data we analyzed. Removing these members causes a modest decrease in credibility thresholds for sites A, B, and C. Site D saw a much larger decrease than other sites when excluding members with coagulation defects. This is because Site D had both a higher proportion of members with coagulation defects, and also Site D's members with coagulation defects had higher average claims amounts than members with coagulation defects in other sites' experience data.
- Exclude Rx and coagulation defects: In this scenario we excluded all prescription drug claims and we also excluded members with coagulation defects. Claims for members with coagulation defects are driven by factor treatments which we classify as prescription drugs, so there is some overlap in the "exclude Rx" and "exclude coagulation defects" scenarios. The results for this scenario are similar to the "exclude Rx" scenario: membership thresholds for full credibility are increased, but not quite as much as they were in the "exclude Rx" scenario.
- Please note that volatility may be affected by changes in membership (i.e., turnover), changes in reimbursement, and changes in care management. The potential effects of these changes are not part of this analysis.

Conclusion

As demonstrated in this paper, the number of members required to establish full credibility and take downside risk can vary significantly, depending on a number of variables that can be explored using experience data for the members. An exploration of the volatility and frequency of claims for the members can help determine the number of members required for downside risk for a given risk tolerance, but ultimately the entity taking downside risk must choose a threshold based on its chosen risk tolerance.

One way to establish an entity's risk tolerance is to estimate the amount of financial downside risk in an arrangement. It is possible to "back into" the desired values of α and ε by examining what each value of α and ε means in terms of real-world financial results, as shown in the example in Figure 6 above. Such sensitivity testing is important to help an entity get comfortable with the range of potential real-world effects of a new payment model.

When dealing with experience data, it is possible to establish full credibility by using multiple years of data. However, payment models often use an annual basis for adjudication. In other words, only the member months available in one year of the performance period are usually available for adjudication purposes. Therefore, it is crucial to examine the credibility of the membership for a payment model, not only in terms of total member months in the experience data, but also on an annual basis in the performance period.

The number of children being managed by CARE Award programs is often substantially lower than the membership thresholds described in this paper. Substantial work may be required in order to sufficiently expand a network in order to attribute membership levels described in this paper. Providers will potentially need access to an entire state's population of CMC and a different care management model infrastructure to achieve these thresholds.

Entities looking to develop a payment model should also keep in mind that past experience may not be a predictor of the future. Full credibility of experience data depends not only on the volume of experience but also on its appropriateness, and even the best data is not a perfect predictor of the future.

Appendix: Experience Data Summary

FIGURE 9: PERCENTAGE OF MEMBERS BY CRG

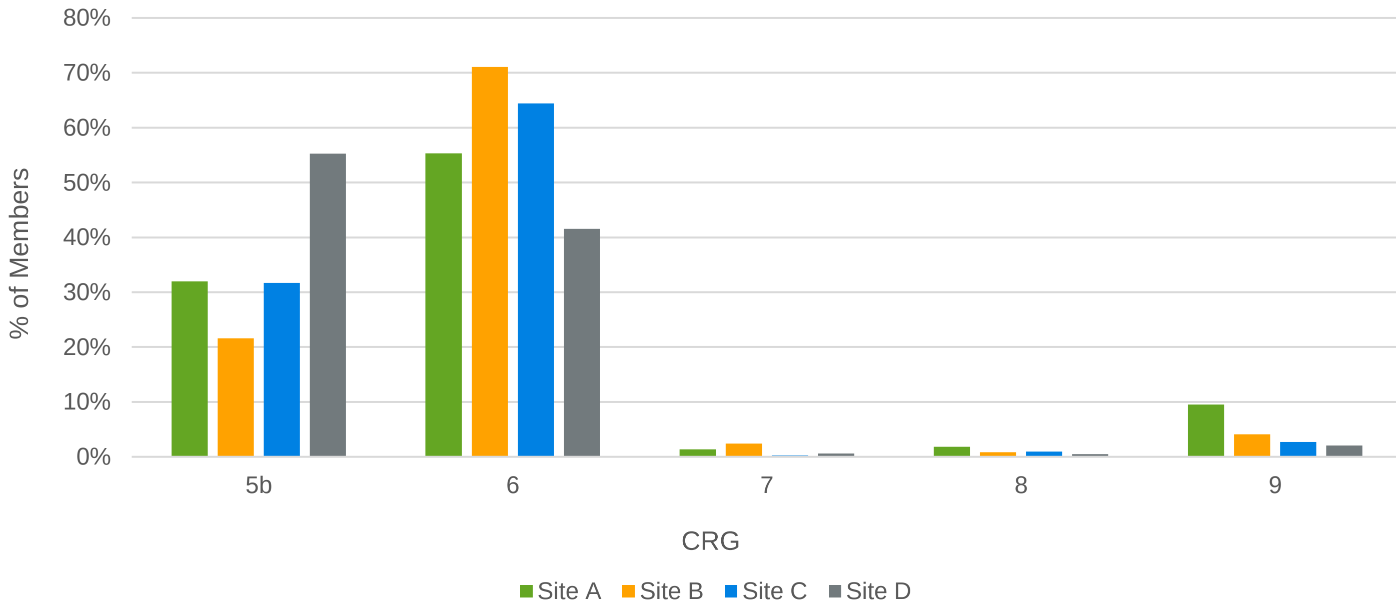


FIGURE 10: PERCENTAGE OF MEMBERS BY ALLOWED PMPY, ALL CRGS

FIGURE 11: PERCENTAGE OF MEMBERS BY ALLOWED PMPY, CRG 5B

FIGURE 12: PERCENTAGE OF MEMBERS BY ALLOWED PMPY, CRG 6

FIGURE 13: PERCENTAGE OF MEMBERS BY ALLOWED PMPY, CRG 7

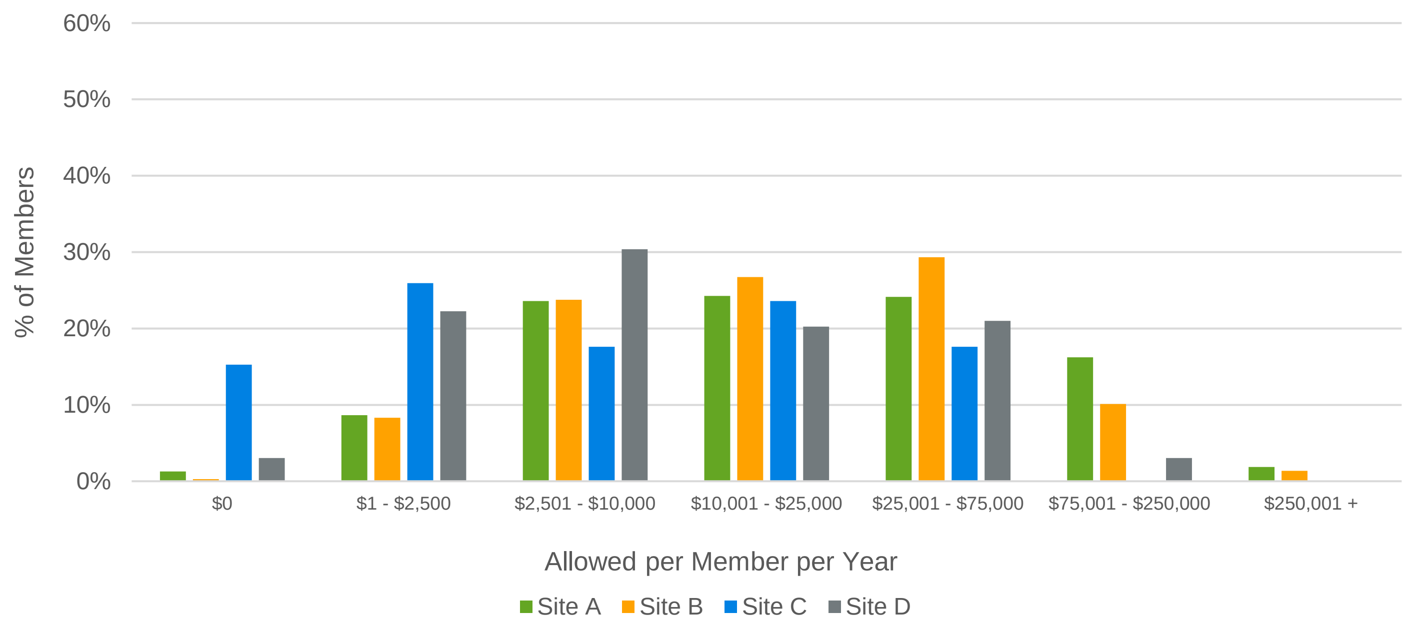


FIGURE 14: PERCENTAGE OF MEMBERS BY ALLOWED PMPY, CRG 8

FIGURE 15: PERCENTAGE OF MEMBERS BY ALLOWED PMPY, CRG 9

Limitations

The authors are consulting actuaries for Milliman The authors are members of the American Academy of Actuaries and meet the qualification standards of the American Academy of Actuaries to render the actuarial opinion contained herein.

The average claims cost PMPM for children with complex medical conditions can vary greatly and the numbers in this report should not be considered to be representative of average claims costs.

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