# Why is end-of-life spending so high? Evidence from cancer patients

# On-Line Appendices

Dan Zeltzer (corresponding author, dzeltzer@tauex.tau.ac.il), Liran Einav, Amy Finkelstein, Tzvi Shir, Salomon M. Stemmer, and Ran D. Balicer

## 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). For patients with limited ability to support themselves, home care in Israel is subsidized by the social security agency, based on Activities of Daily Life measures.

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 Construction and Performance of Prediction Algorithms

## B.1 Mortality Predictors

For training our algorithms that predict mortality at different points in time, 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 A7 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 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.

Finally, for each patient, we observe the Johns Hopkins ACG Resource Utilization Bands (RUB) and the probability of major health events, both of which are based on administrative claims data.

**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.[18] There are 200 predictors in this group.

We also use EMR information on ATC1-level prescriptions. Prescription events are 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 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:

[18]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).

Medication Possession Ratio (MPR) and Proportion of Days Covered (PDC) during the previous year.

We observe EMR data for all services that are provided by Clalit. This excludes admissions to hospitals that are not owned by Clalit, from which Clalit purchases services as external providers.

### 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 include stage and grade data in training the prediction algorithm. For the rest of the analysis, we categorize cancer cases based on topography.

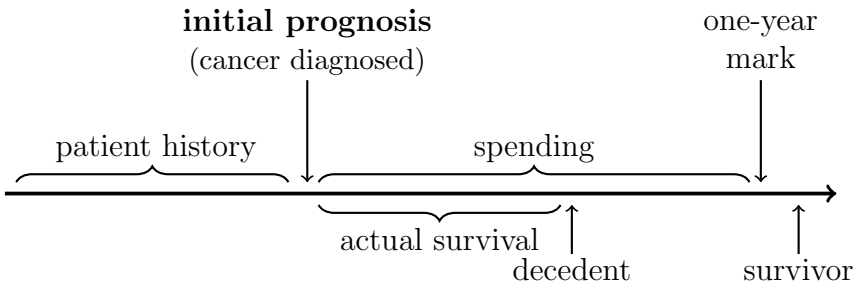
### Clinical Events

For training the algorithm that predicts current one-year mortality prognosis at the start of major clinical events, we record, for each patient, the sequence of the following major clinical events that the patient has underwent during the year since initial diagnosis: low-intensity and high-intensity admissions (Low- and High-Admission), chemotherapy or biological drug treatment (Drug Therapy), emergency department visit that did not result in an admission (ED Visit), and radiation therapies (Radiation Therapy). For each clinical event, we record the number of the event (0 is the initial diagnosis, which in some case does not coincide with any of the above event types but is nonetheless included as a baseline, for completeness of the sample, 1 is the first clinical event of one of the above types, 2 is the second clinical event, up to 7, denoting the seventh clinical event; for expositional clarity, we include only the first seven events for each patient. Less than 2% of cases have additional events). Based on EMR data, we record spells of drug or radiation therapies that are recorded as a single treatment plan as one event, even if they were performed over the course of multiple visits. In the training of the current prognosis algorithm, which is described in detail in Section B.3, we use as additional predictors the type and sequential order of previous events, the total number of previous events, and the start time of each event, denoted both in terms of days since initial diagnosis and in terms of days before the index event for which current prognosis is predicted.

## B.2 Construction of the Initial Prognosis Algorithm

We predict one-year mortality from the date of initial cancer diagnosis. The timing is illustrated below. We refer to this predicted one-year mortality risk 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 $\alpha$ is a learning-rate parameter.

To avoid overfitting, the criterion function penalizes model complexity. Hyper-parameters, including the penalty weight, the learning rate, the number of trees, and the tree maximal depth were tuned using Bayesian optimization. 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:

$$Pr[D|Balanced] = \frac{Pr[D]Pr[Balanced|D]}{Pr[D]Pr[Balanced|D] + (1 - Pr[D])Pr[Balanced|S]}, \tag{A1}$$

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 $\mu_D$ 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 A7 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 A8 shows the model calibration, overall and by age group. The test AUC (area under the receiver operating characteristic curve) is above 91.1 for the prediction of initial prognosis, which reflects high precision and recall.[19] It is only slightly lower than the train AUC (which is 92.8). 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 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 prediction of initial one-year mortality prognosis, the most important features, as measured by gain, are cancer type, patient age, number of unplanned admissions days the year prior to the initial diagnosis of cancer, and whether the patient had prior malignancy in the five years prior to the initial cancer diagnosis.

## B.3 Construction of Current Prognosis Algorithm

For studying the joint evolution of mortality prognosis and spending for patients during the course of treatment, we also predict each patient's one-year mortality risk at the start of major clinical events. We refer to these predictions as the patient's "current prognosis."

We train a prognosis algorithm to predict one-year mortality on the first day of each of the following types of clinical events: high-intensity hospital admissions, low-intensity hospital admissions, drug therapy, radiation therapy, and emergency room visit. We also include the initial diagnosis as event "zero" for each patient. We use the same train-test split and basic architecture as our initial prognosis algorithm, discussed in Section B.2. We sample at the patient (not event) level, so all events for a given patient are included in either the train or the test sample. The train sample consists of 292,487 patient-event observations.

For training the algorithm, we use the same predictive model and types of predictors as we used to generate the predictor of initial mortality risk, but we include, in addition, all interim information that is available at the time of prediction, including events that

[19] 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.

occurred after the initial diagnosis date, and the nature and sequential order of previous major clinical events. These predictors are discussed in detail in Section B.1. We obtain comparable levels of accuracy (train AUC 91.4; test AUC 90.2). For the prediction of current mortality prognosis at the start of clinical events, the most important features, as measured by gain, are cancer type, number of unplanned admissions in the year prior to the start of the current event and the total length of such admission, number of scheduled narcotic drug prescriptions in the prior 90 day period leading to the current event, patient age, the current event type being a low intensity admission, and, separately, the previous event type being a low intensity admission.

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. Our test sample consists of 292,284 patient-events. Overall, it contains 2,610 non-empty distinct patient histories, each defined by the patient's cancer type and an ordered list of between zero and seven clinical events. For the analysis of the change in current prognosis, we calculate one-year forward spending from the beginning of each event, which is the overall spending over the one-year period from the start of the event (or until death). When calculating spending one-year forward, we exclude spending on the current event and adjust spending for survival duration.

## B.4 Construction of Monthly Mortality Prognosis

Our analyses rely almost exclusively on the initial or current mortality prognosis. However, we also briefly evaluated the sensitivity of the reweighting method of survivor spending by decedent mortality prognosis, discussed in Section 3.3, to an alternative construction of the initial mortality prognosis.

The sensitivity analysis consists of two steps. First, we retrain our algorithm to predict the prognosis at the beginning of every month since initial diagnosis (we refer to this as the monthly mortality prognosis). Second, we use the monthly mortality prognoses as an alternative measure of patient risk with which we reweight survivor monthly spending. This section briefly describes this sensitivity analysis and the results.

### Construction and Performance of the Monthly Prognosis Algorithm

We train a prognosis algorithm to predict one-year mortality for patients still alive on the first day of each month, beginning with the initial diagnosis. We use the same train-test split and basic architecture as our original (initial-diagnosis) algorithm. But we retrain the algorithm on 11 separate data sets, each including all patients still alive on the first day of the month, and use as predictors all available information up to month $t$ from diagnosis, for months 1, 2, 3, and up to 11 (for month 0, the time of diagnosis, we reuse the initial prognosis algorithm).[20] We train our prognosis algorithm separately for each of the months.

[20] A *month* here refers to a 30-day period. For example, a patient who is sampled to be included in the training set and who died 100 days after the initial diagnosis will be included in the training samples for predicting current prognosis on months 0, 1, 2, and 3, each time using all available data up to that point in time, with the mortality outcome coded

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 initial diagnosis date. We obtain comparable levels of accuracy (train AUC between 92.4–98.5; test AUC between 90.3–91.3). Appendix Figure A9 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. We then associate each individual in the test sample with a history of predicted mortality scores, $(\hat{p}_0, \hat{p}_1, \hat{p}_2, \ldots, \hat{p}_l)$, where $l \leq 11$ for decedents and $l = 11$ for survivors.

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, $\{y_{il}\}$, and the number of days survived each month, $T_{it} \in (1, 30]$. We then bin all person-months by partitioning their predicted mortality scores to 20 equally sized bins and by month-from-diagnosis. Denote this partition, which has 240 bins, by $\Pi$. Let $\mu^I$ 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 $I \in \{D, S\}$. The top panel of Appendix Figure A2 shows the distribution of cell sizes in these partitions, for survivors, decedents, and for both groups combined. For each bin $\pi \in \Pi$, we calculate the average adjusted monthly spending, separately for survivors and decedents:

$$\bar{y}^I(\pi) = \sum_{\{i,t:\hat{p}_{it} \in \pi, i \in I\}} \frac{y_{it}}{T_{it}/30}. \tag{A2}$$

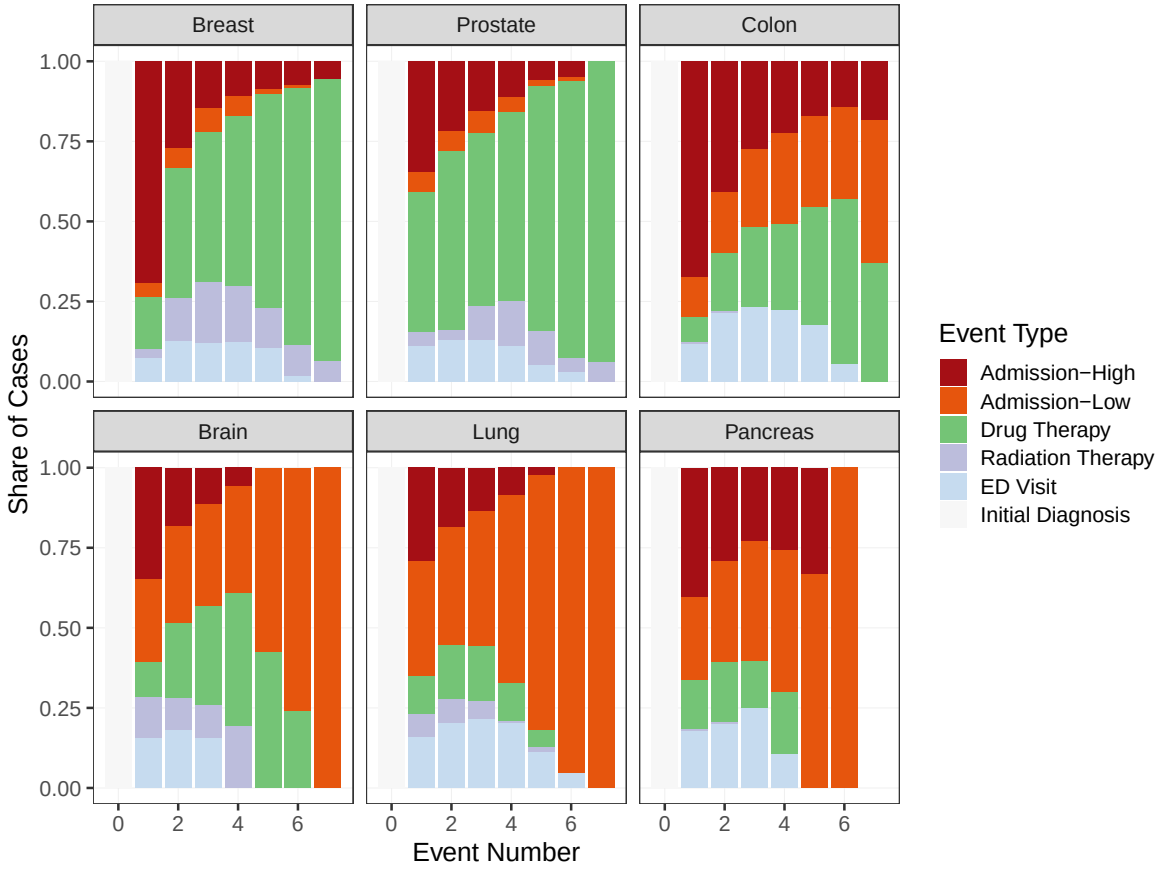
Finally, we reweight survivor spending by decedent interim risk:

$$\bar{y}^{S^{\text{reweighted}}} = \sum_{\pi \in \Pi} \bar{y}^S(\pi)\mu^D(\pi). \tag{A3}$$

**Reweighting Survivor Spending Using Decedent Monthly Prognosis**

Appendix Table A8 shows the results of reproducing Table 2 using the monthly mortality prognosis instead of the initial mortality prognosis. Comparing different reweighting schemes, two points become clear. First, accounting for monthly risk helps explain a greater share of the difference between decedent and survivor spending. However, 40% of the raw difference between decedent and survivor average spending (which is 13,204 minus 4,671) remains unexplained even when accounting for monthly prognosis. In addition, an even greater share of the unexplained difference between decedent and survivor spending is now concentrated in admissions, particularly low-intensity admissions.

as (one-year) "decedent" in all of them; a patient who died 400 days after initial diagnosis will be included in all monthly prediction training sets, with the one-year mortality outcome coded as "survivor" on months 0 and 1, and "decedent" on months 2 and above (since $400 - 60 < 365$).

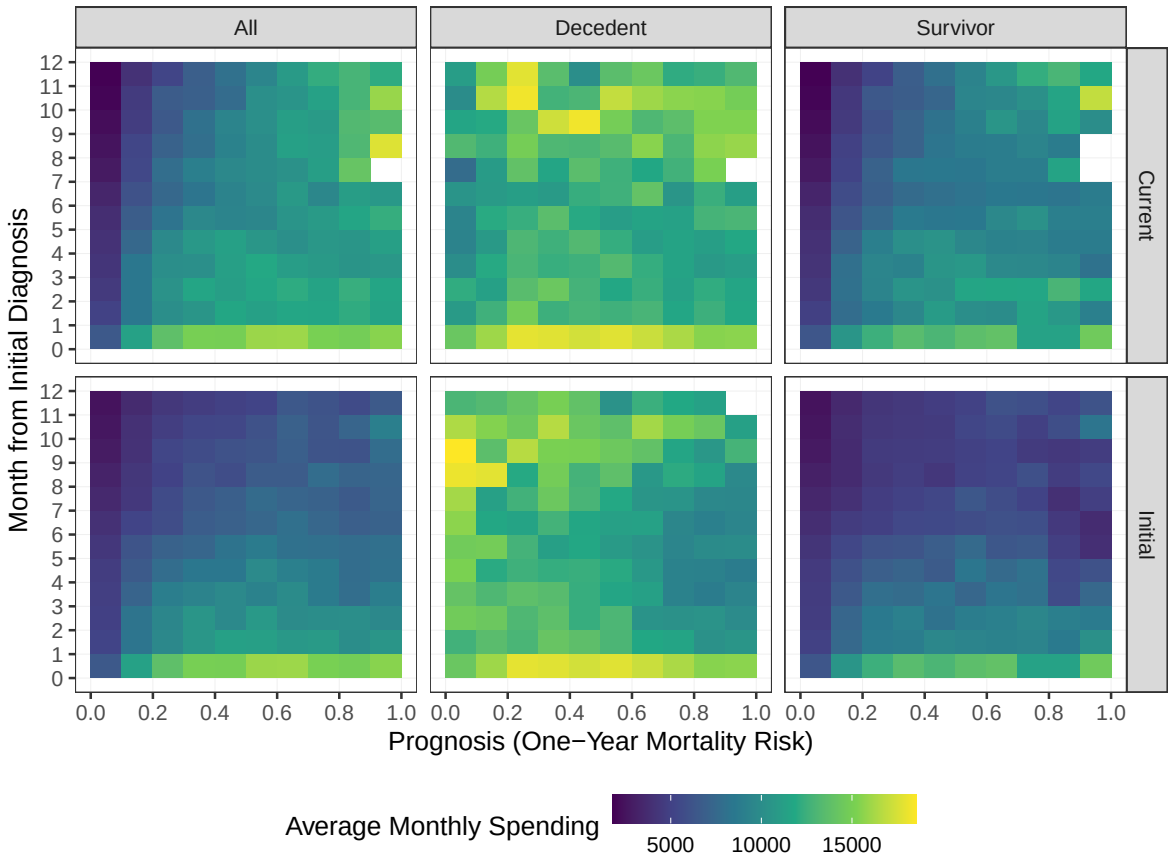



Appendix Figure A1: Share of Cases Receiving Different Major Clinical Events by Event Sequential Number, by Cancer Type

*Notes:* Figure shows, for the sample of major clinical events of cancer cases of each type, the share of cases still in treatment and their most recent major event, as a function of the (sequential) number of the treatment event. Colors denote the type of the most recent event. The three top panels show data for the three most common cancer types (Breast, Prostate, and Colon, which together account for a third of all cases and have mortality rates of 4.0%, 4.8%, and 18.6%, respectively); the three bottom panels show data for the three cancer types for with the highest one-year mortality rate (Brain, Lung, and Pancreas, which together account for 11.5 percent of cases and have mortality rates of 47.3%, 52.5%, and 67.8%, respectively). The last data point for Pancreas is empty: no patient diagnosed with Pancreatic cancer in our sample had more than six clinical events in the year following initial diagnosis. N=156,391 patient-events (across all six cancer types).

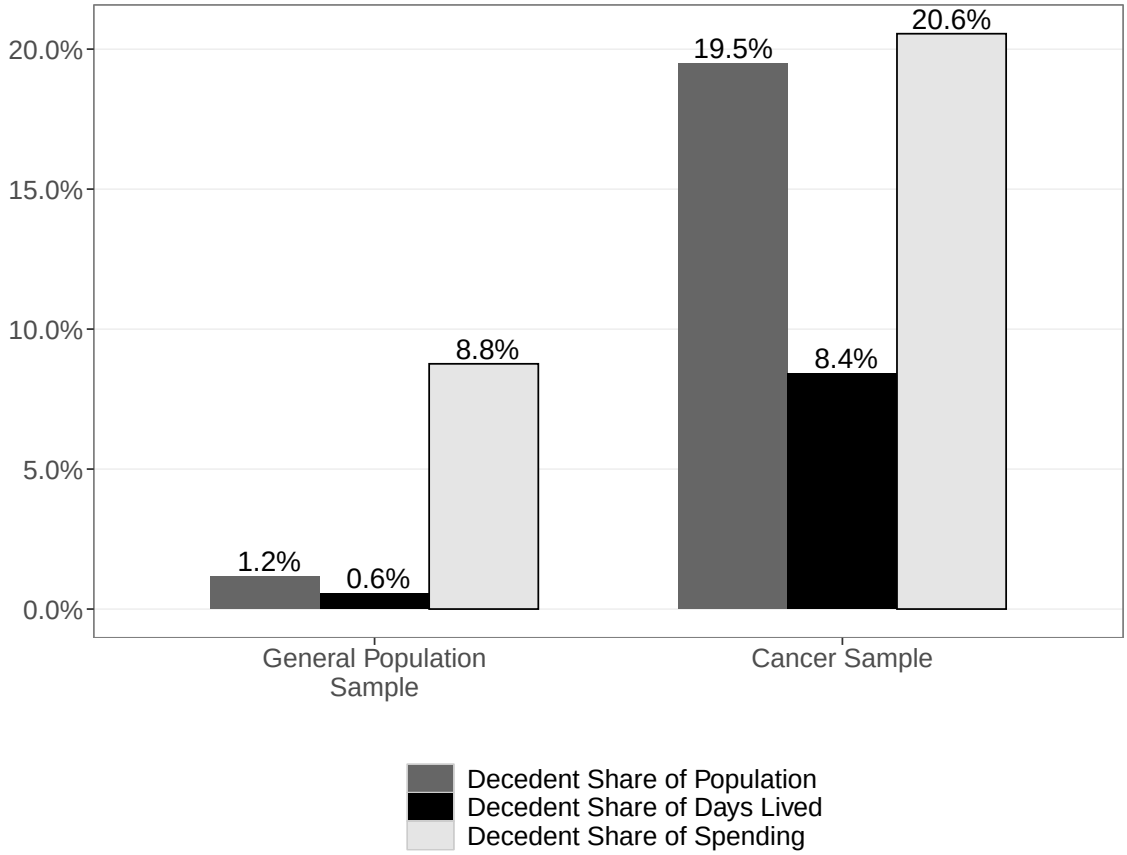

Appendix Figure A2: Number of Cases by Mortality Prognosis and Time Since Diagnosis

*Notes:* Each facet shows a heat-map plot of sample size as a function of risk and time since diagnosis. The x-axis shows initial mortality prognosis, the y-axis shows time since initial cancer diagnosis, and color shades denote the number of cases in our sample. Column panels show data for different subsamples: all cancer patients (left), cancer decedent (middle), and cancer survivor (right). Row panels show data using two different measures of mortality risk: initial mortality risk (bottom) and current mortality risk (top). $N = 83,181$ patients.



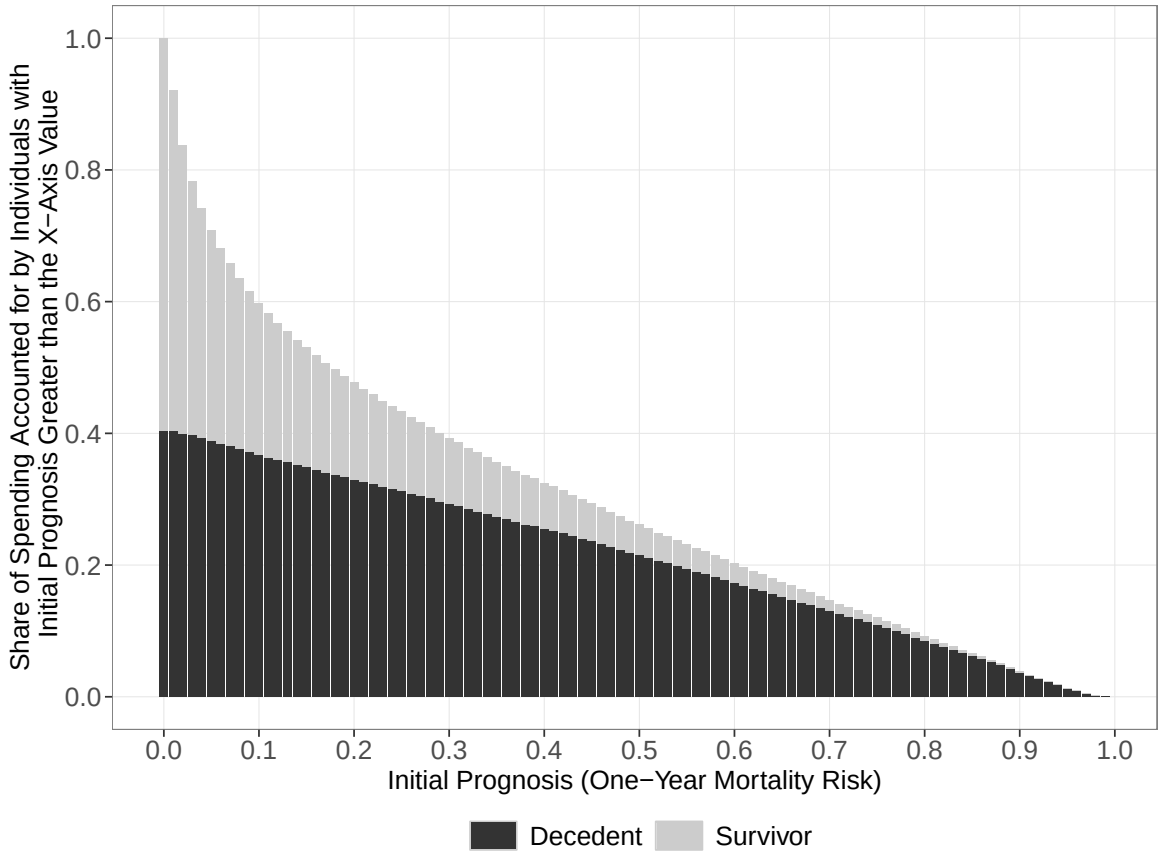

Appendix Figure A3: Average Monthly Spending by Predicted Mortality Risk and Time Since Diagnosis

*Notes:* Each facet shows a heat-map plot of average monthly spending as a function of risk and time since diagnosis. The x-axis shows initial mortality prognosis, the y-axis shows time since initial cancer diagnosis, and color shades denote average monthly spending. Column panels show data for different subsamples: all cancer patients (left), cancer decedent (middle), and cancer survivor (right). Row panels show data using two different measures of mortality risk: initial mortality risk (bottom) and current mortality risk (top). Cells appearing in white contain 10 patients or fewer; data for these cells are not reported. $N = 83,181$ patients.



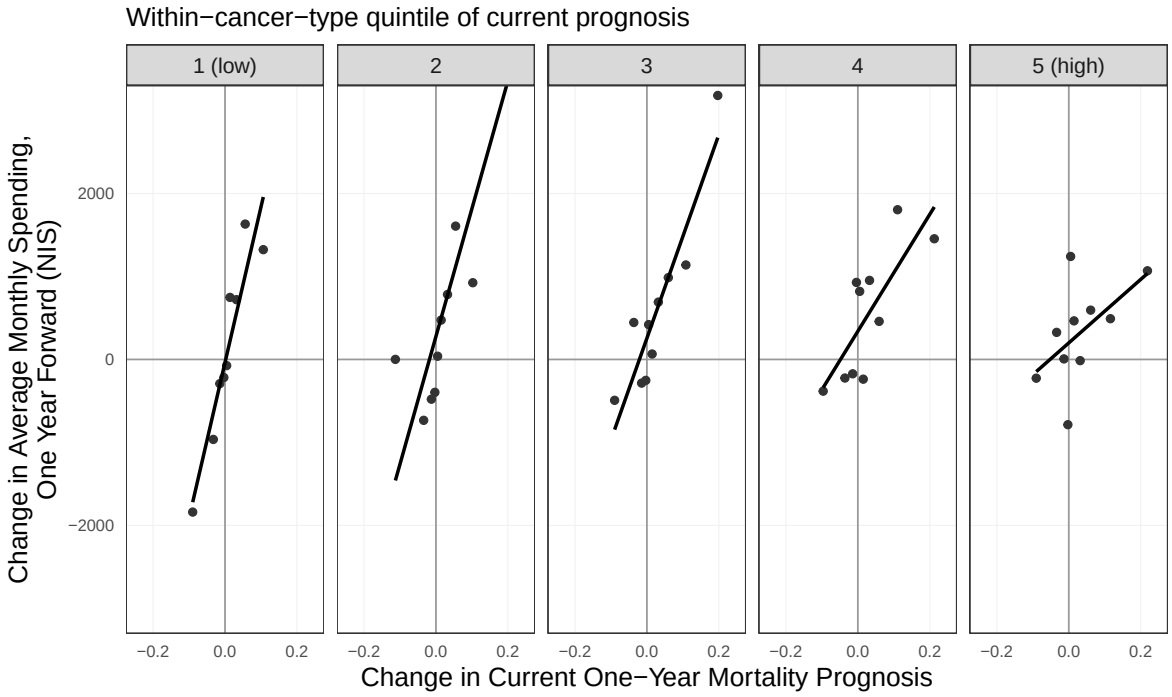

Appendix Figure A4: Spending Concentration, Different Subpopulations

*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; $N = 166,839$ for the Cancer Sample), which we later randomly split into training and test sets. Sample definitions are discussed in Section 3.



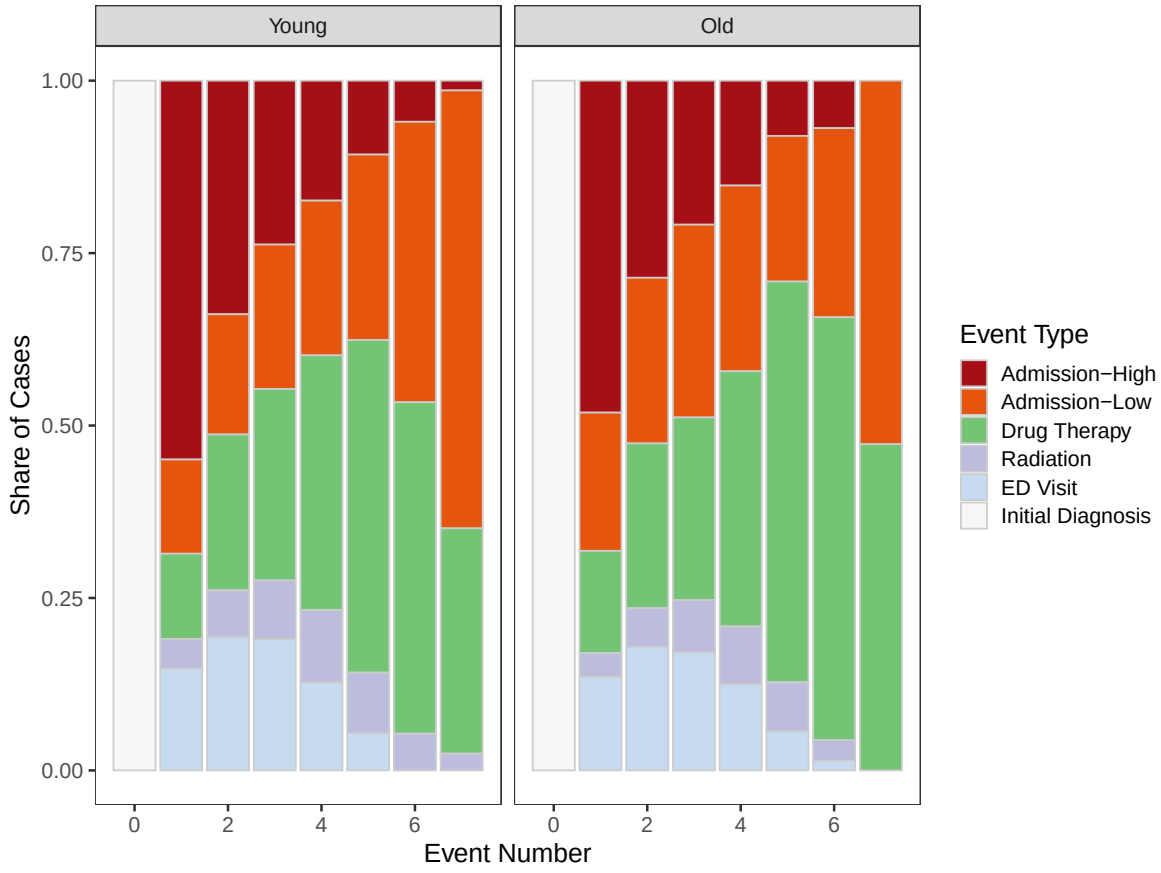

Appendix Figure A5: The Share of Average Monthly Spending Accounted for by Individuals with Different Prognoses

*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 months 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 (2)). $N = 83,181$ patients.



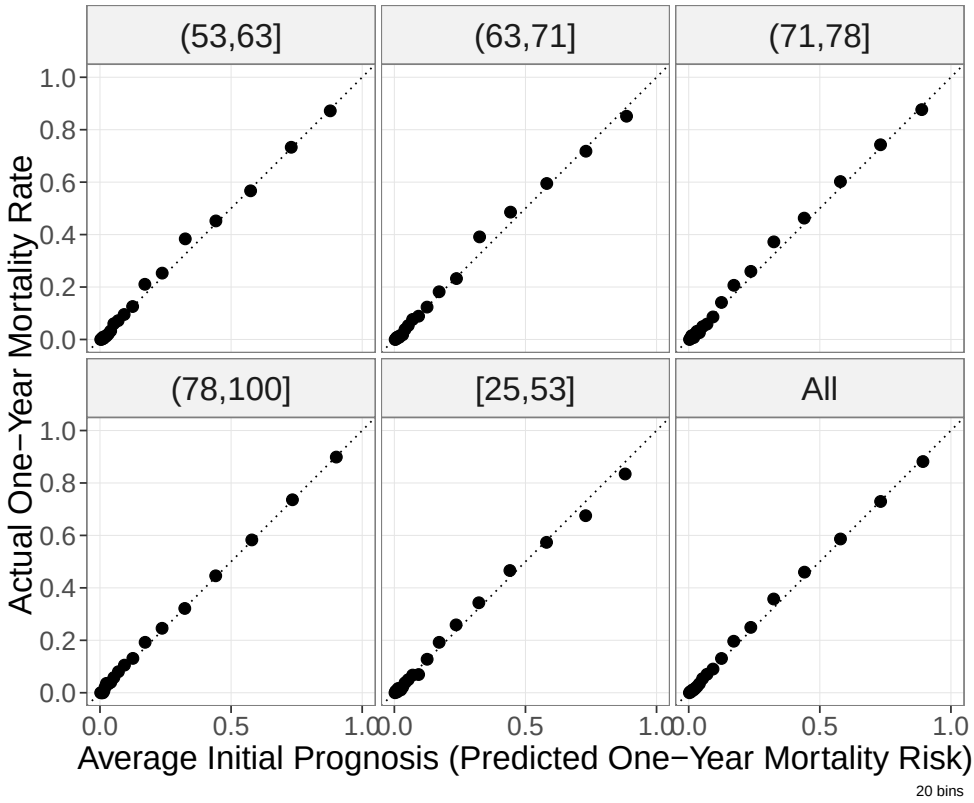

Appendix Figure A6: Change in Future Spending Over Change in Current Prognosis, by Current Prognosis Relative to Cancer Type

*Notes:* Figure shows, for the sample of 207,607 clinical histories of cancer patients in our sample with one more clinical events after initial diagnosis, the relationship between change in current prognosis and change in forward spending, by quintile of current prognosis. Quintiles are calculated within cancer type. Each observation in the underlying data is a pair of consecutive clinical events. The x-axis shows the change in predicted mortality prognosis between the start of the most recent and the start of the current clinical events. The y-axis shows the change in one-year forward spending between the two events. Linear fit is shown in each panel.



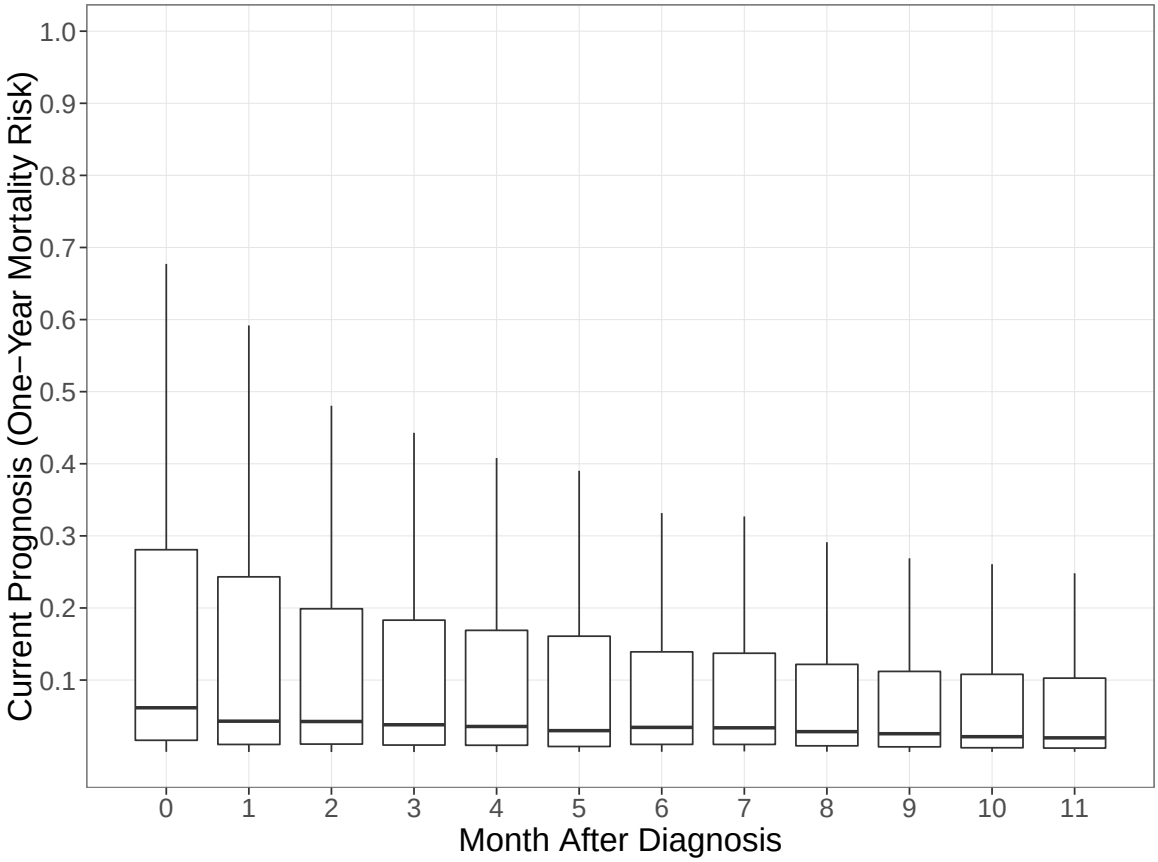

Appendix Figure A7: Distribution of Number of Cases by Type and Number of Major Clinical Events and Patient Age Group

*Notes:* Figure shows, using the sample for which we predict current mortality based on major clinical events (N = 292,284 patient-events), which we use for the prediction of current mortality risk at the start of major clinical events, the share of cases still in treatment and their most recent major event, as a function of the number of events performed. Colors denote the type of the most recent event. Admission-High and Admission-Low denote high- and low-intensity admissions. Drug Therapy is a spell of either chemotherapy or biological drug treatment. Radiation Therapy denotes a spell of such therapy. ED visit is emergency department visit that did not result in an admission to a hospital. Initial Diagnosis denotes initial cancer diagnosis. Facets show data separately for patients older than the median for their cancer type ("Old") and younger than this median ("Young").




Appendix Figure A8: Model Calibration, by Age Group

*Notes:* Figure shows our final predictions from a model trained on the training sample 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 within each age quintile by their predicted one-year mortality risk at the initial cancer diagnosis 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 range of ages included in each sample is shown in the panel header. The model seems to be well calibrated for all age groups. $N = 83,181$ patients.




Appendix Figure A9: 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 B. 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, no further than 1.5 * IQR from the hinge. Outliers—data points beyond the end of the whiskers—are not shown. The sample includes all 83,181 patients (month 0) and the subset who are alive on the first day of each subsequent month.

Appendix Table A1: 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 | 6,020.96 | 30.0 | 3.4 | 2.6 |
| | Neurology | 5,259.96 | 5.2 | 1.4 | 1.5 |
| | Orthopedic Surgery | 3,788.69 | 32.9 | 1.7 | 1.9 |
| | General Surgery | 3,215.90 | 48.3 | 23.1 | 16.8 |
| | Other | 2,827.37 | 42.2 | 18.9 | 14.3 |
| | ICU | 2,427.11 | 16.0 | 0.1 | 0.2 |
| | Urology | 2,068.50 | 24.9 | 7.4 | 5.4 |
| Low | Oncology | 1,560.34 | 5.6 | 11.0 | 16.5 |
| | Internal Medicine | 1,444.29 | 5.8 | 29.4 | 25.9 |
| | Geriatry | 816.60 | 6.5 | 2.0 | 5.6 |
| | Rehabilitation | 670.37 | 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 Cost Per Day 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 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 that are to Clalit-owned hospitals, for which we have detailed procedure data. The rest of the analysis uses all 159,653 admissions, including those with multiple wards.

Appendix Table A2: Admission Characteristics by Hospital Ownership

| | **Hospital Owner** | |
|---|---|---|
| | Clalit (1) | Non Clalit (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 3.1 discusses the institutional setting. 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 A1 for details.

## Appendix Table A3: Additional Descriptive Statistics

| | Sample Size | | One-Year Mortality | Age | Average Monthly Spending (NIS) | | Percentiles of Predicted Mortality | | | Decedent with Pred. Mort. ≥ 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. All Cancer Types** | | | | | | | | | | |
| All | 83,181 | 100.0 | 19.6 | 67 | 4,757 | 5,411 | 37.8 | 81.1 | 94.1 | 24.0 |
| Age>65 | 44,620 | 53.6 | 27.0 | 75 | 4,110 | 4,962 | 54.4 | 87.4 | 95.5 | 27.4 |
| Age>85 | 4,697 | 5.6 | 47.8 | 88 | 2,649 | 3,902 | 80.2 | 94.5 | 98.1 | 38.0 |
| **B. By Cancer Type** | | | | | | | | | | |
| Breast | 13,379 | 16.1 | 4.0 | 61 | 5,250 | 5,374 | 4.3 | 18.6 | 51.5 | 2.2 |
| Prostate Gland | 8,164 | 9.8 | 4.8 | 70 | 3,291 | 3,374 | 5.8 | 25.7 | 54.9 | 2.0 |
| Colon | 8,015 | 9.6 | 18.6 | 72 | 4,763 | 5,404 | 31.4 | 63.9 | 82.7 | 6.8 |
| Bronchus and Lung | 6,278 | 7.5 | 52.5 | 69 | 5,584 | 8,241 | 79.9 | 91.6 | 95.6 | 32.7 |
| Skin | 5,297 | 6.4 | 5.3 | 64 | 1,696 | 1,744 | 7.2 | 24.1 | 57.0 | 1.1 |
| Bladder | 4,938 | 5.9 | 11.9 | 71 | 2,857 | 3,051 | 17.1 | 49.3 | 76.3 | 3.7 |
| Hemato. and Reticul. Systems | 4,428 | 5.3 | 23.9 | 70 | 8,453 | 9,855 | 41.5 | 72.9 | 89.7 | 10.2 |
| Lymph Nodes | 2,910 | 3.5 | 19.0 | 64 | 8,759 | 9,954 | 34.8 | 65.4 | 84.1 | 7.4 |
| Stomach | 2,851 | 3.4 | 44.9 | 71 | 5,674 | 7,847 | 69.3 | 86.3 | 92.9 | 19.0 |
| Rectum | 2,321 | 2.8 | 15.9 | 68 | 6,733 | 7,399 | 24.5 | 58.6 | 82.0 | 7.0 |
| Corpus Uteri | 2,173 | 2.6 | 8.0 | 64 | 3,402 | 3,546 | 11.2 | 31.4 | 57.2 | 1.7 |
| Thyroid Gland | 2,127 | 2.6 | 4.1 | 53 | 2,102 | 2,159 | 2.6 | 11.5 | 71.5 | 17.2 |
| Pancreas | 2,047 | 2.5 | 67.8 | 72 | 4,925 | 8,641 | 89.8 | 95.9 | 97.9 | 51.4 |
| Kidney | 2,000 | 2.4 | 12.4 | 66 | 2,732 | 2,955 | 19.9 | 55.2 | 82.0 | 7.3 |
| Cervix Uteri | 1,934 | 2.3 | 4.7 | 41 | 2,617 | 2,676 | 4.4 | 21.9 | 60.6 | 4.4 |
| Meninges | 1,528 | 1.8 | 9.8 | 64 | 3,314 | 3,530 | 13.3 | 37.4 | 58.8 | 0.7 |
| Brain | 1,225 | 1.5 | 47.3 | 62 | 7,554 | 10,538 | 71.5 | 88.3 | 94.3 | 22.1 |
| Ovary | 1,194 | 1.4 | 16.2 | 62 | 3,782 | 4,172 | 25.2 | 61.0 | 80.7 | 6.2 |
| Rectosigmoid Junction | 908 | 1.1 | 11.0 | 69 | 5,578 | 5,946 | 21.9 | 54.4 | 75.7 | 5.0 |
| Other | 7,518 | 9.0 | 26.3 | 66 | 5,760 | 6,862 | 48.3 | 80.7 | 92.8 | 17.5 |
| Unknown Primary Site | 1,946 | 2.3 | 75.2 | 73 | 4,062 | 9,253 | 94.0 | 97.4 | 98.8 | 69.9 |

*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 (2)). 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%. $N = 83,181$ patients.

Appendix Table A4: Admission Intensity, by Billing Method

| | Billing Method | Average Cost Per Day (NIS) (1) | Avg Length of Stay (2) | Share of Admissions (3) |
|---|---|---|---|---|
| All | Procedure Based | 3,895 | 4.5 | 32.8 |
| | Per Diem | 1,406 | 7.7 | 67.2 |
| Decedent | Procedure Based | 3,366 | 7.8 | 14.6 |
| | Per Diem | 1,354 | 9.5 | 85.4 |
| Survivor | Procedure Based | 4,048 | 4.0 | 40.2 |
| | Per Diem | 1,450 | 6.6 | 59.8 |

*Notes:* Table shows alternative classification of admissions, based on whether it was billed using procedure-based bundled episode billing or per-diem. Average Cost Per Day 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). Avg Length of Stay is the average admission length, in days. Share of Admissions is the share of each class out of all sampled admissions. $N = 159,653$ admissions.

Appendix Table A5: Average Monthly Spending with Alternative Admission Grouping

| Category | Survivor | | Decedent | Difference | |
|---|---|---|---|---|---|
| | Unweighted | Reweighted by Decedent Risk | | Decedent - Survivor (Reweighted) | Percent of Total Difference |
| | (1) | (2) | (3) | (4) | (5) |
| All Inpatient | 1,735 | 4,172 | 9,152 | 4,980 | 100.0 |
| **A. By Ward** | | | | | |
| Low Intensity | 482 | 1,800 | 5,302 | 3,502 | 70.3 |
| Internal Medicine | 200 | 697 | 2,429 | 1,732 | 34.8 |
| Oncology | 207 | 784 | 2,220 | 1,436 | 28.8 |
| Geriatry | 28 | 160 | 358 | 198 | 4.0 |
| Rehabilitation | 46 | 159 | 295 | 136 | 2.7 |
| High Intensity | 1,254 | 2,372 | 3,850 | 1,479 | 29.7 |
| General Surgery | 474 | 1,037 | 1,405 | 368 | 7.4 |
| ICU | 14 | 39 | 202 | 163 | 3.3 |
| Neurology | 64 | 143 | 271 | 129 | 2.6 |
| Urology | 107 | 101 | 199 | 97 | 2.0 |
| Orthopedic Surgery | 67 | 164 | 205 | 41 | 0.8 |
| Gastroenterology | 145 | 300 | 256 | -44 | -0.9 |
| Other | 383 | 589 | 1,314 | 725 | 14.6 |
| **B. By Planned Status** | | | | | |
| Unplanned | 409 | 1,194 | 4,019 | 2,825 | 56.7 |
| Planned | 1,326 | 2,978 | 5,133 | 2,156 | 43.3 |
| **C. By Billing Method** | | | | | |
| Per diem | 792 | 2,383 | 6,643 | 4,260 | 85.5 |
| Procedure Based | 943 | 1,789 | 2,509 | 720 | 14.5 |
| **D. By Main Procedure** | | | | | |
| All Clalit Owned Inpatient | 588 | 1,269 | 2,628 | 1,359 | 100.0 |
| Maintenance | 259 | 587 | 1,492 | 905 | 66.6 |
| Surgery | 274 | 465 | 653 | 188 | 13.8 |
| Chemotherapy | 46 | 177 | 347 | 170 | 12.5 |
| Radiation | 9 | 41 | 137 | 96 | 7.1 |

*Notes:* Table summarizes the results of using alternative classification of inpatient admission spending in the comparison of decedent and survivor spending. Panel A shows our baseline classification of admissions (used in Table 2) into high and low intensity admissions, based on the average spending in the ward to which the patient was admitted. In addition, this panels shows the contribution of each of the top ten wards separately. Panel B shows a classification based on whether the admission was planned or unplanned (namely, whether it was scheduled or originated from an emergency department visit). Panel C shows a classification based on whether billing was procedure-based bundled episode or per-diem. Panel D shows an alternative classification based on the main therapeutic procedures coded in the internal hospital records of the admission (based on the sample of admissions to Clalit-owned hospital, for which procedure codes are available and which are further described in Appendix Table A11). Admission costs are attributed to the admission start date, which results in slight differences in reweighted costs between this table and Table 2, in which admission costs are attributed to the month in which they occur. $N = 83,181$ patients.

Appendix Table A6: Procedures in Planned and Unplanned Inpatient, by Admission Time Before Death

| | Procedure Type, Admission With Any (%) | | | | | | |
|---|---|---|---|---|---|---|---|
| | Maintenance | Diagnostics | Surgery | Radiation | Chemotherapy | Other | N of Admissions |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
| **A. Planned Admissions** | | | | | | | |
| Last month | 11.2 | 97.9 | 11.8 | 4.4 | 6.6 | 0.5 | 2,201 |
| 1-3 months | 11.8 | 95.3 | 14.6 | 7.1 | 12.5 | 0.9 | 1,755 |
| 4-12 months | 10.5 | 94.5 | 19.0 | 6.7 | 20.5 | 1.1 | 2,434 |
| Survivors | 9.7 | 91.3 | 41.9 | 3.2 | 8.3 | 1.2 | 20,501 |
| All Planned | 10.0 | 92.4 | 35.6 | 3.9 | 9.5 | 1.1 | 26,891 |
| **B. Unplanned Admissions** | | | | | | | |
| Last month | 11.8 | 99.2 | 8.6 | 3.8 | 3.9 | 0.9 | 3,018 |
| 1-3 months | 11.9 | 96.6 | 9.8 | 6.1 | 7.1 | 0.9 | 2,109 |
| 4-12 months | 11.5 | 93.5 | 13.7 | 6.4 | 13.0 | 1.8 | 2,555 |
| Survivors | 8.5 | 88.8 | 24.0 | 2.6 | 6.9 | 1.0 | 16,095 |
| All Unplanned | 9.6 | 91.3 | 19.7 | 3.5 | 7.2 | 1.1 | 23,777 |
| **C. Low Intensity** | | | | | | | |
| Last month | 8.7 | 98.6 | 5.2 | 4.9 | 4.8 | 0.4 | 4,264 |
| 1-3 months | 8.9 | 96.1 | 6.0 | 8.9 | 10.7 | 0.5 | 2,791 |
| 4-12 months | 7.8 | 93.6 | 7.1 | 9.5 | 21.5 | 1.1 | 3,059 |
| Survivors | 5.6 | 93.8 | 5.4 | 7.1 | 15.4 | 1.1 | 11,944 |
| All Low Intensity | 6.9 | 95.0 | 5.7 | 7.3 | 13.6 | 0.9 | 22,058 |
| **D. High Intensity** | | | | | | | |
| Last month | 18.1 | 98.9 | 20.9 | 0.9 | 3.9 | 1.4 | 1,582 |
| 1-3 months | 17.6 | 95.9 | 22.8 | 1.4 | 5.6 | 1.4 | 1,315 |
| 4-12 months | 15.2 | 94.7 | 26.7 | 2.2 | 7.8 | 1.8 | 2,277 |
| Survivors | 10.9 | 88.8 | 45.0 | 0.9 | 3.7 | 1.1 | 26,404 |
| All High Intensity | 11.8 | 90.1 | 41.6 | 1.1 | 4.1 | 1.1 | 31,578 |

*Notes:* Table shows results parallel to those 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 A1 for details. Sampled admissions include Clalit-owned-hospital admissions that started and ended during the year after diagnosis.

Appendix Table A7: Select Predictors

| | Train Set (1) | Test Set (2) |
|---|---|---|
| **Sample Size** | | |
| Number of Beneficiaries | 83,658 | 83,181 |
| **Outcomes** | | |
| 1-Year All-Cause Mortality (%) | 19.4 | 19.6 |
| **Demographics** | | |
| Age (mean) (minimum = 25) (y) | 65 | 65 |
| Sex (% Female) | 52.3 | 52.0 |
| Ethnicity (% Arabs) | 8.8 | 8.7 |
| Supplementary Insurance (%) | 70.3 | 70.0 |
| Disability (%) | 3.8 | 3.7 |
| **Chronic Conditions,† %** | | |
| Hyperlipidemia | 47.9 | 47.9 |
| Hypertension | 48 | 48 |
| Arthropathy | 27.6 | 27.3 |
| Diabetes | 22.1 | 22.0 |
| IHD | 21.5 | 21.6 |
| Arrhythmia | 9.5 | 9.6 |
| Neurological | 7.9 | 7.9 |
| Kidney | 7.9 | 8.0 |
| Gastritis | 9.7 | 9.6 |
| CRF | 6.2 | 6.1 |
| Osteoporosis | 10.6 | 10.4 |
| CVA | 7.6 | 7.5 |
| Depression | 7.2 | 7.1 |
| Valvular Cardiac | 5.8 | 5.7 |
| CHF | 5.5 | 5.5 |
| COPD | 6.9 | 7.0 |
| **Prior Utilization, mean 1yr count (% non zero)** | | |
| Prescription Drugs | 1493 (97.2) | 1470.9 (97.3) |
| Laboratory Tests | 36.1 (85.1) | 35.8 (84.9) |
| Imaging Events | 2.2 (71.1) | 2.2 (70.8) |
| Ambulatory Encounters | 154.6 (66.6) | 150.6 (66.5) |
| Emergency Room Visits | 0.5 (32) | 0.5 (32.3) |
| Hospital Visits | 2 (73) | 2 (73) |
| **Prior Utilization, mean 1yr cost (% non zero)** | | |
| Total Spending (NIS) | 16,881 (99.8) | 16,873 (99.7) |
| **ACG Score,*** | | |
| Healthy or Low | 18.6 | 18.9 |
| Moderate | 56.1 | 56.8 |
| High or Very High | 25.2 | 24.4 |
| **Clinical Measurements†, last measurement, mean (% non missing)** | | |
| BMI | 28 (54.2) | 28 (54.2) |
| Diastolic Blood Pressure (mm Hg) | 75.1 (66.4) | 75.3 (66.5) |
| Systolic Blood Pressure (mm Hg) | 129.1 (66.4) | 129.2 (66.5) |
| Hemoglobin (g/dL) | 12.9 (85.7) | 12.9 (85.7) |
| Hematocrit, (%) | 3 (10.3) | 3 (10.3) |
| Red Blood Cells | 4.5 (85.6) | 4.5 (85.5) |
| Platelets (1000/uL) | 261.8 (85.7) | 261.1 (85.7) |
| Neutrophiles | 5.3 (84.5) | 5.3 (84.4) |
| Lymphocytes | 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.1 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.

Appendix Table A8: Average Monthly Spending, Reweighted by Monthly Prognosis

| Category | Survivor | | Decedent | Difference | |
|---|---|---|---|---|---|
| | Unweighted | Reweighted by Decedent Risk | | Decedent - Survivor (Reweighted) | Percent of Total Difference |
| | (1) | (2) | (3) | (4) | (5) |
| Total | 4,671 | 9,649 | 13,204 | 3,555 | 100.0 |
| All Inpatient: | 1,735 | 5,053 | 9,152 | 4,099 | 115.3 |
| Planned | 1,326 | 3,543 | 5,133 | 1,590 | 44.7 |
| Unplanned | 409 | 1,510 | 4,019 | 2,509 | 70.6 |
| Low Intensity | 482 | 2,436 | 5,302 | 2,866 | 80.6 |
| High Intensity | 1,254 | 2,618 | 3,850 | 1,233 | 34.7 |
| Other Services: | 2,936 | 4,596 | 4,052 | -544 | -15.3 |
| Drugs | 1,119 | 2,012 | 1,733 | -279 | -7.8 |
| Outpatient | 1,239 | 1,809 | 1,566 | -243 | -6.8 |
| Imaging | 191 | 267 | 222 | -45 | -1.3 |
| Other | 387 | 508 | 530 | 23 | 0.6 |

*Notes:* Table 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 those shown in Table 2, but with survivor spending being reweighted (in columns 2) by month (since-diagnosis) and monthly prognosis instead of by month and initial prognosis. Monthly prognosis is calculated every month, starting from each patient's initial prognosis, for all patients still alive. Appendix B provides additional details on this risk measure and the reweighting based on it. Decedent spending is adjusted for survival duration (see equation (2)). 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 3,555, 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 A1 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, respectively. All spending measures are in current New Israeli Shekels (NIS). $N = 83,181$ patients.

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 | 4,982.37 | 22.2 | 1.5 | 1.0 |
| | Neurology | 4,401.93 | 8.2 | 1.2 | 1.2 |
| | Orthopedic Surgery | 3,840.70 | 35.2 | 1.0 | 0.9 |
| | ICU | 2,544.43 | 15.9 | 0.3 | 0.3 |
| | General Surgery | 2,372.18 | 22.2 | 11.9 | 11.0 |
| | Other | 2,036.29 | 25.2 | 12.0 | 10.1 |
| | Urology | 1,929.81 | 34.4 | 2.5 | 1.9 |
| Low | Oncology | 1,456.86 | 6.1 | 16.4 | 21.9 |
| | Internal Medicine | 1,444.66 | 6.1 | 46.3 | 34.0 |
| | Geriatry | 791.76 | 6.3 | 3.9 | 8.1 |
| | Rehabilitation | 584.21 | 0.0 | 2.9 | 9.5 |
| **B. Survivor** | | | | | |
| High | Gastroenterology | 6,222.13 | 100.0 | 4.2 | 3.7 |
| | Neurology | 5,694.37 | 3.8 | 1.4 | 1.6 |
| | Orthopedic Surgery | 3,776.52 | 32.1 | 2.0 | 2.6 |
| | General Surgery | 3,519.27 | 53.0 | 27.7 | 20.8 |
| | Other | 3,144.64 | 45.7 | 21.7 | 17.2 |
| | ICU | 2,152.78 | 16.1 | 0.0 | 0.1 |
| | Urology | 2,092.08 | 23.7 | 9.4 | 7.7 |
| Low | Oncology | 1,679.62 | 5.1 | 8.7 | 12.9 |
| | Internal Medicine | 1,443.88 | 5.6 | 22.3 | 20.4 |
| | Geriatry | 851.87 | 6.7 | 1.2 | 3.9 |
| | Rehabilitation | 732.75 | 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 those shown in Appendix Table A1, 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 admissions 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 A1 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, including those with multiple wards.

Appendix Table A10: Spending and Mortality Risk by Number of Event and Patient Age Group

| | No. of Cases | | Current Mortality Risk | | Avg Monthly Spending | |
|---|---|---|---|---|---|---|
| Event Number | Old | Young | Old | Young | Old | Young |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| 0 | 40,689 | 42,492 | 0.255 | 0.132 | 6,010 | 6,559 |
| 1 | 35,571 | 36,182 | 0.272 | 0.155 | 6,161 | 7,304 |
| 2 | 28,364 | 28,560 | 0.293 | 0.187 | 6,449 | 8,316 |
| 3 | 18,532 | 19,459 | 0.298 | 0.208 | 6,423 | 8,738 |
| 4 | 8,406 | 9,466 | 0.257 | 0.187 | 6,175 | 7,924 |
| 5 | 3,097 | 4,098 | 0.210 | 0.186 | 4,799 | 8,086 |
| 6 | 1,134 | 1,896 | 0.247 | 0.232 | 5,365 | 8,228 |
| 7 | 332 | 986 | 0.381 | 0.341 | 7,509 | 10,796 |

*Notes:* Table shows summary statistics for the sample for which we predict current mortality based on major clinical events (N = 292,284 patient-events). Event number refers to the number of major clinical events since initial cancer diagnosis. Old and Young refer to patients whose age at diagnosis is above and below the median age of patients with the same cancer type.

Appendix Table A11: Admission Intensity, by Main Therapeutic Procedure

| | Main Procedure | Average Cost Per Day (NIS) (1) | Avg Length of Stay (2) | Share of Admissions (3) |
|---|---|---|---|---|
| All | Maintenance | 1,679 | 6.1 | 61.7 |
| | Surgery | 3,363 | 5.6 | 28.1 |
| | Chemotherapy | 2,214 | 7.2 | 7.8 |
| | Radiation | 1,592 | 8.8 | 2.5 |
| Decedent | Maintenance | 1,452 | 7.4 | 73.7 |
| | Surgery | 2,342 | 11.7 | 12.8 |
| | Chemotherapy | 2,073 | 9.4 | 9.5 |
| | Radiation | 1,556 | 11.8 | 4.0 |
| Survivor | Maintenance | 1,833 | 5.4 | 57.0 |
| | Surgery | 3,726 | 4.7 | 34.0 |
| | Chemotherapy | 2,327 | 6.1 | 7.1 |
| | Radiation | 1,646 | 6.4 | 1.9 |

*Notes:* Table shows alternative classification of admissions, based on the main procedure performed during the admission. Average Cost Per Day 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). Avg Length of Stay is the average admission length, in days. Share of Admissions is the share of each class out of all sampled admissions. Sample is based on the 53,952 admissions to Clalit-owned hospitals, for which we have detailed procedure data.