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ABSTRACT

Medicare's prospective payment system for long-term acute-care hospitals (LTCHs) gives providers modest reimbursements for short patient stays before jumping discontinuously to a large lump-sum payment after a pre-specified number of days. Using Medicare claims data, we show that LTCHs strategically discharge patients after they exceed the large-payment threshold. We find this behavior is more common among for-profit facilities, facilities acquired by leading LTCH chains, and facilities located within standard acute-care hospitals. Using a dynamic structural model, we evaluate counterfactual payment policies recently considered as alternatives for the existing scheme and find that they would provide substantial savings for CMS.

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1 Introduction

Medicare faces the dual mandate of promoting high-quality care while also constraining costs. One prominent effort aimed at achieving these competing goals is Medicare's prospective payment system (PPS) that gives hospitals a fixed, predetermined reimbursement for a patient's stay based on her diagnosis. An advantage of this system is that it provides an incentive to deliver care efficiently, as extraneous procedures and tests would increase costs but not yield any additional revenue. One drawback of such a policy, however, is that hospitals may base their treatment decisions not on clinical guidelines for effective care, but on the financial incentives created by the payment system. In this paper, we examine an inpatient hospital segment heavily influenced by Medicare's PPS, long-term acute-care hospitals (LTCHs), and show that the financial incentives embedded in the payment system lead providers to discharge patients when it is most profitable for them to do so rather than when it is most beneficial for the patient. By altering the payment system to remove hospitals' incentives to distort patient care, we show that Medicare could save hundreds of millions of dollars each year without adversely affecting patients.

Long-term care hospitals specialize in treating patients with serious medical conditions that require prolonged care. As an organizational form, LTCHs exist largely as a response to the PPS Medicare introduced for general acute-care hospitals. Under this system, traditional hospitals often lose money on patients who stay for extended periods, giving them an incentive to discharge patients to LTCHs that then receive new Medicare payments for admitting the patients — that is, both hospitals benefit financially. Such an arrangement directly impacts the largest segment of Medicare spending, as both traditional and long-term acute-care hospitals receive reimbursements under Medicare Part A, from which payments to all types of hospitals totaled over $145 billion for inpatient stays in 2015 compared to, for example, $85 billion for drug payments under Part D.[1] Despite the obvious importance of inpatient hospitals to overall health-care spending — and despite the clear role the PPS plays in influencing these costs — comparatively little research in economics has focused on how financial incentives affect this segment of Medicare.

[1] Budget in Brief, Department of Health and Human Services, FY 2015 (`http://www.hhs.gov/about/budget/fy2015/budget-in-brief/cms/medicare/index.html`).

Under the current PPS, Medicare reimburses LTCHs a fixed amount per admission based on the patient's diagnosis-related group (DRG). These per-stay reimbursements are substantially larger than those for general acute-care hospitals.[2] To dissuade LTCHs from exploiting their higher reimbursement status by admitting patients and then quickly discharging them back to acute-care hospitals, Medicare classifies patients as short-stay outliers (SSOs) if they stay fewer than a pre-specified number of days (depending on their DRG) and reimburses LTCHs significantly less for these patients.

Having reimbursements depend on a patient crossing a threshold for her length of stay results in a narrow window during which an LTCH achieves maximum profitability for each patient. In response to this financial incentive, LTCHs may seek to discharge patients immediately after they cross the SSO threshold, which industry participants have dubbed the "magic day" (Berenson 2/9/2010). This suggests that the financial incentives created by Medicare's payment system may inadvertently shape patient care: keeping patients longer than is medically necessary represents poor quality care due to both the psychological burden a patient experiences by remaining at a hospital and the increased health risks associated with infections and medical errors, whereas prematurely discharging a patient simply because she has reached the magic day could mean that she has not yet received adequate treatment.

Previous reports have claimed that corporate executives pressure LTCH administrators to discharge patients immediately after they pass the SSO threshold. A 2015 *Wall Street Journal* article (Weaver et al. 2/17/2015), for instance, described meetings at which hospital staffers would discuss treatment plans, "armed with printouts from a computer tracking system that included, for each patient, the date at which reimbursement would shift to a higher, lump-sum payout." Reports also suggest that LTCH administrators "sometimes ordered extra care or services intended in part to retain patients until they reached their thresholds, or discharged those who were costing the hospitals money regardless of whether their medical conditions had improved," while "bonuses depended in part on maintaining a high share of patients discharged at or near the threshold dates to meet earnings goals."

[2]We focus on Medicare patients in this paper as they make up the bulk of LTCH patients (see Section 2 below).

Given the financial incentives created by Medicare's PPS, our paper examines the prevalence of strategic discharge among LTCHs.[3] Using Medicare claims data from fiscal years 2004-2013, we first present descriptive evidence that shows LTCHs are much more likely to discharge patients during the window immediately after they cross the threshold for lump-sum payments compared to what would be expected if patients were discharged based solely on clinical measures. We exploit the sharp discontinuity in payments around the SSO threshold to identify this practice, finding that LTCHs discharged 25.7 percent of patients during the three days immediately after crossing the threshold compared to 6.8 percent in the three days immediately preceding it.

Based on the anecdotal evidence referenced above, the nearly fourfold increase in discharges just past the SSO threshold would seem to stem largely from strategic behavior by LTCHs. To cleanly link it to Medicare's nonlinear reimbursement policy, however, we must overcome several empirical challenges. For one, we do not observe many of the factors that influence hospitals' discharge decisions, such as a patient's desire to be released or the full details of her individual medical needs. To establish a causal link between the PPS and strategic discharge, we therefore exploit several key sources of variation in the data. Most importantly, the SSO threshold varies across DRGs within a year and within a DRG across years. Using both this time-series and cross-sectional variation, we consistently show that LTCHs discharge patients on the magic day for any given DRG in any given year. Furthermore, if facilities discharged patients purely for clinical reasons, we would expect to observe a smooth distribution of discharges over the length of patients' stays; instead, we observe a discontinuous jump in discharges on the magic day that corresponds to the discontinuous jump in payments. We also show that in 2002, when the current PPS system was not in place — and thus LTCHs did not face a discontinuity in the reimbursement schedule — discharges had no discernible spike around what would become magic days in later years.

Another threat to identification is that discharges could cluster on the magic day because the SSO threshold is based on a DRG's average length of stay from the previous year and patients with similar diagnoses undergo similar treatments. The strong association between discharges

[3] We use the term "strategic discharge" to refer to cases where patients are discharged for financial reasons rather than clinical ones.

and the financial motives of providers we show through several pieces of novel evidence suggests that this type of coincidence is not driving our results. For instance, we show that the likelihood that a patient is released on the magic day is greater among the DRGs for which it is most profitable. In addition, we illustrate that discharges of patients to their homes — which is the easiest type of discharge to manipulate — exhibit the clearest evidence of strategic behavior, whereas discharges due to death are unrelated to reimbursements, a key falsification test. We also establish that for-profit hospitals are more likely to engage in strategic discharge than non-profit hospitals, as are facilities co-located within standard acute-care hospitals that have fewer barriers to transfer. Lastly, we find that facilities operated by the two dominant LTCH chains are more likely to strategically discharge patients — and when these chains acquire new facilities, the acquired facilities become more likely to do so as well.

Although our descriptive analysis provides compelling evidence that LTCHs strategically discharge patients in response to the discontinuity in the PPS, it cannot directly answer how LTCHs would behave under alternative payment schemes. This is an important question to consider, however, as the costs of strategic discharge are potentially very large for Medicare — perhaps as much as $2 billion between 2007-2013 by some estimates (Weaver et al. 2/17/2015). In light of these costs, the Medicare Payment Advisory Commission (MedPAC) proposed a new formula in 2014 that would reduce the payment penalty for patients discharged before reaching the SSO threshold. This new formula would eliminate the large jump in reimbursements associated with crossing the threshold and therefore make strategic discharges less lucrative. As policy makers currently debate how to redesign the LTCH PPS to discourage strategic discharges, we develop and estimate a dynamic structural model of LTCHs' discharge decisions that can predict the likely effects of such changes.

Conceptually, our model is based on an LTCH deciding each day whether to discharge a patient that day or to keep her in the facility for an additional day. In doing so, the LTCH weighs the financial incentives of immediately discharging the patient against the numerous monetary and non-pecuniary reasons to hold the patient in the facility for an additional night (e.g., the costs of treatment, the risk incurred by releasing the patient too early, the disutility of providing unnecessary treatments, and the marginal benefit of treatment to the patient). Here we exploit the nonlinear reimbursement schedule that generates a sharp jump in payments on the magic day and enables us to separately identify the financial motives underlying facilities' discharge decisions from other confounding factors. In our model, we allow LTCHs to respond differently to financial incentives depending on their characteristics, such as for-profit status or patient mix.

Using our estimated model, we find that LTCHs would discharge patients almost a week earlier, on average, if they did not face the financial incentives created by the current PPS. Moreover, for those patients still in an LTCH within three days of what would have been the magic day under the current PPS, 22 percent fewer patients would be held until that magic day. These earlier discharges lead to substantial savings for Medicare. Across the nine most common DRGs (which make up 26 percent of all observations in our data), we estimate that Medicare would save over $500 million each year.

We also use our estimated model to consider an alternative payment scheme recently proposed by MedPAC. The proposed formula would eliminate the sharp jump in payments at the magic day, replacing it with higher average per-diem payments for days before the SSO threshold. As a result, patients who are close to what would have been the magic day are now discharged sooner because LTCHs no longer have an incentive to extend marginal patients' stays in order to receive a lump-sum payment. Patients with lengths of stay well before the old magic day, however, may be held longer as LTCHs take advantage of the larger per-diem payments. Based on our findings, among those patients still in an LTCH within three days of what would have been the magic day under the current PPS, the proposed formula would decrease the number of them held until what would have been the magic day by about 9 percent, reducing the average stay by about a day relative to the status quo. This provides more modest savings than the previous counterfactual, on the order of about $21 million each year for the nine most common DRGs.

Finally, we consider a more basic cost-plus counterfactual reimbursement scheme in which LTCHs receive a fixed five percent mark-up over their reported costs. We find that, although it may reduce the strategic discharge incentives created by the current PPS, hospitals respond to the incentives of receiving a constant mark-up over their incurred costs by holding patients longer than they do under the status quo. This highlights the nuances involved in adequately reimbursing LTCHs while also taking into account the strategic incentives created by such reimbursement policies.

Our results contribute to several streams of literature. We add to existing work examining the incentives to reduce health care expenditures that has focused primarily on individual patients (e.g., responding to cost-sharing in their insurance plans[4]) or on individual physicians (e.g., on where to admit patients[5]). By focusing on how inpatient hospitals respond to incentives to reduce expenditures, our paper offers an important contribution to this growing literature. In related ongoing work, developed independently from our own, Einav et al. (2016) also look at the discharge practices of LTCHs and report similar findings.

Our work also relates to others who have examined the unintended consequences of Medicare reimbursement policies (e.g., Altman 2012, Decarolis 2015, Dafny 2005). Most directly related to our work, Kim et al. (2015) document several stylized facts for LTCHs following Medicare's change to the PPS in 2002, including a spike in discharges immediately after the SSO threshold. We further these results by considering a broader set of DRGs and estimating a structural model of LTCH behavior that allows for counterfactual policy analysis. In addition, we explicitly outline an identification strategy for uncovering strategic behavior by LTCHs, as well as establish for the first time (to our knowledge) several institutional nuances, such as the post-acquisition discharge policies of Kindred and Select's LTCHs and the behavior of co-located LTCHs.

We also provide new evidence in the long line of literature on for-profit healthcare providers (e.g., Schlesinger & Gray 2006, Dranove 1988, Chakravarty et al. 2006, Wilson 2013). In showing that for-profit LTCHs seek to maximize reimbursements from Medicare more often than not-for-profits do, we bolster similar findings in this vein, such as those in Silverman & Skinner (2004). Others, such as Grieco & McDevitt (forthcoming), have found that for-profit health-care providers often provide lower-quality care. This may also be the case for LTCHs given previous reports that they at times provide sub-standard care. For example, Berenson (2/9/2010) finds

[4] See, for example, Manning et al. (1987), Newhouse (1993), or Einav et al. (2013).

[5] See, for example, Ho & Pakes (2014).

that LTCHs have been cited at a rate almost four times that of regular acute-care hospitals for serious violations of Medicare rules and have had a much higher incidence of infections and bedsores. In a separate ongoing project (Eliason et al. 2016), we investigate the relationship between LTCHs' strategic discharge behavior and these alternative measures of quality.

The remainder of our paper continues in Section 2, which provides background details on LTCHs. Section 3 discusses the data. Section 4 provides descriptive evidence of strategic discharge by LTCHs. Section 5 describes our structural model of LTCH discharge decisions. Section 6 presents our estimates of this model, and shows our counterfactual analysis of Medicare's proposed reimbursement plan, along with other schemes. Section 7 concludes. The appendices contain robustness checks of our main results for several DRGs, summary statistics for LTCHs across all DRGs, a thorough example of the exact calculations used to compute reimbursements to LTCHs, and several figures relevant for our counterfactual analysis.

2 Overview of Long-term Care Hospitals

Long-term care hospitals are post-acute care facilities that provide extended care for patients with prolonged medical needs. To qualify as an LTCH, a facility must meet Medicare's qualifications for being a general acute-care hospital in addition to having an average length of stay greater than 25 days for its Medicare patients.

As an organizational form, LTCHs were established in the 1980s during Medicare's transition to PPS, under which general acute-care hospitals began to receive a set payment for each treatment rather than one based on their direct costs. CMS exempted hospitals with long average length of stays from the new PPS due to concerns that they would not be financially viable under this system. Medicare then further adjusted the LTCH reimbursement scheme in 2002 to its current form, which we discuss in greater detail below.

Over the past three decades, LTCHs have been the fastest growing segment of Medicare's post-acute care program (Kim et al. 2015). As recently as the 1980s, fewer than 10 such facilities existed in the U.S. By 2012, there were 420 Medicare-certified LTCH facilities with payments from Medicare accounting for about two-thirds of their overall revenue, totaling \$5.5 billion (Medicare Payment Advisory Commission 2014). Most LTCHs operate as for-profit entities, and coinciding with industry growth over the past decade, the market has consolidated considerably. The two leading firms, Kindred Healthcare (Kindred) and Select Medical (Select) now operate 38 percent of all LTCHs, having grown largely through acquisitions.

LTCHs receive payments from both patients and their insurers. For Medicare patients, the focus of our study, those transferred to an LTCH from an acute-care hospital do not pay an additional deductible, whereas those admitted from the community do pay one (\$1,216 in 2014) unless they have been discharged from a hospital within the last 60 days. In either case, an additional copayment is charged if the beneficiary stays longer than 60 days (a rare event).[6] Patients' payments are a small portion of the total payment received by LTCHs, however; even for a patient admitted from the community who pays a deductible and stays for 75 days in an LTCH (a very rare event), the payment received from Medicare may be ten times greater than the payment received from the patient. For more typical cases, where the patient is transferred from an acute-care facility (and so pays no deductible) and stays for less than 60 days, Medicare is the sole source of revenue for the LTCH.

Before 2002, Medicare paid LTCHs for care based on their average cost per discharge. After 2002, Medicare began paying for LTCH care with a PPS intended to cover all of the operating and capital costs of covered services. Medicare calculates the PPS by starting with an LTCH Standard Federal Rate, or LTCH base rate, which was \$39,794.95 in FY2010. Two adjustments are then applied to this base rate. The first is a hospital wage index adjustment that incorporates geographic differences in costs due to health-sector wages. The second is a Medicare severity long-term care diagnosis related group (MT-LTC-DRG) adjustment. The MT-LTC-DRG weight adjusts the payment to account for patient diagnoses (principal and secondary), procedures, age, sex, and discharge status based on the expected relative costliness of patients in each group. The final adjusted amount is know as the full LTCH payment. (For an example of this calculation, see "Full MS-LTC-DRG payment" in Appendix C.)

[6] This was \$304 per day between 61 and 90 days. Beyond 90 days the patient has a lifetime reserve of 60 days covered by Medicare where the copay was \$608 in 2014.

The LTCH PPS uses the same DRG groups as the acute inpatient PPS, but accounts for differences in costs between regular inpatient cases and long-term care cases because the afflictions of patients requiring longer stays are typically more severe and costly to treat than those of patients with the same diagnosis who require shorter stays. For this reason, full LTCH payments are usually larger than Medicare payments for similar patients being treated in other types of facilities, such as the in-patient prospective payments (IPPS) received by general acute-care hospitals. For example, for DRG 207, respiratory system diagnosis with prolonged mechanical ventilation, the standard IPPS payment in 2014 was \$30,480 while the LTCH payment was \$80,098.[7]

To discourage needless transfers between facilities and to ensure that only those patients truly needing long-term care are admitted to LTCHs, the full LTCH prospective payment is only paid for episodes of treatment lasting longer that five-sixths of the geometric mean of the length of stay for each DRG. Shorter stays are reimbursed as short-stay outliers, which are intentionally set to be much smaller than the full long-term care payments, and closer to the IPPS amount paid to acute-care hospitals for similar services.

For these short stays, Medicare pays LTCHs the least of the following:

1. The full MS-LTC-DRG payment, or
2. 100 percent of the cost of the case, or
3. 120 percent of the MS-LTC-DRG specific per-diem amount multiplied by the length of stay, or
4. A blend of the inpatient MS-DRG amount and 120 percent of the LTCH per-diem amount, where the portion coming from the LTCH per-diem amount increases with the length of stay.

[7] See Medicare Payment Advisory Commission (2014), chapter 11.

See Appendix C for an example that calculates each of these amounts.[8,9]

The combination of these short-stay payments that lead up to the full lump-sum payment result in a payment structure that increases linearly with a patient's length of stay before culminating with a discrete jump in payoffs on the magic day. The nonlinearities in Medicare's reimbursement of LTCHs thus create a strong incentive to keep patients just beyond the SSO threshold. As an example, consider Figure 1 that shows the average Medicare payments (solid line) broken down by length of stay in 2013 for services provided to patients with DRG 207, the most common DRG in the data, with the gray bands indicating the 25th and 75th percentiles. In this year, the SSO threshold was 26.7 days, and the jump in payments just beyond this point is immediately evident. The dashed line shows an estimate of the average costs for these patients by day of discharge.[10]

The quotes from industry sources in the Introduction convey the type of pressure put on LTCH employees to keep patients longer than medically necessary, but then discharge them quickly after the SSO threshold in order to maximize the facility's profits. Figure 1 clearly illustrates the source of this pressure for DRG 207: the average payment on day 26 is $53,762.53, but then jumps to $77,049.16 just one day later. If we impute daily costs from hospital charges and cost-to-charge ratios (see footnote 10), this corresponds to an average profit per patient jumping from $-4,332.62 on the day before the SSO threshold to $27,508.59 on the magic day. After the SSO threshold is reached, the LTCH receives no further payments, so profits begin to fall as the hospital continues to incur costs while caring for the patient. In the case of DRG 207, Figure 1 indicates that additional costs completely exhaust profits after day 40, leading

[8] Starting in calendar year 2013 there is also a "very short stay outlier" payment. Cases with stays less than or equal to the IPPS average length of stay are reimbursed at weakly lower rates than SSOs. These payments are set to the least of the four possibilities enumerated in the SSO case above but replace the blended case with just the inpatient MS-DRG amount.

[9] To discourage LTCHs from avoiding extremely high-cost patients, Medicare will share costs beyond what are reimbursed through the standard long-term care payment. In 2015, for example, if the costs incurred by an LTCH were more than the full long-term care payment *plus* $14,972, then Medicare will pay 80 percent of the difference. According to our data, this happens in about 10 percent of long-term stays for DRG 207.

[10] We use our claims data (introduced below) to estimate costs as covered charges×cost-to-charges ratio, which is the same formula used by CMS to estimate 100 percent of the cost of care for SSOs. The cost-to-charge ratio (CCR) is calculated for each hospital based on their annual cost reports as the overall ratio of total costs to total covered charges. In reality, the CCR likely varies by patient within a hospital. For example, sicker patients who stay longer are probably more expensive and have higher CCRs than less-sick patients within the same DRG. In this case, the cost estimate is biased upward for the shorter stays and downward for the longer stays.

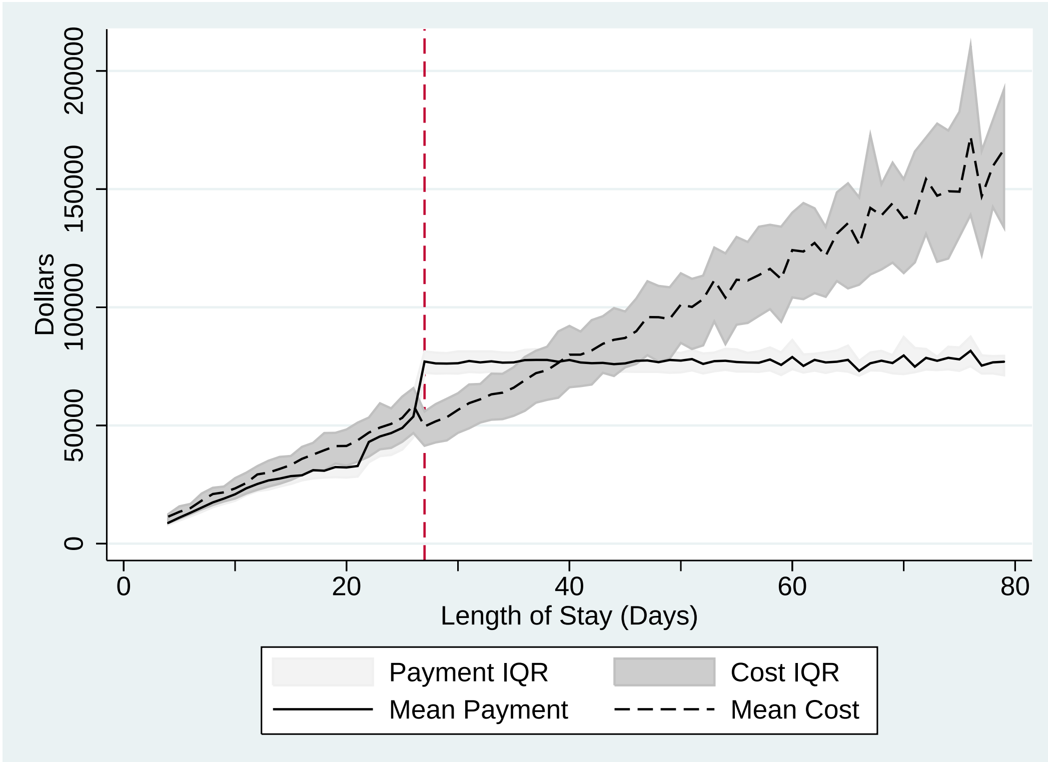


Figure 1: Revenues and Costs for DRG 207 Patients by Length of Stay, FY 2013

to a roughly 2 week window of profitability for the hospital. In 2013, 45 percent of discharges occur within that window compared to 5 percent in 2002, the year before the current PPS was introduced

Another distinguishing feature of the LTCH market is that nearly one-third operate within general acute-care hospitals, so-called hospital-within-hospitals (HwH). Although co-located, both the LTCH and general acute-care hospital are organizationally, managerially, and financially independent. Such an arrangement yields some efficiencies, as it allows for the sharing of fixed costs such as laboratories. More controversially, this arrangement makes it easier to transfer patients between co-located hospitals, which benefits them both: a transfer allows the LTCH to receive a separate payment from Medicare, while the acute-care hospital frees up a bed for a new patient with a new reimbursement. As noted in Kahn et al. (2015), a patient in an acute-care general hospital co-located with an LTCH is more likely to be transferred to an LTCH, with patients potentially selected based on factors other than clinical appropriateness. Because LTCHs do not operate emergency rooms, they have considerable discretion over which patients to admit. Such behavior has prompted plans from Medicare to reduce payments to LTCHs that receive more than 25 percent of their patients from a single hospital.[11]

3 Data Description and Motivating Facts

For our analysis, we use a claims dataset from CMS linked to hospital characteristic data from CMS and the American Hospital Association. The claims data come from the de-identified Limited Data Set (LDS) version of the Long-Term Care Hospital PPS Expanded Modified MEDPAR file, which contains records for 100 percent of Medicare beneficiaries' stays at long-term acute care hospitals.[12] Our particular data are limited to long-term stays for fiscal years 2002, when the old reimbursement system was still in effect, and 2004 through 2013.[13] The data include the billed DRG, Medicare payment amounts, covered costs, length of stay, diagnosis and procedural details, race, age, gender, the type of hospital admission, whether the patient was discharged alive, and, if so, the discharge destination (i.e., discharge to home care, to a general hospital, etc). The CMS certification number of the hospitals allows us to link these claims data to data on hospital characteristics, although the de-identification of patients means we cannot measure patient-level outcomes such as readmissions.

The hospital data come from two sources, the American Hospital Association (AHA) Guide and Medicare's Provider of Services (POS) files.[14] The POS files contain data on hospital characteristics including name, location, hospital type, size, for-profit status, medical school affiliation, services offered, and the hospital's CMS certification number.

Hospitals are added to the POS file when they are certified as Medicare and Medicaid

[11]To discourage LTCHs as being treated as though they were extensions of short-term acute-care hospitals, Medicare stipulated in 2005 that if more than 25 percent of the LTCH's discharges were admitted from its co-located hospital, then the net payment amount for those discharges beyond the 25 percent mark became the lesser of the LTC-DRG or the amount Medicare would have paid under IPPS. In 2007, it was expanded to include all LTCH hospitals and the 25 percent threshold was raised for some hospitals to as much as 75 percent. See *Long Term Care Hospital Prospective Payment System: Payment System Fact Sheet Series.* The Medicare Learning Network. December 2014.

[12]For further information, please see `https://www.cms.gov/Research-Statistics-Data-and-Systems/Files-for-Order/LimitedDataSets/LTCHPPSMEDPAR.html`.

[13]CMS has not made 2003 data available to researchers.

[14]See `https://www.cms.gov/Research-Statistics-Data-and-Systems/Downloadable-Public-Use-Files/Provider-of-Services/index.html`.

providers. Historical versions are saved each year, so in principle one could use these reports to construct a panel dataset of all eligible providers. However, once a hospital is in the POS file, CMS regional offices administer surveys and update the dataset irregularly. As a result, we may not observe the correct instance of when time-varying hospital characteristics actually change. As ownership, and the timing of ownership changes, are of particular interest to us, we address this issue by supplementing the POS data with data from the AHA Guide.

The AHA administers an annual survey of hospitals in the U.S. and uses them to compile a comprehensive hospital directory known as the AHA Guide. These guides contain various details about hospitals, such as their organizational structure, services provided, bed count, among others. We used hard copies of the guide to record data on hospital ownership changes for LTCHs. We then linked this to the POS data to improve the data quality relating to ownership and ownership changes. In addition, we collected hospital system affiliation and co-location data from the AHA Guide. We count LTCHs listed as being located within another hospital in the AHA Guide as hospital-within-hospitals.

Much of our analysis focuses on hospital stays coded as DRG 207, respiratory system diagnosis with at least 96 hours of ventilator support, and discharged to home care or nursing facilities. We focus on DRG 207 because it is the most common DRG and also the most highly reimbursed, although we extend our analysis to the other eight most common DRGs in the appendices to highlight the robustness of our results.[15] Our complete dataset contains records for 1.45 million long-term hospital stays between 2004 and 2013 classified into as many as 751 DRGs.[16] Of these, 170,365 are classified in DRG 207, with 90,755 terminating in discharges to home or a nursing facility.

Table 1 contains summary statistics for these 90,755 stays.[17] For this sample, the mean length of stay is 42.43 days and 87 percent of patients stay at least until the SSO threshold. The

[15]Below we will also leverage the data from all nine of these DRGs in two additional ways. First, we will use the variation in the size of the magic day payment to show that patients with DRGs where the jump in payment is greatest are most likely to be strategically discharged. Second, we will use data from all nine DRGs when we estimate our structural model.

[16]We omit data from 2002 as the PPS policy does not apply.

[17]See Appendix A for complete summary statistics for all LTCH episodes of hospitalization, for all stays coded to DRG 207, and for the other eight DRGs that we focus on.

Table 1: Summary Statistics for Patients Discharged to Home or Nursing Facility Care with DRG 207 (2004-2013)

Variable	**Mean**	**Std. Dev.**
Length of Stay	42.425	24.062
Released After SSO Threshold	0.867	0.34
Total Payment[1] ($)	71,107.908	23,259.546
Amount Paid by Medicare ($)	70,530.388	28,385.701
Estimated Costs ($)	74,390.038	47,003.876
Portion Discharged to Home Care	0.234	0.424
Portion Discharged to Nursing Facility	0.766	0.423
Admission Type: Emergency	0.011	0.103
Admission Type: Urgent	0.196	0.397
Admission Type: Elective	0.787	0.41
Admission Type: Other	0.006	0.076
Admitted from Community	0.115	0.32
Admitted from Nursing Facility	0.01	0.102
Admitted from General Hospital	0.867	0.34
Admitted from Other Source	0.002	0.049
Male	0.484	0.5
White	0.746	0.435
Black	0.191	0.393
Asian	0.014	0.119
Hispanic	0.024	0.154
Age less than 25	0.002	0.043
Age between 25 and 44	0.038	0.192
Age between 45 and 64	0.218	0.413
Age between 65 and 74	0.361	0.48
Age bewteen 75 and 84	0.291	0.454
Age over 85	0.089	0.285
$N = 90,755$		

[1] Some observations were omitted because they reported Medicare payments of $0. The majority of these are believed to be readmissions that did not quality for additional Medicare payments. Limitations in our data do not allow us to link these to their initial admission so we had to drop them.

average total payment to hospitals is \$71,108; most of this, \$70,530, comes from Medicare. The rest is paid as a deductible or co-insurance, or covered by a third party. The admission type refers to how the hospitalization was initiated. About 1 percent of these episodes originated from an emergency room, just under 20 percent started in an urgent care facility, and almost 79 percent came from an elective admission. The admission source identifies the type of facility that the patient was in immediately before being transferred to an LTCH: 87 percent of patients transferred from a general acute-care hospital, while almost 12 percent were admitted directly from the community. Age, race, gender, and ethnicity are also summarized in the table. About 25 percent of these patients are under age 65, the age of universal Medicare coverage, because they qualified for Medicare in other ways, such as by receiving Social Security Disability Insurance or by having end-stage renal disease.

Table 2 contains summary statistics for our sample of LTCHs, with the bottom panel displaying summary statistics weighted by hospital size (bed count). As mentioned above, the largest two firms are Kindred and Select, which together operate almost 40 percent of the facilities, although theirs tend to be a bit smaller than the average facility. Nearly one-third of LTCHs are hospitals within hospitals. For-profits comprise two thirds of LTCHs, whereas government-owned LTCHs make up 7 percent of the sample but contain 16.6 percent of total beds; just under 10 percent of LTCHs are affiliated with medical schools. Across all types of LTCHs, the average bed count is 70.

4 Evidence for Strategic Discharges

In this section, we provide evidence that the financial incentives created by the PPS influence LTCHs' discharge decisions. The crux of our analysis is that the discontinuous jump in payments at the SSO threshold (e.g., Figure 1) corresponds to a discontinuous jump in discharges. To establish that the discontinuity in payments *causes* the discontinuity in discharges, we exploit several institutional details for identification: (i) variation in the SSO threshold across years within the same DRG, (ii) variation in the SSO threshold across DRGs in the same year, (iii) the change to

Table 2: Summary Statistics for LTCHs (2004-2013)

Variable	**Mean**	**Std. Dev.**
Kindred Healthcare	0.158	0.365
Select Medical	0.203	0.402
Hospital within hospital	0.328	0.470
For-profit	0.657	0.475
Not-for-profit	0.274	0.446
Government owned	0.069	0.254
Bed count	69.66	87.49
Affiliated with medical school	0.091	0.287
Weighted by bed count		
Kindred Healthcare	0.199	0.399
Select Medical	0.131	0.337
Hospital within hospital	0.187	0.39
For-profit	0.559	0.496
Not-for-profit	0.275	0.446
Government owned	0.166	0.372
Affiliated with medical school	0.180	0.384
$N = 4,108$		

the LTCH reimbursement system that introduced the reimbursement discontinuity after 2002, (iv) variation in the size of the payment discontinuity at the SSO threshold across different DRGs, (v) differences in the ease of manipulating discharges across discharge destinations, and (vi) variation in the incentives faced by hospitals to engage in strategic discharge based on their type (for-profit vs. not-for-profit, owned/acquired by a major chain vs. independently operated, and co-located with an acute-care hospital vs. a standalone facility). The central message that emerges from these different sources of variation is a clear one: the observed discharge patterns in the data stem from deliberate choices made by LTCHs in response to Medicare's PPS rather than a coincidental improvement in patients' health that occurs right after reaching the SSO threshold. In Section 4.1, we rely mainly on histograms to provide visual evidence in support of our arguments. In Section 4.2, we quantify the extent of strategic discharge in regression form.

4.1 Graphical Evidence

We first examine the distribution of discharges to home or a nursing facility for a single DRG, DRG 207, relative to its SSO threshold. The discontinuity in discharges at the SSO threshold is immediately apparent in Figure 2, which shows a marked spike in discharges on the magic day to go along with a pronounced dip in discharges on the days immediately preceding it. The x-axis in Figure 2 has been normalized to show the day of discharge relative to the magic day, as the magic day change over the years. Typically, one would expect a smooth distribution of discharges absent any deliberate manipulation by LTCHs; the discontinuous jump in discharges that appears on the days immediately after the SSO threshold suggests that LTCHs base their decisions on criteria other than just clinical guidelines.

Given that the SSO threshold is intentionally set on a specific day by Medicare, however, we cannot rule out that the underlying treatment regimen for DRG 207 naturally leads to a mass of discharges on that day. To link the spike in discharges to facilities' financial incentives, we will leverage several sources of variation in the data to illustrate a consistent pattern of strategic behavior, starting in this subsection with a series of suggestive histograms. We summarize key features of the histograms, such as the percentage of patients discharged on the magic day, in Table 3 at the end of this subsection, and in our discussion we frequently refer to statistics appearing there.

For our first source of identifying variation, we show how the distribution of patients' lengths of stay has evolved over time. Figure 3 presents the years 2002, 2004 and 2013, where the dashed vertical line denotes the magic day in 2013, the 27th day, and the solid vertical line denotes the magic day in 2004, the 30th day. In panel (a), we see that in 2002, when Medicare's reimbursement schedule did not include a lump-sum payment, there is no spike in discharges. After implementing the LTCH PPS, however, a distinct spike emerges on the magic day in panel (b) for 2004 and panel (c) for 2013. In 2004, 2.1 percent of patients are discharged on the day right before the magic day compared to 4.6 percent on the magic day, a 2.2-fold increase. In 2013, by contrast, 1.4 percent of patients are discharged on the day right before the magic day compared to 10.2 percent on the magic day, a substantially larger 7.3-fold increase.

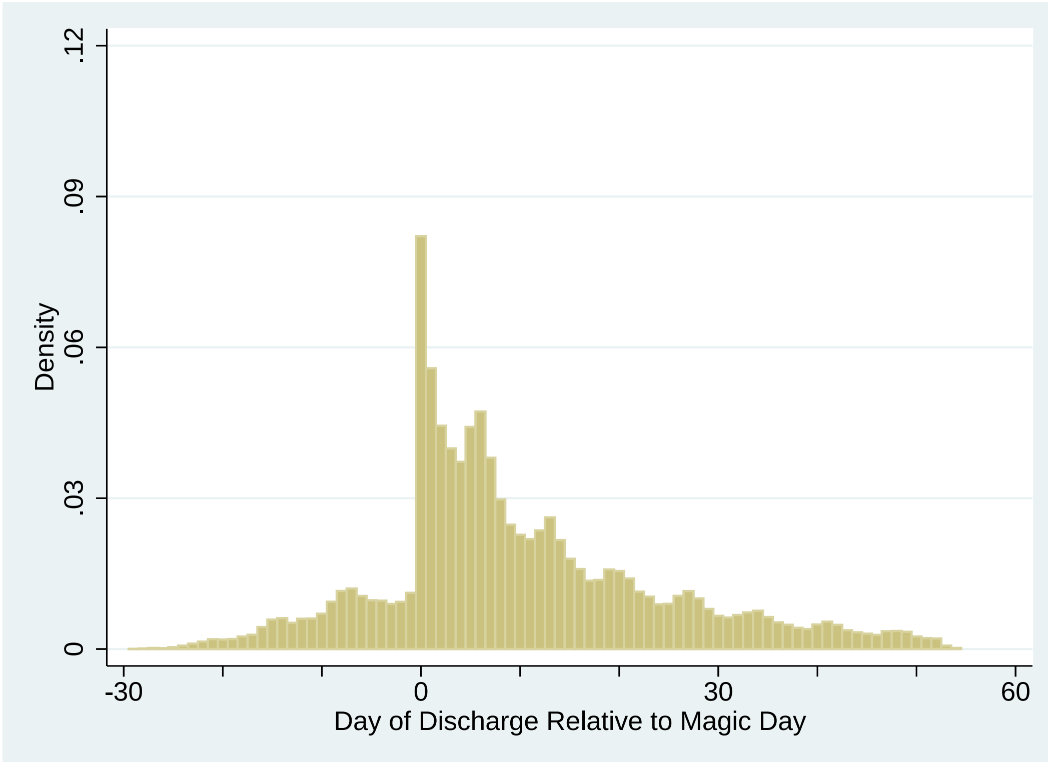
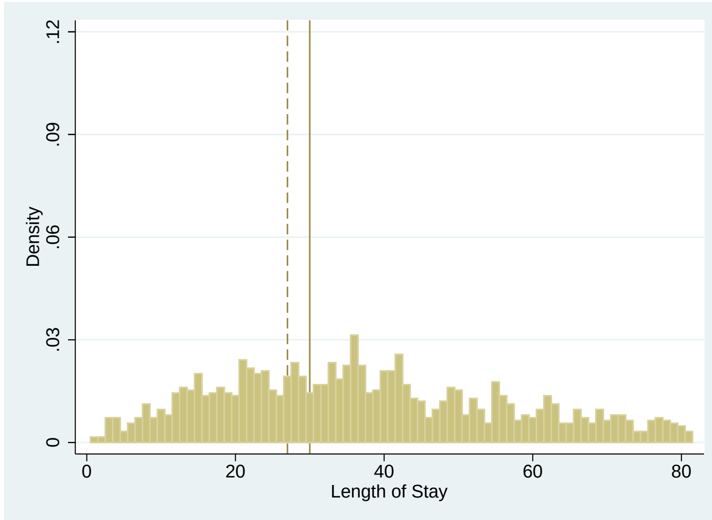


Figure 2: Distribution of Length of Stay Relative to Magic Day

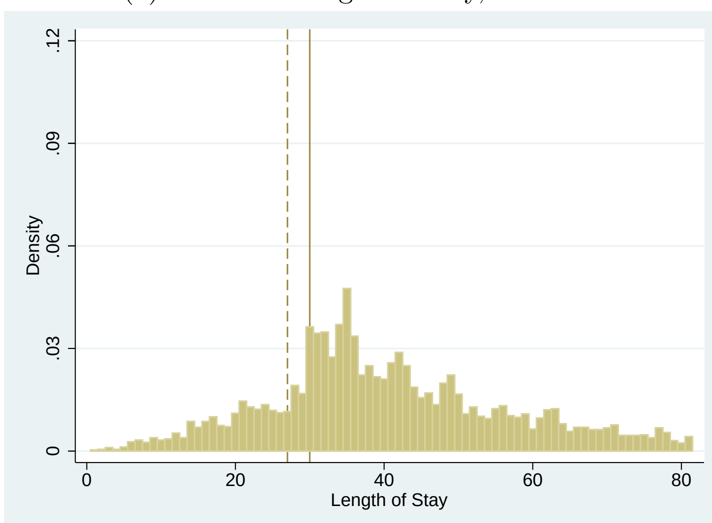
We wish to make two points here. First, comparing panel (a) with panels (b) and (c), it is clear that when there is no discontinuity in the reimbursement scheme, there is also no spike in discharges around what would subsequently become magic days. Second, comparing panels (b) and (c), we see the spike in discharges in 2004 occurs at day 30, the magic day for that year, while in 2013 this spike occurs on day 27, the magic day for that year.[18] Though theoretically possible, it is unlikely that medical advances caused this shift. Rather, the more likely reason that discharges spike earlier in 2013 is that this is when LTCHs receive larger payments. The lack of a similar spike in 2002 further bolsters this claim. Furthermore, we show the same distinct pattern across other common DRGs in the appendix (see Figure 9 in Appendix B). It is even more unlikely that any coincident medical advances occurred in each of these different DRGs in a way that happened to shift discharges to precisely after their DRGs' SSO threshold.[19]

[18] One might also notice the increase between 2004 and 2013 in the ratio of patients released on the magic day relative to the preceding day. We are currently exploring this pattern in ongoing work and view an explanation of this trend, such as LTCH learning how to best maximize profits given the parameters of the PPS, as beyond the scope of the current paper.

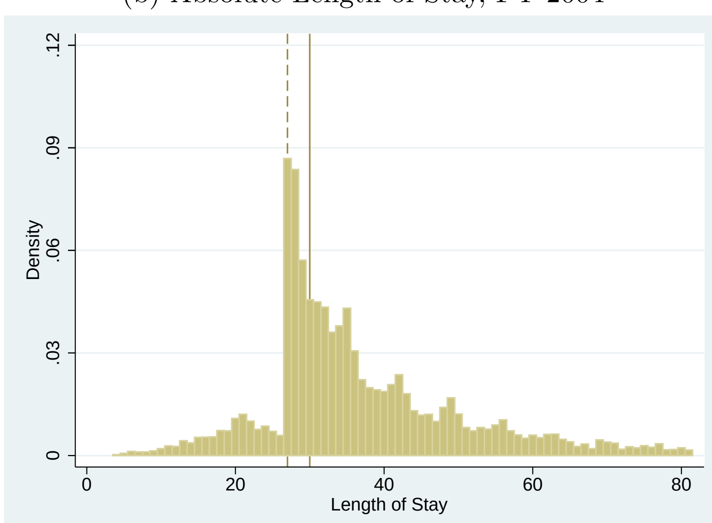
[19] In Section 4.2, we relate the likelihood of strategically discharging a patient to that patient's DRG's lump sump payment to build the argument that strategic discharges are most likely for those DRGs where the discontinuity



(a) Absolute Length of Stay, FY 2002



(b) Absolute Length of Stay, FY 2004



(c) Absolute Length of Stay, FY 2013

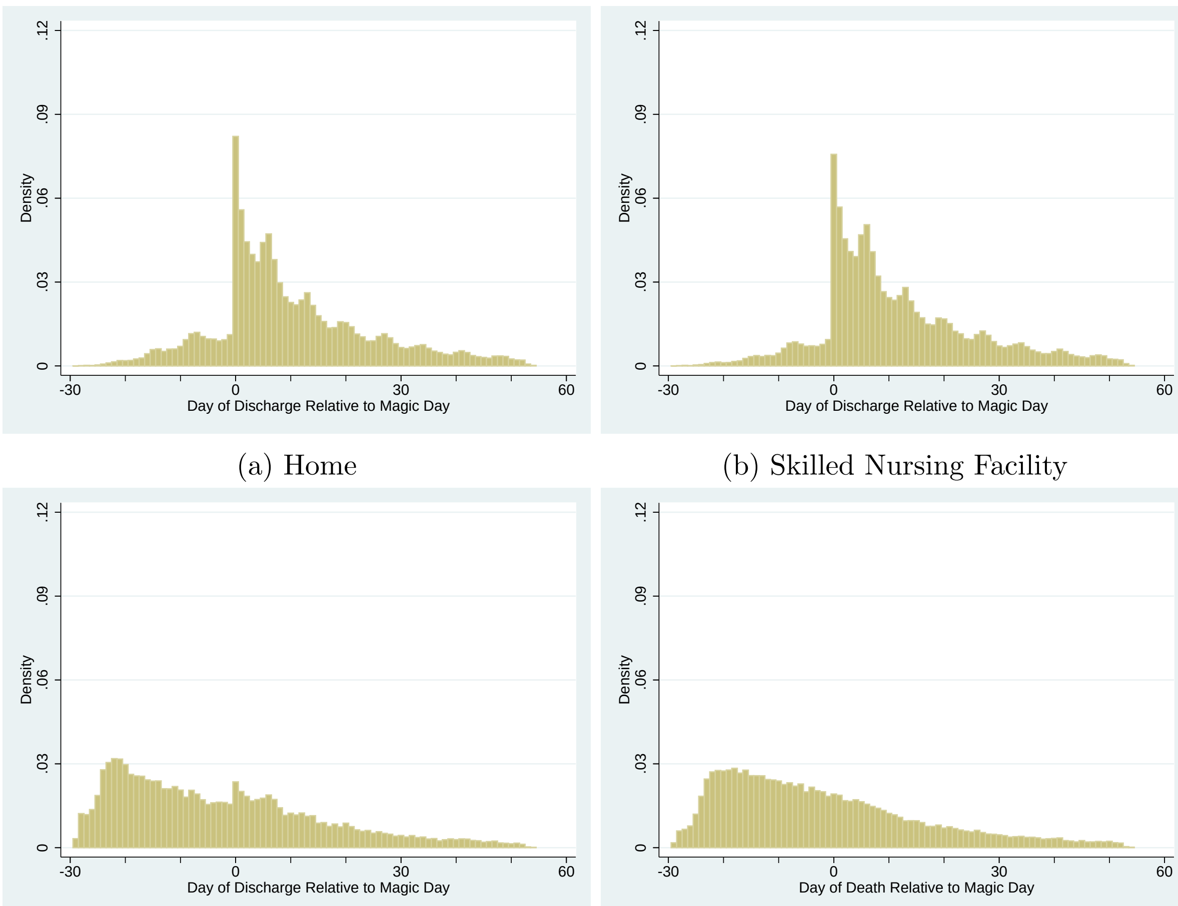
Figure 3: Discharge patterns for DRG 207. Solid vertical line is SSO threshold in 2004. Dashed vertical line is SSO threshold in 2013.

For our second source of variation, we look at differences in discharge patterns by destination, categorized by how easily an LTCH could alter a patient's treatment plan based on financial incentives. Discharges to home are the easiest for LTCHs to manipulate in this regard because they have the least oversight. Discharges to skilled nursing facilities would be slightly more difficult because trained medical staff evaluate a patient following admission. Discharges to acute-care hospitals will then be comparatively harder to manipulate because they have even more extensive admission screening. Finally, discharges due to death will be extremely hard to manipulate (for obvious reasons). In Figure 4, we show that discharge patterns exactly line up with this hypothesis. The spike is most pronounced for discharges to home and least for discharges due to death, which shows no bump at all on the magic day. For patients discharged to home, LTCHs discharge 6.1 times as many patients on the magic day relative to the day before it, whereas for patients discharged due to death the corresponding ratio is 1.0.

For our final source of variation, we consider how discharge patterns vary based on several different categorizations of LTCHs. Across the three types we consider, LTCHs facing the strongest incentives to strategically discharge patients consistently discharge more patients on the magic day. First, for-profit LTCHs presumably have a stronger incentive to engage in strategic discharge because they have an explicit mandate to maximize profits. In keeping with this motivation, Figure 5 shows that for-profits discharge 9.2 times as many patients on the magic day compared to the day before it, whereas not-for-profit LTCHs have a spike about half as large, at 4.6 times.

The second hospital type we consider is whether an LTCH is owned and operated by one of the two dominant chains, Kindred or Select. These chains have grown extensively over the past decade by acquiring existing LTCHs, as well as through greenfield investment. As maximizing reimbursements is a primary way to increase corporate earnings — and thus may be a central component of their growth strategies — it is possible that Kindred and Select may implement their discharge policies at the LTCHs they acquire. To this point, Berenson (2/9/2010) provides an example from 2007 where an inspector for Medicare found that "a case manager at a Select

is greatest.



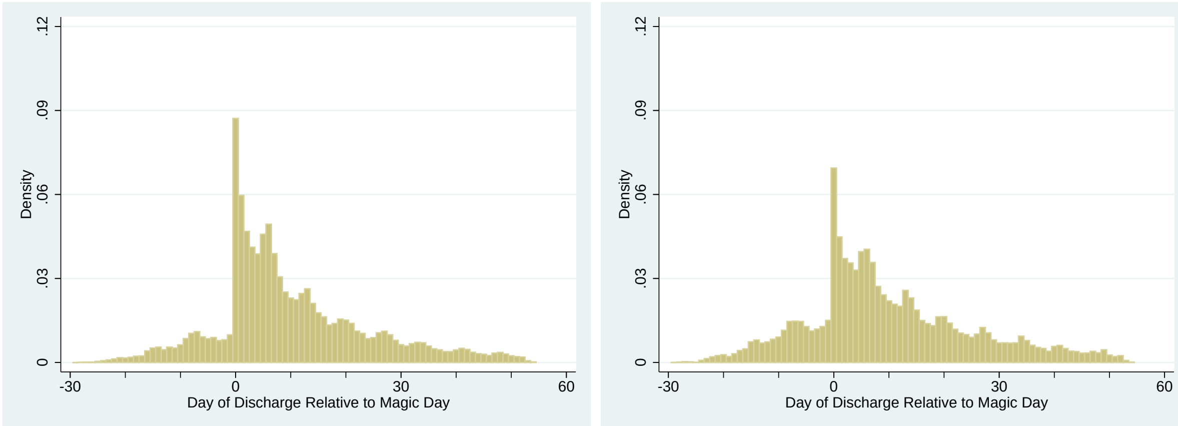
(a) Home

(b) Skilled Nursing Facility

(c) Acute-care Hospital

(d) Death

Figure 4: Discharge Patterns for DRG 207 by Destination, FY 2004-2013



(a) For-Profit LTCHs

(b) Not-for-profit LTCHs

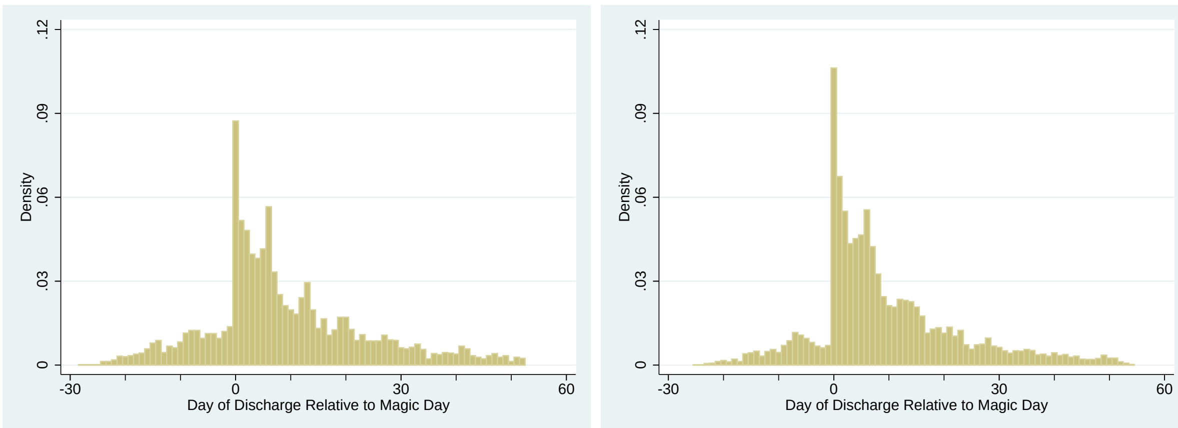
Figure 5: Discharge patterns for DRG 207 by LTCH Profit Type, FY 2004-2013

hospital in Kansas had refused to discharge a patient despite the wishes of her physician and family. The hospital calculated it would lose $3,853.52 if it discharged the patient when the family wanted, the inspector found." The discharge patterns in Figure 6 are consistent with such a corporate strategy. When Kindred and Select acquire LTCHs, the ratio of discharges on the magic day relative to the day before it increases from 8.7 to 15.1, suggesting that target LTCHs adopt their acquirers' discharge policies.[20]

The final type of LTCH we consider is whether the LTCH operates within an acute-care hospital, which we refer to as a HwH. Co-located LTCHs may face fewer barriers for manipulating discharges, and therefore we may see a larger spike of discharges on the magic day. Officially, hospitals have little control over such facilities and patients can choose where to go; however, hospital discharge teams often steer patients to a favored facility. In line with our expectations, Figure 7 shows a larger spike in discharges on the magic day for co-located LTCHs compared to standalone LTCHs, at 10.1 percent and 7.3 percent, respectively. Co-located LTCHs discharge 8.4 times as many patients on the magic day relative to the day before it, while for standalone LTCHs the number is 6.6.

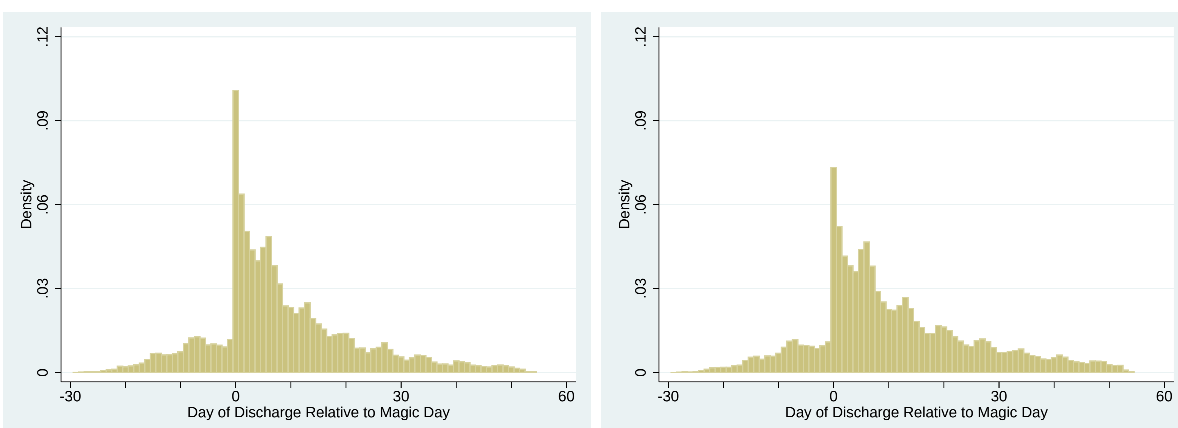
To conclude this subsection, we provide Table 3 that contains statistics supporting the claims made about each histogram above, and shows that the differences we refer to are both statistically

[20]We also show below that Kindred- and Select-operated LTCHs are more likely to strategically discharge patients; that is, overall their facilities are more likely to strategically discharge patients, and when they acquire a new facility, that facility is more likely strategically discharge patients than it was before acquisition.



(a) Before Acquired by Select or Kindred (b) After Acquired by Select or Kindred

Figure 6: Discharge patterns for DRG 207 Pre- and Post-Acquisition, FY 2004-2013



(a) Co-located LTCHs (b) Standalone LTCHs

Figure 7: Discharge patterns for DRG 207 by LTCH location type, FY 2004-2013

and economically significant.

Table 3: Share of discharges on the magic day and the preceding day

Comparison Set	Day before magic day	Magic Day	Ratio	P-value[1]	Diff-in-Ratios	P-value[2]
Home	0.017	0.103	6.06	0.000		
Nursing Facility	0.009	0.076	8.44	0.000	-2.38	0.010
Acute Care Hospital	0.016	0.024	1.5	0.001	4.56	0.000
Death	0.018	0.019	1.06	0.517	5.01	0.000
2004	0.016	0.036	2.25	0.000	3.19	0.000
2013	0.016	0.087	5.44	0.000		
For-profit	0.010	0.092	9.20	0.000	4.60	0.000
Not-for-profit	0.015	0.069	4.60	0.000		
Select or Kindred	0.010	0.089	8.91	0.000	3.29	0.000
Other	0.013	0.073	5.62	0.000		
Before Acquisition	0.014	0.087	6.21	0.000	8.93	0.000
After Acquisition	0.007	0.106	15.14	0.000		
Co-located	0.012	0.101	8.42	0.000	1.78	0.074
Not Co-located	0.011	0.073	6.64	0.000		

P-values from Wald tests of nonlinear hypotheses. Difference-in-ratios for nursing facility, acute-care hospital, and death discharges are all with respect to home discharges. Except for the discharge destination rows, the statistics include hospital stays ending in discharge to home or nursing facility care.

[1] P-value under the null hypothesis that the ratio is equal to one.

[2] P-value under the null hypothesis that the difference-in-ratios equals zero.

4.2 Probit model

The preceding figures provide strong visual evidence of a sharp jump in discharges on the magic day, with the magnitude varying based on factors correlated with LTCHs' financial incentives. To quantify these patterns in a rigorous yet parsimonious way, Table 4 shows results from a series of probit regressions that take the decision to discharge a patient on a given day as the dependent variable:

$$Pr(discharge|t, s) = \Phi(\gamma_0 + \gamma_1 t + \gamma_2 t^2 + \lambda_s), \quad (1)$$

where t is the (absolute) day of the hospital stay and s is the day relative to the magic day ($s = 0$ indicates the day is the magic day, $s < 0$ indicates days before the magic day, and $s > 0$ indicates days after the magic day).

These probits control for both the absolute day of a given stay and the relative position of the patient to the SSO threshold. A quadratic function of the number of days spent in the hospital is included to capture the non-strategic impact of time spent in the hospital on the probability of discharge, whereas the relative days capture the strategic component. That is, one would expect the likelihood of being discharged for clinical reasons on, say, the 25th day, not to vary much within a DRG across years. However, if the 25th day happens to be the magic day in one year but the 26th day in another, the year in which it coincides with the magic day should have a higher likelihood of discharge if LTCHs are deliberately manipulating discharges to maximize reimbursements.

In Table 4, we show the estimated marginal effects from this model for DRG 207. In Table 15 in Appendix B, we show the analogous results for the next three most common DRGs 189, 871, and 177.[21] The sample used here is based on stays that ended in a discharge to home care or a nursing facility. In all cases, we see a sharp jump in discharges on the magic day relative to the day before, and this pattern is remarkably consistent across years. For instance, in 2010 when the magic day threshold was 29 days for DRG 207, the probability of discharge increases from 1.11 percent on the day before the magic day to 8.86 percent on the magic day, a nearly eightfold increase that we refer to as the "magic day effect." In 2013, when the threshold day was two days earlier at 27 days, the rate increased from 1.3 percent to 9.7 percent, a similar order of magnitude as in 2010.

We would also expect the magic day effect to become more pronounced when the financial incentives to manipulate discharges become stronger. Note that the effect is strongest in DRG 207, which has the highest payment/cost ratio on the magic day. For DRG 207, profits jump by close to $30,000 by discharging on the magic day compared to the day before, and the median magic day effect across all years in our data is 7.96. This compares to a payment bump of $12,000

[21]The actual parameter estimates for DRG 207 appear in Table 14 in Appendix D. Parameter estimates for the other DRGs are available from the authors upon request.

Table 4: Marginal Effects on Probability of Discharge
DRG 207

Day of stay (t)	Probability of Discharge on Magic Day[1]	Probability of Discharge on Day Preceding Magic Day[2]	Hazard Ratio[3]
27	9.71***	1.27***	7.63***
	(0.337)	(0.059)	[0.000]
28	9.27***	1.19***	7.80***
	(0.319)	(0.057)	[0.000]
29	8.86***	1.11***	7.96***
	(0.320)	(0.060)	[0.000]
30	8.48***	1.04***	8.12***
	(0.336)	(0.064)	[0.000]

Note: Standard errors in parentheses. P-values in brackets. This sample contains only episodes of hospitalization that terminated in discharge to home care or nursing facilities. For results for other common DRGs, see Table 15

[1] $\Phi(\gamma_0 + \gamma_1 t + \gamma_2 t^2 + \lambda_0) * 100$

[2] $\Phi(\gamma_0 + \gamma_1 t + \gamma_2 t^2 + \lambda_{-1}) * 100$

[3] Hazard ratio: $\frac{\Phi(\gamma_0+\gamma_1 t+\gamma_2 t^2+\lambda_0)}{\Phi(\gamma_0+\gamma_1 t+\gamma_2 t^2+\lambda_{-1})}$. Square brackets contain the p-value from a Wald test for $H_0 : HR = \frac{\Phi(\gamma_0+\gamma_1 t+\gamma_2 t^2+\lambda_0)}{\Phi(\gamma_0+\gamma_1 t+\gamma_2 t^2+\lambda_{-1})} = 1$.

for DRG 189 which has a median magic day effect of 6.29 and DRG 871, which has a payment bump of $11,000 and a magic day effect of 6.55. These two DRGs have similar payment amounts and similar magic day effects. Finally, DRG 177 has a smaller payment bump of only $9,000 and a median magic day effect of only 3.77.

We also interact the SSO threshold with various LTCH characteristics, which allows discharge practices with respect to the magic day to vary by hospital type. The estimating equation for these models has the form

$$Pr(discharge|t, s, i) = \Phi(\gamma_0 + \gamma_1 t + \gamma_2 t^2 + \lambda_s X_i), \tag{2}$$

where X_i includes characteristics of the LTCH such as whether it is a for-profit LTCH, a HwH, owned by Select of Kindred, or acquired by Select or Kindred. Using this model, the probability of discharge at hospital i is a function of the absolute day of stay, t, the relative day of stay, s, and the hospital's characteristics. We limit the hospital characteristics to allow for a single partition of hospitals into types, as allowing for overlapping types would muddle the interpretation of the marginal effects.

Table 5 contains estimates for the marginal effects from four interacted probit models (each model is separated by a line in the table). We estimate the magic day effect to be nearly twice as large for for-profit LTCHs (9.60) compared to not-for-profits (4.99). For Kindred and Select, we estimate the magic day effect to be 10.01, whereas it is only 6.12 for other LTCHs. Interestingly, while Kindred and Select are more likely to strategically discharge patients than other hospitals (the second estimated model), individual LTCHs increase their strategic discharge behavior after being acquired by these chains (model 3) from 6.70 to 16.82. Lastly, the magic day effect for co-located LTCHs is about 30 percent higher than for standalone facilities, 9.42 compared to 7.34.

Table 5: Probit Marginal Effects by LTCH Type,
DRG 207 at Day 29

Model #/Partition	Predicted Prob. of Discharge. SSO Threshold Day[1]	Predicted Prob. of Discharge. Preceding Day[2]	Hazard Ratio[3]	Difference in Hazard Ratios[4]
Model #1:				
For-profit	9.28***	0.967***	9.60***	4.61***
	(0.363)	(0.052)	[0.000]	[0.000]
Not for profit	7.61***	1.53***	4.99***	
	(0.604)	(0.160)	[0.000]	
Model #2:				
Kindred and Select[5]	9.54***	0.95***	10.01***	3.90***
	(0.426)	(0.059)	[0.000]	[0.000]
Other	8.02***	1.31***	6.12***	
	(0.458)	(0.101)	[0.000]	
Model #3:				
After Acquisition[6]	11.07***	0.66***	16.82***	10.12***
	(0.662)	(0.089)	[0.000]	[0.000]
Before Acquisition[7]	9.94***	1.48***	6.70***	-0.84
	(0.778)	(0.172)	[0.000]	[0.43]
Never Acquired	8.53***	1.13***	7.54***	
	(0.357)	(0.067)	[0.000]	
Model #4:				
HwH	11.31***	1.20***	9.42***	2.08
	(0.508)	(0.099)	[0.000]	[0.054]
Not HwH	7.73***	1.05***	7.34***	
	(0.344)	(0.066)	[0.000]	

Note: Standard errors in parentheses. P-values in brackets. This sample contains only episodes of hospitalization that terminated in discharge to home care or nursing facilities.

[1] $\Phi(\gamma_0 + \gamma_1 t + \gamma_2 t^2 + \lambda_0) * 100$

[2] $\Phi(\gamma_0 + \gamma_1 t + \gamma_2 t^2 + \lambda_{-1}) * 100$

[3] Hazard ratio (HR): $\frac{\Phi(\gamma_0+\gamma_1 t+\gamma_2 t^2+\lambda_0)}{\Phi(\gamma_0+\gamma_1 t+\gamma_2 t^2+\lambda_{-1})}$. Square brackets contain the p-value from a Wald test for $H_0 : HR = \frac{\Phi(\gamma_0+\gamma_1 t+\gamma_2 t^2+\lambda_0)}{\Phi(\gamma_0+\gamma_1 t+\gamma_2 t^2+\lambda_{-1})} = 1$.

[4] Brackets contain p-value for Wald test statistic for the differences in risk ratios: $H_0 : HR^{\text{type } 1} - HR^{\text{type } 2} = 0$.

[5] Difference in hazard ratio for both Select and Kindred relative to the hazard rate of the "Other" category.

[6] Difference between hazard ratio for post-acquisition LTCHs and pre-acquisition LTCHs.

[7] Difference between hazard ratio for pre-acquisition LTCHs and "never acquired" LTCHs.

5 Quantifying the Response to Financial Incentives

The results above strongly suggest that LTCHs respond to financial incentives when discharging patients. In this section, we propose a dynamic model to isolate the effect of Medicare's payment policy on discharges, which then allows us to analyze how alternative policies would affect discharge decisions.

Before introducing the model, we should note that it is just one of several inputs that would be necessary to conduct a complete welfare analysis of Medicare's payment policies. At least two key ingredients are missing. First, we cannot recover the marginal benefit patients receive from an additional day of care, as we lack the necessary data on patients' medical histories following discharge to estimate such a benefit. Second, we do not have clear information on the marginal costs of providing an additional day of treatment. Although we do have data on hospital charges and hospital-level cost-to-charge ratios, which should be correlated with hospital costs, they are at best an indicator of *average* costs per day. As such, we view them as a potential control for cross-hospital differences in costs rather than as a direct measure of marginal costs.

Because we cannot directly measure hospitals' costs or patients' benefits, we use a structural model to recover the effect of payment policies on discharges. In the model, we will allow for a length-of-stay parameter which, under reasonable assumptions, effectively controls for the impact of both marginal hospital costs and expected patient benefits on hospitals' discharge decisions.

Even though our model does not allow us to compute a direct welfare calculation from alternative payment policies, it can still significantly advance the ongoing debate on reimbursement schemes by identifying how sensitive discharges are to payments. If the distribution of discharges, and its key moments such as the average length of stay, vary substantially in response to alternative payment schemes, then determining the optimal payment scheme is an important policy goal. Moreover, our analysis gives us a precise understanding of how the policy affects a patient's length of stay. Under the reasonable assumption that treatment costs increase as a patient stays longer in the hospital, the length of stay itself becomes a useful metric for analyzing the impact of payment policies on hospital costs. Finally, our results highlight the extent to which payment policies can be used by policy makers to influence lengths of stay and establish that it is important to understand exactly how additional days of hospital treatment affect patient outcomes.

5.1 A Model of Hospital Discharge Decisions

We model the daily decision of an LTCH to discharge a patient.[22] The patient arrives at the LTCH at $t = 0$. Each day, the LTCH receives a flow utility for treating the patient equal to

$$u_t = \lambda_t + \alpha p_t,$$

where λ_t represents the non-revenue benefits (and costs) of keeping the patient for another night.[23] The key assumption is that these benefits can be represented as a function of the number of days since a patient was admitted, as well as observable hospital and patient characteristics. The payment p_t is the marginal payment for treating a patient on day t, as defined by Medicare's PPS, and takes the form:

$$p_t = \begin{cases} p & t < t^m \\ P - (t^m - 1) \cdot p & t = t^m \\ 0 & t > t^m \end{cases}, \tag{3}$$

where p represents the per-diem payment for stays shorter than the SSO threshold, t^m. We estimate p from patient-level payments data and allow it to depend on hospital and patient characteristics. The variable P is the payment governed by the long-term PPS, so $P - (t^m - 1) \cdot p$ is the marginal payment on the day the patient crosses the SSO threshold. Finally, once the patient crosses the threshold, the hospital receives no additional payments.

Each day the LTCH decides whether to discharge the patient that day. In doing so, it weighs the financial incentives of discharging today against the numerous non-pecuniary reasons to keep the patient in the facility (e.g., the risk incurred by releasing the patient too early, the disutility the patient experiences from unnecessary treatments, and the marginal benefit of treatment to the patient), as well as the costs of providing further treatment. If the patient is discharged, then treatment ends and the LTCH may use the bed to treat other patients. We normalize the

[22]While in the full model we will allow for both hospital and patient heterogeneity, we suppress them in this section for expositional clarity. For example, when estimating the model we will allow for an LTCH's response to daily payments to depend on its for-profit status.

[23]We use the notation u_t for flow payoffs since we are not assuming that the LTCH is necessarily profit maximizing.

value of an open bed to 0, so that the flow value of treating a patient at day t is relative to the value of having an open bed. Otherwise, the patient continues to be treated and the LTCH will face a new discharge decision tomorrow. In deciding whether or not to discharge the patient, the hospital observes a vector of choice-specific idiosyncratic shocks $\varepsilon_t = (\varepsilon_{kt}, \varepsilon_{dt})$, the components of which relate to keeping or discharging the patient, respectively. The Bellman equation for the LTCH's dynamic problem is therefore

$$V_t(\varepsilon_t) = u_t + \max\{\varepsilon_{kt} + \delta EV_{t+1}, \varepsilon_{dt}\}, \tag{4}$$

where EV_{t+1} is the expected continuation value of having a patient at time $t+1$. Since the model is non-stationary, we assume that the time horizon is finite. Specifically, we define a parameter $\Lambda = EV_{T+1}$ that represents the termination value of treating a patient beyond day T (i.e., not discharging on day T) and estimate this value as a part of the model, allowing a distinct Λ for each DRG. We set $T \gg t_m$ and high enough relative to the average length of stay in the data so that the vast majority of patients are discharged prior to day T.

Following the literature on dynamic models, we assume that ε is distributed according to a Type-I extreme value distribution. Thus, the probability that the patient is discharged on day t (given no earlier discharge) is

$$D_t = \Pr(\text{discharge on t}|\text{no discharge } 1 \ldots t-1) = \frac{1}{1 + e^{EV_{t+1}}}. \tag{5}$$

Applying the inclusive sum formula for extreme value (Rust 1987), the expected value of a patient in day t before drawing ε_t is

$$EV_t = u_{t+1} + \log(\exp(EV_{t+1}) + 1).^{24} \tag{6}$$

The model can be solved via backward induction from the terminal period T given parameters $(\lambda_t, \alpha, \delta)$ and the payment policy p_t to recover continuation values and discharge probabilities

[24] Note that Euler's constant term in this formula is implicitly absorbed into λ_t without loss of generality.

for each day.

5.2 Estimation

We estimate the model using the nine most common DRGs in the data. Our estimation sample is summarized in Table 12 in Appendix A.

5.2.1 Payment Policies

The first step in our estimation is to recover the payment policy for each hospital-patient pair. We assume that hospitals form expectations about the monetary value of each additional day spent in the hospital based on Medicare's payment policy. Following (3), we assume that the payment policy reflects a per-diem payment for stays shorter than the SSO threshold and a single fixed payment for all stays that exceed the threshold.[25] Using data we have on total payments, length of stay, and hospital characteristics, we estimate the series of short-stay per-diem payments the hospital expects to receive, as well as the lump-sum payment received on the magic day.

We estimate the per-diem rate using a linear model that allows for a distinct rate for each hospital, year, and DRG. Specifically, we estimate the following equation on a sample restricted to include only observations with lengths of stay shorter than the SSO threshold:

$$r_{ihy} = \alpha_y(Z_i, X_h)d_{ihy} + \eta_{ihy}, \tag{7}$$

where r_{ihy} is the total payment for patient i at hospital h in year y. The length of stay is denoted by d_{ihy}, and η_{ihy} represents measurement error in payments and unanticipated shocks to total payments. The estimating sample includes only those observations where $d_{yhi} < t_y^m$, where t_y^m is the SSO threshold for year y (this will also vary with the specific DRG for patient i). The α parameter represents a per-diem payment for short stays — using the notation of (3), $p = \hat{\alpha}$ — and is allowed to vary by patient characteristics, Z_i, and hospital characteristics, X_h. Our

[25]Strictly speaking, a per-diem rate factors into payments for only a subset of short stays (see Section 2 as well as Appendix C). However, Figure 1 suggests that a daily per-diem rate does approximate the payment structure laid out by (3).

specification allows α to be a function of the year, patient DRG, hospital MSA, and hospital type, where the hospital type is the interaction of for-profit and HwH status. Explicitly, the functional form is

$$r_{ihy} = (\alpha^1_{y,DRG_i} + \alpha^2_{y,MSA} + \alpha^3_{y,type})d_{ihy} + \eta_{ihy}. \tag{8}$$

In choosing this form, we have tried to allow for a great deal of flexibility in estimating the payment policy. There is a distinct α^1 for each year from 2004-2013 and for each of the nine DRGs; this captures the differences in Medicare payments for different conditions over time. There is also a distinct α^2 for each year and MSA combination; this captures geographic and temporal differences in wages, a feature of Medicare's SSO payment policy. Finally, there is a distinct α^3 for each year and LTCH type;[26] this allows for the possibility that different types of hospitals have different cost-reporting policies or varying abilities to extract payments from Medicare. Per-diem payments for short stays (p) are then set equal to $\hat{\alpha}^1_{y,DRG_i} + \hat{\alpha}^2_{y,MSA} + \hat{\alpha}^3_{y,type}$ for each day up to the SSO threshold.

Our data contain 61,590 patients who were released prior to the SSO threshold. Specification (8) estimates 1,874 parameters, allowing us to flexibly estimate a payment rate for each observation based on patient and hospital characteristics. Including this level of heterogeneity allows us to explain a substantial portion of the variation in payments: the OLS model achieves an R^2 of 0.964 and an adjusted R^2 of 0.963. In panel (a) of Table 6, we report the mean, median, 25th and 75th percentiles of the distribution of the per-diem payment rates by hospital type. For-profit standalone LTCHs have, on average, per-diem rates that are \$89 lower than not-for-profit standalone LTCHs, whereas for-profit HwHs and for-profit standalone LTCHs have only a \$7 difference between them. The column of interquartile ranges in Table 6, however, shows considerable heterogeneity in the per-diem rates within hospital types. Much of this heterogeneity is explained by differences in per-diem payments across DRGs, as shown in Appendix Table 12.

The full PPS payment, P, is paid out on the magic day, which we are able to compute directly from the payment policy, as explained in Section 2 and Appendix C. The policy adjusts the full

[26] LTCH type refers to the interaction between for-profit status and HwH status. Thus, there are four types: for-profit and HwH, for-profit and standalone, not-for-profit and HwH and not-for-profit and standalone.

Table 6: Per-diem estimates (in $)

	Mean	**25th Percentile**	**Median**	**75th Percentile**
Panel A: Per-diem rate				
Overall	1,249	1,050	1,195	1,414
For-profit, HwH	1,235	1,005	1,179	1,480
For-profit, standalone	1,228	1,043	1,178	1,368
Not-for-profit, HwH	1,280	1,055	1,220	1,503
Not-for-profit, standalone	1,317	1,117	1,257	1,507
Select	1,250	1,024	1,206	1,482
Kindred	1,232	1,049	1,187	1,377
Other	1,257	1,058	1,198	1,405
Panel B: Full LTCH PPS payment				
Overall	44,626	30,938	35,155	61,702
For-profit, HwH	46,876	30,517	35,195	72,845
For-profit, standalone	43,817	31,318	35,208	43,111
Not-for-profit, HwH	44,177	33,746	33,746	68,396
Not-for-profit, standalone	45,256	30,853	35,302	63,558
Select	47,480	31,310	35,577	73,571
Kindred	46,358	33,097	36,889	59,953
Other	42,661	30,092	34,059	42,658
Panel C: Magic day payments				
Overall	16,308	8,742	12,450	22,710
For-profit, HwH	17,763	8,965	13,529	29,478
For-profit, standalone	16,351	9,209	12,630	20,749
Not-for-profit, HwH	14,437	7,018	11,352	23,111
Not-for-profit, standalone	15,536	7,918	11,127	24,193
Select	18,114	9,592	13,742	30,162
Kindred	18,448	10,666	14,591	25,715
Other	14,555	7,763	11,234	18,895
N = 377,513				

payment based on the patient's DRG and a wage index for the hospital's location (here, the CBSA). Thus, P is specific to each hospital, year, and DRG. The magic day payment is then the difference between P and the sum of the per-diem payments up to the day immediately preceding the magic day. Panel (B) of Table 6 contains descriptive statistics for these full payments, breaking them out by hospital types. The differences in full payments across hospital types primarily reflect differences in location (as wage indices vary by geography), weightings across years, and the case-mix of DRGs admitted to each hospital. Among not-for-profit hospitals, there is a difference in mean full PPS payments at HwH and standalone LTCHs of \$1,079. This is a relatively small difference compared to the \$3,059 difference between for-profit HwH and standalone LTCHs. Again, these differences stem from the varying geographic locations of hospitals, how many long-term stays each hospital has each year, and how the DRG case-mix varies across hospitals.

Table 12 illustrates how the DRG case-mix contributes to the variation in full payments. Full PPS payments range from an average of \$78,749 for DRG 207 to \$27,153 for DRG 949. An LTCH with more admissions for DRG 207 will thus have a higher mean full PPS payment. Table 12 also shows that there is some variation in DRG case-mix among LTCH types. For example, for-profit HwH LTCHs account for just 17 percent of total hospital stays but 23 percent of DRG 207 stays. By contrast, for-profit standalone LTCHs account for 57 percent of hospital stays but only 50 percent of DRG 207 stays.

Turning our attention back to Table 6, Panel (c) contains the resulting magic day payments. Recall that the the magic day payments are the difference between the full long-term PPS amount and the sum of per-diem payments in the days preceding the magic day. Magic day payments are the highest, on average, at for-profit HwH LTCHs. This is partly because these types of hospitals have more DRG 207 cases. Once again, there is substantial variation in magic day payments due largely to differences across DRGs. Among for-profit HwH LTCHs, the 25th percentile magic day payment is \$8,965, while the 75th percentile is \$29,478.

5.2.2 Parameterization

For our parameterization of λ_t, recall that these parameters represent the costs and non-pecuniary benefits of keeping a patient in the hospital on day t. As such, we allow them to be a function of the time spent in the hospital and, because they likely vary by diagnosis, we allow this function to be fully interacted with the patient's DRG. In addition, we include an estimate of hospital-year-specific average daily costs in order to capture heterogeneity across hospitals. Our estimate of average daily costs comes from estimating an equation analogous to (7), except the dependent variable is the product of claim-specific covered charges and hospital-specific cost-to-charge ratios. For average costs, however, we do not limit the sample to only those episodes of hospitalization that were shorter than the SSO threshold. Our cost estimates appear in Table 7.

Table 7: Average daily cost estimates (in $)

	Mean	**25th Percentile**	**Median**	**75th Percentile**
Overall	1,319	1,075	1,280	1,526
For-profit, HwH	1,266	1,003	1,237	1,501
For-profit, standalone	1,300	1,078	1,267	1,488
Not-for-profit, HwH	1,398	1,100	1,365	1,640
Not-for-profit, standalone	1,401	1,135	1,372	1,631
Select	1,279	1,028	1,267	1,497
Kindred	1,293	1,078	1,253	1,487
Other	1,348	1,089	1,301	1,558
N = 377,513				

In the data, we observe a weekly cycle in the probability of discharge. Specifically, discharges drop off precipitously on Saturdays and Sundays. We build this into the model by including a series of dummy variables for each day of the week.

We also include patient characteristics, Z_i. These are important for two reasons. First, factors such as age and race relate to health and recovery times, and thus impact the costs and benefits of keeping a patient in the hospital. Second, we want to allow for the possibility that strategic discharge practices vary based on patient characteristics. As a measure of this, we interact patient characteristics with an indicator variable for whether the patient is before of after the SSO threshold for her stay. Looking at how the hazard rate for different types of patients varies before and after this threshold will shed light on additional factors driving strategic discharges.

Our final specification of λ_t takes the form

$$\lambda_{i,t} = \gamma_{0,DRG}+\gamma_{1,DRG}t+\gamma_{2,DRG}t^2+\beta\hat{c}_h+\psi_{\text{day of week}}+\phi_0 Z_i*\mathbf{1}_{\text{before threshold}}+\phi_1 Z_i*\mathbf{1}_{\text{after threshold}}. \quad (9)$$

5.2.3 Likelihood

We use the dynamic model to estimate $\theta = \{\lambda, \beta, \alpha\}$.[27] We observe each patient's day of discharge and have the payment plan associated with each patient, p_{hi}, estimated from the previous section. As LTCHs behave optimally according to (5), each patient's contribution to the model likelihood is denoted

$$\Pr(d_{hi}|p_{hi}, \theta) = D_t(p_{hi}; \theta) \prod_{\tau=1}^{d_{hi}-1} (1 - D_\tau(p_{hi}; \theta)) \ , \quad (10)$$

where $D_t(p_{hi}; \theta)$ is the probability of a patient being discharged on day t given that she has not been discharged prior to t, as defined in (5). Given that optimal decisions are independent across patients, the likelihood function is

$$L(\theta) = \prod_{i=1}^{N} \Pr(d_{hi}|p_{hi}, \theta).$$

6 Estimation Results and Counterfactual Policy Analysis

We begin this section by presenting the estimates of the model outlined above. We then use our model to explore alternative payment policies and their effects on discharges and Medicare expenditures.

[27] Given that the time periods are days and we have a finite horizon, we set the discount factor to $\delta = 1$. An annual discount rate of 0.95 is equivalent to a daily discount rate of 0.99986.

6.1 Estimation Results

Table 8 presents estimation results for a number of specifications of the model that differ based on the form of λ in equation (9). The model fits the observed discharge patterns quite closely (see Figure 11 in Appendix E). By allowing different types of hospitals to respond differently to the financial incentives of keeping patients until the magic day, as shown in all three columns, we see that all four types of hospitals respond to the prospect of higher payments by keeping patients longer. However, we see differences in the sensitivity of each hospital type to financial incentives, with for-profit HwHs being the most sensitive and not-for-profit standalones being the least sensitive. The differences between every possible pair of α coefficients is statistically significant at the 1 percent level, and the magnitudes suggest the differences are economically important as well. The α coefficient of for-profit HwHs is as much as 58 percent larger than the coefficient of the not-for-profit standalone LTCHs, depending only slightly on the specification. A similar ranking is apparent in the β coefficients, which describe sensitivity to costs.[28]

Column (2) displays the estimates for a specification that includes race and age in the functional form of λ. These results suggest that black patients are more likely to be retained in the hospital on any given day, and thus tend to have longer hospital stays. Young patients, on the other hand, tend to have shorter hospital stays. In column (3), we interact these characteristics with an indicator for before or after the SSO threshold. These results show that before the magic day, black patients have a lower likelihood of being discharged than non-black patients. After the magic day, however, black patients are more likely to be discharged on any given day. Model simulations show that black patients are 3 percent more likely to remain hospitalized until the magic day. Among patients who make it to the magic day, 77 percent of black patients are discharged within two weeks following the magic day compared to only 66 percent of non-black patients.

[28]However, as noted previously, we are cautious in our exact interpretations of these β coefficients.

Table 8: Model Estimates

For-profit		(1)	(2)	(3)
α's*				
	For-profit, HwH	0.876***	0.902***	0.889***
		(0.012)	(0.013)	(0.013)
	For-profit, standalone	0.761***	0.769***	0.775***
		(0.006)	(0.007)	(0.007)
	Not-for-profit, HwH	0.667***	0.682***	0.662***
		(0.016)	(0.018)	(0.018)
	Not-for-profit, standalone	0.561***	0.578***	0.563***
		(0.011)	(0.012)	(0.012)
β's*				
	For-profit, HwH	0.248***	0.215***	0.222***
		(0.004)	(0.004)	(0.004)
	For-profit, standalone	0.108***	0.069***	0.075***
		(0.002)	(0.002)	(0.002)
	Not-for-profit, HwH	0.094***	0.070***	0.074***
		(0.006)	(0.006)	(0.006)
	Not-for-profit, standalone	-0.039***	-0.068***	-0.062***
		(0.004)	(0.005)	(0.005)
Patient Characteristics				
	Black		0.012***	
			(0.00050)	
	Under 65 years old		-0.010***	
			(0.0004)	
Patient Characteristics, before and after the SSO threshold				
	Black, Before SSO threshold			0.124***
				(0.002)
	Black, After SSO threshold			-0.003***
				(0.001)
	Under 65, Before SSO threshold			-0.051***
				(0.001)
	Under 65, After SSO threshold			0.000
				(0.001)
Day of week dummies			X	X
DRG specific λ		X	X	X
DRG specific Ω		X	X	X
N = 377,513				

*Coefficients for α and β were multiplied by 10,000 for readability.

6.2 Simulating Alternative Reimbursement Schemes

Our model shows how LTCHs respond to financial incentives, which permits us to simulate how their discharge practices would change under different conditions. Figure 8 compares simulated discharge practices from the baseline model with simulated discharge practices of three alternative payment policies, while Table 9 contains key comparisons between the baseline and counterfactual outcomes.

We begin by investigating how discharge patterns would change if LTCHs did not consider Medicare payments — that is, if α were 0. In this scenario, the only drivers of discharge decisions are the non-pecuniary benefits and costs of keeping a patient in the hospital for another night. Panel (a) of Figure 8 shows the predicted distribution of discharges (dashed line) for the nine DRGs pooled together, based on the estimates in column (3) of Table 8, while panel (b) shows the predicted discharges for just DRG 207. In each of these figures, the horizontal axis has been renormalized to display the day of discharge relative to the magic day, which varies over time.

Clearly, without the lump-sum payment that awaits LTCHs if they hold patients until the magic day, patients are discharged much earlier. On average, the estimates in column (3) of Table 8 predict discharges will occur 3.2 days after the magic day. In the counterfactual scenario, by contrast, the mean discharge day falls to 3.1 days before the magic day. That is, on average patients are discharged nearly a week earlier than under the current PPS. In addition to length of stay, from a budgetary prospective we want to examine the share of patients retained long enough to secure a magic day payment. In the baseline model, 78 percent of patients are held at least until the magic day; in the counterfactual, this share drops to 39 percent. Although this difference is striking, we are particularly interested in the action centered around the magic day where the day-to-day payment differences are the largest. Focusing just on patients still in the hospital at least three day prior to the magic day, 88 percent remained in the hospital long enough for the hospital to collect the magic day payment in the baseline model, whereas only 69 percent of these patients remained in the hospital through the magic day in the counterfactual. This indicates much higher discharge probabilities in the counterfactual for the days immediately preceeding the magic day.

On average, these shorter hospital stays yield considerable savings for Medicare. Using a simple calculation based on the average payment of $1,249 per patient per day, Medicare would save $7,868.70 per patient.[29] During our sample when 377,513 patients with one of the nine DRGs were admitted to LTCHs and discharged to home or a nursing facility, the aggregate savings would have been $2.97 billion. This understates the full savings to Medicare, however, since it abstracts from the lump-sum magic day payment. Leaving the Medicare PPS policy intact but removing the response of LTCHs to economic incentives decreases the average total Medicare payments per hospital stay by $13,610. This is a 25 percent decrease in payments. Applied to our sample, this suggests aggregate potential savings of $5.14 billion over 2004-2013.

We base our second counterfactual on a new LTCH reimbursement formula that was recently proposed to stem strategic discharges.[30] The proposal consists of a per-diem payment rate based on the full LTCH payment divided by the geometric mean LOS, and so we refer to this scheme as the "per-diem counterfactual." Medicare would pay twice the per-diem rate on the first day, and then a per-diem rate on each day thereafter until reaching the full LTCH payment on the day preceding the mean LOS. As a result, the reimbursement policy is completely linear until the mean LOS is realized, at which point the reimbursement ceases. This payment scheme is illustrated in panel (a) of Figure 12 in Appendix E. For patients close to the magic day, this should dampen the incentive to keep them in the hospital solely to reach the SSO threshold. Often, however, the new per-diem rates will be higher than the old rates, which may prompt LTCHs to keep patients longer than they would have under the old system at all length of stays. We use our model estimates to simulate and measure how much this new payment schedule would alter discharge patterns.

Panels (c) and (d) of Figure 8 show the predicted probability of discharge on a given day under this counterfactual compared to the baseline model. One immediate observation is how closely

[29] The $1,249 figure is our estimate of the average per-diem payment from Medicare to LTCHs and 6.3 is the (rounded) average reduction in the number of days spent in the hospital, leading to a total savings of $\$1,249 * 6.3 = \$7868.7$. Note that this calculation assumes Medicare is making a per-diem payment every day. It does not incorporate the magic day lump sum or the post-magic day zero payments. It also does not weight the different DRGs that all have different per diems and different changes in the length of stay (between the baseline and the counterfactual).

[30] See Medicare Payment Advisory Commission (2014), chapter 11.

this counterfactual follows the counterfactual just discussed, where hospitals do not respond to financial incentives. These two lines have similar contours but the per-diem counterfactual is shifted later relative to the cost-minimization counterfactual. This comparison suggests that, although both counterfactuals effectively remove the incentives associated with the magic day payment, the per-diem counterfactual does in fact increase the incentive to hold patients longer on any given day of a hospital stay.

Compared to the baseline model, the per-diem counterfactual has a 1.1-day shorter mean length of stay for the nine pooled DRGs, a meager 3 percent decrease. Highlighting the policy's impact on strategic discharge behavior, patients that are still in the hospital three days before the magic day are now 9 percent less likely to remain there until the magic day than in the baseline model, and 22 percent less likely to be discharged in the three days after the magic day.

While shorter stays yield savings, the increased per-diem rate partially offsets them. On average, the per-diem payment scheme saves about \$550 per hospital stay compared to the current policy, which would amount to an aggregate savings of \$207.6 million across our sample. Our estimate is the first we are aware of in the literature that quantifies the effects of MedPAC's proposed policy change.

Finally, panels (e) and (f) of Figure 8 show the simulated discharge probabilities for a payment system based on reported costs. In this counterfactual, we construct a set of alternative payments equal to each patient's estimated daily cost plus five percent and refer to it as the "cost-plus" counterfactual, as illustrated in panel (b) of Figure 12 in Appendix E. This counterfactual has an average length of stay 5.4 days past the magic day, somewhat longer than the baseline model.

Overall, the cost-plus counterfactual shows 78 percent of patients being held past the magic day, which is the same as the baseline model. Focusing only on patients remaining in the hospital until at least three days prior to the magic day, however, yields an important insight. Of these patients, the same portion are held until the magic day as in the baseline model (88 percent), although many fewer are discharged during the three days following the magic day (14 percent instead of 32 percent). This suggests that discharge practices are similar in the baseline and the cost-plus counterfactual immediately preceding the magic day. After the magic day, however, LTCHs in the baseline discharges patients much sooner than do LTCHs in this counterfactual.

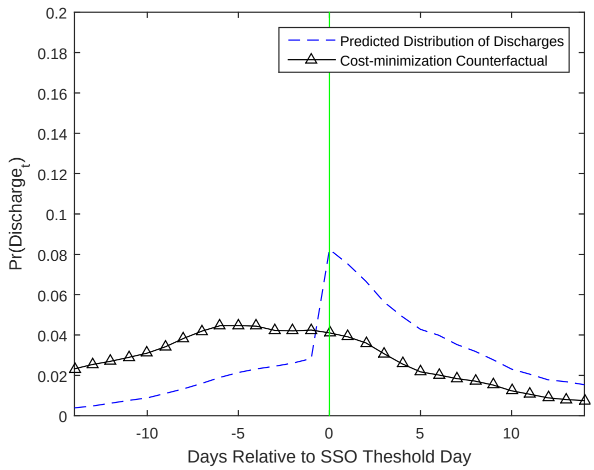
Table 9: Counterfactual Outcomes

	Baseline model	Counterfactual 1: $\alpha = 0$	Counterfactual 2: Per-diem payments	Counterfactual 3: Cost-plus payments
Share of patients discharged before magic day	0.22	0.61	0.33	0.22
Share of patients discharged after magic day	0.78	0.39	0.67	0.78
Share of patients with longer stay compared to baseline		0.00	0.04	0.40
Share of patients with shorter stay compared to baseline		0.44	0.12	0.05
Mean day of discharge relative to magic day	3.22	-3.13	2.14	5.42
St. dev. day of discharge	7.42	9.16	7.83	9.90
Mean percent change in LOS relative to baseline		-22	-3	24
Of patients in the hospital 3 days prior to the magic day:				
Percent held until the magic day	88	69	80	88
Percent discharged within 3 days after the magic day	32	26	25	14
Mean payments ($1000s)	40.25	26.64	39.70	45.10
St. dev. payments	22.17	15.71	20.28	23.28
Percent change in payments relative to baseline		-25	-4	26
Mean Costs ($1000)	36.79	26.52	35.24	42.93
St. dev. payments	19.22	15.27	19.03	22.19
Percent change in costs relative to baseline		-22	-3	23

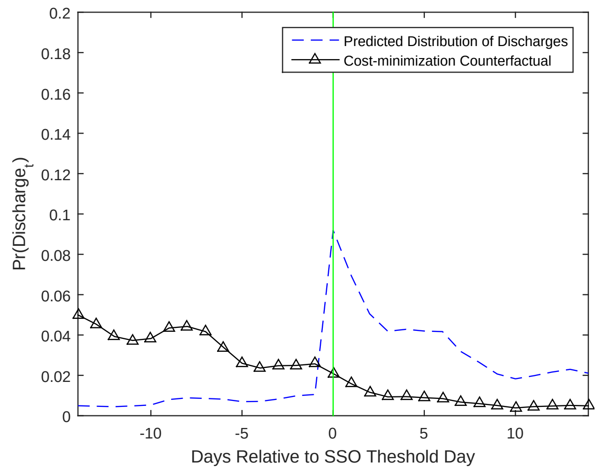
Note: Baseline model and counterfactuals based on simulations with 100,000 patient draws.

7 Conclusion

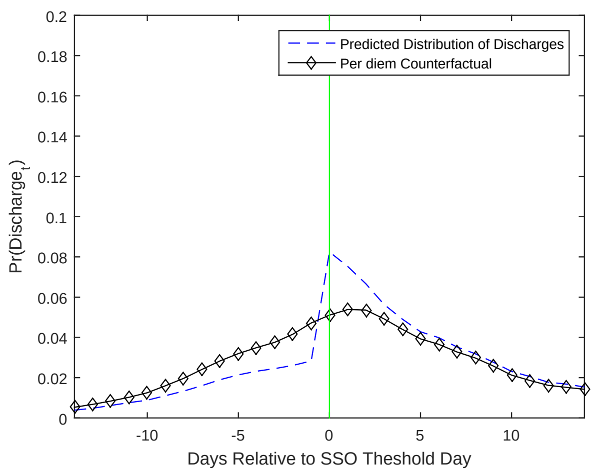
Our paper shows that Medicare's prospective payment system for long-term care hospitals influences hospitals' discharge decisions. Because the current reimbursement formula provides a large jump in payments for patients who stay past a certain threshold, LTCHs respond to these financial incentives by keeping patients until right after they reach this point. Our findings sug-



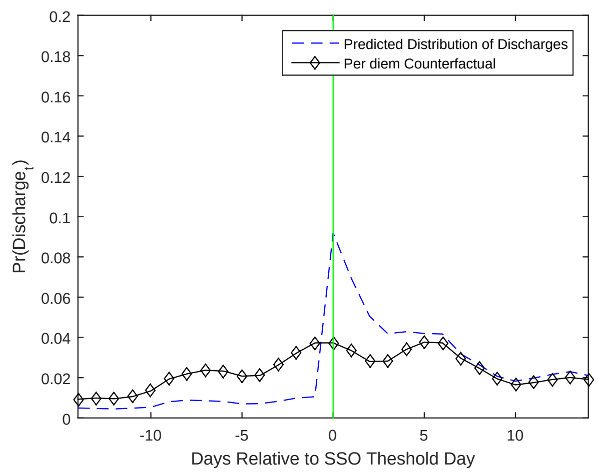
(a) Cost minimization counterfactual, all DRGs



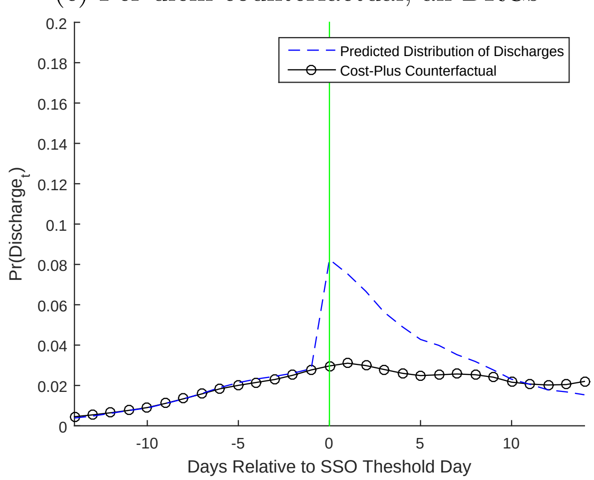
(b) Cost minimization counterfactual, DRG 207



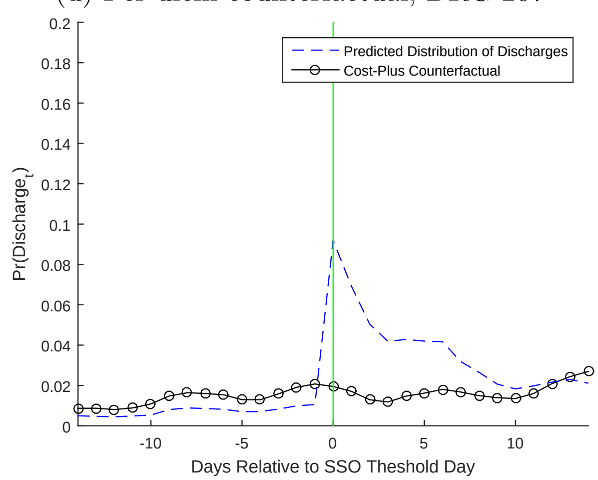
(c) Per-diem counterfactual, all DRGs



(d) Per-diem counterfactual, DRG 207



(e) Cost-plus counterfactual, all DRGs



(f) Cost-plus counterfactual, DRG 207

Figure 8: Predicted discharge probabilities for counterfactuals

gest that LTCHs keep patients too long as a result of this payment scheme, resulting in needless costs for Medicare and an untold burden for patients.

Our descriptive evidence documents strategic discharging by LTCHs. For the most common DRG, a patient's probability of being discharged increases approximately eightfold as she moves to the magic day from the day right before it. We can cleanly identify this as deliberate manipulation by LTCHs — rather than coincidental timing — by exploiting changes in the SSO thresholds within a DRG over time along with differences in thresholds across DRGs. Moreover, in the year before Medicare changed its LTCH PPS to include the large lump-sum payments, no spike in discharges occurred.

We also consider several nuances of the LTCH market. Consistent with reports from industry insiders, we find that for-profit LTCHs are much more likely to discharge patients just after they cross the SSO threshold. The two largest chains, Select and Kindred, also appear to transfer their corporate strategy of manipulating discharges to the LTCHs they acquire. We further find that LTCHs co-located with general acute-care hospitals are more likely to strategically discharge patients, perhaps because they face fewer barriers for transferring patients across floors in order to maximize Medicare payments.

Our dynamic structural model of LTCHs' discharge behavior allows us to evaluate recently proposed changes to MedPAC's reimbursement formula that would reduce the payment penalty for patients discharged before reaching the SSO threshold. We show that removing the sharp jump in payments associated with the SSO threshold would save over $200 million each year for the nine most common DRGs as LTCHs respond to the new policy by discharging patients sooner.

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A Complete Summary Statistics

Table 10: Summary Statistics for All Patients (2004-2013)

Variable	Mean	Std. Dev.
Length of Stay	28.766	41.844
Released on or after magic day	0.681	0.466
Total Payment ($)	31,933.43	24,332.54
Amount Paid by Medicare ($)	31,814.61	26,883.69
Estimated Costs ($)	37,578.69	37,022.04
Portion Discharged Alive	0.861	0.346
Portion Discharged Dead	0.139	0.346
Portion Discharged to Home Care	0.34	0.474
Portion Discharged to Hospital	0.123	0.329
Portion Discharged to Nursing Facility	0.391	0.488
Admission Type: Emergency	0.011	0.104
Admission Type: Urgent	0.198	0.398
Admission Type: Elective	0.785	0.411
Admission Type: Other	0.006	0.079
Admission Source: Community	0.186	0.389
Admission Source: Nursing Facility	0.025	0.155
Admission Source: General Hospital	0.777	0.416
Admission Source: Other Source	0.007	0.085
Male	0.484	0.5
White	0.729	0.445
Black	0.202	0.401
Asian	0.012	0.111
Hispanic	0.033	0.18
Age less than 25	0.001	0.038
Ave between 25 and 44	0.039	0.193
Age between 45 and 64	0.191	0.393
Age between 65 and 74	0.305	0.46
Age between 75 and 84	0.301	0.459
Age over 85	0.164	0.37
$N = 1,452,287$		

Table 11: Summary Statistics for DRG 207 Patients (2004-2013)

Variable	Mean	Std. Dev.
Length of Stay	38.06	40.24
Released on or after magic day	0.672	0.47
Total Payment ($)	57,609.66	33,061.67
Amount Paid by Medicare ($)	57,536.17	37,143.23
Estimated Costs ($)	67,061.07	51,780.64
Portion Discharged Alive	0.736	0.441
Portion Discharged Dead	0.264	0.441
Portion Discharged to Home Care	0.132	0.338
Portion Discharged to Hospital	0.166	0.372
Portion Discharged to Nursing Facility	0.437	0.496
Admission Type: Emergency	0.011	0.105
Admission Type: Urgent	0.202	0.402
Admission Type: Elective	0.781	0.414
Admission Type: Other	0.006	0.076
Admission Source: Community	0.122	0.327
Admission Source: Nursing Facility	0.013	0.115
Admission Source: General Hospital	0.857	0.35
Admission Source: Other Source	0.003	0.054
Male	0.502	0.5
White	0.745	0.436
Black	0.192	0.394
Asian	0.015	0.122
Hispanic	0.024	0.154
Age less than 25	0.002	0.04
Ave between 25 and 44	0.03	0.17
Age between 45 and 64	0.187	0.39
Age between 65 and 74	0.355	0.478
Age between 75 and 84	0.32	0.466
Age over 85	0.107	0.309
$N = 170,365$		

Table 12: Summary Statistics for Nine Most Common DRGs

	DRG									
	177	189	190	193	207	539	592	871	949	Pooled
Mean length of stay	25.3	26.4	21.0	22.3	42.4	33.2	30.4	26.0	24.2	30.0
Standard deviation	(12.6)	(20.2)	(10.0)	(12.2)	(24.1)	(15.0)	(16.6)	(14.1)	(18.1)	(19.6)
Payment and Cost Estimates (in $)										
Mean daily payments	1,186	1,245	1,139	1,124	1,639	1,013	974	1,100	981	1,249
Mean full payments	33,466	39,929	27,289	28,401	7,8749	36,334	33,594	33,307	27,153	44,626
Mean magic day payments	9,116	1,3264	8,087	7,846	33,562	8,857	11,765	12,356	9,488	16,308
Mean daily cost est.	1,267	1,341	1,191	1,184	1,689	1,081	1,026	1,179	1,098	1,319
Discharge Type										
Discharged alive	0.84	0.83	0.89	0.85	0.73	0.94	0.87	0.83	0.95	0.82
Discharged to home	0.29	0.29	0.54	0.39	0.13	0.41	0.30	0.28	0.41	0.28
Discharged to hospital	0.09	0.11	0.08	0.09	0.16	0.13	0.12	0.10	0.14	0.12
Discharged to nursing facility	0.46	0.42	0.26	0.37	0.44	0.39	0.44	0.44	0.39	0.40
LTCH Type										
For-profit, HwH	0.14	0.17	0.14	0.12	0.23	0.17	0.18	0.13	0.17	0.17
For-profit, standalone	0.61	0.56	0.57	0.63	0.50	0.54	0.58	0.67	0.56	0.57
Not-for-profit, HwH	0.07	0.08	0.05	0.06	0.09	0.10	0.07	0.06	0.03	0.07
Not-for-profit, standalone	0.17	0.18	0.23	0.18	0.18	0.18	0.18	0.16	0.14	0.24
Number of obs.[1]	38,318	71,563	28,139	26,492	90,755	18,923	36,669	50,494	16,160	377,513

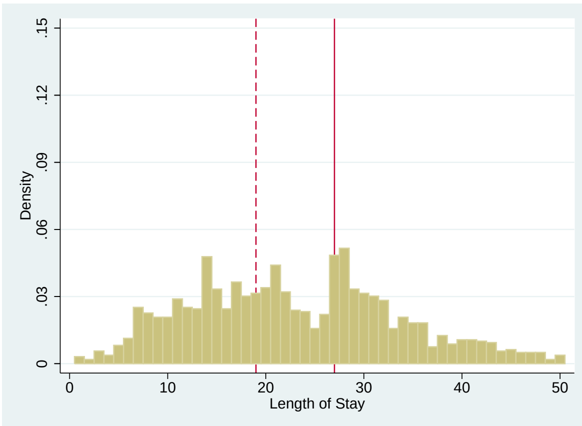
[1] This count includes hospital stays that result in a discharge to home care or a nursing facility. This is the sample we use to estimate the model in Section 5. See Table 13 for the descriptions on these DRGs.

B Other DRGs

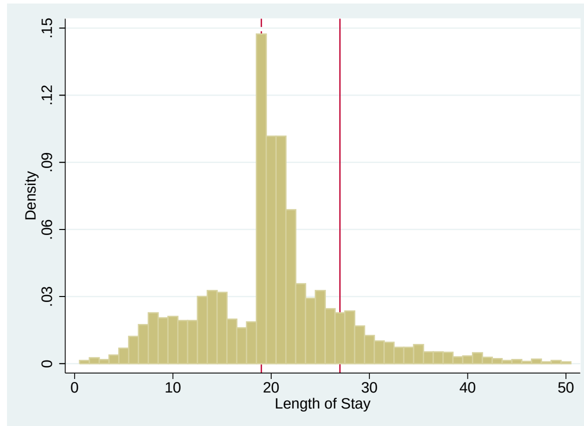
While our paper at times focuses on DRG 207, in this appendix we extend the analysis to other DRGs, summarized above in Appendix A. Our structural estimation uses the nine most common DRGs in order to increase the variation in magic days in the data. Table 13 describes each of these DRGs. Figure 9 plots discharge patterns for the next three most common DRGs after DRG 207 in 2004 and 2013, along with their respective SSO thresholds. Figure 10 plots realized Medicare payments and discharge patterns that suggest other DRGs have similar discharge practices.

Table 13: DRG Descriptions

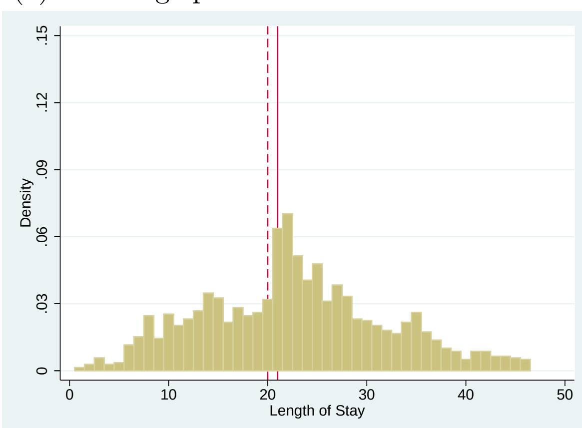
DRG	Description
177	Respiratory infections and inflammations with major complicating conditions
189	Pulmonary edema and respiratory failure
190	Chronic obstructive pulmonary disease with major complicating conditions
193	Simple pneumonia and pleurisy with major complicating conditions
207	Respiratory system diagnosis with ventilator support of over 96 hours
539	Osteomyelitis with major complicating conditions
592	Skin ulcers
871	Septicemia without mechanical ventilation of over 96 hours with major complicating conditions
949	Aftercare with complication conditions or major complicating conditions



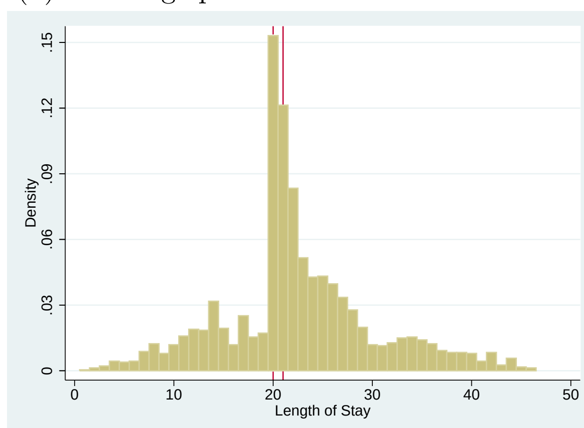
(a) Discharge practices for DRG 189 in 2004



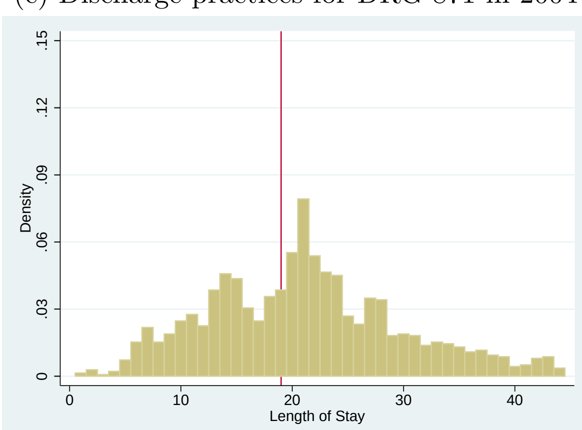
(b) Discharge practices for DRG 189 in 2013



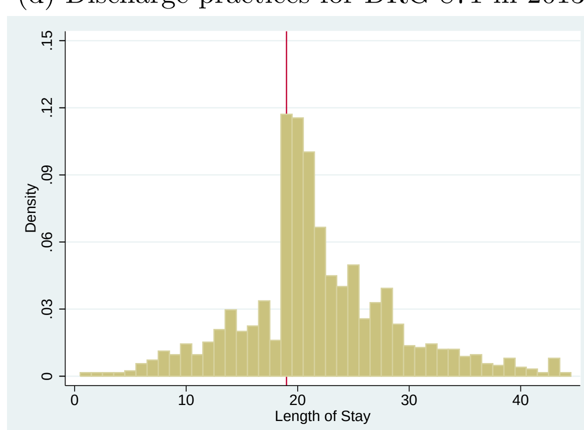
(c) Discharge practices for DRG 871 in 2004



(d) Discharge practices for DRG 871 in 2013

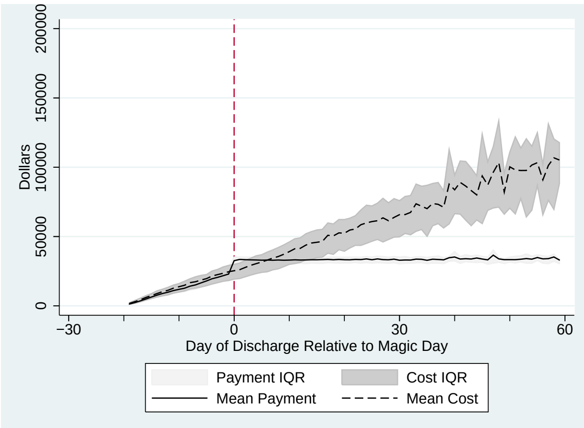


(e) Discharge practices for DRG 177 in 2004

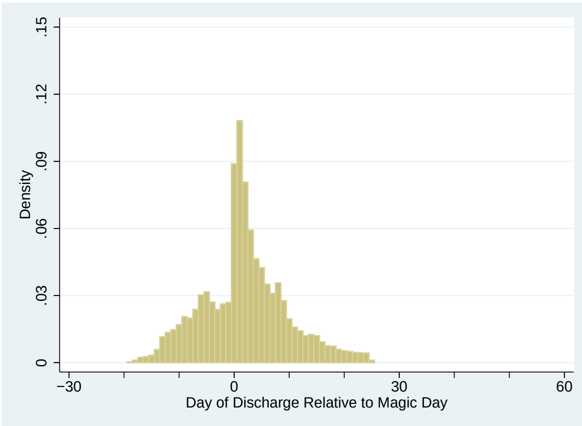


(f) Discharge practices for DRG 177 in 2013

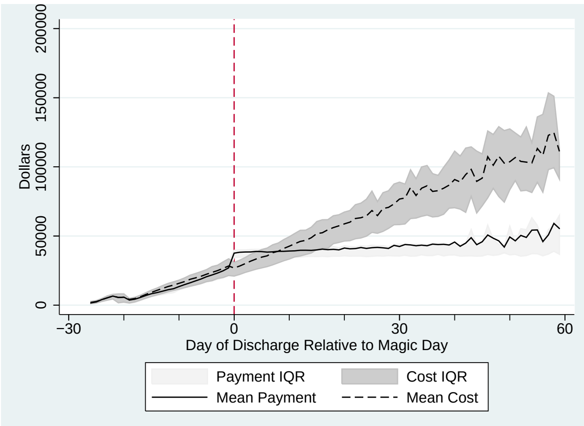
Figure 9: Discharge timing across DRGs and years



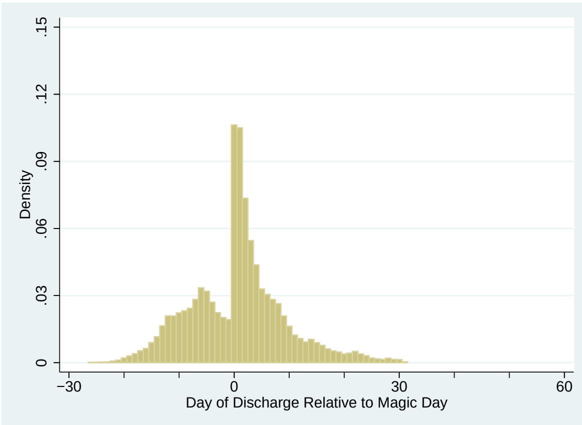
(a) Payoffs and Costs for DRG 177



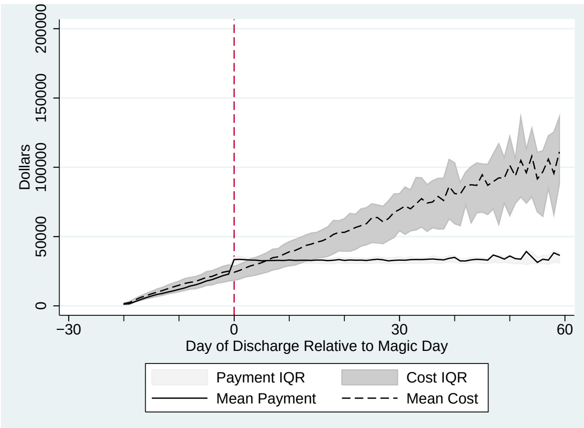
(b) Lengths of stay for DRG 177



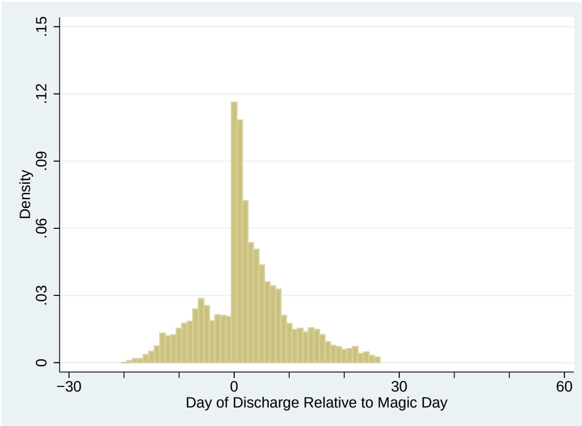
(c) Payoffs and Costs for DRG 189



(d) Lengths of stay for DRG 189



(e) Payoffs and Costs for DRG 871



(f) Lengths of stay for DRG 871

Figure 10: Costs, payoffs and discharge patterns for other DRGs

C Payment Example

Full MS-LTC-DRG payment

Example of Full LTCH-PPS Payment in 2010, DRG 207	
LTCH Base Rate	\$39,794.95
Labor-related portion of base rate	\$39,794.95 × 0.75779 = \$30,156.22
Non-labor related portion of base rate	\$39,794.95 × 0.24221 = \$9,638.73
Labor-related portion adjusted for wage index (CBSA 16974)	\$30,156.22 × 1.0471 = \$31,576.57
Wage-adjusted LTCH Base Rate	\$41,215.31
MS-LTC-DRG 207 Relative Weight	2.0288
Total Adjusted Federal Prospective Payment	\$41,215.31 × 2.0288 = \$83,617.62

For more examples of computing full LTCH-PPS payments, see CMS document: `https://www.cms.gov/Medicare/Medicare-Fee-for-Service-Payment/LongTermCareHospitalPPS/Downloads/LTCH_sso_ex_2007and2008.zip`.

100 percent of cost of case

$$\text{cost of case} \quad = \quad \text{(covered charges)} \times \text{(cost-to-charge ratio)}$$

The hospital-specific cost-to-charge ratio is just what it sounds like. It is calculated for each hospital using cost data from the most recent cost report submitted from that hospital. Hospital CCR has two parts: operative CCR (total Medicare operating costs / total Medicare operating charges) and capital CCR (total Medicare capital costs / total Medicare capital charges). The CCR for each year is published in the LTCH Impact Files in August before the year begins and is based on most recent historical Medicare cost reports which are required on an annual basis.

$$\$45,501.00 \times 0.311 = \$14,150.81 = \text{Estimated Cost}$$

*Assumes covered charges = \$45,501.00 and hospital CCR = 0.311.

120 percent of per-diem amount

*LTC-DRG average length of stay: 26.6 days. This case assumes an 8 day length of stay.

$$\begin{aligned}
\text{MS-LTC-DRG per diem} &= \text{Full LTC-DRG Payment / Average Length of Stay of the LTC-DRG} \\
&= \$45,060.70/26.6 \text{ days} \\
&= \$1,698.34 \text{ per day} \\
\text{120 percent of per-diem amount} &= \$1,698.34 \times 8 \text{ days} \times 1.2 \\
&= \$16,304.06
\end{aligned}$$

Blend Alternative

Computing the IPPS payment is considerably more involved, so for this example we simply assume it is \$24,442.17. The portion coming from the 120 percent of LTCH per diem is: $\frac{\text{length of stay}}{\text{SSO threshold}} = \frac{8}{22.2} = 0.36$. The rest comes from the inpatient comparable per-diem amount that, after a complex series of calculations, is \$24,442.17. The blended amount is then:

$$0.36 \times \$16,304.06 + 0.64 \times \$24442.17 = \$21,512.45$$

Since the "100 percent of cost" amount is the least, the law indicates that it is the will be paid out.

D Probit Model: Coefficient Estimates and other DRGs

Table 14 contains the estimated coefficients from the probit model for DRG 207. Table 15 presents the estimated marginal effects of the baseline probit model for other DRGs. Table 16 shows (a sample of) the estimated probit coefficients for the interacted models for DRG 207.

Table 14: Probit Estimates for DRG 207

	Coefficients	Std. Err.
Days relative to magic day (λs)		
-14	0	(Omitted group)
-13	-0.021	(0.022)
-12	0.068**	(0.026)
-11	0.103***	(0.029)
-10	0.193***	(0.032)
-9	0.333***	(0.036)
-8	0.446***	(0.041)
-7	0.497***	(0.046)
-6	0.482***	(0.051)
-5	0.486***	(0.053)
-4	0.514***	(0.062)
-3	0.522***	(0.066)
-2	0.568***	(0.070)
-1	0.665***	(0.075)
0	1.601***	(0.080)
1	1.470***	(0.087)
2	1.414***	(0.089)
3	1.413***	(0.094)
4	1.430***	(0.099)
5	1.566***	(0.104)
6	1.659***	(0.105)
7	1.608***	(0.109)
8	1.538***	(0.113)
9	1.495***	(0.117)
10	1.496***	(0.121)
11	1.518***	(0.125)
12	1.596***	(0.129)
13	1.693***	(0.132)
14	1.646***	(0.135)
Underlying Hazard Rate		
t	-0.048***	(0.009)
t^2	0.0004***	(0.0001)
Constant	-1.893***	(0.107)

Table 15: Marginal Effects on Probability of Discharge
Other DRGs

Day of stay (t)	Probability of Discharge on Magic Day[1]	Probability of Discharge on Day Preceding Magic Day[2]	Hazard Ratio[3]
		DRG 189	
19	11.02***	1.73***	6.39***
	(0.358)	(0.074)	[204.9]
20	11.40***	1.81***	6.29***
	(0.353)	(0.080)	[203.3]
21	11.77***	1.90***	6.20***
	(0.352)	(0.086)	[201.3]
22	12.11***	1.98***	6.12***
	(0.354)	(0.093)	[199.0]
23	12.23***	2.06***	6.05***
	(0.358)	(0.101)	[196.5]
24	12.72***	2.13***	5.98***
	(0.364)	(0.109)	[193.8]
25	12.99***	2.19***	5.92***
	(0.372)	(0.117)	[191.0]
26	13.23***	2.25***	5.87***
	(0.382)	(0.125)	[188.0]
27	13.43***	2.30***	5.83***
	(0.393)	(0.134)	[184.9]
		DRG 871	
19	11.80***	1.72***	6.87***
	(0.716)	(0.088)	[115.7]
20	13.02***	1.99***	6.55***
	(0.619)	(0.119)	[103.7]
21	14.22***	2.27***	6.27***
	(0.629)	(0.183)	[91.43]
		DRG 177	
19	9.56***	2.54***	3.77***
	(0.499)	(0.120)	[86.05]
20	10.22***	2.77***	3.69***
	(0.567)	(0.139)	[91.55]

Note: Standard errors in parentheses. P-values in brackets. This sample contains only episodes of hospitalization that terminated in discharge to home care or nursing facilities.

[1] $\Phi(\gamma_0 + \gamma_1 t + \gamma_2 t^2 + \lambda_0) * 100$

[2] $\Phi(\gamma_0 + \gamma_1 t + \gamma_2 t^2 + \lambda_{-1}) * 100$

[3] Hazard ratio: $\frac{\Phi(\gamma_0+\gamma_1 t+\gamma_2 t^2+\lambda_0)}{\Phi(\gamma_0+\gamma_1 t+\gamma_2 t^2+\lambda_{-1})}$. Square brackets contain the p-value from a Wald test for $H_0 : HR = \frac{\Phi(\gamma_0+\gamma_1 t+\gamma_2 t^2+\lambda_0)}{\Phi(\gamma_0+\gamma_1 t+\gamma_2 t^2+\lambda_{-1})} = 1$.

Table 16: Selected Probit Coefficients by Subgroup, DRG 207 at $day = 29$

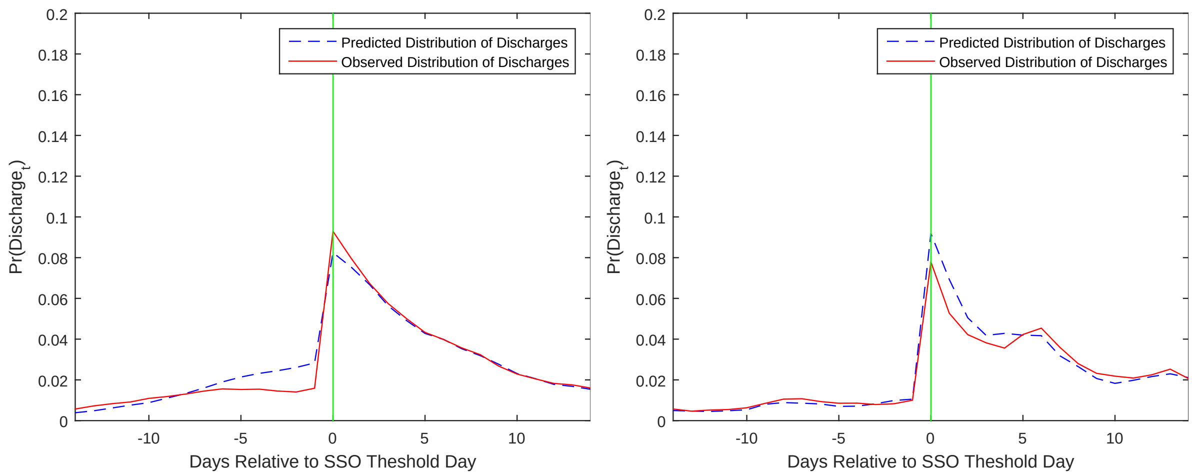
Model #/Partition	SSO Threshold Day	Preceding Day
Model #1:		
For-profit	2.96***	1.95***
	(0.332)	(0.333)
Not for profit	2.85***	2.12***
	(0.340)	(0.332)
Model #2:		
Kindred and Select	3.09***	2.05***
	(0.322)	(0.324)
Other	2.99***	2.17***
	(0.328)	(0.322)
Model #3:		
After Acquisition	3.27***	2.02***
	(0.247)	(0.245)
Before Acquisition	3.21***	2.32***
	(0.254)	(0.249)
Never Acquired	3.13***	2.22***
	(0.246)	(0.242)
Model #4:		
HwH	2.36***	3.41***
	(0.284)	(0.284)
Not HwH	2.31***	3.19***
	(0.282)	(0.287)

Note: Standard errors in parentheses.

E Additional Figures Relating to Counterfactual Analysis

Figure 11 displays the observed (solid line) discharge probabilities over time and the predicted (dashed line) discharge probabilities corresponding to the estimates in column (1) of Table 8, where the horizontal axis in these figures is the number of days relative to the magic day (vertical line).[31] Panel (a) compares the predicted and observed discharge distributions for the entire sample of pooled DRGs while panel (b) focuses on just DRG 207.

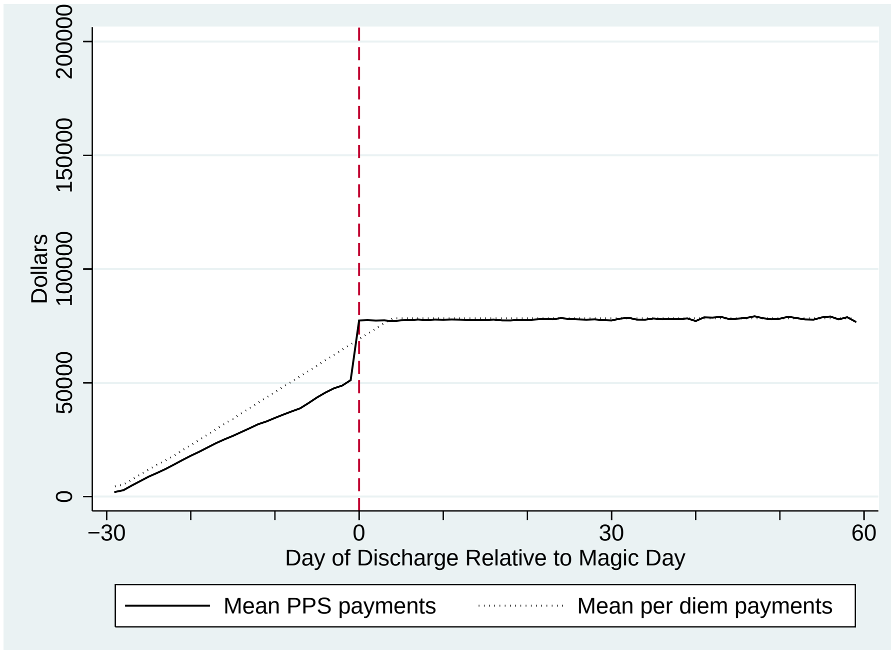
Figure 11: Observed and predicted discharge probabilities



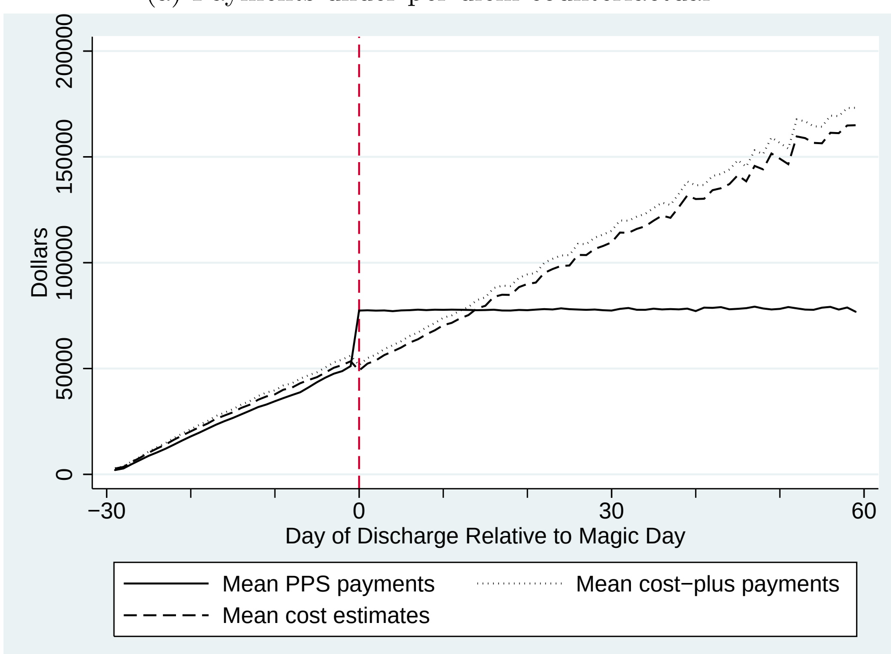
(a) Pooled DRGs (b) DRG 207

Figure 12 compares the reimbursement schemes we consider in the counterfactual analysis to the current PPS.

[31]The predicted discharge probabilities are computed by simulating the model 100,000 times.



(a) Payments under per-diem counterfactual



(b) Payments under cost-plus counterfactual

Figure 12: Counterfactual Reimbursement Policies for DRG 207.