Elevated End-of-Life Spending: A New Measure of Potentially Wasteful Healthcare Spending at End of Life

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Abstract

Medicare spending in the United States is concentrated among a small group of patients at end of life (EoL) and EoL spending varies considerably across geographic regions, which may represent evidence of wasteful medical spending. We calculate a new measure of *elevated* EoL spending by taking the difference in monthly Medicare spending between decedents and survivors with the same ex ante predicted mortality risk, where risk is predicted using machine learning models. We find large variation in elevated EoL spending across health referral regions (HRRs) in the United States. There is no evidence that HRR-level elevated EoL spending is correlated with health care quality measures, including those specific to EoL care, whereas total EoL spending (without controlling for enrollees' mortality risk) is positively correlated with some quality measures. We also find no evidence that elevated EoL spending is correlated with patient preferences for EoL care, but it is positively and significantly correlated with physician preferences for treatment intensity. Our findings suggest that elevated EoL spending captures a different type of resource use relative to conventional measures of EoL spending, and may be valuable for identifying potentially wasteful spending.

Key Words: End-of-life, Medicare, waste in healthcare, healthcare quality, patient preferences, physician preferences

Introduction

Medicare spending is highly concentrated at the end of life (EoL). One-quarter of annual Medicare spending in the United States is spent on patients in their last 12 months of life, while only five percent of Medicare patients die each year.[1,2] Further, research has documented substantial variation in EoL spending across geographic regions in the U.S.[3-5] These findings have been posed and debated as evidence for wasteful healthcare spending at the end of life,[5-7] with an underlying assumption that high spending among decedents largely represents physicians' presumably well intended but futile treatment to save patients who ultimately died. Previous studies have considered high total Medicare spending or Medicare acute care spending in the last six or 12 months of life as reflecting potentially wasteful healthcare utilization.[2,6,8]

However, the concentration of Medicare spending near the end of life may not necessarily reflect futile treatments, but instead could be explained by the fact that patients near the end of life are generally sicker, often with multiple chronic conditions that could warrant additional care than general patient population.[7] In other words, the high spending captured by conventional EoL measures may have justifiably occurred among patients with multiple chronic conditions even if they did not end up dying. Indeed, by comparing Medicare spending between decedents and survivors with the same level of mortality risk that was predicted by machine learning methods using prior medical history such as diagnoses and procedures, Einav et al. found that up to one-half of the concentration of Medicare spending on the decedents can be explained by the fact that we spend more generally on relatively sicker patients, whether they die or surive.[2] However, that still leaves the 50 percent of total EoL spending among decedents unaccounted for. This additional spending among decedents relative to survivors with the same level of predicted mortality risk, or elevated EoL spending among decedents, could better represent healthcare resources focused on keeping patients alive as they approached the (almost) inevitable death, therefore better reflecting potentially unnecessary or futile healthcare spending on patients that were ultimately going to die, compared to spending measures derived from decedents alone.

Higher elevated EoL spending could still be justified if it is associated with higher quality of care, such as lower mortality and higher utilization of palliative care at the end of life. That is, clinicians in some regions or organizations might use resources relatively intensively in an attempt to prevent patients from dying, and this treatment style may be associated with high-quality for all patients, including those who are very sick but survive. Elevated EoL spending may also be justified if it reflects patient preferences for how they would like to be treated.[9-11] On the other hand, elevated EoL spending may represent unnecessary utilization if it is not associated with quality care or patient preferences, but instead is purely driven by how physicians believe patients should be treated.[5] Evidence for this question is important to further understand the source of EoL spending and to improve the value of healthcare.

In this study, we examined whether elevated EoL spending can be a useful tool to identify potential wasteful spending. Specifically, we applied machine learning predictive modeling to calculate the elevated EoL Medicare spending in each hospital referral region (HRR) in the U.S. that remains after accounting for differences in predicted risk of mortality between decedents and survivors, thereby removing the portion of spending that could be justified by higher clinical risk among patients near the end of life. We first compared this measure of elevated EoL spending with another commonly used measure of EoL spending — total Medicare spending in the last six months of life. We then examined whether the geographic variation in both measures was associated with various measures of quality of care and both physician and patient preferences for care. This study helps differentiate the elevated EoL spending from other commonly used EoL spending measures and assess the usefulness of this new EoL measure in more accurately capturing potentially wasteful spending near patients' end of life.

Study Data and Methods

Data and Study Population

Our primary data source was Medicare claims data files of 2015 and 2016 for a 20% random sample of traditional Medicare fee-for-services (FFS) patients. Specifically, we used Master Beneficiary Summary file, carrier file, outpatient file, Medicare Provider Analysis and Review (MedPAR) file for inpatient and skilled nursing facility care, home health file, and hospice file.

We first included all patients who were continuously enrolled in both Medicare Parts A & B without Medicare Advantage enrollment in 2015 and were alive as of January 1, 2016. Among these patients, we identified those who died in 2016 using the date of death in the 2016 Master Beneficiary Summary file. We further required both survivors and decedents to have continuous enrollment in both Medicare fee-for-service Parts A & B for 12 months (for survivors) or until death (for decedents) in 2016. We excluded patients who lived outside the 50 states and DC. Following the standard machine learning procedure, we randomly split the sample into training (2/3 of all patients) and test (1/3 of all patients) sets. The training set was used to develop the prediction algorithms (described further below) and the test set was used to apply the resulting algorithms to generate predicted mortalities. All results in this study were reported using patients in the test set.

We also used several publicly available datasets for Medicare spending and quality of care, including the Dartmouth Atlas for EoL inpatient spending, Hospital Compare data for hospital quality measures, and Medicare Geographic Variation files for preventable utilization measures and patient characteristics at the hospital referral region level. The latter two datasets are made available by the Centers for Medicare and Medicaid Services (CMS).

End-of-life Spending Measures

Elevated End-of-Life Spending

Following the methods developed by Einav et al. and Zeltzer et al.,[2,12] we calculated an elevated EoL spending measure for 2016 for each decedent by comparing the monthly total Medicare spending of decedents to the monthly total Medicare spending of survivors with the same level of predicted mortality. Specifically, we first calculated the predicted probability of death in 2016 for all patients (both survivors and decedents) included in the study. The outcome variable of this prediction was the death status in 2016 and predictors included a comprehensive set of patient characteristics over the entire year of 2015, including Medicare spending, utilization, comorbidities, and demographics. We used an ensemble of three machine learning algorithms for prediction, including LASSO, random forests, and gradient-boosting trees. These algorithms have shown good performance for predicting death and other health outcomes.[2,13] Details of the prediction models are available in the supplemental material (Appendix Methods S1 and Appendix Table S1 and Appendix Figure S1).

We grouped decedents and survivors into bins of predicted mortality. We split the entire sample into 100 bins of equal size between 0 and 1 of the predicted mortality values. Therefore, each bin has a width of 0.01. We then calculated the geographically adjusted[14] monthly Medicare spending in 2016 for each person, including payments made by Medicare, patients, and other payers across all care settings. For decedents, monthly spending was calculated across the period when they were alive. For survivors, monthly spending was calculated across 12 months in 2016. To calculate an HRR-level elevated EoL spending measure, we first calculated the difference between the average monthly Medicare spending among decedents and the average monthly Medicare spending among survivors in each bin of the predicted mortality range within each HRR. We then took the average of this spending difference across different bins of each HRR, weighted by the number of patients (both survivors and decedents) in each bin. Details of this calculation are available in the supplemental material (Appendix Methods S2).

Comparator End-of-Life Spending Measures

We compared the elevated EoL spending measure with two other EoL spending measures that have been previously used in the literature to examine potentially wasteful spending. For each HRR, we first calculated average geographically adjusted[14] monthly spending in the last six months of life among Medicare beneficiaries who died, without adjusting for patients' health. Specifically, this measure includes all Medicare Parts A and B spending six months before death of each decedent. As a sensitivity analysis, we also compared the elevated EoL spending measure with the monthly inpatient spending per decedent in the last six months of life from the Dartmouth Atlas.[15] We note that our elevated EoL spending measure could be either higher or lower than the monthly EoL spending in the last six months of life for a given HRR, as the former was calculated based on the period when the decedents were alive in 2016, and could for instance reflect a higher level of (monthly) spending closer to EoL if the decedents died shortly after January 1, 2016.

Healthcare Quality Measures

We examined the association of EoL spending measures with three sets of healthcare quality measures derived from Medicare FFS data. The first set was preventable utilization measures, including hospital admission rates for older adults with COPD or asthma, heart failure, and urinary tract infection, obtained from the Medicare Geographic Variation Public Use File.[16] We used these three measures for patients who were 75 or older. The second set was risk-adjusted mortality measures within 30-day after hospital admission for five conditions, including AMI, COPD, heart failure, pneumonia, and stroke. We obtained these measures at the hospital level from CMS Hospital Compare[17] and aggregated them into HRR level by calculating the average across all hospitals in each HRR, weighted by the number of eligible patients for each measure.

Finally, we calculated three claims-based EoL utilization measures commonly used as proxies for EoL care quality using our 20% Medicare FFS patient sample, including the proportion of cancer patients receiving chemotherapy in the last 14 days of life, the proportion of decedents with an ICU admission in the last month of life, and the proportion of decedents who used hospice services in the last three days of life.[18-20]

Physician Beliefs and Patient Preferences Measures

We used survey data from Cutler et al.[5] that elicited beliefs and preferences for care from over 1,000 physicians (including primary care physicians and cardiologists) and approximately 3,000 Medicare FFS patients in HRRs across the country. Following the study, we computed the share of physicians in each HRR who could be categorized as "cowboys"; i.e., those who consistently recommended intensive care beyond current clinical guidelines, and the share of those deemed to be "comforters," meaning they consistently recommended palliative care for the severely ill. We also computed the share of two analogous categories of patients: those who would desire aggressive care (such as being put on life-sustaining respirator) at the end of life, and those who would desire comfort care at the end of life.

Statistical Analysis

We first compared the elevated EoL spending with monthly EoL spending in the last six months of life for each HRR. To examine the association between elevated EoL spending and monthly total EoL spending with each healthcare quality measure, we used linear regressions where each healthcare quality measure was the outcome and the logged EoL spending measure (either elevated or total) was the key independent variable. Each regression controlled for HRR-level patient demographics (mean age, mean age squared, % female, % black, % Hispanic, % other race, and % of Medicare patients enrolled in Medicaid) and clinical risk (CMS HCC score) and was weighted by the number of Medicare beneficiaries (survivors and decedents in the test sample) in each HRR. P-values were adjusted by using Bonferroni corrections to account for multiple comparisons. In addition, we examined the associations between physician and patient preferences measures as independent variables and logged elevated or total EoL spending the as dependent variable, using an HRR-level regression model with all four preferences measures (shares of cowboy physicians, comforter physicians, patients desiring aggressive care, and patients desiring comfort care in each HRR) included as independent variables. Following Cutler at al.,[5] for the analysis examining physician and patient preferences, we controlled for the percentage of surveyed physicians in each HRR who were in primary care specialties, and focused on the 74 largest HRRs where at least three physicians and three patients were surveyed. About one-half of Medicare enrollees live in these HRRs.

As a sensitivity analysis, we performed the above analyses using the Dartmouth Atlas measure of inpatient spending in the last six months of life rather than total Medicare spending in the last six months of life. We also examined the Dartmouth measure of Medicare spending in the last two years of life as an additional comparison measure. In addition, we recalculated the elevated EoL spending by taking the difference in median instead of mean monthly Medicare spending between decedents and survivors in each bin of the predicted mortality range within each HRR and repeated all the analyses.

Results

Variation in End-of-Spending across HRRs

The average elevated EoL spending varied considerably across the 306 HRRs, ranging from $12,264 in Panama City, FL to $997 in St. Cloud, MN, a difference of over tenfold, with a median value of $4,691. The elevated EoL spending was primarily driven by the difference in inpatient spending between decedents and survivors with the same predicted mortality risk in an HRR, which accounted for 71.34% of elevated EoL spending across all HRRs. Differences in inpatient spending accounted for a higher proportion (over 80%) of elevated EoL spending in HRRs with high elevated EoL spending. The unadjusted average monthly Medicare spending in the last six months of life had a smaller variation, ranging from $8,515 in Los Angeles, CA to $4,193 in Neenah, WI, with a median value of $6,114. The correlation between elevated EoL spending and monthly Medicare spending in the last six months of life was 0.37 ($P < 0.001$).

The differences between the two EoL spending measures are illustrated in Table 1. Among the 5 HRRs with the highest elevated EoL spending, elevated EoL spending ranges from 26.3 to 75.1 percent higher than total monthly Medicare spending in the last six months of life. Among the five HRRs with the lowest elevated EoL spending, the percentage differences ranged from -57.7 to -82.4. These results indicate that these two EoL spending measures potentially capture different utilization patterns among patients near the end of life. The differences between EoL elevated spending and the Dartmouth inpatient EoL spending across HRRs were even more prominent, as shown in Appendix Table S2.

We divided HRRs into four groups based on standardized elevated EoL spending (Y-axis) and monthly Medicare spending in the last six months of life (X-axis) (Figure 1), where each measured was transformed to have mean of zero and standard deviation of one. Some HRRs had high spending for both EoL measures. For example, Blue Island, IL had an elevated EoL spending of \$8,844 (99^{th} percentile, 2.7 standard deviations [SDs] from mean) and an unadjusted monthly spending in the last six months of life of \$8,034 (97^{th} percentile, 2.1 SDs from mean). Other HRRs in this quadrant included Victoria, TX, Slidell, LA, and Gulfport, MS. Similarly, some HRRs had low spending for both EoL measures. For example, Neenah, MI had an elevated EoL spending of \$1,260 (1^{st} percentile, -2.5 SDs from mean) and a monthly spending in the last six months of life of \$4,193 (1^{st} percentile, -2.1 SDs from mean). In contrast, we also found certain HRRs with high spending for one EoL measure but low for another. For example, Bronx, NY had an elevated EoL spending of \$3,416 (14^{th} percentile, -1.0 SD from mean) but an unadjusted monthly spending in the last six months of life of \$8,151 (98^{th} percentile, 2.2 SDs from mean). Appendix Figure S2 similarly shows that HRRs high in Dartmouth inpatient EoL spending could be low in elevated EoL spending, and vice versa.

Relationship between EoL Spending and Quality of Care

The associations between care quality measures and EoL spending varied by EoL spending measures (Table 2). We did not find a statistically significant association between elevated EoL spending in an HRR and 11 different quality measures in that HRR. In contrast, monthly Medicare spending in the last six months of life was significantly associated with six quality measures. Specifically, higher monthly Medicare spending in the last six months of life was associated with worse performance on four measures: increased hosptialization rates among patients with COPD or asthma, increased hospitalization rates among patients with urinary tract infection, and higher utilization of ICU care in the last month of life. However, it was also associated with better performance on three quality measures: decreased mortality for COPD, heart failure, and stroke patients. Beyond statistical significance, the magnitudes of the associations between elevated EoL spending and quality tend to be much smaller than between total EoL spending and quality. The significant relationships with quality measures were also found for Dartmouth inpatient EoL spending (Appendix Table S3). The analyses using Medicare spending in the last two years of life yielded very simialr results (results available upon request).

Relationship of Physician and Patient Preferences with End-of-Life Spending Measures

Figure 2 presents results regarding whether physician and patient preferences for treatments are correlated with elevated and total EoL spending in an HRR. Physician preferences were significantly associated with elevated EoL spending in the expected direction: an increase of 10 percentage points (ppts) in the share of cowboy physicians in an HRR was associated with an approximately 4 ppts increase in elevated EoL spending ($p<0.05$). Similarly, a 10 ppts increase in the share of comforter physicians was associated with a reduction in elevated EoL spending of about 3.4 ppts ($p<0.05$). However, there was no statistically significant relationship between patient preferences for EoL care and elevated EoL spending, although the coefficients had the expected signs. In contrast, the associations between total unadjusted EoL spending and these same measures of physician and patient preferences were larger and more precisely estimated.

Elevated EoL Spending based on Median Monthly Medicare Spending

Using the elevated EoL spending by comparing median monthly Medicare spending between decedents and survivors found similar results to those in the primary analysis (Appendix Figures S3-S4, Tables S4-S5). The association between the median elevated EoL spending and monthly Medicare spending in the last six months of life was lower (correlation coefficient: 0.27, $P < 0.001$). The median elevated EoL spending was not significantly associated with physician or patient preferences across HRRs (Figure S4), which could be due to less variation in the measure relative to the mean-based measure and small sample size.

Discussion

The concentration of Medicare spending at the end of life is commonly interpreted as evidence of waste.[6,7] However, at least part of the EoL spending is likely to be driven by the fact that at an earlier point in time, those who ultimately died were generally sicker than those who survived.[2] Therefore, existing EoL spending measures that exclusively rely on data from decedents make it difficult to distinguish medical resources spent purely on keeping dying patients alive—a better candidate for wasteful or futile spending—from generally higher intensity of treating sicker patients. Accordingly, targeting geographic regions with higher spending for patients' last 12 months or 6 months of life may not provide the best opportunities to improve EoL care and reduce unnecessary EoL utilization and spending. In this study, we find that elevated EoL spending, a new measure that uses machine learning methods to account for differences in *ex ante* patient clinical risk, can be a valuable tool for identifying potentially wasteful spending.

We find that elevated EoL spending captures different utilization patterns than the conventional measure of EoL spending in the last six months of life. The two measures were modestly positively correlated, and many regions with high spending according to one measure had low spending according to the other. McAllen, Texas, for example, which has been among the most expensive regions in terms of per capita Medicare spending over the past two decades, had very high spending in the last six months of Medicare beneficiaries' lives, but was close to the median in terms of elevated EoL spending. A potential implication is that the very high total EoL spending in McAllen may reflect physicians' treatment intensity for chronically ill (though not necessarily dying) patients. Indeed, we found that the monthly average Medicare spending among survivors in 2016 was $799 in McAllen, about 14% higher than the corresponding national average adjusted for mortality risk.

The higher elevated EoL spending could nonetheless be justified if it represents treatment style factors that lead to better health outcomes for both survivors and decedents, such as use of expensive but effective treatments, or if it reflects patients' preferences for receiving aggressive care at end of life. Our findings suggest that neither was the case. We find that the elevated EoL spending measure and the conventional EoL measure were differentially associated with an extensive set of quality of care measures. Higher monthly Medicare spending in the last six months of life was associated with lower risk-adjusted mortality for five common conditions, suggesting that certain factors (such as treatment style) that produced higher total EoL spending could also produce better mortality outcomes. On the other hand, we found no evidence of an association between elevated EoL spending and any of the eleven quality measures that we examined. That is, the treatment styles in HRRs where decedents receive much more medical care than survivors who had similar *ex ante* mortality risk did not appear to provide value to patients in general. In other words, factors that produced higher elevated EoL spending did not also lead to better health outcomes.

Interestingly, the fact that the conventional EoL spending measure was positively associated with COPD admission rates could occur because it captures physicians' treatment style towards chronically ill patients whose hospitalizations are often unnecessary and preventable, as opposed to the elevated EoL spending which better reflects resources spent on patients for whom death was more imminent and hospitalizations were more justified. Additionally, the elevated EoL spending was not associated with measures of patient preferences for EoL care. By contrast, the mean elevated EoL spending was strongly correlated with physician preferences for aggressive vs. comfort care. Taken together, these findings suggest that treatment style preferences unrelated to the improvement of quality do drive elevated EoL spending.

We contribute to the literature on EoL care and spending by showing that elevated EoL spending is distinct from commonly used EoL spending measures. By removing the portion of healthcare spending on survivors with similar level of predicted mortality risk to those who died, elevated EoL spending makes it possible to isolate the part of EoL spending on saving patients who ultimately were going to die, which is precisely the part of spending that may be avoided and that represent better opportunities for cost saving. However, reducing this part of spending will require physicians to be able to accurately predict patient prognosis, which is challenging. Further research is needed to develop improved prediction models with more comprehensive patient information (e.g., laboratory test results and vital signs in the electronic health record data) which may assist physicians in better predicting patient mortality. It is noteworthy that our findings are also consistent with a handful of prior studies that explicitly account for higher clinical risk among decedents in examining EoL treatment intensity. For instance, Barnato et al.[20] developed hospital EoL treatment intensity measures that used observe-to-expected treatment ratios to account for differences in patient severity across hospitals, and found that these measures reflect hospital-specific treatment style. Kelley et al.[21] examined variation in Medicare spending stratified by predicted one-year mortality among older adults with serious illness, and found that nonmedical characteristics such as race and regional practice patterns had greater influence on treatment and spending among those with the highest predicted mortality.

By quantifying and validating elevated EoL spending as a potentially improved measure of wasteful EoL spending, our study offers three immediate policy implications. First, we provide a new basis to estimate the fraction of Medicare spending on patients near the end of life that was potentially avoidable to allow better assessment of the fiscal impact on Medicare expenditure. Second, the pattern of geographic variation we identified in elevated EoL spending makes it possible to target certain areas (e.g., Panama City, FL) with high elevated EoL spending and to analyze area-specific underlying drivers. Third, and relatedly, the finding that inpatient spending accounted for the majority of elevated EoL spending suggests that spending on hospital services remains a promising target for cost-saving near end of life.

The study has several limitations. First, the validity of the elevated EoL spending measure depends on being able to accurately predict mortality with our observed variables.

Although our machine learning based predictions for mortality performed well statistically, only a small proportion of decedents had a high predicted mortality. This is consistent with previous studies indicating that death is difficult to predict.[2,12] Alternative prediction algorithms or a more comprehensive set of predictors that utilize additional data sources such as electronic health records (unavailable to us) may yield different results. Second, diagnosis codes in the claims data used for mortality risk prediction may also represent physicians' diagnostic intensity ("upcoding"), which may vary across regions.[22] Therefore, the predicted mortality could overestimate patient clinical risk in certain regions. However, comparing decedents and survivors at the same level of predicted mortality within a HRR may mitigate this issue. Third, our study was limited to spending among older adults enrolled in FFS Medicare. This limits the generalizability of our findings to other patient populations such as those in Medicare Advantage. Fourth, the measures on patient preferences for EoL care were elicited from respondents who were not near the end of life, and preferences could change as people develop more substantial health conditions. Finally, unobserved factors may confound the relationship between EoL spending measures and healthcare quality measures. Therefore, our estimates do not reflect the causal relationships between EoL spending, quality, and patient or physician preferences.

In conclusion, we examined a new measure of elevated EoL spending that isolates spending focused on keeping dying patients alive by removing the portion of spending on generally sicker patients. Distinct from conventional measures of EoL spending, the new measure of elevated EoL spending was not associated with higher quality of care or patient preferences for care at end of life, but associated with physician preferences for treatment intensity, suggesting that it is potentially better at capturing wasteful spending at end of life. An important line of future research is to establish the role and quantitative importance of specific provider (both physician and hospital) treatment style and services in determining elevated spending at the end of life.

Data Availability Statement

The hospital referral region level data analyzed in this study constructed using Medicare Parts A & B claims are available publicly at:

https://drive.google.com/drive/folders/1PqWjpPf3fHxwiL3UW2L-gAptKRCxNkyr

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Table 1. Differences between elevated EoL spending and monthly Medicare spending in the last six months of life across HRRs

HRR	Elevated EoL spending	Monthly total EoL spending in the last six months of life	Percentage difference, %
5 HRRs with the highest elevated EoL spending per decedent			
Panama City, FL	$12,264	$7,006	75.1
Scranton, PA	$10,422	$6,056	72.1
Hinsdale, IL	$9,017	$5,941	51.8
Flint, MI	$9,005	$7,129	26.3
Sayre, PA	$8,993	$5,533	62.5
5 HRRs with the lowest elevated EoL spending per decedent			
Traverse City, MI	$2,032	$4,875	-58.3
Salem, OR	$2,020	$4,781	-57.7
Great Falls, MT	$1,696	$4,258	-60.2
Neenah, MI	$1,260	$4,193	-69.9
St. Cloud, MN	$997	$5,676	-82.4
5 HRRs with highest percentage difference between elevated EoL and monthly total EoL spending			
Panama City, FL	$12,264	$7,006	75.1
Scranton, PA	$10,422	$6,056	72.1
Sayre, PA	$8,993	$5,533	62.5
Hinsdale, IL	$9,017	$5,941	51.8
Danville, PA	$7,785	$5,400	44.2
5 HRRs with lowest percentage difference between elevated EoL and monthly total EoL spending			
San Angelo, TX	$1,696	$4,258	-60.2
Bryan, TX	$2,690	$7,146	-62.4
Bronx, NY	$2,208	$5,922	-62.7
Traverse City, MI	$1,260	$4,193	-69.9
Salem, OR	$997	$5,676	-82.4

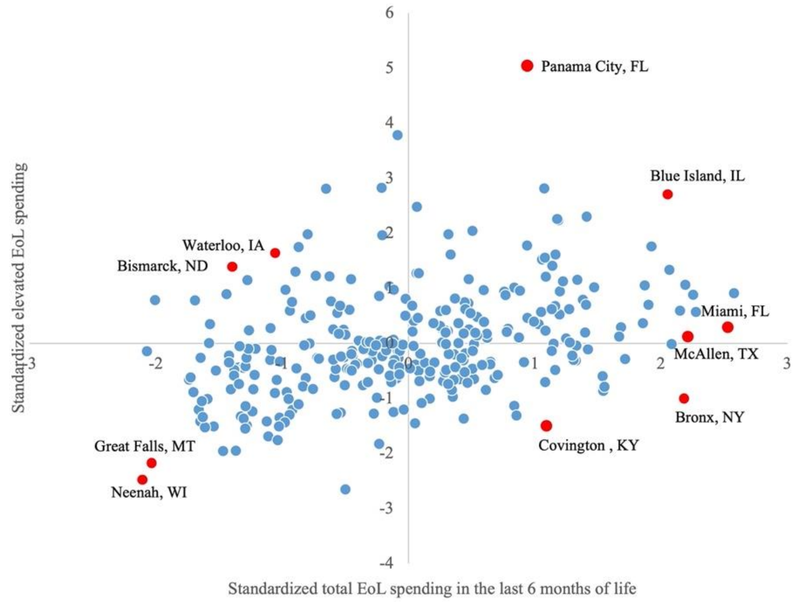
Notes: Percentage differences were calculated as dollar differences between elevated EoL spending and monthly total EoL spending in the last six months of life, divided by monthly total EoL spending for a given HRR.

Table 2. Associations between EoL spending measures and quality of care measures

	Elevated EoL spending (log)	Monthly Medicare spending in the last six months of life (log)
Preventable utilization (per 100,000 population)		
COPD or asthma admission rate (>= 75 yrs)	-70.20 (62.92)	738.00 (208.46) **
Heart failure admission rate (>= 75 yrs)	-52.68 (75.43)	316.64 (266.82)
Urinary tract infection Admission Rate (>= 75 yrs)	-11.51 (49.15)	927.62 (196.46) ****
Mortality		
30-day hospital mortality, AMI	0.08 (0.22)	0.13 (0.60)
30-day hospital mortality, COPD	-0.41 (0.15)	-1.93 (0.49) ***
30-day hospital mortality, heart failure	-0.11 (0.23)	-2.22 (0.71) *
30-day hospital mortality, pneumonia	-0.09 (0.25)	-1.19 (0.88)
30-day hospital mortality, Stroke	-0.03 (0.27)	-2.76 (0.64) ****
End of life quality		
Proportion of deceased cancer patients receiving chemotherapy in the last 14 days of life	-0.002 (0.004)	0.03 (0.014)
Proportion of decedents with ICU admission in the last month of life	0.04 (0.015)	0.23 (0.039) ****
Proportion of decedents who used hospice in the last 3 days of life	0.01 (0.020)	0.06 (0.057)

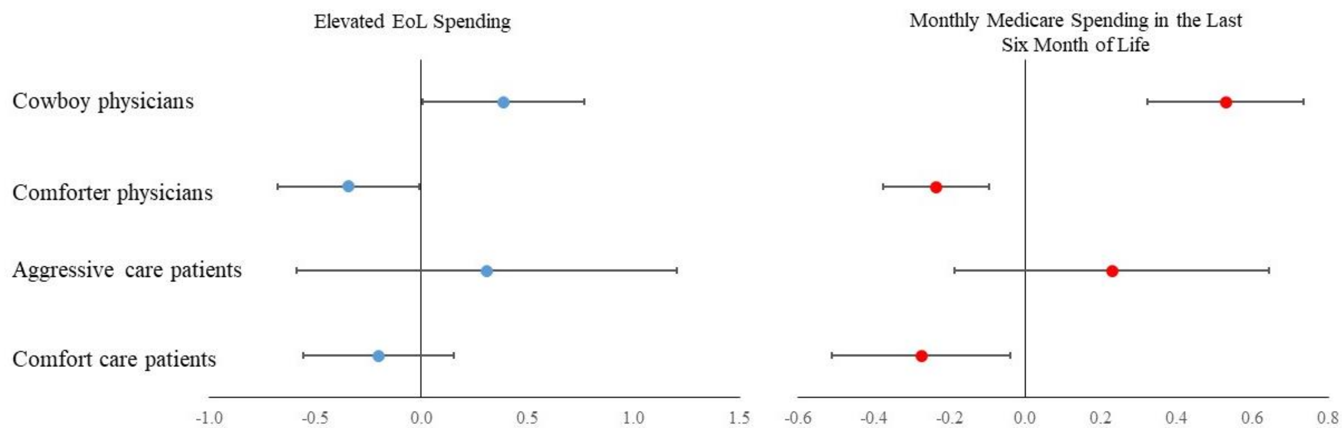
Notes: This table presents the results of two multivariable regressions, one for each column. Regressions were weighted by the number of fee-for-service beneficiaries that were eligible for each quality measure in each HRR. p values were adjusted with the Bonferroni correction. Standard errors in parentheses. *adjusted p < 0.10 ** adjusted p < 0.05 *** adjusted p < 0.01 **** adjusted p < 0.001. N = 306 HRRs.

Figure 1. Standardized elevated end-of-life spending versus monthly total Medicare spending in the last six months of life in 2016 across hospital referral regions



Notes: Each dot represents a hospital referral region (HRR). Both elevated end-of-life spending and total Medicare spending in the last six months of life were monthly, and were standardized across HRRs with mean zero and standard deviation of one to facilitate comparison.

Figure 2. Associations between physician and patient preference and end-of-life (EoL) spending measures



Notes: Each panel shows results from a single regression using logged end-of-life spending as the dependent variable and the continuous shares of four physician and patient preferences measures as independent variables. The unit of analysis is HRR**.** Each regression controls additionally for fraction of primary care physicians among surveyed physicians in a given HRR. Regressions were weighted by number of survey respondents (physicians and patients). Coefficients and 95% confidence interval bars plotted represent the estimated percentage points change in each dependent variable in response to a 10 percentage points increase in the independent variable. N = 74 HRRs.

Supplemental Material

Appendix Methods S1: Predictive modeling for mortality

1. Outcome for prediction

The outcome of the prediction model is mortality. We identified if a patient was deceased after January 1st, 2016 using the Medicare Master Beneficiary Summary File, which provides the date of patient death (if ever). In the manuscript, we refer to "survivors" as patients who survived 12 months after January 1st, 2016, and to "decedents" as patients who died during the 12 months after January 1st, 2016.

2. Predictors

Following the methods by Einav et al. and other literature on predicting mortality, we constructed over 2,000 predictors for mortality. These predictors are categorized into four groups, including demographics/enrollment, measures of previous healthcare spending, measures of previous healthcare utilization, and clinical risk measures (Appendix Table S1).

Appendix Table S1: Predictors for Mortality

Predictors	Measurement
Demographics/Enrollment	
Age	Measured as a continuous variable in years as of December 31, 2015.
Race	Unknown, White, Black, Other, Asian, Hispanic, North American Native
Gender	Male/Female
Medicaid enrollment	Dually enrolled in Medicaid in at least one month in 2015.
Medicare enrollment reason: disability	
Medicare enrollment reason: ESRD	
Geographic location	Measured by the 306 hospital referral regions based on patients' residential zip codes
Healthcare spending	
Total Medicare spending	Each variable was measured at the quarter level, as well as the day, 1-3 days, 1-7 days prior to January 1, 2016. All spending measures were geographically adjusted to account for the variations in payment rates across regions
Physician Medicare spending	
Inpatient Medicare spending	
Outpatient Medicare spending	
SNF Medicare spending	
HHA Medicare spending	
Hospice Medicare spending	
Total out-of-pocket spending	
Out-of-pocket physician spending	
Out-of-pocket inpatient spending	
Out-of-pocket outpatient spending	
Out-of-pocket SNF spending	
Out-of-pocket HHA spending	

Out-of-pocket hospice spending	
Healthcare utilization	
Number of inpatient visits	Each variable was measured at the quarter level, as well as the day, 1-3 days, 1-7days prior to January 1, 2016
Number of inpatient days	
Number of inpatient procedures	
Number of inpatient ED visits	
Number of outpatient ED visits	
Number of physician visits	
Number of SNF stays	
Number of SNF covered days	
Number of HHA visits	
Number of hospice stays	
Number of hospice covered days	
Clinical risk measures	
Indicators for Gagne Conditions	Measured for the day, 1-3 days, 1-7 days, 0-1 month, and 1-12 months prior to January 1, 2016.
Indicators for AHRQ CCS	
Indicators for 27 CCW chronic conditions	Measured as of the end of 2015
CMS HCC Score	

Notes: ESRD: end-stage renal disease; SNF: skilled nursing facility; HHA: home health agency; ED: emergency department; CCS: Clinical Classifications Software; HCC: Hierarchical condition category.

3. Prediction algorithm

3.1 *Overview of the prediction procedure*

Appendix Figure S1 presents the overview of the prediction procedure. We first randomly split the sample into training/calibration (two thirds) and test (one third) sets. The training/calibration set was used to train the prediction algorithm for mortality and the test set was used to apply the prediction algorithm and report the results. For the training/calibration set, 90% of the data were used to train the prediction algorithm, 2.5% of the data were used to calculate the ensemble weights, and 7.5% of the data were used to calibrate the predictions.

Mortality is a relatively rare outcome (only 4.65% of patients died in 2016). Following Einav et al. and previous literature, we trained the prediction algorithms using a "balanced sample" to improve the prediction. Specifically, we randomly selected a subset of survivors that has the same size with the decedents in the training, calibration, and ensemble sets. Therefore, these three sets had 50% of survivors and 50% of decedents. The training set was further split into 5 equal-sized folds to tune the prediction algorithm.

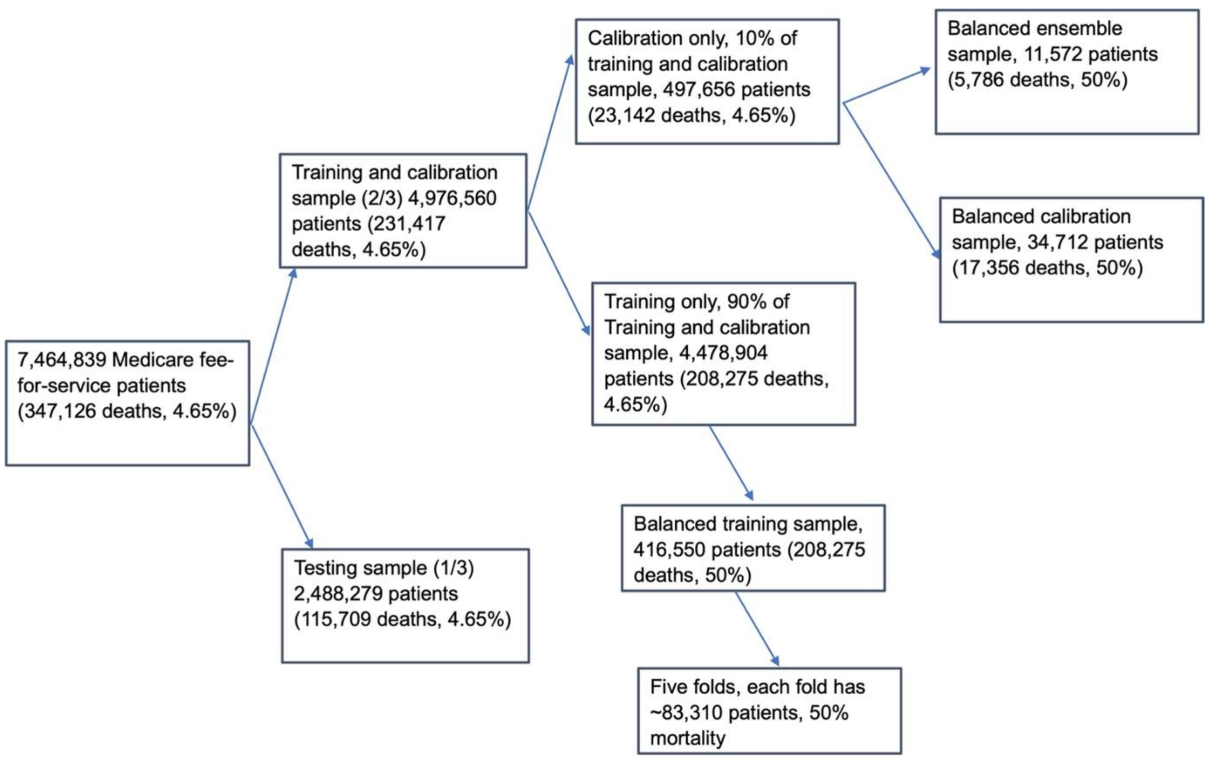
3.2 *Prediction algorithms*

We used an ensemble of LASSO, random forests, and gradient boosting trees. They have been widely used to predict mortality and other health outcomes. As presented in Appendix Figure S1, we tuned each algorithm using 5-fold cross-validation. Specifically, for each vector of tuning parameters of each algorithm, we estimated the algorithm five times. Each time we left out one of the folds when we estimated the model and we use the left-out fold to calculate the performance of the tuning parameters. We used the area under the receiver operating characteristic curve (AUC) as the performance measure. The parameters of each algorithm were selected for the largest AUC.

For random forests, we tunned two parameters, including (a) the number of predictors that are being considered for each split within a tree and (d) the minimal number of patients in a node after which no additional splits are allowed. The AUC was largest when nodes with fewer than 25 patients are not split any further and the number of predictors considered at each split was 250.

For gradient boosting trees, we tuned three parameters: (a) the number of trees used in the gradient boosting procedure; (b) the depth of each tree; and (c) the learning rate used to update between trees. The AUC was largest with 1,000 trees, a tree depth of 4, and a learning rate of 0.1. LASSO only has one parameter to tune: the weight on the penalty for large coefficient vector in terms of the L1 norm (λ). The AUC was largest when $\lambda = 0.0005$.

Appendix Figure S1: Overview of the prediction procedure



3.3 *Estimating the ensemble predictor*

The final prediction for mortality was estimated by combining the predictions made by LASSO, random forests, and gradient boosting trees. Specifically, the ensemble predictor $\widehat{p_{ens}}$ was estimated as:

$$\widehat{p_{ens}} = \widehat{\beta_{lasso}} * \widehat{p_{lasso}} + \widehat{\beta_{rf}} * \widehat{p_{rf}} + \widehat{\beta_{gb}} * \widehat{p_{gb}}$$

Where $\widehat{p_x}$ is the prediction from each individual prediction algorithm (i.e., LASSO, random forests, and gradient boosting) and $\widehat{\beta_x}$ is the associated weight. We first estimated each of the prediction algorithm using the balanced training sample and calculated predicted mortality using the ensemble sample. Therefore, each patient in the ensemble set had three values of the predicted mortality from each of the prediction algorithm. The weight of each algorithm was estimated by running a linear regression of the actual mortality on the predictions from each algorithm. We estimated the linear model without a constant, so that the final ensemble was a linear combination of the three individual predictors. The weight for each algorithm was 0.84 for gradient boosting trees, 0.13 for random forests, and 0.03 for LASSO.

3.4 Addressing class imbalance

As we trained the prediction algorithms using the balanced training set (50% survivors and 50% decedents), the resulting predicted mortality would be biased upwards. Following Einav et al., we calibrated the predicted mortality so the predictions will reflect the real-world mortality. We first applied the prediction algorithms and calculated the ensemble predictor of mortality for each patient in the calibration set (a balanced sample). Then we fit a cubic relationship between the ensemble predictor of mortality and the actual mortality. The coefficients of this regression were applied to the ensemble predictor of mortality in the test sample to calculate final prediction of mortality for the test set.

The resulting AUC in the test set was 0.876, which falls within the typical range of AUCs for predicting mortality and slightly higher than the AUC reported by Einav et al., which was 0.867.

Appendix Methods S2: Calculating Elevated EoL Spending

The variable of interest in our study is the elevated EoL spending at the hospital referral region level. Using the predicted mortality, we categorized all patients (both survivors and decedents) in the test set into 100 bins of equal size between 0 and 1 of the predicted mortality values. Therefore, each bin has a width of 0.01 and included survivors and decedents with the same level of predicted mortality. The HRR level elevated EoL spending was calculated as:

$$HRR\ elevated\ EoL\ spend_h = \sum_{k=1}^{H_k}[(\frac{1}{N_{D_k}}\sum_{i\ \in D_k} actualEoLspend_i - \frac{1}{N_{S_k}}\sum_{j\ \in S_k} spend_j)\frac{N_{D_k}+N_{S_k}}{N_H}]$$

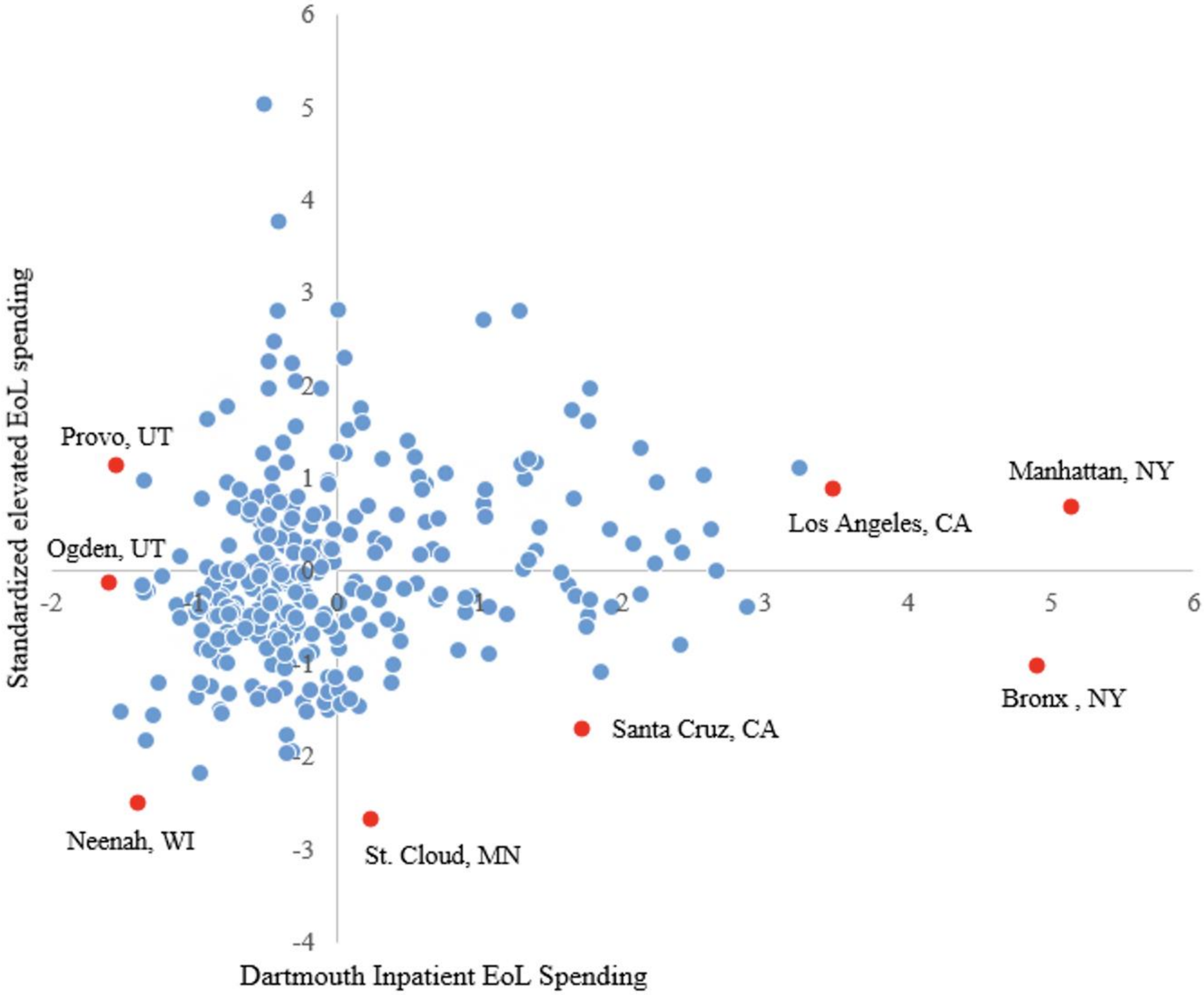
Where k indexes the bins of the predicted mortality that have at least one decedent and one survivor in HRR H. H_k is the total number of bins in each HRR. D_k and S_k denote the set of decedents and survivors in bin k, and N_{D_k} and N_{S_k} denote the number of decedents and survivors in bin k. N_H is the total number of patients across all bins in HRR H. Therefore, the HRR level elevated EoL spending was calculated as a weighted average of bin-level differences in mean monthly spending between decedents and survivors, with the fraction of individuals in each bin as the weight.

Appendix Table S2. Differences between Elevated EoL Spending and Dartmouth inpatient EoL Spending among Top HRRs, 2016

HRR	Elevated EoL spending	Dartmouth inpatient EoL spending	Percentage difference, %
5 HRRs with the highest elevated EoL spending per decedent			
Panama City, FL	$12,264	$2,237	448.2
Scranton, PA	$10,422	$2,299	353.3
Hinsdale, IL	$9,017	$2,562	251.9
Flint, MI	$9,005	$3,357	168.3
Sayre, PA	$8,993	$2,300	291.0
5 HRRs with the lowest elevated EoL spending per decedent			
Traverse City, MI	$2,032	$2,367	-14.1
Salem, OR	$2,020	$2,344	-13.8
Great Falls, MT	$1,696	$1,965	-13.7
Neenah, MI	$1,260	$1,683	-25.1
St. Cloud, MN	$997	$2,701	-63.1
5 HRRs with highest percentage difference between elevated EoL and Dartmouth inpatient EoL spending			
Panama City, FL	$12,264	$2,237	448.2
Scranton, PA	$10,422	$2,299	353.3
Provo, UT	$6,568	$1,594	312.1
Sayre, PA	$8,993	$2,300	291.0
Winston-Salem, NC	$8,515	$2,281	273.2
5 HRRs with lowest percentage difference between elevated EoL and Dartmouth inpatient EoL spending			
Salem, OR	$2,020	$2,344	-13.8
Neenah, WI	$1,260	$1,683	-25.1
Santa Cruz, CA	$2,406	$3,627	-33.6
Bronx, NY	$3,416	$5,606	-39.1
St. Cloud, MN	$997	$2,701	-63.1

Notes: Authors' analysis of data of a 20% Medicare FFS claims data in 2016 and data from the Dartmouth Atlas.

Appendix Figure S2. Elevated EoL Spending Versus Dartmouth Inpatient EoL Spending in 2016, by HRRs



Notes: Authors' analysis of data of a 20% Medicare FFS claims data in 2016 and data from the Dartmouth Atlas. Each dot represents a hospital referral region (HRR).

Appendix Table S3. Association between EoL Spending Measures and Quality of Care Measures

	Elevated EoL spending (log)	Dartmouth inpatient EoL spending (log)
Preventable utilization (per 100,000 population)		
COPD or asthma admission rate (>= 75 yrs)	-70.2 (62.9)	-55.0 (100.3)
Heart failure admission rate (>= 75 yrs)	-52.68 (75.43)	440.1 (150.9)
Urinary tract infection Admission Rate (>= 75 yrs)	-11.51 (49.15)	-236.9 (87.3)
Mortality		
30-day hospital mortality, AMI	0.08 (0.22)	-1.29 *** (0.30)
30-day hospital mortality, COPD	-0.41 (0.15)	-0.73 (0.29)
30-day hospital mortality, heart failure	-0.11 (0.23)	-1.83 (0.40) ****
30-day hospital mortality, pneumonia	-0.09 (0.25)	-1.40 (0.52)
30-day hospital mortality, Stroke	-0.03 (0.27)	-1.94 (0.41) ****
End of life quality		
Proportion of deceased cancer patients receiving chemotherapy in the last 14 days of life	-0.002 (0.004)	0.003 (0.006)
Proportion of decedents with ICU admission in the last month of life	0.04 (0.015)	-0.007 (0.031)
Proportion of decedents who used hospice in the last 3 days of life	0.01 (0.020)	-0.16 (0.034) ****

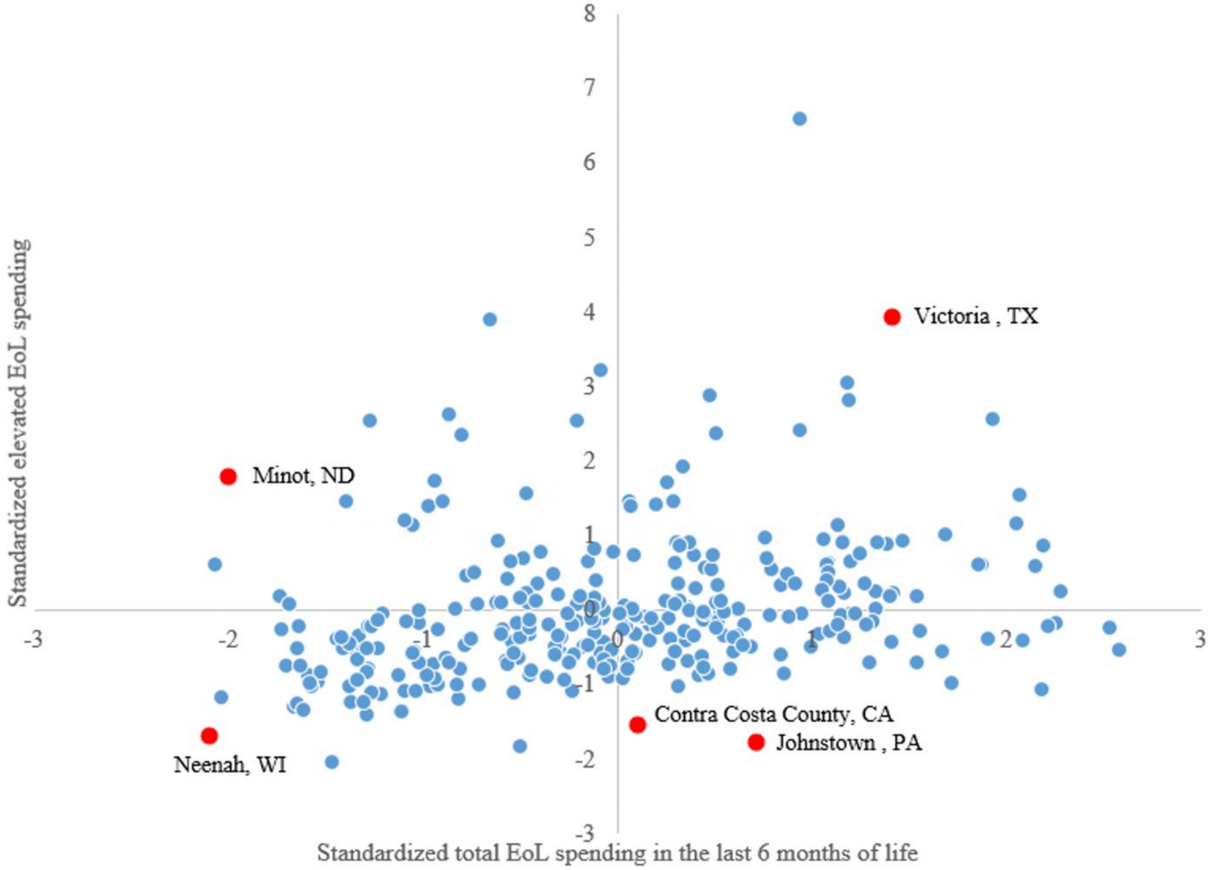
Notes: Authors' analysis of data of a 20% Medicare FFS claims data in 2016 and data from the Dartmouth Atlas. N = 306 HRRs. This table presents the results of multivariable regressions. Regressions are weighted by the number of fee-for-service beneficiaries that were eligible for each quality measure in each HRR. p values were adjusted with the Bonferroni correction. *adjusted p < 0.10 ** adjusted p < 0.05 *** adjusted p < 0.01 **** adjusted p < 0.001

Appendix Table S4. Differences between Median Elevated EoL Spending and Medicare Spending in the Last Six Months of Life across HRRs among top HRRs, 2016

HRR	Median elevated EoL spending	Monthly total EoL spending in the last six months of life	Percentage difference, %
5 HRRs with the highest elevated EoL spending per decedent			
Panama City, FL	$12,456	$7,006	77.8
Victoria, TX	$8,876	$7,441	19.3
Sayre, PA	$8,805	$5,533	59.1
Scranton, PA	$7,902	$6,056	30.5
Slidell, LA	$7,654	$7,224	5.9
5 HRRs with the lowest elevated EoL spending per decedent			
Contra Costa County, CA	$1,484	$6,232	-76.2
Neenah, MI	$1,280	$4,193	-69.5
Johnstown, PA	$1,166	$6,790	-82.8
St. Cloud, MN	$1,080	$5,676	-81.0
Salem, OR	$808	$4,781	-83.1
5 HRRs with highest percentage difference between elevated EoL and monthly total EoL spending			
Panama City, FL	$12,456	$7,006	77.8
Sayre, PA	$8,805	$5,533	59.1
Provo, UT	$6,991	$4,960	40.9
Minot, ND	$5,982	$4,284	39.6
San Mateo County, CA	$7,091	$5,334	32.9
5 HRRs with lowest percentage difference between elevated EoL and monthly total EoL spending			
Bronx, NY	$2,103	$8,151	-74.2
Contra Costa County, CA	$1,484	$6,232	-76.2
St. Cloud, MN	$1,080	$5,676	-81.0
Johnstown, PA	$1,166	$6,790	-82.8
Salem, OR	$808	$4,781	-83.1

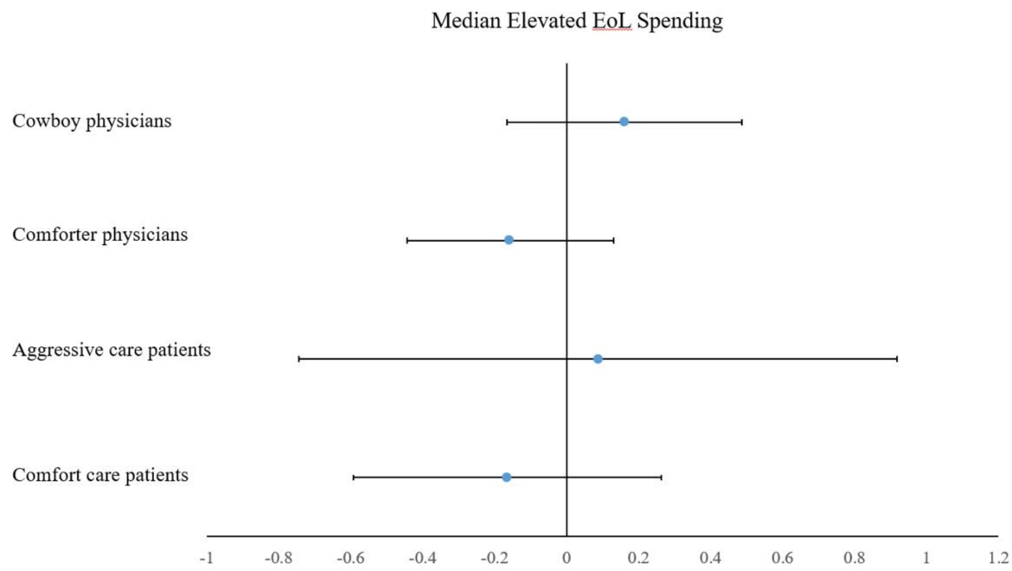
Notes: Authors' analysis of data of a 20% Medicare FFS claims data in 2016 and data from the Dartmouth Atlas.

Appendix Figure S3. Median Elevated EoL Spending Versus Total Medicare Spending in the Last Six Months of Life in 2016 across Hospital Referral Regions



Notes: Authors' analysis of data of a 20% Medicare FFS claims data in 2016. Each dot represents a hospital referral region (HRR).

Figure S4. Associations between Physician and Patient Preference and Median End-of-Life (EoL) Spending Measures



Notes: This figure shows results from a single regression using logged median elevated EoL spending as the dependent variable and the continuous shares of four physician and patient preferences measures as independent variables. The unit of analysis is HRR. Each regression controls additionally for fraction of primary care physicians among surveyed physicians in a given HRR. Regressions were weighted by number of survey respondents (physicians and patients). Coefficients and 95% confidence interval bars plotted represent the estimated percentage points change in each dependent variable in response to a 10 percentage points increase in the independent variable. N = 74 HRRs.

Appendix Table S5. Association between EoL Spending Measures and Quality of Care Measures

	Median elevated EoL spending using median monthly spending (log)	Monthly Medicare spending in the last six months of life (log)
Preventable utilization (per 100,000 population)		
COPD or asthma admission rate (>= 75 yrs)	12.18 (55.57)	738.00 (208.46) **
Heart failure admission rate (>= 75 yrs)	29.2 (73.59)	316.64 (266.82)
Urinary tract infection Admission Rate (>= 75 yrs)	60.77 (49.71)	927.62 (196.46) ****
Mortality		
30-day hospital mortality, AMI	0.26 (0.19)	0.13 (0.60)
30-day hospital mortality, COPD	-0.16 (0.16)	-1.93 (0.49) ***
30-day hospital mortality, heart failure	0.22 (0.22)	-2.22 (0.71) *
30-day hospital mortality, pneumonia	0.18 (0.23)	-1.19 (0.88)
30-day hospital mortality, Stroke	-0.03 (0.22)	-2.76 (0.64) ****
End of life quality		
Proportion of deceased cancer patients receiving chemotherapy in the last 14 days of life	-0.001 (0.004)	0.03 (0.014)
Proportion of decedents with ICU admission in the last month of life	0.04 (0.01) *	0.23 (0.039) ****
Proportion of decedents who used hospice in the last 3 days of life	0.02 (0.02)	0.06 (0.057)

Notes: Authors' analysis of data of a 20% Medicare FFS claims data in 2016. N = 306 HRRs. This table presents the results of multivariable regressions. Regressions are weighted by the number of fee-for-service beneficiaries that were eligible for each quality measure in each HRR. p values were adjusted with the Bonferroni correction. *adjusted p < 0.10 ** adjusted p < 0.05 *** adjusted p < 0.0