The Medicare Care Choices Model Was Associated with Reductions in Disparities in the Use of Hospice Care for Medicare Beneficiaries with Terminal Illness

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Appendix S1: Methods

This appendix provides an overview of our analysis approach, including a detailed description of our Bayesian hierarchical modeling approach. Details of the analysis, including sample identification and outcome construction, are described elsewhere (Kranker et al. 2023a, 2023b).

MCCM has been deemed exempt from the Common Rule (institutional review board) under 45 CFR 46.104(d)(5) because the model is considered research designed by a federal agency to study, evaluate, improve, or otherwise examine the public benefit or public service programs. Institutional review board approval was not required for this evaluation of public benefits and services.

1. Overview

Our goal was to determine whether the Medicare Care Choices Model (MCCM) decreased service use and Medicare fee-for-service expenditures, increased the frequency of hospice use (or led to earlier hospice use), or improved quality of care and experiences of care at the end of life among enrolled beneficiaries. Our exploration of MCCM's effects on health equity rest on the same design as the broader evaluation, which we describe briefly here.

We used claims data to measure a range of claims-based outcomes from date of MCCM enrollment until death, and then we estimated impacts of the model—overall and for key subgroups. We used a matched comparison group design. Specifically, we measured differences in outcomes between deceased beneficiaries enrolled in MCCM and a matched comparison group of deceased beneficiaries who were not referred to or enrolled in MCCM, but were otherwise similar to MCCM enrollees. We limited our potential comparison group to beneficiaries who (1) lived in the market area of a hospice participating in MCCM; (2) satisfied model eligibility criteria observable in Medicare claims and enrollment data; and (3) resembled MCCM enrollees on observed characteristics, such as expected length of life and past experience of care.[1] We designed this comparison group to provide a counterfactual of beneficiaries' outcomes had they not enrolled in MCCM and thus received usual care, which in some cases would include receipt of Medicare's hospice benefit. Our Bayesian hierarchical modeling approach, described later in this appendix, improves the precision of the

[1] The following eligibility criteria were not directly observable in CMS administrative data: (1) 6-month prognosis, which requires clinical judgement, and (2) residing in a traditional home and not a long-term care or assisted living facility.

estimates and adjusts for observed differences between MCCM beneficiaries and the matched comparison group (that is, controls for residual differences that remain after matching). This combination of matched comparison group with regression-adjusted treatment effect estimation forms the backbone of our evaluation strategy. The sections that follow describe both of these components of our design in more detail.

2. Comparison group selection

To reduce the risk that regional differences drive the impact estimates, we drew comparison beneficiaries from the regions served by MCCM hospices. This was especially important in 2020 and 2021, when the COVID-19 pandemic might have had different effects in various parts of the country. However, drawing comparison beneficiaries from the same areas as MCCM beneficiaries introduces the potential for either beneficiary selection or spillover to affect the impact estimates. Considering the low rates of referral and enrollment in areas served by MCCM hospices, we think these concerns are minimal.[2] Low MCCM enrollment rates among eligible beneficiaries suggest (1) that selection bias would be similar regardless of whether we matched to non-enrolled beneficiaries from within or outside of areas served by MCCM hospices and (2) that spillover was negligible.

A primary challenge to constructing the comparison group was to narrow the pool of potential comparison beneficiaries to those who met all MCCM eligibility criteria—specifically, those with a certifiable prognosis of six months or less to live. Beneficiaries' prognoses were not typically assessed and reported in extant data sources. Instead of attempting to approximate comparison beneficiaries' prognoses, we used actual dates of death to determine when each beneficiary would have been eligible for MCCM. To implement this approach, we restricted our attention to beneficiaries who had already died by the end of the model, what we call a decedents approach. A unique advantage of the decedents approach was that we could use our comparison group selection approach to ensure the distribution of the length of follow-up—the time from enrollment to death, or survival time—was similar between MCCM and comparison groups. Because we know when each comparison beneficiary died, we could count backward to establish pseudo-enrollment dates for each comparison beneficiary and match in a way that ensured balance on survival times between intervention and comparison beneficiaries. Balance on survival time was essential because different distributions of the length of follow-up between the intervention and comparison groups would likely lead to different mean outcomes between the two groups as well, biasing impact estimates.

For MCCM beneficiaries, we measured outcomes between enrollment in MCCM and death. Because comparison beneficiaries did not enroll in the model or the evaluation, for these beneficiaries we had to set a *pseudo-enrollment* date, that is, the date after which we begin measuring outcomes. We considered multiple potential pseudo-enrollment dates for each beneficiary and then picked the best available pseudo-enrollment date using `GroupMatch` (Pimentel et al. 2019), a matching technique

[2] We observed referrals to MCCM for 11,094 eligible beneficiaries, of whom 7,263 (65 percent) enrolled in MCCM. As a point of comparison, our potential comparison group included 1,934,407 unique beneficiaries who lived in the market areas of MCCM hospices and met MCCM eligibility criteria observable in Medicare claims and enrollment data. The latter figure suggests that less than 0.6 percent of eligible beneficiaries in these markets were referred to MCCM and less than 0.4 percent enrolled.

designed for interventions with rolling enrollment. `GroupMatch` allowed us to use variable-ratio optimal matching and select just one observation—the best pseudo-enrollment date—per comparison beneficiary. We used various additional matching strategies to ensure intervention beneficiaries and their matched comparison beneficiaries had the same qualifying conditions, lived in the same areas, and (as mentioned above) had the same length of time between (pseudo-) enrollment and death.

For a full description of the many matching strategies we employed to select the comparison group, please see Kranker et al. (2023a, b). As Table 1 of our article shows, our matching approach resulted in strong overall similarity at baseline between MCCM and matched comparison beneficiaries. Exhibit S2-1 in Appendix S2 summarizes selected baseline characteristics in underserved and reference groups separately for MCCM enrollees and matched comparison beneficiaries; it shows that our comparison group selection approach also resulted in good balance within the subgroups of interest.

3. Bayesian hierarchical modeling for health equity analysis

In this section we describe the Bayesian hierarchical modeling approach we used to estimate variation in MCCM's effect across subgroups of interest, particularly underserved communities. These analyses focused on impacts on measures of the quality of end-of-life care for the following groups:

1. Non-White or Hispanic beneficiaries, compared to non-Hispanic White beneficiaries
2. Beneficiaries dually eligible for Medicare and Medicaid, compared to beneficiaries eligible for Medicare only
3. Beneficiaries who live in rural areas, compared to beneficiaries who live in non-rural areas

These subgroups' low levels of participation in MCCM make it difficult to detect either impacts for the subgroups themselves or differences in impacts between a subgroup and its reference group. To mitigate this concern, we estimated effects on health equity in a hierarchical Bayesian modeling framework, which increases the precision and plausibility of the impact estimates. Specifically, this approach offers two key advantages over a more traditional (frequentist) subgroup analysis.

1. *Increase efficiency (statistical power).* A Bayesian model makes these gains possible by incorporating structured assumptions—for example, about how subgroup impacts relate to the overall MCCM impact—that enhance both the precision and the plausibility of the impact estimates. Encoding these assumptions in a Bayesian model increases the precision and plausibility of impact estimates for small subgroups that might otherwise produce extreme, highly uncertain estimates (Vollmer et al. 2020). For example, although comparatively few rural beneficiaries enrolled in MCCM, we can obtain a stronger estimate of the model's effect on these beneficiaries by placing the impact for rural beneficiaries in the context of the overall impact. To the extent that the impact for rural beneficiaries appears to be extreme compared with the overall impact, the model moderates the estimate, thereby increasing its precision. These precision gains are especially important for evaluating MCCM, in which overall enrollment is

moderate and the underserved communities of interest in this analysis are quite small in both absolute and relative terms.

2. *Guard against spurious findings.* A Bayesian approach guards against spurious findings due to multiple comparisons by fitting a single, unified model that estimates impacts for all subgroups simultaneously. In this context, the Bayesian model's natural penalty on model complexity reduces the likelihood of observing extreme impact estimates for small subgroups by chance alone, obviating the need for post-hoc corrections (Gelman et al. 2012).

The regression equation for this unified Bayesian model follows the form of what Imbens and Wooldridge (2009) call the unconfoundedness approach to treatment effect regressions:

(1) $$y_i^1 = \alpha_{g[i]} + m_i\delta_{g[i]} + X_{ir}'\beta + \varepsilon_i, \qquad \varepsilon_i \sim N(0, \sigma^2)$$

This regression predicts the outcome y for a beneficiary i in the follow-up period (superscript 1) as a function of a subgroup-specific intercept $\alpha_{g[i]}$, controls β for covariates X_{ir}, and a subgroup-specific treatment effect $\delta_{g[i]}$, included when the treatment indicator $m_i = 1$. Among the covariates X_{ir} we include pre-intervention measures of the outcome variables, for deconfounding; for a full list of covariates, please see Exhibit S1-1.

The subscript $g[i]$ refers to the subgroup g to which beneficiary i belongs. Rather than estimating an overall intercept α and model effect δ, in the Bayesian health equity analyses we estimate subgroup-specific intercepts $\alpha_{g[i]}$ and model effects $\delta_{g[i]}$. These terms include components that enable us to account for the effects of membership in individual subgroup variables as well as the interaction among different subgroup variables. For example, we decompose $\alpha_{g[i]}$ as follows:

(2) $$\alpha_{g[i]} = \alpha_0 + \alpha_{c[i]}^{Diagnosis} + \alpha_{d[i]}^{Dual} + \cdots + \alpha_{g[i]}^{Residual}$$

In Equation (2), the first term, α_0, represents an overall intercept. The terms between the overall intercept and the ellipses represent the main effects of individual subgroup variables, such as race/ethnicity category and dual eligibility for Medicare and Medicaid. Unlike in a traditional regression, in which we would model only the nonreference levels of the main effects, in the Bayesian model we include effects for all levels of these subgroup variables and impose constraints to ensure model identifiability. For example, dual eligibility status has two categories: eligible or not eligible. We therefore estimate two parameters, α_{Yes}^{Dual} and α_{No}^{Dual}, with the following prior distribution and constraints:

(3) $$\alpha_{Yes}^{Dual}, \alpha_{No}^{Dual} \sim N\left(0, \sigma_{\alpha_{Dual}}^2\right), \alpha_{Yes}^{Dual} + \alpha_{No}^{Dual} = 0.$$

We place a standard weakly informative prior on the top-level variance parameters: $\sigma_\alpha, \sigma_\delta \sim \mathrm{N}^+(0,1)$. Finally, the $\alpha_{g[i]}^{Residual}$ term represents the interaction of all the subgroup variables—for example, the effect of being both non-White or Hispanic and dually eligible. The $\delta_{g[i]}$ terms subsume analogous components.

Because the Bayesian statistical framework increases precision and plausibility for small subgroups, in this model we included finer-grained subgroup definitions than those reported elsewhere. For example, the Bayesian model categorized beneficiaries' ethnicity as non-Hispanic White, Black, or other, rather than simply non-Hispanic White or non-White and Hispanic. The model included the following subgroups as components:

- Survival time category: 1 to 30 days, 31 to 90 days, 91 to 180 days, 181 to 365 days, or more than 365 days
- Race and ethnicity: non-Hispanic White, Black, or other
- Dual eligibility: dually eligible for Medicaid or Medicare-only
- Rural status: rural versus other (that is, nonrural)
- Diagnosis group: cancer only, cancer and either congestive heart failure or chronic obstructive pulmonary disease, HIV/AIDS, congestive heart failure only, congestive heart failure only, congestive heart failure and congestive heart failure[3]
- MCCM model cohort of the hospice: cohort one (2016 start date) or cohort two (2018 start date)
- COVID-19 cohort: before COVID-19 pandemic (enrolled before September 1, 2019) or during COVID-19 pandemic (enrolled on or after September 1, 2019)
- Year of enrollment: 2016, 2017, 2018, 2019, 2020, or 2021
- Hospice of the intervention beneficiary (one of 79 unique hospices)

The Greek letters (α, δ, and β) in equation (1) are the parameters we estimated. To estimate these models, we used Markov Chain Monte Carlo, specifically Hamiltonian Monte Carlo implemented in Stan (Stan Development Team, 2020). All models converged, as evidenced by large effective sample sizes and Gelman-Rubin statistics close to 1.0. We use logistic regression models for binary outcomes, such as whether the beneficiary entered hospice, and a negative binomial model with survival time as the offset for the days at home outcome.

Appropriate standard errors and weighting. We assigned beneficiaries to the intervention or comparison group based on their enrollment on an individual level. That is, we did not assign entire hospice market areas to the intervention or comparison group. Therefore, it was not appropriate to calculate standard errors that account for clustering on hospice market areas or any other geographic regions (Abadie et al. 2023). Because we include only one observation per beneficiary, it was also not necessary to cluster standard errors at the beneficiary level. The inclusion of hospice as one of the subgroup components in the model allows us to account for regional effects associated with a hospice's market area and correlation due to these effects.

We followed beneficiaries after their enrollment (or pseudo enrollment) until they died. That is, we reported a single impact estimate rather than different impact estimates for different follow-up lengths ("in last X days of life"). Thus, the Bayesian hierarchical models produced the average impact *per beneficiary*, averaging across beneficiaries that have shorter and longer survival times. For

[3] These mutually exclusive diagnosis categories were created as part of comparison group selection to account for the distribution of qualifying diagnoses—including multiple qualifying diagnoses—across beneficiaries.

example, impacts on Medicare expenditures can be interpreted as the average change in Medicare expenditures that result from enrolling one more beneficiary in MCCM. For the comparison group, we also employed matching weights to balance the intervention and comparison groups, to account for our matched comparison group design. (Weights equal 1 for intervention beneficiaries and equal $1/n$ for the comparison beneficiaries, where n equals the number of matched comparison beneficiaries matched to the beneficiary enrolled in MCCM. The sum of the weights across comparison group beneficiaries equaled the overall number of MCCM enrollees.)

The target of inference in a Bayesian model is the posterior distribution of each parameter, which describes the range of values each parameter is most likely to inhabit, based on the data used to fit the model and prior assumptions that describe the relationships among the parameters. Estimating the full posterior distribution for each model parameter—for example, for MCCM's impact in each subgroup—makes it possible to describe conclusions probabilistically. For example, we can use the posterior distribution to determine the probability that the impact for a subgroup meets policy-relevant thresholds, such as the probability that MCCM increased take-up of the Medicare hospice benefit. We can also compare posterior distributions for different model parameters to obtain probability statements about differences in impacts, such as the probability that MCCM increased hospice use more for dually eligible beneficiaries than for Medicare-only beneficiaries. In addition, we use the posterior distribution to define what is called a credible interval, the Bayesian analogue of a confidence interval; in a Bayesian analysis, the bounds of a credible interval are calculated from quantiles of the posterior distribution. For example, the bounds of a 90 percent credible interval are the 5th and 95th percentiles of the posterior distribution.

Prior assumptions. As noted before, the advantage of the Bayesian model lies in its ability to incorporate structured assumptions about the relationships among observations in the data. These assumptions take the form of probability distributions for model parameters, called prior distributions. We introduce prior distributions that make weak regularizing assumptions but do not impose any assumptions about the magnitude or direction of expected model effects. Such weakly informative priors are the current best practice in the Bayesian literature (Stan Development Team 2020). Importantly, we center the prior on δ_0, which represents the overall effect of MCCM, at zero, indicating our *a priori* agnosticism about the model's impacts; this prior implies that, in the absence of evidence to the contrary, the model assumes MCCM has no effect. This prior reflects the current guidance in the literature, but scholarly interest is growing in developing evidence-based prior distributions that incorporate information about the effectiveness of previous, similar interventions.

Exhibit S1-1. Variables used for regression adjustment

Demographics and eligibility

1. Age at (pseudo) enrollment
2. Age category (younger than 65, 65 to 74, 75 to 84, and 85 or older)
3. Sex
4. Dually eligible
5. Non-Hispanic White
6. Black
7. Other race
8. Old-Age and Survivors Insurance
9. Disability insurance benefits
10. End-stage renal disease
11. Both disability insurance benefits and end-stage renal disease
12. Rural zip code
13. Northeast
14. Midwest
15. South
16. West
17. Zip code demographics first principal component
18. Zip code demographics second principal component
19. Zip code demographics third principal component
20. Had two hospital encounters (inpatient stay, ED visit, or observation stay) in the 12 months before enrollment
21. Part D drug plan requirement
22. Had three office visits for with the same provider for the MCCM-qualifying terminal condition in the 12 months before enrollment
23. Participated in an ACO at the time of enrollment
24. Year of (pseudo) enrollment
25. Quarter of (pseudo) enrollment
26. Date of (pseudo) enrollment occurred more than 6 months before the start of the COVID-19 public health emergency (on or before August 31, 2019)
27. Time from (pseudo) enrollment to death
28. Time from (pseudo) enrollment to death squared
29. Time from (pseudo) enrollment to death cubed
30. Indicator for which MCCM hospice enrolled the beneficiary

Health status (at baseline)

31. HCC: first principal component
32. HCC: second principal component
33. HCC: third principal component
34. HCC: fourth principal component
35. HCC: fifth principal component
36. HCC: sixth principal component
37. HCC: seventh principal component
38. HCC: eighth principal component
39. HCC Score at (pseudo) enrollment
40. HCC Score one year before (pseudo) enrollment
41. HCC: Ischemic or Unspecified Stroke
42. HCC: Kidney Disease
43. HCC: Diabetes with Acute or Chronic Complications
44. HCC: Hip Fracture/Dislocation
45. HCC: Artificial Openings for Feeding or Elimination
46. HCC: Dementia with or Without Complication
47. HCC: Multiple Sclerosis
48. HCC: Parkinson's and Huntington's Diseases
49. HCC: Coma, Brain Compression/Anoxic Damage
50. HCC: Respirator Dependence/Tracheostomy Status
51. HCC: Cardio-Respiratory Failure and Shock
52. HCC: Acute Myocardial Infarction
53. Had primary diagnosis of cancer
54. Had primary diagnosis of CHF
55. Had primary diagnosis of COPD
56. Had primary diagnosis of HIV/AIDS
57. Breast cancer
58. Colorectal cancer
59. Lung cancer
60. Prostate cancer
61. Other cancer

Health care use at baseline: variables used in all regression models

62. Advance care planning visit in the two years before enrollment
63. Admitted to hospital on (pseudo-) enrollment date
64. Discharged from hospital on (pseudo-) enrollment date
65. Inpatient stay on (pseudo-) enrollment date
66. Number of days between enrollment or pseudo-enrollment date and most recent inpatient discharge (using admission date)
67. Length of stay for most recent baseline inpatient stay
68. Flag for no inpatient stays in baseline year
69. Discharged from SNF on (pseudo-) enrollment date
70. Total Medicare Part A and B expenditures in quarter 1 before (pseudo) enrollment
71. Total Medicare Part A and B expenditures in quarters 2 to 4 before (pseudo) enrollment
72. Number of inpatient admissions in quarter 1 before (pseudo) enrollment
73. Number of inpatient admissions in quarters 2 to 4 before (pseudo) enrollment
74. Number of outpatient ED visits and observation stays in quarter 1 before (pseudo) enrollment
75. Number of outpatient ED visits and observation stays in quarters 2 to 4 before (pseudo) enrollment
76. Diagnostic tests and procedures indicating advanced stage or poor prognosis cancer in quarter 1 before (pseudo) enrollment
77. Diagnostic tests and procedures indicating advanced stage or poor prognosis cancer in quarters 2 to 4 before (pseudo) enrollment
78. Diagnoses indicating advanced stage or poor prognosis cancer in quarter 1 before (pseudo) enrollment

79. Diagnoses indicating advanced stage or poor prognosis cancer in quarters 2 to 4 before (pseudo) enrollment
80. Drugs indicating advanced stage or poor prognosis cancer in quarter 1 before (pseudo) enrollment
81. Drugs indicating advanced stage or poor prognosis cancer in quarters 2 to 4 before (pseudo) enrollment
82. Flag for receipt of hormonal therapies in quarter 1 before (pseudo) enrollment
83. Flag for receipt of hormonal therapies in quarters 2 to 4 before (pseudo) enrollment
84. Hospitalization with lung volume reduction surgery, oxygen therapy, or ventilation in quarter 1 before (pseudo) enrollment
85. Hospitalization with lung volume reduction surgery, oxygen therapy, or ventilation in quarters 2 to 4 before (pseudo) enrollment
86. History of an automatic implantable cardioverter defibrillator in the 12 months before enrollment
87. History of artery bypass surgery in the 12 months before enrollment
88. History of percutaneous coronary intervention in the 12 months before enrollment

Health care use at baseline: variables used in outcome-specific regression models[a]

89. Inpatient expenditures in quarter 1 before (pseudo) enrollment
90. Inpatient expenditures in quarters 2 to 4 before (pseudo) enrollment
91. Drug expenditures in quarter 1 before (pseudo) enrollment
92. Drug expenditures in quarters 2 to 4 before (pseudo) enrollment
93. SNF expenditures in quarter 1 before (pseudo) enrollment
94. SNF expenditures in quarters 2 to 4 before (pseudo) enrollment
95. Home health expenditures in quarter 1 before (pseudo) enrollment
96. Home health expenditures in quarters 2 to 4 before (pseudo) enrollment
97. DME expenditures in quarter 1 before (pseudo) enrollment
98. DME expenditures in quarters 2 to 4 before (pseudo) enrollment
99. Hospice expenditures in quarter 1 before (pseudo) enrollment
100. Hospice expenditures in quarters 2 to 4 before (pseudo) enrollment
101. Other expenditures in quarter 1 before (pseudo) enrollment[b]
102. Other expenditures in quarters 2 to 4 before (pseudo) enrollment[b]
103. Outpatient ED visits in quarter 1 before (pseudo) enrollment
104. Outpatient ED visits in quarters 2 to 4 before (pseudo) enrollment
105. Outpatient observation stays in quarter 1 before (pseudo) enrollment
106. Outpatient observation stays in quarters 2 to 4 before (pseudo) enrollment
107. Ambulatory visits with primary care providers in quarter 1 before (pseudo) enrollment
108. Ambulatory visits with primary care providers in quarters 2 to 4 before (pseudo) enrollment
109. Ambulatory visits with specialist physicians in quarter 1 before (pseudo) enrollment
110. Ambulatory visits with specialist physicians in quarters 2 to 4 before (pseudo) enrollment
111. Ambulatory visits with primary care providers and specialist physicians in quarter 1 before (pseudo) enrollment
112. Ambulatory visits with primary care providers and specialist physicians in quarters 2 to 4 before (pseudo) enrollment
113. Number of days in hospice in quarter 1 before (pseudo) enrollment
114. Number of days in hospice in quarters 2 to 4 before (pseudo) enrollment
115. Number of post-acute care days in quarter 1 before (pseudo) enrollment
116. Number of post-acute care days in quarters 2 to 4 before (pseudo) enrollment
117. Number of home health visits in quarter 1 before (pseudo) enrollment
118. Number of home health visits in quarters 2 to 4 before (pseudo) enrollment
119. Inpatient days in quarter 1 before (pseudo) enrollment
120. Inpatient days in quarters 2 to 4 before (pseudo) enrollment
121. Inpatient ICU days in quarter 1 before (pseudo) enrollment
122. Inpatient ICU days in quarters 2 to 4 before (pseudo) enrollment
123. Days in hospital without ICU in quarter 1 before (pseudo) enrollment
124. Days in hospital without ICU in quarters 2 to 4 before (pseudo) enrollment
125. EMS ambulance transports in quarter 1 before (pseudo) enrollment
126. EMS ambulance transports in quarters 2 to 4 before (pseudo) enrollment

[a] These variables were selectively included in regressions with the corresponding outcome. For example, when analyzing impacts on inpatient expenditures, we added to the regression models two variables with inpatient expenditures in (1) quarter 1 and (2) quarters 2 to 4 before (pseudo) enrollment.

[b] *Other expenditures* include outpatient emergency department visits, ambulatory care visits, and other clinically necessary services.

ACO = accountable care organization; CHF = congestive heart failure; COPD = chronic obstructive pulmonary disease; DME = durable medical equipment; ED = emergency department; EMS = emergency medical services; HCC = hierarchical condition category; HIV/AIDS = human immunodeficiency virus/acquired immunodeficiency syndrome; ICU = intensive care unit; SNF = skilled nursing facility.

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Appendix S2: Supplemental Results

This appendix contains results to support the findings presented in the main text. These include tables describing enrolled and comparison beneficiaries (Section 1) and detailed impact estimates (Section 2), both shown separately by underserved community. Section 1 also explores the disparities in end-of-life care that affect underserved communities and that directed our analysis of MCCM's potential to reduce disparities.

1. Description of enrolled and comparison beneficiaries by underserved community

Exhibit S2-1 compares the characteristics of beneficiaries enrolled in the Medicare Care Choices Model (MCCM) by underserved community, and also compares beneficiaries enrolled in MCCM to matched comparison beneficiaries in the same underserved communities. After comparison group selection, the characteristics of MCCM and matched comparison beneficiaries were similar within each community.

However, these tables show important differences *between* underserved and reference communities. For example, beneficiaries who were dually eligible for Medicare and Medicaid were approximately three times as likely to be non-White or Hispanic (34.3 percent) than were beneficiaries eligible for Medicare only (10.9 percent). In the same vein, non-White or Hispanic beneficiaries were over three times as likely to be dually eligible as non-Hispanic White beneficiaries (28.8 versus 8.7 percent). These contrasts also underscore the overlap between dually eligible and non-White or Hispanic beneficiaries. Contrasts between rural and non-rural beneficiaries are less marked, though rural beneficiaries were more likely to qualify for Medicare because of a disability (26.0 percent versus 16.3 percent) and be diagnosed with COPD (40.7 percent versus 32.3 percent).

Exhibit S2-1. Baseline characteristics of MCCM and comparison beneficiaries, by underserved or reference community

	MCCM beneficiaries						Comparison beneficiaries					
Characterstic	Non-White or Hispanic	Non-Hispanic White	Dual	Non-dual	Rural	Nonrural	Non-White or Hispanic	Non-Hispanic White	Dual	Non-dual	Rural	Nonrural
Number of beneficiaries	702	4,451	589	4,564	674	4,456	1,851	13,418	1,757	13,512	1,908	13,066
Demographics												
Race/ethnicity (%)												
Non-Hispanic white	0	100	65.7	89.0	93.2	85.4	0	100	66.3	90.4	95.0	86.6
Black or African-American	59.5	0.0	22.6	6.2	4.3	8.7	64.4	0.0	23.0	6.0	3.1	8.7
Other, unknown, missing race/ethnicity	40.5	0.0	11.7	4.7	2.5	5.9	35.6	0.0	10.6	3.6	1.9	4.7
Age (years)	74.8	77.7	70.8	78.2	75.4	77.6	73.7	77.6	70.7	77.9	76.3	77.2
Gender (%)												
Male	44.0	50.4	36.3	51.2	50.0	49.4	48.9	52.6	42.3	53.4	52.9	52.1
Female	56.0	49.6	63.7	48.8	50.0	50.6	51.1	47.4	57.7	46.6	47.1	47.9
Medicare enrollment												
Dual eligibility (%)	28.8	8.7	100	0	17.8	10.5	31.2	8.6	100	0	17.8	10.5
Original reason for Medicare entitlement (%)												
Medicare entitlement: OASI	71.7	83.2	50.6	85.6	72.8	82.9	66.4	84.4	47.9	86.6	77.8	82.8
Medicare entitlement: disability	26.2	16.2	47.0	13.8	26.0	16.3	31.3	15.1	49.6	12.9	21.6	16.4
Medicare entitlement: ESRD	1.6	0.4	1.9	0.4	1.0	0.5	1.6	0.3	1.8	0.3	0.2	0.5
Medicare entitlement: disability and ESRD	0.6	0.2	0.5	0.2	0.1	0.2	0.7	0.3	0.7	0.3	0.4	0.3
Location												
Resides in rural zip code (%)	6.7	14.3	20.5	12.4	100	0	6.2	14.8	22.2	12.6	100	0
Region (%)												
Northeast region	11.5	19.7	14.6	19.1	7.7	20.3	10.8	20.0	14.5	19.4	7.1	20.6
Midwest region	15.1	20.3	21.9	19.3	28.0	18.3	13.7	20.0	22.1	18.9	27.0	18.0
South region	58.7	37.3	52.1	38.7	50.7	38.7	60.5	36.7	51.7	38.1	50.6	38.1
West region	14.7	22.7	11.4	23.0	13.4	22.8	15.0	23.3	11.7	23.6	15.3	23.2

Characterstic	MCCM beneficiaries						Comparison beneficiaries					
	Non-White or Hispanic	Non-Hispanic White	Dual	Non-dual	Rural	Nonrural	Non-White or Hispanic	Non-Hispanic White	Dual	Non-dual	Rural	Nonrural
Regions' characteristics												
Median household income ($)	60,869	69,397	55,297	69,905	49,972	71,067	59,697	68,263	54,837	68,802	48,030	70,152
Speak English well (%)	96.4	97.5	96.9	97.4	98.7	97.2	96.2	97.6	96.8	97.5	98.7	97.2
Postsecondary education (%)	59.9	64.4	55.7	64.8	52.6	65.5	58.5	62.5	55.0	62.9	51.5	63.7
Unemployed (%)	4.9	3.7	4.7	3.7	3.8	3.9	5.4	3.8	4.8	3.8	3.8	4.0
Population density (#/mile^2)	4,215	2,163	2,858	2,388	162	2,795	4,156	1,843	2,668	2,059	150	2,438
Health status												
MCCM-qualifying diagnosis (%)												
Primary diagnosis cancer	74.5	71.3	64.3	72.7	68.2	72.2	74.2	71.3	64.0	72.7	68.1	72.2
Primary diagnosis CHF	39.0	37.8	42.4	37.4	37.7	38.0	37.9	38.0	42.4	37.4	37.8	37.9
Primary diagnosis COPD	26.8	34.4	42.3	32.2	40.7	32.3	24.0	34.7	42.5	32.2	40.8	32.3
Primary diagnosis HIV/AIDS	1.6	0.2	2.0	0.2	0.1	0.4	2.1	0.1	2.0	0.2	0.1	0.4
Days between (pseudo-) enrollment and death	194	200	251	192	219	195	182	199	243	190	216	193
HCC score at enrollment	5.8	5.5	6.0	5.5	5.4	5.6	5.6	5.4	5.8	5.4	5.1	5.5
Comorbid conditions (%)												
Ischemic or unspecified stroke	12.4	8.8	9.5	9.3	9.2	9.4	10.7	9.0	10.6	9.0	7.5	9.5
Dialysis status	11.8	4.5	9.3	5.0	4.6	5.6	12.0	4.7	10.8	4.9	4.4	5.8
Kidney disease	52.8	48.3	43.1	49.7	45.3	49.6	51.1	50.9	47.3	51.4	49.3	51.2
Diabetes with complications	46.0	31.8	40.1	32.9	33.8	33.7	48.2	34.3	45.0	34.9	35.2	36.0
Dementia	17.1	15.0	13.2	15.5	13.6	15.5	14.9	12.4	14.7	12.5	11.3	12.9
Coma	5.8	6.5	7.3	6.3	5.0	6.6	4.7	4.5	3.8	4.6	3.9	4.6
Cardio-respiratory failure	32.3	37.5	41.4	36.2	42.3	35.9	29.9	37.1	39.0	35.8	36.4	36.3
Acute myocardial infarction	13.8	11.3	14.6	11.2	9.6	11.9	10.5	11.0	12.3	10.8	11.7	10.8
ADLs at most recent assessment	4.8	4.7	4.6	4.7	4.5	4.8	4.7	4.4	4.5	4.5	4.3	4.5

Characterstic	MCCM beneficiaries						Comparison beneficiaries					
	Non-White or Hispanic	Non-Hispanic White	Dual	Non-dual	Rural	Nonrural	Non-White or Hispanic	Non-Hispanic White	Dual	Non-dual	Rural	Nonrural
Health care use in the year before enrollment												
Medicare spending ($)	94,401	77,743	85,647	79,285	69,456	81,604	90,919	78,069	79,752	79,643	67,204	81,413
Outpatient ED visits and observation stays	1.8	1.6	2.4	1.5	2.4	1.5	2.1	1.7	2.5	1.7	2.4	1.7
Inpatient admissions	2.6	2.3	2.9	2.2	2.4	2.3	2.5	2.2	2.7	2.2	2.1	2.3

Sources: MCCM program data, Medicare Enrollment Database, Master Beneficiary Summary File, and Medicare claims data, January 1, 2013, to December 31, 2021.

ADL = activities of daily living; CHF = congestive heart failure; COPD = chronic obstructive pulmonary disease; ED = emergency department; ESRD = end-stage renal disease; HCC = hierarchical condition category; HIV/AIDS = human immunodeficiency virus/acquired immunodeficiency syndrome; MCCM = Medicare Care Choices Model; OASI = Old-Age and Survivors Insurance.

Exhibit S2-2 highlights disparities in end-of-life care between underserved and reference communities. This analysis focuses on the follow-up period because it is not feasible to assess end-of-life care outcomes in baseline data; it uses the comparison group because we wish to understand the end-of-life care landscape in the absence of MCCM. Dually eligible and non-White or Hispanic beneficiaries in the comparison group were at least 10 percentage points less likely to elect the Medicare hospice benefit than the corresponding reference groups. These underserved communities were also more likely to receive aggressive life-prolonging treatments in the last 30 days of life. Rural beneficiaries were more than twice as likely to visit the emergency department more than once in the last 30 days of life, compared to nonrural beneficiaries.

Exhibit S2-2. Disparities in end-of-life care for underserved communities: Outcomes for comparison group beneficiaries

End-of-life care outcome	Non-White or Hispanic (N = 1,851)	Non-Hispanic White (N = 13,418)	Dual (N = 1,757)	Non-dual (N = 13,512)	Rural (N = 1,908)	Nonrural (N = 13,066)
Elected the Medicare hospice benefit (%)	53.6	66.6	55.4	66.1	63.0	65.2
Received any aggressive life-prolonging treatments in last 30 days of life (%)	80.6	76.0	78.9	76.3	76.2	76.7
Number of days at home	167.3	178.4	218.1	171.6	197.2	173.8
Percentage of days at home	79.6	83.1	81.9	82.7	85.4	82.2
More than one outpatient emergency department visit in last 30 days of life (%)	3.4	3.2	4.8	3.1	7.8	2.6

Sources: MCCM program data, Medicare Enrollment Database, Master Beneficiary Summary File, and Medicare claims data, January 1, 2013, to December 31, 2021.

2. Impact estimates

This section provides detailed impact estimates for all end-of-life care outcomes, comparing each underserved community to the corresponding reference group. For each group, we give the regression-adjusted mean outcome among MCCM enrollees, the impact estimate and 90 percent credible interval, and the percentage impact. We also present the difference in impact estimates for the two groups, the 90 percent credible interval for the difference, and the probability that MCCM reduced the disparity.

Exhibit S2-3 compares MCCM impacts for non-White or Hispanic beneficiaries to impacts for non-Hispanic White beneficiaries. MCCM was most successful at reducing the disparity in hospice use between non-White or Hispanic beneficiaries and non-Hispanic White beneficiaries, and increased the disparity in the percentage with an aggressive life-prolonging treatment in the last 30 days of life.

Exhibit S2-4 compares MCCM's impacts on dually eligible and non-dually eligible beneficiaries. As with non-White or Hispanic beneficiaries, MCCM most likely reduced the disparity in hospice use between dually eligible and non-dually eligible beneficiaries, and least likely that MCCM reduced the disparity in the percentage receiving aggressive life-prolonging treatments in the last 30 days of life. In addition, for this comparison we assessed the impact of MCCM, holding the distribution of background characteristics constant across dually eligible and non-dually eligible beneficiaries. This analysis shows that much of the difference in impacts between the two groups reflects differences in their characteristics.

Exhibit S2-5 compares MCCM's impact on rural and nonrural beneficiaries. Impacts were generally similar for these populations. However, there is some indication that MCCM led to greater reductions in emergency department use in the last 30 days of life among rural than nonrural beneficiaries.

Exhibit S2-3. Differences in Medicare expenditures, health care service use, and quality of care between deceased MCCM enrollees and matched comparison beneficiaries, by race and ethnicity

Outcome	Non-White or Hispanic beneficiaries			Non-Hispanic White beneficiaries			Difference in impact estimates[a] [90% CI]	Probability that MCCM reduced the disparity[b]
	MCCM mean	Impact estimate [90% CI]	Percentage impact	MCCM mean	Impact estimate [90% CI]	Percentage impact		
Percentage who used the Medicare hospice benefit	75	+21.8 [18.9, 24.3]	+41	84	+17.7 [16.3, 19.1]	+27	+4.1 [1.3, 6.1]	98
Percentage who received an aggressive life-prolonging procedure, surgery, or diagnostic test in the last 30 days of life	67	-13.6 [-15.8, -10.4]	-17	60	-15.7 [-17.3, -14.2]	-21	+2.1 [0.2, 5.6]	3
Number of days at home	174	+6.8 [5.0, 8.9]	+4	185	+6.6 [5.6, 7.7]	+4	+0.2 [-1.6, 2.4]	52
Percentage with more than one outpatient emergency department visit in last 30 days of life	3.0	-0.4 [-1.5, 1.0]	-12	2.4	-0.8 [-1.4, -0.3]	-26	+0.4 [-0.5, 1.9]	32

Sources: Medicare Enrollment Database, Master Beneficiary Summary File, and Medicare claims data, January 1, 2013, to December 31, 2021. The estimates cover beneficiaries who enrolled through June 30, 2021, and who died on or before December 31, 2021, and their experiences in the model.

Notes: We base impact estimates on regression-adjusted differences between MCCM enrollees (N = 5,153) and matched comparison beneficiaries (N = 15,269 before weighting), estimated with a Bayesian regression model. There were 4,451 MCCM enrollees who were non-Hispanic White and 702 who were non-White or Hispanic. There were 13,418 matched comparison beneficiaries who were non-Hispanic White and 1,851 who were non-White or Hispanic.

[a] Differences in impact estimates in this column reflect differences in the characteristics of non-White or Hispanic beneficiaries versus non-Hispanic White beneficiaries, and how those differences may translate into different impacts of MCCM.

[b] Values in this column represent the probability that MCCM has a larger impact in the hypothesized direction for non-White or Hispanic beneficiaries than for non-Hispanic White beneficiaries.

CI = credible interval; MCCM = Medicare Care Choices Model.

Exhibit S2-4. Differences in Medicare expenditures, health care service use, and quality of care between deceased MCCM enrollees and matched comparison beneficiaries, by dual eligibility

Outcome	Dually eligible beneficiaries			Non-dually eligible beneficiaries			Difference in impact estimates[a] [90% CI]	Probability that MCCM reduced the disparity[b]	Difference in impacts, holding covariates constant[c] [90% CI]
	MCCM mean	Impact estimate [90% CI]	Percentage impact	MCCM mean	Impact estimate [90% CI]	Percentage impact			
Percentage who received the Medicare hospice benefit	76	+20.4 [17.4, 22.8]	+37	84	+18.0 [16.6, 19.4]	+27	+2.4 [-0.6, 4.4]	92	+0.3 [-2.3, 2.1]
Percentage who received an aggressive life-prolonging procedure, surgery, or diagnostic test in the last 30 days of life	65	-14.0 [-16.1, -11.7]	-18	61	-15.6 [-17.2, -14.1]	-20	+1.6 [-0.01, 3.8]	5	+0.4 [-1.2, 2.6]
Number of days at home	225	+6.9 [4.2, 9.3]	+3	178	+6.6 [5.6, 7.7]	+4	+0.3 [-2.6, 2.5]	62	-0.8 [-3.3, 1.1]
Percentage with more than one outpatient emergency department visit in last 30 days of life	3.9	-0.9 [-2.0, 0.4]	-18	2.3	-0.8 [-1.3, -0.2]	-25	-0.1 [-0.9, 1.1]	64	+0.1 [-0.4, 1.0]

Sources: Medicare Enrollment Database, Master Beneficiary Summary File, and Medicare claims data, January 1, 2013, to December 31, 2021. The estimates cover beneficiaries who enrolled through June 30, 2021, and who died on or before December 31, 2021, and their experiences in the model.

Notes: We base impact estimates on regression-adjusted differences between MCCM enrollees (N = 5,153) and matched comparison beneficiaries (N = 15,269 before weighting), estimated with a Bayesian regression model. There were 589 MCCM enrollees who were dually eligible for Medicare and Medicaid and 4,564 who were eligible only for Medicare (that is, non-dually eligible). There were 1,757 matched comparison beneficiaries who were dually eligible for Medicare and Medicaid and 13,512 who were eligible only for Medicare.

[a] Differences in impact estimates in this column reflect differences in the characteristics of dually eligible and non-dually eligible beneficiaries, and how those differences might translate into different impacts of MCCM.

[b] Values in this column represent the probability that MCCM has a larger impact in the hypothesized direction for dually eligible beneficiaries than for non-dually eligible beneficiaries.

[c] Differences in impact estimates in this column hold constant the characteristics of dually eligible and non-dually eligible beneficiaries, so that differences in characteristics do not contribute to differences in the impact of MCCM.

CI = credible interval; MCCM = Medicare Care Choices Model.

Exhibit S2-5. Differences in Medicare expenditures, health care service use, and quality of care between deceased MCCM enrollees and matched comparison beneficiaries, by rural status

Outcome	Rural beneficiaries			Nonrural beneficiaries			Difference in impact estimates[a] [90% CI]	Probability that MCCM reduced the disparity[b]	Difference in impacts, holding covariates constant[c] [90% CI]
	MCCM mean	Impact estimate [90% CI]	Percentage impact	MCCM mean	Impact estimate [90% CI]	Percentage impact			
Percentage who received the Medicare hospice benefit	81	+18.0 [15.4, 20.3]	+29	83	+18.3 [16.9, 19.7]	+28	-0.3 [-2.8, 1.8]	43	+0.2 [-2.2, 1.9]
Percentage who received an aggressive life-prolonging procedure, surgery, or diagnostic test in the last 30 days of life	62	-14.1 [-16.4, -11.5]	-19	61	-15.6 [-17.2, -14.1]	-20	+1.5 [-0.4, 3.9]	10	+0.3 [-1.3, 2.7]
Number of days at home	204	+6.6 [4.2, 8.8]	+3	180	+6.7 [5.6, 7.7]	+4	-0.1 [-2.5, 2.1]	48	-0.2 [-2.4, 2.0]
Percentage with more than one outpatient emergency department visit in last 30 days of life	6.0	-1.9 [-3.5, -0.4]	-24	2.0	-0.6 [-1.1, -0.1]	-24	-1.3 [-2.7, 0.1]	94	-0.8 [-1.9, 0.2]

Sources: Medicare Enrollment Database, Master Beneficiary Summary File, and Medicare claims data, January 1, 2013, to December 31, 2021. The estimates cover beneficiaries who enrolled through June 30, 2021, and who died on or before December 31, 2021, and their experiences in the model.

Notes: We base impact estimates on regression-adjusted differences between MCCM enrollees (N = 5,153) and matched comparison beneficiaries (N = 15,269 before weighting), estimated with a Bayesian regression model. There were 685 MCCM enrollees living in rural areas and 4,468 in non-rural areas. There were 2,086 matched comparison beneficiaries living in rural areas and 13,183 in non-rural areas.

[a] Differences in impact estimates in this column reflect differences in the characteristics of rural and non-rural beneficiaries, and how those differences may translate into different impacts of MCCM.

[b] Values in this column represent the probability that MCCM has a larger impact in the hypothesized direction for rural beneficiaries than for non-rural beneficiaries.

[c] Differences in impact estimates in this column hold constant the characteristics of rural and nonrural beneficiaries, so that differences in characteristics do not contribute to differences in the impact of MCCM.

CI = credible interval; MCCM = Medicare Care Choices Model.