APPENDIX

Methods Appendix

This appendix provides an overview of our analysis approach, including a detailed description of how we constructed the analytic files and measures used in the analysis, the process for constructing the comparison group, and a description of the statistical methods we used. This study was part of our mixed-methods independent evaluation of the Medicare Care Choices Model (MCCM), and methods and results for our team's larger evaluation are described elsewhere (Kranker et al. 2023).

1. Overview

The goal of our analyses was to determine whether 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 (patterns in end-of-life care) and experiences of care at the end of life among enrolled beneficiaries. 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 evaluation design in this study. Specifically, we measured differences in outcomes between deceased beneficiaries enrolled in MCCM and a matched comparison group of deceased beneficiaries who (1) lived in the market area of a hospice participating in MCCM; (2) were not referred to or enrolled in MCCM; (3) satisfied the model eligibility criteria we can observe in Medicare claims and enrollment data, and (4) resembled MCCM enrollees in terms of prognosis (expected length of life), prior experience of care, and other observed characteristics.[1] We designed this comparison group to provide a counterfactual of beneficiaries' outcomes had they not enrolled in MCCM and, thus, received usual care or received the Medicare hospice benefit. Regression models, described later in this appendix, improve the precision of the estimates, and adjust for observed differences between MCCM beneficiaries and the matched comparison group (that is, they control for residual differences that remain after matching).

We drew comparison beneficiaries from the regions served by MCCM hospices. A careful comparison group selection approach provides both the rigor to estimate impacts of MCCM and, as we describe later, the flexibility to examine impacts under alternative definitions of the beneficiary study population. The benefit of the internal comparison areas is that it limits the risk that regional differences unrelated to true model impacts might drive the impact estimates. This was especially important in 2020 and 2021, when the COVID-19 pandemic might have had different effects in different parts of the country. Drawing comparison regions from the same areas as MCCM beneficiaries introduces the potential for either beneficiary selection or spillover to affect the impact estimates, but we think these concerns are minimal considering the enrollment rates.[2] Low MCCM enrollment rates among eligible beneficiaries suggest (1) that selection bias would be similar regardless of whether we matched to non-enrolled

[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.
[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 (described below in Section 2.4) included 1,934,407 unique beneficiaries who lived in the market areas of MCCM hospices and met MCCM eligibility criteria we can observe in Medicare claims and enrollment data. This 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 were 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—to limit the sample to those with a certifiable prognosis of six months or less to live. Beneficiaries' prognoses were not universally assessed and reported in extant data sources. Instead, we used actual dates of death to determine the period in which each beneficiary would have been certified as having a prognosis of less than six months to live. In this decedent approach, we measured regression-adjusted differences in outcomes between (1) beneficiaries who died and were enrolled in MCCM and (2) a matched comparison group of beneficiaries who died; were not enrolled in or referred to MCCM; lived in the market area of a hospice participating in MCCM; satisfied the model eligibility criteria we can observe in Medicare claims and enrollment data (see Footnote 1); and otherwise appeared similar to MCCM enrollees on health status, prior experience of care, and other observed baseline characteristics. A unique advantage of the decedents approach was that we could 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. If the length of follow-up were to have different distributions between the intervention and comparison groups, we would expect mean outcomes to differ between the two groups as well, biasing impact estimates.

Because comparison beneficiaries did not enroll in the model or the evaluation, we had to determine, for each matched comparison beneficiary, when to begin measuring outcomes—a *pseudo-enrollment* date. We considered multiple potential pseudo-enrollment dates for each beneficiary, and then we picked the best available pseudo-enrollment date using a novel matching technique named `GroupMatch` (Pimentel et al. 2019). `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 matching techniques (discussed more in Section 3 of this appendix) 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 enrollment (or pseudo-enrollment) and death.

2. Analytic file construction

In this section, we describe how we constructed the analytic files for the impact analysis. We start with a concise overview of the data sources used and then describe the approaches to identifying the beneficiaries we included in the intervention and potential comparison groups. We also provide detailed descriptions of the variables we constructed and included in the analytic files.

2.1. Data sources

The analytic files combined Medicare fee-for-service claims and enrollment data with other Medicare data sets and publicly available data.

2.1.1. Medicare claims and enrollment data

We used Medicare Part A, B, and D claims and Medicare enrollment data as key inputs to our analytic files for the impact evaluation. These files enabled us to generate outcomes measures to estimate the impacts of the model (including measures of end-of-life care, service use, and Medicare fee-for-service expenditures) and to construct beneficiary-level covariates for matching, balance tests, and regression models. These files span from 2014 (to accommodate constructing certain measures with two-year look-back periods for beneficiaries enrolled as early as January 1, 2016) to December 31, 2021, allowing for 90 days of run-out (in accordance with standard research practices).[3]

We also used software developed by the Centers for Medicare & Medicaid Services (CMS), coupled with International Classification of Diseases 9 and 10 diagnosis codes found in claims data, to assign hierarchical condition category flags and calculate hierarchical condition category scores. We used the Medicare Enrollment Database and the Master Beneficiary Summary File (by year) to extract information on beneficiaries, including (1) Medicare Part A, B, C, and D enrollment and termination dates, (2) residence state and zip code, (3) whether Medicare was the primary payer for a beneficiary's medical expenses, (4) reasons for entitlement, (5) Medicare–Medicaid dual eligibility, and (6) basic demographic information.

MCCM hospices submitted claims to receive payment for model services. We used these data to identify the list of beneficiaries enrolled in MCCM when we constructed our beneficiary finder file (see details below). In addition, we used these data to measure Medicare payments for MCCM services and to construct measures of MCCM service receipt.

2.1.2. Other Medicare data sources

We supplemented claims and enrollment data with additional CMS data sets to obtain details on beneficiaries' participation in other Center for Medicare & Medicaid Innovation (the Innovation Center) models, receipt of long-term care services, and difficulties with activities of daily living. We also used the Chronic Conditions Warehouse beneficiary crosswalk to link across different files.

- *Master Data Management.* This data set provides information on the enrollment of Medicare beneficiaries in CMS Innovation Center models. We used the Master Data Management to identify

[3] We extracted claims in early April 2022 to allow for at least 90 days of claims runout.

beneficiaries who were participating in the CMS Innovation Center's accountable care organization models or the Oncology Care First Model.

- *Minimum Data Set and Outcome and Assessment Information Set.* The Minimum Data Set collects information on all users of nursing facilities for quality purposes, and Outcome and Assessment Information Set does the same for all recipients of home health care. We used the 2015 to 2021 Minimum Data Set and Outcome and Assessment Information Set data to determine whether beneficiaries were likely living in a long-term care nursing setting or in an assisted living facility, respectively, at the time of enrollment (or pseudo-enrollment). We also used the Outcome and Assessment Information Set data to identify any recorded activities of daily living for beneficiaries within 30 days of their [pseudo-] enrollment date.
- *Chronic Conditions Warehouse Beneficiary Crosswalk Files.* We used the Chronic Conditions Warehouse beneficiary crosswalk files to link Medicare claims and enrollment data to other data sources. These crosswalk files link beneficiaries' Chronic Conditions Warehouse identification numbers to their Health Insurance Claim number, Social Security number, or Medicare Beneficiary Identifier.

2.1.3. Publicly available data

The final data sets used were the American Community Survey, the Federal Office of Rural Health Policy, and the Dartmouth Atlas.

- *American Community Survey*. This ongoing survey is used to measure topics such as education and employment. We used the five-year American Community Survey files to identify characteristics of the zip codes where each beneficiary lived. We used the 2015 data (2011–2015) for Cohort 1 hospices, which started enrolling MCCM beneficiaries in 2016, and we used the 2017 data (2013–2017) for Cohort 2 hospices, which started enrolling MCCM beneficiaries in 2018. We accessed the data through the Agency for Healthcare Research and Quality's Social Determinants of Health data files.[4]
- *Federal Office of Rural Health Policy*. The Federal Office of Rural Health Policy data identify which areas of the country are defined as rural. We downloaded the rural zip code-level definitions of "rural" from the office's website.[5]
- *The Dartmouth Atlas.* This project aggregates Medicare and Medicaid data at the geographic level to provide information on national and regional health care markets. We downloaded data from the Dartmouth Atlas to identify the zip codes in each hospital referral region.[6] As we describe later, MCCM hospice market areas were defined as one or more hospital referral region where a hospice's enrollees commonly lived.

2.2. Identifying MCCM enrollees

The study population for the decedents analysis in the final report was first limited to 5,774 beneficiaries who enrolled in MCCM between January 1, 2016, and June 30, 2021 (the last date beneficiaries could be enrolled in MCCM), and who had a verified death date on or before December 31, 2021.[7] To be included

[4] https://www.ahrq.gov/sdoh/data-analytics/sdoh-data.html.
[5] https://www.hrsa.gov/rural-health/about-us/definition/datafiles.html.
[6] https://data.dartmouthatlas.org/supplemental/.
[7] The December 2021 cutoff aligns with the end of MCCM. Using this cutoff allows for up to six months of observability before death, and adequate claims runout per the requirements outlined in Section 2.1.1 above.

in the intervention group, the beneficiary had to have at least one paid Medicare hospice claim with the associated MCCM demonstration identification number (73).[8] We assigned an MCCM enrollment date based on the earliest MCCM paid claim date.

Next, we restricted the intervention group to 5,153 beneficiaries who met the model eligibility criteria that we could assess using Medicare claims and enrollment data. We did this so that the same criteria would apply to both MCCM enrollees and the comparison group. Specifically, beneficiaries had to meet the following seven criteria:[9]

1. *Has been enrolled in Medicare Part A and B for the past 12 months*. Beneficiary was continuously enrolled in Medicare fee for service Part A and B with Medicare as their primary payer for the 12 months prior to their enrollment (or pseudo-enrollment) date. Data came from the Medicare Enrollment Database.
2. *Had a Medicare Care Choices Model- (MCCM-) qualifying diagnosis.* Beneficiary had at least one inpatient, outpatient, or carrier claim in the 12 months before their enrollment (or pseudo-enrollment) date with an International Classification of Diseases 10 Clinical Modification or International Classification of Diseases 9 Clinical Modification primary diagnosis for an MCCM-qualifying condition: cancer, chronic obstructive pulmonary disease, congestive heart failure, or human immunodeficiency virus/acquired immunodeficiency syndrome (HIV/AIDS). Exhibit M.1 provides all the International Classification of Diseases 9 and 10 codes used to identify these conditions. This definition is from MCCM Resource Manual.
3. *Had at least one hospital encounter in past 12 months.* Beneficiary had one hospital encounter (inpatient stay, emergency department visit, or observation stay) in the 12 months before their enrollment (or pseudo-enrollment) date. To identify hospital encounters, we used the approach described outlined in Section 2.6 to count the number inpatient admissions, emergency department visits, or observation stays in the 12 months before their enrollment (or pseudo-enrollment) date, and then included those beneficiaries had at least one encounter.
4. *Had at least three office visits with any Medicare clinician in past 12 months.* Beneficiary had at least three office visits with any Medicare eligible providers within the last 12 months before their enrollment (or pseudo-enrollment) date, including visits in a Federally Qualified Health Center, rural health clinic, and critical access hospital setting.

[8] Enrollees were screened for eligibility at the time of MCCM enrollment, and MCCM claims were later validated by the Medicare Administrative Contractor based on program eligibility standards. We initially considered using MCCM program data as a data source to identify MCCM enrollees, but ultimately decided on limiting the intervention group to those beneficiaries with positive paid MCCM claims to ensure that these beneficiaries were eligible and would continue receiving services. That is, we did not include beneficiaries who were enrolled in the model but did not receive any services according to MCCM claims data. Our understanding is that because the sites did not have the ability to verify all the information needed for enrollment, beneficiaries could be enrolled in the model but not have claims paid because the Medicare Administrative Contractor deemed the beneficiary was ineligible. Among 7,399 beneficiaries who were enrolled in the model (in MCCM program data) or had MCCM claims before July 1, 2021, there were 6,559 beneficiaries (89 percent) who had a MCCM claim with a positive payment amount to participating hospices for providing MCCM services from January 1, 2016, to June 30, 2021. A small number (N = 138) of these 5,774 beneficiaries were represented in MCCM claims but not included in the MCCM program data.

[9] In Exhibit S.2 in the Supplemental Results appendix, we report the number of observations that we originally identified, the number excluded with each additional criterion.

5. *Have not used Medicare hospice benefit in past 30 days*. Beneficiary was not using the Medicare hospice benefit at enrollment (or pseudo-enrollment) and were not entered hospice in the 30 days prior to enrollment date. Data comes from the Medicare Enrollment Database. (We were unable to screen for enrollment in the Medicaid hospice benefit.)
6. *Did not reside in an institutional setting in the past 30 days*. The actual eligibility rule is that an individual must live in a regular home, but this cannot be identified with available data. Instead, we excluded beneficiaries that resided in an institutional setting. Note that we could not reliably observe *all* instances of beneficiaries living outside of a traditional home setting because not beneficiaries receive the care or assessments needed to identify them. However, since this rule was enforced for all enrollees, we thought it was important to remove them from the comparison group. We do this as follows: To identify those that live in a nursing home, we used the Minimum Data Set assessments and identified those that had assessments indicating that they were living in a long-term care setting within four months before their enrollment date.[10] If yes, the individual was deemed ineligible. To identify those in assisted living facilities and other congregate facilities, we identified those that had had a Part B medical claim with a place of service code indicating assisted living (13), group home (14), custodial care facility (33), or residential substance abuse treatment facility (55), or had a specific procedure codes (99324–99328 or 99334–99337) indicating care received in a domiciliary or rest home within 64 days before enrollment.[11] We used 64 days to allow for the gap between part B home visits (which allow us to identify their residence.)[12] because the two service types are often collocated. We also identified those residing in assisted living facilities using Outcome and Assessment Information Set assessments. If the individual had an Outcome and Assessment Information Set assessment within 4 months (123 days) before their enrollment (or pseudo-enrollment) date that indicated the individual lived in an assisted living facility, we excluded that individual.
7. *Met more strict inclusion criteria applicable at time of enrollment (if applicable)*. During the first year, CMS also required enrollment in Medicare Part D and at least two hospital encounters (January 1, 2016, to March 31, 2016) and at least three office visits with the same provider for the MCCM-qualifying terminal condition (January 1, 2016, to December 31, 2016), but these stricter eligibility requirements were discontinued. We applied these criteria only in the periods where they were applicable.[13]

We could not verify life expectancy of six months or fewer. Finally, so that outcomes could be measured accurately, we restricted the sample to beneficiaries enrolled in fee-for-service Medicare Part A and B with Medicare as the primary payer from the date they enrolled MCCM through their date of death.

[10] The four-month requirement excludes beneficiaries who may be in the facility for short-term skilled nursing facility services for 100 days or less.
[11] We allowed for 64 days because current research suggests that is a typical gap between home care visits.
[12] We did not include place of service codes for nursing facility (32) because this resulted in a large number of otherwise eligible MCCM enrollees being labeled ineligible. It is likely that place of service code 32 is picking up skilled nursing facility stays in addition to longer term nursing facility stays.
[13] During the COVID-19 pandemic, CMS broadened access to telehealth services, and telehealth encounters were counted in determining MCCM eligibility. We included telehealth visit procedure codes in our measure of total office visits after March 6, 2020 (when the change in the eligibility criterion occurred).

Exhibit M.1. Diagnosis codes indicating each of the four MCCM-eligible conditions

Condition		Code system	Codes
Congestive heart failure		ICD-9-CM	4280, 4281, 4289, 40201, 40211, 40291, 40401, 40411, 40491, 42820, 42821, 42822, 42823, 42830, 42831, 42832, 42833, 42840, 42841, 42842, 42843
		ICD-10-CM	I110, I130, I501, I502, I5020, I5021, I5022, I5023, I503, I5030, I5031, I5032, I5033, I504, I5040, I5041, I5042, I5043, I509
Chronic obstructive pulmonary disease		ICD-9-CM	4920, 4928, 4940, 4941, 49120, 49121, 49122, 49320, 49321
		ICD-10-CM	J430, J431, J432, J438, J439, J440, J441, J449, J470, J471, J479
HIV/AIDS		ICD-9-CM	042
		ICD-10-CM	B20
Cancer	Breast	ICD-9-CM	1740, 1741, 1742, 1743, 1744, 1745, 1746, 1748, 1749, 1750, 1759
		ICD-10-CM	C50011, C50012, C50019, C50021, C50022, C50029, C50111, C50112, C50119, C50121, C50122, C50129, C50211, C50212, C50219, C50221, C50222, C50229,C50311, C50312, C50319, C50321, C50322, C50329, C50411, C50412, C50419, C50421, C50422, C50429, C50511, C50512, C50519, C50522, C50529, C50611, C50612, C50619, C50621, C50622, C50629, C50811, C50812, C50819, C50821, C50822, C50829, C50911, C50912, C50919, C50921, C50922, C50929, C7981, C946
	Colorectal	ICD-9-CM	1520, 1521, 1522, 1530, 1531, 1532, 1533, 1534, 1535, 1536, 1537, 1538, 1539, 1540, 1541, 1548, 20901, 20902, 20903, 20910, 20911, 20912, 20913, 20914, 20915, 20916, 20917
		ICD-10-CM	C170, C171, C172, C180, C181, C182, C183, C184, C185, C186, C187, C188, C189, C19, C20, C218, C785, C7A010, C7A011, C7A012, C7A020, C7A021, C7A022, C7A023, C7A024, C7A025, C7A026, C7A029, C7A094, C7A095, C7A096, C883
	Lung	ICD-9-CM	1622, 1622, 1623, 1623, 1624, 1624, 1625, 1628, 1629, 1764
		ICD-10-CM	C3400, C3401, C3402, C3410, C3411, C3412, C342, C3430, C3431, C3432, C3480, C3481, C3482, C3490, C3491, C3492, C4650, C4651, C4652, C7800, C7801, C7802, C7A090
	Prostate	ICD-9-CM	185
		ICD-10-CM	C61
	Other	ICD-9-CM	1400, 1401, 1403, 1404, 1405, 1406, 1408, 1409, 179, 181, 193, 1410, 1411, 1412, 1413, 1414, 1415, 1416, 1418, 1419, 1420, 1421, 1422, 1428, 1429, 1430, 1431, 1438, 1439, 1440, 1441, 1448, 1449, 1450, 1451, 1452, 1453, 1454, 1455, 1456, 1458, 1459, 1460, 1461, 1462, 1463, 1464, 1465, 1466, 1467, 1468, 1469, 1470, 1471, 1472, 1473, 1478, 1479, 1480, 1481, 1482, 1483, 1488, 1489, 1490, 1491, 1498, 1499, 1500, 1501, 1502, 1503, 1504, 1505, 1508, 1509, 1510, 1511, 1512, 1513, 1514, 1515, 1516, 1518, 1519, 1523, 1528, 1529, 1542, 1543, 1550, 1551, 1552, 1560, 1561, 1562, 1568, 1569, 1570, 1571, 1572, 1573, 1574, 1578, 1579, 1580, 1588, 1589, 1591, 1598, 1599, 1600, 1601, 1602, 1603, 1604, 1605, 1608, 1609, 1610, 1611, 1612, 1613, 1618, 1619, 1620, 1630, 1631, 1638, 1639, 1639, 1640, 1640, 1641, 1641, 1642, 1642, 1643, 1643, 1648, 1648, 1649, 1649, 1650, 1650, 1658, 1658, 1659, 1700, 1701, 1702, 1703, 1704, 1705, 1706, 1707, 1708, 1709, 1710, 1712, 1713, 1714, 1715, 1716, 1717, 1718, 1719, 1720, 1721, 1722, 1723, 1724, 1725, 1726, 1727, 1728, 1729, 17301, 17302, 17309, 1760, 1761, 1762, 1763, 1765, 1768, 1769, 1800,1801, 1808, 1809, 1820, 1821, 1828, 1830, 1832, 1833, 1834, 1835, 1838, 1839, 1840, 1841, 1842, 1843, 1844, 1848, 1849, 1860, 1869, 1871, 1872, 1873, 1874, 1875, 1876, 1877, 1878, 1879, 1880, 1881, 1882, 1883, 1884, 1885, 1886, 1887, 1888, 1889, 1890, 1891, 1892, 1893, 1894, 1898, 1899, 1900, 1901, 1902, 1903, 1904, 1905, 1906,1907, 1908, 1909, 1910, 1911, 1912, 1913, 1914, 1915, 1916, 1917, 1918, 1919, 1920, 1921, 1922, 1923, 1928, 1929, 1930, 1940, 1941, 1943, 1944, 1945, 1946, 1948, 1949, 1950, 1951, 1952, 1953, 1954, 1955, 1958, 1982, 2733, 20000, 20001, 20002, 20003, 20004, 20005, 20006, 20007, 20008, 20010, 20011, 20012, 20013, 20014, 20015, 20016, 20017, 20018, 20020, 20021, 20022, 20023, 20024, 20025, 20026, 20027, 20028, 20030, 20031, 20032, 20033, 20034, 20035, 20036, 20037, 20038, 20040, 20041, 20042, 20043, 20044, 20045, 20046, 20047, 20048, 20050, 20051, 20052, 20053, 20054, 20055, 20056, 20057, 20058, 20060, 20061, 20062, 20063, 20064, 20065, 20066, 20067, 20068, 20070, 20071, 20072, 20073, 20074, 20075, 20076, 20077, 20078, 20080, 20081, 20082, 20083, 20084, 20085, 20086, 20087, 20088, 20100, 20101, 20102, 20103, 20104, 20105, 20106, 20107, 20108, 20110, 20111, 20112, 20113, 20114, 20115, 20116, 20117, 20118, 20120, 20121, 20122, 20123,

Condition		Code system	Codes
			20124, 20125, 20126, 20127, 20128, 20140, 20141, 20142, 20143, 20144, 20145, 20146, 20147, 20148, 20150, 20151, 20152, 20153, 20154, 20155, 20156, 20157, 20158, 20160, 20161, 20162, 20163, 20164, 20165, 20166, 20167, 20168, 20170, 20171, 20172, 20173, 20174, 20175, 20176, 20177, 20178, 20190, 20191, 20192, 20193, 20194, 20195, 20196, 20197, 20198, 20200, 20201, 20202, 20203, 20204, 20205, 20206, 20207, 20208, 20210, 20211, 20212, 20213, 20214, 20215, 20216, 20217, 20218, 20220, 20221, 20222, 20223, 20224, 20225, 20226, 20227, 20228, 20230, 20231, 20232, 20233, 20234, 20235, 20236, 20237, 20238, 20240, 20241, 20242, 20243, 20244, 20245, 20246, 20247, 20248, 20250, 20251, 20252, 20253, 20254, 20255, 20256, 20257, 20258, 20260, 20261, 20262, 20263, 20264, 20265, 20266, 20267, 20268, 20270, 20271, 20272, 20273, 20274, 20275, 20276, 20277, 20278, 20280, 20281, 20282, 20283, 20284, 20285, 20286, 20287, 20288, 20290, 20291, 20292, 20293, 20294, 20295, 20296, 20297, 20298, 20300, 20301, 20302, 20310, 20311, 20312, 20380, 20381, 20382, 20400, 20401, 20402, 20410, 20411, 20412, 20420, 20421, 20422, 20480, 20481, 20482, 20490, 20491, 20492, 20500, 20501, 20502, 20510, 20511, 20512, 20520, 20521, 20522, 20530, 20531, 20532, 20580, 20581, 20582, 20590, 20591, 20592, 20600, 20601, 20602, 20610, 20611, 20612, 20620, 20621, 20622, 20680, 20681, 20682, 20690, 20691, 20692, 20700, 20701, 20702, 20720, 20721, 20722, 20780, 20781, 20782, 20800, 20801, 20802, 20810, 20811, 20812, 20820, 20821, 20822, 20880, 20881, 20882, 20890, 20891, 20892, 20900, 20920, 20921, 20922, 20923, 20924, 20925, 20926, 20927, 20929, 20930, 20931, 20932, 20933, 20934, 20935, 20936, 20970, 20971, 20972, 20973, 20974, 20979, 23879, 27789
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Condition		Code system	Codes
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ICD-9-CM = International Classification of Diseases, Ninth Revision, Clinical Modification; ICD-10-CM = International Classification of Diseases, Tenth Revision, Clinical Modification.

2.3. Identifying MCCM hospices' market areas

Our process for identifying potential comparison beneficiaries required identifying a *geographic market area* for each MCCM hospice.[14] For each hospice, we identified a market area that consists of one or more hospital referral regions. These regions were defined in 1996 to represent regional health care

[14] Our impact analyses focused on beneficiaries enrolled in MCCM, so hospices needed to enroll at least one beneficiary in MCCM to be included in the impact analyses. We were not able to, but did not need to, identify market areas for the participating hospices that enrolled zero beneficiaries.

markets for tertiary medical care (Dartmouth Atlas Project 2020a). We chose to define hospice market areas by hospital referral regions because they are small enough to capture local variation in patterns of end-of-life care (Dartmouth Atlas Project 2020b) but are still large enough to provide an adequate number of comparison beneficiaries to support our design.

Three factors influence whether any particular hospital referral region is included in the market area for a given hospice: (1) the geographic location of the hospital referral region relative to the hospital referral region of the hospice, (2) the zip code of residence of all beneficiaries who filed claims at the hospice, and (3) the zip code of residence for beneficiaries enrolled in MCCM by the hospice. More specifically, we defined the market area for any hospice to include all hospital referral regions that meet **any** of the following criteria:

1. The hospice was physically located in the hospital referral region
1. Among beneficiaries who received hospice services from the hospice (regardless of participation in MCCM), at least 25 percent had a zip code of residence in the hospital referral region and the region was adjacent to the hospital referral region where the hospice was physically located
2. At least 25 percent of the beneficiaries enrolled in MCCM by the hospice had a zip code of residence in the hospital referral region
3. At least 10 percent of the beneficiaries enrolled in MCCM by the hospice had a zip code of residence if the 10 percent number constitutes at least 5 beneficiaries
4. At least 10 of the beneficiaries enrolled in MCCM by the hospice had a zip code of residence in the hospital referral region

To implement the first two criteria, we reviewed all Medicare fee-for-service hospice claims submitted by the hospice during the year before model implementation (2015 for Cohort 1 hospices and 2017 for Cohort 2 hospices) and assigned the hospice to an hospital referral region based on the facility zip code recorded on their claims.[15] Next, we assigned each Medicare fee-for-service beneficiary in the hospice's claims to a single hospital referral region based on the beneficiary's zip code of residence recorded on the hospice claims, then counted the number of beneficiaries served by the hospice who were from each hospital referral region.[16] We used files provided by the Dartmouth Atlas (Dartmouth Atlas Project 2020a) to map all zip codes to hospital referral regions and to identify neighboring (adjacent) hospital referral regions. Finally, for each hospice, we determined the proportion of beneficiaries who live in each hospital referral region and selected all hospital referral regions that meet the 25 percent threshold.

The last three criteria were based on enrolled MCCM beneficiaries. We identified all enrolled beneficiaries (through June 2021) and their zip codes from the MCCM program data and mapped the beneficiaries' zip codes to a hospital referral region using the Dartmouth Atlas. For each hospice, we then determined the total number of beneficiaries that live in each hospital referral region and identified the regions that met any of the three criteria.

[15] After the hospice's facility zip code on each claim was mapped to a hospital referral region using the Dartmouth Atlas, we selected the hospital referral region that was recoded most often among the hospice's claims. If two hospital referral regions were recorded the same number of times, we chose the one recorded most recently.

[16] For cases where the beneficiary had multiple hospice claims and the zip codes of residence on these claims indicated the beneficiary lived in more than one hospital referral region, we assigned the beneficiary to a single region, selecting the hospital referral region corresponding to the most days of service.

In the end, we were able to identify a market area for each MCCM hospice: we identified a total of 102 unique hospital referral regions as the market areas for the 89 hospices that enrolled at least one beneficiary in MCCM. Sixty hospices (67 percent) had a market area comprising a single hospital referral region—the region where the hospice was physically located—and the remaining 29 hospices (33 percent) had a market area that included two or more hospital referral regions.[17]

There was some overlap in the market areas of the MCCM hospices. Specifically, among all hospital referral regions that were selected as belonging to a hospice's market area, 25 percent of the time the hospital referral region was in the market area of two or three different hospices.[18] There were a few beneficiaries enrolled in MCCM who lived outside the hospital referral regions that we selected as the market areas of the MCCM hospices, but this was rare.[19]

2.4. Identifying potential comparison beneficiaries

We identified potential comparison beneficiaries from among fee-for-service Medicare beneficiaries who lived in the MCCM hospices' market area (Section 2.3), met the MCCM eligibility criteria observable in Medicare claims and enrollment data (Section 2.2), and subsequently died between January 1, 2016, and December 31, 2021 (the end of the analysis period). From the potential comparison pool, we removed any beneficiaries who were (1) ever enrolled in MCCM or (2) ever referred to MCCM (according to MCCM program data) but did not enroll.

To identify the potential comparison beneficiary pool, we took the following steps. First, we identified the set of potential comparison beneficiaries who died between January 1, 2016, and December 31, 2021. We then excluded those beneficiaries who never lived in any of the MCCM hospice market areas during the potential pseudo-enrollment period (January 1, 2016, to June 30, 2021) or who did not have a claim with an MCCM qualifying diagnoses during the potential baseline period (January 1, 2015, to June 30, 2021) or were referred or enrolled in MCCM (according to MCCM program data and Medicare claims).

For each remaining potential comparison beneficiary, we created 29 potential pseudo-enrollment dates which were then used to construct time-varying eligibility measures, such as the number of office visits in the 12 months before the pseudo-enrollment date. To assign pseudo-enrollment dates, we calculated the empirical distribution of survival times (in days) for the enrolled group that met all inclusion criteria and then used this distribution to assign 29 different possible survival times for each potential comparison beneficiary.[20] To ensure that we had copies of each comparison beneficiary with short and

[17] Twenty-one hospices had 2 hospital referral regions, 6 hospices had 3 hospital regions, 1 hospice had 4 hospital regions, and 1 hospice had 4 hospital regions. The last market area corresponds to a hospice located close to the borders of a relatively large number of small hospital referral regions; the hospice eventually withdrew from MCCM.
[18] Seventy-six of the hospital referral regions had 1 hospice whose market area includes the hospital referral region, 21 of the hospital referral regions had 2 hospices, and 5 of the hospital referral regions had 3 hospices.
[19] The market areas we selected included the hospital referral region of 7,139 of the 7,263 MCCM beneficiaries, or 98 percent. Here, 7,263 is total number of beneficiary-hospice records in MCCM program data as of December 2021. The final impact analysis, which excludes beneficiaries for various reasons (see Section 2.2 above), is based on 5,153 MCCM enrollees.
[20] Specifically, we observed the survival times for MCCM enrollees in our analysis sample and measured the distribution in the following increments: minimum, 1st percentile, 2nd percentile, 3rd percentile, 4th percentile, 5th percentile, 7.5th percentile, 10th percentile, 12.5th percentile, 15th percentile, 17.5th percentile, 20th percentile, 22.5th percentile, 25th

long survival times, we used stratified random draws so that one observation falls in each stratum. Thus, we created 29 "copies" for each eligible beneficiary (that is, 29 observations of the same individual, same date of death, and a unique pseudo-enrollment date). This step was designed to *approximately* balance between the survival time distributions for beneficiaries in the intervention and potential comparison groups.

Finally, we assessed whether the beneficiary met our inclusion criteria on each pseudo-enrollment date, keeping only the copies where the pseudo-enrollment date fell between January 1, 2016, and June 30, 2021, and where the beneficiary met the inclusion criteria on the pseudo-enrollment date. Inclusion criteria included requiring the beneficiary to have died before January 1, 2022; lived in one of the hospice market areas on their pseudo-enrollment date; and met MCCM eligibility criteria on their pseudo-enrollment date (as best we could determine using claims and enrollment data, per the criteria described in Section 2.2 of this appendix.) That is, we applied the time-varying eligibility criteria to each person/enrollment date combination and excluded any copy that did not meet the criteria.

The potential comparison group comprised 1,959,525 unique beneficiaries, with 1 to 29 potential pseudo-enrollment dates available for each beneficiary. In total, there were 25,394,282 potential comparison observations that met our inclusion criteria. We then removed a relatively small number of potential comparison observations that had outlier values for one or more matching variables and could not possibly be good matches for any intervention beneficiary, which left 25,117,555 potential comparison observations for 1,954,272 unique beneficiaries. Finally, we dropped comparisons who did not meet the exact-match restrictions for any enrolled beneficiaries (see details below), which left a final sample of 23,687,256 potential comparison observations for 1,934,407 unique beneficiaries (12.2 observations per unique beneficiary on average) to use in matching.

2.5. Constructing baseline measures to use in matching and as control variables

To conduct propensity score matching, we constructed the following kinds of variables:

- Demographic and Medicare enrollment characteristics, which include beneficiaries' age, sex, race, Medicaid status, and characteristics of their local area (such as average income)
- Prior health care use, which includes beneficiaries' use of health care services such as hospitalizations, emergency department, and Part B drug use over the prior year
- Health at enrollment, which includes beneficiaries' qualifying MCCM diagnosis, hierarchical condition category score at enrollment, and hierarchical condition category score in the year prior to enrollment
- Disease-specific measures, which include measures specific to the MCCM qualifying diagnosis

percentile, 27.5th percentile, 30th percentile, 35th percentile, 40th percentile, 45th percentile, …, 90th percentile, 95th percentile, and maximum. Next, we created 29 copies of each potential comparison beneficiary. Each copy was assigned a survival time: for the first copy, we randomly drew a survival time between the minimum and 1st percentile; for the second copy, we randomly drew a survival time between the 1st and 2nd percentile; for the third copy, we randomly drew a survival time between the 2nd and 3rd percentile; and so on. Finally, for each potential comparison copy, we set the pseudo-enrollment date equal to their date of death minus the survival time. Using this procedure, MCCM enrollees' and the potential comparison group beneficiaries' distributions of survival times were reasonably balanced before matching.

The details of these variables are available in our final evaluation report (Kranker et al. 2023), including each variable's data source. (We always used the same data source for both intervention and potential comparison beneficiaries when constructing variables.)

Two categories of matching variables consisted of many potentially correlated predictors: binary hierarchical condition category flags (63 variables) and county-level demographic variables (10 variables). Including all 73 of these variables in the propensity score model could have negatively impacted the balance on other matching variables. To reduce this likelihood while still achieving adequate balance on each variable, we conducted a principal component analysis for the two sets of variables. Then we included the principal component scores in the propensity score model instead of using all 73 indicator variables in matching. Principal component analysis is a common dimension-reduction technique that can be used to represent the most important patterns in a set of covariates, using as few variables as possible. By matching on the principal component scores, we aimed to achieve balance on the underlying variables, without having to include dozens of additional covariates in the propensity score model.

We fit each model using only the intervention beneficiaries because our goal was to match the patterns in the intervention group. We selected the number of principal component scores to include in the final models based on the percentage of the total variance explained for each additional principal component. Our propensity score models included eight principal components corresponding to hierarchical condition category flags and three corresponding to county-level demographics. Because hierarchical condition category flags are all binary, we used a specialized version of principal components analysis designed for binary data (Landgraf and Lee 2020); for county-level demographics, we used standard principal components analysis designed for continuous measures.

2.6. Constructing outcome measures

Once we identified the comparison group (as described in Section 3 of this appendix), we constructed the following key outcomes measures:

1. *Received an aggressive life-prolonging procedure, surgical procedure, or diagnostic test in the last 30 days of life*. This measure indicates whether a beneficiary received aggressive life-prolonging procedures, any of a broad range of surgical procedures, or any of a broad range of diagnostic tests (after enrollment or pseudo-enrollment) that are generally believed to be inappropriate at the end of life and are therefore indicative of low-quality care in the last 30 days of life. The measure includes very aggressive interventions, such as mechanical ventilation (CPT 94003), hemodialysis (CPT 90935-90940), enteral or parenteral nutrition (CPT 43761; HCPCS B40-B42, B50-B52, B90, B99), and cardiopulmonary resuscitation (CPT 92950) (Wasp et al. 2020; De Schreye et al. 2017, 2018). In addition, at the end of their lives, beneficiaries with cancer might receive infusion or oral chemotherapy (RC 0331-0335; ICD-9-CM 9925; CPT 96401-96450, 96521-96542; HCPCS J85-J99, Q0083-Q0085) (Wasp et al. 2020; De Schreye et al. 2017; Earle et al. 2005). Beneficiaries with chronic obstructive pulmonary disease might receive endotracheal intubation or tracheotomy (CPT 31500, 31605), lung volume reduction surgery (CPT 32491), coronary or abdominal surgery (CPT 229x, 441x-442x, 451x, 492x-493x, 929x-935x; HCPCS G0269), or spirometry (CPT 940x, 94150, 94200, 94375, 94727). The measure also includes a wide range of major surgeries, such as thoracic, abdominal, or orthopedic surgeries. However, the measure also includes apparently trivial diagnostic

procedures such as phlebotomy for blood tests (CPT 99195), or electrocardiography (CPT 930x). However, even these superficially minor procedures are inappropriate because, in terminally ill persons, they are likely to uncover significant abnormalities such as anemia, kidney failure, or electrolyte abnormalities, that will prompt hospitalization and lead to a cascade of aggressive, inappropriate treatments (De Schreye et al. 2017, 2018). The measure indicates whether the beneficiary received one or more of the above-mentioned treatments or tests from after enrollment (or pseudo-enrollment) in the last 30 days of life.

CMS designed MCCM to maintain or improve the quality of end-of-life care for Medicare beneficiaries. We analyzed Medicare claims data for MCCM and comparison beneficiaries to see whether MCCM improved various measures of end-of-life care, such as decreasing the percentage of beneficiaries receiving an inappropriate procedure, surgical procedure, or diagnostic test in the last 30 days of life; increasing beneficiaries' days at home; and decreasing the percentage of beneficiaries dying in an acute care hospital (Breslow 2015; Grunfeld et al. 2008; Earle et al. 2004, 2005; Emanuel and Emanuel 1998). We hypothesized that MCCM could improve, or at least not diminish, the quality of end-of-life care, especially during the crucial last 30 days of life. At this stage, it becomes clearer to beneficiaries, caregivers, and clinicians that death is approaching, and it becomes increasingly inappropriate to pursue heroic life-prolonging procedures such as CPR, or intubation and mechanical ventilation, or aggressive treatments such as hemodialysis or major surgeries. It also becomes inappropriate to conduct diagnostic testing to uncover abnormalities that will likely lead to painful and ultimately futile hospitalizations, treatments, and procedures. The focus of care in the last few weeks of life should therefore be maximizing comfort and time at home with loved ones and family. Because peer-reviewed studies that have analyzed potentially inappropriate aggressive life-prolonging treatments as measures of the quality of end-of-life care (and the related National Quality Forum-endorsed measures) have focused on specific diseases or conditions, we created a composite outcome for having any aggressive life-prolonging procedure, surgical procedure, or diagnostic test in the last 30 days of life.

2. *Number of days at home*. This is a measure of the number of days the beneficiary spent at home from the time of enrollment (or pseudo-enrollment) to the time of death or the study period end. We define this measure as the number of days between enrollment and death for a beneficiary, less days spent in hospitals, inpatient hospice, inpatient rehabilitation facilities, long-term care hospitals, and skilled nursing facilities. The measure was adapted from Lee et al. (2019) and Medicare Payment Advisory Commission (2015).
3. *More than one emergency department visit in last 30 days of life.* This measure indicates whether a decedent had more than one emergency department visits in the last 30 days of life. Emergency department visits were identified the same way as we described above. This measure is based on National Quality Forum measure 0211.
4. *More than one hospitalization in last 30 days of life.* This measure indicates whether a decedent had more than one inpatient admission in the last 30 days of life. Inpatient admissions were identified the same way as we described above. This measure is based on National Quality Forum measure 0212.
5. *Any intensive care unit admission in last 30 days of life.* This measure indicates whether a decedent had any intensive care unit admissions in the last 30 days of life. Intensive care unit admissions were

identified the same way as we described above. This measure is based on National Quality Forum measure 0213.

6. *Death in an inpatient facility*. This is a measure indicates whether a beneficiary died in an inpatient facility. It is defined as having one or more inpatient facility (hospital, skilled nursing facility, rehabilitation hospital, or long-term acute care hospital) claims in which discharge status is "expired" (discharge status code 20).
7. *Medicare Part A and B expenditures plus MCCM payments*. This measure is the sum of (1) Medicare payments for Part A and B services (described next) and (2) expenditures for services provided through MCCM. The latter expenditures are the sum of Medicare payments to participating hospices for MCCM services, identified with the associated MCCM demonstration identification number (73).
8. *Medicare Part A and B expenditures*. This measure is the sum of Medicare payments across inpatient, outpatient, skilled nursing facility, home health, hospice, carrier (or Part B), and durable medical equipment claims. These payments will include any payments that CMS made to providers for (1) participating in advanced alternative payment models (participating providers receive a 5 percent increase in their professional claims), or (2) for their performance under the Merit-Based Incentive Payment System. Medicare adjusts payments to providers through the amounts they pay on Part B claims, and these adjustments are already factored into the Part B claims in the Research Identifiable File. This measure excludes MCCM payments and non-claims payments—that is, payments from CMS to providers that were made separately from claims.
9. *Inpatient expenditures*. This measure is the sum of Medicare Part A payments for inpatient claims with admission dates during the study period.
10. *Hospice expenditures*. This measure is the sum of Medicare payments for hospice services that started during the study period excluding MCCM payments.
11. *Other expenditures*. This measure is Medicare Part A and B expenditures minus inpatient expenditures and hospice expenditures (as defined above).
12. *Number of inpatient admissions*. This measure is the number of Medicare-paid hospital admissions reported in the Research Identifiable File inpatient claims file for the beneficiary in the study period. Multiple claims for admissions that involved transfers between hospitals were combined into a single record, as were multiple claims for the same beneficiary at the same facility with overlapping dates, so that these count as one admission.
13. *Number of outpatient emergency department visits and observation stays*. This measure is the sum of the number of Medicare-paid outpatient emergency department visits and the number of observation stays that did not lead to a hospitalization.
    - *Number of outpatient emergency department visits*. This measure is the number of Medicare-paid outpatient emergency department visits for the beneficiary that did not lead to a hospitalization. Visits that did not lead to a hospitalization are identified in the outpatient department Research Identifiable File hospital claims file using revenue center line items equal to 045X or 0981.
    - *Number of outpatient observation stays*. This measure is the number of Medicare-paid outpatient observation stays for the beneficiary that did not lead to a hospitalization. Stays that

did not lead to a hospitalization are identified in the outpatient department Research Identifiable File hospital claims file using revenue center line items equal to 0760 or 0762, a corresponding Healthcare Common Procedure Coding System code of G0378, and a length of stay of at least eight hours.

14. *Used the Medicare hospice benefit*. This measure is an indicator of whether the beneficiary used the Medicare hospice benefit at any point during the study period. We consider a beneficiary to have used the Medicare hospice benefit if they have one or more hospice claims where the demonstration identification number was not equal to 73, which would indicate participation in MCCM. This definition was adapted from National Quality Forum measure 0215.
15. *Number of days in hospice*. This measure is the total number of Medicare-paid days for hospice care received by the beneficiary. The number of days in hospice is defined as the sum of days across all of a beneficiary's hospice claims whose admission date was in the period. The measure is set to zero if a beneficiary did not use the hospice benefit during the study period.

The financial outcome measures are measured from the day after enrollment (or pseudo-enrollment) to the end of the study period (December 31, 2021). We used this study period since it captures all the expenditures that Medicare has paid. The following utilization measures are measured from the day after the enrollment (or pseudo-enrollment) date to the beneficiary's death or the end of the study period, whichever comes first.

For additional context and interpretation, our Supplemental Results appendix also includes results for secondary measures of expenditures, health care service use, and end-of-life care; these other outcomes measures are defined in our final evaluation report (Kranker et al. 2023).

3. Identifying the matched comparison beneficiaries

To select matched comparison beneficiaries and their associated pseudo-enrollment dates, we used a matching technique called `GroupMatch` (Pimentel et al. 2019). `GroupMatch` is a propensity score matching procedure designed for situations in which the intervention group is enrolled into a model on a rolling basis, and there is no corresponding enrollment date for members of the comparison group. The key innovation of `GroupMatch` is that the model considers many potential pseudo-enrollment dates for each potential comparison beneficiary, while simultaneously imposing restrictions such that at most one version of each potential comparison is selected for the final match. We implemented this algorithm in such a way that each potential comparison beneficiary is selected as a comparison beneficiary (exactly) once or not at all. An optimal matching algorithm determines the resulting matched comparison group, including the choice of pseudo-enrollment date for each member. We used exact matching and calipers to make sure intervention and comparison beneficiaries matched closely on key matching variables, as described in more detail below.

We favored `GroupMatch`, and more generally the optimal matching algorithm that it extends (Hansen 2006), based on its advantageous theoretical properties and our organization's track record using optimal matching to produce well-matched comparison groups for previous evaluations. By considering many potential pseudo-enrollment dates for each potential comparison beneficiary, `GroupMatch` can identify a comparison group that more closely resembles the intervention group than alternative approaches that choose a fixed pseudo-enrollment date per beneficiary. Each potential comparison

beneficiary is used exactly once (with their corresponding optimized pseudo-enrollment date) or not at all.[21] At the same time, by using variable-ratio matching (where the number of comparisons assigned to each intervention beneficiary can vary), we make the best possible use of our comparison pool: we select more comparisons for intervention beneficiaries with many high-quality matches and fewer comparisons for intervention beneficiaries with few high-quality matches. We allowed one to three comparison beneficiaries to match to each intervention beneficiary.

Propensity scores. As in optimal matching (Hansen 2006), `GroupMatch` assigns matches that minimize the difference in propensity scores between the MCCM and comparison groups.[22] The propensity score summarizes the beneficiary's characteristics in a single value; by matching the MCCM and comparison groups' propensity score distributions, we can theoretically expect the two groups to have similar covariate distributions (Rosenbaum and Rubin 1983; Rosenbaum 1989; Stuart 2020). After an initial round of matching, we manually removed a few terms with zero prevalence in the MCCM group that led to unstable estimates of the propensity scores, and also excluded potential comparison beneficiaries who had these characteristics from the pool.[23]

For this evaluation, we estimated propensity scores separately for each of the six qualifying condition groups listed in Exhibit M.2. Estimating propensity score models for the six groups had two advantages. First, it allowed the relationship between the matching variables and MCCM participation to vary across groups. For example, it allowed any particular variable to be more or less strongly associated with MCCM participation among beneficiaries with cancer compared to the association among beneficiaries with congestive heart failure. Second, separating the propensity score models let us tailor the variables included to those that are most salient for each set of diagnoses. Specifically, the propensity score models contained a set of core matching variables common to each diagnosis group, plus additional variables specific to the diagnosis group. For example, in the cancer-only diagnosis group, we included indicators for cancer type (such as breast, colorectal, and lung) in addition to the core matching variables. In addition, we were able to include interaction terms targeting subgroup balance, for

[21] This is the key innovation in the `GroupMatch` algorithm, which grew out of the need to apply this restriction on other evaluations with rolling enrollment. Allowing each potential comparison to take on different pseudo-enrollment dates avoids the arbitrariness of selecting a single date at random but introduces the challenge of accounting correctly for correlation between two pseudo-enrollment dates for the same comparison if both are selected. To solve this problem, `GroupMatch` takes as input the beneficiary ID number, which it uses to ensure that at most one version of a beneficiary is matched.

[22] The `GroupMatch` algorithm extends the optimal matching approach in the `optmatch` package in R as implemented by Ben Hansen and coauthors. The main difference between `GroupMatch` and `optmatch` is precisely the feature mentioned in the previous footnote: `GroupMatch` allows us to give the algorithm more than one copy of each potential comparison beneficiary and subsequently constrains the algorithm to pick only one copy in the matched comparison group. Otherwise `GroupMatch` solves the same optimization problem as `optmatch` and requires that the solution meets the same constrains (for example, for this analysis, we required that the solution include no more than three comparison beneficiaries for each intervention beneficiary). The main input to the `optmatch` package is a large matrix containing the distances between each intervention and potential comparison beneficiary (of the difference in propensity scores between two beneficiaries). This distance matrix can be manipulated before matching using all our usual matching techniques (including exact matching, calipers, and penalties).

[23] For example, if none of the enrolled beneficiaries in the chronic obstructive pulmonary disease-only diagnosis group (group 4 in Exhibit M.2) were in a skilled nursing facility on their enrollment date, we removed all potential comparison beneficiaries in the chronic obstructive pulmonary disease-only diagnosis group who were in a skilled nursing facility on their pseudo-enrollment date and removed this variable from the propensity score model for the beneficiaries with chronic obstructive pulmonary disease (only). Removing these variables improved the fit of the propensity score models and the stability of the estimated propensity scores.

diagnosis groups where these were relevant. (Exhibit S.3 in the Supplement Results appendix categorizes the variables, identifying those used in matching across diagnosis groupings and those specific to one or more diagnoses.) Because only 20 intervention beneficiaries were in Group 6, we were able to use only the most important matching variables for that group.

Exhibit M.2. Qualifying condition groupings used to estimate propensity scores

Group	Qualifying condition combinations included
1	Cancer
2	Cancer and COPD
	Cancer and CHF
	Cancer and COPD and CHF
3	CHF
4	COPD
5	COPD and CHF
6	HIV/AIDS
	HIV/AIDS and cancer
	HIV/AIDS and cancer and COPD
	HIV/AIDS and cancer and CHF
	HIV/AIDS and COPD
	HIV/AIDS and COPD and CHF

CHF = congestive heart failure; COPD = chronic obstructive pulmonary disease; HIV/AIDS = human immunodeficiency virus/acquired immunodeficiency syndrome.

Matching constraints. We placed several constraints on the matching algorithm to ensure that certain key covariates are well-balanced between the intervention and comparison groups. These constraints fall into three categories:

1. *Exact matching*. Exact matching is the strictest constraint applied to the matching algorithm and is appropriate for binary or categorical variables. For variables with exact matching constraints, we required matched comparison beneficiaries to have the same value as that of the intervention beneficiary. We matched exactly on the beneficiary's qualifying condition group (from Methods appendix Exhibit M.2), as well as hospice market area; whether the beneficiary's (pseudo-) enrollment date occurred before September 1, 2019 (about six months before the COVID-19 pandemic began); and the beneficiary's dual eligibility status.[24]
2. *Strict calipers*. A caliper is a constraint that is appropriate for continuous variables. Whereas exact matching requires matched comparisons to have the same value of a variable as the intervention beneficiary, a caliper restricts the matched comparisons to have a value of the variable within a small window around the value of the intervention beneficiary. For example, we placed calipers on both

[24] An added benefit of exact matching was that we could run the optimal matching algorithm separately for subgroups of beneficiaries, decreasing computation time.

the survival time and (pseudo-) enrollment date variables to ensure that intervention and matched comparison beneficiaries have similar survival times and were enrolled around the same date.[25]

3. *Penalized calipers*. Like the strict calipers described above, a penalized caliper defines a small window around the intervention beneficiary's value of a certain variable. However, instead of not allowing potential comparisons to match to the intervention beneficiary if their value of the variable falls outside the window, a penalized caliper imposes a penalty on these potential comparisons—making them less likely to match. A penalized caliper can also serve as an alternative to exact matching on a binary or categorical variable; in this case, rather than removing potential comparisons from consideration if they do not have the same value of the variable as the intervention beneficiary, we penalize the match. This type of constraint is appropriate for cases when a strict caliper may be overly restrictive, leaving some intervention beneficiaries without any potential comparisons that meet all the matching criteria. We applied penalized calipers to both categorical variables (such as hospital referral region) and continuous variables (such as the number of days between hospital admission and enrollment).[26]

In some cases, we applied more than one of these constraints on the same variable. For example, for any given matched set, we placed the following restrictions on enrollment date: (1) we did not allow any matches with enrollment dates more than one year apart, (2) we penalized any potential matches that are more than six months apart (so matches more than six months apart are very rare), and (3) we had even tighter restrictions on beneficiaries enrolled during the COVID-19 pandemic, depending on whether they enrolled before or after vaccines became widely available (for this purpose, defined as December 1, 2020).

[25] For beneficiaries with shorter survival times, we matched closely on survival time. For beneficiaries in the right tail of the distribution (longer time between MCCM enrollment and death) where survival times are more dispersed, we allowed for wider calipers.

[26] As discussed earlier, beneficiaries included in our analysis were eligible for the model at their enrollment or pseudo-enrollment, as best we can determine from claims. Model eligibility requirements changed over time, and we accounted for this in matching using calipers that required matched comparison beneficiaries to meet, at a minimum, all the same eligibility criteria that MCCM participant met.

4. Regression models for estimating impacts

In this section, we describe the regression models we used to estimate impacts. The regression models used a data set that combines data for the beneficiaries who enrolled in MCCM during the model period with data for the matched comparison beneficiaries. We included one observation per beneficiary.

Our main impact estimation regression model included observations from model years 2016 to 2021, pooling data from the two MCCM cohorts (that started in 2016 and 2018) and their matched comparison beneficiaries. The unit of observation was a beneficiary. Specifically, we compared outcomes of beneficiaries enrolled in MCCM to those of matched comparison beneficiaries by estimating the following regression:

$$(1)\ y_i^1 = \alpha + MCCM_i\,\delta + Y_i^{0'}\gamma + X_{ir}^{'}\beta + \mu_r + \varepsilon_i$$

In this model, y_i^1 represents the outcome for beneficiary i in the intervention period—that is, measured after enrollment in MCCM for intervention group beneficiaries and after the pseudo-enrollment date for matched comparison group beneficiaries. $MCCM_i$ is an indicator variable that equals 1 for the beneficiaries enrolled in MCCM and 0 for beneficiaries in the matched comparison group. Y_i^0 is a vector of pre-intervention outcomes measured at baseline—that is, before the intervention. We cannot include all considered outcome variables in Y_i^0 because some outcomes are not defined at baseline (for example, outcomes related to health care use in the last 30 days of life), but we can include a vector of variables that capture pre-intervention Medicare expenditures and health care service use. X_{ir} is a set of independent beneficiary- or region-level covariates, which is a subset of the variables used to obtain the matched comparison group (Exhibit M.3 shows the variables included in Y_i^0 and X_{ir}); μ_r is a hospice market area fixed effect; and ε_i is an error term that is independent of the included regressors and has the same distribution for all beneficiaries.[27]

Exhibit M.3. Variables used for regression adjustment

Variables included as covariates in regression models
Demographics and eligibility
Age at (pseudo) enrollment
Age category (younger than 65, 65 to 74, 75 to 84, and 85 or older)
Sex
Dually eligible
Non-Hispanic White
Black
Other race
Old-Age and Survivors Insurance
Disability insurance benefits
End-stage renal disease

[27] We combined hospice market areas for hospices that enrolled fewer than 25 beneficiaries into one residual market area category. This affected 44 hospices and about 10 percent of beneficiaries.

Variables included as covariates in regression models
Both disability insurance benefits and end-stage renal disease
Rural zip code
Northeast
Midwest
South
West
Zip code demographics 1st principal component
Zip code demographics 2nd principal component
Zip code demographics 3rd principal component
Had two hospital encounters (inpatient stay, ED visit, or observation stay) in the 12 months before enrollment
Part D drug plan requirement
Had three office visits for with the same provider for the MCCM-qualifying terminal condition in the 12 months before enrollment
Participated in an ACO at the time of enrollment
Year of (pseudo) enrollment
Quarter of (pseudo) enrollment
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)
Time from (pseudo) enrollment to death[a]
Time from (pseudo) enrollment to death squared[a]
Time from (pseudo) enrollment to death cubed[a]
Indicator for which MCCM hospice enrolled the beneficiary
Health at (pseudo) enrollment
HCC: 1st principal component
HCC: 2nd principal component
HCC: 3rd principal component
HCC: 4th principal component
HCC: 5th principal component
HCC: 6th principal component
HCC: 7th principal component
HCC: 8th principal component
HCC Score at (pseudo) enrollment
HCC Score one year before (pseudo) enrollment
HCC: Ischemic or Unspecified Stroke
HCC: Kidney Disease
HCC: Diabetes with Acute or Chronic Complications
HCC: Hip Fracture/Dislocation
HCC: Artificial Openings for Feeding or Elimination
HCC: Dementia with or Without Complication
HCC: Multiple Sclerosis
HCC: Parkinson's and Huntington's Diseases
HCC: Coma, Brain Compression/Anoxic Damage
HCC: Respirator Dependence/Tracheostomy Status
HCC: Cardio-Respiratory Failure and Shock
HCC: Acute Myocardial Infarction

Variables included as covariates in regression models
Had primary diagnosis of cancer
Had primary diagnosis of CHF
Had primary diagnosis of COPD
Had primary diagnosis of HIV/AIDS
Breast cancer
Colorectal cancer
Lung cancer
Prostate cancer
Other cancer
Health care use at baseline: variables used in all regression models
Advance care planning visit in the two years before enrollment
Admitted to hospital on (pseudo-) enrollment date
Discharged from hospital on (pseudo-) enrollment date
Inpatient stay on (pseudo-) enrollment date
Number of days between enrollment or pseudo-enrollment date and most recent inpatient discharge (using admission date)
Length of stay for most recent baseline inpatient stay
Flag for no inpatient stays in baseline year
Discharged from SNF on (pseudo-) enrollment date
Total Medicare Part A and B expenditures in quarter 1 before (pseudo) enrollment
Total Medicare Part A and B expenditures in quarters 2 to 4 before (pseudo) enrollment
Number of inpatient admissions in quarter 1 before (pseudo) enrollment
Number of inpatient admissions in quarters 2 to 4 before (pseudo) enrollment
Number of outpatient ED visits and observation stays in quarter 1 before (pseudo) enrollment
Number of outpatient ED visits and observation stays in quarters 2 to 4 before (pseudo) enrollment
Diagnostic tests and procedures indicating advanced stage or poor prognosis cancer in quarter 1 before (pseudo) enrollment
Diagnostic tests and procedures indicating advanced stage or poor prognosis cancer in quarters 2 to 4 before (pseudo) enrollment
Diagnoses indicating advanced stage or poor prognosis cancer in quarter 1 before (pseudo) enrollment
Diagnoses indicating advanced stage or poor prognosis cancer in quarters 2 to 4 before (pseudo) enrollment
Drugs indicating advanced stage or poor prognosis cancer in quarter 1 before (pseudo) enrollment
Drugs indicating advanced stage or poor prognosis cancer in quarters 2 to 4 before (pseudo) enrollment
Flag for receipt of hormonal therapies in quarter 1 before (pseudo) enrollment
Flag for receipt of hormonal therapies in quarters 2 to 4 before (pseudo) enrollment
Hospitalization with lung volume reduction surgery, oxygen therapy, or ventilation in quarter 1 before (pseudo) enrollment
Hospitalization with lung volume reduction surgery, oxygen therapy, or ventilation in quarters 2 to 4 before (pseudo) enrollment
History of an automatic implantable cardioverter defibrillator in the 12 months before enrollment
History of artery bypass surgery in the 12 months before enrollment
History of percutaneous coronary intervention in the 12 months before enrollment
Health care use at baseline: variables used in outcome-specific regression models [b]
Inpatient expenditures in quarter 1 before (pseudo) enrollment
Inpatient expenditures in quarters 2 to 4 before (pseudo) enrollment
Drug expenditures in quarter 1 before (pseudo) enrollment
Drug expenditures in quarters 2 to 4 before (pseudo) enrollment
SNF expenditures in quarter 1 before (pseudo) enrollment

Variables included as covariates in regression models
SNF expenditures in quarters 2 to 4 before (pseudo) enrollment
Home health expenditures in quarter 1 before (pseudo) enrollment
Home health expenditures in quarters 2 to 4 before (pseudo) enrollment
DME expenditures in quarter 1 before (pseudo) enrollment
DME expenditures in quarters 2 to 4 before (pseudo) enrollment
Hospice expenditures in quarter 1 before (pseudo) enrollment
Hospice expenditures in quarters 2 to 4 before (pseudo) enrollment
Other expenditures in quarter 1 before (pseudo) enrollment[c]
Other expenditures in quarters 2 to 4 before (pseudo) enrollment[c]
Outpatient ED visits in quarter 1 before (pseudo) enrollment
Outpatient ED visits in quarters 2 to 4 before (pseudo) enrollment
Outpatient observation stays in quarter 1 before (pseudo) enrollment
Outpatient observation stays in quarters 2 to 4 before (pseudo) enrollment
Ambulatory visits with primary care providers in quarter 1 before (pseudo) enrollment
Ambulatory visits with primary care providers in quarters 2 to 4 before (pseudo) enrollment
Ambulatory visits with specialist physicians in quarter 1 before (pseudo) enrollment
Ambulatory visits with specialist physicians in quarters 2 to 4 before (pseudo) enrollment
Ambulatory visits with primary care providers and specialist physicians in quarter 1 before (pseudo) enrollment
Ambulatory visits with primary care providers and specialist physicians in quarters 2 to 4 before (pseudo) enrollment
Number of days in hospice in quarter 1 before (pseudo) enrollment
Number of days in hospice in quarters 2 to 4 before (pseudo) enrollment
Number of post-acute care days in quarter 1 before (pseudo) enrollment
Number of post-acute care days in quarters 2 to 4 before (pseudo) enrollment
Number of home health visits in quarter 1 before (pseudo) enrollment
Number of home health visits in quarters 2 to 4 before (pseudo) enrollment
Inpatient days in quarter 1 before (pseudo) enrollment
Inpatient days in quarters 2 to 4 before (pseudo) enrollment
Inpatient ICU days in quarter 1 before (pseudo) enrollment
Inpatient ICU days in quarters 2 to 4 before (pseudo) enrollment
Days in hospital without ICU in quarter 1 before (pseudo) enrollment
Days in hospital without ICU in quarters 2 to 4 before (pseudo) enrollment
EMS ambulance transports in quarter 1 before (pseudo) enrollment
EMS ambulance transports in quarters 2 to 4 before (pseudo) enrollment

[a] This is not used in hazard models.

[b] 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.

[c] *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.

The Greek letters (α, δ, γ, β, and μ_r) are the parameters we estimated. The key parameter of interest is δ, which represents the impact of the model. In a linear model, δ equals the difference in regression-adjusted mean outcomes between the intervention and comparison groups. The parameters γ and β represent the effects of baseline outcomes and covariates, respectively. These terms improve the precision of the impact estimates and net out effects of any observed residual differences in characteristics between the intervention and comparison groups that remain after matching. We note in particular that including baseline outcomes (Y_i^0) is important because any pre-intervention differences in health care use could be associated with health care use in the study period and thereby affect impact estimates if not accounted for.[28,29] Finally, we included a fixed effect for each hospice market area, which we defined to include a single hospice and all matched comparison beneficiaries. These fixed effects net out the effects of any characteristics shared within a hospice's market area, including characteristics of the health care system, care delivery patterns, local policies, and other factors.[30] Collectively, these terms improve the precision of the impact estimates by reducing the amount of unexplained variation in the outcome (ε_i).

We estimated the regression shown in Equation (1) using a model that corresponds to the distribution of the outcome variable. We used ordinary least squares to estimate the models described by Equation (1) for most outcomes, including Medicare Part A and B expenditures, service use, and other continuous outcomes.[31,32] We used similar regression models for binary outcomes (such as enrollment in the hospice benefit). For binary outcomes, we used a logistic regression model that is analogous to Equation (1). Then, we expressed impacts from these models as average marginal effects, so they are on the same scale as the outcome (that is, in percentage point impacts). For one time-to-event outcome, we used Cox proportional hazard models that were analogous to Equation (1) and reported the estimated coefficient δ as a hazard ratio.

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

[28] By including baseline outcomes on the right-hand side of the regression in Equation (1), we implicitly assume unconfoundedness of MCCM enrollment conditional on the baseline outcomes. That is, when comparing intervention and matched comparison beneficiaries with the same pre-(pseudo-) enrollment outcomes, there are no unobserved beneficiary characteristics that correlate with MCCM enrollment: that is, there is no selection on unobserved variables conditional on baseline outcomes (Imbens and Wooldridge 2009).

[29] Note that in this model, the parameter γ governs regression to the mean whenever the vector of pre-intervention outcomes, Y_i^0 includes the pre-intervention outcome model corresponding to the outcome measure, y_i^1..

[30] Our model with hospice market area fixed effects is analogous to what we would do if instead this were a randomized controlled trial, stratified by hospice market area, with random assignment of beneficiaries within each market area to the intervention or comparison group.

[31] To obtain impacts on Medicare Part A and B expenditures plus MCCM payments per enrollee, we (1) estimated regression-adjusted impacts on Medicare Part A and B expenditures (without MCCM payments) and (2) added average (unadjusted) MCCM payments. We used seemingly unrelated estimation to combine the two estimates and obtain standard errors.

[32] For the sake of internal consistency, we calculated regression-adjusted means and impact estimates for Medicare Part A and B expenditures, inpatient expenditures, and hospice expenditures. Then, we manipulated the regression output to compute regression adjusted means and impacts for "other expenditures." Standard errors were calculated by seemingly unrelated estimation. Running a separate regression model to estimate impacts on "other expenditures" gives modestly different results. Specifically, a separate regression yields an estimate of -$4,140 (with standard error $497) compared to our reported estimate of -$3,936 (with standard error $506).

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-level regions (Abadie et al. 2023). Because we include only one observation per beneficiary, it was also not necessary to cluster standard errors on the beneficiary level. Instead, we calculated robust standard errors.

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 regression models produced the average impact *per beneficiary*, averaging across beneficiaries that have shorter and longer survival times. For 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 number of MCCM enrollees.)

5. Accounting for differences due to impacts on hospice enrollment

One possible effect of the model is that it increases enrollment in the Medicare hospice benefit. Because beneficiaries receiving hospice benefits must forgo payment for treatments of their terminal conditions, Medicare expenditures (per day) and rates of service use might be lower after a beneficiary enrolls in hospice. By extension, MCCM's impacts on hospice use could have driven at least some of the model's overall impacts on Medicare expenditures for beneficiaries in MCCM.

To disentangle the impact of MCCM on expenditures and hospice use, we used a simple model in which beneficiaries can either be in hospice (h) or the community (c). Total expenditures from enrollment to death, y, are the weighted sum of expenditures for beneficiaries in hospice (y_h) and expenditures for beneficiaries in the community (y_c), where weights are the fractions of time from enrollment to death spent in hospice (f_h) and the community (f_c), respectively:

$$(3)\quad y = y_h f_h + y_c f_c$$

In this model, the difference in expenditures between MCCM enrollees (indicated by 1) and comparison group beneficiaries (indicated by 0) is the difference:

$$(4)\quad \Delta y = y_1 - y_0 = \left(y_{h1} f_{h1} + y_{c1} f_{c1}\right) - \left(y_{h0} f_{h0} + y_{c0} f_{c0}\right)$$

After some algebra to rearrange terms, we can write the difference in expenditures as:

$$(5)\quad \Delta y = \underbrace{(y_{h0} - y_{c0})(f_{h1} - f_{h0})}_{A} + \underbrace{(y_{h1} - y_{h0}) f_{h0}}_{B} + \underbrace{(y_{c1} - y_{c0}) f_{c1}}_{C} + \underbrace{(y_{h1} - y_{h0})(f_{h1} - f_{h0})}_{D}$$

The four terms in equation (5) show that the effect of MCCM on Medicare expenditures can be decomposed into the following:

A. The effect on expenditures that is the result of MCCM moving some beneficiaries from the community to hospice or prolonging the time that beneficiaries spend enrolled in the Medicare hospice benefit. The term $y_{h0} - y_{c0}$ is the difference in expenditures between hospice and the community that we see in the comparison group, and the term $f_{h1} - f_{h0}$ is the difference in the fraction of time in hospice between MCCM enrollees and beneficiaries in the comparison group.

B. The effect of MCCM on expenditures for beneficiaries in hospice.

C. The effect of MCCM on expenditures for beneficiaries in the community.

D. The interaction of effects (A) and (B). This term captures the effect of MCCM on expenditures for beneficiaries in hospice among the beneficiaries who moved from the community to hospice.

Equation (5) shows that the total impact of MCCM on expenditures (or other outcomes) operates through the expenditure difference between being in hospice and being in the community multiplied by the impact of MCCM on time spent in hospice $\left(\left(y_{h0} - y_{c0}\right)\left(f_{h1} - f_{h0}\right)\right)$ and the remainder $\left(\Delta y - \left(y_{h0} - y_{c0}\right)\left(f_{h1} - f_{h0}\right)\right)$.

To disentangle the total impact of MCCM on the key outcomes total Medicare expenditures, we separately measured expenditures (1) for the time from MCCM enrollment until enrollment in the Medicare hospice benefit and (2) for the time from hospice enrollment to death.[33] For beneficiaries who did not enroll in the Medicare hospice benefit, we set outcomes corresponding to the time from hospice enrollment until death to zero dollars. We also created a variable for the fraction of time after Medicare hospice enrollment relative to the total study period.[34]

We jointly estimated regressions for the following four outcomes: (1) the fraction of the study period spent in hospice, (2) the total outcome during the study period, (3) the outcome before enrollment in the Medicare hospice benefit, and (4) the outcome after hospice enrollment. Each regression was specified the same as in equation (1) and included Y_i^0, X_{ir}, and μ_r as covariates. We specified a general linear model with a log link function and a negative binomial distribution for outcome (1) and standard linear models for outcomes (2) to (4). By estimating these regressions jointly, we were able to obtain robust standard errors that account for dependencies between these outcomes.

We then obtained predicted outcomes corresponding to the terms in equation (5) that allowed us to construct the impact of MCCM that operated though hospice enrollment and the impact that was attributable to other factors. Specifically, we obtained the term $y_{h0} - y_{c0}$ by calculating the difference in predicted outcomes for the periods after and before hospice enrollment, respectively, for each beneficiary in the comparison group. We calculated $f_{h1} - f_{h0}$ as the impact of MCCM on the fraction of

[33] A few beneficiaries in our sample enrolled and then disenrolled from the Medicare Hospice Benefit before their death. We excluded the 0.5 percent of beneficiaries from this analysis for whom more than 30 days passed between hospice disenrollment and death.

[34] For most beneficiaries, this variable equals the fraction of the study period spent in hospice. For some beneficiaries who disenrolled from the hospice benefit before their death, this variable can (slightly) overstate the fraction of the study period spent in hospice.

the study period after enrollment in the hospice benefit. Finally, we obtained the impact of MCCM that did not operate through hospice (for each beneficiary) as the difference between the overall impact of MCCM on Medicare expenditures during the study period and $(y_{h0} - y_{c0})(f_{h1} - f_{h0})$. Finally, we took averages for each of these parameters, averaging across MCCM enrollees.

6. Sensitivity analyses

As we demonstrate below, our we achieved excellent balance between MCCM enrollees and comparison beneficiaries for all the variables we included in matching (and especially close balance for matching variables deemed the most important). In addition, we included a similarly wide range of covariates in the regression analysis to increase the precision of the impact estimates and adjust for any residual differences that remained after matching. The doubly robust approach of matching and regression adjustment using an extensive list of baseline characteristics makes it less likely that important characteristics, that could spuriously affect estimates of model effects (that is, unobserved confounders), remain unaccounted for.[35] However, the possibility of bias from unobserved imbalances between the two groups cannot be ruled out absent a randomized trial. Unobserved confounders might be correlated with enrollment in MCCM and with outcomes such as whether a beneficiary enters hospice. For example, although we observe services and the associated diagnoses that a beneficiary received during the year before enrollment or pseudo-enrollment, we cannot directly observe other information about disease severity or the beneficiary's long-term prognosis that might be available to beneficiaries and clinicians. MCCM enrollees could have had, on average, more (or less) severe illnesses or worse (or better) prognoses than those beneficiaries who were eligible but who did not enroll, even after matching on observable service use, diagnoses, and Medicare expenditures. This type of unobserved differences between the two groups might have caused MCCM enrollees to be more likely to forgo aggressive medical treatment and enter hospice more often than (and sooner after enrollment) than those in the comparison group. As another example, beneficiaries who chose to enroll in MCCM could have been more accepting of their prognosis and more willing to consider receiving hospice benefits than those in the comparison group, which could lead to impact estimates that are biased by self-selection.[36,37] Selection bias and other unobserved confounding could make our impact estimates appear larger or smaller in magnitude than the true effects of the model. In more extreme cases, biases

[35] All else equal, using a more extensive the list of matching (control) variables decreases the number of factors that remain unaccounted for in the analysis. In addition, limiting the comparison group to a matched subsample that closely matches the intervention group on an array of observed characteristics will also reduce differences between the two groups on unobserved characteristics that are correlated with the matching variables (Stuart 2010).

[36] This issue is partially addressed because we excluded from the potential comparison group beneficiaries who were referred to MCCM but chose not to enroll. (None of the comparison beneficiaries were referred to the model according to MCCM program data.) The potential for selection bias remains, however, because our intervention group only includes beneficiaries who were referred to MCCM *and chose to enroll in* MCCM.

[37] We considered addressing potential selection bias by using an intent-to-treat evaluation design, in which everyone who qualifies for the model is included in the "intervention" group (not just those that enroll). This would avoid the potential problem in which people who enroll in the model might have different unobserved characteristics than those in the comparison group, biasing impact estimates. Unfortunately, we were not able to use an intent-to-treat approach to evaluate MCCM because the number of beneficiaries who enrolled in the model is small relative to the number who were eligible for MCCM and lived in the market of a participating hospice. Including so many nonparticipants in the intervention group would severely dilute the impact estimate, making it nearly impossible to detect an impact that might truly exist.

could make it appear that there are large and policy-relevant impacts of the model when, in fact, there are none.

Given these concerns, we assessed the threat of selection bias in our impact estimates by using the *E*-value approach described in Ding and VanderWeele (2016) and VanderWeele and Ding (2017). The approach assesses how strong unobserved confounding would need to be to fully explain the estimated impact estimate. Specifically, the approach uses minimal assumptions to quantify an *E*-value—the threshold for the weakest correlations (measured on a risk ratio scale) between (1) a hypothetical unmeasured confounder and enrollment and (2) the confounder and the outcome variable of interest that would lead to the observed impact estimate if the model truly had no effect. Larger *E*-values indicate that larger unobserved differences between the intervention and comparison groups, on variables strongly related to outcomes, would be necessary to produce the observed impact estimate if the true impact of the model is zero; meanwhile, *E*-values close to 1 (the minimum) indicate the observed differences could be explained by very small (or negligible) differences between the intervention and comparison groups. In other words, this *E*-values captures the degree of confounding that, if removed, would cause the estimated impact of the model to go to zero effect. In another test for selection, if we assume that the unmeasured confounder is perfectly correlated with enrollment (for example, a binary measure that equals one for 100 percent of MCCM enrollees and 0 percent of comparison beneficiaries), we can calculate the correlation required for an unobserved confounder to have with the outcome variable in order to fully explain the observed impact. These two estimates describe the strength of confounding required to move the point estimate of the impact to zero. We also estimate the correlation required of a hypothetical confounder that, if removed, would move the 90 percent confidence interval around the impact estimate to include zero. Details on the derivation of the formulas used to calculate these values for binary outcomes, continuous outcomes, and in hazard models are available in Ding and VanderWeele (2016), VanderWeele and Ding (2017), and Linden et al. (2020).

After we establish the threshold for an unobserved confounder to explain away our impact results, we benchmark these values against observed associations in our regression models and with other estimates found in the literature to assess whether it is likely an unobserved confounder exists with the required correlation with both enrollment and the outcome. For example, if the unobserved confounder must be more strongly correlated with enrollment and the outcome than all other covariates in the model, including those known in the literature to be strongly and robustly correlated with the outcome, it would be unlikely that such unobserved confounders or selection bias exists that can fully explain away the estimated impacts. On the other hand, if an unobserved confounder that is only weakly correlated with enrollment or the outcome variable would be enough to explain away the observed impacts, then we would have less confidence in our estimated impacts. Intuitively, a higher *E*-value means that an unobserved confounder would have to have a stronger correlation with enrollment and the outcome to explain away the estimated impacts and is therefore less likely to exist; an *E*-value closer to one means a relatively small level of selection bias could have produced the observed impact estimate if the impact of the model was truly zero, and an *E*-value or relative risk of 1 (the smallest possible value these statistics can take) means that no residual confounding would be necessary to fully explain the impact regression results.

7. Subgroup analyses

We conducted several subgroup analyses to provide insight into where, when, for whom, and in what context MCCM is most effective. Subgroup analyses focused on impacts on our primary outcome measures for the following groups:

1. Beneficiaries with different survival times: 1 to 30, 31 to 90, 91 to 180, 181 to 365, and more than 365 days
2. Beneficiaries with each of the three most common qualifying conditions: cancer, congestive heart failure, and chronic obstructive pulmonary disease[38]

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 other enrollees. To mitigate this concern, we estimated subgroup effects 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. These assumptions enable the Bayesian model to increase 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 some subgroups of interest are quite small.
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 builds on the main frequentist regression equation:

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

In Equation (6), we introduce the subscript $g[i]$, which refers to the subgroup g to which beneficiary i belongs. Rather than estimating an overall intercept a, model effect δ, and relationship with pre-intervention outcomes γ, we now estimate subgroup-specific intercepts $a_{g[i]}$ and model effects $\delta_{g[i]}$.

[38] Our model estimated results for the 20 beneficiaries with HIV/AIDS, but we did not report these results due to the small sample sizes.

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:

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

In Equation (7), 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 diagnosis category and dual eligibility for Medicare and Medicaid.[39] Finally, the $\alpha_{g[i]}^{Residual}$ term represents the interaction of all the subgroup variables—for example, the effect of having both a cancer diagnosis and being 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 included the 20 beneficiaries with a qualifying diagnosis of HIV/AIDS and categorized beneficiaries' ethnicity as non-Hispanic White, Black, or other, rather than simply non-Hispanic White or non-White and Hispanic. (We do not report estimates for enrollees with HIV/AIDS in this article, however, because the statistical precision is very poor.) 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, non-rural)
- 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 (see Exhibit M.2 in the Methods appendix)
- MCCM model cohort of the hospice: cohort one (2016 start date) or cohort two (2018 start date)
- COVID-19 cohort: before COVID-19 pandemic or during COVID-19 pandemic (see definition above);
- Year of enrollment: 2016, 2017, 2018, 2019, 2020, or 2021
- Hospice of the intervention beneficiary (up to 79 unique hospices)

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.

Otherwise, the Bayesian regression models follow the conventions used in the frequentist models, including the set of covariates X_i used for regression adjustment (see Exhibit M.3 for the complete list).

[39] 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: $\alpha_{Yes}^{Dual}, \alpha_{No}^{Dual} \sim N\left(0, \sigma_{\alpha_{Dual}}^2\right)$, $\alpha_{Yes}^{Dual} + \alpha_{No}^{Dual} = 0$. We place a standard weakly informative prior on the top-level variance parameters: $\sigma_\alpha, \sigma_\delta \sim N^+(0,1)$.

We use linear models for continuous outcomes, such as Medicare expenditures; 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. As in the frequentist models, we weight each observation using the weights w_i, which reflect matching weights for matched comparison beneficiaries.

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 reduced Medicare expenditures. We can also compare posterior distributions for different model parameters to obtain probability statements about differences in impacts, such as the probability that MCCM reduced expenditures more for beneficiaries with a qualifying diagnosis of cancer than for beneficiaries with other qualifying diagnoses.

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 will 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.

Robustness analyses. We used a frequentist subgroup analysis approach as a robustness check for the Bayesian analyses. The frequentist subgroup analysis regression models were similar to our main analysis, but it included interaction terms between subgroup identifiers and MCCM enrollment as follows:

- For estimating effects on beneficiaries with different survival times, we chose to interact the intervention group indicator with the subgroup indicator and other key covariates, including age, gender, race/ethnicity, living in a rural area, dual-eligibility status, hierarchical condition category score, MCCM qualifying diagnosis, Medicare Part A and B expenditures in the baseline year, inpatient hospitalizations in the baseline year, and emergency department visits and observation stays in the baseline year. We did not have sufficient degrees of freedom to estimate a fully interacted model. (We assigned comparison beneficiaries to the same survival time category as their matched MCCM enrollee.)
- For estimating effects on beneficiaries with cancer, congestive heart failure, and chronic obstructive pulmonary disease, we used a hybrid approach because the subgroups were not mutually exclusive categories: some of the beneficiaries were assigned to two or even three of the subgroups. (We

exact-matched on primary MCCM diagnosis, so all matched sets have the same values for these covariates.) First, we obtained impact estimates by estimating separate regression models for the three qualifying condition groups (analogous to a fully interacted model). Second, we tested for differences in impacts between subgroups using a pooled regression model with interactions between qualifying condition indicators variables and the intervention group indicator variable.

Supplemental Results Appendix

This appendix contains results to support the findings presented in the main text. These include tables describing participating hospices and enrolled beneficiaries (Section 1), matching results (Section 2), full results for our full analysis sample (Section 3), and subgroup analyses results (Section 4). The appendix concludes with results from sensitivity analyses using E-values (Section 5) and robustness analysis (Section 6).

1. Description of participating hospices and enrolled beneficiaries

Exhibit S.1 compares the characteristics of hospices that participated in MCCM with all hospices nationwide. Hospices selected to participate in MCCM tended to be larger than hospices nationally, were more often a nonprofit organization, tended to be older, were more likely located in the Northeast or Midwest, and more likely facility-based.

The last column in the table shows the characteristics of the 81 hospices that received MCCM payments. There were not large differences between these hospices and those who did not receive payments, although nonprofit and large hospices were modestly more likely to enroll beneficiaries and receive positive payments for providing MCCM services than for-profit, medium sized, and small sized hospices.

Exhibit S.1. Characteristics of all MCCM hospices, hospices participating in the model extension, and all hospices nationwide

Hospice characteristic	All hospices nationwide (N = 4,361)	MCCM hospices (N = 141)	Received positive MCCM payments (N=81)
Ownership (percentage)			
Nonprofit	24	69	67
For profit	63	17	16
Government	3	1	1
Other	10	13	16
Size (percentage)			
Large (at least 20,000 days of routine home care in 2016)	32	77	83
Medium (3,500 to 19,999 days of routine home care in 2016)	48	20	16
Small (fewer than 3,500 days of routine home care in 2016)	20	3	1
Age (percentage)			
Founded in 1980s	13	52	53
Founded in 1990s	24	34	33
Founded in 2000s	30	10	9
Founded in 2010s	33	4	5
Census region (percentage)			
Northeast	10	20	20
Midwest	22	34	35

Hospice characteristic	All hospices nationwide (N = 4,361)	MCCM hospices (N = 141)	Received positive MCCM payments (N=81)
South	39	32	33
West	28	14	12
Location (percentage)			
Rural	21	16	12
Not rural	79	84	88
Facility type (percentage)			
Freestanding	81	68	72
Facility-based	19	32	28
Religious affiliation (percentage)			
Yes	2	3	5
No	98	97	95
Chain affiliation (percentage)			
Yes	43	46	44
No	57	54	56
Hospice level of care (mean percentage of days)			
Routine home care	98.2	97.0	96.5
General inpatient care	1.3	2.4	2.9
Continuous home care	0.1	0.2	0.2
Inpatient respite care	0.4	0.4	0.4
Duration of stay for hospice enrollees (mean percentage of stays)			
Fewer than 7 days	28.3	32.1	33.6
Seven to 180 days	56.0	55.4	54.6
More than 180 days	15.7	12.5	11.7
Quality of care ratings (mean)			
Overall rating[a]	80.2	80.9	80.8

Sources: Mathematica's analysis of MCCM program data, January 1, 2016 to December 31, 2021, merged with a data set constructed by Abt Associates for previous MCCM evaluation reports (Abt Associates 2020a, 2020b).

Note: We imputed missing data for a small number of non-MCCM hospices. Percentages might not sum to 100 percent due to rounding. For the characteristics of hospice subgroups, see Kranker et al. (2023).

[a] Quality ratings were from the Consumer Assessment of Healthcare Providers and Systems (CAHPS) hospice survey.

MCCM = Medicare Care Choices Model.

In Exhibit S.2, we report the number of beneficiaries who had MCCM services that we originally identified, the number excluded with each additional criterion, and the dollar value of the claims paid for MCCM services for each of these excluded groups. The 5,153 MCCM enrollees in the last row represent the analysis sample for our impact analyses. We report on the characteristics of these beneficiaries in our impact analyses in Exhibit S.3 (in the next section of this appendix).

Exhibit S.2. Sample sizes for report after sequentially applying model inclusion criteria using claims

#	Criteria	Number of beneficiaries		CMS payments for MCCM claims ($)	
		Excluded	Remaining	Excluded	Remaining
—	Beneficiaries who had MCCM services before July 1, 2021[a]	—	6,559	—	$16,731,828
1	Exclude beneficiaries alive after December 31, 2021 (that is, after the model ended)	785	5,774	$4,985,900	$11,745,928
2	Exclude beneficiaries who were not observable during the entire baseline period[b]	51	5,723	$75,408	$11,670,520
3	Exclude beneficiaries without one of the four MCCM qualifying conditions	167	5,556	$383,004	$11,287,516
4	Exclude beneficiaries residing in an institutional setting	134	5,422	$347,500	$10,940,016
5	Exclude beneficiaries receiving hospice benefits	1	5,421	$588	$10,939,428
6	Exclude beneficiaries without a hospital encounter	42	5,379	$79,084	$10,860,344
7	Exclude beneficiaries without three office visits	15	5,364	$31,780	$10,828,564
8	Exclude beneficiaries who did not meet more strict inclusion criteria applicable at time of enrollment	109	5,255	$400,720	$10,427,844
9	Exclude beneficiaries who were not observable in the entire study (follow-up) period[b]	102	**5,153**	$270,168	**$10,157,676**

Sources: Mathematica's analysis of Medicare Enrollment Database, Master Beneficiary Summary File and Medicare claims data, January 1, 2013, to December 31, 2021.

Notes: Bolded green text indicates the final sample and final payments included.

[a] The first row is limited to beneficiaries with at least one paid Medicare hospice claim for MCCM services.

[b] *Observable* beneficiaries were enrolled in Medicare Parts A and B fee for service with Medicare as the primary payer.

MCCM = Medicare Care Choices Model.

2. Results of propensity score matching and final analysis number of observations

Our matching approach proved feasible, and we successfully identified matched comparison beneficiaries for each of the 5,153 MCCM enrollees.[40] Specifically, 5,030 MCCM enrollees (97.6 percent) were matched to 3 comparison beneficiaries, 56 (1.1 percent) were matched to 2 comparison beneficiaries, and 67 (1.3 percent) were matched to 1 comparison beneficiary.[41] Across the matched sets, there are 15,269 unique matched comparison beneficiaries in total, or an average ratio of 2.96 comparison beneficiaries per intervention beneficiary.

Each matched comparison beneficiary was given a single pseudo-enrollment date through the methods described earlier. Pseudo-enrollment dates for matched comparison beneficiaries were broadly the same as the enrollment dates for MCCM enrollees, with similar percentages of beneficiaries in each group enrolling per year. At their pseudo-enrollment date, the matched comparison beneficiaries always resided in the market area of the hospice that enrolled the intervention beneficiary in MCCM. Because some MCCM hospices had market areas with more than one hospital referral region, 82 percent of the comparison beneficiaries lived in the same hospital referral region as the MCCM beneficiary in their matched set.

In Exhibit S.3, we present descriptive statistics for each of the baseline characteristics (matching variables) for MCCM enrollees, the potential comparison group before matching, and the matched comparison group. The standardized difference column in the table presents the difference between MCCM enrollees and matched comparison beneficiaries after matching, expressed in standard deviation units.

Exhibit S.3. Matching variables and characteristics of deceased MCCM enrollees and comparison beneficiaries, before and after matching

Variable	Used in matching[a]	Enhancements[b]	Potential comparison group (N = 23,687,256)	MCCM participants (N = 5,153)	Matched comparison group (N = 15,269)	Standardized difference
COVID-19 cohort	Yes*	Exact matching	29.0	29.0	29.0	0.000
Dual eligibility	Yes*	Exact matching	19.4	11.4	11.4	0.000
Primary diagnosis cancer	Yes*	Penalized caliper[c]	44.6	71.8	71.7	0.001
Primary diagnosis CHF	Yes*	Penalized caliper[c]	49.5	38.0	38.0	0.000
Primary diagnosis COPD	Yes*	Penalized caliper[c]	36.0	33.4	33.4	-0.001
Primary diagnosis HIV/AIDS	Yes*	Penalized caliper[c]	0.4	0.4	0.4	0.000
Indicator for rural zip code	Yes*	Penalized caliper	21.8	13.3	13.7	-0.012

[40] There were 2,263 MCCM enrollees with cancer only (Group 1 in Exhibit M.2 in the Methods appendix), 1,421 with cancer and either congestive heart failure or chronic obstructive pulmonary disease (Group 2), 632 with congestive heart failure only (Group 3), 310 with chronic obstructive pulmonary disease only (Group 4), 507 with congestive heart failure and chronic obstructive pulmonary disease (Group 5), and 20 with HIV/AIS (Group 6).

[41] MCCM participants were slightly less likely to be matched to three comparison beneficiaries if they (1) had HIV/AIDS or (2) had cancer only (that is, cancer without congestive heart failure, chronic obstructive pulmonary disease, or HIV/AIDS).

Variable	Used in matching[a]	Enhancements[b]	Potential comparison group (N = 23,687,256)	MCCM participants (N = 5,153)	Matched comparison group (N = 15,269)	Standardized difference
Medicare A/B as primary payer in previous 2 years	Yes*	Penalized caliper	96.4	95.8	98.8	-0.152
Age	Yes*	Penalized caliper	79.0	77.3	77.1	0.025
Age less than 65	Yes*	n/a	8.0	6.7	5.1	0.065
Age 65-80	Yes*	n/a	40.7	51.7	56.6	-0.098
Age 80 or over	Yes*	n/a	51.3	41.5	38.3	0.066
Medicare entitlement: OASI	Yes	n/a	79.0	81.6	82.1	-0.013
Medicare entitlement: disability	Yes	n/a	19.1	17.6	17.1	0.013
Medicare entitlement: ESRD	Yes	n/a	1.0	0.6	0.5	0.014
Medicare entitlement: disability/ESRD	Yes	n/a	0.9	0.2	0.3	-0.016
Male	Yes*	Exact matching*	50.5	49.5	52.1	-0.052
Female	Yes*	Exact matching*	49.5	50.5	47.9	0.052
Northeast region	Yes	n/a	20.6	18.6	18.8	-0.007
Midwest region	Yes	n/a	28.3	19.6	19.2	0.009
South region	Yes	n/a	39.0	40.2	39.6	0.011
West region	Yes	n/a	12.0	21.6	22.3	-0.016
Days in COVID-19 period	Yes*	Strict caliper	94.6	77.1	82.1	-0.031
HCC score at enrollment	Yes*	n/a	4.7	5.6	5.4	0.062
HCC score one year before enrollment	Yes	n/a	2.6	3.1	3.2	-0.057
HCC: Ischemic or unspecified stroke	Yes	n/a	10.6	9.3	9.2	0.004
HCC: Dialysis status	Yes	n/a	7.0	5.5	5.6	-0.004
HCC: Kidney disease	Yes	n/a	50.7	48.9	50.9	-0.040
HCC: Diabetes with acute/chronic complications	Yes	n/a	36.0	33.7	36.0	-0.048
HCC: Dementia with or without complication	Yes	n/a	23.8	15.3	12.7	0.070
HCC: Coma	Yes	n/a	3.8	6.4	4.5	0.076
HCC: Cardio-respiratory failure	Yes	n/a	34.3	36.8	36.2	0.012
HCC: Acute myocardial infarction	Yes	n/a	13.3	11.6	10.9	0.021
Primary diagnosis breast cancer	Condition	n/a	5.0	8.8	8.0	0.025
Primary diagnosis colorectal cancer	Condition	n/a	4.6	7.9	7.6	0.013
Primary diagnosis lung cancer	Condition	n/a	10.6	24.3	21.2	0.070
Primary diagnosis other cancer	Condition	n/a	32.3	62.7	60.5	0.045
Primary diagnosis prostate cancer	Condition	n/a	6.9	9.4	10.2	-0.030
Days from most recent IP discharge and enrollment	Yes	Penalized caliper	90.3	69.5	66.3	0.040
Logit of propensity score	Yes*	n/a	-8.0	-4.7	-4.9	0.213
Non-Hispanic White	Yes	Penalized caliper	81.9	86.4	87.7	-0.037
Black or African American	Yes	n/a	10.2	8.1	8.0	0.006
Other, unknown, missing race/ethnicity	Yes	n/a	7.9	5.5	4.4	0.049

Variable	Used in matching[a]	Enhancements[b]	Potential comparison group (N = 23,687,256)	MCCM participants (N = 5,153)	Matched comparison group (N = 15,269)	Standardized difference
Days between enrollment and death	Yes*	Strict caliper	184.5	198.8	196.5	0.009
Medicare Part A and B expenditures Q1	Yes	n/a	24,458	31,211	30,621	0.023
Medicare Part A and B expenditures Q2	Yes	n/a	13,498	20,493	20,343	0.006
Medicare Part A and B expenditures Q3	Yes	n/a	10,547	15,328	15,590	-0.012
Medicare Part A and B expenditures Q4	Yes	n/a	9,499	12,981	13,101	-0.006
Medicare Part A and B expenditures Q5-Q8 (total)	Balance	n/a	24,371	36,016	37,827	-0.039
Inpatient admissions Q1	Yes	n/a	0.8	1.1	1.0	0.049
0 inpatient admissions Q1	Yes	Penalized caliper	0.5	0.3	0.3	-0.009
1-2 inpatient admissions Q1	Yes	Penalized caliper	0.5	0.6	0.6	-0.025
3+ inpatient admissions Q1	Yes	Penalized caliper	0.1	0.1	0.1	0.057
Inpatient admissions Q2	Yes	n/a	0.4	0.5	0.5	0.006
Inpatient admissions Q3	Yes	n/a	0.3	0.4	0.4	-0.012
Inpatient admissions Q4	Yes	n/a	0.3	0.3	0.3	-0.008
Outpatient ED visits/observation stays Q1	Yes	n/a	0.5	0.7	0.7	0.002
Outpatient ED visits/observation stays Q2-4	Yes	n/a	0.9	1.0	1.1	-0.093
Advanced care planning visit in previous 2 years	Yes	n/a	11.5	21.9	16.8	0.123
Inpatient stay on enrollment date	Yes	n/a	19.2	0.4	0.5	-0.007
Admitted to hospital on enrollment date	Yes	n/a	2.5	0.3	0.2	0.018
Discharged from hospital on enrollment date	Yes	n/a	1.5	1.7	1.4	0.024
Length of most recent inpatient stay	Yes	n/a	6.7	6.7	6.1	0.100
Inpatient days Q1	Yes	n/a	6.8	7.0	6.3	0.093
Inpatient days Q2-4	Yes	n/a	6.7	8.1	7.9	0.020
Inpatient expenditures Q1	Yes	n/a	14,032	14,129	14,070	0.003
Inpatient expenditures Q2-4	Yes	n/a	14,467	18,139	17,978	0.005
Admitted to SNF on enrollment date	Yes	n/a	1.2	0.0	0.4	-0.248
Discharged from SNF on enrollment date	Yes	n/a	1.2	0.5	0.7	-0.027
Any DME claims Q1-4	Yes	n/a	59.3	72.6	71.5	0.025
DME hospital bed claims Q1-4	Yes	n/a	0.2	0.3	0.2	0.085
DME oxygen claims Q1-4	Yes	n/a	1.6	2.1	2.0	0.022
Any DME walker/cane claims Q1-4	Yes	n/a	0.1	0.1	0.1	0.034
DME wheelchair claims Q1-4	Yes	n/a	0.4	0.4	0.3	0.050
SNF stay on enrollment date	Yes	n/a	3.2	0.1	0.1	-0.014
SNF days Q1	Yes	n/a	5.0	3.7	3.4	0.033
SNF days Q2-4	Yes	n/a	6.5	4.9	4.7	0.009
Post-acute care Q1	Yes	n/a	10.5	11.6	9.9	0.110
Post-acute care Q2-4	Yes	n/a	17.5	15.1	13.5	0.059

Variable	Used in matching[a]	Enhancements[b]	Potential comparison group (N = 23,687,256)	MCCM participants (N = 5,153)	Matched comparison group (N = 15,269)	Standardized difference
ADLs at most recent assessment	Yes	n/a	4.5	4.7	4.5	0.147
OASIS care assessment D30	Yes	n/a	15.0	36.9	29.0	0.163
OASIS discharge assessment D30	Yes	n/a	26.4	26.5	25.2	0.030
Inpatient ICU days Q1	Yes	n/a	2.5	2.1	1.8	0.056
Inpatient ICU days Q2-4	Yes	n/a	2.2	2.5	2.3	0.021
Outpatient expenditures Q1	Yes	n/a	2,027	3,745	3,861	-0.021
Outpatient expenditures Q2-4	Yes	n/a	4,565	7,628	7,946	-0.026
Part B drug expenditures Q1	Yes	n/a	1,447	4,781	5,051	-0.026
Part B drug expenditures Q2-4	Yes	n/a	3,336	10,175	10,509	-0.015
Unique inpatient procedures Q1	Yes	n/a	1.7	1.4	1.4	0.001
Unique inpatient procedures Q2-4	Yes	n/a	1.7	2.0	2.0	-0.021
Home health days Q1	Yes	n/a	4.6	7.3	5.9	0.140
Home health days Q2-4	Yes	n/a	10.0	9.4	8.1	0.078
ED visits resulting in inpatient admission Q1	Yes	n/a	0.7	0.9	0.8	0.080
ED visits resulting in inpatient admission Q2-4	Yes	n/a	0.8	1.0	1.0	0.003
PCP visits Q1	Yes	n/a	3.4	4.2	4.0	0.052
PCP visits Q2-4	Yes	n/a	7.0	7.8	8.0	-0.021
Specialist visits Q1	Yes	n/a	2.8	4.9	4.8	0.028
Specialist visits Q2-4	Yes	n/a	7.0	10.6	11.0	-0.054
Number of EMS ambulance transports Q1	Yes	n/a	0.5	0.6	0.5	0.063
Number of EMS ambulance transports Q2	Yes	n/a	0.2	0.3	0.25	0.007
Number of EMS ambulance transports Q3	Yes	n/a	0.2	0.2	0.20	-0.001
Number of EMS ambulance transports Q4	Yes	n/a	0.2	0.2	0.16	0.010
Encounters for cancer Q1	Condition	n/a	2.5	7.1	6.8	0.036
Encounters for cancer Q2-4	Condition	n/a	4.7	12.4	12.8	-0.022
Encounters for CHF Q1	Condition	n/a	1.5	2.1	2.0	0.033
Encounters for CHF Q2-4	Condition	n/a	2.7	3.3	3.3	-0.001
Encounters for COPD Q1	Condition	n/a	1.3	2.0	1.8	0.035
Encounters for COPD Q2-4	Condition	n/a	2.6	3.5	3.5	-0.004
Encounters for HIV/AIDS Q1	Condition	n/a	0.0	0.0	0.0	0.014
Encounters for HIV/AIDS Q2-4	Condition	n/a	0.0	0.0	0.0	0.008
Drugs for advanced stage cancer Q1	Condition	n/a	13.2	35.9	35.3	0.014
Drugs for advanced stage cancer Q2-4	Condition	n/a	15.9	35.4	38.2	-0.058
Diagnoses of advanced stage cancer Q1	Condition	n/a	33.1	53.0	53.3	-0.005
Diagnoses of advanced stage cancer Q2-4	Condition	n/a	38.9	51.1	54.3	-0.065

Variable	Used in matching[a]	Enhancements[b]	Potential comparison group (N = 23,687,256)	MCCM participants (N = 5,153)	Matched comparison group (N = 15,269)	Standardized difference
Diagnostic tests/procedures for advanced stage cancer Q1	Condition	n/a	10.8	33.3	31.1	0.046
Diagnostic tests/procedures for advanced stage cancer Q2-4	Condition	n/a	12.2	33.7	34.9	-0.026
Hormonal therapies Q1	Condition	n/a	0.3	1.0	1.0	-0.003
Hormonal therapies Q2-4	Condition	n/a	0.2	0.5	0.6	-0.021
Hospitalization with cardiac procedure Q1	Condition	n/a	0.2	0.1	0.0	0.009
Hospitalization with cardiac procedure Q2-4	Condition	n/a	0.1	0.2	0.1	0.010
Participation in OCM at enrollment	Condition	n/a	2.2	9.9	10.2	-0.010
Participation in ACO at enrollment	Balance	n/a	39.1	43.9	43.5	0.008
Hospitalization with lung-related procedure Q1	Condition	n/a	4.5	5.5	4.4	0.051
Hospitalization with lung-related procedure Q2-4	Condition	n/a	4.1	6.2	6.0	0.010
Automatic implantable cardioverter defibrillator Q1-4	Condition	n/a	0.5	0.4	0.6	-0.017
Coronary artery bypass surgery Q1-4	Condition	n/a	0.4	0.1	0.3	-0.037
Percutaneous intervention Q1-4	Condition	n/a	1.6	1.0	1.3	-0.027
Used the Medicare hospice benefit Q1	Balance	n/a	0.5	1.4	0.3	0.093
Used the Medicare hospice benefit Q2-4	Balance	n/a	1.1	1.6	0.7	0.068

Sources: Mathematica's analysis of Medicare Enrollment Database, Master Beneficiary Summary File, and Medicare claims data, January 1, 2013, to December 31, 2021, and public use files described in the methods appendix.

Note: The fourth, fifth, and sixth columns present the intervention or comparison group mean for continuous variables or the percentage of beneficiaries for binary and categorical variables. The fourth column is based on 23,687,256 observations (copies) for 1,934,407 unique beneficiaries, with beneficiaries weighted equally.

[a] "Yes*" identifies variables used for matching all 6 qualifying condition groups. "Yes" identifies variables used for matching for 5 out of 6 qualifying condition groups (all except the HIV/AIDS group). "Condition" identifies variables used for matching at more than 1 but less than 5 qualifying condition groups. "Balance" identifies variables that were included in this table but not in the matching process.

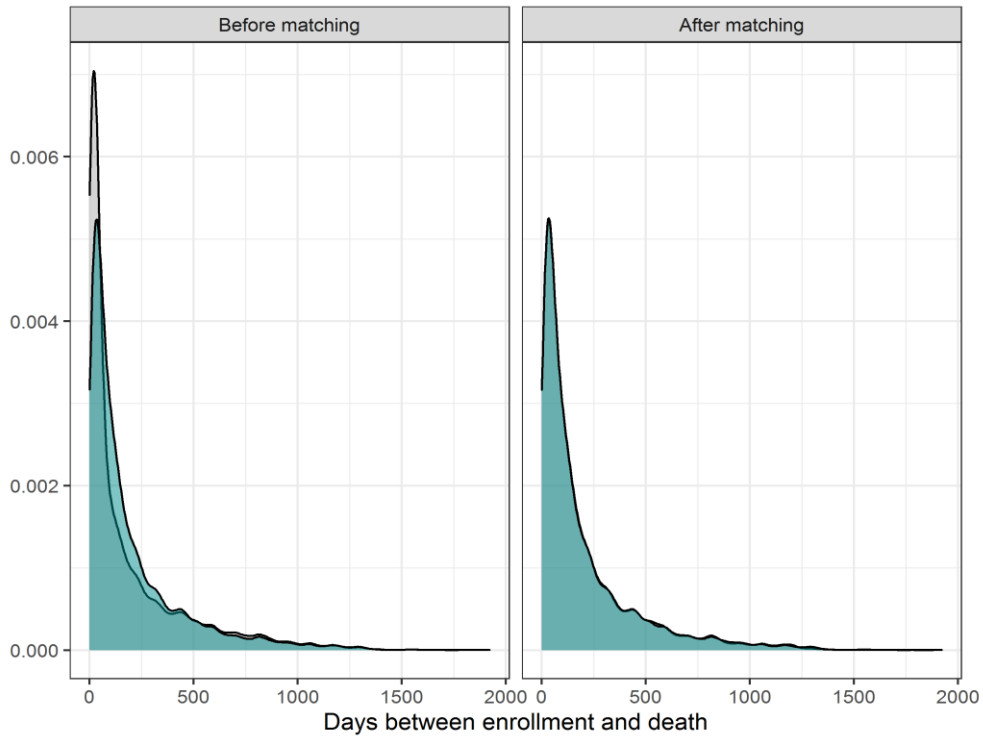
[b] Exact matching" identifies variables used as exact matching variables for all diagnosis groups, while "Exact matching*" identifies variables used as exact-matching variables in the HIV/AIDS qualifying condition group only. "Strict caliper" and "Penalized caliper" identify variables with strict and penalized calipers, respectively.

[c] In addition, we exactly matched on the qualifying condition groups described in Methods appendix Exhibit M.2.

ACO = accountable care organization; ADL = activities of daily living; CHF = congestive heart failure; COPD = chronic obstructive pulmonary disease; DME = durable medical equipment; ED = emergency department; ESRD = end-stage renal disease; HCC = hierarchical condition category; HIV/AIDS = human immunodeficiency virus/acquired immunodeficiency syndrome; ICU = intensive care unit; IP = inpatient; MCCM = Medicare Care Choices Model; n/a = not applicable; OASI = Old-Age and Survivors Insurance; OASIS = Outcome and Assessment Information Set.; OCM = Oncology Care Model; PCP = primary care provider; Q1 = 1st quarter before enrollment or pseudo enrollment; Q2 = 2nd quarter before enrollment or pseudo enrollment; Q3 = 3rd quarter before enrollment or pseudo enrollment; Q4 = 4th quarter before enrollment or pseudo enrollment; SNF = skilled nursing facility.

The table, and other diagnostic analyses not presented here, show that the intervention and comparison groups are closely balanced for many of the matching variables and we generally met or exceeded our goal that differences for high-priority measures would be no larger than 0.10 standard deviations while differences for lower priority measures would be no larger than 0.25 standard deviations. It was especially important that the distribution of survival times—time between enrollment and death—for MCCM and comparison beneficiaries align closely. As Exhibit S.4 and Exhibit S.5 show, we achieved that goal.

Exhibit S.4. Survival time kernel densities for deceased MCCM and comparison beneficiaries, before and after matching



Sources: Mathematica's analysis of Medicare Enrollment Database, Master Beneficiary Summary File, and Medicare claims data, January 1, 2013, to December 31, 2021.

Note: The figure shows survival time kernel densities for deceased MCCM enrollees in green and for comparison beneficiaries in gray. In the right panel (after inverse propensity weighting), the kernel densities for MCCM enrollees and comparison beneficiaries are almost identical.

MCCM = Medicare Care Choices Model.

Exhibit S.5. The distribution of survival times for deceased MCCM and matched comparison beneficiaries, before and after matching

Variable	MCCM enrollees (N = 5,153)	Matched comparison group (N = 15,269)
Percentage of beneficiaries with survival times		
Between 1 and 7 days	3.2	3.1
Between 8 and 30 days	16.3	16.2
Between 31 and 90 days	26.3	26.5
Between 91 and 180 days	20.1	20.3
Between 181 and 365 days	17.2	17.3
More than 365 days	16.9	16.6
Distribution of survival times		
Minimum	1 day	1 day
10th percentile	17 days	17 days
25th percentile	40 days	40 days
50th percentile	105 days	104 days
75th percentile	254 days	252 days
90th percentile	519 days	515 days
Maximum	1,899 days	1,923 days

Sources: Mathematica's analysis of Medicare Enrollment Database, Master Beneficiary Summary File, and Medicare claims data, January 1, 2013, to December 31, 2021.

MCCM = Medicare Care Choices Model.

Notable findings include the following:

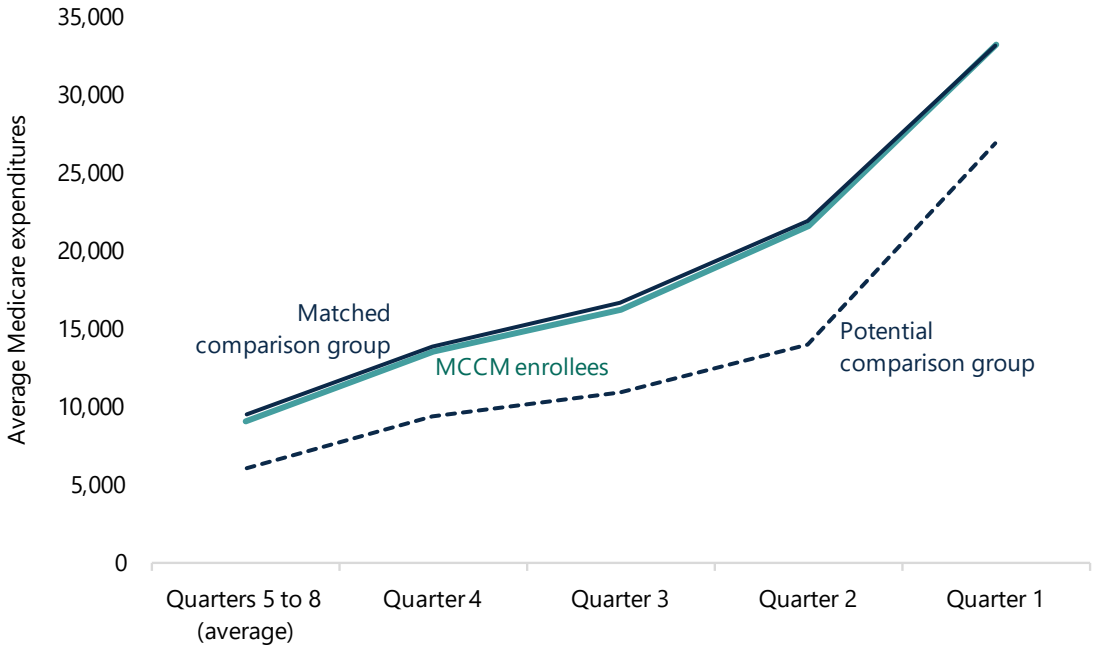
1. Because of the exact-matching constraints discussed earlier, the intervention and matched comparison groups had virtually the same percentage of beneficiaries with each of the four qualifying conditions (cancer, congestive heart failure, chronic obstructive pulmonary disease, and HIV/AIDS), the same percentage who are dually eligible for Medicare and Medicaid, and the same percentage enrolled on or after September 1, 2019 (those most likely affected by the COVID-19 pandemic).
2. Pseudo-enrollment dates for matched comparison beneficiaries were broadly the same as the enrollment dates for MCCM enrollees, with similar percentages of beneficiaries in each group enrolling per year.
3. At their pseudo-enrollment date, the matched comparison beneficiaries always resided in the market area of the hospice that enrolled the intervention beneficiary in MCCM. Because some MCCM hospices had market areas with more than one hospital referral region, 82 percent of the comparison beneficiaries lived in the same hospital referral region as the MCCM enrollee to whom they were matched.
4. The decedents approach was explicitly designed to produce a matched comparison group that closely resembled the intervention group in terms of the distribution of time from enrollment (or pseudo-enrollment) until death—that is, survival time. After matching beneficiaries on survival time (and other variables), MCCM enrollees and matched comparison beneficiaries had highly similar

survival time distributions (Exhibit S.4 and Exhibit S.5). On average, MCCM enrollees lived 198.8 days, compared to 196.5 days in the matched comparison group—a difference of only 0.009 standard deviations (Exhibit S.3). In addition, there was little difference in the survival times *within each matched set*—that is, each MCCM enrollee and their matched comparison beneficiaries had similar survival times.

5. MCCM enrollees and matched comparison beneficiaries were similar in terms of demographics, with good balance on sex (50.5 versus 47.9 percent female), age (both groups age 77 on average), and race/ethnicity (86.4 versus 87.7 percent non-Hispanic White and 8.1 versus 8.0 percent Black).[42]
6. The two groups had similar numbers and distributions of chronic conditions. The average hierarchical condition category score at enrollment for MCCM beneficiaries was 5.6, compared to 5.4 for matched comparison beneficiaries—a difference of 0.06 standard deviations. The two groups also were well matched in the prevalence of many of the specific chronic conditions we examined, such as history of diabetes (33.7 versus 36.0 percent), stroke (9.3 versus 9.2 percent), acute myocardial infarction (11.6 versus 10.9 percent), and dementia (15.3 versus 12.7 percent).
7. Compared with the pool of potential comparison beneficiaries, MCCM enrollees had notably high Medicare fee-for-service expenditures and service use in the year before enrollment, and they had very high expenditures and service use in the quarter before enrollment. Through matching, we were able to identify comparison beneficiaries that also fit this pattern (Exhibit S.6). For instance, in the quarter immediately before the pseudo-enrollment date, matched comparison beneficiaries had $30,621 in Medicare expenditures and 1.03 inpatient admissions on average, similar to MCCM enrollees, who had $31,211 in Medicare expenditures and 1.08 inpatient admissions on average. The two groups also appeared similar on other expenditures and utilization measures and had similar rates of condition-specific medical encounters and procedures.

[42] Although the average age of beneficiaries in the intervention and comparison groups is similar, the comparison group has fewer very old and very young beneficiaries and more beneficiaries in their late 70s and early 80s.

Exhibit S.6. Baseline trends in Medicare Part A and B expenditures, 1 to 8 quarters before enrollment, for MCCM and matched comparison beneficiaries, before and after matching



Sources: Mathematica's analysis of Medicare Enrollment Database, Master Beneficiary Summary File, and Medicare claims data, January 1, 2013, to December 31, 2021.

Note: The figure shows baseline trends in Medicare Part A and B expenditures for deceased MCCM enrollees in green and for comparison beneficiaries in blue. The blue solid line shows the comparison group after matching while the blue dashed line shows the unmatched comparison beneficiaries (potential comparison group) before matching.

MCCM = Medicare Care Choices Model.

3. Impact estimates for the full sample

In this section, we report regression-adjusted intervention and comparison group means and impact estimates for the full sample of MCCM enrollees and matched comparison beneficiaries, including confidence intervals and *p*-values. In Exhibit S.7, we report impact estimates, including confidence intervals and *p*-values corresponding to the following end-of-life care measures: receipt of an aggressive life-prolonging treatment, days at home, and health services use at the very end of life.

Exhibit S.7. Differences in end-of-life care measures between deceased MCCM enrollees and matched comparison beneficiaries

Outcome	MCCM mean	Comparison mean	Impact estimate	Percentage impact	*p*-value	90 percent CI
Percentage who received an aggressive life-prolonging procedure, surgical procedure, or diagnostic test in the last 30 days of life	61.2	76.5	-15.3	-20	< .001	[-16.6, -14.0]
Percentage with an aggressive life-prolonging procedure or surgical procedure	55.2	71.6	-16.4	-23	< .001	[-17.7, -15.1]
Percentage with an aggressive life-prolonging procedure	41.0	58.9	-17.9	-30	< .001	[-19.3, -16.6]
Percentage with a surgical procedure	42.5	57.4	-14.9	-26	< .001	[-16.3, -13.6]
Percentage with a diagnostic test	55.9	72.0	-16.1	-22	< .001	[-17.4, -14.8]
Number of days at home	183.5	178.0	+5.5	+3	< .001	[4.7, 6.2]
Percentage of days between enrollment and death the beneficiary was at home	88	81	+7	+8	< .001	[6.2, 7.2]
Number of days at home in the last 30 days of life	22.4	19.5	+2.9	+15	< .001	[2.6, 3.1]
Percentage with more than one emergency department visit or hospitalization or at least one intensive care unit admission in the last 30 days of life	21.0	36.8	-15.8	-43	< .001	[-16.9, -14.6]
Percentage with more than one outpatient emergency department visit	2.5	3.2	-0.8	-24	0.005	[-1.2, -0.3]
Percentage with more than one hospitalization	5.1	9.7	-4.5	-47	< .001	[-5.2, -3.8]
Percentage with an intensive care unit admission	17.5	32.1	-14.5	-45	< .001	[-15.6, -13.4]
Percentage who died in an acute care hospital	10.4	21.8	-11.4	-52	< .001	[-12.4, -10.5]

Sources: Mathematica's analysis of 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). We rounded numbers in this table after performing the calculations.

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

Exhibit S.8 shows the estimated impacts on Medicare expenditures from enrollment (or pseudo-enrollment) to death. In addition, we include estimated impacts on Medicare expenditures (with and without MCCM payments) *per day*.

Exhibit S.8. Differences in Medicare expenditures between deceased MCCM enrollees and matched comparison beneficiaries

Outcome	MCCM mean	Comparison mean	Impact estimate	Percentage impact	*p*-value	90 percent CI
Medicare expenditures (dollars per beneficiary)						
Medicare Part A and B expenditures plus MCCM payments	48,781	56,385	-7,604	-13	< .001	[-8,910, -6,298]
Medicare Part A and B expenditures	46,810	56,385	-9,576	-17	< .001	[-10,882, -8,269]
Inpatient expenditures	16,284	26,172	-9,887	-38	< .001	[-10,752, -9,023]
Hospice expenditures	8,375	4,128	+4,248	+103	< .001	[3,914, 4,581]
Other expenditures[a]	22,150	26,086	-3,936	-15%	< .001	[-4,769, -3,103]
Skilled nursing facility expenditures	2,627	3,435	-808	-24	< .001	[-1,044, -571]
Home health expenditures	2,436	2,324	+112	+5	0.10	[1, 222]
Part B drug expenditures	6,234	6,823	-588	-9	0.09	[-1,164, -12]
Durable medical equipment expenditures	862	711	+151	+21	0.009	[55, 247]
Other expenditures[b]	9,990	13,025	-3,035	-23	< .001	[-3,426, -2,644]
MCCM payments	1,971	0	+1,971	n/a	n/a	n/a
Medicare expenditures per day (dollars per beneficiary per day)						
Medicare Part A and B expenditures plus MCCM payments	379	520	-141	-27	< .001	[-155, -128]
Medicare Part A and B expenditures	362	520	-158	-30	< .001	[-172, -145]

Sources: Mathematica's analysis of 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). We rounded numbers in this table after performing the calculations.

[a] Medicare Part A and B expenditures minus inpatient expenditures and hospice expenditures. Footnote 32 in the Methods appendix describes our methods for calculating results on this row. The results for subcategories of "other expenditures" (on the following rows) were estimated with separate regression models.

[b] Includes all Medicare Part A and B expenditures not classified above, including outpatient emergency department visits, ambulatory care visits, and other clinically necessary services.

CI = confidence interval; MCCM = Medicare Care Choices Model; n/a = not applicable.

In Exhibit S.9, we report impact estimates on inpatient and outpatient health care use. We also split up the outcome measures "number of outpatient emergency department visits and observation stays" and "number of ambulatory visits with primary care providers and specialist physicians" into their respective components.

Exhibit S.9. Differences in health care service use between deceased MCCM enrollees and matched comparison beneficiaries

Outcome	MCCM mean	Comparison mean	Impact estimate	Percentage impact	*p*-value	90 percent CI
Inpatient care (number per beneficiary)						
Number of inpatient admissions	1.242	1.676	-0.434	-26	< .001	[-0.478, -0.390]
Number of days admitted to a hospital	8.170	12.135	-3.965	-33	< .001	[-4.348, -3.582]
Number of days in hospital intensive care unit	2.560	4.147	-1.586	-38	< .001	[-1.779, -1.393]
Number of days in hospital without intensive care unit	5.610	7.981	-2.371	-30	< .001	[-2.669, -2.074]
Number of 30-day all-cause readmissions	0.303	0.429	-0.126	-29	< .001	[-0.150, -0.102]
Emergency care (number per beneficiary)						
Number of outpatient emergency department visits and observation stays	0.886	1.005	-0.119	-12	< .001	[-0.165, -0.073]
Number of outpatient emergency department visits	0.873	0.994	-0.121	-12	< .001	[-0.167, -0.075]
Number of observation stays	0.175	0.185	-0.010	-6	0.32	[-0.028, 0.007]
Number of emergency medical service ambulance transports	0.954	1.077	-0.123	-11	< .001	[-0.166, -0.079]
Ambulatory visits (number per beneficiary)						
Number of ambulatory visits with primary care providers and specialist physicians	12.885	14.860	-1.975	-13	< .001	[-2.318, -1.632]
Number of ambulatory visits with primary care providers	6.861	7.651	-0.790	-10	< .001	[-1.038, -0.543]
Number of ambulatory visits with specialist physicians	6.024	7.216	-1.192	-17	< .001	[-1.393, -0.991]
Post-acute and home health care (number per beneficiary)						
Number of post-acute care days	16.9	18.8	-1.9	-10	< .001	[-2.7, -1.1]
Number of home health visits	10.9	10.5	+0.4	+4	0.27	[-0.2, 1.0]

Sources: Mathematica's analysis of 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). We rounded numbers in this table after performing the calculations.

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

In Exhibit S.10, we expand on the findings from Exhibit S.9 by reporting estimated impacts on types of health care services that indicate more intensive or unnecessary service use, such as hospital stays that involved a surgery and emergency department visits with a potentially preventable diagnosis.

Exhibit S.10. Differences between deceased MCCM enrollees and matched comparison beneficiaries in exploratory health care service use measures

Outcome	MCCM mean	Comparison mean	Impact estimate	Percentage impact	*p*-value	90 percent CI
Inpatient care (number per beneficiary)						
Inpatient admissions	1.242	1.676	-0.434	-26	< .001	[-0.478, -0.390]
With a surgery	0.267	0.447	-0.180	-40	< .001	[-0.199, -0.161]
Number of days admitted	*2.489*	*4.585*	*-2.096*	-46	*< .001*	*[-2.341, -1.851]*
With an elective procedure	0.048	0.099	-0.050	-51	< .001	[-0.058, -0.043]
Number of days admitted	*0.317*	*0.778*	*-0.462*	-59	*< .001*	*[-0.539, -0.384]*
With a potentially preventable diagnosis	0.437	0.598	-0.161	-27	< .001	[-0.184, -0.138]
Number of days admitted	*2.974*	*4.532*	*-1.559*	*-34*	*< .001*	*[-1.768, -1.349]*
In the last 30 days of life with an aggressive life-prolonging procedure, surgical procedure, or diagnostic test	0.170	0.337	-0.167	-50	< .001	[-0.180, -0.155]
Number of days admitted	*1.475*	*3.206*	*-1.732*	-54	*< .001*	*[-1.889, -1.575]*
Emergency care (number per beneficiary)[3]						
Outpatient emergency department visits and observation stays	0.886	1.005	-0.119	-12	< .001	[-0.165, -0.073]
With a potentially preventable diagnosis	0.212	0.250	-0.038	-15	0.001	[-0.058, -0.019]
In the last 30 days of life with an aggressive life-prolonging procedure, surgical procedure, or diagnostic test	0.162	0.199	-0.037	-19	< .001	[-0.049, -0.024]

Sources: Mathematica's analysis of 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). We rounded numbers in this table after performing the calculations.

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

In Exhibit S.11, we report the estimated impacts on enrollment in the Medicare hospice benefit and time spent time in hospice.

Exhibit S.11. Differences in hospice use between deceased MCCM enrollees and matched comparison beneficiaries

Outcome	MCCM mean	Comparison mean	Impact estimate	Percentage impact	*p*-value	90 percent CI
Percentage who used the Medicare hospice benefit	83.2	65.3	+17.9	+27	< .001	[16.7, 19.0]
Number of days in hospice	41.6	18.7	+22.8	+122	< .001	[20.8, 24.8]
Percentage admitted to hospice less than three days before death	19.6	18.7	+0.9	+5	0.16	[-0.2, 2.0]
Average percentage of days between enrollment and death the beneficiary was in hospice	27.6	15.8	+11.8	+75	< .001	[11.0, 12.6]

Sources: Mathematica's analysis of 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). We rounded numbers in this table after performing the calculations.

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

In Exhibit S.12, we report the estimated hazard ratio of entering hospice, that is, the estimated difference that MCCM enrollees enter hospice, relative to the comparison group, on any given day, which we estimated with a Cox proportional hazard model.

Exhibit S.12. Ratio of the hazard of electing the Medicare hospice benefit between deceased MCCM enrollees and matched comparison beneficiaries

Outcome	Estimated hazard ratio (impact estimate)	*p*-value	90 percent CI
Time from enrollment to entering hospice	1.41	< .001	[1.36, 1.46]

Sources: Mathematica's analysis of 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 Cox proportional hazard model.

A hazard ratio of 1 would indicate no model effect on this outcome, while ratios greater than 1 indicate the propensity to enter hospice was higher for MCCM beneficiaries than matched comparison beneficiaries.

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

Exhibit S.13 contains impact estimates that disentangle regression-adjusted differences in Medicare Part A and B expenditures into estimated impacts that can be attributed to beneficiaries enrolling in the Medicare hospice benefit more often and earlier than beneficiaries in comparison group. The remainder of the impact is, by definition, due to effects of MCCM that happen through other channels, which may include, for example, impacts of symptom management and care coordination that affect beneficiary outcomes before enrollees transitioned to hospice. We describe our method to disentangle these estimated impacts in the Methods appendix (Section 5).

Exhibit S.13. Differences in expenditures and inpatient hospital service use between deceased MCCM enrollees and matched comparison beneficiaries that operate through enrollment in hospice versus other channels

Channel	MCCM mean	Comparison mean	Impact estimate	Percentage of overall impact	*p*-value	90 percent CI
Medicare Part A and B expenditures ($)	46,422	55,892	-9,470		< .001	[-10,774, -8,166]
Through hospice			-4,806	51	< .001	[-5,167, -4,446]
Other channels			-4,663	49	< .001	[-5,908, -3,418]
Inpatient expenditures ($)	16,126	25,888	-9,762		< .001	[-10,626, -8,898]
Through hospice			-2,520	26	< .001	[-2,708, -2,332]
Other channels			-7,242	74	< .001	[-8,041, -6,444]
Number of inpatient admissions	1.224	1.656	-0.432		< .001	[-0.476, -0.389]
Through hospice			-0.159	37	< .001	[-0.171, -0.147]
Other channels			-0.273	63	< .001	[-0.314, -0.233]

Sources: Mathematica's analysis of 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 = 5,126) and matched comparison beneficiaries (N = 15,147 before weighting). The estimated overall impacts are slightly different from those reported in Exhibit S.8 because of different sample restrictions (this analysis excludes a small number of beneficiaries who died more than 30 days after disenrolling from the hospice benefit). We rounded numbers in this table after performing the calculations.

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

4. Subgroup-specific impact estimates

In this section we present the results of the Bayesian subgroup analyses, which examine the variation in MCCM's effects on the seven primary outcome measures across several subgroups of interest. Results include the regression-adjusted mean outcome values in the MCCM and matched comparison groups, impact estimates, credible intervals, and probabilities that impacts achieved relevant thresholds—for example, the probability that a particular subgroup achieved a strong impact in the hypothesized direction.

Exhibit S.14 compares impact estimates among beneficiaries with three of the four qualifying conditions: cancer, congestive heart failure, and chronic obstructive pulmonary disease. In general, impacts are similar for beneficiaries with these three qualifying conditions, with a few notable exceptions. First, there is a moderately high probability that MCCM reduced Medicare Part A and B expenditures plus MCCM payments more for beneficiaries diagnosed with cancer than for other beneficiaries. Second, there is a very high probability that MCCM increased hospice use more among beneficiaries diagnosed with congestive heart failure or chronic obstructive pulmonary disease than other beneficiaries.

Exhibit S.14. Differences in Medicare expenditures, health care service use, and end-of-life care between deceased MCCM enrollees and matched comparison beneficiaries, by primary diagnosis category

Outcome	Beneficiaries with cancer				Beneficiaries with congestive heart failure				Beneficiaries with chronic obstructive pulmonary disease			
	MCCM mean	Impact estimate [90% CI]	Percentage impact	Probability impacts are more favorable[a]	MCCM mean	Impact estimate [90% CI]	Percentage impact	Probability impacts are more favorable[a]	MCCM mean	Impact estimate [90% CI]	Percentage impact	Probability impacts are more favorable[a]
Percentage who received an aggressive life-prolonging procedure, surgical procedure, or diagnostic test in the last 30 days of life	60	-15.8 [-17.4, -14.2]	-21	95	66	-14.2 [-15.8, -12.7]	-18	2	62	-15.3 [-17.2, -13.6]	-20	32
Number of days at home	156	+5.9 [4.9, 6.9]	+4	<1	209	+7.6 [6.2, 9.0]	+4	99	215	+7.4 [6.0, 9.0]	+4	96
Medicare Part A and B expenditures plus MCCM payments	45,301	-7,935 [-9,729, -6,115]	-15	76	54,742	-7,607 [-9,526, -5,649]	-12	40	53,944	-7,277 [-9,196, -5,300]	-12	15
Medicare Part A and B expenditures	43,554	-9,727 [-11,412, -7,976]	-18	52	52,484	-9,750 [-11,566, -7,864]	-16	59	51,683	-9,455 [-11,329, -7,567]	-15	25
Number of inpatient admissions	1.004	-0.447 [-0.525, -0.369]	-31	45	1.618	-0.442 [-0.505, -0.376]	-21	61	1.553	-0.454 [-0.521, -0.388]	-23	76
Number of outpatient emergency department visits and observation stays	0.747	-0.106 [-0.169, -0.042]	-12	19	1.083	-0.116 [-0.180, -0.051]	-10	49	1.091	-0.129 [-0.198, -0.064]	-11	69
Percentage who used the Medicare hospice benefit	86	+16.4 [15.0, 17.7]	+23	<1	77	+21.6 [19.8, 23.3]	+39	>99	79	+20.4 [18.7, 22.1]	+35	>99

Sources: Mathematica's analysis of 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 (described in Section 7 of the Methods appendix). We did not present impacts for the 20 MCCM enrollees (less than 1 percent) with HIV/AIDS because the sample size was too small. There were 3,698 enrollees with cancer, 1,957 with congestive heart failure, and 1,719 with chronic obstructive pulmonary disease. There were

10,922 matched comparison beneficiaries with cancer, 5,810 with congestive heart failure, and 5,131 with chronic obstructive pulmonary disease. We rounded numbers in this table after performing the calculations.

[a] Probabilities are calculated comparing beneficiaries with the qualifying condition to all beneficiaries without the qualifying condition. For example, we compute the probability that MCCM has a more favorable impact—that is, an impact in the hypothesized direction—on each outcome for beneficiaries with a cancer diagnosis than for beneficiaries who do not have a cancer diagnosis, regardless of their other diagnoses.

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

Exhibit S.15 presents impact estimates by beneficiaries' survival time—the length of enrollment in MCCM. For expenditures outcomes, impacts peak among those who survived 91 to 365 days, then decrease among those who survived for more than 365 days. By contrast, impacts on service use and some end-of-life care measures, such as days at home, are largest for beneficiaries who were enrolled for more than 365 days, likely because for these beneficiaries the model had the greatest opportunity to prevent adverse outcomes or facilitate high-quality end-of-life care.

Exhibit S.15. Differences in Medicare expenditures, health care service use, and end-of-life care between deceased MCCM enrollees and matched comparison beneficiaries, by survival time

Survival time	MCCM mean	Comparison mean	Impact estimate	Percentage impact	90 percent CI
End-of-life care					
Percentage who received an aggressive life-prolonging procedure, surgical procedure, or diagnostic test in the last 30 days of life: all decedents	61.2	76.6	-15.4	-20	[-16.9, -14.0]
Survived 1 to 30 days	63.8	78.6	-14.8	-19	[-16.6, -12.9]
Survived 31 to 90 days	67.4	81.1	-13.7	-17	[-15.4, -11.9]
Survived 91 to 180 days	56.7	73.6	-16.9	-23	[-19.2, -14.9]
Survived 181 to 365 days	57.7	73.9	-16.2	-22	[-18.3, -14.3]
Survived more than 365 days	57.5	73.6	-16.2	-22	[-18.2, -14.2]
Number of days at home: all decedents	184	177	+6.7	+4	[5.7, 7.7]
Survived 1 to 30 days	13	11	+1.7	+15	[1.2, 2.3]
Survived 31 to 90 days	49	44	+4.5	+10	[3.6, 5.4]
Survived 91 to 180 days	118	110	+7.2	+7	[5.6, 8.8]
Survived 181 to 365 days	238	230	+8.3	+4	[5.6, 10.9]
Survived more than 365 days	612	599	+13.4	+2	[8.8, 18.0]
Medicare expenditures (dollars per beneficiary)					
Medicare Part A and B expenditures plus MCCM payments: all decedents	48,809	56,559	-7,769	-14	[-9,467, -6,053]
Survived 1 to 30 days	9,358	15,683	-6,341	-40	[-9,348, -3,041]
Survived 31 to 90 days	22,764	31,499	-8,736	-28	[-11,521, -6,083]
Survived 91 to 180 days	40,471	50,462	-10,033	-20	[-13,485, -6,848]
Survived 181 to 365 days	66,401	75,975	-9,629	-13	[-13,225, -6,480]
Survived more than 365 days	126,813	130,136	-3,319	-3	[-7,578, 1,062]
Medicare Part A and B expenditures: all decedents	46,832	56,534	-9,717	-17	[-11,380, -8,022]
Survived 1 to 30 days	8,078	16,465	-8,379	-51	[-11,116, -4,880]
Survived 31 to 90 days	21,799	31,694	-9,891	-31	[-12,249, -7,566]
Survived 91 to 180 days	39,313	50,276	-11,000	-22	[-14,184, -8,419]
Survived 181 to 365 days	64,409	75,381	-11,026	-15	[-14,719, -8,327]
Survived more than 365 days	121,489	129,616	-8,129	-6	[-10,955, -4,425]

Survival time	MCCM mean	Comparison mean	Impact estimate	Percentage impact	90 percent CI
Service use (number per beneficiary)					
Number of inpatient admissions: all decedents	1.230	1.679	-0.437	-26	[-0.490, -0.381]
Survived 1 to 30 days	0.267	0.690	-0.342	-50	[-0.438, -0.237]
Survived 31 to 90 days	0.621	1.063	-0.382	-36	[-0.464, -0.299]
Survived 91 to 180 days	1.071	1.549	-0.480	-31	[-0.575, -0.392]
Survived 181 to 365 days	1.664	2.132	-0.514	-24	[-0.610, -0.423]
Survived more than 365 days	3.030	3.468	-0.504	-15	[-0.596, -0.412]
Number of outpatient emergency department visits and observation stays: all decedents	0.882	1.002	-0.118	-12	[-0.176, -0.063]
Survived 1 to 30 days	0.122	0.214	-0.083	-39	[-0.162, 0.016]
Survived 31 to 90 days	0.334	0.438	-0.097	-22	[-0.170, -0.015]
Survived 91 to 180 days	0.709	0.840	-0.125	-15	[-0.206, -0.054]
Survived 181 to 365 days	1.127	1.266	-0.139	-11	[-0.226, -0.063]
Survived more than 365 days	2.566	2.714	-0.160	-6	[-0.262, -0.080]
Hospice use					
Percentage who used the Medicare hospice benefit: all decedents	83.1	64.9	+18.3	+28	[16.8, 19.6]
Survived 1 to 30 days	77.2	55.8	+21.5	+39	[19.4, 23.6]
Survived 31 to 90 days	85.4	68.4	+17.0	+25	[15.4, 18.6]
Survived 91 to 180 days	85.6	68.6	+17.1	+25	[15.4, 18.8]
Survived 181 to 365 days	84.7	67.2	+17.4	+26	[15.6, 19.3]
Survived more than 365 days	81.7	62.9	+18.7	+30	[16.8, 20.7]

Sources: Mathematica's analysis of 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 (described in Section 7 of the Methods appendix). There were 1,003 enrollees who survived 1 to 30 days, 1,355 who survived 31 to 90 days, 1,038 who survived 91 to 180 days, 886 who survived 181 to 365 days, and 871 who survived more than 365 days. There were 2,957 matched comparison beneficiaries who survived 1 to 30 days, 4,049 who survived 31 to 90 days, 3,079 who survived 91 to 180 days, 2,627 who survived 181 to 365 days, and 2,557 who survived more than 365 days. We rounded numbers in this table after performing the calculations.

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

5. Sensitivity analyses using *E*-values

As described in Section 6 of the Methods appendix, we estimated *E*-values and relative risk ratios for each of the results with the seven primary outcomes. The results from these sensitivity analyses are in Exhibit S.16. Each row represents a different outcome variable. Column 2 shows the *E*-value that would cause the point estimate of the impact estimate to be zero, and Column 4 shows the *E*-value that would cause the 90 percent confidence interval around the point estimate of the impact estimate to include zero (or for the odds ratio or hazard ratio to include one). Column 3 shows the relative risk ratio required, when the unmeasured confounder is perfectly correlated with enrollment, that would cause the point estimate of the impact estimate to be zero effect, and Column 5 shows the relative risk ratio required, when the unmeasured confounder is perfectly correlated with enrollment, that would cause the 90 percent confidence interval around the point estimate of the impact estimate to include zero (or for the odds ratio or hazard ratio to include one).

Exhibit S.16. *E*-values and relative risk bounds for unmeasured confounders

	Confounding that, if removed, would change the impact estimate to zero		Confounding that, if removed, would change the 90 percent confidence interval to include zero	
Outcome	*E*-value	Confounder perfectly correlated with enrollment	*E*-value	Confounder perfectly correlated with enrollment
Received an aggressive life-prolonging procedure, surgical procedure, or diagnostic test in the last 30 days of life	2.29	1.47	2.19	1.42
Days at home[a]	1.17	1.02	1.16	1.02
Medicare Part A and B expenditures plus MCCM payments	1.47	1.11	1.40	1.09
Medicare Part A and B expenditures	1.55	1.14	1.49	1.12
Number of inpatient admissions	1.73	1.22	1.66	1.19
Number of outpatient emergency department visits and observation stays	1.30	1.06	1.21	1.03
Used the Medicare hospice benefit	2.79	1.70	2.66	1.64
Time to using the Medicare hospice benefit (hazard analysis)	1.85	1.41	1.78	1.36

Sources: Mathematica's analysis of 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: *E*-values and other bounds are calculated using impact estimates on regression-adjusted differences between MCCM enrollees and matched comparison beneficiaries.

MCCM = Medicare Care Choices Model.

The following bullets put the results from Exhibit S.16 into context:

- **Total Medicare Part A and B expenditures, including MCCM payments.** We calculated an *E*-value of 1.47, which means that the estimated impact of MCCM enrollment on expenditures (-$7,604) could be explained away by an unmeasured confounder that was associated with both enrollment and expenditures with a relative risk ratio of 1.47, but weaker confounding would not fully explain away the finding.[43] To put this in perspective, we found that the association between hierarchical condition category scores and total Medicare expenditures had a relative risk of 1.06, which means that a hypothetical unmeasured confounder would have to have a stronger association with Medicare expenditures (including MCCM payments) than a 5.6 point change in hierarchical condition category score. Further, this confounder would have to have an equally strong association with MCCM enrollment (even though we already matched on hierarchical condition category scores and other variables that are strong predictors of future expenditures). If the confounder were perfectly correlated with enrollment (completely imbalanced between intervention and comparison beneficiaries), the unmeasured confounder could be less strongly correlated with the outcome variable and explain away our impact estimates in comparison to the *E*-values scenario (in which the confounder is assumed to be partially, but not completely, correlated with enrollment). If perfectly correlated with enrollment, the observed association between MCCM enrollment and decreased expenditures could be explained by an unmeasured confounder that was associated with expenditures by a risk ratio of 1.11. To put this in perspective, the unmeasured confounder would require a stronger association with Medicare Part A and B expenditures than a 0.9 percentage point change in hierarchical condition category scores.
- **Medicare Part A and B expenditures, not including MCCM payments.** We calculated an *E*-value of 1.55. As a benchmark for this outcome, we estimated a relative risk ratio of 1.06 for the association with hierarchical condition category scores.
- **Inpatient admissions.** We calculated an *E*-value of 1.73. Other observed covariates less strongly predict inpatient admissions than this. For example, the relative risk ratios between inpatient admissions during the study period and inpatient hospitalizations in the last quarter of the baseline period was only 1.16.
- **Emergency department visits and observation stays.** We calculated an *E*-value of 1.30. The low *E*-value for emergency department visits and observation stays compared with the relative risk for lagged emergency department visits and observation stays indicates that a lower level of unobserved confounding could explain this estimated impact than for other outcomes such as expenditures or inpatient admissions. The main reason for this is that the model's estimated effect on emergency department visits and observation stays is relatively small compared with the model's effect on the other expenditure and service use outcomes.
- **Using the Medicare hospice benefit.** We calculated an *E*-value of 2.79. In comparison, this confounder would have to be fairly imbalanced and more strongly predict hospice use than other strong predictors in the literature. For example, Obermeyer et al. (2015) found that a

[43] For mean differences, we obtain an approximate *E*-value by using methods developed in Lipsey and Wilson (2001), which use the approximation: RR ≈ e[0.91 * d], where *d* represents the effect size (impact estimate of the intervention divided by standard deviation of the outcome variable).

physician's practice style was the strongest predictor in claims data for whether a terminally ill cancer beneficiary would use hospice. The *E*-value in our analysis is larger than the relative risk ratio for using hospice that is associated with switching from a doctor in the bottom decile of referring beneficiaries to hospice to a doctor in the top decile (Obermeyer et al. 2015).

- **Time to using the Medicare hospice benefit.** For the Cox proportional hazard model in Exhibit S.12, we calculated an *E*-value of 1.85. The unmeasured confounder would require a stronger relationship with this outcome variable and with enrollment than was observed in any of the expenditures and utilization outcomes in the table.
- **Received an aggressive life-prolonging procedure, surgical procedure, or diagnostic test in the last 30 days of life.** We calculated an *E*-value of 2.29. The unmeasured confounder would require a stronger relationship with this outcome variable and with enrollment than was observed in any of the expenditure and utilization outcomes in the table.
- **Days at home.** We calculated an *E*-value of 1.17. By comparison, we found a relative risk ratio of 1.02 for days at home and inpatient hospitalizations in the last quarter of the last quarter of the baseline period.

6. Robustness checks

This section of the appendix presents results from several robustness checks we conducted to assess the sensitivity of the impact analysis results to alternative methodologies. Exhibit S.17 presents the results of our robustness checks for the full sample. The results are organized by outcome measure and include the results from our main impact analyses for comparison (labeled "main analysis"). In the following paragraphs, we describe each check; some checks were relevant to some, but not all, of the outcomes.

- **Unadjusted regression models.** We estimated regression models without control variables to assess the influence of regression adjustment. These models relied entirely on matching to adjust for any observable differences between the intervention and comparison groups. We found little difference between the adjusted and unadjusted impact estimates, which is unsurprising because our analysis sample was well matched on most observable characteristics, especially those we anticipated were most strongly related to outcomes when we designed the matching approach.
- **Adjusting for COVID-19 diagnosis in the follow-up period.** We assessed the rates of COVID-19 diagnoses in the enrolled and matched comparison groups. COVID-19 diagnoses can lead to expensive emergency department visits or hospitalizations, so any imbalance in rates of COVID-19 infections, even if not a direct effect of the model, could bias estimated impacts. Even after matching and controlling for a number of observable differences between the two groups at baseline, we found that MCCM enrollees alive after the COVID-19 pandemic began had somewhat lower rates of COVID-19 than those in the comparison group: Among enrollees who were alive during the pandemic, 6 percent were diagnosed with COVID-19 versus 10 percent of comparison beneficiaries during that time period. Adjusting for COVID-19 diagnoses caused our impact estimates to attenuate slightly, but did not meaningfully change the results.
- **Estimate impacts on net expenditures using a separate regression model**. This check used a single regression model to estimate impacts of MCCM on Medicare Part A and B expenditures plus MCCM payments. This differs from the main approach described in Footnote 31 in the Methods appendix. Results were similar with both approaches (-$7,610 compared to -$7,604).
- **Winsorizing continuous outcome measures.** We winsorized the following continuous outcome measures at the 98th percentile: (1) total Medicare expenditures, including MCCM payments; (2) total Medicare expenditures excluding MCCM payments; (3) emergency department or observation stay visits; (4) inpatient stays; and (5) days at home. Winsorizing is a method that replaces values above a certain threshold (here, the 98th percentile of the pooled treatment and comparison populations) with the value of the outcome variable at that threshold. This method reduces the influence of extreme outliers on the impact estimates, especially when the outcome variable is highly skewed, as can be the case with expenditures outcomes. The estimated impacts were similar when winsorizing outcomes, alleviating concerns that our main findings might have been driven by outliers.
- **Matched set fixed effects.** We added matched set fixed effects to the regression models for our continuous outcome measures: (1) total Medicare expenditures, including MCCM payments; (2) total Medicare expenditures excluding MCCM payments; (3) emergency department or observation stay visits; and (4) inpatient stays. A matched set comprises a single MCCM enrollee

matched to one to three comparison beneficiaries. Matched set fixed effects account for any unobserved variation that is common within each matched set. Including the fixed effects should further control for unobserved confounders and, by explaining variation in outcomes, add precision to the impact estimates.[44] When we included matched set fixed effects, we did not find any meaningful differences in our impact estimates. Confidence intervals were somewhat narrower, and *p*-values were smaller.

- **Generalized linear models (logarithm link function).** We used generalized linear models with a logarithm link function for the following outcomes: (1) total Medicare expenditures, including MCCM payments, and (2) total Medicare expenditures excluding MCCM payments. Using generalized linear models with a log link can reduce the influence of outliers or skewness in the data, which is often the case with expenditures (Manning and Mullahy 2001). When we used this approach, we found that the estimated impacts on expenditures (with and without MCCM payments) were somewhat smaller in terms of percentage impact, but they had the same sign and were statistically significant.
- **Count data regression models.** We estimated negative binomial regression models for the following count outcomes: (1) emergency department or observation stay visits, (2) inpatient stays, and (3) days at home. This allowed us to check the sensitivity of our estimated impacts to the functional form used in the main regression models (ordinary least squares). Negative binomial regression models can better fit the data when the outcome is non-negative and skewed, as we see with count data. We report all results from negative binomial regressions as marginal effects to make them more comparable to the results generated by linear models. When we used count data models, we did not find any meaningful differences in the estimated impacts.
- **Two-part regression models.** We estimated two-part models for the following two count outcomes: (1) emergency department or observation stay visits and (2) inpatient stays. The two-part model approach separately estimates the probability a beneficiary has greater than zero visits or stays using a logistic regression model, and then, conditional on there being more than zero visits, models the number of visits using a negative binomial count data model. The two-part model can account for cases in which there are many zero values for the outcome variable better than ordinary least squares and count data models, because the latter two approaches do not separately model the first stage (that is, model the extensive margin). All results are reported as marginal effects to make them more comparable to the main models. When we used two-part models, we did not find any meaningful differences in our impact estimates (compared with the main approach).
- **Binary outcomes.** We created binary outcomes that identified whether a beneficiary had any of the following events in the follow-up period: (1) inpatient admissions and (2) emergency department visits or observation stays. We used binary outcomes to assess the impact of MCCM at the extensive margin (that is, whether the model influenced whether an enrollee would have any service use) to supplement the main approach. When we examined the outcomes as binary indicators, we found large reductions in the percentage of beneficiaries with an inpatient stay and the percentage with an emergency department visit or observation stay. Impacts on the

[44] The fixed effects address unobserved confounding if potential unobserved confounders are shared (that is, correlated) among beneficiaries in the same matched sets.

extensive margin (whether a beneficiary had any visits) help explain impacts on the main outcome measure (the average number of visits).

- **Partial interaction with survival time.** We modified our main regression analysis to allow for the effect of MCCM enrollment and several other key covariates to vary by survival time category (1 to 30 days; 31 to 90 days; 91 to 180 days; 181 to 365 days; and 365+ days). We interacted the five survival time categories with the following covariates: age, gender, race, rural, dual eligibility status, MCCM qualifying diagnosis, baseline hierarchical condition category score, baseline Medicare Part A and B expenditures, baseline inpatient admissions, and baseline emergency department visits and observation stays. We then aggregated the impact estimates for each beneficiary to estimate an overall impact estimates. Impacts estimates from these models were sometimes larger than we obtained from the main analysis. For example, this model estimated larger impacts on Medicare expenditures ($8,456 per beneficiary) compared with the main analysis ($7,604).

Exhibit S.17. Impact analysis robustness checks

Robustness Check	MCCM mean	Comparison mean	Impact estimate	Percentage impact	*p*-value	90 percent CI
Percentage who received an aggressive life-prolonging procedure, surgical procedure, or diagnostic test in the last 30 days of life						
Main analysis	61.2	76.5	-15.3	-20	< .001	[-16.6, -14.0]
Unadjusted regression models	61.2	77.5	-16.3	-21	< .001	[-17.5, -15.0]
Adjusting for COVID-19 diagnosis in the follow-up period	61.2	76.3	-15.1	-20	< .001	[-16.4, -13.9]
Survival time category interacted with treatment and other key covariates	61.2	76.6	-15.4	-20	< .001	[-16.7, -14.2]
Number of days at home						
Main analysis	183.5	178.0	+5.5	+3	< .001	[4.7, 6.2]
Unadjusted regression models	183.5	175.5	+8.0	+5	0.03	[1.8, 14.1]
Adjusting for COVID-19 diagnosis in the follow-up period	183.5	178.3	+5.2	+3	< .001	[4.5, 6.0]
Winsorize at 98th percentile	179.4	173.8	+5.6	+3	< .001	[4.9, 6.3]
Matched set fixed effects	183.5	178.2	+5.3	+3	< .001	[4.6, 6.1]
Count data regression models	176.8	162.8	+14.0	+9	< .001	[12.9, 15.0]
Survival time category interacted with treatment and other key covariates	183.5	177.5	+6.0	+3	< .001	[5.3, 6.7]
Medicare Part A and B expenditures plus MCCM payments						
Main analysis	48,781	56,385	-7,604	-13	< .001	[-8,910, -6,298]
Unadjusted regression models[a]	48,781	56,808	-8,027	-14	< .001	[-9,763, -6,291]
Adjusting for COVID-19 diagnosis in the follow-up period[a]	48,781	56,054	-7,273	-13	< .001	[-8,574, -5,972]
Estimate impacts on net expenditures using a separate regression model[a]	48,781	56,391	-7,610	-13	< .001	[-8,920, -6,301]

Robustness Check	MCCM mean	Comparison mean	Impact estimate	Percentage impact	*p*-value	90 percent CI
Winsorize at 98th percentile[a]	46,772	54,291	-7,519	-14	< .001	[-8,543, -6,495]
Matched set fixed effects[a]	48,781	56,318	-7,537	-13	< .001	[-8,881, -6,193]
Generalized linear models (logarithm link function)[a]	51,521	54,849	-3,328	-6	0.02	[-5,683, -973]
Survival time category interacted with treatment and other key covariates[a]	48,781	57,237	-8,456	-15	< .001	[-9,660, -7,252]
Medicare Part A and B expenditures						
Main analysis	46,810	56,385	-9,576	-17	< .001	[-10,882, -8,269]
Unadjusted regression models	46,810	56,808	-9,998	-18	< .001	[-11,707, -8,290]
Adjusting for COVID-19 diagnosis in the follow-up period	46,810	56,045	-9,236	-16	< .001	[-10,533, -7,938]
Winsorize at 98th percentile	44,896	54,245	-9,348	-17	< .001	[-10,374, -8,323]
Matched set fixed effects	46,810	56,301	-9,491	-17	< .001	[-10,828, -8,154]
Generalized linear models (logarithm link function)	49,528	54,872	-5,344	-10	< .001	[-7,716, -2,973]
Survival time category interacted with treatment and other key covariates	46,810	57,237	-10,427	-18	< .001	[-11,635, -9,219]
Number of inpatient admissions						
Main analysis	1.242	1.676	-0.434	-26	< .001	[-0.478, -0.390]
Unadjusted regression models	1.242	1.683	-0.441	-26	< .001	[-0.495, -0.388]
Adjusting for COVID-19 diagnosis in the follow-up period	1.242	1.663	-0.421	-25	< .001	[-0.465, -0.377]
Winsorize at 98th percentile	1.163	1.600	-0.437	-27	< .001	[-0.473, -0.400]
Matched set fixed effects	1.242	1.673	-0.431	-26	< .001	[-0.477, -0.384]
Count data regression models	1.248	1.841	-0.593	-32	< .001	[-0.651, -0.535]
Two-part regression models	1.241	1.679	-0.438	-26	< .001	[-0.481, -0.396]
Binary outcome (percentage of beneficiaries)	55.9	74.9	-19.1	-25	< .001	[-20.3, -17.8]
Survival time category interacted with treatment and other key covariates	1.242	1.710	-0.468	-27	< .001	[-0.509, -0.426]
Number of outpatient emergency department visits and observation stays						
Main analysis	0.886	1.005	-0.119	-12	< .001	[-0.165, -0.073]
Unadjusted regression models	0.886	1.026	-0.141	-14	< .001	[-0.193, -0.088]
Adjusting for COVID-19 diagnosis in the follow-up period	0.886	0.999	-0.114	-11	< .001	[-0.160, -0.067]
Winsorize at 98th percentile	0.786	0.913	-0.127	-14	< .001	[-0.158, -0.095]
Matched set fixed effects	0.886	0.996	-0.110	-11	< .001	[-0.157, -0.063]
Count data regression models	0.996	1.212	-0.216	-18	< .001	[-0.272, -0.161]

Robustness Check	MCCM mean	Comparison mean	Impact estimate	Percentage impact	*p*-value	90 percent CI
Two-part regression models	0.891	1.023	-0.133	-13	< .001	[-0.175, -0.090]
Binary outcome (percentage of beneficiaries)	39.2	44.8	-5.6	-12	< .001	[-6.8, -4.3]
Survival time category interacted with treatment and other key covariates	0.886	1.051	-0.165	-16	< .001	[-0.207, -0.123]
Percentage who used the Medicare hospice benefit						
Main analysis	83.2	65.3	+17.9	+27	< .001	[16.7, 19.0]
Unadjusted regression models	83.2	64.4	+18.7	+29	< .001	[17.6, 19.8]
Adjusting for COVID-19 diagnosis in the follow-up period	83.2	65.6	+17.6	+27	< .001	[16.4, 18.7]
Survival time category interacted with treatment and other key covariates	83.2	65.3	+17.9	+27	< .001	[16.8, 19.0]

Sources: Mathematica's analysis of 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: Each row represents a different regression model. We base impact estimates on regression-adjusted differences between MCCM enrollees (N = 5,153) and matched comparison beneficiaries (N = 15,269 before weighting). We rounded numbers in this table after performing the calculations.

[a] Unlike the main analysis approach, these robustness checks use a single regression model to estimate impacts of MCCM on Medicare Part A and B expenditures plus MCCM payments.

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

In Exhibit S.18 and Exhibit S.19, we present frequentist subgroup analysis results as a robustness check for the main subgroup analysis approach (Bayesian analysis) presented above (Exhibit S.14 and Exhibit S.15). The frequentist subgroup impacts generally align with the Bayesian findings, but the frequentist impacts are more variable—especially for smaller subgroups—which is expected without variance shrinkage (towards the mean impact). Estimates from both the frequentist and Bayesian regression models indicate MCCM had similar impacts for beneficiaries with different qualifying conditions (Exhibit S.14 and Exhibit S.18, respectively). That is, the results from frequentist analyses were qualitatively similar to the Bayesian analysis in Section 4 of this appendix.

Exhibit S.18. Differences in Medicare expenditures, health care service use, and end-of-life care between deceased MCCM enrollees and matched comparison beneficiaries, by primary diagnosis category: Robustness check with frequentist regression models

Qualifying diagnosis	MCCM mean	Comparison mean	Impact estimate	Percentage impact	*p*-value	90 percent CI
End-of-life care						
Percentage who received an aggressive life-prolonging procedure, surgical procedure, or diagnostic test in the last 30 days of life: all decedents	61.2	76.5	-15.3	-20	< .001	[-16.6, -14.0]
Beneficiaries with cancer	59.6	75.0	-15.5	-21	< .001	[-17.0, -13.9]
Beneficiaries with CHF	67.8	80.9	-13.0	-16	< .001	[-15.0, -11.1]
Beneficiaries with COPD	60.6	78.0	-17.4	-22	< .001	[-19.6, -15.2]
Number of days at home: all decedents	183.5	178.0	+5.5	+3	< .001	[4.7, 6.2]
Beneficiaries with cancer	155.4	151.0	+4.4	+3	< .001	[3.7, 5.2]
Beneficiaries with CHF	209.9	202.8	+7.1	+4	< .001	[5.7, 8.5]
Beneficiaries with COPD	215.3	209.0	+6.3	+3	< .001	[4.8, 7.8]
Medicare expenditures (dollars per beneficiary)						
Medicare Part A and B expenditures plus MCCM payments: all decedents	48,781	56,385	-7,604	-13	< .001	[-8,910, -6,298]
Beneficiaries with cancer	45,113	53,316	-8,204	-15	< .001	[-9,621, -6,787]
Beneficiaries with CHF	55,186	62,567	-7,381	-12	< .001	[-9,692, -5,069]
Beneficiaries with COPD	54,199	60,305	-6,107	-10	< .001	[-8,326, -3,887]
Medicare Part A and B expenditures: all decedents	46,810	56,385	-9,576	-17	< .001	[-10,882, -8,269]
Beneficiaries with cancer	43,410	53,316	-9,906	-19	< .001	[-11,324, -8,488]
Beneficiaries with CHF	52,864	62,567	-9,702	-16	< .001	[-12,028, -7,376]
Beneficiaries with COPD	51,959	60,305	-8,347	-14	< .001	[-10,582, -6,112]

Qualifying diagnosis	MCCM mean	Comparison mean	Impact estimate	Percentage impact	*p*-value	90 percent CI
Service use (number per beneficiary)						
Number of inpatient admissions: all decedents	1.242	1.676	-0.434	-26	< .001	[-0.478, -0.390]
Beneficiaries with cancer	1.016	1.439	-0.423	-29	< .001	[-0.468, -0.378]
Beneficiaries with CHF	1.667	2.098	-0.431	-21	< .001	[-0.514, -0.348]
Beneficiaries with COPD	1.536	2.019	-0.483	-24	< .001	[-0.571, -0.396]
Number of outpatient emergency department visits and observation stays: all decedents	0.886	1.005	-0.119	-12	< .001	[-0.165, -0.073]
Beneficiaries with cancer	0.769	0.838	-0.068	-8	0.03	[-0.120, -0.017]
Beneficiaries with CHF	1.130	1.194	-0.065	-5	0.21	[-0.149, 0.020]
Beneficiaries with COPD	1.061	1.242	-0.181	-15	0.001	[-0.275, -0.088]
Hospice use						
Percentage who entered the Medicare hospice benefit: all decedents	83.2	65.3	+17.9	+27	< .001	[16.7, 19.0]
Beneficiaries with cancer	86.4	70.9	+15.5	+22	< .001	[14.2, 16.8]
Beneficiaries with CHF	76.0	55.9	+20.1	+36	< .001	[18.1, 22.0]
Beneficiaries with COPD	79.3	59.5	+19.8	+33	< .001	[17.8, 21.8]

Sources: Mathematica's analysis of 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 frequentist regression model. There were 3,698 enrollees with cancer, 1,957 with congestive heart failure, and 1,719 with chronic obstructive pulmonary disease. There were 10,922 matched comparison beneficiaries with cancer, 5,810 with congestive heart failure, and 5,131 with chronic obstructive pulmonary disease. Some beneficiaries had more than one qualifying condition and are included in multiple rows of the table. We rounded numbers in this table after performing the calculations.

CHF = congestive heart failure; CI = confidence interval; COPD = chronic obstructive pulmonary disease; MCCM = Medicare Care Choices Model.

Exhibit S.19. Differences in Medicare expenditures, health care service use, and end-of-life care between deceased MCCM enrollees and matched comparison beneficiaries, by survival time: Robustness check with frequentist regression models

Survival time	MCCM mean	Comparison mean	Impact estimate	Percentage impact	90 percent CI
End-of-life care					
Percentage who received an aggressive life-prolonging procedure, surgical procedure, or diagnostic test in the last 30 days of life: all decedents	61.2	76.5	-15.3	-20	[-16.6, -14.0]
Survived 1 to 30 days	64.4	78.3	-13.9	-18	[-16.6, -11.1]
Survived 31 to 90 days	68.0	80.9	-12.9	-16	[-15.2, -10.6]
Survived 91 to 180 days	55.4	74.6	-19.2	-26	[-22.0, -16.4]
Survived 181 to 365 days	57.7	73.6	-15.9	-22	[-18.9, -12.8]
Survived more than 365 days	57.2	73.6	-16.4	-22	[-19.4, -13.3]
Number of days at home: all decedents	183.5	178.0	+5.5	+3	[4.7, 6.2]
Survived 1 to 30 days	13.4	11.3	+2.0	+18	[1.6, 2.5]
Survived 31 to 90 days	48.9	44.7	+4.2	+9	[3.6, 4.9]
Survived 91 to 180 days	117.6	110.7	+6.9	+6	[5.7, 8.1]
Survived 181 to 365 days	238.0	230.6	+7.4	+3	[5.4, 9.3]
Survived more than 365 days	611.8	601.1	+10.7	+2	[7.7, 13.7]
Medicare expenditures (dollars per beneficiary)					
Medicare Part A and B expenditures plus MCCM payments: all decedents	48,781	56,385	-7,604	-13	[-8,910, -6,298]
Survived 1 to 30 days	9,724	14,841	-5,117	-34	[-6,039, -4,195]
Survived 31 to 90 days	22,345	32,198	-9,852	-31	[-11,074, -8,631]
Survived 91 to 180 days	39,472	51,450	-11,978	-23	[-13,873, -10,083]
Survived 181 to 365 days	65,469	77,131	-11,661	-15	[-14,589, -8,734]
Survived more than 365 days	129,001	131,670	-2,670	-2	[-7,844, 2,505]
Medicare Part A and B expenditures: all decedents	46,810	56,385	-9,576	-17	[-10,882, -8,269]
Survived 1 to 30 days	9,283	14,841	-5,559	-37	[-6,485, -4,633]
Survived 31 to 90 days	21,578	32,198	-10,620	-33	[-11,846, -9,393]
Survived 91 to 180 days	38,096	51,450	-13,354	-26	[-15,255, -11,452]
Survived 181 to 365 days	62,933	77,131	-14,197	-18	[-17,138, -11,257]
Survived more than 365 days	123,260	131,670	-8,410	-6	[-13,606, -3,215]
Medicare Part A and B expenditures in the last 30 days of life: all decedents	12,254	18,808	-6,554	-35	[-6,975, -6,133]
Survived 1 to 30 days	9,283	14,593	-5,310	-36	[-6,042, -4,579]
Survived 31 to 90 days	13,179	21,375	-8,196	-38	[-9,005, -7,386]
Survived 91 to 180 days	12,055	19,539	-7,484	-38	[-8,381, -6,587]
Survived 181 to 365 days	12,623	18,419	-5,796	-31	[-6,790, -4,801]
Survived more than 365 days	14,098	19,319	-5,220	-27	[-6,321, -4,119]

Survival time	MCCM mean	Comparison mean	Impact estimate	Percentage impact	90 percent CI
Service use					
Number of inpatient admissions: all decedents	1,242	1.676	-0.434	-26	[-0.478, -0.390]
Survived 1 to 30 days	0.391	0.649	-0.258	-40	[-0.296, -0.220]
Survived 31 to 90 days	0.688	1.075	-0.387	-36	[-0.434, -0.340]
Survived 91 to 180 days	1.037	1.587	-0.550	-35	[-0.623, -0.477]
Survived 181 to 365 days	1.587	2.176	-0.589	-27	[-0.695, -0.482]
Survived more than 365 days	2.978	3.591	-0.613	-17	[-0.785, -0.441]
Number of outpatient emergency department visits and observation stays: all decedents	0.886	1.005	-0.119	-12	[-0.165, -0.073]
Survived 1 to 30 days	0.181	0.226	-0.045	-20	[-0.079, -0.011]
Survived 31 to 90 days	0.362	0.466	-0.105	-22	[-0.143, -0.066]
Survived 91 to 180 days	0.694	0.871	-0.178	-20	[-0.242, -0.113]
Survived 181 to 365 days	1.099	1.307	-0.207	-16	[-0.302, -0.113]
Survived more than 365 days	2.524	2.862	-0.338	-12	[-0.526, -0.151]
Hospice use					
Percentage who received the Medicare hospice benefit: all decedents	83.2	65.3	+17.9	+27	[16.7, 19.0]
Survived 1 to 30 days	76.6	56.0	+20.5	+37	[17.9, 23.2]
Survived 31 to 90 days	85.5	69.0	+16.5	+24	[14.5, 18.5]
Survived 91 to 180 days	86.2	68.5	+17.7	+26	[15.5, 19.9]
Survived 181 to 365 days	85.0	67.8	+17.2	+25	[14.8, 19.6]
Survived more than 365 days	81.6	63.6	+18.0	+28	[15.4, 20.7]

Sources: Mathematica's analysis of 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 frequentist regression model. There were 1,003 enrollees who survived 1 to 30 days, 1,355 who survived 31 to 90 days, 1,038 who survived 91 to 180 days, 886 who survived 181 to 365 days, and 871 who survived more than 365 days. There were 2,957 matched comparison beneficiaries who survived 1 to 30 days, 4,049 who survived 31 to 90 days, 3,079 who survived 91 to 180 days, 2,627 who survived 181 to 365 days, and 2,557 who survived more than 365 days. We rounded numbers in this table after performing the calculations.

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

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