THE PINCHAS SAPIR CENTER
FOR DEVELOPMENT
Tel Aviv University

המרכז לפיתוח ע"ש פנחס ספיר
ליד אוניברסיטת תל אביב
"עמותה רשומה"
580010221

THE PINHAS SAPIR CENTER FOR DEVELOPMENT
TEL AVIV UNIVERSITY

Why is end-of-life spending so high?

Evidence from cancer patients

Dan Zeltzer, Liran Einav, Amy Finkelstein,

Tzvi Shir, Salomon Stemmer, Ran Balicer

Discussion Paper No. 10-2020

August 2020

אוניברסיטת תל-אביב, תל אביב יפו 6997801 | טל': 03-6409202 | פקס: 03-6405815
Tel Aviv University, Tel Aviv Yafo 6997801 Israel | Tel. 972-3-6409202 | Fax 972-3-6405815 | email: sapircen@tauex.tau.ac.il

Why is end-of-life spending so high?

Evidence from cancer patients

Dan Zeltzer, Liran Einav, Amy Finkelstein,

Tzvi Shir, Salomon Stemmer, Ran Balicer*

March 2, 2020

Abstract

We analyze rich data on 160,000 cancer patients to study why healthcare spending is highly concentrated at the end of life. Among patients with similar initial prognoses, monthly spending in the year post diagnosis is over twice as high for those who die within the year than for survivors. This elevated spending is almost entirely driven by higher inpatient spending, particularly low-intensity admissions. However, most low-intensity admissions do not result in death—even among cancer patients with poor prognoses at the time of the admission—making it difficult to target reductions. In addition, among patients with the same cancer type and initial prognosis, end-of-life spending is substantially more concentrated for younger patients compared to older patients, suggesting that preferences play a role in driving end-of-life spending patterns. Taken together, our results cast doubt on the view that end-of-life spending is a clear and remediable source of waste.

*Dan Zeltzer, dzeltzer@tauex.tau.ac.il, School of Economics, Tel Aviv University, Tel Aviv, Israel; Liran Einav, leinav@stanford.edu, Department of Economics, Stanford University, Stanford, CA, and NBER, Cambridge, MA; Amy Finkelstein, afink@mit.edu, Department of Economics, MIT and NBER, Cambridge MA; Tzvi Shir, tzvish@clalit.org.il, Clalit Research Institute, Clalit Health Services, Tel Aviv, Israel; Salomon Stemmer, shtemers@clalit.org.il, Davidoff Center, Rabin Medical Center, Petach Tiqwa, Israel and Sackler Faculty of Medicine, Tel Aviv University, Tel Aviv, Israel; Ran Balicer, rbalicer@clalit.org.il, Clalit Research Institute, Clalit Health Services, Tel Aviv, Israel and Department of Epidemiology, Faculty of Health Sciences, Ben Gurion University, Beersheba, Israel. Dan Zeltzer acknowledges financial support from the Pinhas Sapir Center for Development. Avichai Chasid provided excellent research assistance.

Keywords: Healthcare, Cancer, Predictive Modeling, End-of-Life

1 Introduction

Medical spending is highly concentrated at the end of life. One widely cited fact is that, in the United States, only 5% of Medicare beneficiaries die each year, but one-quarter of Medicare spending occurs in the last 12 months of life (Riley and Lubitz, 2010). This is frequently touted as indicative of obvious waste and inefficiency: we spend a large share of healthcare dollars on individuals certain to die within a short period (e.g., Emanuel and Emanuel, 1994; Medicare Payment Advisory Commission, 1999).

In this paper we ask: why is spending concentrated at the end of life? Our approach is motivated by existing work that has already ruled out two natural hypotheses for the concentrated spending at the end of life. One is that high end-of-life spending reflects idiosyncratic inefficiencies embodied in the specific institutional features of the US healthcare system. This is not the case. Healthcare spending is similarly—or more—concentrated at the end of life in other OECD countries (French et al., 2017). Another is that the focus on high end-of-life spending is misguided due to classic hindsight bias (Fischhoff, 1975): we spend more on the sick, and the sick are more likely to die, which together accounts for the concentration of spending on those who die. While this qualitative statement is (naturally) true, it cannot explain the quantitative patterns: even conditioning on initial health, spending on decedents is still over twice as high as that on survivors (Einav et al., 2018).

Our contribution is to investigate the sources of elevated spending on decedents compared to ex-ante similar individuals who survive. We focus our analysis on a specific set of individuals: patients newly diagnosed with cancer. Focusing on a specific disease provides us with a relatively more homogeneous set of conditions and treatment options, thereby allowing us to dig deeper into the nature of spending on decedents compared to survivors, albeit on a subset of the population. While our primary focus is descriptive, the results also shed some suggestive light on whether this concentration is—as widely assumed—indicative

of "wasteful" spending, i.e. spending that can easily be reduced without harm to patients.

Cancer is a particularly attractive disease to focus on for several reasons. First, it is common and expensive. Cancer is the second-leading cause of death in developed countries—accounting for over one-fifth of deaths—and treatment options are resource-intensive (Heron, 2013; Emanuel et al., 2002; Bekelman et al., 2016). Second, cancer has a clear diagnosis date, after which major spending decisions occur over a relatively short period. This makes it easier to analyze the course of spending on cancer than on, for example, hypertension, which has a less clear diagnosis date or treatment period. Third, patterns of end-of-life spending for cancer patients are broadly similar to those associated with the general population of patients: spending is also concentrated at the end of life across a range of OECD countries (Bekelman et al., 2016; French et al., 2017) and, as we will show, remains concentrated at the end of life even conditional on initial health. Fourth, cancer affects a wide age range, allowing us to compare treatment patterns between younger and older individuals who have very different residual life expectancies conditional on being cured.

We analyze detailed and comprehensive longitudinal medical data from about half of the Israeli population. The data come from Clalit Health Services, the largest of four HMOs in Israel that provide universal, tax-funded health insurance to all residents. The data include electronic medical records (EMR) as well as claims data. They therefore permit a much richer set of measures of both health and healthcare treatments than are available in the US Medicare claims data, in which end-of-life spending has been extensively analyzed (Barnato et al., 2004; Nicholas et al., 2011; Morden et al., 2012; Teno et al., 2013; Einav et al., 2018). In addition, unlike Medicare which is primarily for the elderly, our data allow analysis of end-of-life spending patterns over the entire age range of patients.[1]

Our primary focus is on 160,000 adults (defined as 25 years old and older) who were

[1]In principle, similar data could also be obtained from electronic medical records from a healthcare system in the United States. But such data would not be representative of the general cancer population and would be incomplete for oncology patients who seek care at multiple health systems. Moreover, as discussed above and documented more below, end-of-life care seems to be the exception that proves the rule on US healthcare exceptionalism, making the need for US-specific data less clear, even for those researchers interested primarily in US patients.

newly diagnosed with cancer in 2001 through 2013. These cancer patients have a 20% annual mortality rate, much higher than the 1.2% annual mortality rate in our overall adult population. For each individual in the data, we generate a prediction of the probability that they will die in the year following their diagnosis. We refer to this prediction as their "initial prognosis." To generate the initial prognosis, we apply standard machine learning techniques to a rich dataset with hundreds of potential predictors, including demographics, healthcare utilization, diagnoses, and various biomarker measures (vital signs, blood test results, and body mass index—BMI) in the prior 12 months.

We condition on this initial prognosis and analyze healthcare use and spending patterns in the 12 months post cancer diagnosis, comparing patients with the same initial prognosis who are ex-post survivors (i.e. those who remain alive 12 months after their cancer diagnosis) and ex-post decedents (those who died within 12 months). To make quantitative comparisons, we focus our analysis on average monthly healthcare use or spending over months that decedents (and likewise survivors) are alive.

We have three main findings. First, the elevated spending on decedents relative to ex-ante similar survivors is almost entirely driven by elevated inpatient spending, particularly low-intensity admissions with few procedures, which also spike in the last few months of life. Although inpatient spending is only 40% of medical spending among survivors, higher spending on inpatient care accounts for 90% of the elevated spending on decedents compared to survivors with similar initial prognoses. Spending on all other care—including outpatient care, radiation and chemotherapy—is only 25% larger among decedents than among survivors with similar initial prognosis. Within inpatient care, spending on decedents is particularly concentrated in low-intensity admissions with few procedures; spending on low-intensity admissions accounts for only one-quarter of inpatient spending among survivors, but for about two-thirds of the elevated inpatient spending on decedents relative to survivors with similar initial prognoses. Moreover, for decedents, spending on low-intensity admissions tends to spike in what is (ex post) the last few months of life, regardless of survival duration,

while spending on chemotherapy and radiation tends to spike right after the initial diagnosis and tails off in the last few months, again regardless of survival duration. These patterns suggest a switch to more maintenance inpatient care at the end of life.

Second, we find these patterns cannot be easily interpreted as indicative of wasteful spending that could be identified and cut without harm to patient health or well-being. We consider whether at the time of admission for a low-intensity stay it is possible to identify the patient as "about to die" and conclude that it is not: even among cancer patients admitted with poor prognoses at the beginning of the month in which the admission occurs, a large share of low-intensity admissions do not end in death within the subsequent two months. This illustrates once again the challenges associated with identifying potentially "wasteful" spending from retrospective analysis of patterns of spending for those who die.

Third, we find evidence consistent with a role for preferences in driving the elevation of end-of-life spending. We take advantage of the breadth of ages affected by cancer to analyze how end-of-life spending varies by age. We find that, conditional on initial prognosis, concentration of spending at the end of life is substantially larger for younger patients. This pattern also holds within cancer type (thus, arguably holding fixed the available "technology" or treatment options). We interpret this as suggestive that preferences—perhaps a greater reluctance to "let go" among the young—contribute to high end-of-life spending.

Taken together, none of these patterns rule out that some or all end-of-life spending is a source of waste and inefficiency in the healthcare system. However, they underscore the challenges of pointing to end-of-life spending patterns as a clear source of *remediable* waste, i.e. spending that can be identified and cut without harm to patient health or well-being. They also raise questions about the utility of the focus on end-of-life care as an area of waste, given the potential that this spending may be driven by patient (or familial) preferences. (Of course, these preferences are expressed without the patient or his family bearing the full cost of the resultant care, but this issue applies broadly to all medical spending, not just end-of-life care.)

The rest of the paper proceeds as follows. Section 2 describes our setting, data, and the construction and performance of our initial prognosis algorithm. Section 3 summarizes basic end-of-life patterns in our population of cancer patients and shows that they are similar to those of the overall adult population. Section 4 presents our core findings on the sources of elevated spending among decedents. The last section concludes.

2 Data and methods

2.1 Setting and data

Our data come from Clalit Health Services, the largest of Israel's four non-profit Health Maintenance Organizations (HMOs) that provide universal tax-funded healthcare coverage from birth to all Israeli residents, in accordance with the National Health Insurance Law (1995). Premiums for Israeli health insurance are essentially fully subsidized by risk-adjusted capitated payments from the government.[2] The coverage broadly resembles that of Medicare Parts A, B, and D, and includes hospital admissions, outpatient services, physician consults, drugs, and durable medical equipment.

Clalit Health Services is an integrated provider and insurer, provides most of the services it finances, and reimburses preauthorized services purchased from external providers. Its members are admitted to all of Israel's thirty general hospitals, eight of which Clalit directly owns and operates. It employs over 11,000 physicians and 10,000 nurses, operates over 1,500 primary clinics across the country, and provides multiple outpatient services. By 2001, Clalit adopted electronic medical records (EMRs) for its enrollees. Clalit covers approximately 4.5 million members of all ages, or about half of the Israeli population. Churn is extremely low: each year, less than 1% of Clalit enrollees switch to another HMO. Thus, most adults remain enrolled with Clalit throughout their lifetime. Appendix A provides more detail on the Israeli Health Insurance System and on our particular data provider, the insurer Clalit.

[2]There are small copays for outpatient services and emergency room visits, no copays for admissions, and a maximum out-of-pocket cap of 800 New Israeli Shekels (NIS, or about USD 200) per quarter.

The data are available longitudinally (from 2000 through 2016) and across all possible care settings. They contain rich, detailed, and comprehensive longitudinal data on a large and stable population. Similar to US Medicare data, the Clalit data include basic demographics, claim-level data on patient encounters, diagnoses and payments, and date of death if any. In addition, through the EMR, we observe a rich set of lab results, screening, imaging, and health measures that are not available in standard claims data, including, for example, vital signs, blood tests, and BMI.

We supplement these data with linked data on the exact timing of the first diagnosis of cancer from the Israel National Cancer Registry, to which reporting has been mandatory since 1982; while this information can also be extracted from claims data, the Registry provides an official first diagnosis. We also take advantage of EMR data from admissions, for the set of admissions in Clalit-owned hospitals for which such data are complete, to characterize the types of procedures performed; Clalit-owned hospitals comprise about 40 perecnt of admissions.

2.2 Analysis sample and key variables

Our main analysis sample includes all Clalit adult (25 years old and older) enrollees who had a new cancer diagnosis between 2001 and 2013. We restrict to patients with at least one year of coverage prior to the initial diagnosis and who remains at Clalit for at least 12 months after the diagnosis date (or until death); these restrictions exclude less than 1% of patients. For the small fraction of patients who are associated with multiple (distinct) cancer diagnoses during the observation period, we restrict attention to the first diagnosis.

For comparative purposes, we also present some analyses for the full population of all 2.3 million adults (aged 25 and older) covered by Clalit as of January 1, 2013, and for the subset of half a million adults who were 65 years old and older (the age group in the focus of most of the existing end-of-life literature). For these samples, we define the analysis start date (i.e. the analog to the diagnosis date in the cancer sample) as January 1, 2013, and

again impose the (minor) sample restriction that these individuals are observed for at least one year prior to and one year subsequent to that date, as long as they survive.

2.2.1 Outcomes

The main outcomes are one-year mortality and the average monthly healthcare spending over this one year. Spending measures are obtained from the administrative records of Clalit. We observe payments for all services detailed in encounter-level claims data (including inpatient admissions, emergency department visits, treatments and diagnostic services provided in outpatient clinics both within and outside hospitals, and prescription drug purchases).[3] Together, these services constitute the vast majority of services used by cancer payments.[4]

We report two types of average monthly spending: unadjusted average monthly spending—which is averaged over all months, including months in which the patient is dead (and spending is therefore mechanically zero)—and adjusted average monthly spending, which averages only over months in which the patient is alive. The adjustment accounts for the shorter survival duration of decedents, and is more useful when comparing spending patterns between decedents and survivors. Specifically, adjusted average monthly spending is defined as:

$$\bar{y}^I = \frac{\sum_{i \in I} y_i}{\sum_{i \in I} (T_i/30)}, \tag{1}$$

where I is a set of individuals, y_i is total healthcare spending of individual i in the 12 months following the index date, and $T_i \in (0, 365]$ is the right-censored number of days individual i survived after the index date.

Table 1 presents summary statistics for the general adult population and the cancer subsample. It shows results overall, as well as separately for decedents (who die within a

[3]The spending measures represent actual payments made by Clalit, not list charges. Even in cases where the hospital is owned by Clalit, it serves as a separate financial entity as Clalit hospitals also serve non-Clalit patients and charge other insurers similar prices.

[4]We do not observe spending directly for about 2.8% of total spending in our cancer sample that consists of office-based consults provided by salaried physicians in Clalit-owned clincs. For these visits, we construct per-visit charges that are based on customary charges by non-employed providers.

year of diagnosis or, in the case of the general adult population, in the calendar year) and survivors. Cancer patients are on average older and sicker than the general population, even before they get diagnosed with cancer. As may be expected, the one-year mortality rate for cancer patients (19.5%) is much higher than that of the general population (1.2%). Cancer mortality is not only higher, but it also has a different time trajectory. In addition, while the annual mortality rate is approximately constant for the general population, those cancer patients that survive a year have a much lower mortality rate in subsequent years; only 81% of cancer patients survive a full year, but of those, 84% survive an additional two years.

The bottom panel of Table 1 shows that decedents are sicker and more expensive than survivors, even before a cancer diagnosis. They have more hospital admissions and spend on average more than survivors in the 12 months prior to the index date. In the year leading to a cancer diagnosis, decedents spend on average NIS 2,300 (approximately USD 575) per month; survivors spend NIS 1,200 (approximately USD 300) per month. Decedents are also older than survivors on average (73 versus 64 years old). These differences highlight the need to adjust for ex-ante risk when discussing the differences in spending between decedents and survivors, as we do below.

In addition to analyzing spending, we also construct several measures of the nature of any inpatient admissions. First, for the 40% of admissions in which we can observe inpatient procedures, we measure whether the admission involved each of six different types of inpatient procedures: diagnostics (lab and imaging), surgeries, inpatient chemotherapies, inpatient radiation therapies, maintenance (e.g., evaluation, feeding, pain management), and all others.[5] Second, we classify all admissions based on whether they are unplanned (i.e. originated through the emergency room) or planned and by whether they are high or low "intensity," with high versus low intensity defined based on the average daily spending for different hospital wards (i.e., hospital units). Appendix Table A2 shows the breakdown

[5]As described in Section 2.1, we can observe inpatient procedure data for patients admitted to Clalit-owned hospitals. Appendix Table A1 shows that the characteristics of patients admitted to Clalit-owned versus other hospitals are similar.

of wards into high and low intensity. As would be expected, the high-intensity wards, such as general surgery, tend to have a much higher share of admissions with surgical procedures than admissions to low-intensity wards, such as oncology or internal medicine.

2.2.2 Mortality predictors

We exploit the richness of the data to code hundreds of potential mortality predictors. Appendix B describes these predictors and their construction in detail. Broadly speaking, they fall into four main categories: demographics, healthcare spending and utilization prior to cancer diagnosis, health conditions prior to cancer diagnosis as recorded in claims data, and health measures prior to the cancer diagnosis from EMR. The first three are standard in claims data, while the fourth is less commonly available.

Our demographic data come from administratively sourced information on birth date, gender, social security transfers, disability, and location-based socioeconomic status. For the year prior to diagnosis, we also measure monthly healthcare utilization and spending by type of service in the claims data, as well as healthcare diagnoses recorded in claims data. We also use the claims data to calculate measures of overall morbidity based on information from all diagnoses documented in clinical encounters over the last year. Specifically, we use the Johns Hopkins Adjusted Clinical Groups (ACG) system to predict resource utilization and the probability of major health events.[6]

Finally, the EMR data provide additional health measures. These include BMI, vital signs measures, blood test results, and information on drug adherence. We also use as a predictor the cancer topography from the national cancer registry data.

[6]This system is used by both commercial insurers and non-commercial healthcare organizations worldwide (as well as by Clalit) to describe or predict a population's past or future healthcare utilization and costs. For more information see The Johns Hopkins ACG System Version 11.0 Technical Reference Guide (2014).

2.3 Prognosis algorithm

A key component of our analysis is comparing spending differences among ex-ante similar patients, some of whom subsequently die and some of whom live. To do so, we generate predicted one-year mortality for each individual. We refer to this measure, which is created at the date of cancer diagnosis (or January 1, 2013 for the general adult population aged 25 and over), as the patient's "initial prognosis."

To create these predictions, we apply standard machine learning techniques to the rich dataset with hundreds of potential predictors described in the preceding section. All predictors are measured on or prior to the diagnosis date. We briefly summarize the prediction algorithm here and provide many more details on its construction and performance in Appendix C.

To model and estimate mortality risk, we use Extreme Gradient Boosting (Chen and Guestrin, 2016), a popular sequential ensemble method that iteratively and greedily constructs a series of classifiers, with each classifier being used to fit the residuals of the previous classifier. This method can flexibly accommodate interactions among predictors and fit an arbitrary differentiable criterion function.

We follow standard practices to avoid over-fitting. In particular, we randomly split our original sample into two equally sized samples: the "test sample," which we do not use as we optimize our prediction algorithm, and the "training sample," which we use to fit our predictive model. The training sample is used only for fitting the predictive model. We tune key parameters by five-fold cross-validation to maximize the area under the curve (AUC) criterion. The trained model is then used to predict mortality in the testing sample, over which the rest of the analysis is performed. Unless otherwise noted, all exhibits are based on the test sample. Appendix C discusses the performance of the algorithm and shows that it does well compared to existing similar exercises.

We use the prognosis algorithm in all of our subsequent analyses to adjust for differ-

ences in ex-ante prognoses among ex-post decedents and ex-post survivors. Specifically, we present graphical analyses of outcomes separately for survivors and decedents with the same prognosis. In addition, to quantify outcome differences for survivors and decedents while adjusting for differences in prognosis, we report differences in outcomes between decedents and survivors reweighted, so that they have the same distribution of prognoses as decedents. Namely:

$$\bar{c}_{\text{survivor(reweighted)}} = \int c_{\text{survivor}} dP_{\text{decedent}}, \tag{2}$$

where c_{survivor} denotes survivor spending, and P_{decedent} is the probability distribution of decedents' one-year mortality prognosis.[7]

Most of our analyses compare ex-post decedents and ex-post survivors with similar initial prognoses. But for some exercises, it is also useful to compare survivors and decedents with similar *current* mortality risk, measured at interim points post-diagnosis after certain care decisions were already made and their outcomes observed. Therefore, beginning with the initial diagnosis, we also predict one-year mortality risk every month, for all patients still alive. We then use the estimated predicted distribution of risk at the beginning of each month as an alternative measure of patient risk with which we reweight survivor monthly spending. Appendix D provides additional details on our construction of these current mortality risk measures.

3 End-of-life patterns

In this section, we present basic end-of-life patterns for our adult cancer population. We show that they are broadly similar to that of the overall adult population (aged 25 and older), as well as to that of the adult population aged 65 and older both in our data and

[7] We approximate this integral by binning. Namely, we partition the range $[0, 1]$ to ten equally-sized bins, based on the percentiles of $\hat{P}_{\text{survivor}}$. We then calculate the mean survivor spending in each bin, and then average across all bins, but using $\hat{P}_{\text{decedent}}$ as weights. Note that, by design, $\bar{c}_{\text{decedent}} = \int c_{\text{decedent}} dP_{\text{decedent}}$, so we only reweight survivor spending.

in US Medicare data. This suggests that our focus on the cancer population, which allows more detailed analyses on the nature of elevated spending for decedents, may shed light more broadly on the reasons for high end-of-life spending.

Specifically, we establish that three key end-of-life patterns in our population are similar to the overall adult (25 and older) population in our data as well as to what has been previously documented in the US Medicare population (age 65 and older) (Riley and Lubitz, 2010; Einav et al., 2018). First, spending is concentrated at the end of life, which motivates the interest in exploring it. Second, death is highly unpredictable (despite rich data and "sophisticated" machine-learning algorithms), which raises the possibility that spending on the ex-post dead is not obviously reflective of ex-ante waste (since it is hard to predict who will die at the time spending decisions are being made). Third, even among patients with similar initial prognoses, spending is substantially higher for decedents than survivors. This last fact suggests that for some (potentially "wasteful") reason, the process by which individuals die is expensive, which serves as the point of departure for our subsequent analyses.

3.1 Spending concentration at the end of life

The widespread interest in end-of-life spending presumably stems from the observation that healthcare spending is disproportionately concentrated at the end of life. We reproduce this finding for our study population of cancer patients. Figure 1 shows the concentration of spending at the end of life for both the general adult population and our cancer sample. We also show the general elderly population (65 years old and older), since it is most comparable to the heavily studied US Medicare population.

Among the general elderly population, 4.4% die each year, and these decedents account for 14% of annual spending. The corresponding numbers for the United States are strikingly similar: Einav et al. (2018) report that 5% of Medicare enrollees die each year, and they account for 15.4% of annual spending.[8] The concentration of spending at the end of life is

[8]An oft-quoted statistic in this context is that one-quarter of spending for Medicare enrollees occurs in the last 12 months of life (Riley and Lubitz, 2010). Our statistic is lower because we compute calendar-year

even higher in the general Israeli adult population: only 1.2% of them die each year, yet they account for 8.8% of annual spending.

About one-fifth of cancer patients die each year and they account for one-fifth of annual healthcare spending. Ostensibly, this suggests that spending is not concentrated at the end of life for cancer patients. However, this is misleading because cancer decedents have much shorter survival durations relative to the general population (compare one-month mortality rates for decedents in Table 1). Indeed, decedent share of spending for cancer patients is almost three times higher than their share of days lived, indicating elevated spending for decedents relative to survivors. Naturally, spending on decedents is somewhat less concentrated in the cancer population than for the general adult population (where decedent share of spending is fourteen times higher than their share of days lived), since virtually all cancer patients receive some non-trivial amount of medical care while many adults receive no care.

For the cancer population, we can further disaggregate by type of cancer, as shown in Appendix Table A3. Breast, prostate, and colon cancer are the three most common cancers, collectively accounting for about one-third of all cancer diagnoses. Mortality rates and spending vary substantially across types of cancer. While we pool all cancer types to generate our main results, cancer type is always included in our mortality prediction algorithm. We will report below on some analyses that are performed separately by cancer type.

3.2 Death is highly unpredictable

Prior work has shown that, for the US Medicare population, it is very hard to predict who will die within the coming year (Einav et al., 2018). The same is true in our setting. Figure 2 shows the distribution of annual mortality risk and average monthly spending in the 12 months post diagnosis for the cancer population and, for comparison, the general adult population. There is a notably thicker right tail of predicted mortality risk among cancer

spending for all those decedents who die within a year, which on average covers only six months of life rather than 12.

patients. But despite this, it is hard to identify a subsample of cancer patients with very high ex-ante death probabilities. The 95th percentile of predicted annual mortality is only 81%, and only one-quarter of those who end up dying within the year have initial mortality prognoses of greater than 80%.

Appendix Table A3 shows comparable statistics by cancer type. Pancreatic cancer has the highest annual mortality rate (two thirds) although it accounts for less than 3% of cancer diagnoses. However, even in this population, less than 5% of patients have an initial annual mortality prognosis above 95%, and less than 55% of those who end up dying within the year have initial mortality prognoses greater than 80%. These findings underscore a fundamental point: there is no sizable mass of cancer patients for whom, at the time of initial diagnosis, death is certain or "near certain" (within the year).

Figure 2 also shows that average monthly spending in the year that follows cancer diagnosis shows an inverted U-shaped pattern with respect to initial prognosis. This of course naturally reflects the fact that higher mortality-risk individuals survive on average for fewer months. As discussed, to adjust for this we report throughout an adjusted average monthly spending measure that averages only over months alive. As expected, Figure 2 shows that adjusted average monthly spending is strongly increasing in mortality risk, presumably reflecting the fact that spending is higher for sicker patients. However, despite this pattern, Appendix Figure A1 shows that individuals with very poor initial prognoses account for only a very small share of total spending. For example, less than 10% of spending on cancer patients is accounted for by individuals with predicted mortality above 80%.

3.3 Elevated spending on decedents compared to ex-ante similar survivors

An obvious explanation for the concentration of spending at the end of life is that spending is higher among sicker patients, and sicker patients are also more likely to die. However, even among patients with similar initial prognoses, spending is substantially higher for decedents

than survivors. This motivates our subsequent investigation into *why* spending is elevated for decedents compared to ex-ante similar individuals who survive.

Figure 3 shows spending by initial prognosis broken out separately for survivors and decedents. As with all our subsequent analyses, we show "adjusted" average monthly spending, i.e., spending averaged only over months alive. The figure shows that even conditional on initial prognosis, spending remains elevated for decedents compared to survivors.

To quantify the elevation of spending among cancer decedents compared to cancer survivors with similar initial prognoses, we reweight the survivor population to match the distribution of initial prognoses among decedents. The first row of Table 2 shows the results. Without adjusting for risk differences, decedents' monthly spending is nearly three times greater than survivors' (NIS 13,189 versus 4,664). Reweighting survivor spending by decedent risk at the time of diagnosis (column 2), the gross difference of NIS 8,525 drops to 7,038. In other words, differences in initial prognosis between ex-post decedents and survivors at the time of diagnosis account for about one-sixth of the elevated spending on decedents. Once we condition on cancer patients' initial prognosis, average monthly spending is still more than twice as high for decedents than survivors. We find a similar ratio among the general and elderly population in Israel (see Appendix Table A4 and Appendix Table A5.) It is also quite similar to prior findings for the elderly in the United States, that indicate that average monthly spending is about 2.5 times higher for decedents than for survivors with the same ex-ante mortality risk (Einav et al., 2018).

4 Sources of elevated spending on decedents

Taken together, the descriptive evidence in the previous section underscores the challenges of identifying obvious cases of "waste" in end-of-life spending: we are unable to identify a substantial share of people with extremely high probability of dying within a year or a substantial share of spending on such individuals. At the same time, evidence that spending remains substantially elevated for decedents compared to survivors with the same initial

prognosis suggests that for some (potentially "wasteful") reason, the process by which individuals die is expensive. This motivates our investigation into the sources of this elevated spending documented in the first row of Table 2. All of these analyses focus exclusively on the cancer population.

4.1 Types of services

The remaining rows of Table 2 analyze spending differences for decedents compared to survivors by type of service. For completeness, we present both unweighted and reweighted results, but we focus our discussion on the latter, which allow us to compare decedents and survivors with the same initial prognosis.

The elevated spending for decedents is almost entirely driven by differences in inpatient spending. Although inpatient spending only accounts for 40% of medical spending among survivors, higher spending on inpatient care accounts for 90% of the elevated spending on decedents. Spending on all other care, including outpatient care, radiation, and chemotherapy, is only 25% larger among decedents than among survivors with a similar initial prognosis.

Elevated inpatient spending in turn is disproportionately concentrated in low-intensity (versus high-intensity) admissions and in unplanned (versus planned) admissions. Despite accounting for only a quarter of inpatient spending among survivors, low-intensity admissions account for almost two-thirds of the elevated spending on decedents. Likewise, unplanned admissions account for only about a quarter of inpatient spending among survivors, but for about half of the elevated spending on decedents.

Table 3 shows that these differences in inpatient spending reflect differences in inpatient use. Most cancer patients—88% of decedents and 79% of reweighted survivors—are admitted to the hospital at least once in the year after their initial cancer diagnosis. Thus, even though decedents survive on average less than half the time decedents do, decedents are still more likely than survivors to have a hospital admission. Moreover, adjusting for survival duration and conditional on having any admission, Panel B shows that decedents are admitted to

the hospital more than twice as often as survivors: 0.81 admissions per month on average, compared to 0.31 admissions by survivors.

As with hospital spending, decedent hospital utilization is also concentrated in low-intensity admissions. In the year following a cancer diagnosis, decedents are much more likely than (reweighted) survivors to have a low-intensity admission (77% relative to 55% for survivors) and less likely to have a high-intensity admission (47% relative to 54% for survivors). Decedent's admissions are also longer on average than survivor's by 1.7 days (9.2 days, compared with 7.5 days for survivors).

4.2 Timing of services

Figure 4 shows decedent spending by type of service as a function of two timelines: Panel A shows months after diagnosis, and Panel B shows months before death. Each line shows the average monthly spending of a group of decedents who survived the same integer number of months. To the extent services reflect treatment plans that are decided in advance, we would expect to see the timing of spending aligned on a prospective time scale (top panels), regardless of eventual survival duration. In contrast, treatment responses to unexpected deterioration may be better aligned with the retrospective time scale (bottom panels), regardless of survival duration.

The results show that regardless of survival duration, low-intensity admissions spike in the last couple of months before death. In contrast, spending on high-intensity admissions and on other services (including outpatient services and drugs) spike two or three months after diagnosis and decreases in the last month or two. Overall, Figure 4 paints a reasonably clear picture (which is consistent with the analysis in the last section), in which the timing of high-intensity admissions and other services is primarily tied to the timing of cancer diagnosis, while the timing of low-intensity admissions is closely linked to the (retrospective) timing of death.

This evidence is consistent with initial treatment plans that fight cancer via scheduled

surgeries, outpatient radiation, and chemotherapy, but changes to a different type of medical treatment for patients for whom treatment has failed. The latter involves increased frequency of unplanned admissions that may aim to monitor and maintain patients without necessarily trying to treat them. Several other pieces of evidence are consistent with this interpretation. First, Figure 5 shows that, in contrast to high-intensity admissions and other services, average monthly spending on low-intensity admissions is strongly increasing with poorer initial prognosis. Namely, the poorer the patient's chance of survival, the greater the patient's spending on low-intensity admissions. Second, Table 4 shows that, closer to death, decedent admissions involve fewer surgeries and more maintenance relative to both decedent admissions farther from death and survivor admissions. Overall, 27.6% of admissions for cancer patients involve surgery. But only 9.4% of decedent admissions in the last month before death involve surgery, compared with 11.2% of decedent admissions that occur four to 12 months before death, and with 33.4% of survivor admissions. Admissions closer to death also involve fewer chemotherapy procedures, more diagnostics, and more maintenance. Radiation does not have a clear trend (possibly because there are both therapeutic and palliative radiation therapies).

The findings that low-intensity admissions tend to spike close to the time of death—regardless of initial prognosis or survival time—might suggest potential cost savings and utility increases if such services were performed at home or in hospice rather than in the hospital. However, for this to be possible, one would need to be able to predict, at the time of admission, that these admissions are very likely at the the end of life. This turns out not to be easy.

To investigate this, we use the prediction of *current* mortality risk (i.e., predicted annual mortality at the beginning of the month of the admission, described in Section 2), rather than *initial* mortality risk that we have been analyzing so far.[9] The thought exercise is whether

[9]This also allows us to ask whether changes in prognoses (and associated changes in spending) can explain the elevation of decedent spending relative to survivor spending for individuals with the same initial prognosis. The answer is no. If we reweight each survivor-month spending by decedent predicted risk at the beginning of each month, Appendix Table A6 shows that differences in interim risk account for only half of

we can identify a group of patients, who, based on their current prognosis are "about to die" and whom the decision maker might therefore prefer not to admit.

Figure 6 therefore shows the fraction of low-intensity and high-intensity admissions that result in death within 60 days, against the most recent (monthly) prognosis predicted by our algorithm. Low-intensity admissions that result in near-term death rise sharply as the current prognosis worsens. However, the results show that it is difficult to draw conclusions about individual short-term survival in real time. Many low-intensity admissions do not result in near-term death, even among individuals with poor current prognoses; for example, among patients who enter a low-intensity admission with a current prognosis of 80% mortality within a year, only half die within the next two months. This makes it difficult to draw sharp conclusions about such admissions being clearly "wasteful."

4.3 Varying patterns by age

An advantage of our focus on cancer is that it is a disease that (unfortunately) affects a wide range of ages. This allows us to look at how end-of-life spending patterns vary with patient age. Among those 65 years old and older, existing evidence suggests a greater concentration of end-of-life spending for younger individuals compared to older individuals (e.g., Levinsky et al., 2001). Likewise, Figure 1 showed that the concentration of spending at the end of life is even higher in the general adult population age 25 and older (where decedent spending is about fourteen times their share of days) than the elderly population age 65 and older (where decedent spending is about seven times their share of days). This raises questions about the role of preferences in driving spending decisions on high-risk patients. Older patients face a lower life expectancy and therefore decision makers (be it the patient, the family, or the doctor) may be more reluctant to authorize intensive treatment when the patient is older than when the patient is younger. Of course, many things differ with age, including types of disease and initial prognosis.

the elevated spending on decedents. Moreover, because interim risk predictions use post-diagnosis spending as a predictor, interpretation becomes more difficult.

Likewise, Figure 3 shows that, both in the general population and in the cancer population, the elevation of spending on decedents versus survivors is particularly pronounced for patients with low predicted mortality. This is also consistent with stronger preferences to fight death intensively among those with initially higher chances of surviving it or greater benefit from doing so. Again, however, differences in disease type—and hence available treatment technologies—may confound such interpretation.

Our focus on cancer patients allows us to address some of these concerns. Specifically, we examine how, conditional on initial prognosis, the elevation of spending on decedents relative to survivors varies by age, both overall and within cancer type. We define cancer type by main typography (e.g. breast, lung, or bladder); Appendix Table A3 provides descriptive statistics by cancer topography. To the extent that each cancer type represents a relatively homogeneous disease and is associated with a given set of treatment options, residual variation by age may primarily capture treatment preferences.

Figure 7 shows that for the cancer population, conditional on initial prognosis, spending declines with age, and this decline is particularly pronounced for decedents compared to survivors. To summarize this, Panel A of Table 5 reports average monthly spending (adjusted for survival duration) separately by age quintile, for all cancer types combined. Column 4 shows that the difference in average monthly spending for decedents, relative to reweighted survivors, decreases monotonically with age, from about NIS 10,500 for the youngest age quintile (53 years old or younger) to about NIS 5,500 for the highest age quintile (78 years old and older).

Panel B of Table 5 and Appendix Figure A2 show that this pattern persists when we further condition on cancer type, thus, arguably holding fixed the available "technology" or treatment options. Namely, even within cancer type and conditional on initial prognosis, spending decreases with age. For example, among breast cancer patients, the difference in spending between decedents and reweighted survivors is NIS 5,600 for the youngest age quintile and NIS 4,000 for the oldest; for lung and bronchus cancer patients, the difference

for the youngest and oldest age quintiles is NIS 6,000 and 4,800, respectively. Appendix Figure A3 and Appendix Figure A4 show this pattern separately for decedents and survivors.

5 Conclusion

Since healthcare spending is highly concentrated at the end of life, end-of-life spending is frequently trumpeted as a source of substantial waste in the healthcare system. We explore this hypothesis, using an extremely rich dataset on a large population and a prediction algorithm we generate to allow us to compare patients with the same initial mortality prognosis. We focus on newly diagnosed cancer patients, who provide a large, yet relatively homogeneous set of medical conditions. The key end-of-life patterns are similar in cancer patients and in a more general adult population. Our analysis therefore focuses on understanding the factors behind the elevated spending on decedents relative to survivors with similar prognoses. We have three main findings.

First, we document that even though inpatient spending accounts for only about two-fifths of spending for survivors in the year post diagnosis, the elevated spending for decedents is almost entirely driven by inpatient spending (particularly low-intensity admissions with few procedures). Moreover, spending on low-intensity admissions tends to spike for decedents in what is (ex post) the last few months of life.

Second, we show yet again that it is hard to establish such spending as ex-ante waste. The finding that low-intensity admissions tend to spike close to the time of death—regardless of initial prognosis or survival time and at the same time that high-intensity admissions and outpatient services like chemotherapy and radiation are tailing off—might suggest scope for reducing costs (and improving patient comfort) if such low-intensity admissions could be replaced by similar services performed at home or in hospice. However, from an ex-ante perspective it is hard to target such care since, we also show, a large share of low-intensity admissions do not result in death, even among patients with poor current prognoses. In other words, while many deaths are preceded by low-intensity admissions, many low-intensity

admissions do not result in death, even among patients with poor current prognoses. This makes it hard to point to clear examples of ex-ante waste.

Third, and relatedly, we present suggestive evidence that preferences may be an important factor behind the elevation of spending at the end of life. Specifically, taking advantage of the breadth of ages affected by cancer, we document that the difference in spending between decedents and survivors with the same initial prognosis is particularly pronounced among younger individuals. These findings are consistent with greater demand (among patients, their families, and their physicians) for treating those with a higher life expectancy (conditional on surviving cancer). Moreover, these findings are consistent with prior evidence that healthcare spending on pets spikes at the end of life as well (Einav et al., 2017). We interpret them as suggestive of a role for preferences—perhaps a greater reluctance to "let go" among the young—in influencing end-of-life spending patterns.

Of course, our analysis is descriptive and naturally cannot fully rule out the possibility that at least some portion of end-of-life spending is a "waste" (loosely defined). However, taken together, the evidence we present points to patterns of end-of-life spending that could potentially be reasonably justified by a fully rational decision making model written by an economist. This raises considerable doubt about the utility of focusing on end-of-life spending as a source of substantial "waste" in healthcare systems and, relatedly, a substantial opportunity to save money without harming patient health or utility. A more fruitful (although also more laborious) path to identifying waste in healthcare systems may lie in credibly documenting the many specific, smaller sources of spending that could be eliminated with little or no harm to patients, as recent research has started to do (Abaluck et al., 2016; Einav et al., 2019; Cooper et al., 2019).

References

Abaluck, Jason, Leila Agha, Chris Kabrhel, Ali Raja, and Arjun Venkatesh, "The determinants of productivity in medical testing: Intensity and allocation of care," *American Economic Review*, 2016, *106* (12), 3730–64.

Barnato, Amber E, Mark B McClellan, Christopher R Kagay, and Alan M Garber, "Trends in inpatient treatment intensity among Medicare beneficiaries at the end of life," *Health Services Research*, 2004, *39* (2), 363–376.

Bekelman, Justin E, Scott D Halpern, Carl Rudolf Blankart, Julie P Bynum, Joachim Cohen, Robert Fowler, Stein Kaasa, Lukas Kwietniewski, Hans Olav Melberg, Bregje Onwuteaka-Philipsen et al., "Comparison of site of death, health care utilization, and hospital expenditures for patients dying with cancer in 7 developed countries," *JAMA*, 2016, *315* (3), 272–283.

Chen, Tianqi and Carlos Guestrin, "Xgboost: A scalable tree boosting system," in "Proceedings of the 22nd ACM SIGKDD international conference on knowledge discovery and data mining" ACM 2016, pp. 785–794.

Cooper, Zack, Fiona Scott Morton, and Nathan Shekita, "Surprise! Out-of-network Billing For Emergency Care in the United States," *NBER Working Paper No. 23623*, 2019.

DeSalvo, Karen B, Vincent S Fan, Mary B McDonell, and Stephan D Fihn, "Predicting Mortality and Healthcare Utilization with a Single Question," *Health Services Research*, 2005, *40* (4), 1234–1246.

Einav, Liran, Amy Finkelstein, and Atul Gupta, "Is American pet health care (also) uniquely inefficient?," *American Economic Review*, 2017, *107* (5), 491–95.

_ , _ , and Neale Mahoney, "Long-Term Care Hospitals: A Case Study in Waste," *NBER Working Paper No. 24946*, 2019.

_ , _ , Sendhil Mullainathan, and Ziad Obermeyer, "Predictive modeling of US health care spending in late life," *Science*, 2018, *360* (6396), 1462–1465.

Emanuel, Ezekiel J and Linda L Emanuel, "The economics of dying—the illusion of cost savings at the end of life," *New England Journal of Medicine*, 1994, *330* (8), 540–544.

_ , Arlene Ash, Wei Yu, Gail Gazelle, Norman G Levinsky, Olga Saynina, Mark McClellan, and Mark Moskowitz, "Managed care, hospice use, site of death, and medical expenditures in the last year of life," *Archives of Internal Medicine*, 2002, *162* (15), 1722–1728.

Fischhoff, Baruch, "Hindsight is not equal to foresight: The effect of outcome knowledge on judgment under uncertainty.," *Journal of Experimental Psychology: Human perception and performance*, 1975, *1* (3), 288.

French, Eric B, Jeremy McCauley, Maria Aragon, Pieter Bakx, Martin Chalkley, Stacey H Chen, Bent J Christensen, Hongwei Chuang, Aurelie Côté-Sergent, Mariacristina De Nardi et al., "End-of-life medical spending in last twelve months of life is lower than previously reported," *Health Affairs*, 2017, *36* (7), 1211–1217.

Genevès, Pierre, Thomas Calmant, Nabil Layaïda, Marion Lepelley, Svetlana Artemova, and Jean-Luc Bosson, "Predicting At-Risk Patient Profiles from Big Prescription Data," *ffhal-01517087v4f [Reprint]*, 2017.

Heron, Melonie, "Deaths: Leading causes for 2010," *National Vital Statistics Reports, National Center for Health Statistics, Center for Disease Control and Prevention*, 2013, *62* (6), 1–96.

Levinsky, Norman G, Wei Yu, Arlene Ash, Mark Moskowitz, Gail Gazelle, Olga Saynina, and Ezekiel J Emanuel, "Influence of age on Medicare expenditures and medical care in the last year of life," *JAMA*, 2001, *286* (11), 1349–1355.

Makar, Maggie, Marzyeh Ghassemi, David M Cutler, and Ziad Obermeyer, "Short-term mortality prediction for elderly patients using Medicare claims data," *International Journal of Machine Learning and Computing*, 2015, *5* (3), 192.

Medicare Payment Advisory Commission, "Report to the congress: Improving care at the end of life," Technical Report 1999.

Morden, Nancy E, Chiang-Hua Chang, Joseph O Jacobson, Ethan M Berke, Julie PW Bynum, Kimberly M Murray, and David C Goodman, "End-of-life care for Medicare beneficiaries with cancer is highly intensive overall and varies widely," *Health Affairs*, 2012, *31* (4), 786–796.

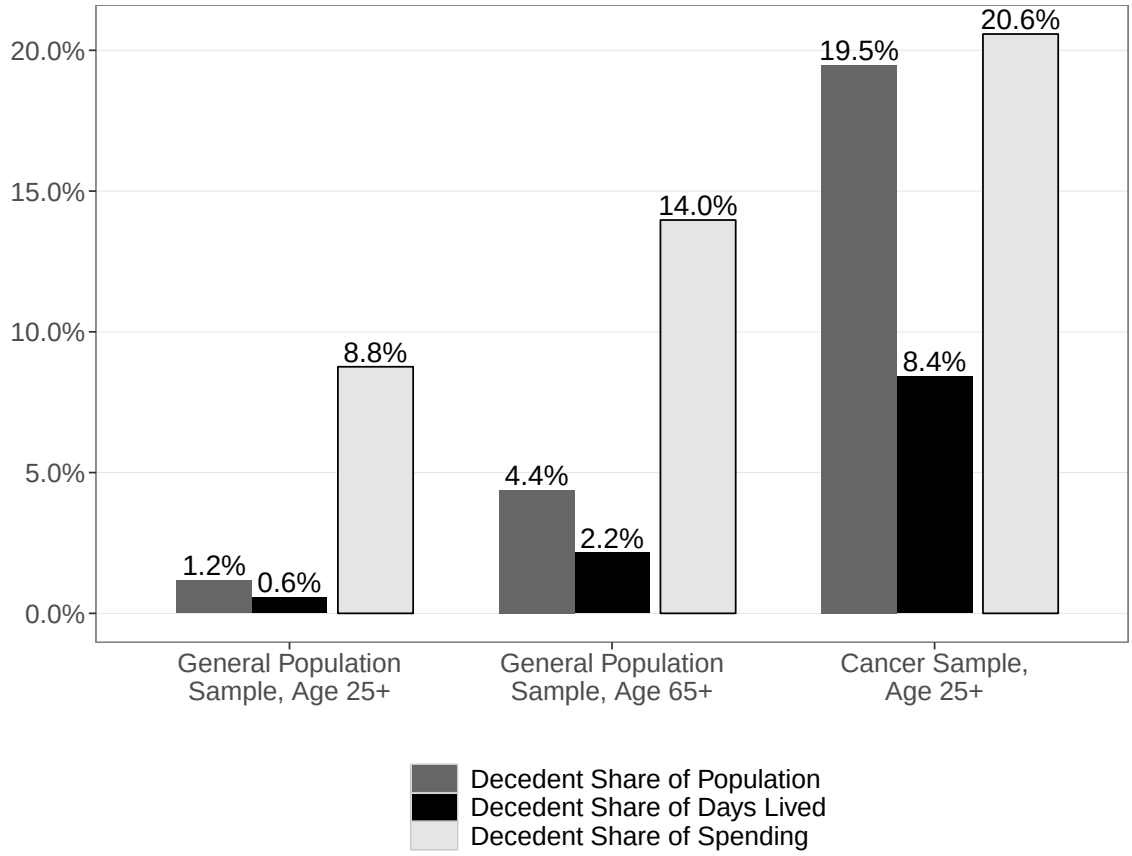
Nicholas, Lauren Hersch, Kenneth M Langa, Theodore J Iwashyna, and David R Weir, "Regional variation in the association between advance directives and end-of-life Medicare expenditures," *JAMA*, 2011, *306* (13), 1447–1453.

Riley, Gerald F and James D Lubitz, "Long-term trends in Medicare payments in the last year of life," *Health Services Research*, 2010, *45* (2), 565–576.

Teno, Joan M, Pedro L Gozalo, Julie PW Bynum, Natalie E Leland, Susan C Miller, Nancy E Morden, Thomas Scupp, David C Goodman, and Vincent Mor, "Change in end-of-life care for Medicare beneficiaries: site of death, place of care, and health care transitions in 2000, 2005, and 2009," *JAMA*, 2013, *309* (5), 470–477.

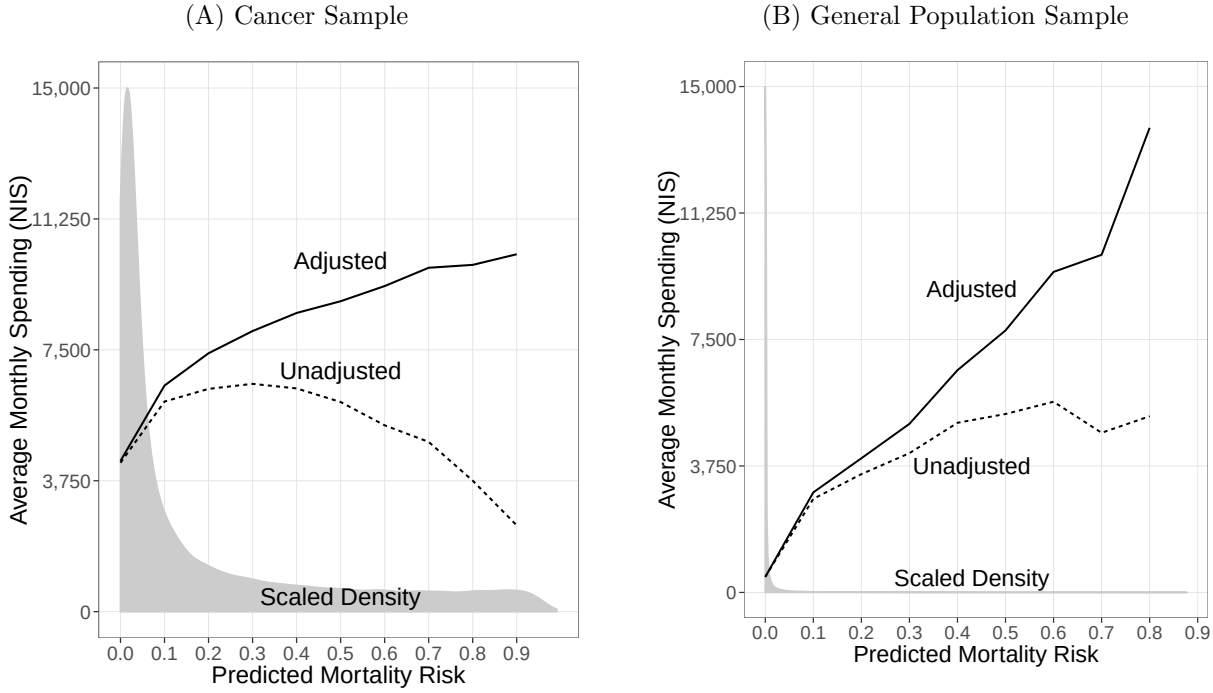
Zeltzer, Dan, Ran D Balicer, Tzvi Shir, Natalie Flaks-Manov, Liran Einav, and Efrat Shadmi, "Prediction Accuracy with Electronic Medical Records Versus Administrative Claims," *Medical Care*, 2019, *57* (7), 551–559.

Figure 1: Spending Concentration, Different Subpopulations



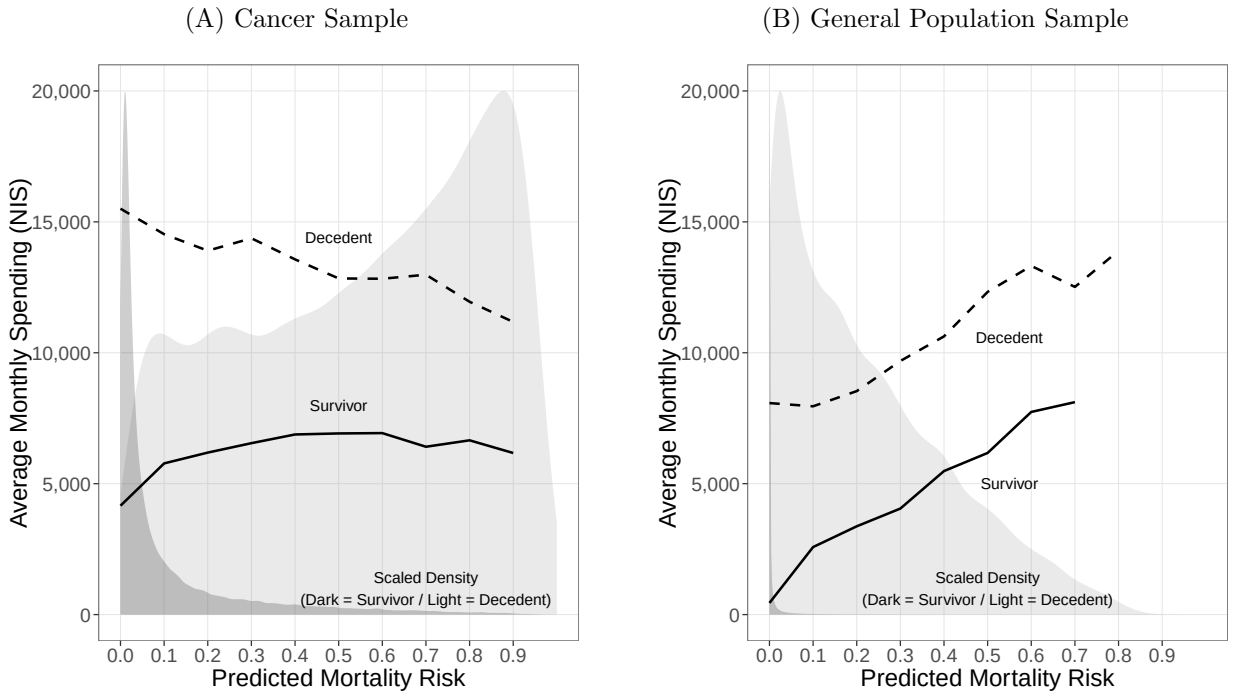
Notes: For the general population, all outcomes are measured from January 1; for the cancer sample, they are measured from the date of diagnosis; we refer to these dates as the "index date." Decedent Share of Population is the share of patients in each sample who died within one year of the index date. Decedent Share of Days Lived is the share of the overall number of days survived by those who eventually die within the year, out of all days survived by patients in the sample (truncated at 365 days for survivors). Decedent Share of Spending is decedent share of overall spending in the 12 months from the index date, not adjusted for differences in survival duration. This figure is based on the full sample ($N = 2.3$ million for the General Population Sample, Age 25+; $N = 534,000$ for the General Population Sample, Age 65+; $N = 166,839$ for the Cancer Sample, Age 25+), which we later randomly split into training and test sets. Sample definitions are discussed in Section 2.

Figure 2: Spending by Predicted Mortality



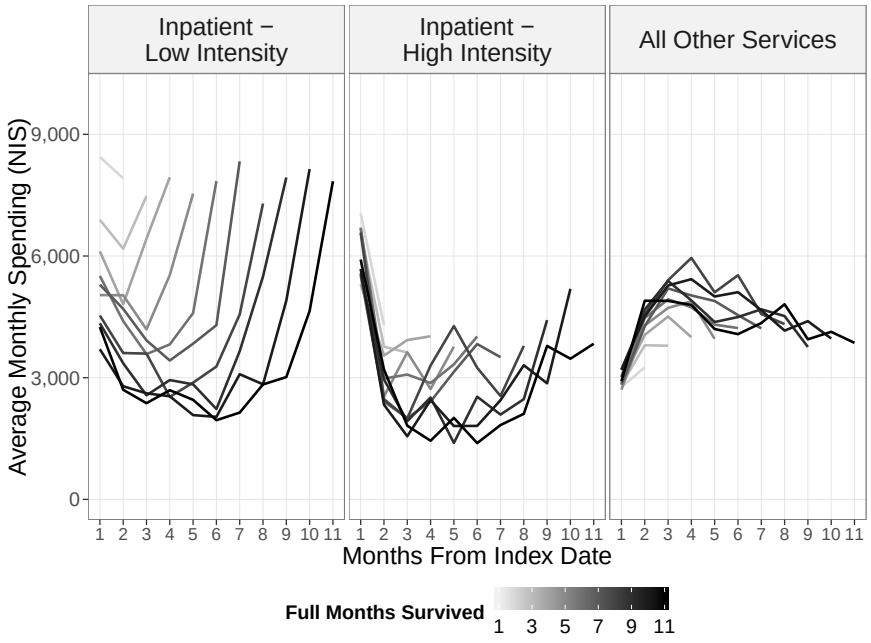
Notes: Figures shows the distribution of annual mortality risk and average adjusted monthly spending in the 12 months post index date as a function of initial predicted mortality risk. The index event is defined as initial cancer diagnosis for the cancer sample, shown in Panel A and January 1, for the general population sample, shown in Panel B. Scaled Density (in gray) is the kernel density estimate of the probability density function of these predictions (which integrates to one), scaled to fit the plot height. Unadjusted spending (dashed line) is average monthly spending, calculated over the entire year following a cancer diagnosis, including months after death with zero spending. Adjusted spending (solid line) is the average spending over the period each patient was alive during the first year after the cancer diagnosis (see equation (1)). All spending measures are in current New Israeli Shekels (NIS). Bins with fewer than 100 patients were omitted.

Figure 3: Decedent and Survivor Spending by Predicted Mortality

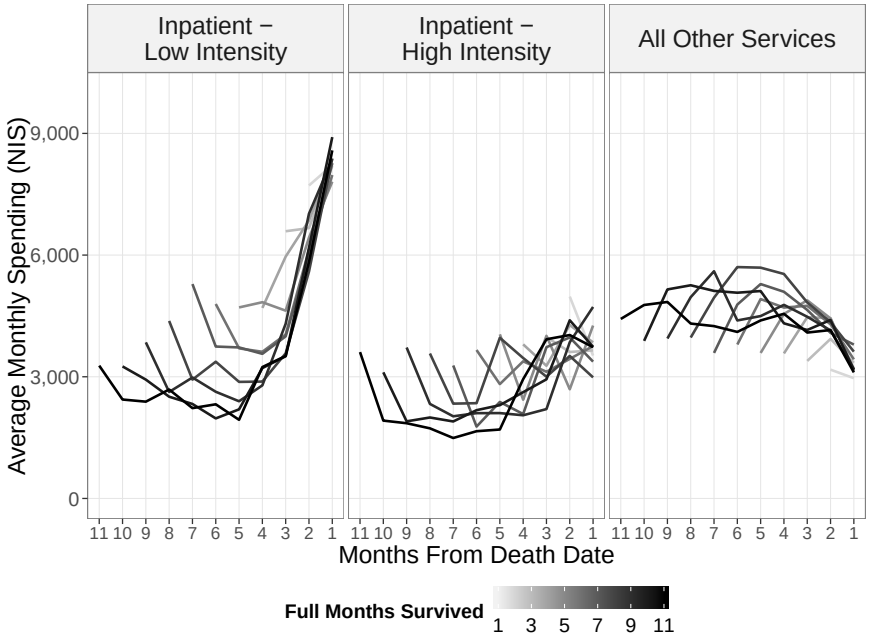


Notes: Figure shows, separately for decedents and survivors, the distribution of annual mortality risk and average adjusted monthly spending in the 12 months post index date as a function of initial predicted mortality risk. The index event is defined as initial cancer diagnosis for the cancer sample, shown in Panel A and January 1, for the general population sample, shown in Panel B. Solid lines show data for Survivors, defined as those patients who survived for at least one year from the index date, and Decedents, defined as those who did not. Decedent spending is adjusted for survival duration (see equation (1)). The shaded areas are scaled densities of predicted mortality for each of these groups. All spending measures are in current New Israeli Shekels (NIS). Bins with fewer than 100 patients were omitted.

Figure 4: Cancer Decedent Spending by Time Before Death and After Diagnosis



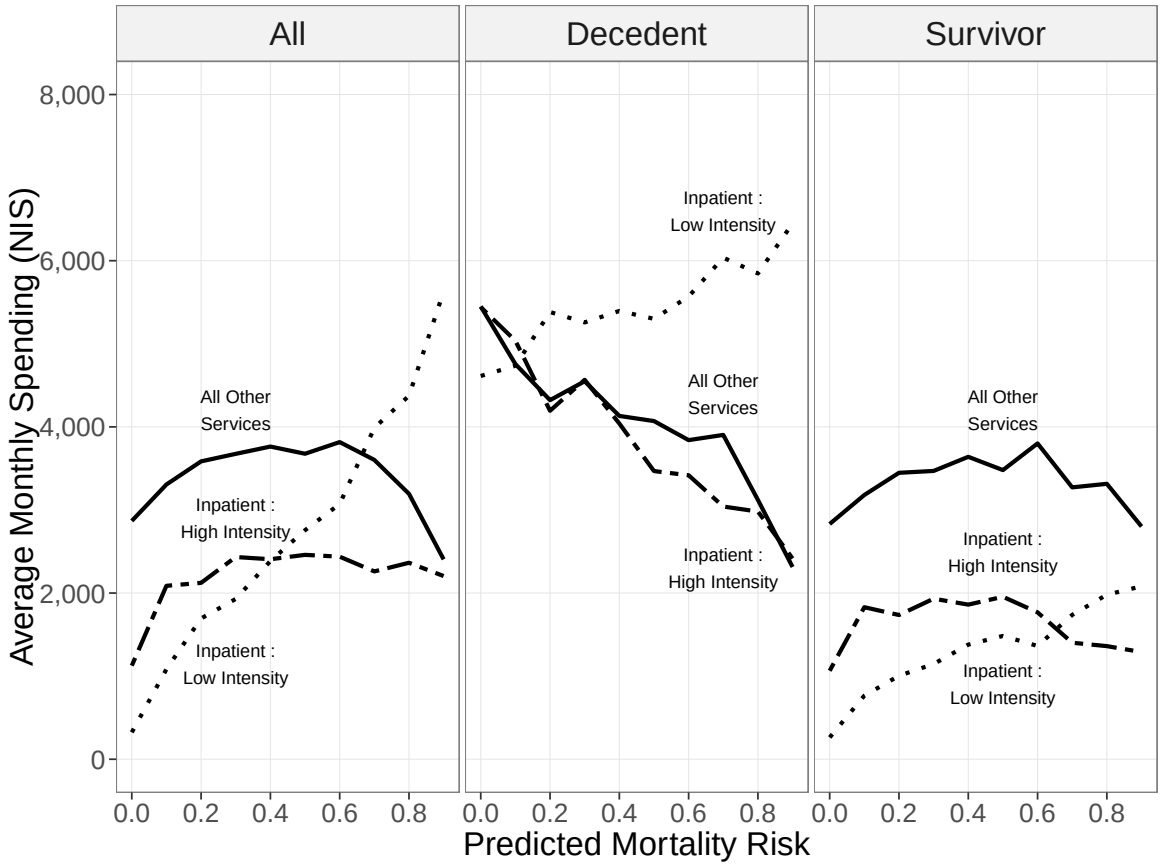
(A)



(B)

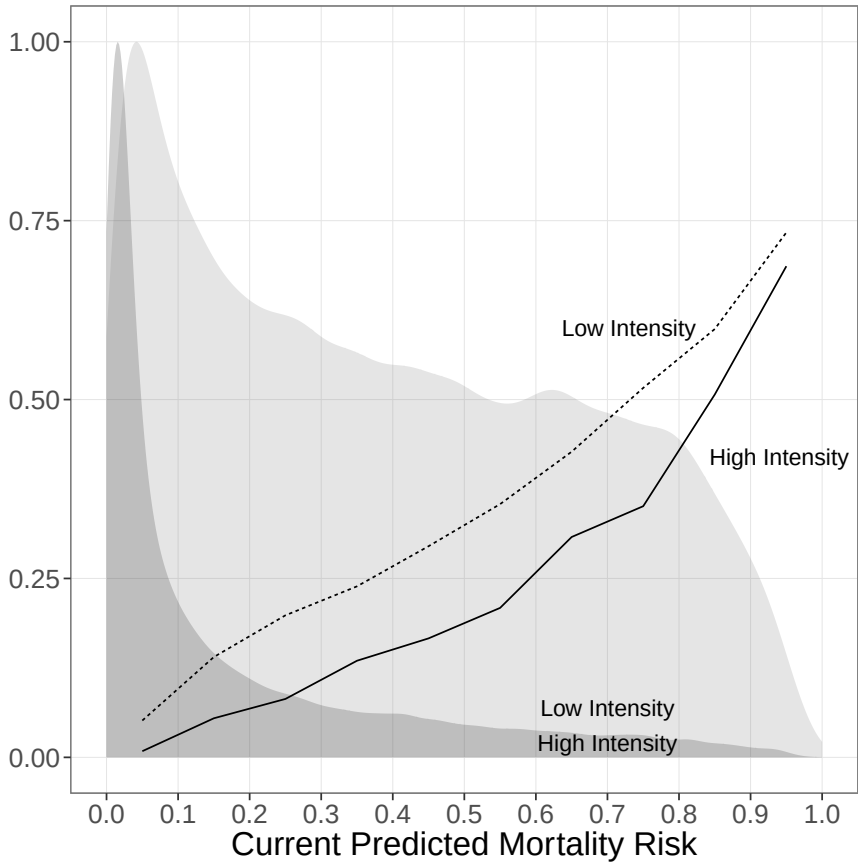
Notes: Both panels show average monthly spending data. In both panels, each line represents average spending for a group of decedents who survived the same integer number of months, excluding partial months' spending, with darker lines representing longer survival. However, in Panel A, the horizontal axis counts the number of months from the index date, whereas in Panel B, the horizontal axis counts the number of months before death. In both cases, we show results separately for low-intensity inpatient admissions, high-intensity inpatient admissions, and all other services. All spending measures are in current New Israeli Shekels (NIS).

Figure 5: Average Monthly Spending on Cancer Patients, by Type of Service and Intensity



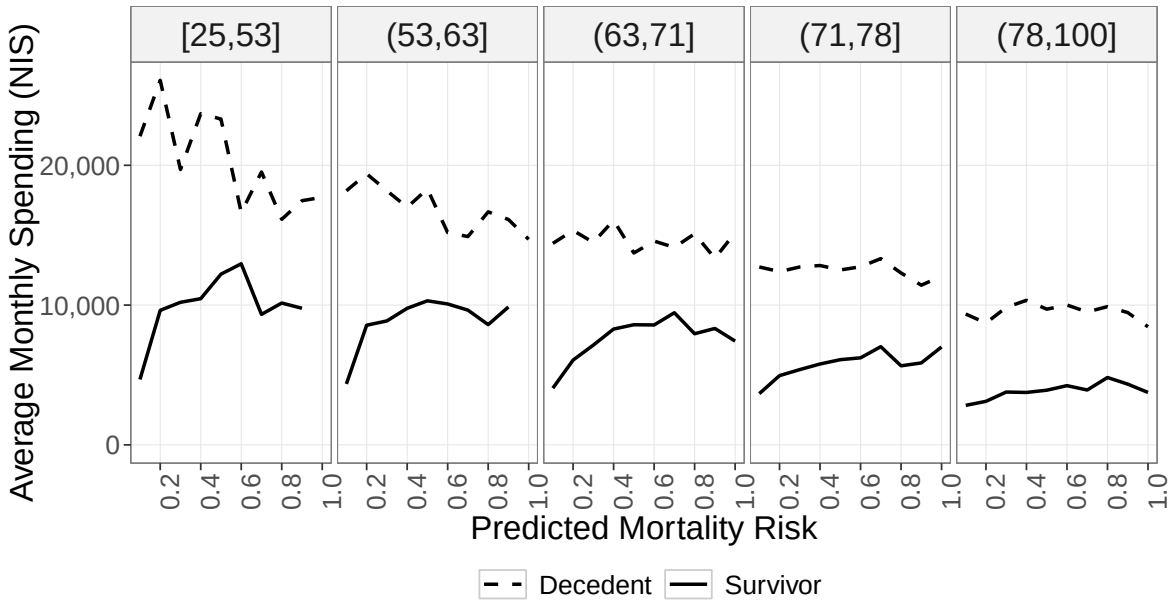
Notes: The figure shows average monthly spending (in the 12 months post diagnosis) as a function of initial predicted mortality risk, separately for low-intensity admissions, high-intensity admissions, and on all other services. Panels show results separately for all patients (left), decedents (middle), and survivors (right). Decedent spending is adjusted for survival duration (see equation (1)). All spending measures are in current New Israeli Shekels (NIS).

Figure 6: Fraction of Admissions Ending in Death Within 60 Days, by *Current* Predicted Mortality



Notes: Figure shows the fraction of admissions ending in death within 60 days of admission, as a function of mortality risk as predicted at the beginning of the month of the admission. Results are shown separately for high-intensity and low-intensity admissions. Shaded areas are scaled densities of predicted mortality risk for high- and low-intensity admissions.

Figure 7: Spending and Mortality of Decedents and Survivors, by Age Quintiles



Notes: Figure shows, separately by age quintiles, average monthly spending on all services by initial predicted mortality risk. Decedent spending is adjusted for survival duration (see equation (1)). The top quintile is top-coded at 100 years of age. All spending measures are in current New Israeli Shekels (NIS).

Table 1: Demographics, Cost, and Mortality

	General Population Sample			Cancer Sample		
	All	Decedent	Survivor	All	Decedent	Survivor
	(1)	(2)	(3)	(4)	(5)	(6)
Characteristics						
Age (mean)	50	78	50	65	73	64
Female (%)	52.4	52.1	52.4	52.1	44.8	53.9
High Socioeconomic Status (%)	21.4	18.8	21.5	23.4	18.7	24.5
Supplementary Insurence (%)	74.8	59.8	75.0	70.1	54.7	73.9
Mortality Rate						
1 month (%)	0.1	10.1	–	3.7	19.0	–
1 year (%)	1.2	100.0	0.0	19.5	100.0	0.0
3 years (%)	3.5	–	2.4	32.4	–	16.0
Utilization						
12 Months Before Index Date						
Average Monthly Spending (NIS)	484	3,648	446	1,406	2,290	1,192
Any Admission (%)	12.1	55.0	11.6	51.4	75.5	45.6
12 Months After Index Date						
Average Monthly Spending (Unadjusted NIS)	556	4,178	514	4,723	4,987	4,660
Average Monthly Spending (Adjusted NIS)	560	8,638	514	5,373	13,140	4,660
Any Admission (%)	12.8	78.8	12.0	73.3	88.3	69.7
Number of Beneficiaries	2,372,582	27,673	2,344,909	166,839	32,517	134,322

Notes: Table shows descriptive statistics for our main samples: the general adult population age 25 and older (columns 1–3) and the subset of the general adult population diagnosed with cancer (columns 4–6). Additional statistics for the subset of the general adult population that is the elderly population (age 65 and older) are shown in Appendix Table A7. This table and Figure 1 describe the full sample, which we later split into training and test sets. All other exhibits are based on the test set. Sample definitions are discussed in Section 2. Columns 1 and 4 shown statistics for all patients; columns 2 and 5 show statistics for ex-post decedents, i.e., those who died within 12 months after the index date; columns 3 and 6 show statistics for ex-post survivors, i.e., those who remain alive after 12 months. The index event is defined as the date of initial prognosis for cancer patients, and January 1 for the general population. Socioeconomic Status is residential zip-code socioeconomic status, sourced from the central bureau of statistics. Supplementary insurance is additional coverage (described in Appendix A). By definition, the mortality rate within one year of the initial prognosis is 100 for decedents and 0 for survivors. Utilization measures are shown for the periods of 12 months before and 12 months after the index date. All spending measures are in current New Israeli Shekels. Spending adjustment for decedent survival duration is described in Section 2. All spending measures are in current New Israeli Shekels (NIS); during our study period the exchange rate was about 4 NIS per USD.

Table 2: Average Monthly Spending of Cancer Patients

Category	Survivor		Decedent	Difference	
	Unweighted	Reweighted by Decedent Risk	Adjusted for Survival Duration	Decedent - Survivor (Reweighted)	Percent of Total Difference
	(1)	(2)	(3)	(4)	(5)
Total	4,664	6,151	13,189	7,038	100.0
All Inpatient:	1,733	2,867	9,152	6,284	89.3
Unplanned	408	905	4,019	3,114	44.2
Planned	1,325	1,962	5,133	3,171	45.1
Low Intensity	480	1,270	5,302	4,032	57.3
High Intensity	1,252	1,597	3,850	2,252	32.0
Other Services:	2,931	3,284	4,037	753	10.7
Outpatient	1,237	1,267	1,565	298	4.2
Drugs	1,117	1,442	1,724	282	4.0
Imaging	190	203	222	19	0.3
Other	387	371	526	155	2.2

Notes: Table shows average monthly spending in the 12 months post cancer diagnosis. Columns show results separately for decedents and survivors. Decedent spending is adjusted for survival duration (see equation (1)). Survivor spending in column 2 is reweighted by decedent risk (see equation (2)). Decedent−Survivor is the difference between Decedent and Survivor (Reweighted) spending. All spending measures are in current New Israeli Shekels (NIS). First row shows total healthcare spending, and subsequent rows show various partitions. All Inpatient refers to spending on all services that are delivered during hospital admissions and Other Services refers to spending on all services that are not part of an admission. Within inpatient, we partition into low intensity versus high intensity, and unplanned versus planned. Low intensity refers to admissions into one of four wards: Internal Medicine, Oncology, Rehabilitation, and Geriatric, which Appendix Table A2 shows involve the lowest average daily admission and few surgeries; High intensity is admission to all other wards. Unplanned refers to admissions through the emergency department; Planned refers to all other admissions. Within Other Services we partition into Outpatient, Drugs, Imaging, and Other. Outpatient, Drugs, and Imaging refer to hospital outpatient services, prescription drugs, (except those administered during admissions), and diagnostic radiology services not during an admission.

Table 3: Admission Statistics for Cancer Patients

	Survivor		Decedent	Difference
	Unweighted	Reweighted by Decedent Risk	All Admissions	Decedent - Survivor (Reweighted)
	(1)	(2)	(3)	(4)
A. Any Admission				
All	0.714	0.796	0.883	0.087
Low Intensity	0.263	0.550	0.771	0.221
High Intensity	0.626	0.538	0.469	−0.069
B. Admissions per Month (if Any During the Year)				
All	0.230	0.314	0.814	0.500
Low Intensity	0.093	0.191	0.590	0.399
High Intensity	0.137	0.123	0.224	0.101
C. Length of Stay (Days)				
All	5.971	7.565	9.255	1.690
Low Intensity	6.395	7.351	8.774	1.423
High Intensity	5.685	7.896	10.521	2.625

Notes: Table shows admission statistics in the 12 months post cancer diagnosis. Columns show results separately for survivors and decedents. Survivor statistics in column 2 are reweighted by decedent risk (see equation (2)). Decedent−Survivor is the difference between Decedent and Survivor (Reweighted) outcomes. In Panel A, any admission shows the fraction of patients with any admission at any time during the first year after initial diagnosis; this is not adjusted for survival duration. In Panel B, to adjust for survival duration, decedent average number of admissions per month is calculated over the period during which each patient was still alive. In Panel C, length of stay is the average duration of stay, over all admissions. Within each panel we partition admissions into low-intensity and high-intensity admissions, as described in the text. Statistics for the general population are shown in Appendix Table A10.

Table 4: Inpatient Procedures by Admission Time Before Death

	Procedure Type, Admission with Any (%)						
	Maintanance	Diagnostics	Surgery	Radiation	Chemotherapy	Other	N of Admissions
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Decedent, by time before death							
Last month	11.5	98.5	9.4	4.3	5.1	0.7	10,606
1–3 months	11.4	95.8	11.2	6.8	9.8	0.9	7,825
4–12 months	11.3	94.4	16.2	6.3	15.6	1.5	9,724
Survivor	9.0	90.2	33.4	2.9	7.6	1.1	73,771
All	9.6	91.9	27.6	3.7	8.3	1.1	101,926

Notes: The fraction of sampled admissions that included procedures of different types. Sampled admissions include Clalit-owned-hospital admissions that started and ended during the year after diagnosis. Appendix Table A8 shows data separately for unplanned and planned admissions and for high- and low-intensity admissions.

Table 5: Average Monthly Spending of Cancer Patients, by Age Quintile

		Survivor		Decedent	Difference
	Age Quintile	Unweighted	Reweighted by Decedent Risk	Adjusted for Survival Duration	Decedent - Survivor (Reweighted)
	(1)	(2)	(3)	(4)	(5)
A. All Cancer Types	[25, 53]	5,395	9,924	20,415	10,490
	(53,63]	5,225	8,976	16,887	7,910
	(63,71]	4,832	7,716	14,572	6,856
	(71,78]	4,326	6,096	12,445	6,349
	(78,100]	3,365	3,981	9,513	5,532
A. By Cancer Type					
Breast	[25, 53]	6,904	7,258	12,897	5,639
	(78,100]	2,481	2,523	6,597	4,074
Prostate	(53, 63]*	2,757	5,921	11,061	5,140
	(78,100]	2,646	2,737	7,168	4,431
Colon	[25, 53]	6,252	7,071	18,391	11,320
	(78,100]	3,739	3,562	9,562	6,000
Bronchus and Lung	[25, 53]	7,875	9,220	15,210	5,990
	(78,100]	4,757	4,376	9,213	4,836
Skin	(53, 63]*	1,499	2,313	15,820	13,507
	(78,100]	1,718	2,475	7,168	4,693
Bladder	[25, 53]	1,987	4,278	14,011	9,733
	(78,100]	2,607	3,149	10,406	7,257
Hematopoietic System	[25, 53]	15,285	18,591	49,118	30,528
	(78,100]	3,824	4,123	10,145	6,022
Lymph Nodes	[25, 53]	9,516	12,196	31,512	19,316
	(78,100]	7,052	7,867	13,244	5,378
Stomach	[25, 53]	6,602	8,151	17,678	9,527
	(78,100]	4,608	4,220	9,240	5,020

Notes: Table shows average monthly spending in the 12 months post cancer diagnosis for different age groups, by quintiles of patient age at the time of cancer diagnosis. Column 1 shows the age range, with square brackets and parentheses denoting included and excluded endpoints, respectively. Columns 2–4 show results separately for decedents and survivors. Decedent spending is adjusted for survival duration (see equation (1)). Survivor spending in column 2 is reweighted by decedent risk (see equation (2)). Decedent−Survivor (column 5) is the difference between Decedent and Survivor (Reweighted) spending. All spending measures are in current New Israeli Shekels (NIS). Panel A shows results for all cancer types, by patient age quintile. Panel B shows results for youngest and oldest age quintiles, for the most common cancer types in our sample. For cases marked by *, the youngest age group [25,53] did not have sufficiently many decedents in all bins for reweighting, so the second-youngest age group (53,63] is shown instead.

Appendix A Israeli Health Insurance System and our Data Provider

In accordance with the 1995 National Healthcare Law, four HMOs provide universal, tax-funded health insurance coverage to all Israeli residents from birth. Coverage has two tiers.

The first tier is a "basic," universal tier that covers hospital, outpatient, office consults, preventive medicine and immunization, diagnostic tests, imaging, drugs, and durable medical equipment (the types of services covered by this universal tier are similar to Medicare Parts A, B, and D). For the universal tier, HMOs receive risk-adjusted capitated payments from the government; premiums are fully subsidized. Patients pay copays for outpatient, emergency, imaging services, and drugs (oncological drugs are exempt from copays). There are no copays for inpatient services. Chronic patients have a maximum out-of-pocket cap of NIS 800 (approximately USD 200) per quarter. The set of services covered under the universal tier (known as the "basket") is reviewed and expanded every year by a professional committee that ranks new technologies to match a predetermined budget increase. Enrollees can switch HMOs every other month and maintain their universal coverage, but the annual switching rate is very low, less than 1%. Clalit therefore continuously collects data on a relatively stable population of enrollees.

The second, coverage tier is a supplementary insurance tier that provides lower copays and additional services, such as enhanced prenatal testing, alternative medicine, and a choice of surgeon for elective surgeries. The supplementary tier is elective (80% of members choose it) and funded by insurance premiums paid by enrollees. Other than by age, premium rates do not vary across individuals. They range from approximately NIS 400 (approximately USD 100) per year for 25-year old enrollees to approximately NIS 1,800 (approximately USD 450) for elderly enrollees (aged 70 or older). Supplementary coverage can be added or dropped every month. To prevent selection, there are service-specific waiting periods for supplementary benefits (e.g., the waiting period is three months for alternative medicine

services and 12 months for oncology benefits not covered by the basic tier, which include second opinion consults, psychotherapy and dietary consults, cost of travel to treatments, and home nursing).

Clalit Health Services has an integrated delivery system. Most of its physicians are salaried. Until 2008, hospitals were reimbursed per diem. Since 2008, for a set of conditions (such as surgeries), hospital reimbursement is based on a procedure-related grouping of services. Patients can also utilize services from external providers, which in non-emergent cases require preauthorization. Our data include detailed claims information for these services.

Appendix B Mortality Predictors

For training our algorithm that predicts mortality at the time of initial diagnosis, we use administrative patients records. These records are maintained by Clalit Health Services and include patient demographic information and zip code location sourced directly from the Ministry of the Interior, detailed claims and EMR data for Clalit Health Services members, and cancer diagnosis information form the national cancer registry. Appendix Table A11 shows summary statistics for a small subset of predictors, showing that they are extremely balanced across the train and test data sets, as expected thanks to the large sample size. The rest of this section describes the set of predictors we use. With the exception of cancer diagnostic data, which is recorded at the day of initial diagnosis, all other data are from the year prior to the initial diagnosis date.

Demographic Data

Demographic data include the following predictors: patient age in years, patient sex, patient ethnicity, patient primary care clinic, socioeconomic status (calculated by the Israeli Central Bureau of Statistics based on residential location), a dummy for whether the patient place of birth is Israel, year of immigration (obtained from government administrative records), and district code. In addition, we also include the following binary (dummy) flags for whether

the patient lives at home or is institutionalized, whether the patient is receiving nursing care at home, whether the patient level of income is exempt from national social security payments, and whether the patient has supplementary insurance coverage (described in Appendix Section A). There are 13 predictors in this group.

Administrative Claims Data

Our first set of claims-based predictors are cost and utilization measures, defined as the total annual cost and event count for each of the following service categories: hospital admissions (planned and unplanned, defined based on whether the admission was through the emergency room); prescription drugs; diagnostic outpatient services; nonsurgical outpatient procedures; surgical outpatient procedures; emergency department visits; primary care visits; specialist consults; laboratory tests; mental health services; imaging; immunization; nursing clinics; dental; rehabilitation; para-medical procedures; alternative-medicine; and durable medical equipment. There are 46 predictors in this group.

Our second set of claims-based predictors are flags for the following chronic conditions or patient health behaviors: Chronic condition flags: Anxiety, Arrhythmia, Arthropathy, Asthma, Blindness, CHF, COPD, CRF, CVA, Deafness, Depression, Diabetes, Disability, Drug, Gastritis, Glaucoma, Hyperlipidemia, Hypertension, Hypothyroidism, IHD, Kidney, Prior malignancy (ever; actively treated in the past five years), Neurological, Neuroses, Osteoporosis, Peptic Ulcer, Prostatic, Valvular Cardiac, and Other. There are 33 predictors in this group.

Our third set of claims-based predictors includes Johns Hopkins Adjusted Clinical Groups (ACG) scores, which is a commercial grade classifier that was validated in Clalit and is used to evaluate morbidity burden. We use the following scores: predicted probability of admission, by type; Resource Utilization Band; Aggregated Diagnosis Groups; predicted probability of high spending in the following year; predicted probability of major events in the following year. See Johns Hopkins Adjusted ACG Version 11.0 documentation for details and definitions of these predictors. There are 51 predictors in this group.

Our fourth set of claims-based predictors includes information on prescription drugs. We consider ATC1-level dispensing events in the previous year. For each of the ACT1 groups, we calculate the following statistics: flag for whether the patient had any event, the number of prescription events, and the number of days since the first and the last prescription event and flags for ten types of controlled substance prescriptions. There are 108 predictors in this group.

Electronic Medical Records Data

EMR data are sourced from patient records that are maintained by EMR systems of Clalit Health Services. These include: Body Mass Index (BMI), Vital signs (value and days since last measurement), reported alcohol use, substance abuse, and smoking status and days since last status evaluation by a physician.

In addition, we use laboratory test results for the 50 most common tests. For each laboratory test, we include a flag for whether it was performed, days since the test was performed, and the most recent result.[10] There are 200 predictors in this group.

We also use EMR information on ATC1-level prescriptions. Prescription events recorded in EMR and are distinct from dispensing information recorded in insurance claims, as EMR records include unfilled prescriptions. We record the number of prescriptions made in the previous year, a flag for whether there were any prescriptions made, and the number of

[10]We include the following tests: Abnormal lymphocytes (ALY) - absolute, Abnormal lymphocytes (ALY) - percent, Anisocytosis - percent, Band form neutrophils (STAB) - absolute, Band form neutrophils (STAB) - percent, Basophils (BASO) - absolute, Basophils (BASO) - percent, Blasts - percent, Eosinophils (EOS) - absolute, Eosinophils (EOS) - percent, Eosinophils (EOSINOP) - percent, Eosinophils (EOSINOPH) - absolute, Hematocrit (HCT), Hematocrit/Hemoglobin ratio, Hemoglobin (HB), Hemoglobin distribution width (HDW), Hypochromia (HYPO) - percent, Immature cells - absolute, Immature cells - percent, large unstained cells (LUC) - absolute, large unstained cells (LUC) - percent, Leukocytes Left Shift (L-shift), Lymphocytes (LI), Lymphocytes (LY) - absolute, Lymphocytes (LY) - percent, Lymphocytes (LYM) - absolute, Lymphocytes (LYMP) - percent, macrocytic (MACRO) - percent, Mean corpuscular hemoglobin (MCH), Mean corpuscular hemoglobin concentration (MCHC), Mean corpuscular volume (MCV), Mean myeloperoxidase index (MPXI), Mean platelet volume (MPV), Microcytes (MICR) - percent, Microcytes (MICRO) - percent, Monocyte (MON) - absolute, Monocyte (MONO) - percent, Monocyte (MONOCYT) - absolute, Monocyte (MONOCYT) - percent, Neutrophils (NEU) - absolute, Neutrophils (NEU) - percent, Neutrophils (NEUT) - absolute, Neutrophils (NEUT) - percent, Neutrophils hypersegmented (HYPER) - percent, Platelet (PLT), Platelet distribution width (PDW), Procalcitonin (PCT), Red blood cells (RBC), Red Cell Distribution Width (RDW), White blood cell (WBC).

days since the first and last prescription of each type. Based on the difference between prescription and dispensing events, we calculate the following drug adherence measures: Medication Possession Ratio (MPR) and Proportion of Days Covered (PDC) during the previous year.

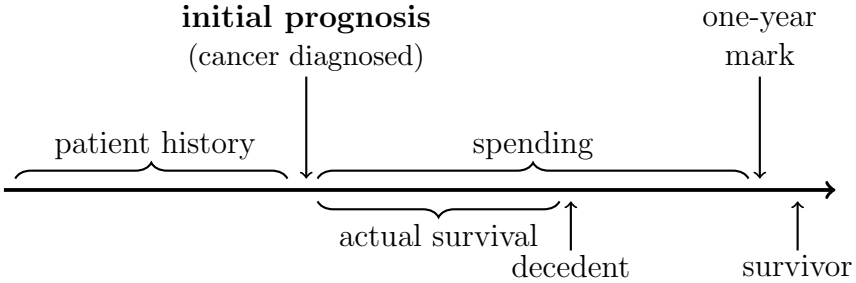
Cancer Diagnostic Data

For each initial cancer diagnosis, we observe the following: cancer type (hierarchically grouped, based on topography), morphology, ICD9 code, stage, and grade. There are nine categorical predictors in this group. One limitation of the national cancer registry data is that stage and grade reporting is not mandatory, and therefore partial. Whenever available, we included stage and grade data in training the prediction algorithm. For the rest of the analysis, we categorized cancer cases based on topography.

Appendix C Construction and Performance of Prediction Algorithm

Construction

We predict one-year mortality from the date of cancer diagnosis or, for the general adult population, from January 1, 2013. The timing is illustrated below. We refer to this predicted one-year mortality as the patient's "initial prognosis."



To predict one-year mortality, we used Extreme Gradient Boosting (XGBoost), a sequential ensemble prediction algorithm from Chen and Guestrin (2016). In each step, the

algorithm fits residuals of the previous step. Initializing the vector of predicted outcomes to be constant, each iteration greedily improves the prediction by following the steps:

1. Greedily grow a tree to $y^{(k)}$, minimizing a loss (criterion) function
2. Grow a new tree to the residuals $e^{(k)} = y - \hat{y}^{(k)}$ and obtaining $\hat{e}^{(k)}$
3. Add the predicted residuals to the previous prediction: $\hat{y}^{(k+1)} = \hat{y}^{(1)} + \alpha\hat{e}^{(k)}$, where α is a learning-rate parameter.

To avoid overfitting, the criterion function penalizes model complexity. Hyper-parameters, including the learning rate, the penalty weight, and the tree maximal depth are tuned using cross validation. The method was implemented using the XGBoost package in R, which is available at The Comprehensive R Archive Network (CRAN).

Because mortality is a relatively low-probability event, a decent overall fit can be obtained by predicting that the outcome never occurs. To avoid this problem, we follow the common practice and "down-sample" the survivor share in the training sample. We consider the subsample of the training sample consisting of all decedents and an equal number of randomly sampled survivors. This yields a balanced sample with a mortality rate of 50%. Predicted mortality scores are then adjusted using Bayes' rule, as follows:

$$Pr[D|Balanced] = \frac{Pr[D]Pr[Balanced|D]}{Pr[D]Pr[Balanced|D] + (1 - Pr[D])Pr[Balanced|S]}, \tag{3}$$

where D and S denote the events of dying and surviving and $Balanced$ denotes the event of being sampled to the balanced sample (conditioning on individual characteristics, X is omitted for brevity). By construction, $Pr[Balanced|D] = 1$ and $Pr[Balanced|S] = \frac{\mu_D}{1-\mu_D}$, where μ_D is the overall mortality rate (in the training sample).

To avoid overfitting, we use cross validation. Namely, we randomly split our original sample into two equally sized training and test samples. To make sure the split is reproducible, we sample individuals based on the division remainder of an MD5 cryptographic

hash function applied to their national ID number. Such sampling procedure is commonly used in large databases. Its advantage over using a random seed is that it determines the assignment of each individual independently of the assignment of others while being randomly distributed in the population. Appendix Table A11 shows that the random split yields balanced training and test samples. The training sample is used only for fitting the predictive model. The trained model is then used to predict mortality in the test sample, which is kept untouched during the training phase, and over which the rest of the analysis is performed. All results are shown for the test sample.

Performance

The algorithm appears to perform well. Appendix Figure A5 shows the model calibration for the general population and the cancer sample. The test AUC (area under the receiver operating characteristic curve) is above 95.7 for the general population sample and 91.4 for the cancer sample, which reflects high precision and recall.[11] It is only slightly lower than the train AUC (which is 98.2 and 95.7, respectively). The algorithm performance matches or improves on other attempts to predict mortality. Using self reported health status of veterans to predict mortality, DeSalvo et al. (2005) obtain an AUC of 0.74. Using administrative prescription data, Genevès et al. (2017) obtain an AUC of 0.81. Using Medicare Claims data and an ensemble of classifiers, Makar et al. (2015) obtain an AUC of 0.82 and Einav et al. (2018) obtain an AUC of 0.87. for admitted patients in Israel, and Zeltzer et al. (2019) obtain an AUC of 0.91.

To quantify the relative contribution of different predictors to predictive performance, we calculate the gain of different predictors. Gain is a measure of the increase in prediction accuracy after each predictor is added to the model and normalized so that the overall

[11] A receiver operating characteristic curve, or ROC curve, is a plot that quantifies the diagnostic ability of a binary classifier system as its discrimination threshold is varied. It is created by plotting the true positive rate (sensitivity) against the false positive rate (one minus specificify) at various threshold settings. The area under this curve is a widely used measure of classification performance. It reflects the probability that given two randomly sampled patients, one who died and one who survived, the model will assign a higher probability of death to the former.

contribution of all predictors is 100% (for details, see Chen and Guestrin, 2016). Higher gain implies a predictor is more important for generating a prediction. For the cancer sample, the most important features in predicting mortality, as measured by gain (in parentheses), are cancer type (0.092), patient age (0.085), number of unplanned admissions days the year prior to the initial diagnosis of cancer (0.067), and whether the patient had prior malignancy in the five years prior to the initial cancer diagnosis (0.024). For the general population, the most predictive features are the probability of extended hospitalization, as predicted by the ACG classifier based on prior utilization (0.340), ACG-predicted probability of hospitalization with an injury (0.101), age (0.077), and whether the patient was ever diagnosed with cancer (0.032).

Appendix D Current Risk Prediction

This section describes our construction and use of a predictor of current mortality risk. The analysis consists of two steps. First, we predict risk at a monthly frequency. Second, we calculate spending as a function of monthly risk, reweighting survivor spending by decedent risk.

In the first step, we predict one-year mortality each month, beginning with the month of initial diagnosis. (For example, for a patient who died 100 days after the index date, we predict mortality using all available information at the index date and one, two, and three months following the index date.) We then associate each individual with a history of predicted mortality scores, $(\hat{p}_0, \hat{p}_1, \hat{p}_2, \ldots, \hat{p}_{11})$, where $l \leq 11$ for decedents and $l = 11$ for survivors.

In these predictions, we use the same predictive model and types of predictors as we used to generate the predictor of initial mortality risk, but we include all interim information that is available at the time of prediction, including events that occurred after the index date. We obtain comparable levels of accuracy (train AUC between 91.3–97.7; test AUC between 87.4–91.4). Appendix Figure A6 shows boxplots of the distribution of one-year mortality risk

as predicted at different number of months after the index date. Over time, the composition of those still alive changes, so the mean decreases. However, all distributions have a thick right tail.

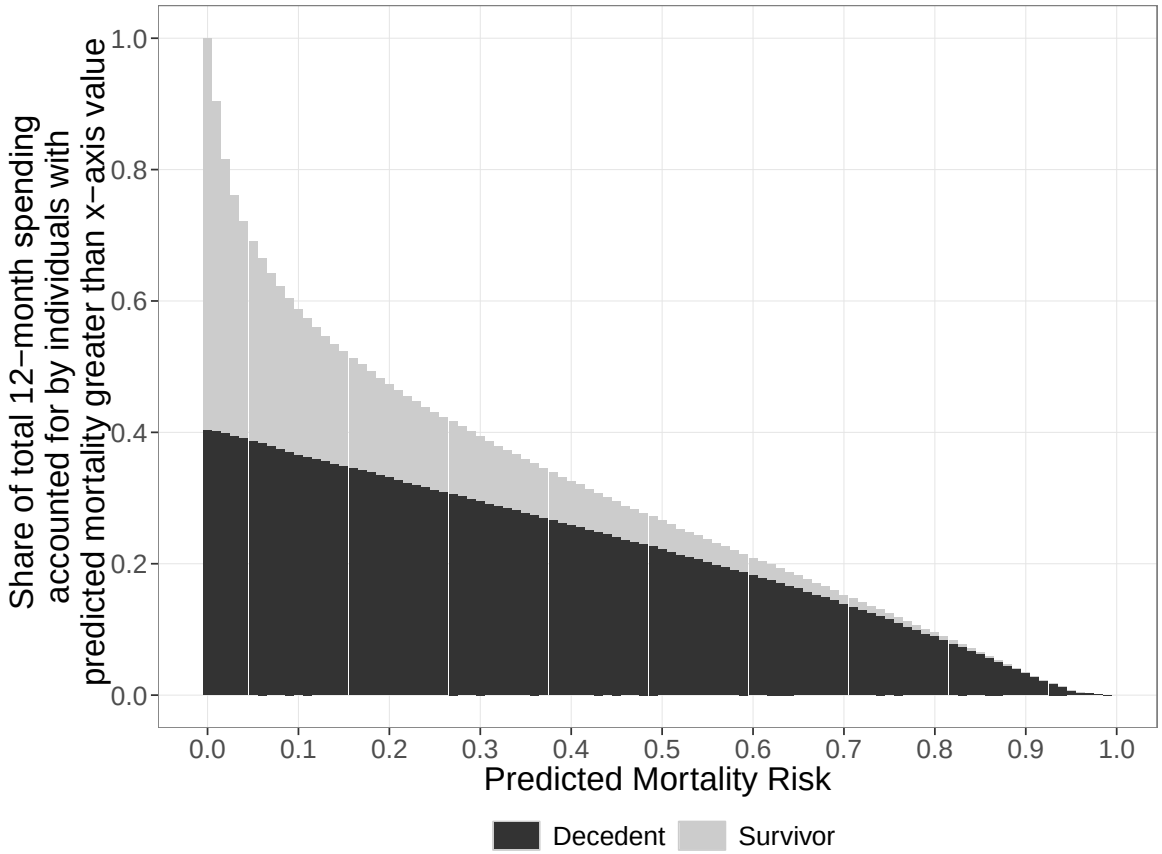
In the second step, we calculate average adjusted monthly spending as a function of predicted interim risk, as follows. For each individual i, we calculate the sequence of monthly spending, $(y_{i1}, y_{i2}, \ldots, y_{il})$, and also keep track of the number of days survived each month, $T_{it} \in (1, 30]$. We then bin the predicted mortality scores of all person-months by partitioning the interval $[0, 1]$ to 20 equally-sized bins. Denote this partition $\Pi = \{\pi_1 = [0, 0.05), \pi_2 = [0.05, 0.1), \ldots, \pi_{20} = [0.95, 1)\}$. Let μ^I for $I \in \{D, S\}$ be the weights of decedent- and survivor-months in each bin. $\mu^I(\pi) = \frac{\#\{(i,t)|\hat{p}_{it} \in \pi, i \in I\}}{\#\{i|i \in I\}}$, so $\sum_{\pi \in \Pi} \mu^I(\pi) = 1$ for $I \in \{D, S\}$. For each bin $\pi \in \Pi$, we calculate the average adjusted monthly spending, separately for survivors and decedents:

$$\bar{y}^I(\pi) = \sum_{\{i,t:\hat{p}_{it} \in \pi, i \in I\}} \frac{y_{it}}{T_{it}/30}. \tag{4}$$

Finally, we reweight survivor spending by decedent interim risk:

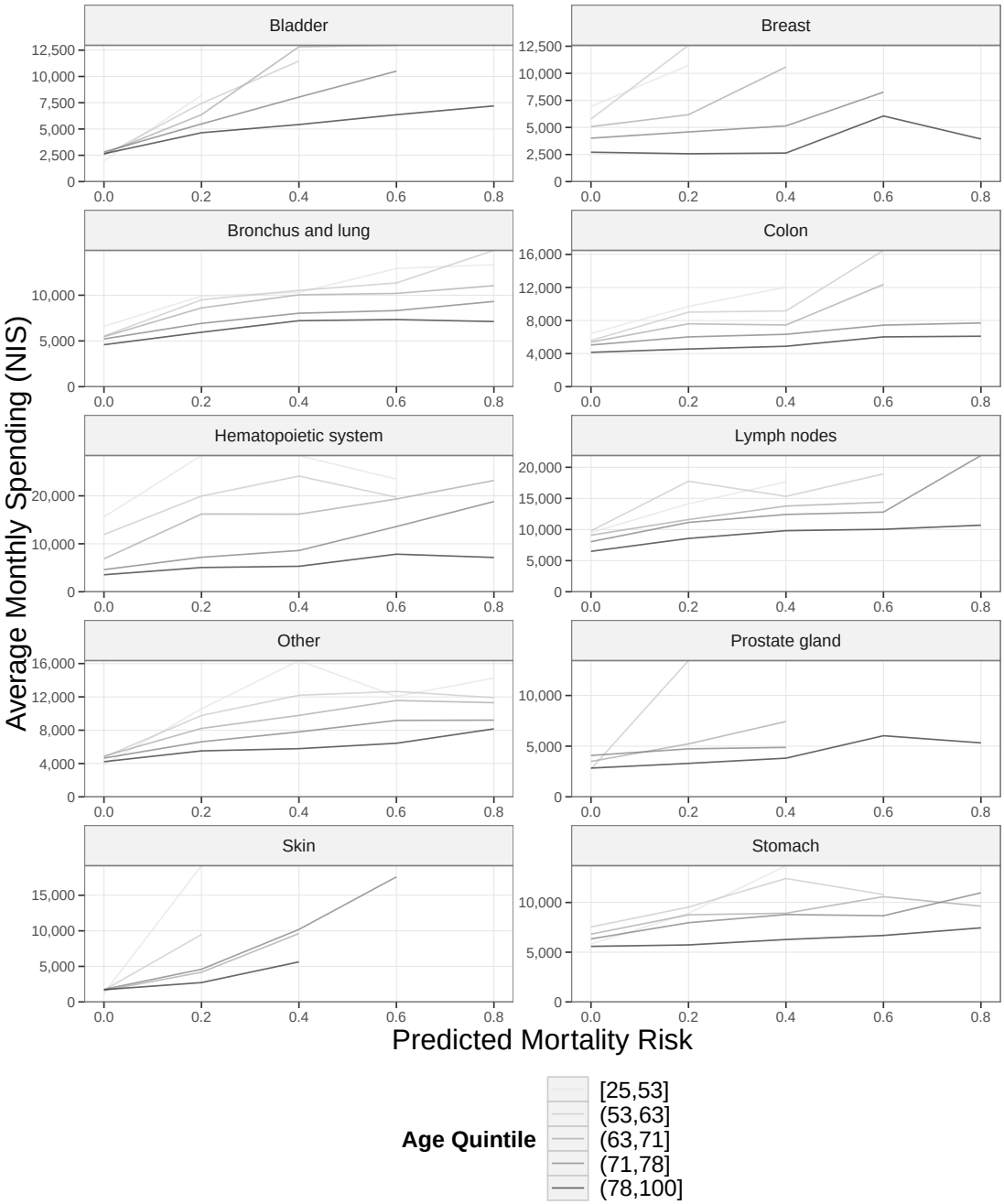
$$\bar{y}^{S^{\text{reweighted}}} = \sum_{\pi \in \Pi} \bar{y}^S(\pi) \mu^D(\pi). \tag{5}$$

Appendix Figure A1: The Share of Total Adjusted Spending Accounted for by Individuals with Different Prognoses



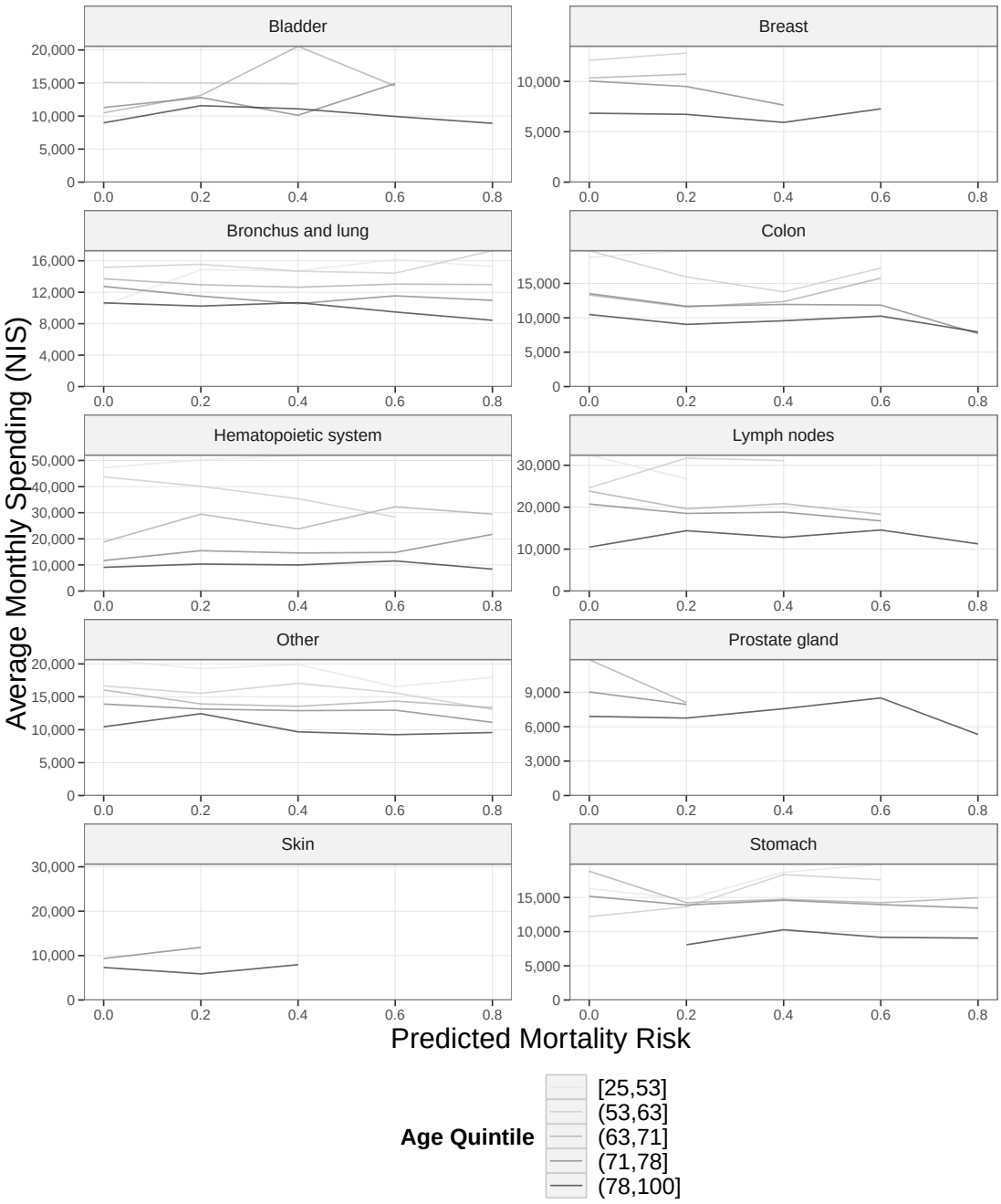
Notes: For each prognosis—predicted one-year mortality risk at the time of initial cancer diagnosis—the figure shows the fraction of spending during the 12 month following the initial diagnosis that is accounted for by decedents and survivors whose predicted mortality probability is greater than each value. The dark shaded bars show the share of Decedent spending. The light shaded bars show the share of Survivor spending. Bars are stacked. Decedent spending is adjusted for survival duration (see equation (1)). Appendix Figure A1 shows the same analysis without adjusting for survival duration.

Appendix Figure A2: Spending and Mortality, Separately by Cancer Type and Age Quintile



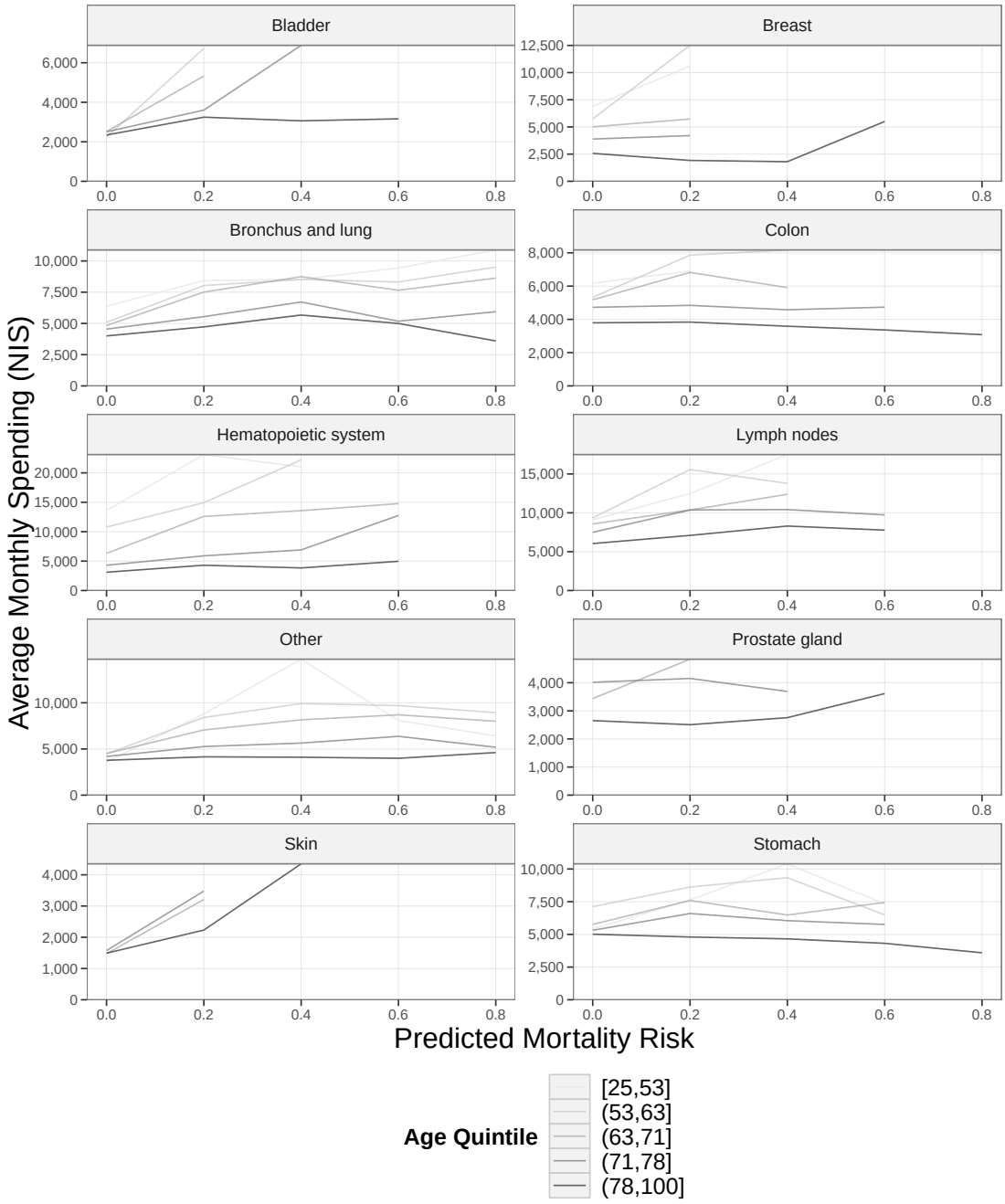
Notes: Figure shows the average monthly spending on all services over predicted mortality risk at the time of initial cancer diagnosis, for the most common cancer types in our sample. Each facet shows data for one cancer type. Different lines within each facet represent different age quintiles, with darker lines for older age groups, as described in the legend at the bottom of the figure. Age ranges are shown with square brackets and parentheses denoting included and excluded endpoints, respectively. Spending is adjusted for survival duration (see equation (1)). Data points based on fewer than ten patients are not shown. Results separately for decedents and survivors are shown in Appendix Figure A3 and Appendix Figure A4.

Appendix Figure A3: Spending and Mortality of Decedents, Separately by Cancer Type and Age Quintile



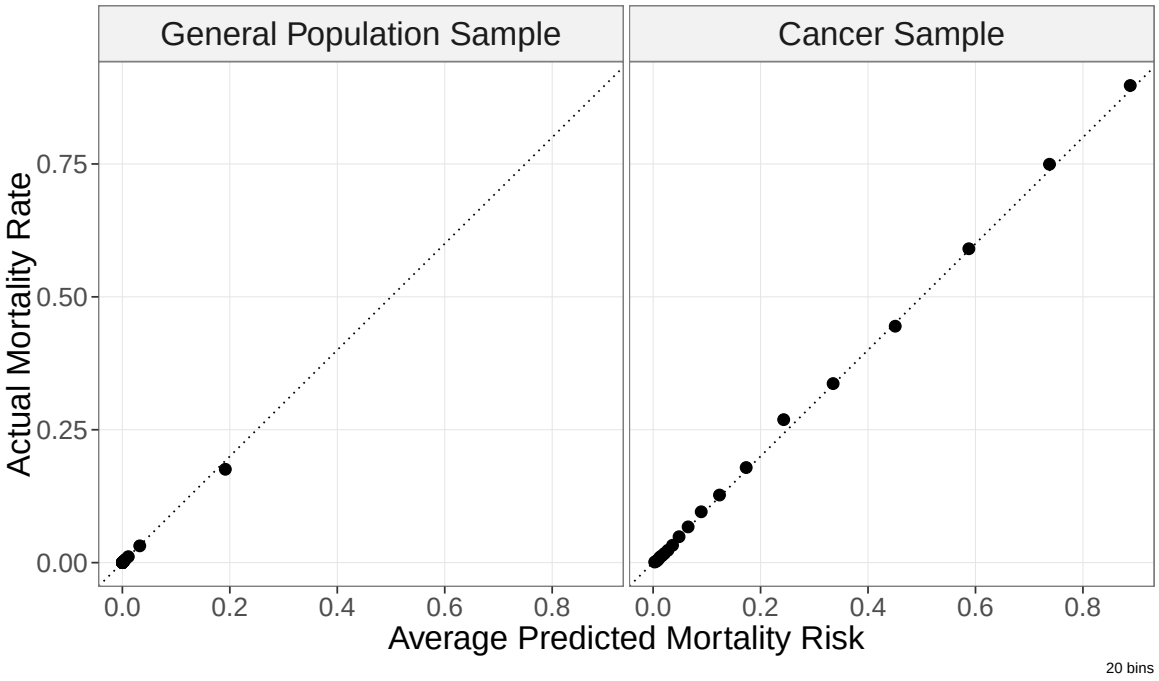
Notes: Figure shows Decedent average monthly spending on all services over predicted mortality risk at the time of initial cancer diagnosis, for the most common cancer types in our sample. Each facet shows data for one cancer type. Different lines within each facet represent different age quintiles, with darker lines for older age groups, as described in the legend at the bottom of the figure. Age ranges are shown with square brackets and parentheses denoting included and excluded endpoints, respectively. Spending is adjusted for survival duration (see equation (1)). Data points based on fewer than ten patients are not shown.

Appendix Figure A4: Spending and Mortality of Survivors, Separately by Cancer Type and Age Quintile



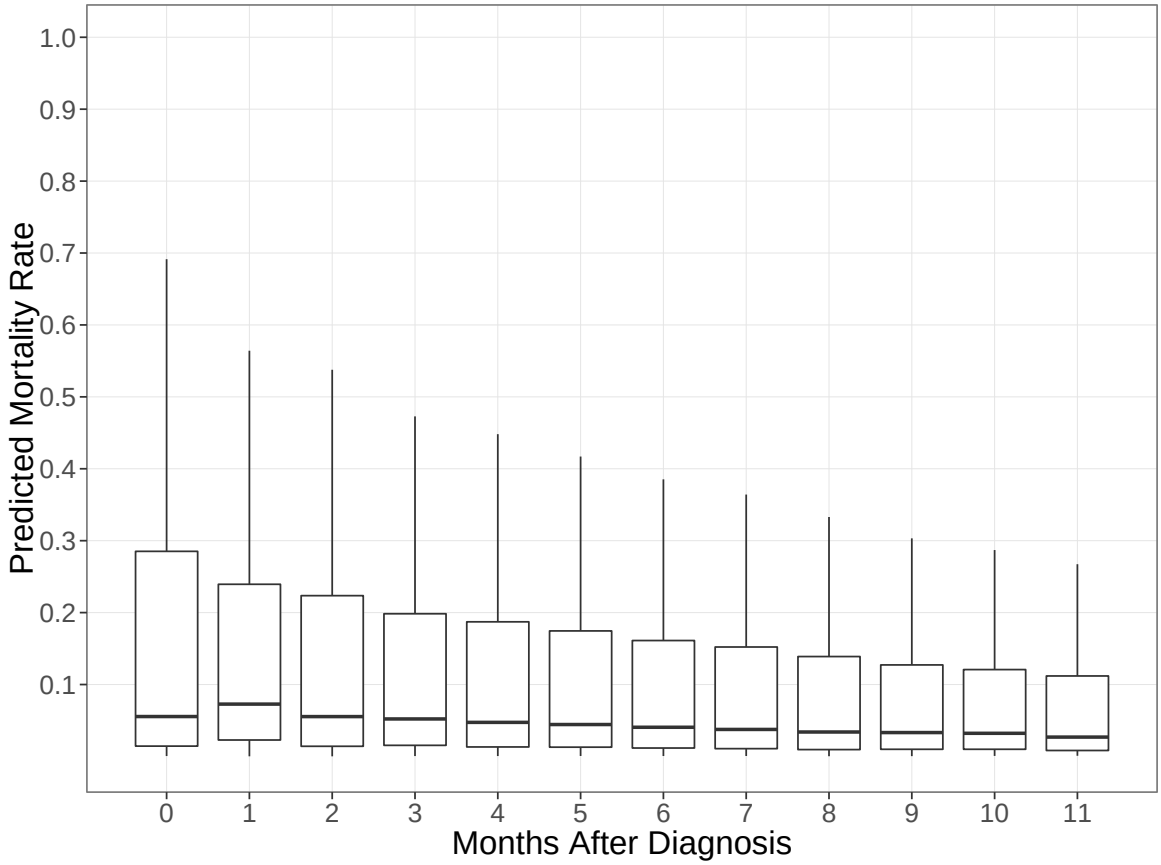
Notes: Figure shows Survivor average monthly spending on all services over predicted mortality risk at the time of initial cancer diagnosis, for the most common cancer types in our sample. Each facet shows data for one cancer type. Different lines within each facet represent different age quintiles, with darker lines for older age groups, as described in the legend at the bottom of the figure. Age ranges are shown with square brackets and parentheses denoting included and excluded endpoints, respectively. Data points based on fewer than ten patients are not shown.

Appendix Figure A5: Predictive Model Fit



Notes: Figure shows our final predictions on the horizontal axis against the actual mortality rate on the vertical axis for bins of beneficiaries in the test sample. To construct this figure, we sorted all individuals in the test sample by their predicted one-year mortality risk at the index date—initial cancer diagnosis for the cancer sample (right panel), and January 1, for the general population sample (left panel)—and divided them into 20 equally sized bins. Within each bin we compute the average predicted mortality (horizontal axis) and the mortality share (vertical axis). The model seems to be well calibrated.

Appendix Figure A6: One-Year Mortality Risk Distribution, Predicted Over Time



Notes: Figure shows box and whisker plots of the distribution of individual prognosis—predicted one-year mortality risk based on data available at different times after the initial diagnosis of cancer. The prediction model and data used are described in Appendix D. The horizontal line is the median prognosis. The lower and upper hinges correspond to the first and third prognosis quartiles (the 25th and 75th percentiles). The upper whisker extends from the hinge to the largest value no further than 1.5 * IQR from the hinge (where IQR is the inter-quartile range, or distance between the first and third quartiles). The lower whisker extends from the hinge to the smallest value at most 1.5 * IQR of the hinge. Outliers—data points beyond the end of the whiskers—are not shown.

Appendix Table A1: Admission Characteristics by Hospital Ownership

	Hospital Owner	
	Clalit	Non Clalit
	(1)	(2)
Age (mean, minimum = 25)	65.8	65.1
Sex (% Female)	50.5	49.4
Number of Chronic Conditions (mean)	4.8	4.6
One-year Mortality (%)	27.6	30.0
ACG Score (%)		
Healthy or Low	17.7	17.6
Moderate	54.2	55.2
High or Very High	28.1	27.1
High Intensity Admissions (%)	57.6	56.1
Number of Admissions	63,422	96,231
Number of Unique Patients	30,324	39,048

Notes: Table shows characteristics of admissions of cancer patients to Clalit and non-Clalit–owned hospitals. Section 2.1 discusses the institutional setting. This table is based on the test sample. One-year mortality is the fraction of admissions ending in death within a year from the time of admission. ACG Score is the Johns Hopkins University Adjusted Clinical Groups (ACG) Resource Utilization Band, which is a summary score for predicted healthcare utilization. Admission intensity is defined based on the ward of admissions, see Appendix Table A2 for details.

Appendix Table A2: Admission Intensity, by Ward

Intensity	Ward	Average Daily Cost (NIS)	Share With Surgical Procedure	Share of Admission	Share of Days
		(1)	(2)	(3)	(4)
High	Gastroenterology	6,024	30.0	3.4	2.6
	Neurology	5,261	5.2	1.4	1.5
	Orthopedic Surgery	3,797	32.9	1.7	1.9
	General Surgery	3,220	48.3	23.1	16.8
	Other	2,840	42.2	18.9	14.3
	ICU	2,431	16.0	0.1	0.2
	Urology	2,070	24.9	7.4	5.4
Low	Oncology	1,560	5.6	11.0	16.6
	Internal Medicine	1,444	5.8	29.4	25.9
	Geriatry	817	6.5	2.0	5.6
	Rehabilitation	670	1.1	1.8	9.2

Notes: Table shows measures of intensity by ward of admission, and our associated classification of admissions into low and high intensity. Average Daily Cost is the average of negotiated payments for all billed services associated with each admission divided by the length of stay, in current New Israeli Shekels (NIS). Share of Admissions is the share of admission to each ward out of all sampled admissions; Share of Days is the same share weighted by the length of admission. Appendix Table A9 shows the same statistics for decedents and survivors separately. Columns 1, 3, and 4 in this table and in Appendix Table A9 are based on the subsample of 137,374 admissions in the test sample in which the patient visited exactly one ward, excluding 14% of admissions with multiple wards. This was done to avoid the need to impute how overall charges are assigned across different wards. Column 2 in this table and in Appendix Table A9 are based on the 53,952 admissions in the test sample that are to Clalit-owned hospitals, for which we have detailed procedure data. The rest of the analysis uses all 159,653 admissions in the test sample, including those with multiple wards.

Appendix Table A3: Additional Descriptive Statistics

	Sample Size		One-Year Mortality	Age	Average Monthly Spending (NIS)		Percentiles of Predicted Mortality			Decedent with Pred. Mort. $\geq$ 80
	N	Percent of Sample	Percent	Median	Unadjusted	Adjusted for Survival	80th	95th	99th	Percent
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
A. General Population Sample										
All	1,186,178	100.0	1.2	48	556	559	0.4	6.0	28.3	0.2
Age>65	247,238	20.8	4.6	75	1,213	1,243	6.6	26.1	49.3	0.2
Age>85	33,735	2.8	14.3	89	1,366	1,478	25.3	44.6	62.1	0.3
B. Cancer Sample - All Types										
All	83,181	100.0	19.6	67	4,751	5,404	38.9	81.4	93.0	25.1
Age>65	44,620	53.6	27.0	75	4,105	4,956	54.9	86.8	94.4	28.1
Age>85	4,697	5.6	47.8	88	2,646	3,897	78.3	92.2	96.2	35.3
C. Cancer Sample - By Type										
Breast	13,379	16.1	4.0	61	5,241	5,364	3.7	19.5	50.3	2.1
Prostate Gland	8,164	9.8	4.8	70	3,286	3,369	6.1	25.3	54.2	3.6
Colon	8,015	9.6	18.6	72	4,757	5,397	33.0	66.2	84.5	7.9
Bronchus and Lung	6,278	7.5	52.5	69	5,579	8,234	80.4	91.0	95.2	34.2
Skin	5,297	6.4	5.3	64	1,689	1,738	6.8	25.4	57.2	1.1
Bladder	4,938	5.9	11.9	71	2,854	3,048	18.0	53.5	76.7	3.4
Hemato. and Reticul. Systems	4,428	5.3	23.9	70	8,443	9,843	44.8	74.4	89.3	12.9
Lymph Nodes	2,910	3.5	19.0	64	8,746	9,940	37.5	65.9	82.0	5.4
Stomach	2,851	3.4	44.9	71	5,668	7,839	68.5	84.6	90.9	18.3
Rectum	2,321	2.8	15.9	68	6,725	7,390	26.3	62.1	81.2	7.6
Corpus Uteri	2,173	2.6	8.0	64	3,390	3,533	11.6	41.7	70.9	2.3
Thyroid Gland	2,127	2.6	4.1	53	2,100	2,157	2.3	15.0	67.0	14.9
Pancreas	2,047	2.5	67.8	72	4,922	8,636	88.8	94.3	96.9	53.6
Kidney	2,000	2.4	12.4	66	2,723	2,946	23.1	62.4	83.8	9.7
Cervix Uteri	1,934	2.3	4.7	41	2,613	2,672	3.5	22.7	60.8	6.7
Meninges	1,528	1.8	9.8	64	3,307	3,523	12.7	34.4	73.6	8.0
Brain	1,225	1.5	47.3	62	7,549	10,531	74.1	89.1	94.6	27.1
Ovary	1,194	1.4	16.2	62	3,778	4,167	27.2	69.9	86.9	13.5
Rectosigmoid Junction	908	1.1	11.0	69	5,572	5,940	35.8	65.3	85.2	15.0
Other	7,518	9.0	26.3	66	5,752	6,853	47.2	80.4	91.8	17.5
Unknown Primary Site	1,946	2.3	75.2	73	4,061	9,250	92.8	96.0	97.6	69.5

Notes: Table shows descriptive statistics for different subsamples. Column 3 shows actual mortality in the 12 months following the index date, which is January 1 for the general population samples and initial cancer diagnosis for the cancer samples. Columns 5 and 6 show spending in current New Israeli Shekels (NIS) over the same period with and without adjustment for survival duration (see equation (1)). Columns 7–9 show different quantiles of the predicted mortality risk, using our prognosis algorithm. Column 10 shows the fraction of decedents with a predicted one-year mortality risk greater or equal to 80%.

Appendix Table A4: Average Monthly Spending of All 25+ Patients

Category	Survivor		Decedent	Difference	
	Unweighted	Reweighted by Decedent Risk	Adjusted for Survival Duration	Decedent - Survivor (Reweighted)	Percent of Total Difference
	(1)	(2)	(3)	(4)	(5)
Total	461	2,732	8,623	5,891	100.0
All Inpatient	202	1,309	6,661	5,352	90.9
Unplanned	89	747	4,423	3,676	62.4
Planned	114	565	2,253	1,688	28.7
Low Intensity	67	767	3,986	3,218	54.6
High Intensity	135	542	2,675	2,133	36.2
Other Services	258	1,423	1,962	539	9.1
Drugs	122	577	836	259	4.4
Outpatient	56	661	847	186	3.2
Imaging	22	42	69	27	0.5
Other	59	144	210	67	1.1

Notes: Table shows average monthly spending in the 12 months following the index date, January 1, 2013, for the general population sample of Clalit members aged 25 years and older. Columns show results separately for decedents and survivors. Decedent spending is adjusted for survival duration (see equation (1)). Survivor spending in column 2 is reweighted by decedent risk (see equation (2)). Decedent−Survivor is the difference between Decedent and Survivor (Reweighted) spending. All spending measures are in current New Israeli Shekels (NIS). First row shows total healthcare spending, and subsequent rows show various partitions. All Inpatient refers to spending on all services that are delivered during hospital admissions, and Other Services refers to spending on all services that are not part of an admission. Within inpatient, we partition into low intensity versus high intensity, and unplanned versus planned. Low intensity refers to admissions into one of four wards: Internal Medicine, Oncology, Rehabilitation, and Geriatric, which Appendix Table A2 shows involve the lowest average daily admission and few surgeries; High intensity is admission to all other wards. Unplanned refers to admissions through the emergency department; Planned refers to all other admissions. Within Other Services we partition into Outpatient, Drugs, Imaging, and Other. Outpatient, Drugs, and Imaging refer to hospital outpatient services, prescription drugs (except those administered during admissions), and diagnostic radiology services not during an admission.

Appendix Table A5: Average Monthly Spending of All 65+ Patients

Category	Survivor		Decedent	Difference	
	Unweighted	Reweighted by Decedent Risk	Adjusted for Survival Duration	Decedent - Survivor (Reweighted)	Percent of Total Difference
	(1)	(2)	(3)	(4)	(5)
Total	985	2,665	7,876	5,211	100.0
All Inpatient	493	1,353	6,257	4,905	94.1
Unplanned	232	788	4,342	3,554	68.2
Planned	262	567	1,932	1,365	26.2
Low Intensity	207	814	3,968	3,153	60.5
High Intensity	286	538	2,290	1,752	33.6
Other Services	492	1,312	1,618	306	5.9
Drugs	237	538	671	133	2.6
Outpatient	129	589	705	115	2.2
Imaging	35	39	52	13	0.3
Other	92	145	190	45	0.9

Notes: Table shows average monthly spending in the 12 months following the index date, January 1, 2013, for the general population sample of Clalit members aged 65 years and older. Columns show results separately for decedents and survivors. Decedent spending is adjusted for survival duration (see equation (1)). Survivor spending in column 2 is reweighted by decedent risk (see equation (2)). Decedent−Survivor is the difference between Decedent and Survivor (Reweighted) spending. First row shows total healthcare spending, and subsequent rows show various partition. All Inpatient refers to spending on all services that are delivered during hospital admissions and Other Services refers to spending on all services that are not part of an admission. Within inpatient, we partition into low intensity versus high intensity, and unplanned versus planned. Low intensity refers to admissions into one of four wards: Internal Medicine, Oncology, Rehabilitation, and Geriatric, which Appendix Table A2 shows involve the lowest average daily cost and few surgeries; High intensity is admission to all other wards. Unplanned refers to admissions through the emergency department; Planned refers to all other admissions. Within Other Services we partition into Outpatient, Drugs, Imaging, and Other. Outpatient, Drugs and Imaging refer to hospital outpatient services, prescription drugs (except those administered during admissions), and diagnostic radiology services not during an admission. All spending measures are in current New Israeli Shekels (NIS).

Appendix Table A6: Average Monthly Spending of Cancer Patients, Reweighted by Current Risk

Category	Survivor		Decedent	Difference	
	Unweighted	Reweighted by Decedent Risk	Adjusted for Survival Duration	Decedent - Survivor (Reweighted)	Percent of Total Difference
	(1)	(2)	(3)	(4)	(5)
Total	4,664	8,864	13,235	4,372	100.0
All Inpatient	1,733	4,175	9,203	5,027	115.0
Unplanned	408	1,368	4,063	2,694	61.6
Planned	1,325	2,807	5,140	2,333	53.4
Low Intensity	480	2,044	5,377	3,333	76.2
High Intensity	1,252	2,131	3,825	1,694	38.8
Other Services	2,931	4,688	4,033	-655	-15.0
Outpatient	1,237	1,745	1,562	-183	-4.2
Drugs	1,117	2,254	1,725	-529	-12.1
Imaging	190	229	220	-9	-0.2
Other	387	460	526	66	1.5

Notes: Table shows shows average monthly spending in the 12 months post cancer diagnosis. Columns show results separately for decedents and survivors. Results in this table are parallel to these shown in Table 2, but with survivor spending being reweighted (in columns 2) by current one-year mortality risk instead of by initial mortailty risk. Current risk is predicted every month, starting from each patient's initial prognosis, for all patients still alive. Appendix D provides additional details on this risk measure and the reweighting based on it. Decedent spending is adjusted for survival duration (see equation (1)). Decedent−Survivor is the difference between Decedent and Survivor (Reweighted) spending. Percent of Total Difference is the difference in column 4, expressed as a fraction of the total difference, NIS 4,372, with negative differences keeping their negative sign. First row shows total healthcare spending, and subsequent rows show various partition. All Inpatient refers to spending on all services that are delivered during hospital admissions and Other Services refers to spending on all services that are not part of an admission. Within inpatient, we partition into low intensity versus high intensity, and unplanned versus planned. Low intensity refers to admissions into one of four wards: Internal Medicine, Oncology, Rehabilitation, and Geriatric, which Appendix Table A2 shows involve the lowest average daily cost and few surgeries; High intensity is admission to all other wards. Unplanned refers to admissions through the emergency department; Planned refers to all other admissions. Within Other Services we partition into Outpatient, Drugs, Imaging and Other. Outpatient, Drugs and Imaging refer to hospital outpatient services, prescription drugs, (except those administered during admissions), and diagnostic radiology services not during an admission. All spending measures are in current New Israeli Shekels (NIS).

Appendix Table A7: Demographics, Cost and Mortality, 65+ Sample

	General Population, 65+ Sample		
	All	Decedent	Survivor
	(1)	(2)	(3)
Characteristics			
Age (mean)	75	83	75
Female (%)	57.0	54.6	57.1
High Socioeconomic Status (%)	24.3	19.7	24.5
Supplementary Insurance (%)	76.0	59.5	76.8
Mortality Rate			
1 month (%)	0.4	10.3	–
1 year (%)	4.4	100.0	0.0
3 years (%)	13.2	–	9.3
Utilization			
12 Months Before Index Date			
Average Monthly Spending (NIS)	1,010	3,255	908
Any admission (%)	25.1	55.5	23.8
12 Months After Index Date			
Average Monthly Spending (Unadjusted NIS)	1,193	3,811	1,073
Average Monthly Spending (Adjusted NIS)	1,220	7,905	1,073
Any admission (%)	27.5	80.0	25.1
Number of Beneficiaries	534,055	23,353	510,702

Notes: Table shows descriptive statistics for the subsample of the general population aged 65 and older. Sample definitions are discussed in Section 2. Column 1 shows statistics for all patients; columns 2 and 3 show statistics for ex-post decedents and survivors, i.e., those who died within 12 months after the index date, January 1, 2013, and those who did not. Socioeconomic Status is residential zip-code socioeconomic status, sourced from the central bureau of statistics. Supplementary insurance is additional coverage (described in Appendix A). By definition, the mortality rate within one year of the initial prognosis is 100 for decedents and 0 for survivors. Utilization measures are shown for the periods of 12 months before and 12 months after the index date. All spending measures are in current New Israeli Shekels. Spending adjustment for decedent survival duration is described in Section 2. This table is based on the full sample, which we later split into training and test sets. All spending measures are in current New Israeli Shekels (NIS).

Appendix Table A8: Procedures in Planned and Unplanned Inpatient, by Admission Time Before Death

	Procedure Type, Admission with Any (%)						
	Maintanance	Diagnostics	Surgery	Radiation	Chemotherapy	Other	N of Admissions
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
A. Planned Admissions							
Last month	11.1	97.8	11.0	4.5	6.4	0.6	4,545
1–3 months	11.4	95.0	13.6	7.4	12.6	0.8	3,590
4–12 months	11.1	95.1	18.6	6.7	18.7	1.3	4,746
Survivors	9.3	91.4	41.1	3.2	8.2	1.2	41,464
All Planned	9.8	92.5	34.8	3.9	9.3	1.1	54,345
B. Unplanned Admissions							
Last month	11.7	99.0	8.2	4.1	4.1	0.8	6,061
1-3 months	11.4	96.5	9.2	6.4	7.4	0.9	4,235
4-12 months	11.6	93.8	14.0	5.9	12.7	1.7	4,978
Survivors	8.5	88.7	23.7	2.6	6.9	1.1	32,307
All Unplanned	9.5	91.3	19.4	3.5	7.2	1.1	47,581
C. Low Intensity							
Last month	8.8	98.5	4.8	5.2	4.8	0.4	8,631
1-3 months	8.7	95.9	6.0	9.3	11.0	0.5	5,670
4-12 months	7.9	94.0	6.9	9.4	20.1	1.1	5,988
Survivors	5.3	93.8	5.4	7.2	15.5	1.1	24,171
All Planned	6.8	95.0	5.6	7.4	13.5	0.9	44,460
D. High Intensity							
Last month	17.9	98.4	19.8	1.1	4.2	1.3	3,205
1-3 months	16.7	95.4	20.6	1.8	5.6	1.4	2,666
4-12 months	16.0	95.1	26.8	1.8	7.3	1.8	4,447
Survivors	10.7	88.9	44.4	0.9	3.6	1.1	52,993
All Unplanned	11.7	90.1	40.9	1.0	3.9	1.1	63,311

Notes: Table shows results parallel to these shown in Table 4, separately for planned and unplanned admissions (Panels A and B) and for low- and high-intensity admissions (Panels C and D). Unplanned admissions are those originated through the emergency room; planned admissions are all other admissions. The intensity of admissions is defined based on the average daily spending for different wards. See Appendix Table A2 for details. Sampled admissions include Clalit-owned-hospital admissions that started and ended during the year after diagnosis.

Appendix Table A9: Admission Intensity, by Ward and Mortality Status

Intensity	Ward	Average Daily Cost (NIS)	Share With Surgical Procedure	Share of Admission	Share of Days
		(1)	(2)	(3)	(4)
A. Decedent					
High	Gastroenterology	4,982	22.2	1.5	1.0
	Neurology	4,402	8.2	1.2	1.2
	Orthopedic Surgery	3,881	35.2	1.0	0.9
	ICU	2,544	15.9	0.3	0.3
	General Surgery	2,373	22.2	11.9	11.0
	Other	2,049	25.2	12.0	10.1
	Urology	1,933	34.4	2.5	1.9
Low	Oncology	1,457	6.1	16.4	21.9
	Internal Medicine	1,445	6.1	46.3	34.0
	Geriatry	792	6.3	3.9	8.1
	Rehabilitation	584	0.0	2.9	9.5
B. Survivor					
High	Gastroenterology	6,226	100.0	4.2	3.7
	Neurology	5,696	3.8	1.4	1.6
	Orthopedic Surgery	3,777	32.1	2.0	2.6
	General Surgery	3,525	53.0	27.7	20.8
	Other	3,157	45.7	21.7	17.2
	ICU	2,164	16.1	0.0	0.1
	Urology	2,093	23.7	9.4	7.7
Low	Oncology	1,680	5.1	8.7	12.9
	Internal Medicine	1,444	5.6	22.3	20.4
	Geriatry	854	6.7	1.2	3.9
	Rehabilitation	733	1.8	1.3	9.0

Notes: Table shows measures of intensity by ward of admission and our associated classification of admissions into low and high intensity. Results parallel to these shown in Appendix Table A2, but shown here separately for decedents and survivors. Average Daily Cost is the average of negotiated payments (in current New Israeli Shekels) for all billed services associated with each admission divided by the length of stay. Share of Admissions is the share of admission to each ward out of all sampled admissions; Share of Days is the same share weighted by the length of admission. This table and Appendix Table A2 are based on the subsample of 137,374 admissions in which the patient visited exactly one ward, excluding 14% of admissions with multiple wards. This was done to avoid the need to impute how overall charges are assigned across different wards. The rest of the analysis uses all 159,653 admissions in the test sample, including those with multiple wards.

Appendix Table A10: Admission Statistics, All Patients

	Survivor		Decedent	Difference
	Unweighted	Reweighted by Decedent Risk	All Admissions	Decedent - Survivor (Reweighted)
	(1)	(2)	(3)	(4)
A. Any Admission				
All	0.133	0.428	0.784	0.356
Low Intensity	0.052	0.328	0.689	0.361
High Intensity	0.100	0.217	0.353	0.136
B. Admissions per Month (if Any During the Year)				
All	0.146	0.198	0.471	0.273
Low Intensity	0.051	0.117	0.342	0.225
High Intensity	0.095	0.081	0.129	0.048
C. Length of Stay (Days)				
All	5.856	8.848	12.492	3.644
Low Intensity	8.472	9.918	11.983	2.065
High Intensity	4.457	7.473	13.842	6.369

Notes: Table shows admission statistics in the 12 months post January 1, 2013, for the general population sample of patients 25 year old and older. Results parallel these shown in Table 3 on admissions of cancer patients following the initial cancer diagnosis. Columns show results separately for survivors and decedents. Survivor statistics in column 2 are reweighted by decedent risk (see equation (2)). Decedent−Survivor is the difference between Decedent and Survivor (Reweighted) outcomes. In Panel A, any admission shows the fraction of patients with any admission at any time during the first year after initial diagnosis; this is not adjusted for survival duration. In Panel B, to adjust for survival duration, decedent average number of admissions per month is calculated over the period during which each patient was still alive. In Panel C, length of stay is the average duration of stay, over all admissions. Within each panel, we partition admissions into low intensity and high-intensity admissions, as described in the text.

Appendix Table A11: Select Predictors

	General Population Sample		Cancer Sample	
	Train Set	Test Set	Train Set	Test Set
	(1)	(2)	(3)	(4)
Sample Size				
Number of beneficiaries	1,186,402	1,186,180	83,658	83,181
Outcome				
1-year All-Cause Mortality (%)	1.2	1.2	19.4	19.6
Demographics				
Age (mean, y, minimum = 25)	50	50	65	65
Sex (% Female)	52.4	52.4	52.3	52.0
Ethnicity (% Arab)	19.6	19.5	8.8	8.7
Supplementary Insurence (%)	74.8	74.8	70.3	70.0
Disability Benefits (%)	2.6	2.5	3.8	3.7
Chronic Conditions (%)				
Hyperlipidemia	40.7	40.6	47.9	47.9
Hypertension	25.7	25.8	48.0	48.0
Arthropathy	24.1	24.0	27.6	27.3
Diabetes	14.1	14.0	22.0	22.0
IHD	9.1	9.0	21.5	21.6
Gastritis	7.7	7.7	9.6	9.5
COPD	2.8	2.7	6.9	7.0
Osteoporosis	6.8	6.9	10.6	10.4
Depression	6.3	6.3	7.2	7.1
Kidney	5.9	5.9	7.9	8.0
Prior Utilization, mean 1y count (% nonzero)				
Prescription Drugs	31.4 (87.2)	31.4 (87.2)	54.1 (97.2)	53.6 (97.3)
Laboratory Tests	24.1 (72.0)	24.1 (71.9)	35.8 (85.1)	35.6 (84.9)
Imaging Events	1.0 (40.9)	1.0 (40.8)	2.1 (71.0)	2.1 (70.7)
Ambulatory encounters	159.7 (38.8)	167.5 (38.9)	240.2 (65.8)	235.2 (65.6)
Emergency Room visits	0.3 (20.2)	0.3 (20.3)	0.5 (32.0)	0.5 (32.3)
Hospital visits	0.0 (12.8)	0.0 (12.8)	2.0 (73.3)	2.0 (73.4)
Prior Utilization, mean 1y cost (% nonzero)				
Total spending (NIS)	5,810 (95.4)	5,803 (95.4)	16,881 (99.8)	16,873 (99.7)
ACG Score,*				
Healthy or Low	36.7	36.6	18.6	18.9
Moderate	50.4	50.5	56.1	56.8
High or Very High	12.9	12.9	25.2	24.4
Clinical Measurements, last measurement, mean (% nonmissing)				
BMI	27.4 (72.2)	27.4 (72.2)	28.0 (54.2)	28.0 (54.2)
Diastolic Blood Pressure (mm Hg)	73.5 (78.4)	73.5 (78.4)	75.1 (66.4)	75.3 (66.5)
Systolic Blood Pressure (mm Hg)	122 (78.4)	122 (78.4)	129.1 (66.4)	129.2 (66.5)
Hemoglobin (g/dL)	13.4 (79.6)	13.4 (79.6)	12.9 (85.7)	12.9 (85.7)
Hematocrit, (%)	3.0 (15.2)	3.0 (15.2)	3.0 (10.3)	3.0 (10.3)
Red Blood Cells	4.7 (79.6)	4.7 (79.6)	4.5 (85.6)	4.5 (85.5)
Platelets (1000/uL)	246.8 (79.6)	246.8 (79.6)	261.8 (85.7)	261.1 (85.7)
Neutrophiles	4.3 (79.4)	4.3 (79.3)	5.3 (84.5)	5.3 (84.4)
Lymphocytes	2.1 (79.3)	2.1 (79.3)	2.1 (84.4)	2.1 (84.4)

Notes: Table shows descriptive statistics for select predictors used in the training of the initial prognosis algorithm, separately for the training and testing subsamples. See Appendix B for detailed variable definitions and a comprehensive list of predictors used. Numbers in parentheses show the fraction of nonmissing observations. Missing measurements for each predictor were coded as a separate category.