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Impact of Inpatient Palliative Care Consultation on 30-day Hospital Readmissions and Near Misses

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Impact of Inpatient Palliative Care Consultation on 30-day Hospital Readmissions and Near Misses

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An abstract of

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Abstract

Impact of Inpatient Palliative Care Consultation on 30-day Hospital Readmissions and Near Misses

By Zachary O. Binney

Introduction: 30-day readmissions are a major financial and quality concern for hospitals. There is limited literature on the role palliative care teams play in reducing readmissions.

Methods: We conducted two analyses of the association between receiving a palliative care consult and risk of all-cause and related 30-day readmissions and near-misses (emergency department visits and observation stays) in a cohort of 34,451 admissions from July 2011-June 2012 at two southern urban academic medical centers. We used propensity scores to match patients with and without a palliative care consult within a pool of 24,809 patients' first admissions during the study period. We used one-to-one nearest-neighbor matching with a caliper. We then adjusted for residual confounding using multivariate conditional logistic regression. We also analyzed 5,649 patients with multiple admissions during the study period as a crossover trial using multivariate conditional logistic regression.

Results: The propensity score-matched cohorts exhibited satisfactory covariate balance. In the matched first admissions there was a trend toward fewer all-cause readmissions and near-misses (adjusted OR (aOR) 0.78, 95% CI 0.59-1.03), but it was not statistically significant. In the crossover analysis there were significant reductions in all-cause readmissions and near misses (aOR 0.76, 95% CI 0.61-0.94), all-cause readmissions only (aOR 0.77, 95% CI 0.62-0.97), and related readmissions only (aOR 0.68, 95% CI 0.49-0.94). There was a trend toward reduced related readmissions and near-misses (aOR 0.76, 95% CI 0.57-1.02).

Discussion: Receiving a palliative care consult was associated with a meaningful reduction in the risk of all-cause and related 30-day readmissions in a cohort of seriously ill patients. The effects may be stronger for patients at higher risk from multiple previous admissions, but the non-significant results in the matched analysis are likely due to a smaller number of observed events. We recommend the use of palliative care consults for patients with serious illness at high risk for readmission.

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Table of Contents

Chapter 1: Literature Review

Hospital Readmissions and Their Impact

Hospital readmissions are regrettably common in U.S. healthcare: roughly one fifth of Medicare beneficiaries experience a 30-day readmission in[1]. The causes for readmissions are myriad, but most researchers attribute them in some form or another to the fragmentation of the U.S. healthcare system[2]. Hospitals, primary care physicians, specialists, nursing homes, assisted living facilities, hospices, diagnostic centers, pharmacies, and others must work together to provide optimal care for patients with complex health problems. However, continuity of care in the U.S. is severely lacking. Overtaxed primary care providers (PCP); poor adoption and even worse integration of electronic health records (EHR); and financing that pays providers and facilities for visits and procedures with minimal if any incentives for care integration, coordination, or communication all contribute to the problem[2].

Some of the most commonly cited causes of hospital readmissions include[3]:

- Poor communication with the patient, especially around what merits contacting their physician and ensuring a full understanding of medications
- Poor transfer of information to other caregivers such as a PCP or nursing home staff, including around end of life care preferences
- Lack of a post-discharge PCP visit
- Poor medication management or reconciliation leading to duplication or interaction

What these boil down to is poor communication and integration across the various members of a health care team – including the patient – that lead to sub-optimal

management of patients with serious illness. Until recently, however, U.S. healthcare stakeholders have not been incentivized to address these problems.

One reason readmissions have become such a major focus recently is their economic impact: one study estimated unplanned 30-day readmissions cost Medicare alone $17.4 billion per year[1]. This has led policymakers to take steps to incentivize hospitals to reduce readmission rates, including the public reporting and comparison of readmission rates via Medicare's Hospital Compare website and enacting the Center for Medicare and Medicaid Services' (CMS) Hospital Readmission Reduction Program (HRRP)[4]. The HRRP is designed to incentivize the reduction of readmission rates for three conditions: heart attack (acute myocardial infarction, AMI), heart failure (HF), and pneumonia. According to the most recent Medicare data, 19.7% of AMI, 24.7% of HF, and 19.7% of pneumonia patients were readmitted within 30 days[5].

To reduce these numbers, the HRRP calculates a hospital's risk-adjusted excess readmission rate – defined as their readmission rate divided by the national average for similar patients – for each of three conditions. The excess readmission rate is calculated for the previous three years (for fiscal year (FY) 2013, July 2008-June 2011). This excess rate minus 1 is applied as a multiplier to a hospital's base Diagnosis-Related Group (DRG) payment for each condition, which reduces the hospital's payments for those conditions by that amount for the following fiscal year; the penalty is capped at 1% of a hospital's total annual Medicare revenue for the program's first year (FY13)[4]. The program is expected to affect 2,217 hospitals, costing them $280 million in FY13[6]. The cap on reductions rises to 2 percent of total Medicare revenue in FY14 and 3 percent in FY15; by FY15 the program will also target readmissions after coronary artery bypass

graft (CABG) surgery, cardiac stenting, and possibly other procedures[6]. Other CMS initiatives contained in the Affordable Care Act (ACA) such as value-based purchasing (payments based on quality metrics) and bundled payment pilots (a lump sum payment for a hospital admission and 30 days of post-acute care) are further incentivizing hospitals to pursue reductions in readmissions.

All of these have spurred hospital interest in reducing readmission rates. Most programs focus on improving discharge planning, medication reconciliation, instituting transitional care programs, and getting patients access to home health services[7]. Since 2007 a number of programs to reduce readmissions have spread from pilot status or nonexistence to a national level. These initiatives include Project Re-Engineered Discharge (RED), centered at Boston University and funded by the Agency for Healthcare Research and Quality (AHRQ), which teaches hospitals how to build and communicate a better discharge plan[8-10]. The Society for Hospital Medicine's Better Outcomes by Optimizing Safe Transitions (BOOST) has a similar focus[11]. The Institute for Healthcare Improvement's State Action on Avoidable Rehospitalizations (STAAR) project seeks to improve care transitions by strengthening collaborations between hospitals and other members of a patient's healthcare team[12]. The Interventions to Reduce Acute Care Transfers (INTERACT) project targets the other end, teaching skilled nursing facilities (SNF) how to minimize the transfer of residents to hospitals[13]. CMS's own Community-based Care Transition Program (CCTP), established by the Affordable Care Act (ACA), seeks to leverage community-based organizations to provide care transition services to Medicare patients[14]. Just five years ago, many of these programs were nonexistent or in their pilot stage[6]; the CCTP began in 2011 and has already

expanded to 82 sites around the country[14]. Moreover, several studies of these and similar programs have demonstrated that readmissions and emergency department (ED) visits can be reduced by strengthening discharge planning and transitional care[10,15-17]. One study of a nurse-directed intervention to improve discharge planning found improvements specific to HF patients[17]. Another randomized trial of a similar program found stronger reductions for patients with multiple previous hospitalizations[10].

Palliative Care

Palliative care is specialized, interdisciplinary care for patients with serious illness at any stage of illness. It focuses on clear patient-provider communication, especially around medical decision-making, advance care planning, and goals of care discussions; the assessment and control of symptoms to improve quality of life; psychosocial and spiritual care and support; and care coordination[18]. These services are in high demand from patients with serious illness[19], but our healthcare system often falls short in providing them[19,20].

Palliative care is often conflated with end-of-life care but can in fact be brought in at any point in a patient's serious illness; the American Society of Clinical Oncology recommends integrating palliative care at or soon after diagnosis for patients with metastatic cancer and/or a high symptom burden[21]. It can be provided in a variety of settings including outpatient clinics, the home, long-term care facilities and, most commonly, on an inpatient basis in acute care hospitals. In recent years hospital-based palliative care teams have grown rapidly; in 2000 only a quarter of hospitals over 50 beds had a team versus nearly two-thirds in 2010[22]. However, access to these services varies

considerably by geography (the south tends to have fewer programs), hospital size (87.9% of hospitals with 300 or more beds have a palliative care team versus 23.2% of hospitals under 50 beds), and financial status (nonprofit hospitals have more programs than for-profit or public hospitals)[22,23].

Numerous studies have documented the clinical benefits of hospital-based palliative care teams. Palliative care has been shown to improve clinical outcomes including patient-provider and family-provider communication[24-26], emotional and spiritual support[24,27-29], care that aligns with the patient's goals[24,26,28,30], and symptom management/quality of life[24,29-33]. Studies have also shown greater patient and family satisfaction when palliative care is involved[24,26,27,33,34]. Several studies have also suggested palliative care is able to reduce healthcare costs through lower use of costly services such as the intensive care unit (ICU)[25,30-32,35]. Although it was not strictly hospital-based palliative care, one randomized trial has found the early integration of palliative care for patients with stage IV non-small cell lung cancer improved symptoms, reduced use of intensive health services, and prolonged survival[36].

Palliative Care's Role in Readmissions

Many of the palliative care team's functions – especially clear goals of care discussions, complex symptom management, and care coordination through better communication and the connecting of patients and families with community-based services for those with serious illness – likely serve to reduce readmissions[37], yet the literature on palliative care and readmissions is lacking. One randomized trial of an in-home palliative care program among terminally ill homebound patients found the

program served to significantly reduce readmissions and ED visits for the rest of the subjects' lives[38]. Another study of an inpatient palliative care team at a long-term care (LTC) facility found patients seen by the palliative care team had fewer ED visits compared to historically matched controls[39]. A recent study of healthcare resource utilization among a group of patients with serious illness 18 months before and after they were referred for an in-home palliative care consults coordinated with their PCP found reduced rates of readmissions but not ED visits[40]. Finally, a study of the probability of a 30-day readmission among patients receiving an inpatient palliative care consult was about 10 percent, with a higher risk of readmission among patients without an advance directive[41]. This study also found higher risk of readmission among those discharged home without care or to a nursing facility compared with those discharged home with hospice or in-home palliative care. However, to date we do not know of any studies comparing the risk of a 30-day readmission among similar patients receiving and not receiving a hospital-based palliative care consult during an inpatient stay. Such a study is needed given the increasing focus of hospitals on reducing readmissions and the growing prevalence of hospital-based palliative care programs.

Chapter 2: Manuscript

Introduction:

Hospital readmissions are regrettably common in U.S. healthcare: roughly one fifth of Medicare beneficiaries experienced a 30-day readmission[1]. The causes for readmissions are myriad, but most researchers attribute them in some form or another to the fragmentation of the U.S. healthcare system[2]. Some of the most commonly cited causes of hospital readmissions include unclear communication with the patient at discharge about appropriate follow-up care, the incomplete transfer of information to other providers outside the hospital, and poor medication management.[3] Until recently, U.S. healthcare stakeholders have not been incentivized to address these problems.

However, readmissions have become a major focus recently due to their economic impact: one study estimated unplanned 30-day readmissions cost Medicare alone $17.4 billion per year[1]. This has led policymakers to incentivize hospitals to reduce readmission rates through public reporting and comparison of readmission rates via Medicare's Hospital Compare website and enacting the Center for Medicare and Medicaid Services' (CMS) Hospital Readmission Reduction Program (HRRP)[4]. The HRRP is designed to reduce readmissions for three conditions: heart attack (acute myocardial infarction, AMI), heart failure (HF), and pneumonia. According to the most recent Medicare data, 19.7% of AMI, 24.7% of HF, and 19.7% of pneumonia patients were readmitted within 30 days[5].

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annual Medicare revenue for the program's first year (FY13)[4]. The cap on reductions rises to 2 percent of total Medicare revenue in FY14 and 3 percent in FY15; by FY15 the program will also expand the set of MS-DRGs subject to readmissions penalties[6]. The program is expected to affect 2,217 hospitals, costing them $280 million in FY13[6]. Other CMS initiatives contained in the Affordable Care Act (ACA) such as value-based purchasing and bundled payment pilots are further incentivizing hospitals to cut readmissions.

Most readmissions reduction programs focus on improving discharge planning, medication reconciliation, instituting transitional care programs, and getting patients access to home health services[7-14]. Studies have demonstrated that these programs can reduce readmissions and emergency department (ED) visits by strengthening discharge planning and transitional care[10,15-17]. One study found improvements specifically for HF patients[17].

Palliative care – specialized interdisciplinary care for patients with serious illness at any stage of illness – may have a role to play in reducing readmissions but has not been sufficiently studied. Palliative care is often conflated with end-of-life care but can in fact be brought in at any point in a patient's serious illness[21]. It can be provided in a variety of settings including outpatient clinics, the home, long-term care facilities and, most commonly, on an inpatient basis in acute care hospitals. In recent years hospital-based palliative care teams have grown rapidly; in 2000 only a quarter of hospitals over 50 beds had a team versus nearly two-thirds in 2010[22]. However, access to these services varies considerably[22,23].

Numerous studies have documented the clinical benefits of hospital-based palliative care teams. Palliative care has been shown to improve clinical outcomes including patient-provider and family-provider communication[24-26], emotional and spiritual support[24,27-29], care that aligns with the patient's goals[24,26,28,30], and symptom management/quality of life[24,29-33]. Studies have also shown greater patient and family satisfaction when palliative care is involved[24,26,27,33,34]. Several studies have also suggested palliative care is able to reduce healthcare costs through lower use of costly services such as the intensive care unit (ICU)[25,30-32,35]. Although it was not strictly hospital-based palliative care, one randomized trial has found the early integration of palliative care for patients with stage IV non-small cell lung cancer improved symptoms, reduced use of intensive health services, and prolonged survival[36].

Palliative care focuses on clear patient-provider communication, especially around medical decision-making, advance care planning, and goals of care discussions; the assessment and control of symptoms to improve quality of life; psychosocial and spiritual care and support; and care coordination[18]. Clear goals of care discussions, complex symptom management, and care coordination through better communication and the connecting of patients and families with community-based services for those with serious illness may serve to reduce readmissions[37], yet the literature on palliative care and readmissions is lacking. One randomized trial of an in-home palliative care program among terminally ill homebound patients found the program served to significantly reduce readmissions and ED visits for the rest of the subjects' lives[38]. Another study of an inpatient palliative care team at a long-term care (LTC) facility found patients seen by the palliative care team had fewer ED visits compared to historically matched controls[39]. A

recent study of healthcare resource utilization among a group of patients with serious illness 18 months before and after they were referred for an in-home palliative care consults coordinated with their PCP found reduced rates of readmissions but not ED visits[40]. Finally, a study of the probability of a 30-day readmission among patients receiving an inpatient palliative care consult was about 10 percent, with a higher risk of readmission among patients without an advance directive[41]. This study also found higher risk of readmission among those discharged home without care or to a nursing facility compared with those discharged home with hospice or in-home palliative care. However, to date we do not know of any studies comparing the risk of a 30-day readmission among similar patients receiving and not receiving a hospital-based palliative care consult during an inpatient stay. Such a study is needed given the increasing focus of hospitals on reducing readmissions and the growing prevalence of hospital-based palliative care programs.

We sought to compare the rates of all-cause and related 30-day readmissions and near misses – defined as ED visits or overnight observation stays – among patients receiving and not receiving a palliative care consult (PCC) from our health system's inpatient multidisciplinary palliative care team. We chose all-cause readmissions because our hypothesis allows the palliative care team to reduce readmissions via better care of comorbidities that were not the cause of the patient's initial admission. We investigated related readmissions because we hypothesized such readmissions would be more sensitive to the services a PCC adds to a patient's care. We elected to include readmissions and near misses because both are germane to the question of whether palliative care can minimize hospital use among seriously ill patients. However, in

recognition of the financial and health policy importance of inpatient readmissions specifically, we repeated our analysis using only inpatient readmissions as well. We hypothesized that receiving a PCC during an inpatient stay would reduce that patient's likelihood of having an all-cause readmission or near miss within 30 days. We further hypothesized that the association between PCC and a reduction in readmissions and near misses would be stronger among related readmissions.

Methods:

We used administrative data from two academic medical centers (AMC) to investigate differences in the probability of 30-day readmissions and near-misses among hospital inpatients who received usual care versus usual care plus a palliative care consult (PCC) during their stay. We considered "readmissions" to be subsequent inpatient stays within 30 days of the initial discharge; "near misses" were emergency department (ED) visits or overnight stays coded as "observation" rather than "inpatient" across the same time period. We used two analytical methods to investigate the association: propensity score matching and crossover trial analysis.

Sample

Our sample consisted of all inpatient discharges from July 2011 through June 2012 at two AMCs in the same urban area and healthcare system: the system's flagship quaternary AMC and another tertiary AMC. We excluded patients under 18 years old, confirmed dead via healthcare system records within 30 days of discharge, or who had Medicare Severity Diagnosis Related Groups (MS-DRGs) excluded from University Health Consortium (UHC) readmission calculations due an expectation of multiple admissions (e.g. inpatient chemotherapy). The initial sample included 45,556 inpatient admissions, of which 7,045 met exclusion criteria (197 (0.4%) for age under 18; 1,949 (4.3%) for death within 30 days; 4,899 for ineligible MS-DRG). An additional 4,060 admissions were excluded due to missing data (race (2,203), insurance status (1,842), MSDRG (15)), leaving a final sample of 34,451 inpatient admissions across 24,809 patients (Figure 1).

Exposure

Our exposure was receipt of a PCC from the healthcare system's inpatient palliative care team as identified via hospital billing records. Although different palliative care teams serve each hospital, the makeup of the teams is similar and both teams are under the umbrella of the healthcare system's Palliative Care Center. Each team consisted of two hospice and palliative medicine physicians, two nurse practitioners, and a dedicated chaplain; one of the facilities also had a nurse educator. Although no two consults are identical, a typical consult consists of a symptoms assessment, identification of an authorized surrogate decision maker, advance care planning, and a goals of care discussion. As a consult-based specialty, all PCCs originate from a request from the patient's attending physician.

Outcome

Our primary outcomes were all-cause 30-day readmissions, defined as any inpatient admission for the same patients where the admission date of the readmission is ≤ 30 days after the index admission's discharge date; and all-cause 30-day near-misses, which include readmissions as well as ED visits and overnight stays coded as "observation" rather than "inpatient." Readmissions were identified according to UHC criteria, which exclude obstetric patients, newborns, chemotherapy, radiation therapy, dialysis, and rehabilitation patients as multiple visits are often planned for these populations. We also investigated the association between PCC and related 30-day readmissions and near-misses, where the second admission is related to the cause of the first as outlined in UHC criteria (the encounters must match on primary diagnosis, primary procedure, or MS-DRG, or the readmission's primary diagnosis is a complication code). We identified readmissions using the healthcare system's integrated

Clinical Data Warehouse (CDW), which is set up to track readmissions and near misses, both all-cause and related, using UHC criteria.

Other Patient Factors

We collected a range of administrative data for all discharges. Demographic factors included age at discharge, race (white, black, other), sex, marital status (married vs. not married), and insurance type (Medicare, Medicaid, commercial, other). Admissions characteristics included length of stay (LOS), use of mechanical ventilation, and medical versus surgical admissions as defined by MS-DRG. To adjust for differences in the referral patterns of physicians to palliative care, we calculated the proportion of patients referred for PCC by each attending physician with 10 or more patients over the study period; the median was 2.4% of patients referred for PCC. We then categorized all attending physicians regardless of how many admissions they had as "high" and "low" users of palliative care depending on whether they referred more or less than 2.4% of their patients for PCC. We matched patients on comorbidities using the Elixhauser index, which consists of 31 conditions covering major sources of morbidity and mortality; it was designed specifically for use with administrative healthcare data[42]. The presence of comorbidities was assessed using primary and secondary diagnosis codes present on admission and/or discharge. We utilized both an unweighted count of comorbidities and a weighted Elixhauser score derived from the association between each comorbidity and in-hospital mortality[43]. These weighted scores are useful as an indication of the relative severity of each comorbidity. Because including only the weighted and unweighted scores in our propensity score model did not yield a sufficient match on many individual comorbidity shown to be related to readmissions in the literature[44], we added select

individual comorbidities to our propensity score model, as well. A more detailed explanation of variable selection is available in Appendix A-1.

Statistical Analysis

Bivariate comparisons in our full sample (N=34,451) of covariates with receipt of a PCC and all-cause 30-day readmissions were calculated using Chi Square tests for categorical and two-sample t-tests for continuous variables. Log transformations were utilized to normalize LOS data for statistical testing. We then used two distinct analytical methods to investigate the association between PCC and 30-day readmissions.

Our first analysis matched PCC and non-PCC discharges using propensity score matching (PSM) methods as outlined by Rubin[45-47]. We used a subset of each patient's first discharge during the study period (N=24,809) (Figure 1) to construct propensity score models to estimate the probability of each discharge receiving a PCC from a set of demographic and healthcare variables. We restricted this analysis to first discharges to maintain equal risk periods and independence between observations. We began with a model that included all demographic and healthcare variables (age, gender, race, marital status, insurance, LOS, attending PCC referral level, medical versus surgical admission, previous hospitalizations, and unweighted and weighted comorbidity scores); we later included the individual comorbidities congestive heart failure (CHF), valvular disease, pulmonary circulation disorders, peripheral vascular disease (PVD), complicated hypertension, paralysis, neurological disorders, chronic pulmonary disease, uncomplicated and complicated diabetes, renal failure, liver disease, lymphoma, cancer, metastatic cancer, rheumatoid arthritis, coagulation disorders, weight loss, fluid and electrolyte disorders, and depression to improve matched cohort balance on these

diseases associated with 30-day readmissions[44]. We split our first discharge sample into quintiles by propensity score to investigate common support (overlapping scores) and covariate balance between PCC and non-PCC subjects; these results were acceptable and are available in Appendix A-2 and A-3. We then randomized the order of our data set and matched PCC with non-PCC patients with the same number of previous hospitalizations (0, 1-2, or 3+ in the preceding 365 days) using one-to-one nearest neighbor matching without replacement, constrained by a caliper of 0.10 times the standard deviation of the logit of the patient's propensity score. We forced an exact match on previous hospitalizations due to that variable's strength as a predictor of subsequent readmissions. A validated SAS macro was used for the matching[48]. Unmatched patients (N=45 PCC and 23,384 non-PCC patients) were excluded from further analysis. The success of the matching was assessed by comparing balance among all covariates of interest in the matched cohort (N=1,380). Balance was assessed using standardized differences for categorical and continuous variables, as well as quantile-quantile (QQ) plots for continuous variables[49,50]. We used multivariate conditional logistic regression to assess the association between PCC and 30-day readmissions and near misses. The dependent variable in our regression was none versus any all-cause or related readmissions or near misses within 30 days. The primary independent variable was receipt of a PCC. To guard against residual confounding from a misspecified propensity score [51] we began with a model adjusted for all covariates contained in the propensity score model, and then used hierarchical backwards elimination[52] to arrive at the most parsimonious model for all-cause and related readmissions separately.

To account for potential inter-hospital variations such as the composition of the palliative care teams and other support structures, we repeated our analysis using propensity scores calculated after stratifying by hospital. The propensity score distributions and all results were similar, so we elected to retain the combined facility model in the analyses reported below. More information on the stratified analysis is available in Appendix A-6.

Our second analysis treated patients with multiple admissions across the study period (N=5,649 patients, 15,291 admissions) (Figure 1) as subjects in a crossover trial. We used conditional logistic regression stratified on individual patients to assess the association between PCC and 30-day readmissions in these patients. Although crossover trials eliminate confounding for individual-level variables that are static across the one-year study period (age, gender, race, and insurance), we adjusted for other variables such as comorbidities and MS-DRG that may change between discharges. As in the PSM analysis, we began with a model adjusted for all covariates contained in the propensity score model and used hierarchical backwards elimination[52] to arrive at the most parsimonious model for all-cause and related readmissions separately.

Propensity Score Model Performance and Validation

We based variable selection for our propensity score models on theoretical and previously-demonstrated associations with our exposure and/or outcome[53]. We used C-statistics[52] to assess the discriminatory performance of the logistic propensity score models (these were not used to guide variable selection). To check goodness of fit we used the Hosmer-Lemeshow test and compared observed and predicted values by decile. To validate the performance of our models we re-ran them for an identically-determined

set of inpatient admissions from the year immediately prior to the study period (July 2010-June 2011).

All analyses were performed in SAS version 9.3 (SAS Institute, Cary, NC). All hypothesis tests were 2-sided at the 0.05 significance level. The healthcare system's IRB approved the study.

Results:

First Discharge Propensity Score Matching Analysis

Of the 24,809 first discharges eligible for analysis, 735 (3.0%) received a PCC. 690 (93.8%) of these PCC recipients were matched with an equal number of discharges that did not have a PCC. In the matched cohort 281 subjects had an all-cause readmission, 93 had a near-miss without a readmission, 73 had a related readmission, and 23 had a related near-miss without a readmission.

We achieved good balance on all covariates both within hospital strata and overall. Table 1 shows the greatest standardized difference for variables on which we were interested in matching was 0.20, within the 0.25 standard deviation rule of thumb proposed by Cochran[54]; most standardized differences were much smaller.

As also seen in Table 1, the matched cohort was substantially different from the unmatched patients across most demographic and health variables. Unmatched PCC subjects tended to be sicker (mean unweighted Elixhauser score 10.0 (SD 2.1) vs. 6.4 (2.7); mean weighted Elixhauser score 36.8 (9.8) vs. 22.0 (10.0); higher prevalence of many comorbidities) and also had a longer LOS (median 43.0 days vs. 12.0 days) than their matched counterparts.

Unmatched non-PCC subjects tended in the opposite direction, being overall younger (mean age 58.1 (SD 17.1) vs. 65.5 (SD 14.8) years) and healthier (mean unweighted Elixhauser score 3.4 (SD 2.3) vs. 6.2 (2.5); mean weighted Elixhauser score 8.2 (8.9) vs. 21.9 (11.1); lower prevalence of many comorbidities) than their matched counterparts. They were also less likely to have spent time in the hospital in the previous

year (14.5% with at one or more previous hospitalizations vs. 20.9% of matched subjects).

All-Cause Readmissions

The adjusted average treatment effect on the treated (ATT) for PCC exhibited a downward trend but was not significant for all-cause 30-day readmissions and near misses (Table 3, OR 0.78, 95% CI 0.59-1.03). For readmissions only, the association is similar though no longer significant (OR 0.84, 95% CI 0.62-1.13).

Related Readmissions

In the crude models, the associations for related readmissions and near-misses (Table 3, OR 0.67, 95% CI 0.43, 1.04) and related readmissions only (OR 0.71, 95% CI 0.43, 1.16) were both stronger than the respective all-cause associations, but neither result was significant. In the adjusted models, the association between PCC and a related 30-day readmission or near miss (OR 0.64, 95% CI 0.32-1.22) or related readmissions (OR 0.70, 95% CI 0.34-1.47) remained virtually unchanged. Neither result was significant.

Propensity Score Model Performance

As seen in Table 3, the propensity score model had what is conventionally considered excellent discrimination[52] (C-statistic 0.920). Although the Hosmer-Lemeshow goodness-of-fit tests were significant, the decile comparisons demonstrated acceptable model fit (Figures 1a and 1b). The validation model performed similarly (Table 3).

Multiple Discharge Crossover Trial Analysis

Of the 15,291 discharges across 5,649 patients eligible for analysis, 779 (5.1%) discharges received a PCC. 4,676 (30.6%) of these discharges had an all-cause

readmission, 1,805 (11.8%) had a near-miss without a readmission, 2,090 (13.7%) had a related readmission, and 437 (2.9%) had a related near-miss without a readmission. Table 2 outlines the characteristics of these patients at the time of their first admission during the study period. The probability of receiving a PCC and having an all-cause 30-day readmission or near-miss both rose as patients moved from earlier to later admissions over the study period (Figure 2).

All-Cause Readmissions

The adjusted average treatment effect on the treated (ATT) for PCC was significant for all-cause 30-day readmissions and near misses (Table 3, OR 0.76, 95% CI 0.61-0.94). For readmissions only, the association is similar (OR 0.77, 95% CI 0.62-0.97).

Related Readmissions

In the adjusted models, the association between PCC and a related 30-day readmission was similar to its all-cause counterpart and borderline significant (OR 0.76, 95% CI 0.57-1.02). The association for related readmissions was stronger than its all-cause counterpart (OR 0.68, 95% CI 0.49-0.94) and statistically significant.

Discussion:

Receiving a palliative care consult was associated with a roughly 20 to 30% reduction in the odds of all-cause and related 30-day readmissions in a cohort of seriously ill patients. There were statistically significant declines in the crossover analysis for all-cause readmissions and near-misses, all-cause readmissions, and related readmissions; there was a trend toward reduced related readmissions and near-misses. In the propensity score matched analysis the direction and magnitude of the effects were similar but not significant; this is likely due to fewer outcome events in this group due to the exclusion of subsequent admissions. Nonetheless, the consistency in the direction and magnitude of our estimates across both analyses leads us to conclude that a consult from a hospital-based palliative care team reduces the risk of 30-day readmissions in all patients with serious life-limiting illnesses.

We did not design this study to ascertain why palliative care might reduce 30-day readmissions. However, we observed that among the matched cohort 21.8% of patients receiving PCC were discharged to hospice versus just 0.5% of control patients who were similarly ill. Hospice is designed specifically to provide immediate 24-hour support in the event of a health crisis to avoid ED visits and hospital admissions. Indeed, similar in-home palliative care programs have been shown to reduce hospital admissions[38]. If we control for hospice referrals in either analysis the association disappears (data not shown). Thus the palliative care team may be operating to reduce readmissions through enhanced hospice referrals. However, this in no way undermines the palliative care team's work as many of these patients are likely referred to hospice because they had a

PCC (less than 1% of matched seriously ill controls were referred to hospice in our study).

Readmissions to either hospital in the study were included – a patient could have been admitted to one hospital and then readmitted to the other hospital – but readmissions to other hospitals were not considered due to a lack of data. For all analyses the patient was assigned to the original admitting hospital; any readmission would be considered primarily the responsibility of the hospital that originally discharged them. Cross-readmissions represented approximately 8.0% of all readmissions and near-misses over the study period. There is little reason to believe patients were differentially likely to be readmitted to a non-study hospital by exposure status, so it is unlikely this issue affected the associations we observed in this study.

Our study has several strengths. We used a large administrative dataset readily available to many hospitals who can replicate our analyses. Our sample is from two hospitals who had a steady, mature, well-defined palliative care consulting service over the entire study time frame. Finally, we have a diverse sample of patients that span a broad range of demographics and disease patterns, demonstrating the ability of a palliative care service to exert a broad-based impact on clinically and financially relevant quality metrics for U.S. hospitals.

Our study has also several limitations. First, it includes only academic medical centers (AMC) in a single urban area and health system; these hospitals have notably high patient severity scores even among AMCs. Our hospitals also have robust interdisciplinary palliative care teams that include board-certified physicians, nurse practitioners, nurses, chaplains, and social workers. Our results may not be generalizable

to other hospitals in different geographic areas with different demographics, less severely ill patient populations, or less robust palliative care teams. Second, we did not conduct any subset analyses by demographics such as race or socioeconomic status (SES) to investigate differential effects in these populations due to sample size limitations; there may be relevant differences in how palliative care inflects readmissions rates for white vs. minority and low SES vs. high SES patients. We also did not perform any subset analyses of palliative care's ability to influence readmission risk in specific populations that are high-risk or of special relevance to Medicare such as AMI, heart failure, and pneumonia. More targeted studies of these populations are needed. Third, our propensity-matched results should not be generalized beyond the population with serious life-limiting illnesses. Our matched patients were older and sicker on a number of metrics than our unmatched controls (Table 1). There are large swaths of non-PCC patients without an appropriate PCC counterpart, and we cannot say that palliative care would have the same effect for them in reducing readmissions. Fourth, our analyses, as all observations studies are, are subject to bias from unmeasured confounders; some authors have suggested this problem is more acute in propensity score matching, where forcing balance on matched covariates may actually exacerbate imbalance in unmeasured confounders[55]. Our results should be interpreted with caution in light of this.

Finally, we did not have complete mortality data for all patients; we could only confirm a patient's death if it was reported to our healthcare system. This impacts two areas. First, we may have inadvertently included some patients who died within 30 days of their last admission, though we believe this to be unlikely as many patients sought care elsewhere in the healthcare system and would have had their deaths reported to us.

Second, we were unable to match patients on how long they had left to live, which impacts their eligibility for hospice and their likelihood of pursuing subsequent hospital-based curative therapies. We attempted to control for this by matching on both the presence of individual comorbidities such as metastatic cancer and congestive heart failure as well as patterns of disease through weighted and unweighted comorbidity indexes, but there may be some residual confounding. This confounding most likely biased our results towards the null. In the crossover analysis, as patients' diseases progressed from earlier to later discharges their probability of getting a PCC and having a 30-day readmission both rose (Figure 2). Even as a patient approaches death and curative care turns futile, patients more often than not continue to make ED and hospital visits in the U.S. healthcare system. Thus any bias that disease progression introduces likely leads to an underestimate of the relationship between PCC and readmissions. Although patients who are referred to hospice at the end of life often avoid subsequent readmissions, this is rare for patients not receiving a PCC (<1% in our matched controls). That said it is possible that disease progression also biased our results away from the null if controls were far enough upstream in their disease process that hospice would have been inappropriate and palliative care's ability to reduce readmissions would have been subsequently hamstrung. We consider this unlikely given the chronic underutilization of hospice: Medicare eligibility guidelines allow six months of services, while the average and median lengths of stay in 2011 were just 69.1 and 19.1 days, respectively[56].

To summarize, receiving a palliative care consult was associated with a meaningful reduction in the risk of all-cause and related 30-day readmissions in a cohort of seriously ill patients. We recommend the use of palliative care consults for all patients

with serious, life-limiting illness at high risk for readmission. We encourage additional multi-center studies to confirm our findings and advocate for more detailed studies to identify any differential effects of palliative care by race and SES or patterns of chronic disease in an effort to better target scarce healthcare resources.

Figure 1. Flowchart of analytic sample selection.

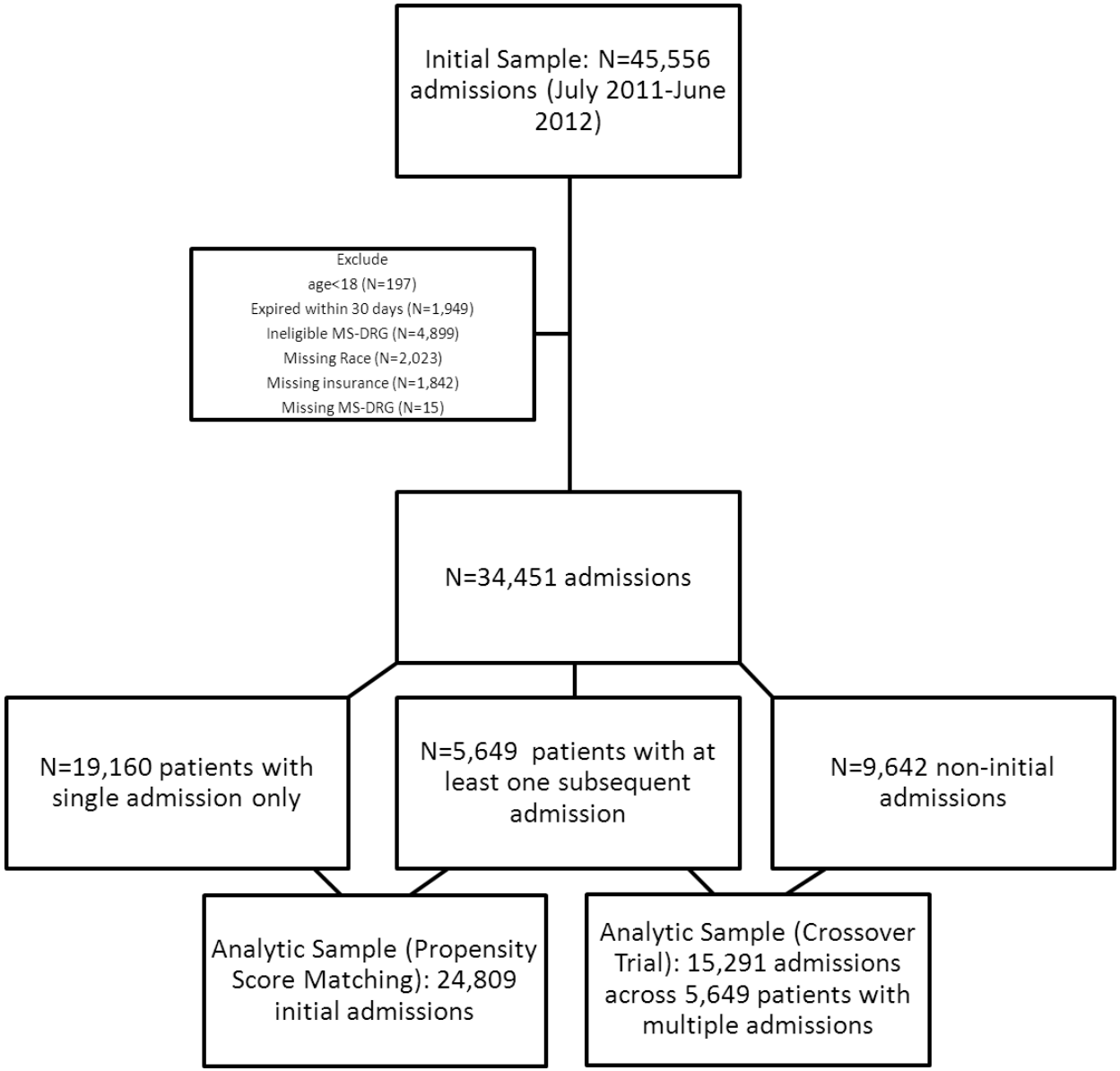


Table 1. Characteristics of first inpatient discharges with and without a PCC at two southern urban AMCs, July 2011-June 2012.

	Pre-Matching (N=24,809)		Matched (N=1,380)			Unmatched (N=23,429)	
	PCC (N=735)	No PCC (N=24,074)	PCC (N=690)	No PCC (N=690)	Standardized Difference	PCC (N=45)	No PCC (N=23,384)
Age, Years; Mean (SD)	64.3 (17.2)	58.3 (17.1)	64.4 (17.4)	65.5 (14.8)	-0.07	63.3 (15.3)	58.1 (17.1)
Race					-0.01		
White (%)	44.4%	54.0%	45.4%	45.8%		28.9%	54.3%
Black (%)	52.9%	43.6%	52.3%	51.9%		62.2%	43.4%
Sex (% Female)	54.4%	53.9%	54.6%	54.2%	0.01	51.1%	53.9%
Insurance					0.02		
Medicare (%)	65.3%	50.3%	65.5%	64.5%		62.2%	49.9%
Medicaid (%)	14.0%	9.7%	13.8%	15.5%		17.8%	9.5%
Commercial (%)	19.5%	37.4%	19.4%	18.7%		20.0%	38.0%
Marital Status (% Married)	37.8%	49.0%	37.5%	37.3%	0.01	42.2%	49.4%
Attending Referral Level (% High)	93.7%	54.0%	93.3%	95.8%	-0.11	100.0%	52.8%
MS-DRG (% Surgical)	25.9%	18.0%	23.8%	21.3%	0.06	57.8%	17.9%
Mechanical Ventilation (% Yes)	31.0%	8.1%	28.8%	24.9%	0.09	64.4%	7.6%
Hospice Discharges (%)	21.8%	0.5%	21.9%	3.3%	0.58	20.0%	0.4%
LOS[a], Days; Median (Range)	13.0 (1.0-422.0)	4.0 (1.0-149.0)	12.0 (1.0-97.0)	11.0 (1.0-136.0)	0.08	43.0 (4.0-422.0)	4.0 (1.0-149.0)
Previous Hospitalizations[b]					0.00		
1-2 Hospitalizations (%)	17.3%	11.9%	17.0%	17.0%		22.2%	11.7%
3+ Hospitalizations (%)	4.6%	2.8%	3.9%	3.9%		15.6%	2.8%
Comorbidities; No. (SD)	6.6 (2.8)	3.5 (2.3)	6.4 (2.7)	6.2 (2.5)	0.06	10 (2.1)	3.4 (2.3)
Comorbidites; Weighted Score (SD)	22.9 (8.6)	8.6 (9.3)	22 (10.2)	21.9 (11.1)	0.01	36.8 (9.8)	8.2 (8.9)
Comorbidities							
CHF (%)	41.9%	19.1%	41.0%	40.7%	0.01	55.6%	18.4%
Cardiac Arrhytmia (%)	52.8%	24.8%	50.4%	47.5%	0.06	88.9%	24.1%

Valvular Disease (%)	20.3%	10.9%	19.7%	18.0%	0.04	28.9%	10.6%
Pulmonary Circulation Disorders (%)	14.8%	4.7%	14.8%	13.2%	0.05	15.6%	4.4%
PVD (%)	11.6%	8.8%	11.5%	9.7%	0.06	13.3%	8.8%
Hypertension - Uncomplicated (%)	55.2%	58.0%	54.2%	64.1%	-0.20	71.1%	57.9%
Hypertension - Complicated (%)	26.4%	18.8%	25.2%	23.2%	0.05	44.4%	18.7%
Paralysis (%)	6.8%	2.3%	7.1%	7.3%	-0.01	2.0%	2.1%
Neurological Disorders (%)	29.3%	9.7%	28.0%	27.1%	0.02	48.9%	9.1%
Chronic Pulmonary Disease (%)	27.9%	18.6%	28.1%	29.0%	-0.02	24.4%	18.3%
Diabetes - Uncomplicated (%)	8.6%	8.3%	8.7%	8.6%	0.01	6.7%	8.3%
Diabetes - Complicated (%)	10.6%	8.0%	10.1%	10.3%	0.00	17.8%	7.9%
Hypothyroid (%)	13.3%	11.0%	13.3%	12.5%	0.03	13.3%	10.9%
Renal Failure (%)	37.0%	21.0%	34.8%	32.3%	0.05	71.1%	20.6%
Liver Disease (%)	16.3%	6.9%	15.1%	13.8%	0.04	35.6%	6.7%
Peptic Ulcer Disease (%)	3.5%	1.4%	3.3%	2.9%	0.02	6.7%	1.3%
AIDS (%)	3.0%	1.9%	3.0%	2.5%	0.04	2.2%	1.9%
Lymphoma (%)	5.2%	2.7%	5.1%	4.6%	0.02	6.7%	2.7%
Cancer - Metastatic (%)	26.1%	5.9%	24.9%	26.4%	-0.03	44.4%	5.3%
Cancer (%)	37.6%	13.2%	35.8%	38.0%	-0.04	64.4%	12.5%
Rheumatoid Arthritis (%)	5.9%	4.4%	5.5%	4.6%	0.04	11.1%	4.4%
Coagulation Disorder (%)	24.4%	9.4%	22.8%	22.2%	0.01	48.9%	9.0%
Obesity (%)	11.2%	14.4%	10.9%	9.1%	0.06	15.6%	14.5%
Weight Loss (%)	41.0%	7.9%	38.6%	39.3%	-0.01	77.8%	7.0%
Fluid and Electrolyte (%)	72.1%	33.8%	70.6%	69.7%	0.02	95.6%	32.7%
Anemia - Blood Loss (%)	6.4%	2.1%	5.9%	5.1%	0.04	13.3%	2.0%
Anemia - Deficiency (%)	0.8%	0.1%	0.9%	0.1%	0.10	0.0%	0.1%
Alcoholism (%)	7.1%	3.4%	7.3%	6.1%	0.05	4.4%	3.3%
Drug Abuse (%)	6.8%	4.1%	6.7%	5.2%	0.06	8.9%	4.1%
Psychoses (%)	8.3%	2.6%	8.0%	4.2%	0.16	13.3%	2.5%
Depression (%)	28.3%	12.2%	27.3%	25.8%	0.03	44.4%	11.9%

Abbreviations: PCC, Palliative Care Consult; AIDS, Acquired Immune Deficiency Syndrome; AMC, Academic Medical Center; LOS, Length of Stay; PVD, Peripheral vascular disease.

[a]LOS was severely right-skewed and log-transformed to normalize for statistical testing. The non-transformed data are presented here.

[b]Within 365 days

Table 2. Characteristics of patients with multiple discharges at two southern urban AMCs, July 2011-June 2012.

	Multiple Discharges Over Study Period[a] N = 5,649 Patients; 15,291 Discharges
Age, Years; Mean (SD)	58.6 (17.2)
Race	
White (%)	46.7%
Black (%)	50.8%
Sex (% Female)	51.7%
Insurance	
Medicare (%)	57.3%
Medicaid (%)	12.1%
Commercial (%)	29.2%
Marital Status (% Married)	45.6%
Attending Referral Level (% High)	67.2%
MS-DRG (% Surgical)	20.0%
Mechanical Ventilation (% Yes)	12.6%
Hospice Discharges (%)	1.4%
LOS[b], Days; Median (Range)	6.0 (1.0-157.0)
Previous Hospitalizations[c]	
1-2 Hospitalizations (%)	47.5%
3+ Hospitalizations (%)	14.9%
Comorbidities; No. (SD)	4.5 (2.5)
Comorbidites; Weighted Score (SD)	12.6 (10.2)
Comorbidities	
CHF (%)	28.0%
Cardiac Arrhytmia (%)	30.6%
Valvular Disease (%)	13.5%
Pulmonary Circulation Disorders (%)	7.6%
PVD (%)	11.4%
Hypertension - Uncomplicated (%)	57.8%
Hypertension - Complicated (%)	29.5%
Paralysis (%)	3.1%
Neurological Disorders (%)	12.6%
Chronic Pulmonary Disease (%)	22.5%
Diabetes - Uncomplicated (%)	9.0%
Diabetes - Complicated (%)	11.4%
Hypothyroid (%)	11.5%
Renal Failure (%)	34.5%
Liver Disease (%)	10.1%
Peptic Ulcer Disease (%)	1.8%
AIDS (%)	3.0%

Lymphoma (%)	4.4%
Cancer - Metastatic (%)	8.7%
Cancer (%)	16.1%
Rheumatoid Arthritis (%)	4.9%
Coagulation Disorder (%)	14.2%
Obesity (%)	12.3%
Weight Loss (%)	13.6%
Fluid and Electrolyte (%)	45.9%
Anemia - Blood Loss (%)	2.9%
Anemia - Deficiency (%)	0.2%
Alcoholism (%)	3.8%
Drug Abuse (%)	5.3%
Psychoses (%)	3.2%
Depression (%)	14.3%

Abbreviations: PCC, Palliative Care Consult; AIDS, Acquired Immune Deficiency Syndrome; AMC, Academic Medical Center; LOS, Length of Stay; PVD, Peripheral vascular disease.

[a]Data for patient's first admission in study period.

Table 3. Association of PCC with all-cause 30-day readmissions.

	Unadjusted		Adjusted	
	mOR	95% CI	mOR	95% CI
First Admissions During Study Period (N=1,380)				
All-Cause				
Readmissions + Near-Misses (N=373)	0.86	0.68, 1.10	0.78[a]	0.59, 1.03
Readmissions Only (N=281)	0.91	0.70, 1.18	0.84[a]	0.62, 1.13
Related				
Readmissions + Near-Misses (N=96)	0.67	0.43, 1.04	0.64[b]	0.32, 1.22
Readmissions Only (N=73)	0.71	0.43, 1.16	0.70[b]	0.34, 1.47
Multiple Admissions Over Study Period (N=15,291 Admissions, 5,649 Patients)				
All-Cause				
Readmissions + Near-Misses	0.65	0.54, 0.80	0.76[c]	0.61, 0.94
Readmissions Only	0.65	0.54, 0.80	0.77[c]	0.62, 0.97
Related				
Readmissions + Near-Misses	0.63	0.48, 0.83	0.76[d]	0.57, 1.02
Readmissions Only	0.56	0.41, 0.75	0.68[d]	0.49, 0.94

Abbreviations: PCC, Palliative Care Consult; AMC, Academic Medical Center; mOR, matched odds ratio; CI, confidence interval.

[a]Adjusted for age, race, weighted comorbidity score, insurance, complicated diabetes, cancer, and weight loss.

[b]Adjusted for insurance, mechanical ventilation, congestive heart failure, valvular disease, pulmonary circulation disorders, peripheral vascular disease, complicated hypertension, neurological disorders, chronic obstructive pulmonary disease, complicated and uncomplicated diabetes, renal failure, liver disease, cancer and metastatic cancer.

[c]Adjusted for unweighted comorbidity score, previous hospitalizations, congestive heart failure, complicated hypertension, and renal failure.

[d]Adjusted for medical versus surgical admission, attending PC referral level, mechanical ventilation, previous hospitalizations, congestive heart failure, and metastatic cancer.

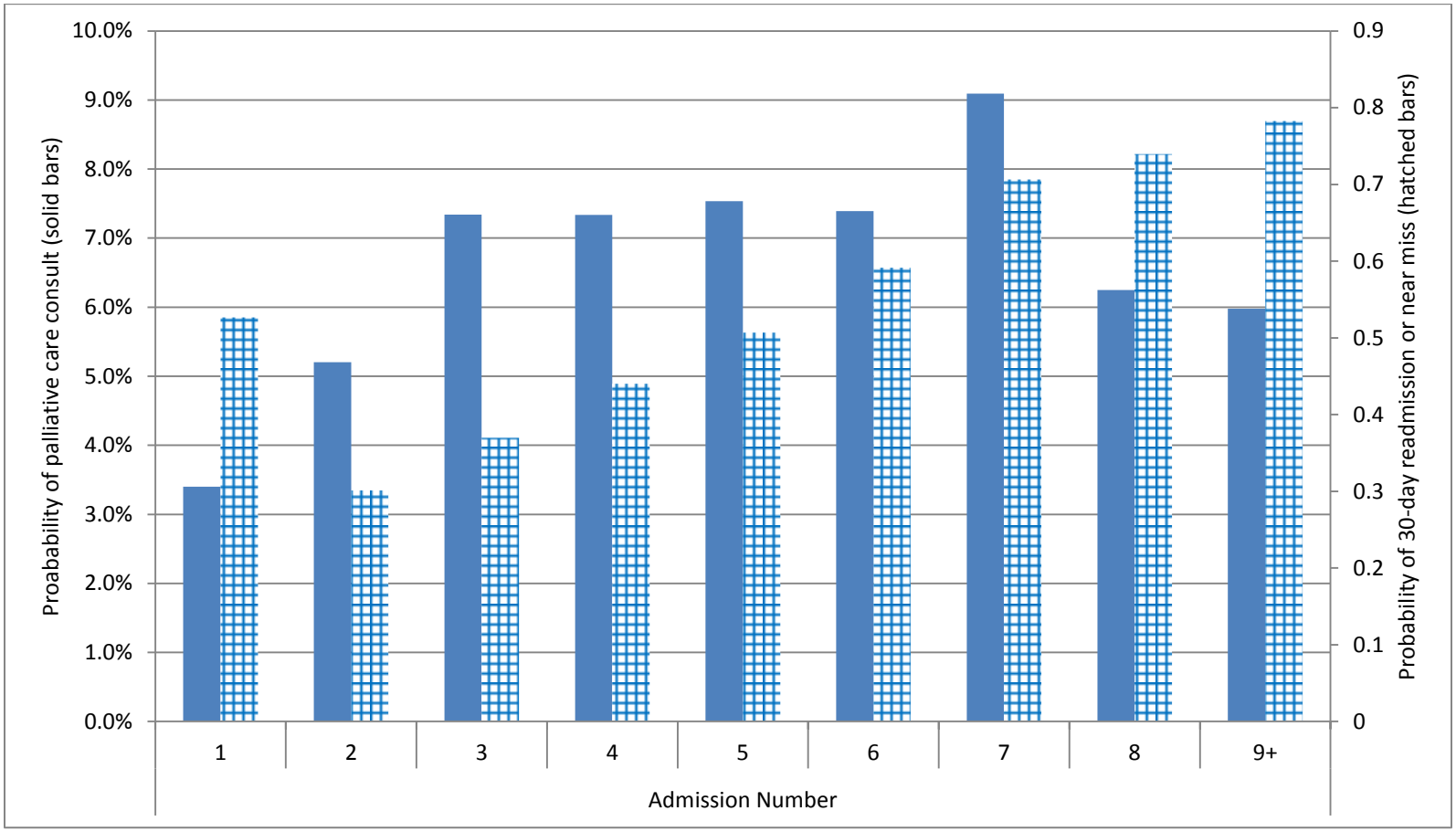
Table 4. Discrimination and fit statistics of propensity score models.

	Discrimination		Goodness of Fit	
	C-Statistic	Interpretation[a]	H-L statistic	P-value
Propensity Score Regression Model (N=39,350)	0.921	Excellent	17.81	0.0027
Propensity Score Validation Model (N=40,252)	0.923	Excellent	27.80	0.0005

Abbreviations: H-L, Hosmer-Lemeshow test.

[a]Interpretation per Kleinbaum et al in *Logistic Regression: A Self-Learning Text*, 3rd ed.

Figure 2. Probabilities of palliative care consult and all-cause 30-day readmissions and near-misses by admission number among patients with multiple admissions (N=5,649 patients, 15,291 admissions).



Chapter 3: Public Health Impact

End-of-life care is an area where controlling spiraling healthcare costs while simultaneously maintaining or improving care quality is critical given the aging of the U.S. population[57] and the tremendous expenditures that occur in the final year of life[58]. As outlined above, hospital readmissions are a major economic and health burden on the U.S. population. Roughly one fifth of Medicare beneficiaries experienced a 30-day readmission in 2003-2004, costing Medicare alone $17.4 billion per year[1]. According to the most recent Medicare data, 19.7% of AMI, 24.7% of HF, and 19.7% of pneumonia patients were readmitted within 30 days[5]. Many of the patients experiencing these readmissions have serious life-limiting illnesses whose palliative and end-of-life care needs are seriously underserved by the existing U.S. health system. The services palliative provides – clear patient-provider communication, especially around medical decision-making, advance care planning, and goals of care discussions; the assessment and control of symptoms to improve quality of life; psychosocial and spiritual care and support; and care coordination[18] – are in high demand from our healthcare system's sickest patients[19]. Numerous studies have documented the clinical benefits of hospital-based palliative care teams. Palliative care has been shown to improve clinical outcomes including patient-provider and family-provider communication[24-26], emotional and spiritual support[24,27-29], care that aligns with the patient's goals[24,26,28,30], and symptom management/quality of life[24,29-33]. Studies have also shown greater patient and family satisfaction when palliative care is involved[24,26,27,33,34]. Several studies have also suggested palliative care is able to reduce healthcare costs through lower use of costly services such as the intensive care unit (ICU)[25,30-32,35]. Yet nearly a third of U.S. hospitals

over 50 beds still have no palliative care service, and among those that do there is tremendous geographic and other variability in the services provided[22]. It is our hope that this study will encourage hospitals to further adopt and encourage the use of palliative care – whose benefits for public health are outlined above – by demonstrating its benefits for a top quality metric with major financial implications.

Appendix

A-1: Defining our Covariates of Interest and Propensity Score Modeling Strategy

Although the consensus when calculating propensity scores is to include as many variables in your PS model as possible to achieve the necessary balance in your covariates, with a large administrative dataset like we had available to us there is a virtually unlimited number of potential covariates. To settle on an initial list of covariates we used two strategies:

1. Identification of covariates used in similar studies to ours in the literature; similar studies included work on palliative care and health services outcomes such as costs [35,59] as well as readmission prediction tools[60]
2. Meetings between the chief researcher and a Clinical Advisory Panel (CAP) consisting of 5 board-certified hospice and palliative medicine physicians at the health system (Paul Desandre, DO; Anjali Grandhige, MD; Michael O'Neill, MD; Tammie Quest, MD; Laura Waddle, MD)

Covariates from the existing literature were used as a base (SEE below), which the CAP and chief researcher then refined. As a guide the team used the Directed Acyclic Graph (DAG) diagram in Figure A-1a, developed via procedures outlined below. Green circles indicate potential confounders (i.e. covariates with an open backdoor path from PCC to 30-day readmission), while red circles indicate covariates posited to be along the causal path that we wanted to avoid controlling for (i.e. matching on). That said, we included in our propensity score models any covariates we thought were related to receipt of a PCC,

as the purpose of a propensity score model is simply to achieve balance among as many observed covariates as possible. However, when assessing balance we paid special attention to those covariates we did consider possible confounders. Some variables the team would have liked to include – such as measures of self-reported health and functional status – were not included due to lack of data.

Once we had our list of potential covariates for matching we wanted to investigate their distribution in our data by both receipt of PCC (exposure) and 30-day readmission (outcome) (Table A-1a). Although many of the p-values below are significant, our large sample size required we *not* rely on statistical tests, rather looking at the data and determining if any values were clinically meaningfully different. We decided that many of them were and that matching would be necessary for this cohort.

Variable Selection for Initial Propensity Score Model

Readmissions

We identified covariates related to 30-day readmission rates by examining research around predictive models for readmission risk. Since readmission reduction programs are most effective if they target high-risk populations this literature is extensive. A recent meta-analysis from the Department of Veteran's Affairs (VA) identified 30 studies on the topic[60]. Most studies focused on demographic factors such as age, race, and gender; medical comorbidities; previous hospitalizations; mental illness; and drug abuse. Several studies also considered cognitive impairment; other prior healthcare utilization such as emergency department (ED) visits; lab findings; and social determinants of healthcare such as socioeconomic status (SES), insurance class, marital

status, and access to care. A handful incorporated self-rated health/quality of life and functional status, as well.

Palliative Care

We identified variables related to the receipt of a palliative care consult by reviewing one published study[35] and a conference presentation[59] (with additional personal correspondence from the author) most similar to ours: they used propensity score matching to address the relationship between palliative care and hospital-based health services outcomes (i.e. costs for hospitalized patients). These studies matched on age, gender, marital status, insurance status, seven broad categories of primary diagnosis, a comorbidity index (Elixhauser), physician specialty, ICU use, and discharge disposition. We did not incorporate discharge disposition as we hypothesized this was one of the ways in which palliative care could affect readmission rates.

Formation of Initial Propensity Score Model

We combined many of the readmissions and palliative care covariates to form our initial propensity score model. We had to exclude some variables – such as functional status – due to a lack of data. All the variables used are listed in Table 1 and Table A-1a.

Table A-1a. Unadjusted bivariate associations of covariates of interest with exposure (PCC) and outcome (all-cause 30-day readmissions and near-misses) in unmatched sample, July 2011-June 2012 (N=34,451).

	PCC			All-Cause 30-day Readmissions and Near Misses		
	PCC (N=1,322)	No PCC (N=33,129)	P-Value	Readmission (N=8,127)	No Readmission (N=26,324)	P-Value
Age, Years; Mean (SD)	62.7 (17.6)	57.7(17.2)	<0.0001	55.6 (17.7)	58.6 (17.1)	<0.0001
Race			<0.0001			<0.0001
White (%)	40.8%	50.6%		39.1%	53.7%	
Black (%)	56.7%	47.1%		58.3%	44.1%	
Sex (% Female)	53.7%	53.4%	0.8167	53.0%	53.5%	0.3547
Insurance			<0.0001			<0.0001
Medicare (%)	63.9%	52.2%		53.8%	52.3%	
Medicaid (%)	15.7%	10.9%		16.1%	9.5%	
Commercial (%)	19.6%	34.7%		28.7%	35.8%	
Marital Status (% Married)	40.2%	47.4%	<0.0001	41.2%	48.9%	<0.0001
Attending Referral Level (% High)	94.6%	59.1%	<0.0001	73.4%	56.4%	<0.0001
MS-DRG (% Surgical)	21.5%	16.4%	<0.0001	15.2%	17.1%	<0.0001
Mechanical Ventilation (% Yes)	26.3%	7.4%	<0.0001	7.9%	8.1%	0.59
Hospice Discharges (%)	23.6%	0.6%	<0.0001	0.6%	1.8%	<0.0001
LOS[a], Days; Median (Range)	12.0 (1.0-422.0)	5.0 (1.0-200.0)	<0.0001	6.0 (1.0-200.0)	5.0 (1.0-422.0)	<0.0001
Previous Hospitalizations[b]; No. (SD)			<0.0001			<0.0001
1-2 Hospitalizations (%)	35.2%	26.6%		31.8%	25.5%	
3+ Hospitalizations (%)	21.4%	11.4%		24.1%	7.9%	
Comorbidities; No. (SD)	6.5 (2.7)	3.7 (2.3)	<0.0001	4.4 (2.4)	3.7 (2.4)	<0.0001
Comorbidites; Weighted Score (SD)	22.6 (10.7)	9.5 (9.5)	<0.0001	12.5 (10.0)	9.3 (9.7)	<0.0001
Comorbidities						

CHF (%)	42.5%	21.9%	<0.0001	26.8%	21.4%	<0.0001
Cardiac Arrhytmia (%)	52.1%	25.4%	<0.0001	27.4%	26.1%	0.0240
Valvular Disease (%)	19.4%	10.9%	<0.0001	11.3%	11.2%	0.70
Pulmonary Circulation Disorders (%)	14.2%	5.2%	<0.0001	7.0%	5.1%	<0.0001
PVD (%)	10.8%	9.6%	0.1433	9.7%	9.7%	0.99
Hypertension - Uncomplicated (%)	52.7%	57.0%	0.0022	54.5%	57.5%	<0.0001
Hypertension - Complicated (%)	30.3%	22.3%	<0.0001	29.4%	20.5%	<0.0001
Paralysis (%)	5.8%	2.3%	<0.0001	3.4%	2.1%	<0.0001
Neurological Disorders (%)	27.9%	10.0%	<0.0001	12.4%	10.1%	<0.0001
Chronic Pulmonary Disease (%)	28.7%	19.3%	<0.0001	21.4%	19.2%	<0.0001
Diabetes - Uncomplicated (%)	9.3%	8.7%	0.3749	9.9%	8.4%	<0.0001
Diabetes - Complicated (%)	11.6%	9.2%	0.0040	12.5%	8.4%	<0.0001
Hypothyroid (%)	13.0%	10.9%	0.0171	10.3%	11.2%	0.03
Renal Failure (%)	41.2%	25.7%	<0.0001	33.9%	23.9%	<0.0001
Liver Disease (%)	15.7%	7.9%	<0.0001	11.1%	7.3%	<0.0001
Peptic Ulcer Disease (%)	2.7%	1.5%	0.0003	1.9%	1.4%	0.01
AIDS (%)	3.7%	2.5%	0.0042	3.8%	2.1%	<0.0001
Lymphoma (%)	5.0%	3.1%	<0.0001	4.4%	2.8%	<0.0001
Cancer - Metastatic (%)	26.0%	6.1%	<0.0001	8.6%	6.3%	<0.0001
Cancer (%)	36.5%	13.1%	<0.0001	16.3%	13.3%	<0.0001
Rheumatoid Arthritis (%)	5.2%	4.7%	0.4211	5.5%	4.5%	0.0004
Coagulation Disorder (%)	23.8%	10.0%	<0.0001	13.4%	9.6%	<0.0001
Obesity (%)	10.2%	13.4%	0.0010	10.9%	13.9%	<0.0001
Weight Loss (%)	3.2%	9.4%	<0.0001	14.8%	9.2%	<0.0001
Fluid and Electrolyte Disorders (%)	71.7%	37.2%	<0.0001	47.8%	35.6%	<0.0001
Anemia - Blood Loss (%)	5.5%	2.2%	<0.0001	2.8%	2.1%	0.00
Anemia - Deficiency (%)	0.5%	0.1%	0.0014	0.1%	0.1%	0.62
Alcoholism (%)	6.1%	3.4%	<0.0001	4.5%	3.2%	<0.0001
Drug Abuse (%)	7.0%	4.8%	<0.0001	7.1%	4.2%	<0.0001
Psychoses (%)	7.7%	2.7%	<0.0001	3.5%	2.7%	<0.0001
Depression (%)	29.4%	12.6%	<0.0001	14.6%	12.9%	<0.0001

Abbreviations: PCC, Palliative Care Consult; AIDS, Acquired Immune Deficiency Syndrome; AMC, Academic Medical Center; LOS, Length of Stay; PVD, Peripheral vascular disease; MS-DRG, Medicaid Severity Diagnosis Related Group.

[a]LOS was severely right-skewed and log-transformed to normalize for statistical testing. The non-transformed data are presented here.

[b]Within 365 days

Our goal was to achieve balance on all covariates not along a causal path, regardless of whether we felt they were already balanced in the unmatched data. Thus we included all variables from Table A-1a *except proportion of discharges to hospice* in our initial propensity score model. If we had included only the covariates we felt were unbalanced in the unmatched data, we feared that would send the already-balanced variables into imbalance by virtue of not being included in the model. Additionally, we had a sufficiently large dataset (almost 35,000 observations) to regress on this many variables while maintaining reasonable precision.

The one exception was comorbidities, where our initial model included only the unweighted count of Elixhauser comorbities and the weighted total Elixhauser score. After running our initial model we looked for balance in each of the 31 individual comorbidities, with a special focus on those shown previously in the literature to be associated with 30-day readmissions[44] (i.e. possible confounders). We then added 20 un-balanced[a] comorbidities into our final propensity score model and checked the balance of all 31 again. Finding sufficient balance, we proceeded with our analysis. The process is outlined below in Table A-1b.

[a] As explained in Section A-3, we took a very strict view of "balanced." Individual co-morbidities whose standardized differences after matching using the initial model would conventionally be considered "balanced" were included in the final model if, in the researchers' estimation, a.) the residual imbalance was still practically meaningful, b.) the co-morbidity could be added into the model without sacrificing performance or precision, and c.) adding the variable into the model improved its balance in the resulting cohort.

Table A-1b. Modeling strategy for propensity score models.

Variable	Associated with Readmissions	Initial Model	Final Model
Age	a, b, c	X	X
Race	a, b, c	X	X
Sex	a, b, c	X	X
Insurance	a, b, c	X	X
Marital Status	c	X	X
Attending Referral Level	a, c	X	X
MS-DRG (Medical vs. Surgical)	a, c	X	X
Mechanical Ventilation	a, c	X	X
Hospice Discharges	a, c	d	d
LOS	a, c	X	X
Previous Hospitalizations	a, b, c	X	X
Comorbidities (unweighted number)	a, b, c	X	X
Comorbidities (weighted score)	a, b, c	X	X
CHF (%)	a, b, c		X
Cardiac Arrhytmia (%)	a		
Valvular Disease (%)	b, c		X
Pulmonary Circulation Disorders (%)	a, b, c		X
PVD (%)	b, c		X
Hypertension - Uncomplicated (%)			
Hypertension - Complicated (%)	a, b, c		X
Paralysis (%)	a, b, c		X
Neurological Disorders (%)	a, b, c		X
Chronic Pulmonary Disease (%)	a, b, c		X
Diabetes - Uncomplicated (%)	a, b, c		X
Diabetes - Complicated (%)	a, b, c		X
Hypothyroid (%)			
Renal Failure (%)	a, b, c		X
Liver Disease (%)	a, b, c		X

Peptic Ulcer Disease (%)	a	
AIDS (%)	a	
Lymphoma (%)	a, b, c	X
Cancer - Metastatic (%)	a, b, c	X
Cancer (%)	a, b, c	X
Rheumatoid Arthritis (%)	a, b, c	X
Coagulation Disorder (%)	a, b, c	X
Obesity (%)	a	
Weight Loss (%)	a, b, c	X
Fluid and Electrolyte Disorders (%)	a, b, c	X
Anemia - Blood Loss (%)	a	
Anemia - Deficiency (%)	b, c	e
Alcoholism (%)	a	
Drug Abuse (%)	a	
Psychoses (%)	a, c	
Depression (%)	a, b, c	X

Abbreviations: MS-DRG, Medicaid Severity Diagnosis Related Group.

[a]Statistical relationship in crude data

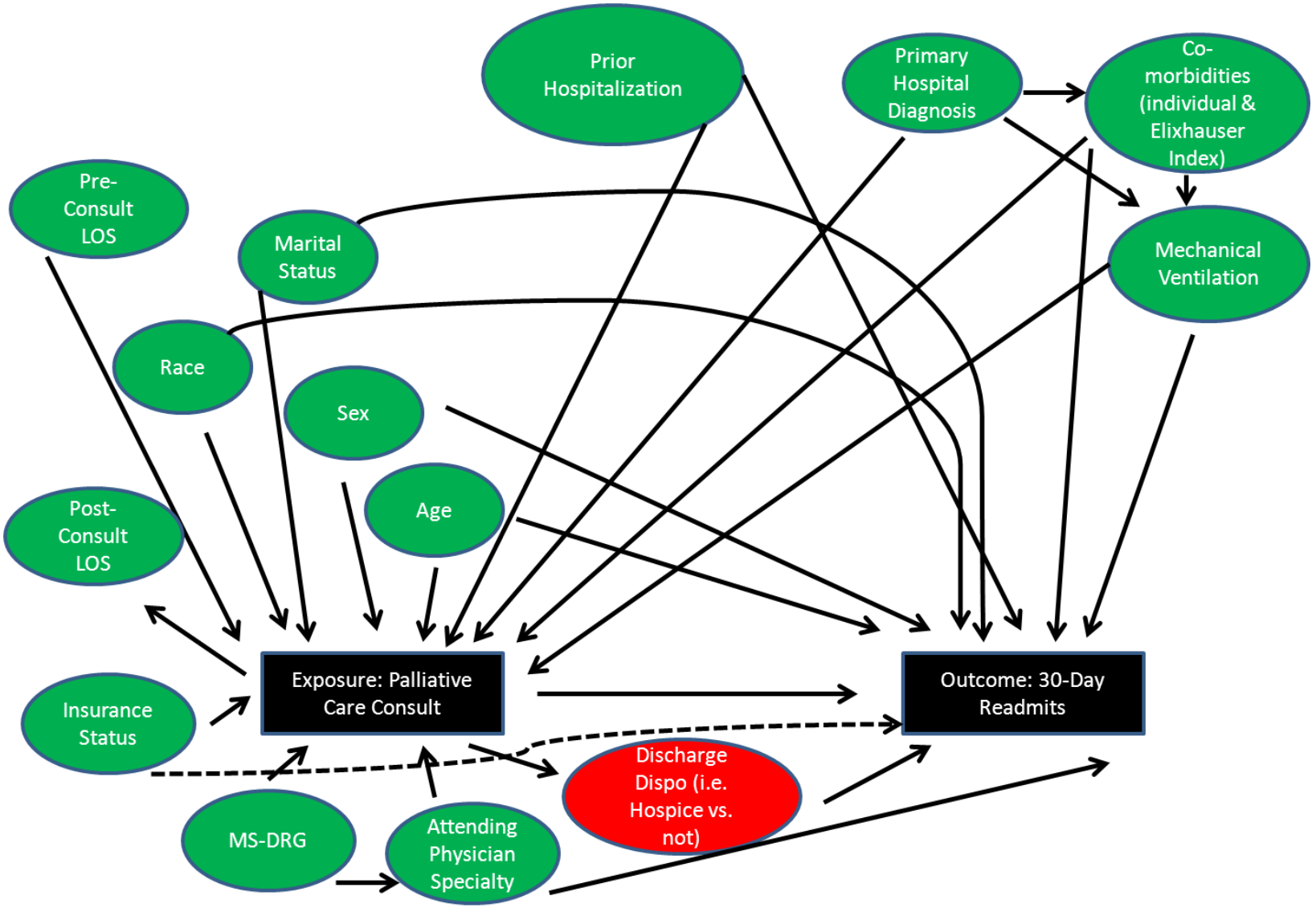
[b]Demonstrated in existing literature

[c]Research panel consensus

[d]Hospice discharges are not included in the model as they are one of the ways in which we suspect PCC acts to reduce readmissions

[e]Sufficiently balanced in initial model

Figure A-1a. Directed Acyclic Graph (DAG) for the association between a PCC and 30-day readmission.



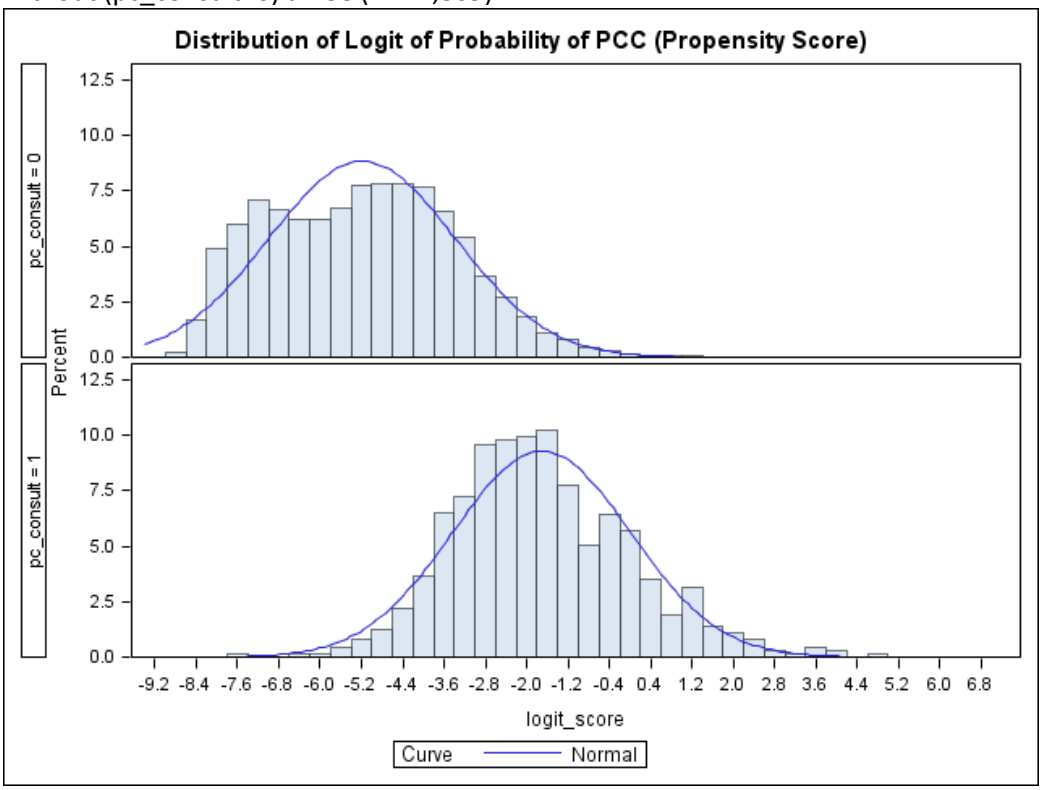
A-2: Propensity Score Common Support

Using propensity score matching on a given cohort assumes, first and foremost, that two groups are *able to be balanced* (i.e. their propensity will not be completely or nearly mutually-exclusive). Ideally we would have propensity scores with a good deal of overlap to allow for sufficient matches to be found within our chosen caliper of 0.10 standard deviations of the logit. Figure A-2a depicts the distribution of propensity scores across both groups and indicates that on the whole patients receiving a PCC had higher propensity scores.

To further investigate the common support question we split the initial sample into quintiles by propensity score and compared the scores' distributions between PCC and non-PCC patients within each quintile (Table A-2a and Figures A-2b-f). The distribution of the scores by quintile was significantly different (Table A-2a); PCC patients were routinely assigned higher propensity scores, as we would expect based on how we constructed the model. This calls into question the generalizability of our results, but the fact that we were able to find matches for so many PCC patients – and the fact that the exposure groups in our matched cohort were well-balanced in terms of covariates (SEE Section A-3) – confirms the internal validity of our analysis. Indeed, we found non-PCC matches for over 95% of our PCC admissions within our caliper.

That said, the lack of overlap indicates issues with the generalizability of our results; there are large swaths of non-PCC patients we cannot find matches for, and we cannot extend the conclusions of this study to these patients.

Figure A-2a. Distribution of Logit propensity scores among those with (pc_consult=1) and without (pc_consult=0) a PCC (N=24,809).



Figures A-2b-f. Distribution of propensity scores among those with (pc_consult=1) and without (pc_consult=0) a PCC by quintile. (b) First quintile, (c) Second Quintile, (d) Third quintile, (e) Fourth quintile, (f) Fifth quintile. N=4,962 per quintile.

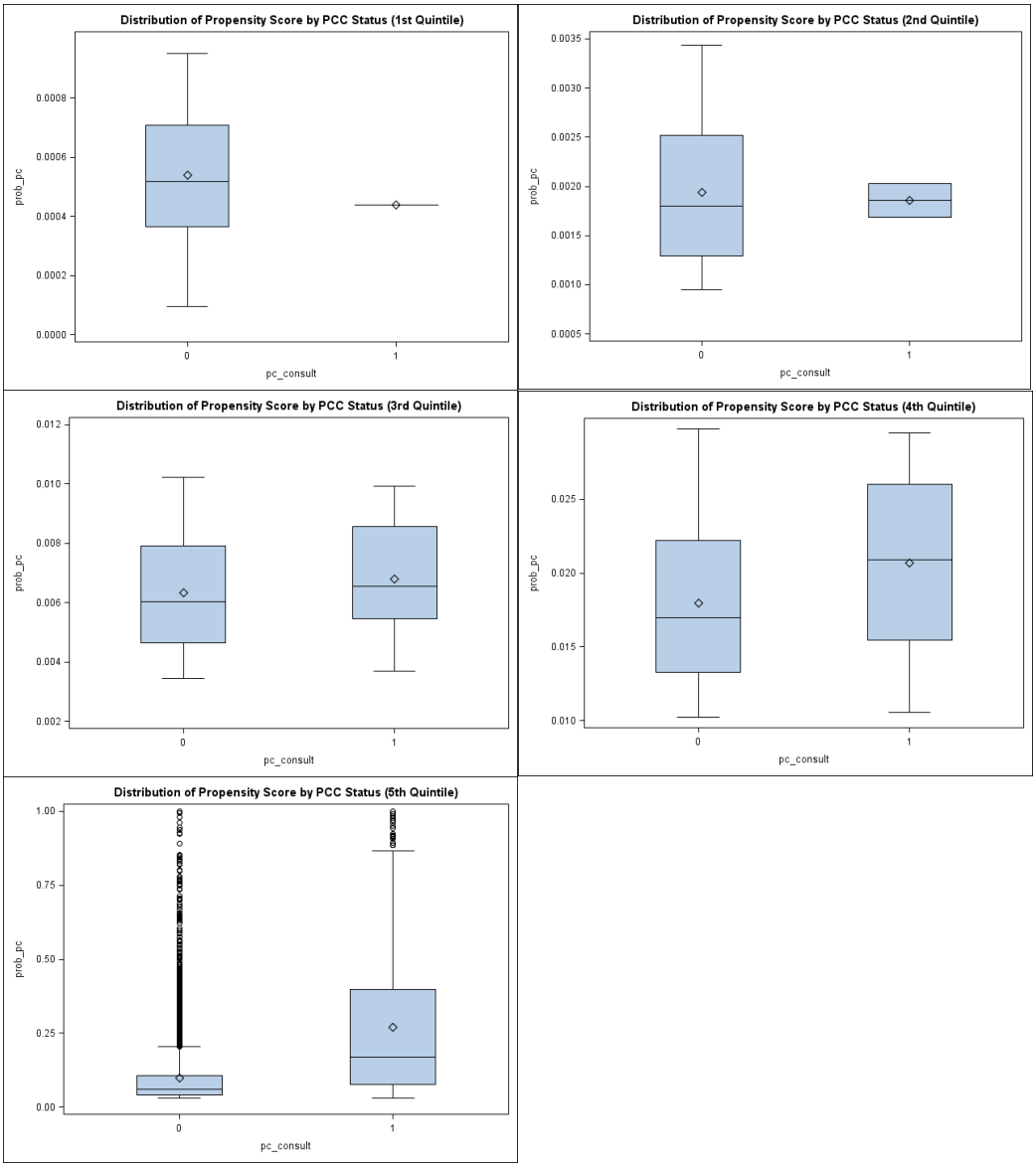


Table A-2a. Distribution of Logit of Propensity Scores by Quintile in Initial Sample (N=24,809).

Quintile of Logit (PS)	Group	N	Mean	Mean 95% CI	Min	Max	P-value (t-test)	P-value (Wilcoxon)
1	No PCC	4,960	0.00	(0.000535, 0.000547)	0.00	0.00	0.62	0.68
	PCC	1	0.00	-	-	-		
2	No PCC	4,960	0.00	(0.00192, 0.00196)	0.00	0.00	0.88	0.91
	PCC	2	0.00	(-0.00034, 0.00405)	0.00	0.00		
3	No PCC	4,944	0.01	(0.00628, 0.00639)	0.00	0.01	0.31	0.31
	PCC	18	0.01	(0.00579, 0.00779)	0.00	0.01		
4	No PCC	4,881	0.02	(0.0178, 0.0181)	0.01	0.03	<0.0001	<0.0001
	PCC	81	0.02	(0.0194, 0.0220)	0.01	0.03		
5	No PCC	4,329	0.10	(0.0961, 0.1029)	0.03	1.00	<0.0001	<0.0001
	PCC	633	0.27	(0.2511, 0.2900)	0.03	1.00		

Abbreviations: PCC, Palliative Care Consult; PS, Propensity Score; CI, Confidence Interval

A-3: Covariate Balance Assessment Pre-Matching

Prior to matching, we assessed covariate balance within quintiles of our propensity score (Table A-3a). The results were mixed, with balance becoming generally worse in higher quintiles of the propensity score. These results are unsurprising in light of the common support analysis in section A-2, which showed PCC subjects to have consistently higher propensity scores than non-PCC subjects. In the middle quintiles there appears to be significant overlap. However, the lowest quintile is almost entirely non-PCC subjects, and the greatest difference in mean propensity scores is in the top quintile.

Table A-3a. Balance[a] of Covariates in PCC vs. non-PCC by Propensity Score Quintile in Initial Sample (N=24,809).

	Quintile of Logit (PS)				
	1	2	3	4	5
Age	-	Balanced	Balanced	Balanced	Balanced
Race	-	Balanced	Balanced	Unbalanced	Balanced
Sex	-	Balanced	Balanced	Balanced	Balanced
Insurance	-	Balanced	Balanced	Balanced	Balanced
Marital Status	-	Balanced	Balanced	Balanced	Balanced
Attending Referral Level	-	Balanced	Unbalanced	Balanced	Balanced
Surgical MS-DRG	-	Balanced	Balanced	Balanced	Unbalanced
Mechanical Ventilation	-	Balanced	Balanced	Unbalanced	Unbalanced
LOS[b]	-	Balanced	Unbalanced	Unbalanced	Unbalanced
Previous Hospitalizations	-	Balanced	Balanced	Balanced	Balanced
Comorbidities (Unweighted)	-	Balanced	Unbalanced	Balanced	Unbalanced
Comorbidities (Weighted Score)	-	Balanced	Balanced	Balanced	Unbalanced

Abbreviations: SD, Standard Deviation; LOS, Length of Stay; PCC, Palliative Care Consult; PS, Propensity Score

[a]Balanced if 2-sample t-test (continuous) or Fisher exact test (categorical) p>0.05.

[b]LOS was severely right-skewed and log-transformed to normalize for statistical testing.

A-4: Covariate Balance Assessment Post-Matching

Although the majority of studies with propensity scores test for balance using hypothesis tests such as Chi Square and t-tests, statisticians note several reasons why this is a poor choice[49,50]. Most notable is the fact that these hypothesis tests are a function of both balance and statistical power – that is, they will vary with the number of observations remaining after matching, the proportion of the matched observations that are exposed, and the variance of the remaining exposed and unexposed observations. Indeed, Imai et al showed that randomly deleting observations (without regard for any matching criteria) from a dataset can reduce t-statistics to levels of statistical insignificance[50].

Instead these statisticians recommend using standardized differences in means and quantile-quantile (QQ) plots for continuous variables to assess balance in matching. We have chosen to follow this approach here. Calculating the standardized differences requires different equations for different types of variables. The two equations are shown below.

1. Continuous variable: $\frac{\overline{X_E}-\overline{X_U}}{\sqrt{\frac{Var(X_E)+Var(X_U)}{2}}}$ where X_E is the value of a covariate in the exposed group and X_U is the value of a covariate in the unexposed group
2. Binary categorical variable: $\frac{p_E-p_U}{\sqrt{\frac{p_E\times(1-p_E)+p_U\times(1-p_U)}{2}}}$ where p_E and p_U are the proportions with the assigned variable in the exposed and unexposed groups, respectively. For N-level categorical variable where N>2, we collapsed the categories into two (race: white vs. non-white; insurance: Medicare vs. other;

previous hospitalizations: none vs. any); the categorization scheme did not affect the standardized differences.

QQ plots for continuous variables were produced using SAS's proc ttest.

We considered the matching to be "not insufficient" if mean differences were within the 0.25 standard deviation rule of thumb proposed by Cochran[54]. However, as the goal of propensity score matching is to minimize the differences between observed covariates *without limit* as long as other concerns[50] – such as precision – do not come into conflict, we did not consider any level of imbalance to be automatically "acceptable" and we sought to minimize imbalance – for example, by adding individual comorbidities to our propensity score model – wherever possible even when superficially acceptable balance had been obtained.

Covariate balance in our pre-matched, matched, and residual unmatched cohorts are displayed in Table 1. Acceptable balance was achieved for all covariates in the matched cohort.

A-5: Model Diagnostics and Performance Assessment

We performed collinearity diagnostics on our final propensity score model, analytical model for single admissions, and analytical models for multiple all-cause and unrelated admissions, presented in tables A-5a, A-5b, A-5c, and A-5d below, respectively. There was no condition index ≥ 30 with two or more "high" (>0.5) variance decomposition proportions (VDP), and so on the advice of Kleinbaum et al[52] we concluded there was no severe collinearity problem present in our model. Although with so many individual comorbidities as well as two composite scores there was the potential for a problem, there were no signs of this in our model results.

Although the purpose of a propensity score model is to reduce confounding, we were also interested in model discrimination as a measure of our model's performance in the data. To assess propensity score model discrimination we calculated the C-statistic, which is a measure of, among every possible pair of PCC and non-PCC admissions, what proportion of the time our model assigned the higher propensity score to the PCC admission. The C-statistic runs from 0 to 1; 0.50 would be expected by random chance alone. Our model had a C-statistic of 0.92, which is conventionally considered "excellent" (Table 3). These suggest our models had good discriminatory capability (i.e. the ability to correctly predict admissions that are more likely to receive a PCC).

To assess goodness-of-fit we used the Hosmer-Lemeshow test at the decile level. Although the Hosmer-Lemeshow test was significant for the model at the 5% level (Table 3), suggesting poor model fit, a deeper look at the observed and predicted number of PCCs in each decile suggests acceptable model fit (Figure A-5a). The significant test statistic may be a function more of the large sample size with which we're working, since

the test's degrees of freedom are dependent not on N but on the number of quantiles with which we're working (g quantiles → g-2 degrees of freedom).

Finally, we validated our propensity score model by re-running it for an identically-defined set of admissions from the year immediately prior. The discrimination and fit statistics were similar (Table 3; Figure A-5b). Overall the propensity score models appeared to perform well, with no collinearity problems, excellent discrimination, acceptable model fit, and good matched covariate balance.

Table A-5a. Collinearity diagnostic matrix for propensity score model (N=24,809).

Variable Name	VDP1	VDP2	VDP3	VDP4	VDP5	VDP6	…
Eigenvalue	0.0107	0.0135	0.0183	0.0545	0.1221	0.17232	…
Condition Index	35.4379	31.541	27.1523	15.7228	10.5081	8.84364	…
	.	.	.	.	.	.	
Intercept	0.7444	0.2316	0	0.0138	0.0049	0.00001	…
Age	0.6134	0.0882	0.0332	0.2145	0.0326	0.0003	…
Sex	0.021	0.0005	0	0.0001	0.007	0.01122	…
Race (Black)	0.0145	0.0221	0.0013	0.0033	0.0025	0.00113	…
Race (Other)	0.0048	0.0007	0.0025	0.0005	0	0.00018	…
Marital Status	0.0006	0.0008	0.0008	0.0104	0.007	0.00052	…
Attending Surgeon	0	0.0014	0.0013	0.0003	0.0035	0.00173	…
Attending High Referrer	0.0899	0.0434	0	0.7283	0.1041	0.00012	…
Unweighted Comorbidity	0.0011	0.0125	0.9827	0.002	0.0001	0.00009	…
Weighted Comorbidity	0.299	0.6707	0.0251	0.0003	0	0.00041	…
Length of Stay	0.0043	0	0.0245	0.0004	0.0055	0.00111	…
Insurance (Medicaid)	0.1033	0.0541	0.0048	0.045	0.0067	0.0006	…
Insurance (Commercial)	0.1379	0.0542	0.0004	0.0457	0.0023	0.00137	…
Insurance (Other)	0.0107	0.0017	0.0001	0.0014	0.0001	0.00087	…
Mechanical Ventilation	0.011	0.0001	0.0068	0.0055	0.0001	0.0032	…
Previous Hospitalizations	0.0617	0.0362	0	0.0103	0.7246	0.01409	…
CHF	0.1369	0.4292	0.063	0.0054	0.0023	0.00318	…
Valvular Disease	0.0002	0.0001	0.1502	0.0106	0.0032	0.00006	…
Pulmonary Circulation Disorders	0.0483	0.1147	0.0489	0.0006	0	0.00011	…
PVD	0.0047	0.0408	0.0903	0.013	0.0017	0.00007	…
Hypertension - Complicated	0.0033	0.0001	0.092	0.0026	0.0092	0.71085	…
Paralysis	0.0792	0.1604	0.0282	0.0002	0.0005	0.00003	…
Neurological Disorder	0.1299	0.2783	0.0578	0.001	0.0052	0.00016	…
Chronic Pulmonary Disease	0.0378	0.0925	0.1212	0.0034	0	0.00178	…
Diabetes - Uncomplicated	0.0009	0	0.0943	0.0001	0.0005	0.00093	…
Diabetes - Complicated	0.001	0	0.1027	0.0002	0.0001	0	…
Renal Failure	0.0687	0.1769	0.0234	0.0002	0.0148	0.62108	…
Liver Disease	0.199	0.409	0.0141	0.0017	0.0011	0.00295	…
Lymphoma	0.0887	0.2139	0.005	0.0003	0	0	…
Cancer - Metastatic	0.1903	0.4202	0.0033	0.0015	0	0.00084	…
Cancer	0.0407	0.1146	0.0489	0.0031	0.0089	0.00015	…
Rheumatoid Arthritis	0.0022	0.0004	0.072	0	0	0.00013	…
Coagulation Disorder	0.037	0.1172	0.0978	0.0011	0.0011	0.00071	…
Weight Loss	0.1056	0.3208	0.0465	0.0016	0.0006	0.00213	…
Fluid or Electrolyte	0.1202	0.2507	0.0947	0.0041	0.022	0.00749	…

Disorder							
Depression	0.0184	0.1198	0.2481	0.0001	0.0002	0.00078	…

Abbreviations: AMC, Academic Medical Center; LOS, Length of Stay; PVD, Peripheral vascular disease; VDP, Variance Decomposition Proportion.

Table A-5b. Collinearity diagnostic matrix for multivariate logistic model, all-cause readmissions + near-misses (N=2,592).

Variable Name	VDP1	VDP2	VDP3	VDP4	VDP5	VDP6	…
Eigenvalue	0.0159	0.3602	0.5113	0.56101	0.59214	0.64957	…
Condition Index	16.8647	3.5421	2.97281	2.83806	2.76245	2.63751	…
	.	.	.	.	.	.	…
Intercept	0.9835	0.0136	0.00003	0	0.0004	0.0007	…
PCC	0.0274	0.4772	0.25117	0.03433	0.06733	0.10387	…
Age	0.9588	0.0351	0.00055	0.00035	0.00002	0.00301	…
MS-DRG (Med vs. Surg)	0.0077	0.0359	0.02783	0.10776	0.22405	0.05577	…
Insurance (Medicaid)	0.3332	0.0128	0.04922	0.09159	0.09979	0.03083	…
Insurance (Commercial)	0.2732	0.0278	0.12713	0.10992	0.13927	0.05346	…
Insurance (Other)	0.0101	0.0071	0.01569	0.02347	0.00349	0.00001	…
Hypertension - Complicated	0.0003	0.1217	0.52174	0.03313	0.00287	0.08663	…
Diabetes - Complicated	0	0	0.22228	0.04793	0.01317	0.35108	…
Liver disease	0.0242	0.0001	0.00248	0.32845	0.07172	0.08149	…
Coagulation Disorder	0.0025	0.0332	0.01373	0.43731	0.19598	0.07613	…
Depression	0.0253	0.0408	0.00171	0.00521	0.29288	0.15551	…

Abbreviations: VDP, Variance Decomposition Proportion; PCC, Palliative Care Consult.

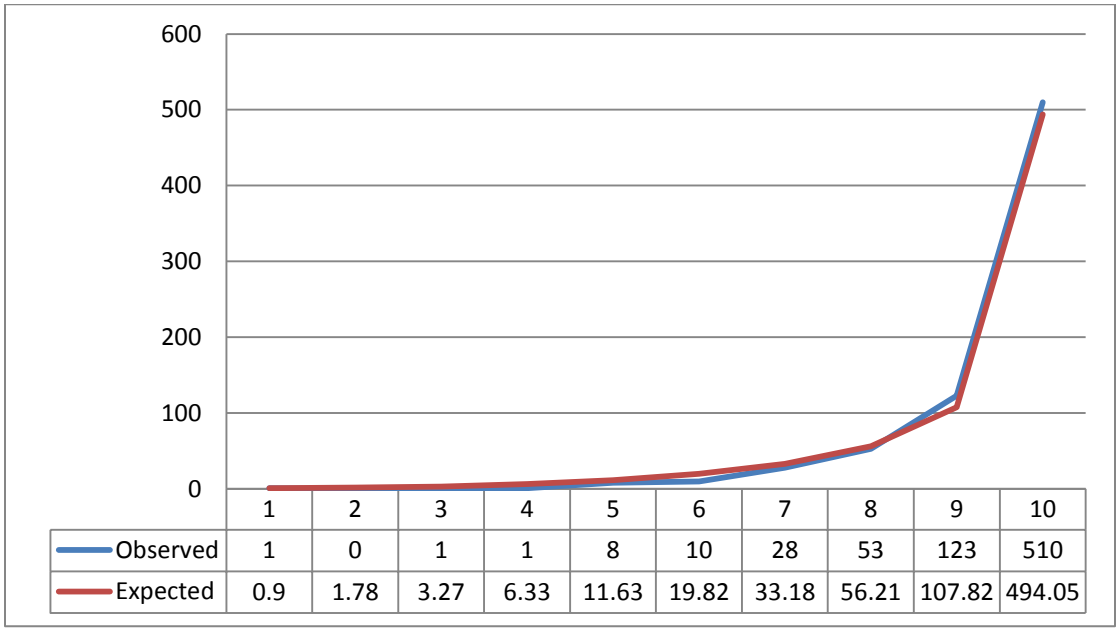
Table A-5c. Collinearity diagnostic matrix for multiple admission conditional logistic model, all-cause readmissions + near-misses (N=15,291).

Variable Name	**VDP1**	**VDP2**	**VDP3**	**VDP4**	**VDP5**	**VDP6**	**…**
Eigenvalue	0.05117	0.1184	0.12067	0.56213	0.73973	0.95761	…
Condition Index	9.32618	6.1301	6.07298	2.81368	2.45276	2.15575	…
	.	.	.	.	.	.	.
Intercept	0.964	0.003	0.00003	0.00632	0.02285	0.0004	…
Palliative Care Consult (PCC)	0.0149	0.0229	0.01428	0.00343	0.15383	0.78632	…
Comorbidities (No.)	0.23132	0.2699	0.4887	0.00006	0.00363	0.00042	…
Previous Hospitalization Class	0.71672	0.0919	0.14923	0.00926	0.02794	0.00056	…
Congestive Heart Failure	0.03187	0.0434	0.10189	0.80839	0.00003	0.00037	…
Complicated Hypertension	0.00109	0.6801	0.20244	0.01053	0.07911	0.01947	…
Renal Failure	0.01502	0.4706	0.42692	0.01266	0.05528	0.01242	…

Abbreviations: VDP, Variance Decomposition Proportion; PCC, Palliative Care Consult

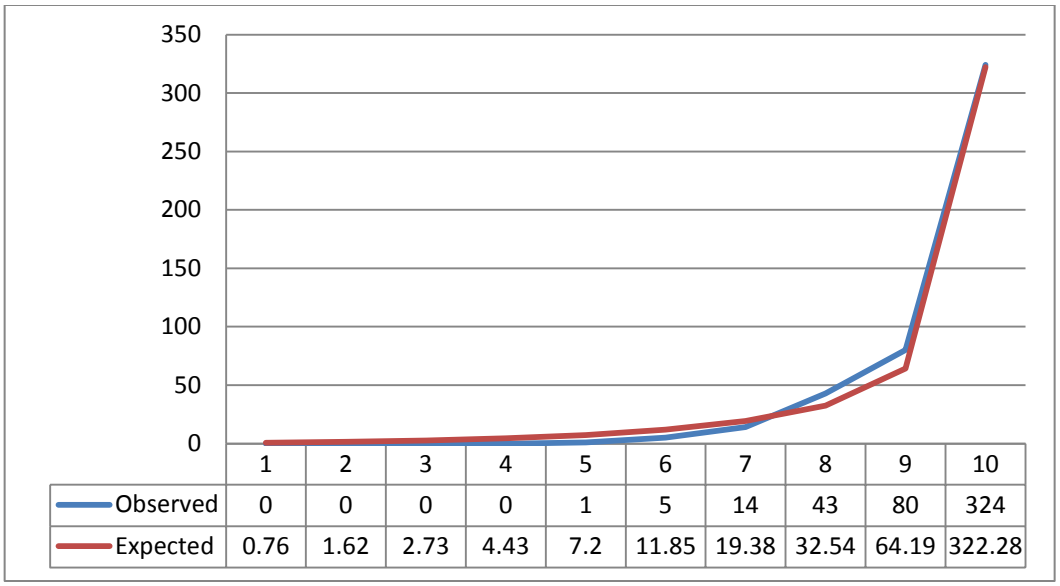
Variable Name	VDP1	VDP2	VDP3	VDP4	VDP5	VDP6	…
Eigenvalue	0.05509	0.1866	0.54642	0.68101	0.92331	1.00314	…
Condition Index	7.98326	4.3374	2.53486	2.2706	1.95005	1.87084	…
	.	.	.	.	.	.	.
Intercept	0.93913	0.0435	0.00797	0.00013	0.00103	0.00012	…
PCC	0.00395	0.0045	0.00402	0.23279	0.5722	0.01261	…
MS-DRG (Med vs. Surg)	0.02572	0.0162	0.14723	0.32757	0.27664	0.03076	…
Attending PC Referral level	0.04975	0.8977	0.02624	0.00002	0.00004	0.00254	…
Mechanical Ventilation	0.00909	0.0012	0.05362	0.40296	0.00491	0.3388	…
Previous Hospitalization Class	0.83148	0.1438	0.01243	0.00031	0.00053	0.0003	…
Congestive Heart Failure	0.00031	9E-05	0.80831	0.02113	0.05259	0.03059	…
Metastatic Cancer	0.00295	0.0044	0.09136	0.28487	0.0153	0.44859	…

Figure A-5a: Observed vs. expected PCCs by decile in propensity score model.



	1	2	3	4	5	6	7	8	9	10
Observed	1	0	1	1	8	10	28	53	123	510
Expected	0.9	1.78	3.27	6.33	11.63	19.82	33.18	56.21	107.82	494.05

Figure A-5b: Observed vs. expected PCCs by decile in propensity score validation model.



	1	2	3	4	5	6	7	8	9	10
Observed	0	0	0	0	1	5	14	43	80	324
Expected	0.76	1.62	2.73	4.43	7.2	11.85	19.38	32.54	64.19	322.28

A-6: Stratification by Hospital

In our unmatched sample (N=24,809), 2.5% of admissions at AMC-1 and 3.6% of patients at AMC-2 received a PCC over the study period. 18.2% of AMC-1 and 19.2% of AMC-2 admissions had a 30-day readmission or near miss event. The likelihood of getting a PCC at either hospital when the propensity score calculation is stratified by hospital is depicted in Figures A-6a; a distribution of the combined scores derived from the sample as a whole is in Figure A-6b. These distributions are very similar. Additionally, when the analyses are repeated using hospital-specific propensity scores and stratified by hospitals, the unadjusted results are similar to those obtained with the combined analysis except with less precision (data not included). The similar crude probabilities of receiving a PCC and having a 30-day readmission; the similar distributions of propensity scores between a stratified and combined sample; and the similar results obtained when repeating the analysis for a stratified sample suggest it is valid to calculate propensity scores from a pooled sample despite baseline differences in hospital patient populations (e.g. AMC-1 offers some specialized services, such as transplant, not available at AMC-2, and AMC-2 serves a more heavily minority and low-SES area than AMC-1).

Figure A-6a. Distribution of logit of propensity scores derived from hospital-stratified sample (N=14,618 for AMC-1, N=10,191 for AMC-2).

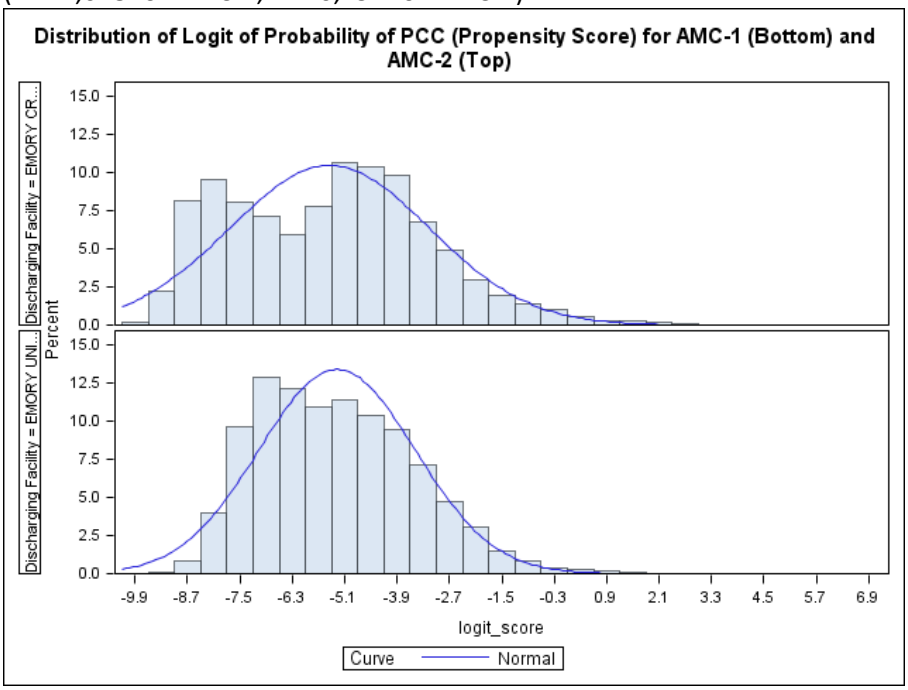
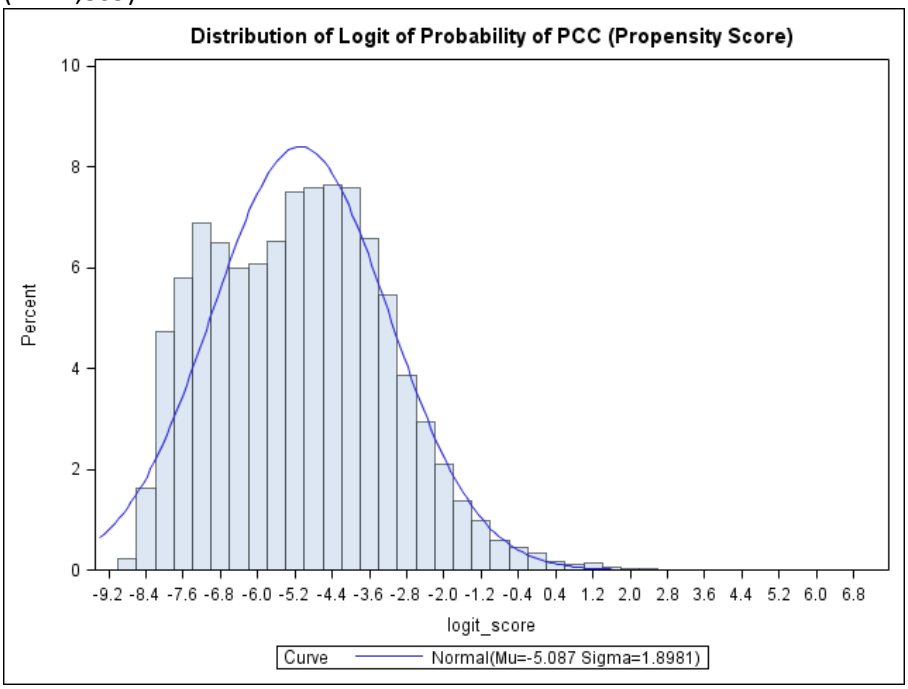


Figure A-6b. Distribution of logit of propensity scores derived from whole initial sample (N=24,809).



A-7: Sensitivity Analyses

Data Set Randomization

When conducting 1-to-1 nearest-neighbor matching, the order of your observations in your initial sample can affect the matched cohort you ultimately end up with for analysis. Thus it is necessary to randomize the order of your data prior to matching. In our case, we created a random uniform variable in SAS and sorted the dataset on those values. To test the sensitivity of our results to random data ordering effects, we repeated the matching and subsequent conditional logistic regression analysis with two different seeds. The results showed minimal variation for all-cause readmissions, but considerable variation for related readmissions due to the smaller number of events. (Table A-7a). However, in no case did changing the randomization alter the conclusion of a hypothesis test, suggesting our randomization was sufficient to remove any effects of data ordering.

Table A-7a. Sensitivity analysis of data set ordering using randomization with different seeds.

		All-Cause Readmissions + Near-Misses		All-Cause Readmissions ONLY		Related Readmissions + Near-Misses		Related Readmissions ONLY	
Seed	**N**	**OR**	**95% CI**	**OR**	**95% CI**	**OR**	**95% CI**	**OR**	**95% CI**
287[a]	1,380	0.78	0.59, 1.03	0.84	0.62, 1.13	0.65	0.30, 1.41	0.91	0.37, 2.30
302	1,378	0.82	0.62, 1.07	0.86	0.64, 1.16	0.54	0.23, 1.28	1.08	0.38, 3.12
8675309	1,382	0.81	0.61, 1.06	0.85	0.63, 1.15	0.53	0.25, 1.11	0.6	0.24, 1.53

Abbreviations: OR, Odds Ratio; CI, Confidence Interval

[a]This seed was used in the analysis presented in the manuscript. It was chosen as the number of passing yards by winning quarterback Joe Flacco in Superbowl XLVII. The research team chose this as the most impeccable reflection of randomness they could think of.

1. Jencks SF, Williams MV, Coleman EA. Rehospitalizations among patients in the Medicare fee-for-service program. N Engl J Med 2009;360:1418-28.
2. Bodenheimer T. Coordinating care--a perilous journey through the health care system. N Engl J Med 2008;358:1064-71.
3. Hines S. Reducing Avoidable Hospital Readmissions: Health Research and Educational Trust; 2010 June 4, 2010.
4. Readmissions Reduction Program. 2012. (Accessed February 7, 2013, at http://cms.gov/Medicare/Medicare-Fee-for-Service-Payment/AcuteInpatientPPS/Readmissions-Reduction-Program.html/.)
5. Center for Medicare and Medicaid Services Hospital Compare web site. (Accessed February 7, 2013, at http://www.medicare.gov/hospitalcompare/.)
6. Boutwell A. Time to Get Serious About Hospital Readmissions. Health Affairs Blog2012.
7. Minott J. Reducing Hospital Readmissions. Washington, DC: Academy Health; 2008.
8. Anthony D, Chetty VK, Kartha A, McKenna K, DePaoli MR, Jack BW. Re-engineering the Hospital Discharge: An Example of a Multifaceted Process Evaluation. In: Henriksen K, Battles JB, Marks ES, Lewin DI, eds. Advances in Patient Safety: From Research to Implementation (Volume 2: Concepts and Methodology). Rockville, MD: Agency for Healthcare Research and Quality; 2005:379-94.
9. Greenwald JL, Denham CR, Jack BW. The Hospital Discharge: A Review of a High Risk Care Transition With Highlights of a Reengineered Discharge Process. Journal of Patient Safety 2007;3:97-106 10.1097/01.jps.0000236916.94696.12.
10. Jack BW, Chetty VK, Anthony D, et al. A Reengineered Hospital Discharge Program to Decrease RehospitalizationA Randomized Trial. Annals of internal medicine 2009;150:178-87.
11. BOOST, Better Outcomes for Older Adults Through Safe Transitions. Society of Hospital Medicine, 2013. (Accessed February 8, 2013, at http://www.hospitalmedicine.org/AM/Template.cfm?Section=Home&TEMPLATE=/CM/HTMLDisplay.cfm&CONTENTID=27659.)
12. State Action on Avoidable Hospital Readmissions Overview. Institute for Healthcare Improvement, 2013. (Accessed February 8, 2013, at http://www.ihi.org/offerings/Initiatives/STAAR/Pages/default.aspx.)
13. Ouslander JG, Lamb G, Tappen R, et al. Interventions to reduce hospitalizations from nursing homes: evaluation of the INTERACT II collaborative quality improvement project. Journal of the American Geriatrics Society 2011;59:745-53.
14. Community-based Care Transitions Program. Center for Medicare and Medicaid Innovation. (Accessed February 8, 2013, at http://innovation.cms.gov/initiatives/CCTP/index.html.)
15. Coleman EA, Parry C, Chalmers S, Min SJ. The care transitions intervention: results of a randomized controlled trial. Archives of internal medicine 2006;166:1822-8.
16. Naylor MD, Brooten D, Campbell R, et al. Comprehensive discharge planning and home follow-up of hospitalized elders: a randomized clinical trial. JAMA : the journal of the American Medical Association 1999;281:613-20.
17. Rich MW, Beckham V, Wittenberg C, Leven CL, Freedland KE, Carney RM. A Multidisciplinary Intervention to Prevent the Readmission of Elderly Patients with Congestive Heart Failure. New England Journal of Medicine 1995;333:1190-5.
18. Morrison RS, Meier DE. Clinical practice. Palliative care. N Engl J Med 2004;350:2582-90.
19. Teno JM, Clarridge BR, Casey V, et al. Family perspectives on end-of-life care at the last place of care. JAMA : the journal of the American Medical Association 2004;291:88-93.

20. A controlled trial to improve care for seriously ill hospitalized patients. The study to understand prognoses and preferences for outcomes and risks of treatments (SUPPORT). The SUPPORT Principal Investigators. JAMA : the journal of the American Medical Association 1995;274:1591-8.
21. Smith TJ, Temin S, Alesi ER, et al. American Society of Clinical Oncology Provisional Clinical Opinion: The Integration of Palliative Care into Standard Oncology Care. Journal of Clinical Oncology 2012.
22. Growth of Palliative Care in U.S. Hospitals 2012 Snapshot: Center to Advance Palliative Care; 2012.
23. Goldsmith B, Dietrich J, Du Q, Morrison RS. Variability in access to hospital palliative care in the United States. Journal of palliative medicine 2008;11:1094-102.
24. Casarett D, Pickard A, Bailey FA, et al. Do palliative consultations improve patient outcomes? Journal of the American Geriatrics Society 2008;56:593-9.
25. Gade G, Venohr I, Conner D, et al. Impact of an inpatient palliative care team: a randomized control trial. Journal of palliative medicine 2008;11:180-90.
26. Lamba S, Murphy P, McVicker S, Harris Smith J, Mosenthal AC. Changing end-of-life care practice for liver transplant service patients: structured palliative care intervention in the surgical intensive care unit. J Pain Symptom Manage 2012;44:508-19.
27. Gelfman LP, Meier DE, Morrison RS. Does palliative care improve quality? A survey of bereaved family members. J Pain Symptom Manage 2008;36:22-8.
28. Gries CJ, Curtis JR, Wall RJ, Engelberg RA. Family member satisfaction with end-of-life decision making in the ICU. Chest 2008;133:704-12.
29. Higginson IJ, Finlay I, Goodwin DM, et al. Do hospital-based palliative teams improve care for patients or families at the end of life? J Pain Symptom Manage 2002;23:96-106.
30. Hanson LC, Usher B, Spragens L, Bernard S. Clinical and economic impact of palliative care consultation. J Pain Symptom Manage 2008;35:340-6.
31. Ciemins EL, Blum L, Nunley M, Lasher A, Newman JM. The economic and clinical impact of an inpatient palliative care consultation service: a multifaceted approach. Journal of palliative medicine 2007;10:1347-55.
32. Elsayem A, Swint K, Fisch MJ, et al. Palliative care inpatient service in a comprehensive cancer center: clinical and financial outcomes. Journal of clinical oncology : official journal of the American Society of Clinical Oncology 2004;22:2008-14.
33. Zimmermann C, Swami N, Rodin G, et al. Cluster-randomized trial of early palliative care for patients with metastatic cancer. ASCO Meeting Abstracts 2012;30:9003.
34. Ringdal GI, Jordhoy MS, Kaasa S. Family satisfaction with end-of-life care for cancer patients in a cluster randomized trial. J Pain Symptom Manage 2002;24:53-63.
35. Morrison RS, Penrod JD, Cassel JB, et al. Cost savings associated with US hospital palliative care consultation programs. Archives of internal medicine 2008;168:1783-90.
36. Temel JS, Greer JA, Muzikansky A, et al. Early palliative care for patients with metastatic non-small-cell lung cancer. N Engl J Med 2010;363:733-42.
37. Beresford L. Where is Palliative Care in the Readmissions Boom? AAHPM Quarterly 2011 Fall 2011:12-5.
38. Brumley R, Enguidanos S, Jamison P, et al. Increased satisfaction with care and lower costs: results of a randomized trial of in-home palliative care. Journal of the American Geriatrics Society 2007;55:993-1000.
39. Comart J, Mahler A, Schreiber R, Rockett C, Jones RN, Morris JN. Palliative Care for Long-Term Care Residents: Effect on Clinical Outcomes. The Gerontologist 2012.

40. Lukas L, Foltz C, Paxton H. Hospital outcomes for a home-based palliative medicine consulting service. Journal of palliative medicine 2013;16:179-84.
41. Enguidanos S, Vesper E, Lorenz K. 30-day readmissions among seriously ill older adults. Journal of palliative medicine 2012;15:1356-61.
42. Elixhauser A, Steiner C, Harris DR, Coffey RM. Comorbidity measures for use with administrative data. Medical care 1998;36:8-27.
43. van Walraven C, Austin PC, Jennings A, Quan H, Forster AJ. A modification of the Elixhauser comorbidity measures into a point system for hospital death using administrative data. Medical care 2009;47:626-33.
44. Silverstein MD, Qin H, Mercer SQ, Fong J, Haydar Z. Risk factors for 30-day hospital readmission in patients >/=65 years of age. Proceedings (Baylor University Medical Center) 2008;21:363-72.
45. Rubin DB. Estimating causal effects from large data sets using propensity scores. Annals of internal medicine 1997;127:757-63.
46. Rubin DB. Using Propensity Scores to Help Design Observational Studies: Application to the Tobacco Litigation. Health Services & Outcomes Research Methodology 2001;2:169-88.
47. Rubin DB, Thomas N. Matching using estimated propensity scores: relating theory to practice. Biometrics 1996;52:249-64.
48. Coca-Perraillon M. Local and global optimal propensity score matching. SUGI Global Forum 2007. Paper 185-20072007.
49. Ho DE, Imai K, King G, Stuart EA. Matching as Nonparametric Preprocessing for Reducing Model Dependence in Parametric Causal Inference. Political Analysis 2007;15:199-236.
50. Imai K, King G, Stuart EA. Misunderstandings between experimentalists and observationalists about causal inference. Journal of the Royal Statistical Society: Series A (Statistics in Society) 2008;171:481-502.
51. Hill J. Discussion of research using propensity-score matching: comments on 'A critical appraisal of propensity-score matching in the medical literature between 1996 and 2003' by Peter Austin, Statistics in Medicine. Statistics in medicine 2008;27:2055-61; discussion 66-9.
52. Kleinbaum DG, Klein M. Logistic Regression: A Self-Learning Text. 3rd edition ed. New York: Springer; 2010.
53. Brookhart MA, Schneeweiss S, Rothman KJ, Glynn RJ, Avorn J, Sturmer T. Variable selection for propensity score models. American journal of epidemiology 2006;163:1149-56.
54. Cochran WG. The Effectiveness of Adjustment by Subclassification in Removing Bias in Observational Studies. Biometrics 1968;24:295-313.
55. Brooks JM, Ohsfeldt RL. Squeezing the Balloon: Propensity Scores and Unmeasured Covariate Balance. Health services research 2012.
56. NHPCO Facts and Figures: Hospice Care in America. Alexandria, VA2012 October 2012.
57. Vincent GK, Velkoff VA. The Next Four Decades, The Older Population in the United States: 2010 to 2050: Population Estimates and Projections. Washington, D.C.: United States Census Bureau; 2010.
58. Calfo S, Smith J, Zezza M. Last Year of Life Study. Washington, DC: Centers for Medicare and Medicaid Services, Office of the Actuary.
59. Starks H, Wang S. Cost Savings Vary By Length of Stay for In-Patients Receiving Palliative Care Consult Services (317-A). Journal of pain and symptom management 2012;43:348-9.
60. Kansagara D, Englander H, Salanitro A, et al. Risk Prediction Models for Hospital Readmission: A Systematic Review. Washington DC2011.