Should Hospitals Keep Their Patients Longer? The Role of Inpatient and Outpatient Care in Reducing Readmissions

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Twenty percent of Medicare fee-for-service patients are readmitted to the hospital within 30 days of discharge, resulting in substantial costs to the U.S. government. As part of the 2010 Affordable Care Act, the Hospital Readmissions Reduction Program financially penalizes hospitals with higher than expected readmissions. Utilizing data on the over 6.6 million Medicare patients treated between 2008 and 2011, we estimate the reductions in readmission and mortality rates of an inpatient intervention (keeping patients in the hospital for an extra day) versus providing outpatient interventions. We find that for heart failure patients, the inpatient and outpatient interventions have practically identical impact on reducing readmissions. For heart attack and pneumonia patients, keeping patients one more day can potentially save 5 to 6 times as many lives over outpatient programs. Moreover, we find that even if the outpatient programs were cost-free, incurring the additional costs of an extra day may be a more cost-effective option to save lives. While some outpatient programs can be very effective at reducing hospital readmissions, we find that 1) inpatient interventions can be just as, if not more, effective and 2) to the extent that hospitals can implement such an inpatient intervention, it may be reasonable to hold them accountable for some of their excess readmissions.

Key words: Healthcare, Medicare, Econometric Analysis, Readmissions, Length-of-stay, Mortality

1. Introduction

Section 3025 of the Patient Protection and Affordable Care Act (ACA), signed into law in March of 2010, outlines the *Hospital Readmissions Reduction Program (HRRP)* that addresses the high readmission rates for Medicare patients. About one in every five Medicare fee-for-service (FFS) patients is readmitted, costing Medicare about 17.4 billion dollars per year (Jencks et al. 2009). Effective since fiscal year 2013, the HRRP financially penalizes hospitals with higher than expected readmissions following discharge for acute myocardial infarction (AMI), heart failure (HF), and pneumonia (PNE). Three-quarters of hospitals that are subject to the HRRP—2,610 hospitals—will receive reduced reimbursements in the fiscal year 2015, and Medicare estimates the total penalty to be about 428 million dollars[1]. The purpose of the HRRP is to provide incentives for hospitals to reduce ‘preventable’ Medicare readmissions. In this paper, we examine and compare different methods to reduce readmissions.

In anticipation and response to the HRRP, hospitals have implemented a number of different approaches to reduce readmissions. Improving outpatient management is a common approach, with variations including discharge management (Jack et al. 2009, Koelling et al. 2005), coordination of care via nurse practitioners (Innovative Care Models 2008a,b), and outpatient care including telemedicine (Innovative Care Models 2008c) and nutrition counseling (Koelling et al. 2005). Helm et al. (2013) propose to combine machine learning techniques to generate individualized readmission predictions with optimized outpatient follow-up schedules in order to reduce readmissions. These programs have demonstrated varying results, with some large successes, but also outright failures or just minimal improvements (Bradley et al. 2013)[2]. Given the vast attention on outpatient follow up and care, there has been growing criticism that the HRRP unfairly penalizes hospitals for factors outside of their control[3]. In particular, some people have raised concerns that hospitals should not be responsible for patients’ post-discharge behavior.

Rather than focusing on the potential impact on readmissions of the penalty introduced by the HRRP, our paper assesses the welfare implications of possible responses by hospitals to reduce readmissions. To that end, we consider whether there are practices within a hospital’s control that can reduce readmission rates and, possibly, mortality rates. Specifically, we compare the potential gains from changing inpatient care to those made possible by outpatient programs. To the best of our knowledge, we are the first to explore how hospitals may modify inpatient care as an appropriate and desirable response to reduce excess readmissions. Given the growing emphasis on reducing readmissions, as indicated by the new Medicare penalties, our work provides insight into the possible levers available to hospitals to achieve this goal[4].

The inpatient intervention we consider is an increase in patient Length of Stay (LOS), with the idea that an extra day may provide benefits such as allowing a patient to reach a higher level of stability as well as providing more time for patients to be educated about their post-discharge behavior, thereby resulting in a reduction in the risk of hospital readmission. In the prior literature, there is mixed evidence on the role of LOS in reducing readmission rates. While Baker et al. (2004) and Jaeker and Tucker (2013) found no association between hospital LOS and readmissions, Kc and Terwiesch (2012) found that for some cardiac

[1] Kaiser Health News: “Medicare fines 2,610 hospitals in third round of readmission penalties” by Jordan Rau. October 2, 2014.

[2] See Hansen et al. (2011) and Rennke et al. (2013) for further reviews of various readmission programs.

[3] New York Times: “Hospitals Question Medicare Rules on Readmissions” by Reed Abelson. March 29, 2013.

[4] Zhang et al. (2014) provide a theoretical model to determine whether hospitals will be incentivized to reduce readmissions in response to the HRRP. A number of additional studies consider the likely impact of other facets of the ACA, see Kolstad and Kowalski (2012), Long et al. (2009, 2011), and Aizawa and Fang (2013) on insurance coverage and Hanchate et al. (2012), Miller (2012), and Hofer et al. (2011) on healthcare utilization.

surgery patients in Intensive Care Units (ICU), a reduction in ICU LOS resulted in an increase in ICU readmission risk[5] and Carey (2014) found a similar relationship for AMI patients hospitalized in New York State. Focusing on Medicare fee-for-service patients hospitalized for HF during the time period 1993-2006, Bueno et al. (2010) documented an increase in 30-day readmission rates and a decrease in hospital LOS and mortality, but they were unable to show a relationship between these two trends. Utilizing an instrumental variables methodology, we measure the impact of an increase in hospital LOS on the readmission and mortality rates for all Medicare patients hospitalized for HF, AMI, or PNE.

An interesting feature of Medicare that we utilize in this study is its coverage choices. The first option, which covers about 75% of all Medicare beneficiaries, is to enroll in traditional Medicare in which Medicare directly pays service providers in a Fee-For-Service (FFS) manner. Service providers have an incentive to provide more care and to perform more tests in this setting; for instance, hospital readmissions are not necessarily bad because hospitals are paid twice for each patient that comes back to the hospital. The remaining 25% of Medicare beneficiaries receive coverage through a Medicare Advantage (MA) plan. A beneficiary can choose a private insurer (e.g. BlueCross/BlueShield, Aetna and United Health Care) that is approved by Medicare. Medicare then pays the insurance company a *capitated* payment for each patient covered via MA. The majority of these plans pay service providers on a FFS basis. If health expenditures for a patient (including inpatient care) exceed this budget, the insurance company will incur a loss; if the expenses fall below the budget, the insurance company will have a surplus. As such, insurance companies that provide MA coverage have an incentive to reduce excess readmissions, and thus provide better outpatient care to keep their patients as healthy as possible (Bayer 2010).

We utilize a dataset from the Centers for Medicare & Medicaid Services (CMS) that consists of all Medicare in-hospital patient visits between 2008 and 2011. Since our study compares outcomes for Medicare patients insured under FFS and those insured under MA, and hospitals were not required to provide data on MA patients prior to 2008, the earliest year we can study is 2008 (MLN Matters 2008). A potential challenge in comparing FFS and MA patients is that insurance companies may make their MA patients appear 'sicker' in the CMS database than they truly are in order to qualify for higher capitated payments from the government[6]. We provide a number of robustness checks to show that upward risk-adjustment for

[5] Kc and Terwiesch (2012) showed that congestion in the cardiac ICU resulted in shorter ICU LOS and that shorter ICU LOS increased the likelihood for ICU readmission because patients were less stable upon discharge. Due to demand pressures from more critical patients, keeping patients in the ICU longer was not an option in their study. However, because we consider a patient's entire hospital stay, we believe there likely is more flexibility in keeping patients longer.

[6] LOS has been found to be shorter for MA patients (Cher and Lenert 1997, Retchin et al. 1997, Philbin and DiSalvo 1998), which may be attributable to upward risk-adjustment. The findings from these studies may not be robust because of significant underreporting of inpatient hospital stays for HMO enrollees in administrative records (Riley et al. 1998). As of 2008, such reporting deficiencies have been reduced (MLN Matters 2008).

MA patients is unlikely to significantly impact our estimation of the potential benefits of the MA systems' outpatient and coordinated care.

Estimating the impact of LOS on the probability of readmission (or mortality) is complicated; it is not possible to perfectly measure a patient's severity level and unobservable severity factors might be positively correlated with both LOS and readmission (or mortality) risk. To circumvent this problem we use an instrument for LOS based on a patient's admission day-of-week. In our data we find that the residuals from a LOS equation for HF patients admitted on Sunday or Monday are negative, suggesting that they are 'prematurely' discharged. That is, based on standard protocols for treating HF patients, these patients would be ready for discharge on the weekend but hospitals prefer to discharge them before the weekend (see Varnava et al. (2002) and Wong et al. (2009)). This variation in LOS based on admission day-of-week helps us capture the impact of shorter LOS on increased readmission (or mortality) risk. One potential concern with this instrumental variable is that it may be related to patient severity, so that the increased readmission risk we measure may be due to patients admitted on Sunday or Monday being sicker than patients admitted on other days. Importantly, we find no evidence to support this; HF patients admitted on Sunday or Monday do not appear to be sicker than patients admitted on other days. Analysis of the LOS residuals for AMI and PNE patients identifies Monday/Tuesday admissions and Sunday/Monday admissions as suitable instruments for these two patient groups, respectively. Our estimates of the effect of LOS on readmissions and mortality are obtained from a two-stage least squares model that includes hospital fixed effects in both stages.

Our key findings are:

- For HF patients with high severity, one more hospital day decreases readmission risk by 7%. This relationship between LOS and readmissions does not exist for PNE or AMI patients, but we show that longer LOS can reduce their mortality risks by 22% and 7% respectively.
- Patients are more likely to be readmitted if they are covered under Medicare FFS instead of MA. For instance, we find that the readmission risk for high severity HF patients decreases by 7% on average if they are covered under MA instead of FFS. Comparing this result to our first finding on the impact of LOS on readmissions, we therefore show that a simple inpatient intervention (i.e., keeping patients one more day) can achieve comparable results to what may be achieved via outpatient management.
- Keeping all FFS PNE patients in the hospital for one more day would save 19,063 lives while an alternative policy of switching these patients to MA would save only 3,177 lives over the course of four years. Using hospital cost estimates and value of life estimates, we show that the value of the additional 15,886 saved lives exceeds the costs of an extra day in the hospital for these patients.
- Keeping all FFS AMI patients in the hospital for one more day saves 2,577 lives over four years compared to only 515 lives that would be saved if these patients were switched to MA. Under reasonable assumptions, we find that the value of these saved lives would exceed the cost of the inpatient intervention.

In sum, our findings document a significant impact of inpatient interventions on readmission and mortality risks. In some cases the impact of keeping a patient one more day in the hospital is *more* beneficial than what could be achieved via switching all patients to MA and providing them with the various outpatient programs and primary care included in such plans.

The remainder of the paper is structured as follows: Section 2 describes the dataset and the sample we use for our analyses. Section 3 describes our econometric model and explains why admission day-of-week is a valid instrument. In Section 4 we present results for HF patients, including a number of robustness checks. Section 5 presents results for AMI and PNE patients. In Section 6, we discuss the policy implications of our findings from a social planner's perspective. Finally, we conclude in Section 7.

2. Setting

2.1. Data

We utilize data on all inpatient hospitalizations for Medicare beneficiaries, both traditional Medicare and MA patients. These data are drawn from the 100% sample in the Medicare Provider Analysis and Review (MedPAR) inpatient file[7].

Since one of the goals of our study is to estimate the impact of MA plans in reducing readmissions, the earliest year we can study is 2008. Prior to 2008, hospitals provided data on MA patients on a voluntary basis and data for this time period is extremely limited and possibly inaccurate. Starting in 2008, Medicare hospital providers that receive Disproportionate Share payments, Indirect Medical Education or Direct Medical Education adjustments were required to submit claims information for beneficiaries enrolled in MA plans (MLN Matters 2008). We therefore restrict our analysis to the time period 2008 through 2011 (the latest year that was available to us).

For each hospitalization, we have the patient's demographic information including age, gender, race, coverage choice, and hospitalization characteristics including admission and discharge dates (which enable us to compute the patient's LOS and account for potential seasonal variations), the primary condition or other coexisting conditions identified by up to 10 International Classification of Diseases, Ninth Revision, Clinical Modification (ICD-9-CM) codes, the Medicare Severity adjusted Diagnosis Related Group (MS-DRG) classification (indicating the DRG to which the claims that comprise the stay belong for payment purposes), hospital and admission type (e.g., elective or emergency basis). We also generate a severity of illness measure, the Elixhauser index (Elixhauser et al. 1998), using the ICD-9-CM codes and the MS-DRG classification. We do not use any financial data because they are not included in the MedPAR file for MA patients.

[7] See http://www.resdac.org/cms-data/files/medpar-rif for a description of this dataset.

2.2. Patient Outcomes

The main patient outcome of this study is 30-day hospital readmission, and we follow CMS in defining this measure (see CMS.gov (2014), Krumholz et al. (2008a,b,c) for details). That is, we assess *unplanned*[8] and *all-cause*[9] readmission within 30 days of discharge from a hospitalization to *any* hospital.

In addition, we consider 30-day mortality, defined as death within 30 days of discharge from a hospitalization, and 30-day adverse outcome, defined as the occurrence of 30-day hospital readmission and/or 30-day mortality. Note that in all of the three patient outcome models, we exclude patients who die during their hospitalization.

2.3. Selection of Patient Samples

We examine three distinct patient samples–patients with Heart Failure (HF), Pneumonia (PNE), or Acute Myocardial Infarction (AMI)–because the HRRP pertains to patients with these diagnoses[10]. We use the primary ICD-9 codes to identify patients with these ailments.

Appendix Tables A.1 through A.3 describe our sample selection process for the HF patients, AMI patients and PNE patients, respectively. We only consider hospital stays with admission and discharge that occur between January 1, 2008 and November 30, 2011. Because the outcomes we study are events which occur within 30 days of discharge, we exclude admissions and discharges that occur during December 2011 to avoid potential censoring of our outcome variables. Due to data fidelity concerns, we exclude visits with overlapping admissions (i.e., admissions that occur prior to discharge of the previous hospital stay). Following CMS (Krumholz et al. 2008a,b,c), we focus on acute care stays. Stays that involve hospital transfers are excluded as it is difficult to control for what happens in two different hospitals and during the transfer time.

We exclude stays that are not paid under the prospective payment system (PPS)[11]; after this significant payment change, patient care also began to change since payments were no longer based on the amount of time patients spent in the hospital, but rather based on the average cost to treat the particular DRG. We restrict our analysis to hospitals for which the MedPAR inpatient file includes both FFS and MA patients in order to estimate the difference in care and outcomes across FFS and MA. (In other words, hospitals that treated only FFS patients are not included.)

[8] CMS has a pre-specified list that identifies planned readmissions (e.g., readmissions for maintenance chemotherapy) (Krumholz et al. 2008a,b,c).

[9] In other words, the patient need not be hospitalized under the same diagnosis as the previous hospitalization.

[10] Note that in fiscal year 2015 the program is expanding to include: chronic obstructive pulmonary disease (COPD), elective total hip arthroplasty (THA), and total knee arthroplasty (TKA). However, as the initial program focuses on HF, PNE and AMI, we do as well.

[11] Medicare switched to the current DRG code based prospective payment system (PPS) in 1983.

We then keep the patients with the specific conditions on which we are focusing: HF, AMI or PNE. Following CMS (Krumholz et al. 2008a,b,c), we exclude admissions within 30 days of a prior hospitalization's discharge; that is, an admission within 30 days of a prior admission will be counted as a readmission, but that admission itself will not be used as an observation in our patient outcome models[12]. Since the HRRP only penalizes hospitals that have more than 25 visits for each corresponding condition, we exclude hospitals that have less than 25 visits for each condition. Patients who are discharged to destinations that provide inpatient related services are excluded. We only include patients 65 years and older, which is the primary indication for Medicare eligibility. Next, we exclude patients who died during their hospital stay, who left against medical advice, who do not have their race reported, as well as those who do not reside in the U.S.

We focus on emergency and urgent (i.e., non-elective) patients to leverage the *random* variation in admission day-of-week to construct an instrumental variable (see Section 3.1 for details). Such an identification strategy is not possible for elective patients whose admissions are mostly scheduled. Finally, we exclude patients who are LOS outliers (greater than the 99th percentile value) and those who are cost outliers[13].

2.4. Summary Statistics

Table 1 presents means and standard deviations for the three patient samples (HF, AMI and PNE). Our initial empirical analysis is focused on HF patients because they account for the biggest share of the patients for whom hospitals can be assessed penalties. Analysis of the AMI and PNE patients is discussed in Section 5. Table 1 shows that 22% of HF patients are readmitted within 30 days of discharge. Heart failure patients have an average LOS of 4.75 days and those who are readmitted stay an additional 6.01 days. Length of stay varies by day of admission from a low of 4.55 for Sunday admits to a high of 4.93 for Friday admits; in Section 3, we discuss how this variation enables us to construct an instrument to deal with the bias attributable to unobservable patient severity characteristics. Finally, note that HF patients can be classified into two categories, MCC and non-MCC, based on the observed severity of their diagnoses, where MCC patients are those with major complications or co-morbidities[14]. As expected, HF patients with more severe conditions have a longer LOS for their initial hospitalization.

[12] In our final sample, an individual patient may have multiple admissions, which are each counted as a separate observation. We found that about 30% of our observations are from patients with multiple visits during the study period. Our results are robust to randomly selecting one observation per patient, so we present the results allowing for multiple observations from each patient.

[13] MedPAR inpatient file identifies unusually high cost stays for PPS providers.

[14] For HF patients CMS defines three categories: MCC (major complications or comorbidities), CC (complications or comorbidities) and non-CC (absence of complications or comorbidities). The ICD-9-CM codes for CC are 40201, 40401, 40403, 40411, 40413, 40491, 40493, 42810, 42820, 42822, 42830, 42832, 42842, and 42840, and the ICD-9-CM codes for MCC are 42821, 42823, 42831, 42833, 42841, and 42843. We combined CC and non-CC patients and call this group non-MCC. Source: Table 6J and 6I, Centers for Medicare & Medicaid Services, http://www.cms.gov/Medicare/Medicare-Fee-for-Service-Payment/AcuteInpatientPPS/Acute-Inpatient-Files-for-Download-Items/FY2014-FinalRule-CorrectionNotice-Files.html

Table 1 **Summary statistics**

	HF			AMI			PNE
	Non-MCC	MCC	All	Non-MCC	MCC	All	All (MCC)
Num. of obs.	783646	815226	1598872	2234	670664	672898	1308691
Age	80.32	80.39	80.36	78.56	78.23	78.23	79.66
	(8.28)	(8.18)	(8.23)	(8.71)	(8.47)	(8.47)	(14.66)
Elixhauser Score	3.20	3.98	3.60	2.65	2.75	2.75	3.11
	(1.49)	(1.60)	(1.59)	(1.57)	(1.56)	(1.56)	(3.11)
Female	0.56	0.55	0.56	0.51	0.48	0.48	0.54
Race - White	0.80	0.83	0.81	0.83	0.87	0.87	0.87
Race - Black	0.15	0.13	0.14	0.10	0.08	0.08	0.08
Race - Hispanic	0.03	0.02	0.02	0.04	0.02	0.02	0.02
Race - Other	0.03	0.02	0.02	0.03	0.03	0.03	0.03
Had surgical procedure(s)	0.38	0.38	0.38	0.70	0.77	0.77	0.31
Medicare Advantage (MA)	0.20	0.21	0.21	0.25	0.23	0.23	0.19
Average LOS (days)	4.64	4.86	4.75	4.65	4.88	4.88	5.09
	(3.05)	(3.10)	(3.08)	(3.13)	(3.31)	(3.30)	(3.13)
Monday	4.51	4.73	4.62	4.31	4.70	4.7	5.03
Tuesday	4.59	4.8	4.7	4.57	4.73	4.73	5.09
Wednesday	4.68	4.88	4.78	4.48	4.83	4.83	5.16
Thursday	4.79	5.05	4.92	4.72	4.99	4.99	5.22
Friday	4.8	5.06	4.93	5.17	5.10	5.1	5.19
Saturday	4.62	4.83	4.73	4.65	5.04	5.03	5.02
Sunday	4.46	4.63	4.55	4.59	4.81	4.81	4.94
% Admitted							
Monday	17.21	17.2	17.21	15.63	15.57	15.57	16.16
Tuesday	15.46	15.49	15.48	15.63	14.55	14.55	14.82
Wednesday	14.46	14.53	14.5	12.5	14.37	14.36	14.21
Thursday	14.44	14.39	14.42	15.63	14.15	14.16	14.18
Friday	14.68	14.33	14.51	15.63	14.39	14.39	14.47
Saturday	11.63	11.63	11.62	12.5	13.48	13.48	12.9
Sunday	12.12	12.43	12.27	12.5	13.49	13.5	13.26
Readmission in 30 days	0.22	0.22	0.22	0.18	0.17	0.17	0.16
Avg readmitted LOS (days)	6.09	5.94	6.01	5.05	5.22	5.22	6.31
	(6.07)	(5.65)	(5.86)	(5.05)	(5.22)	(5.22)	(5.99)
Death in 30 days	0.08	0.08	0.08	0.08	0.07	0.07	0.08
Adverse Outcome in 30 days	0.29	0.29	0.29	0.24	0.24	0.24	0.23

Note. Averages (standard deviation in parentheses for continuous variables) are reported. Adverse outcome corresponds to either a readmission or death within 30 days. MCC and non-MCC are CMS defined severity groups based on ICD-9-CM codes, where MCC indicates that the patient had "major complications or comorbidities" during the hospital stay in addition to the primary indicator for hospital admission. Non-MCC indicates the absence of such major complications and comorbidities. CMS also uses ICD-9-CM codes for risk adjustment, as specified in Horwitz et al. (2011). Note that the groupings of MCC and non-MCC may vary when using MS-DRG codes to do severity categorization (e.g. Carey (2014)).

Note that the sample sizes given in Table 1 may not be exactly equivalent to the sample sizes in our regressions in Sections 4 and 5. This is because 1) patients who die within 30 days or who have scheduled readmissions were excluded from the readmissions models; 2) a few patients stayed in the hospital for less than 1 full day and, as will be explained below, our model uses logarithm of hospital LOS as a dependent variable, thereby requiring a LOS of at least 1 day; and 3) some samples are dropped because they are perfect predictors of the outcome of interest[15].

3. Econometric Model

Our goal is to estimate the impact of hospital LOS and Medicare coverage choice (FFS or MA) on 30-day hospital readmission (R), 30-day mortality (D) and 30-day adverse outcome (A) where $A = 1$ if $R = 1$ or $D = 1$. To do this, we start with the following equation:

$$y_i^* = \beta X_i + \gamma FFS_i + \theta \log(LOS_i) + \xi M_i + \psi YR_i + \eta H_i + \epsilon_i \quad (1)$$

$$y_i = 1_{\{y_i^* > 0\}} \quad (2)$$

where y_i is the binary outcome of interest and can be equal to R, D or A. Thus, y_i^* can be interpreted as the latent risk of the event occurring.

In equation (1), X_i is a vector of patient characteristics: age, gender, race, Elixhauser co-morbidities[16], and a dummy variable for having one or more surgical procedures (any minor/major diagnostic or therapeutic procedures)[17]. FFS_i is a dummy variable for patients enrolled in traditional FFS (it is equal to 0 if patients are enrolled in an MA plan). M_i, YR_i and H_i are all vectors: M_i is the month of hospital admission; YR_i is the year of hospital admission; H_i is the hospital in which patient i is treated. Hence, we include month and year dummies as well as hospital fixed effects; the inclusion of the hospital fixed effects controls for the potential impact of unobservable attributes of the more than 3000 hospitals in our study. As is standard practice, we take the logarithm of the patient's LOS in order to account for the heavy tails in this distribution. We assume that the error term ϵ_i is a standard normal random variable to fit the Probit model.

While the Elixhauser co-morbid conditions have been widely used in previous research, these measures are not a perfect control for patient severity[18]. Unobservable severity factors might be positively correlated with both LOS and the dependent variable in equation (1). Since sicker patients tend to stay longer in the hospital and are also more likely to be readmitted or die, we might draw an erroneous conclusion that

[15] For example, if all patients in hospital i die within 30 days of discharge, then a hospital fixed effect for hospital i would be a perfect predictor of mortality and all patients treated in hospital i would be dropped from the mortality regression.

[16] Elixhauser et al. (1998) defines 30 comorbid conditions using the ICD-9-CM and MS-DRG codes. Equation (1) includes 30 dummy variables, one for each of the 30 conditions.

[17] While we do not have any data on the socio-economic status of the patients, this is not a concern because while we expect patients with lower socio-economic status to be more likely to be readmitted, we also expect them to be less likely to be prematurely discharged as hospitals are hesitant to send patients home without a solid support system to help manage their recovery. If there were a positive correlation between premature discharge and socio-economic status, this could result in us erroneously concluding that premature discharge increases the likelihood of readmission when the true effect may be due to socio-economic status.

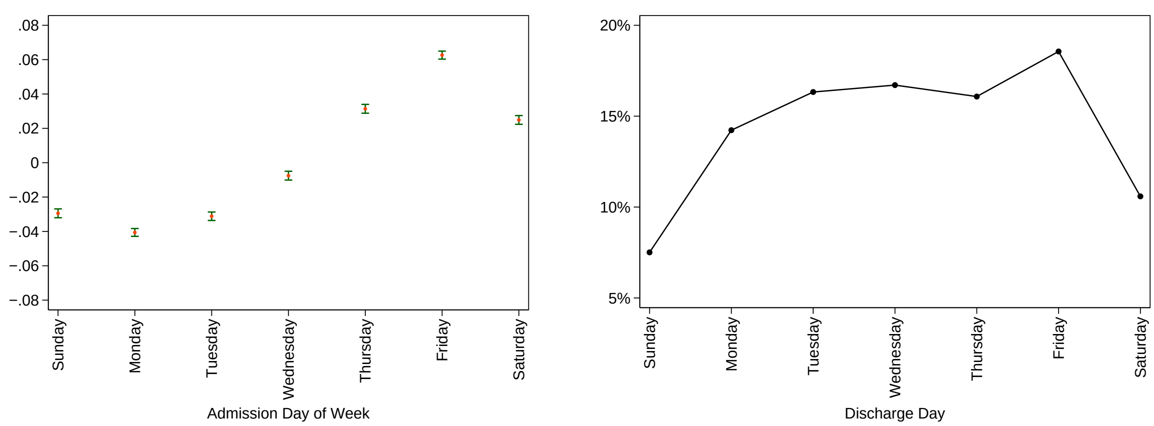
[18] We considered using alternative risk-adjustment variables: (1) using the ICD-9-CM codes from inpatient and outpatient claims from 12 months prior to admission to build risk history and (2) using chronic conditions from the Beneficiary Summary File (BSF). We concluded that these alternatives are inferior to using Elixhauser co-morbidities because of their possible incompleteness for MA patients as hospitals are not required to report information on outpatient claims for MA patients.

longer LOS leads to higher readmission or mortality risks. In the following subsection, we describe our instrumental variable approach to address this possible endogeneity in $\log(LOS)$.

3.1. Instrument for LOS

A valid instrumental variable is correlated with the endogenous variable ($\log(LOS)$) and uncorrelated with the unobservable noise (Wooldridge 2010). We now propose an instrument that is based on a patient's admission day-of-week and evaluate whether it satisfies these two properties[19].

Table 1 shows that the average LOS for HF patients differs based on day of admission. We estimated a regression of the logarithm of LOS on patient observables (age, gender, race, Elixhauser, had surgical procedure(s) or not, FFS or MA), time dummies (month and year of hospital admission) and hospital fixed effects. Figure 1(a) shows the average residual from this regression plotted against the admission day-of-week. Patients admitted on Sunday, Monday or Tuesday have negative residuals, suggesting that they are 'prematurely' discharged.



(a)Average of residuals and their 95% lower and upper bounds from regression of $\log(LOS)$ on observables plotted against admission day-of-week

(b)Percentage of discharges by day-of-week

Figure 1 Day-of-week effects on LOS for HF patients

The average LOS for HF patients in our sample is 4.75 days. This is consistent with the typical protocol for treating HF patients, which requires several days of monitoring fluid intake and output (Yancy et al. 2013). As such, patients admitted on Sunday, Monday or Tuesday are likely to be ready for discharge on the weekend. There is substantial evidence (e.g. Varnava et al. (2002), Wong et al. (2009)) that hospitals prefer to discharge patients just prior to the weekend rather than keeping the patients over the weekend when

[19] Timing of admission via time of day or day of week has been used as an instrument in a number of healthcare settings (e.g. Ho et al. (2000), Ryan et al. (2005), Goyal et al. (2013), Baiocchi et al. (2014)).

many services are not available[20]. Indeed, there seems to be evidence of this preference in our data where discharge rates peak on Friday and fall sharply on Saturday and Sunday (see Figure 1(b)). This suggests that we may be able to leverage the variation in LOS due to this "weekend effect" as an identification strategy and isolate a valid instrumental variable. Note that what we are considering a weekend effect is different than seen in Rinne et al. (2014), which examines the impact of a weekend discharge on hospital readmissions and finds no effect. In contrast, we consider the effect of being discharged 'early' due to the hospitals' penchant to discharge before the weekend.

Further details on the residuals of our $\log(LOS)$ regression are shown in Figure 2 where the histograms of the residuals are plotted by admission day of the week. An interesting observation from Figure 2 is that the histogram for Tuesday admissions is bi-modal, indicating that HF patients admitted on Tuesday may be likely to be prematurely discharged prior to the weekend, or conversely, likely to be kept longer in the hospital, i.e. over the weekend to wait for further treatment and monitoring on Monday. The histograms in Figure 2 therefore suggest that Tuesday admission may not be a useful instrument and we will use Sunday/Monday admissions as the instrument but test the sensitivity of the results to excluding patients who were admitted on Tuesday. Note that this bi-modal phenomenon also occurs for Wednesday admits but we do not include Wednesday admits in our instrument based on Figure 1(a). Still, we consider a robustness check excluding Wednesday admits.

There might be concerns that the type of care provided to patients on Sundays and Mondays is different than other days of the week and this in turn may be the primary driver of any differences in outcomes we measure for Sunday/Monday admits, rather than the effect of shorter LOS. For instance, with less staffing and resources available on weekends, one may question if patients admitted on Sundays have worse outcomes because of lack of access to care. Ryan et al. (2005) found that while cardiac patients who are admitted on the weekend have longer delays to catheterization, there does not seem to be any difference in outcomes. Thus, it does not seem that being admitted on weekends, in and of itself, results in worse outcomes. When considering Monday admissions, it is common for many surgeries to be scheduled on Mondays–especially the more complex ones. Thus, while we focus on emergency and urgent patients, the availability of surgical staff may be reduced for patients admitted to a surgical service. For patients admitted to a medical service, surgical schedules are unlikely to have a significant impact on their care. In Section 4.2, we will provide a robustness check which excludes patients who have a surgical procedure during their hospital stay.

[20] In discussions with administrators at a major medical center, we were informed that cardiac stress tests, which are often required before discharging HF patients, typically cannot be administered on the weekend. In addition, social workers are generally not available and it is difficult to arrange for home health aides on the weekend.

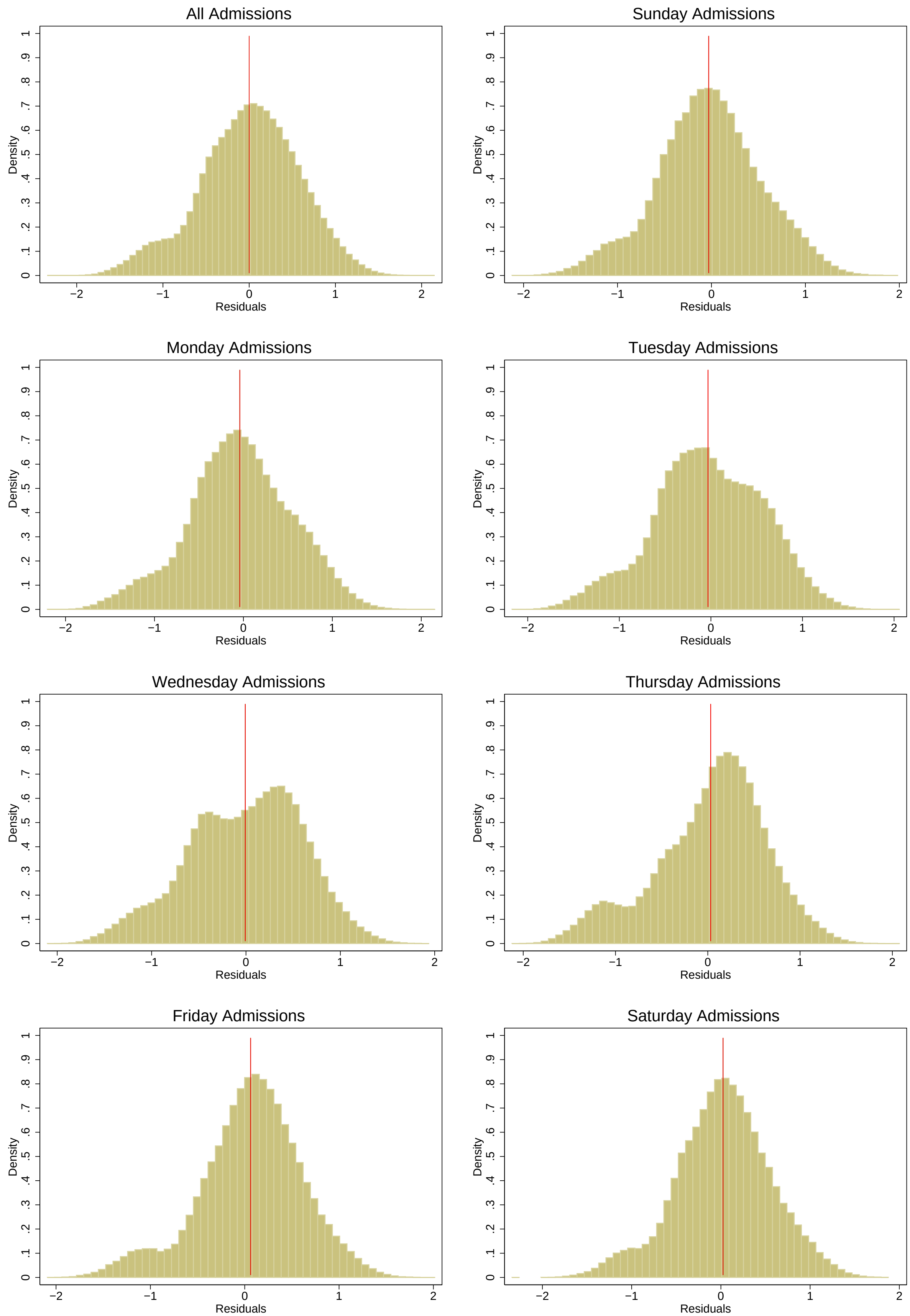


Figure 2 **Residual histograms of $log(LOS)$ regression for HF patients by admission day-of-week**

Another concern may be related to whether Sunday/Monday admits are different than patients admitted on the other days. While it is impossible to check whether our instrument is correlated with the unobservables, we believe the unobserved severity is likely to be related to other observable measures of severity, e.g. the age and the Elixhauser score. Thus, we examine whether the mean age and Elixhauser score depend on the admission day-of-week. Such an approach of comparing the instrumental variable to observable covariates was also used in Kc and Terwiesch (2012).

Table 2 shows the mean (and standard deviation) Elixhauser score for the Non-MCC, MCC, and All patients across all admission days of week. For All patients, the t-tests provide evidence that patients admitted on Sunday/Monday are younger and have higher Elixhauser scores, both at significance level $p < .001$. These two results are conflicting; both age and Elixhauser scores are measures of severity, and one measure (Elixhauser) indicates sicker patients are admitted on Sunday/Monday while the other (age) indicates the opposite. Based on our hypothesis that shorter LOS will increase readmission risk and that Sunday/Monday admits have shorter LOS, having less severe patients admitted on Sunday/Monday could result in conservative estimates of the true effect of LOS on readmissions. Thus, the results regarding age are not a concern. However, if more severe patients are admitted on Sunday/Monday, it would be difficult to assess whether any increase in readmission risk is due to the fact that patients are sicker or because they had a shorter LOS. Thus, the results regarding the Elixhauser score could invalidate our proposed IV.

Table 2 **Means and standard deviations of Elixhauser score by admission day for HF patients**

	Non-MCC		MCC		All	
	Avg	Std. dev.	Avg	Std. dev.	Avg	Std. dev.
Monday	3.23	1.50	3.99	1.60	3.62	1.60
Tuesday	3.22	1.49	3.99	1.60	3.61	1.60
Wednesday	3.19	1.49	3.98	1.60	3.59	1.60
Thursday	3.20	1.49	3.99	1.61	3.60	1.60
Friday	3.19	1.49	3.99	1.60	3.59	1.60
Saturday	3.17	1.47	3.96	1.58	3.57	1.57
Sunday	3.20	1.48	3.98	1.59	3.60	1.59
All	3.20	1.49	3.98	1.60	3.60	1.59

For the MCC HF cohort, however, we find weak evidence ($p = .081$) to fail to reject the null hypothesis that the difference of means in Elixhauser score between Sunday/Monday admits and the remaining days (3.989 versus 3.982) is zero. When excluding Saturday admits, we fail to reject the null hypothesis ($p = .729$) that the means are the same.[21]

In the non-MCC HF cohort, Sunday/Monday admits still have statistically higher ($p < .001$) Elixhauser scores. These findings suggest that Sunday/Monday admission is a reasonable instrument for the MCC

[21] We further check the robustness of our results in Section 4.2 by excluding Saturday admissions in our regression.

patient cohort, but perhaps not for the non-MCC patient cohort. The difference between the two severity groups support these findings. The motivation for using Sunday/Monday admits as an instrument is that (1) patients have shorter LOS when admitted on Sunday or Monday because of the weekend effect and that (2) emergency and urgent patients cannot decide when to get sick and be admitted to the hospital. Factor (2) does not seem to hold for non-MCC patients; because HF is a chronic and not an acute condition, there may be some leeway for low severity (non-MCC) patients to determine when to go to the hospital. On the other hand, postponing visiting the hospital until the middle of the week is not a realistic option for patients with major complications or comorbidities (MCC). We will see in Section 5 that for acute conditions (AMI and PNE), patient severity does not differ by admission day-of-week.

Additionally, we note that Card et al. (2009) identify AMI and respiratory failure as "non-deferrable" diagnoses (i.e. just as likely to be admitted on the weekend as on a weekday). Although HF is not identified as one, we believe one can safely assume that HF admitted on emergency and urgent basis are "non-deferrable" diagnoses as well.

3.2. Estimation

We now introduce our instrumental variable estimation approach. In the first stage, we fit a linear model for $\log(LOS)$:

$$\log(LOS_i) = \hat{\beta} X_i + \hat{\gamma} FFS_i + \hat{\xi} M_i + \hat{\psi} YR_i + \hat{\eta} H_i + \hat{\phi} Z_i + \nu_i \tag{3}$$

In the second stage, Probit models for each of the binary patient outcomes, R, D and A, are estimated:

$$y_i^* = \beta X_i + \gamma FFS_i + \theta \log(LOS_i) + \xi M_i + \psi YR_i + \eta H_i + \epsilon_i \tag{4}$$

$$y_i = 1_{\{y_i^* > 0\}} \tag{5}$$

Thus, the first stage uses Z_i as an instrument for $\log(LOS)$ in the second stage. For HF patients, we let Z_i be an indicator that equals to 1 if the patient is admitted on Sunday or Monday, and 0 otherwise. These equations are estimated jointly via Full Maximum Likelihood Estimation (Wooldridge 2010). We report robust standard errors for Equation (3), clustered by Sunday/Monday versus other days of the week[22], and robust standard errors for Equation (4).

Based on Cher and Lenert (1997), Retchin et al. (1997), Philbin and DiSalvo (1998), we expect the coefficient on FFS, $\hat{\gamma}$, to be positive in the first stage. Relating back to our discussion on the capitated nature of MA plans, we expect MA plans to have better continuity of care, outpatient management, and primary

[22] We also tried clustering by day of week and found that our instrument was still significant, though at the level of $p < .01$ or $.05$, rather than $p < .001$ or $.01$, which we see when clustering by Sunday/Monday versus other days of the week.

care. Thus, we expect the coefficient on FFS, γ, in the second stage to also be positive. In examining the admission day-of-week effect in Section 3.1, we expect the coefficient for our Sunday/Monday admission day instrument (Z_i), $\hat{\phi}$, to be negative. Finally, we hypothesize that these 'premature' discharges due to hospitals' desire to discharge patients before the weekend will increase the risk of the patient outcome, R, D or A, so that θ is negative.

4. Results for Heart Failure Patients

We start by examining the estimation results for HF patients. In Section 5, we will consider the remaining two conditions which round out the three initial HRRP conditions.

4.1. Readmission in 30 days

As the HRRP of the ACA penalizes hospitals solely based on readmissions, we start with readmissions. We will also consider mortality in the subsequent section because CMS posts both readmission and mortality rates on its Hospital Compare website.

Table 3 Readmission in 30 days Model Results for HF Patients

	Probit	IV (SunMon adm) Probit		
	All	All	w/o Tues	w/o Tues/Wed
Second Stage (Readmission)				
log(LOS)	0.11***	-0.15**	-0.09*	-0.04
	(0.00)	(0.05)	(0.04)	(0.04)
FFS	0.07***	0.07***	0.07***	0.07***
	(0.00)	(0.00)	(0.00)	(0.00)
Age, Gender, Race	Yes	Yes	Yes	Yes
Elixhauser Categorical Vars	Yes	Yes	Yes	Yes
Had surgical procedure(s)	Yes	Yes	Yes	Yes
Month, Year Dummies	Yes	Yes	Yes	Yes
Hospital FE	Yes	Yes	Yes	Yes
First Stage ($\log(LOS)$)				
IV		-0.05**	-0.06**	-0.08**
		(0.00)	(0.00)	(0.00)
FFS		0.01	0.01	0.01
		(0.00)	(0.00)	(0.00)
Age, Gender, Race	Yes	Yes	Yes	Yes
Elixhauser Categorical Vars	Yes	Yes	Yes	Yes
Had surgical procedure(s)	Yes	Yes	Yes	Yes
Month, Year Dummies	Yes	Yes	Yes	Yes
Hospital FE	Yes	Yes	Yes	Yes
Num. of obs.	1469557	1469557	1241956	1028893
Wald χ^2 test		26.53	21.85	16.62
Wald p-value		0.00	0.00	0.00

Note. Robust standard errors in parentheses. $*(p < 0.05), **(p < 0.01), ***(p < 0.001)$.

Table 3 shows that when we do not instrument $\log(LOS)$, the coefficient of $\log(LOS)$ on the probability of readmission is positive. Using Sunday/Monday admits to instrument $\log(LOS)$ results in a negative coefficient on $\log(LOS)$; the average marginal effect of a one-day increase in LOS is a reduction in the readmission probability from .226 to .215, which is a 5% decrease. Note the coefficient on Sunday/Monday admits is -0.05 in the first stage and is significant at the .01 level. These results include both MCC and non-MCC patients. Based on our earlier discussion in Section 3.1, there may be concerns about the validity of our instrument for the non-MCC patients. Thus, these results may be slightly biased. In all specifications with the Sunday/Monday admits as an instrumental variable, we have a negative coefficient on $\log(LOS)$. However, when excluding patients admitted on Tuesday or Wednesday, the significance is lost–we believe that this may be due to the 30% reduction in sample size.

Table 3 also shows that FFS patients are more likely to be readmitted. One may be concerned about the robustness of our estimate for FFS patients due to potential risk-adjustment issues for MA patients. In particular, because CMS payments for MA patients are risk-adjusted, insurance companies that cover MA patients may have an incentive to make their patients seem sicker when reporting information to CMS. We examine this possibility in Section 4.2 and conclude that this phenomenon is unlikely to be an issue in our sample.

Table 4 **Readmission in 30 days Model Results for HF Non-MCC and MCC Patients**

	Non-MCC patients			MCC patients		
	All	w/o Tues	w/o Tues/Wed	All	w/o Tues	w/o Tues/Wed
log(LOS)	-0.05	-0.00	0.02	-0.22***	-0.15**	-0.09
	(0.07)	(0.06)	(0.05)	(0.06)	(0.05)	(0.05)
FFS	0.08***	0.08***	0.08***	0.06***	0.06***	0.06***
	(0.00)	(0.01)	(0.01)	(0.00)	(0.00)	(0.01)
IV	-0.05**	-0.06**	-0.07**	-0.05**	-0.07**	-0.08**
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Num. of obs.	719920	608362	504161	749122	633009	524000
Wald χ^2 test	4.33	2.95	2.22	25.24	21.93	16.46
Wald p-value	0.04	0.09	0.14	0.00	0.00	0.00

Note. Robust standard errors in parentheses. $*(p < 0.05), **(p < 0.01), ***(p < 0.001)$.

Recalling the potential issues with our instrument for non-MCC patients, we further split our analysis across patients of different severity. Table 4 summarizes these results. We find a large and significant effect of LOS on readmission for the MCC patients; the average marginal effect of a one-day increase in LOS is a reduction in the readmission probability from .229 to .212, a 7% decrease[23]. We again observe that FFS

[23] We also re-estimated the regression in column 4 by controlling for discharge to a skilled nursing facility. Since such patients are expected to be sicker than other patients, it is not surprising that we found they stay in the hospital longer and are more likely to be readmitted. Importantly, including this variable increased the magnitude of the coefficient on log(LOS) in the second stage to -0.23.

patients are more likely to be readmitted; the average marginal effect of all patients covered under FFS versus under MA is a 7% decrease in readmission probability, from .232 to .215. We note that the results of the Wald χ^2 test suggest that our instrument is able to control for a substantial portion of the endogeneity bias in our sample. This, along with the results of our t-tests comparing the mean age and Elixhauser scores of MCC patients admitted on Sunday/Monday versus other days, supports the reliability of the IV estimates. In contrast, we find no impact of LOS on readmission for non-MCC patients. The results of the Wald χ^2 test suggest that even though some of the bias may have been corrected, the results are very weak. This is likely due to the issues discussed in Section 3.1 regarding the validity of Sunday/Monday admissions as an instrument for non-MCC patients. As such, we focus on the MCC results going forward.

4.2. Robustness Checks

Table 5 presents a number of robustness checks for the readmission model. The first issue that we address is the potential for Medicare patients covered under MA appearing sicker than they truly are. Under the Medicare Prescription Drug, Improvement, and Modernization Act of 2003[24], CMS payments for MA patients are adjusted based on the severity of each enrollee's condition. Thus, this risk adjustment exists within our patient sample. One concern about comparing FFS and MA patients is that there might be a tendency for insurance companies to make MA patients 'appear' to be more sick in order to receive a higher capitated payment from the government. If this were true, then the coefficient on FFS would be biased upward, resulting in over estimates for the reduction in readmission risk when covered under MA.

We do not believe upward risk-adjustment is impacting our results for the following reasons: (1) When we restrict the sample to FFS patients, we still find a significant and practically similar in magnitude effect of LOS on readmissions: see Table A.4 in the appendix. Table A.4 also shows that when we restrict the sample to MA patients, we obtain almost identical coefficient estimates. However, we lose statistical significance, which we believe is due to the much smaller sample sizes. (2) While CMS pays the MA insurance carriers based on risk-adjustment of patients, most MA plans have FFS payment agreements with hospitals that are similar to those used for Medicare FFS patients. Hence, we do not expect inpatient claims, which are reported by hospitals, to be significantly impacted. Our severity measures, as given by the Elixhauser scores, are based on inpatient claims. As discussed in footnote 18 above, Elixhauser co-morbidities are the preferred method for measuring severity of MA patients because the source for other risk measures is outpatient data; hospitals are not required to report information on outpatient claims for MA patients. Thus, any upcoding would be done by the hospitals, which have little incentive to do so, as they are most commonly paid on a FFS basis. (3) Since non-profit hospitals have little incentive to upcode (see the discussion in Powell

[24] http://www.gpo.gov/fdsys/pkg/PLAW-108publ173/html/PLAW-108publ173.htm

et al. (2012)), we restricted our analysis to non-profit hospitals in Column 1 of Table 5 and found similar results: the coefficient on $\log(LOS)$ is negative and significant and the coefficient on FFS is identical to the coefficient estimated for the complete sample.

Table 5 Robustness Check of Readmission in 30 days Model Results for HF MCC Patients

	Non-profit	Big	No Maryland	Urban	Teaching	w/o Surgical Procedures	w/o Sat Admits
log(LOS)	-0.27***	-0.25**	-0.22***	-0.27***	-0.23**	-0.24**	-0.30***
	(0.07)	(0.08)	(0.06)	(0.07)	(0.08)	(0.09)	(0.07)
FFS	0.06***	0.06***	0.06***	0.07***	0.06***	0.06***	0.06***
	(0.01)	(0.01)	(0.00)	(0.00)	(0.01)	(0.01)	(0.00)
IV	-0.05**	-0.06**	-0.05**	-0.05**	-0.06**	-0.05***	-0.05**
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Num. of obs.	560306	473864	748227	551266	405885	468272	661987
Wald χ^2 test	25.15	20.12	25.04	25.26	16.54	13.49	35.08
Wald p-value	0.00	0.00	0.00	0.00	0.00	0.00	0.00

Note. Robust standard errors in parentheses. $*(p < 0.05), **(p < 0.01), ***(p < 0.001)$.

In Column 2, we restrict the analysis to hospitals that are in the top quartile for number of patients as we anticipate that the effects of LOS on readmissions will be larger for these hospitals that are more likely to treat complex cases for which an extra day in the hospital can have a significant impact. In Column 3, we eliminate patients in Maryland hospitals because Maryland's system of reimbursement is a fixed payment across all hospitals and insurance plans (Murray 2009). Columns 4 and 5 restrict to urban and teaching hospitals, respectively, because these are the hospitals for which the requirement to report MA hospitalizations is most likely to be binding.[25] In Column 6, we exclude patients with a surgical procedure during their hospital stay as an increase in complex scheduled surgeries on Mondays may reduce the availability of staff to treat the emergency and urgent patients who are admitted to a surgical service. In all five of these columns, the coefficient on $\log(LOS)$ is negative and significant. As expected, the coefficient for large hospitals is bigger than the baseline coefficient in Table 3. The coefficient on $\log(LOS)$ is also larger for urban and non-profit hospitals perhaps because these hospitals serve a sicker population where premature discharge is more detrimental.

Finally, in Column 7, we exclude Saturday admits, resulting in a sample for which we were unable to reject the null hypothesis that the mean Elixhauser scores between Sunday/Monday admits and the other days are not different. We find that the coefficient on $\log(LOS)$ is still negative, and is larger than the

[25] The requirement to report information on the stays of MA patients is only for hospitals that receive Disproportionate Share payments, Indirect Medical Education or Direct Medical Education adjustments. These payments are made to hospitals which devote significant resources to treating the under-insured population and to providing medical education. Thus, these hospitals are likely to be teaching hospitals and/or hospitals located in urban areas.

Table 6 **Mortality and Adverse Outcomes in 30 days Model Results for MCC HF Patients**

	Mortality	Adverse Outcome
log(LOS)	-0.11	-0.22***
	(0.08)	(0.06)
FFS	0.01	0.05***
	(0.01)	(0.00)
IV	-0.05**	-0.05**
	(0.00)	(0.00)
Num. of obs.	812403	814928
Wald χ^2 test	24.54	45.39
Wald p-value	0.00	0.00

Note. Robust standard errors in parentheses. $*(p < 0.05), **(p < 0.01), ***(p < 0.001)$.

coefficient reported in Table 4 for all MCC patients. This may be because excluding Saturday admissions strengthens our instrument, resulting in better control for possible endogeneity bias. Indeed, we can see that the Wald χ^2 statistic is much larger (35.08 versus 25.24) when excluding Saturday admits.

4.3. Mortality and Adverse Outcome in 30 days

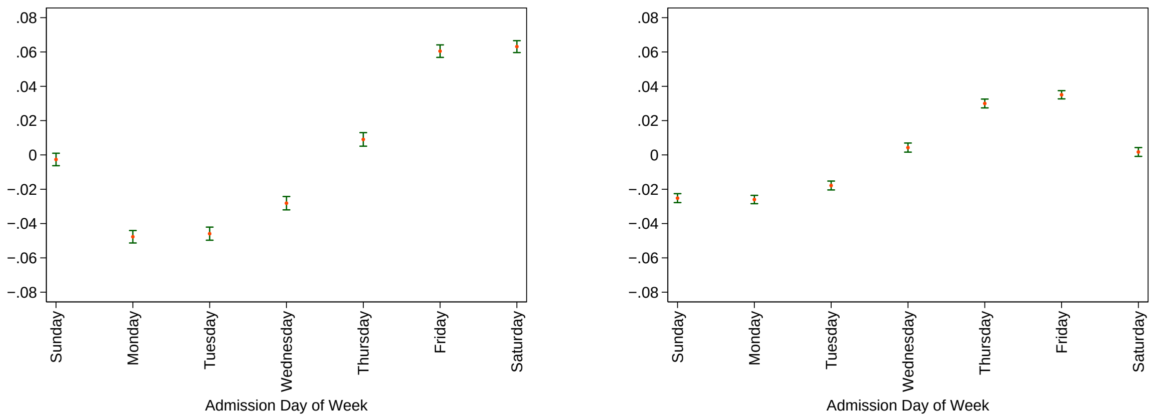
Table 6 shows the results of estimating equations (3) and (4) using 30-day mortality and 30-day adverse outcome as the dependent variable. Due to the concerns regarding our instrumental variable for non-MCC patients, we only report results for MCC patients[26]. While the coefficient on $\log(LOS)$ is negative for the MCC patients when considering 30-day mortality, it is not significant. We suspect this lack of significance might be due to the fact that HF is a chronic disease in which case it is plausible that factors other than hospital LOS are much larger drivers of mortality risk. Using 30-day adverse outcomes (30-day readmission or mortality) as the dependent variable, we find a negative and significant effect of $\log(LOS)$. This significance is likely driven by readmissions, rather than mortality.

5. Results for AMI and PNE Patients

We now extend our analysis to the AMI and PNE patients. Summary statistics for these patients are shown in Table 1.

In Section 3.1, we use the residual plot in Figure 1(a) to determine a reasonable instrument for $\log(LOS)$ for the HF patients: Sunday/Monday admissions. Similarly, Figure 3 plot residuals from regressions of $\log(LOS)$ on patient observables and seasonality and hospital fixed effects against admission day-of-week for the AMI and PNE patients. (We also generated residual histograms similar to Figure 2 and observed evidence of bi-modality for Tuesday admissions for the PNE patients, but not for the AMI patients.)

[26] When running the same specifications for the non-MCC patients, we do not find statistically significant results for $\log(LOS)$. Additionally, the results of the Wald χ^2 test suggest that our instrument is weak.



(a)AMI patients (b)PNE patients

Figure 3 **Averages of residuals for AMI and PNE patients plotted against admission day-of-week**

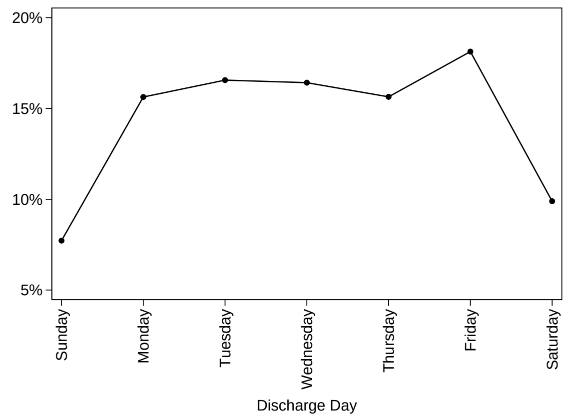
Similar to the findings for the HF patients, Figure 4 shows that discharge rates for AMI and PNE patients peak on Friday and fall sharply on Saturday and Sunday. Based on our observations, we use Monday/Tuesday admissions as an instrument in the AMI model and Sunday/Monday admissions as an instrument in the PNE model[27].

We again use t-tests to compare the mean age and Elixhauser scores of AMI (PNE) patients admitted on Monday/Tuesday (Sunday/Monday) versus the other days of the week. In both cohorts, we fail to reject the null hypothesis that patients admitted on the days for the proposed instrument have the same mean Elixhauser score as patients admitted on other days. This is consistent with our results for the MCC HF cohort, but is in contrast to our results for the non-MCC HF cohort. Similar to our results for the All HF cohort, we find evidence that AMI (PNE) patients admitted on Monday/Tuesday (Sunday/Monday) are younger.

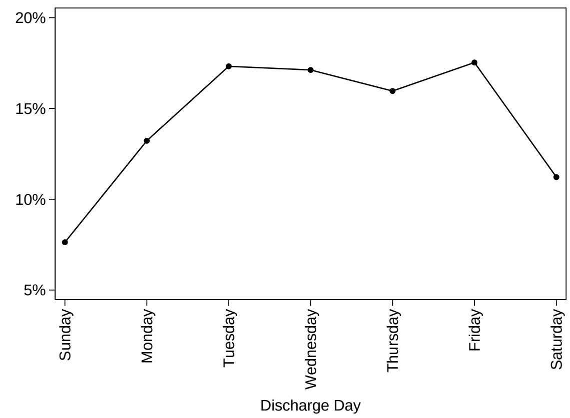
5.1. Results for AMI Patients

Table 1 shows that seventeen percent of the AMI patients are readmitted within 30 days of their initial hospitalization. The average LOS is 4.88 days and those who are readmitted stay an additional 5.22 days. Similar to HF patients, average LOS varies by day of admission from a low of 4.70 for Monday admits to a high of 5.10 for Friday admits. AMI patients can be classified into two categories, MCC and non-MCC,

[27] Carey (2014) also examines the impact of LOS on readmission risk for AMI patients and uses the number of procedures as an instrument. For our patient cohort, we find that the number of procedures is not a valid instrument because the correlation between the number of procedures and the residuals of both an OLS (linear probability model) and probit estimate of the readmission model in Equation (1) are statistically different from 0. We suspect that the differences in the validity of number of procedures as an instrument may be attributable to the difference in patient cohorts: Carey (2014) considers all AMI patients treated in New York state in 2008, while we consider non-elective HF, AMI, and PNE patients treated across the US from 2008 to 2011.



(a)AMI patients



(b)PNE patients

Figure 4 Percentage of discharges by day-of-week

based on the observed severity of their diagnoses, where MCC patients are those with major complications or co-morbidities[28].

The results of estimating equations (3) and (4) on AMI patients are shown in Table 7 for all three outcomes: readmission, mortality and adverse outcome. Note that we do not include results for the non-MCC AMI patients because AMI is an acute condition where most patients are MCC; indeed, only 2,234 of the 672,898 AMI patients are non-MCC. Moreover we find that non-MCC AMI patients are treated at a non-representative sample of the U.S. hospitals, covering only 1/3 of all hospitals. Many of these hospitals are perfect predictors for mortality (e.g. all non-MCC AMI patients treated at specific hospital survive), so that our final regression sample covers less than 5% of all hospitals. Furthermore, in the non-MCC AMI sample, the rate of mortality is three times higher than in the full sample, raising questions about the reliability of any results based on the non-MCC AMI cohort.

Keeping MCC AMI patients an extra day in the hospital does not reduce their readmission risk but is associated with a significant decrease in 30-day mortality risk (about 7% with significance $p < .05$). The absence of an impact on readmission risk is consistent with clinical studies that have shown that a sizable portion of AMI patients could be safely discharged within several days after an infarction and keeping these patients an extra day is not beneficial (Desideri et al. 2003). Moreover, the fact that AMI is an acute condition (and not a chronic condition like HF) might explain the significant effect of LOS on mortality but no effect on readmission.

[28] For AMI patients CMS defines two categories: MCC (major complications or comorbidities and non-MCC (absence of complications or comorbidities). The MCC ICD-9-CM codes are: 41001, 41011, 41021, 41031, 41041, 41051, 41061, 41071, 41081, and 41091. Note, there are no CC AMI conditions. All ICD-9-CM codes not mentioned are Non-CC. Source: Table 6J and 6I, Centers for Medicare & Medicaid Services, http://www.cms.gov/Medicare/Medicare-Fee-for-Service-Payment/AcuteInpatientPPS/Acute-Inpatient-Files-for-Download-Items/FY2014-FinalRule-CorrectionNotice-Files.html.

Table 7 Outcome Model Results for MCC AMI Patients (MonTues adm used as instrument)

	Readmission	Mortality	Adverse Outcome
log(LOS)	0.11	-0.18*	0.03
	(0.06)	(0.08)	(0.06)
FFS	0.07***	0.01	0.06***
	(0.01)	(0.01)	(0.00)
IV	-0.07**	-0.07***	-0.07***
	(0.00)	(0.00)	(0.00)
Num. of obs.	620085	669383	670662
Wald χ^2 test	0.81	15.97	5.73
Wald p-value	0.37	0.00	0.02

Note. Robust standard errors in parentheses. $*(p<0.05), **\ (p<0.01), ***(p<0.001)$.

5.2. Results for Pneumonia Patients

Table 1 shows that sixteen percent of PNE patients are readmitted within 30 days of their initial hospitalization. The average LOS is 5.09 days and those who are readmitted stay an additional 6.31 days. As with HF and AMI patients, LOS varies by day of admission for PNE patients with a range from 4.94 days for Sunday admits to 5.22 for Thursday admits. Note that for PNE patients, there is no severity categorization by CMS into MCC versus non-MCC patients, as there is for HF (and AMI) patients.

The results of estimating equations (3) and (4) for the PNE patients are shown in Table 8 for all three outcomes: readmission, mortality and adverse outcome. We find no effect of $\log(LOS)$ on readmission risk but a negative and significant impact on mortality risk for the MCC patients (the average marginal effect of a one-day increase in LOS is a 22% decrease in the readmission probability). The absence of an effect of LOS on readmissions is consistent with the clinical literature that has found that much of the variation in hospital LOS for PNE patients is attributed more to physician preference rather than directly observable medical necessity, i.e. a good portion of the variation in LOS occurs above the minimum LOS required for treatment (Halm et al. 2001). Additionally, like AMI, Pneumonia is more of an acute, rather than chronic, condition (although chronic conditions can make one more susceptible to acquiring PNE). Thus, the effect of LOS is more likely to manifest itself in mortality risk.

6. Policy Implications

In this section, we utilize our results from Sections 4 and 5 to estimate the impact of various policy changes that hospitals or CMS can implement to reduce 30-day readmissions and deaths. In our analysis, we take the perspective of the social planner who aims to reduce adverse outcomes and overall costs. Having observed that keeping a patient in the hospital for one more day and covering patients under MA are both strategies for reducing 30-day readmissions and deaths, we consider the following **four policies**: (1) **Keep the status quo -** The benchmark, (2) **Switch all patients to MA -** The idea would be that such a coverage change would better align incentives for insurance companies to potentially increase the investment in outpatient

Table 8 Outcome Model Results for PNE Patients (SunMon adm used as instrument)

	Readmission	Mortality	Adverse Outcome
log(LOS)	-0.01	-0.50***	-0.22**
	(0.08)	(0.09)	(0.07)
FFS	0.05***	0.02***	0.05***
	(0.00)	(0.01)	(0.00)
IV	-0.04**	-0.04**	-0.04**
	(0.00)	(0.00)	(0.00)
Num. of obs.	1205400	1307481	1308654
Wald χ^2 test	4.08	61.00	33.12
Wald p-value	0.04	0.00	0.00

Note. Robust standard errors in parentheses. $*(p<0.05), **(p<0.01), ***(p<0.001)$.

programs, thereby reducing readmissions. Note that this policy change is likely an upper bound to the true impact of investing in outpatient programs as MA plans may utilize additional mechanisms to reduce readmissions, (3) **Increase LOS by one day for FFS patients only -** This allows us to compare the effect of inpatient care to outpatient care (given in policy #2) and (4) **Switch all patients to MA and increase LOS by one day -** This demonstrates the gains possible when implementing changes to both inpatient and outpatient care for all patients.

To compare the cost-effectiveness of these four policies, we first discuss the cost estimates we will use. Taheri et al. (2000) estimate the *cost of an additional day in the hospital* to be $420 in 1998, which is $610 in 2014 when adjusted for inflation. Importantly, Taheri et al. (2000) show that the direct cost of the last day represents only 2.4% of the total hospitalization cost. The Henry J. Kaiser Family Foundation (2014) provide an alternative measure and report that the average hospital expenses for a day of inpatient care in the U.S. was $1,960 in 2011, or $2,094 in 2014 dollars. However, this measure includes an adjustment for outpatient care and is therefore likely to be an overestimate of the actual costs of inpatient care. Based on these two references, we assume that the cost of keeping a patient in the hospital one more day is $610 or $2,094, depending on whether one uses the *marginal* or *average* cost estimate.

Second, we consider the *cost of various outpatient readmission reduction programs*. The Evercare program of United Health Care (part of a MA program) required hiring a Nurse Practitioner at $90,000 per year in 1999 for every 85 patients (Kane et al. 2003), which translates to $1,154 per patient in 2014 dollars. Naylor et al. (2004) showed that a program with advanced practice nurses' home visits cost $104,019 to treat 118 patients in 1999, which translates to $1,259 per patient in 2014 dollars. Jerant et al. (2001) estimated the costs of telecare-based programs to range from $2,164 per patient for telephone interventions to $10,706 per patient for video conferencing interventions, both in 2014 dollars. In summary, we find that all of these outpatient readmission reduction programs cost more than a single hospital day when considering the marginal costs ($610) from Taheri et al. (2000), but most are less costly when considering the average costs of a hospital day ($2,094) from The Henry J. Kaiser Family Foundation (2014).

Lastly, we use the estimates provided in Murphy and Topel (2006) for the *benefits of reduced mortality*. They calculated the value of a life-year for an average 80 year-old (the approximate mean age of the patients in our sample) to be $150,000 per person in 1999, which translates to $214,492 per year or $17,874 per month in 2014 dollars. Recognizing this may be an overestimate for individuals with serious medical conditions, we also consider how robust our insights are to alternative value of life estimates.

6.1. Heart Failure Patients

Starting with MCC HF patients, Table 9 summarizes the estimated readmission rates under the aforementioned four policies, constructed using the result from Column 4 of Table 4[29]. Remarkably, we find that policies #2 and #3 result in the exact same overall readmission rate of 0.215. In terms of readmission counts, for the 749,122 MCC HF patients in our four year cohort, covering all patients under MA (policy #2) would result in 161,061 readmissions, while increasing the LOS of FFS patients (policy #3) would *also* result in 161,061 readmissions. This is a reduction of 10,488 readmissions compared to doing nothing (policy #1). Hence, our findings indicate that devoting more hospital resources to inpatient care has similar implications for reducing readmissions as switching HF patients to a capitated insurance system that offer more outpatient interventions. Furthermore, because we estimate that the inpatient and outpatient interventions have practically similar benefits in reducing readmissions, we believe that from the social planner's perspective the cost-effective intervention for MCC HF patients depends on the type of outpatient program. In some instances, such as if an additional hospital day costs $610, it will be more cost-effective to invest in keeping patients in the hospital one more day. In other instances, such as if the cost of an additional hospital day is the average cost estimate of $2,094 and the outpatient program is similar to Evercare ($1,154), it may be more cost-effective to implement a low-cost, effective outpatient program.

Table 9 Estimated readmission rates of MCC HF patients (Column 4 in Table 4) under various policy changes.

	Patient Group		
Policy Change	MA patients	FFS patients	Full population
(1) No change (baseline)	**0.216**	**0.232**	**0.229**
(2) All under MA coverage	0.216	0.214	0.215
(3) Increase LOS by 1 day for FFS patients	0.216	0.215	0.215
(4) All under MA, Increase LOS by 1 day for ALL patients	0.199	0.198	0.198

[29] It is possible that the effect of increasing LOS by 1 day is even higher (e.g., see Column 7 of Table 5); however, for the purposes of this analysis we use the result from Column 4 of Table 4, which is likely to be slightly conservative in its estimate of the effect of LOS on readmissions. Note that the effect of FFS does not vary in the different patient samples we consider.

Note that we do not consider the effect of these various policy changes on the non-MCC HF patients. In Table 4, there was no significant effect of $\log(LOS)$ on readmissions for the non-MCC HF population. This may be due to the concerns surrounding our instrument, or it may be because increasing LOS (policy #3) would have no impact on readmission rates. On the other hand, switching everyone to MA (policy #2) does have a measurable effect. For the non-MCC HF patients, it seems that in order to reduce readmissions, it may be more effective for hospitals to invest in outpatient interventions, rather than the inpatient intervention of increasing LOS.

In sum, our results for HF patients indicate that similar reductions in 30-day readmissions are possible using inpatient versus outpatient interventions. Depending on the cost for an additional hospital day, increasing a patient's LOS by one day may be more cost-effective than many outpatient readmission reduction programs. While we do not make any claims as to the potential effectiveness of the HRRP of the ACA, our findings do suggest there are factors within the control of hospitals to reduce readmissions. Thus, it seems reasonable for CMS to provide an incentive for hospitals to reduce readmissions. Assuming an effective incentive for hospitals to take action exists, our findings suggest that it may be more cost effective for hospitals to increase patient LOS rather than invest in outpatient programs.

6.2. AMI Patients

Considering targeted interventions for MCC AMI patients, Table 10 summarizes the estimated mortality rates—based on the results in Table 7—under the same policy changes shown in Table 9 for MCC HF patients. We find that for this group of patients, increasing LOS by one day is more effective in reducing mortality rates than switching patients to MA. In particular, switching all FFS patients to MA coverage results in an absolute reduction of mortality risk of 0.1% across the entire cohort, whereas keeping these patients one additional day results in an absolute reduction of mortality risk of 0.5%. Among the 669,383 MCC AMI patients in our four year sample, 77% (see Table 1) or 515,425 patients have FFS coverage. If we kept each of the patients in the hospital one additional day, this would result in $(.075 - .070) \times 515,425 = 2,577$ lives saved (for at least 30 days after hospital discharge) while the MA intervention saves only $(.075 - .074) \times 515,425 = 515$ lives. That is, the inpatient intervention saves an additional 2,062 lives compared to the MA intervention.

We explore whether inpatient interventions (policy #3) are cost-effective over the baseline of doing nothing (policy #1). If hospitals kept all 515,425 MCC AMI FFS patients for one more day, the extra costs would range from \$314,409,250 (using Taheri's estimate of the marginal cost of an extra day) to \$1,079,299,950 (using Kaiser's estimate of the average cost of a hospital day). Since we are saving 2,577 lives for at least 30 more days (recall that our outcome is 30-day mortality) as a result of this intervention, the total value of these saved lives is $\$17,874 \times 2,577 = \$46,061,298$ for each month these patients live when using Murphy

Table 10 **Estimated mortality rates of MCC AMI patients under various policy changes.**

	Patient Group		
Policy Change	MA patients	FFS patients	Full population
(1) No change (baseline)	**0.065**	**0.075**	**0.073**
(2) All under MA coverage	0.065	0.074	0.072
(3) Increase LOS by 1 day for FFS patients	0.065	0.070	0.069
(4) All under MA, Increase LOS by 1 day for ALL patients	0.060	0.069	0.067

and Topel (2006) to estimate the value of an additional month. This means that the patients would need to live $\$314,409,250/\$46,061,298 = 6.8$ months (using the marginal cost estimate) or 23.4 months (using the average cost estimate) in order for the inpatient intervention to be cost-effective over the baseline of doing nothing. In our data, we find that MCC AMI FFS patients who survive for 30 days after hospital discharge live for another 30 months on average[30], suggesting that the inpatient intervention is cost-effective. The cost effectiveness of the inpatient intervention is robust to reductions in the value of living an additional month of up to $1-6.8/30 = 77\%$ of the estimates from Murphy and Topel (2006) when the marginal cost estimate of an additional hospital day is used. On the other hand, the cost effectiveness of the inpatient intervention is more sensitive to the estimated value of living an additional month when the average cost estimate of an additional hospital day is used—if the value were reduced by more than 22%, then doing nothing would be more cost effective.

As an alternative benchmark, we now consider the cost-effectiveness of the inpatient intervention (policy #3) compared to switching everyone to MA (policy #2). Recall that the capitated nature of MA provides insurance companies an incentive to invest in better outpatient management and continuity of care; thus, we use this intervention as a proxy for the potential reductions in mortality due to investments in outpatient care. Suppose such investments were *free*, which is in contrast to the $610 or $2,094 cost of keeping a patient in the hospital for one more day. As indicated earlier, the inpatient intervention (policy #3) saves an additional 2,062 lives compared to switching everyone to MA (policy #2). Following similar calculations as above, we find that the patients would need to live 8.5 months (using the marginal cost estimate) or 29.2 months (using the average cost estimate) in order for the inpatient intervention to be cost-effective over cost-free outpatient interventions. As discussed in the previous paragraph, we find that the MCC AMI FFS patients in our data who survive for 30 days after hospital discharge live for another 30 months on average. Hence, even if it were possible to implement outpatient readmission reduction programs without cost, it would be more beneficial to keep patients one additional day in the hospital, despite the costs associated with the extra care. Again, we find that the cost effectiveness of the inpatient intervention is robust to reductions

[30] Note that our estimates for average survival are conservative as our data are truncated with the last recorded date of death being December 26, 2012; for any patient missing a date of death (i.e., they did not die before 12/26/2012) we assigned a death date of December 26, 2012.

in the value of living an additional month of up to 72% when the marginal cost estimate of an additional hospital day is used. However, if we use the average cost estimate of an additional hospital day, a cost-free outpatient intervention would be more cost effective if the value of living an additional month was reduced by more than 3%.

In sum, we find that keeping MCC AMI patients one more hospital day substantially reduces 30-day mortality risks. Moreover, the cost of this additional day is likely to be exceeded by the benefits of the additional lives saved. When we use the marginal cost estimates of an additional hospital day, our findings are very robust to alternative estimates of the value of life that recognize that the patients we consider may be sicker than the average 80 year old. Because the average cost estimates for an additional hospital day are much higher, the robustness of our results is weaker when we use the alternative estimates of the value of living an additional month.

6.3. Pneumonia Patients

Table 11 uses the results from Table 8 and reports the estimated mortality rate for PNE patients under various policy changes. We again see that keeping patients an additional day can be extremely effective for reducing mortality, and is more effective than putting all patients under MA coverage. For the 1,059,060 PNE FFS patients in our four year cohort, increasing their LOS by one day saves 19,063 lives whereas switching all of them to MA would only save 3,177 lives; the inpatient intervention saves an additional 15,886 lives compared to the MA intervention. Following the same methodology described above, we calculate the extra costs of keeping the PNE FFS patients in the hospital for one more day to range from \$646,026,600 (using the marginal cost estimate) to \$2,217,617,640 (using the average cost estimate). In addition, the benefits of saving 19,063 lives is \$340,732,062 for each month the patients live. This means that the patients would need to live 1.9 months (using the marginal cost estimate) or 6.5 months (using the average cost estimate) for the inpatient intervention to be cost-effective over doing nothing. In our data, we find that PNE FFS patients who survive for 30 days after hospital discharge live for another 27.8 months on average, making the inpatient intervention highly cost-effective. Additionally, the cost effectiveness of the inpatient intervention is robust to reductions in the value of living an additional month of up to 93% (using the marginal cost estimate of a hospital day) or 77% (using the average cost estimate of a hospital day). When comparing to the alternative of a cost-free switch of all FFS patients to MA (as an estimate for cost-free outpatient care), we find that the patients would need to live 2.3 months (using the marginal cost estimate) or 7.8 months (using the average cost estimate) for it to be more cost-effective than *free* MA care. These results are robust to reductions in the value of living an additional month of up to 92% (using the marginal cost estimate of a hospital day) or 72% (using the average cost estimate of a hospital day). In sum, keeping PNE patients in the hospital one more day seems to be a cost-effective intervention for reducing 30-day mortality rates.

These results are robust to the possibility that Murphy and Topel (2006) vastly overestimates the value of life for our average patient.

Table 11 **Estimated mortality rates of PNE patients under various policy changes.**

	Patient Group		
Policy Change	MA patients	FFS patients	Full population
(1) No change (baseline)	**0.091**	**0.097**	**0.096**
(2) All under MA coverage	0.091	0.094	0.093
(3) Increase LOS by 1 day for FFS patients	0.091	0.079	0.081
(4) All under MA, Increase LOS by 1 day for ALL patients	0.073	0.076	0.075

7. Conclusion

About one in every five Medicare fee-for-service patients is readmitted to the hospital. Starting in fiscal year 2013, hospitals are penalized under the ACA's Hospital Readmissions Reduction Program (HRRP) if they have higher than expected readmissions within 30 days following discharge for heart attack, heart failure and pneumonia. It remains to be seen whether the penalties imposed by the HRRP are sufficient incentive for hospitals to reduce readmissions. Regardless, it is clear that eventually hospitals will have to make adjustments to reduce readmissions. Improving outpatient management is a common approach that hospitals use to reduce readmissions. In this paper, we compare the potential gains from using an inpatient intervention, i.e. keeping patients in the hospital longer, versus those made possible by outpatient programs, such as those provided to patients covered under Medicare Advantage.

Using an instrumental variables methodology and a dataset from CMS that consists of all Medicare in-hospital patient visits between 2008 and 2011, we find that over the course of four years: (1) Comparable reductions in readmissions for heart failure patients are possible by requiring these patients to select an MA plan or keeping all of them in the hospital for one more day; (2) Keeping all FFS pneumonia patients in the hospital for one more day saves an additional 15,886 lives above those that would be saved if the patients had been switched to an MA program, and the value of these saved lives exceeds the cost of the extra hospital day; and (3) Keeping all FFS heart attack patients in the hospital for one more day saves an additional 2,062 lives above those that would be saved under an MA program; under reasonable assumptions, the value of these saved lives exceeds the cost of the extra hospital day.

While we use a very comprehensive database, we excluded elective patients from our analysis because our instrument for LOS, day of the week on which the patient was admitted, is only valid for patients admitted on an emergency or urgent basis. Hence, one limitation of our study is that the results may not apply to elective patients. A second limitation is that, while we provide convincing evidence that an extra day in the hospital significantly reduces readmissions for heart failure patients and mortality risk for heart attack and pneumonia patients, we do not know exactly why the extra day is beneficial. An extra day may provide more time for patients to be educated about their post-discharge behavior and/or it may enable the patient to reach a higher level of stability.

Our findings show that, across all three patient categories, heart failure, heart attack and pneumonia, increasing a patient's LOS by one day can have a similar, and sometimes even better, effect on reducing readmissions or mortality than what might be achievable with outpatient interventions. While it is certainly the case that outpatient management and care, which is often out of the control of hospitals, can be effective tools for improving patient outcomes, it may be reasonable to hold hospitals responsible for 30 day outcomes. Indeed, our results suggest that there are tangible levers within the hospitals' control, i.e. inpatient care, which can be effective in reducing readmissions and deaths.

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Appendix

Table A.1 HF Patients Data Selection

Sample	Observations	% prior	% initial
All Admissions in 2008-2011, except for Dec 2011 admits/discharges	66477052	NA	100.0
Excluding overlapping admissions	62355807	93.8	93.8
Excluding post-acute care	51357148	82.4	77.3
Excluding stays with hospital transfers	46702233	90.9	70.3
Excluding those in facilities not paid under PPS	44652724	95.6	67.2
Excluding stays that are neither FFS nor MA	44237900	99.1	66.5
Excluding 100% FFS hospitals	43742321	98.9	65.8
Excluding non-HF patients	2372547	5.4	3.6
Excluding those admitted within 30 days of prior admission's discharge	2162510	91.1	3.3
Excluding hospitals with less than 25 visits	2161283	99.9	3.3
Excluding patients with inpatient service related discharge destinations	2045579	94.6	3.1
Excluding non-elderly admissions	1787720	87.4	2.7
Excluding those that died during the stay	1784087	99.8	2.7
Excluding those that left against medical advice	1777157	99.6	2.7
Excluding those with unknown race or not residing in the US	1772912	99.8	2.7
Excluding elective patients (including unknown elective status)	1627724	91.8	2.4
Excluding cost outliers	1613119	99.1	2.4
Excluding length of stays beyond the 99th percentile (18 days)	1598872	99.1	2.4

Table A.2 AMI Patients Data Selection

Sample	Observations	% prior	% initial
All Admissions in 2008-2011, except for Dec 2011 admits/discharges	66477052	NA	100.0
Excluding overlapping admissions	62355807	93.8	93.8
Excluding post-acute care	51357148	82.4	77.3
Excluding stays with hospital transfers	46702233	90.9	70.3
Excluding those in facilities not paid under PPS	44652724	95.6	67.2
Excluding stays that are neither FFS nor MA	44237900	99.1	66.5
Excluding 100% FFS hospitals	43742321	98.9	65.8
Excluding non-AMI patients	986958	2.3	1.5
Excluding those admitted within 30 days of prior admission's discharge	955475	96.8	1.4
Excluding hospitals with less than 25 visits	949561	99.4	1.4
Excluding patients with inpatient service related discharge destinations	848250	89.3	1.3
Excluding non-elderly admissions	743714	87.7	1.1
Excluding those that died during the stay	741461	99.7	1.1
Excluding those that left against medical advice	737944	99.5	1.1
Excluding those with unknown race or not residing in the US	735832	99.7	1.1
Excluding elective patients (including unknown elective status)	697038	94.7	1.0
Excluding same day discharge (for AMI patients only)	697036	100.0	1.0
Excluding cost outliers	679352	97.5	1.0
Excluding length of stays beyond the 99th percentile (19 days)	672898	99.0	1.0

Table A.3 PNE Patients Data Selection

Sample	Observations	% prior	% initial
All Admissions in 2008-2011, except for Dec 2011 admits/discharges	66477052	NA	100.0
Excluding overlapping admissions	62355807	93.8	93.8
Excluding post-acute care	51357148	82.4	77.3
Excluding stays with hospital transfers	46702233	90.9	70.3
Excluding those in facilities not paid under PPS	44652724	95.6	67.2
Excluding stays that are neither FFS nor MA	44237900	99.1	66.5
Excluding 100% FFS hospitals	43742321	98.9	65.8
Excluding non-PNE patients	1897521	4.3	2.9
Excluding those admitted within 30 days of prior admission's discharge	1835169	96.7	2.8
Excluding hospitals with less than 25 visits	1834047	99.9	2.8
Excluding patients with inpatient service related discharge destinations	1696574	92.5	2.6
Excluding non-elderly admissions	1431587	84.4	2.2
Excluding those that died during the stay	1427956	99.7	2.1
Excluding those that left against medical advice	1423896	99.7	2.1
Excluding those with unknown race or not residing in the US	1420389	99.8	2.1
Excluding elective patients (including unknown elective status)	1332612	93.8	2.0
Excluding cost outliers	1321541	99.2	2.0
Excluding length of stays beyond the 99th percentile (18 days)	1308691	99.0	2.0

Table A.4 Readmission Model Results for HF Patients - Separate Regressions for FFS and MA Patients

	FFS			MA		
	Non-MCC	MCC	All	Non-MCC	MCC	All
log(LOS)	-0.06	-0.21**	-0.15**	-0.05	-0.22	-0.16
	(0.08)	(0.07)	(0.05)	(0.18)	(0.14)	(0.11)
IV	-0.05**	-0.05**	-0.05**	-0.05***	-0.05**	-0.05**
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Num. of obs.	573541	589258	1163372	144348	158357	304925
Wald χ^2 test	3.88	18.97	20.75	0.79	5.34	5.80
Wald p-value	0.05	0.00	0.00	0.38	0.02	0.02

Note. Robust standard errors in parentheses. $*(p < 0.05), **(p < 0.01), ***(p < 0.001)$.