Strategic Patient Discharge: The Case of Long-Term Care Hospitals*

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Abstract

Medicare's prospective payment system for long-term acute-care hospitals (LTCHs) provides modest reimbursements at the beginning of a patient's stay before jumping discontinuously to a large lump-sum payment after a pre-specified number of days. We show that LTCHs respond to the financial incentives of this system by disproportionately discharging patients after they cross the large-payment threshold. We find this occurs more often at for-profit facilities, facilities acquired by leading LTCH chains, and facilities co-located with other hospitals. Using a dynamic structural model, we evaluate counterfactual payment policies that would provide substantial savings for Medicare.

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1 Introduction

Medicare strives to enact policies that effectively balance the costs and quality of medical care delivered to its beneficiaries. One prominent effort aimed at achieving this elusive goal is the prospective payment system (PPS) that gives hospitals a fixed, predetermined reimbursement for each patient's stay. An advantage of this system is that it provides an incentive to minimize the cost of care, as extraneous procedures and tests would increase hospitals' costs but not yield any additional revenue. One drawback of such a policy, however, is that hospitals may base their decisions not on clinical guidelines for effective care, but on maximizing their reimbursements given the financial incentives of 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 hospitals disproportionately discharge patients when it is most profitable for them to do so. As a result, the average LTCH keeps patients about a week longer than they would if reimbursements were not tied to their lengths of stay. In an attempt to mitigate this effect, a recently proposed change to the reimbursement system would dampen hospitals' incentives to keep patients in their facilities for solely financial reasons, which we estimate would have reduced Medicare's payments to LTCHs by hundreds of millions of dollars over the past ten years.

Long-term care hospitals specialize in treating patients with serious medical conditions who require prolonged care. As an organizational form, LTCHs exist largely as a response to the PPS Medicare introduced for general acute-care hospitals in the 1980s. Under this system, traditional hospitals often lose money on patients who stay for extended periods, whereas LTCHs have a different reimbursement system that factors in the additional costs of treating patients with long-term conditions. This gives acute-care hospitals an incentive to discharge certain patients to LTCHs that then receive new Medicare payments upon admission — 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, for which spending on all inpatient stays exceeded $145 billion in 2015.[1]

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

Because reimbursements increase substantially when a patient's length of stay exceeds the

[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`).

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

SSO threshold, LTCHs have a narrow window during which they can maximize their profits for each patient and often discharge them 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 medically necessary in order to reach the threshold potentially 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.[3]

Previous reports suggest that corporate executives pressure LTCH administrators to discharge patients immediately after they pass the SSO threshold in order to earn higher profits. 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." LTCH administrators also "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."

Given the financial incentives created by Medicare's PPS, our paper examines the prevalence of strategic discharging at LTCHs.[4] Using Medicare claims data from fiscal years 2004-2013, we first provide descriptive evidence that 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 criteria. To identify this practice, we exploit the sharp discontinuity in payments around the SSO threshold, finding that LTCHs discharged 25.7 percent of patients during the three days immediately after crossing the threshold compared to 6.8 percent of patients during the three days immediately preceding it.

Based on the anecdotal evidence referenced above, this nearly fourfold increase in discharges for patients just past the SSO threshold would seem to stem largely from strategic behavior by LTCHs. To cleanly link it to Medicare's reimbursement policy, however, we must first 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 extent of her medical needs. To establish that the link between the PPS and strategic discharging is causal, we

[3] We note that Einav et al. (2018), a paper that we discuss at some length below, do not find evidence that strategic discharge increases a patient's mortality rate 30 or 90 days after being discharged from the LTCH alive. An unanswered question to date is whether the prevalence of strategic discharge increases a patient's risk of infection, medical errors, or dying while still at the facility.

[4] We use the term "strategic discharge" to refer to hospitals discharging patients for financial reasons rather than clinical ones.

therefore use 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 find that LTCHs discharge patients on the magic day for any given DRG in any given year. Furthermore, if facilities discharged patients solely 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 the magic days in later years.

Another threat to identification is that discharges could cluster on the magic day simply because the SSO threshold is based on a DRG's average length of stay and patients with similar diagnoses receive similar treatments. The strong association we find between the timing of discharges and the financial motives of providers suggests that this type of coincidence does not explain our results. For instance, we show that a patient is more likely to be released on the SSO threshold day if her DRG has a larger lump-sum payment. In addition, we show that discharges of patients to their homes — which are 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 find that for-profit hospitals are more likely to engage in strategic discharge than non-profit hospitals, as are facilities co-located with standard acute-care hospitals that may face fewer barriers for transferring patients. Further, we find that facilities operated by the two dominant LTCH chains are more likely to strategically discharge patients — and when these chains acquire competing facilities, the newly acquired facilities become more likely to do so as well. Lastly, we show that African-American patients are particularly susceptible to being strategically discharged.

Although our descriptive analysis provides compelling evidence that the current PPS leads LTCHs to discharge patients strategically, it does not allow us to predict how LTCHs would behave under alternative payment schemes. Policy makers have a keen interest in making such predictions, 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 eliminate the large jump in reimbursements associated with crossing the SSO threshold, making strategic discharges less lucrative for LTCHs. We develop and estimate a dynamic structural model of LTCHs' discharge decisions that can predict the likely impact of such policy changes.

Conceptually, our model is based on an LTCH deciding each day whether to discharge a patient immediately or to keep her in the facility for an additional day. In making its decision, the

LTCH weighs the revenue-based incentives of discharging the patient against the numerous cost-based and non-pecuniary reasons to keep the patient longer (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 at the SSO threshold to separate the revenue-based motives for facilities' discharge decisions from other confounding factors. We find that for-profit hospitals and LTCHs housed within acute-care hospitals respond more strongly to financial incentives, and that these incentives have a larger effect on the discharge decisions of African-American and elderly patients.

The parameters we estimate in our structural model allow us to perform a counterfactual analysis of several alternative payment policies. First, we consider the effect of eliminating the financial incentives of the SSO threshold. Given this change, we find that LTCHs would discharge patients about a week earlier, on average, which would result in substantial cost savings for Medicare — over \$500 million per year across the nine most common DRGs that make up 44% of all spending at LTCHs and 40% of all stays (no other DRG comprises more than 1.5% of the sample).

Next, we consider the new payment formula proposed by MedPAC that would eliminate the large lump-sum payments of the current PPS, replacing them with higher per-diem payments before the threshold. Under this system, patients are more likely to be discharged in the days prior to what would have been the SSO threshold because LTCHs no longer have an incentive to extend stays to secure a lump-sum payment. At the same time, the larger per-diem payments themselves may provide an incentive to delay discharges prior to reaching the SSO threshold. Based on our findings, the proposed formula would reduce 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 \$46 million each year for the nine most common DRGs.

Finally, we consider a more basic cost-plus reimbursement scheme in which LTCHs receive a fixed five percent mark-up over their reported costs, which resembles the Medicare's policy prior to implementing the PPS for LTCHs in 2003. We find that, although it would eliminate the spike in discharges associated with the current PPS, hospitals would hold patients longer than they would under the status quo because they profit from receiving a constant mark-up each day. This underscores the challenges associated with adequately reimbursing LTCHs while also taking into account the strategic incentives generated by such payment policies.

These results contribute to several streams of literature. First, we add to existing work on the incentives to reduce health-care expenditures that to this point has focused primarily on patients (e.g., responding to cost-sharing in their insurance plans[5]) or on physicians (e.g., on

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

where to admit patients[6]). By showing how inpatient hospitals respond to incentives to reduce expenditures, our paper offers an important contribution to this growing literature.

Our paper also contributes to previous work on the unintended consequences of Medicare reimbursement policies (e.g., Altman 2012, Decarolis 2015, Dafny 2005). Most directly related, Kim et al. (2015) document several stylized facts for LTCHs following Medicare's change to a PPS in 2002, including a spike in discharges immediately after the SSO threshold. We extend 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 several novel institutional details, such as the post-acquisition discharge policies of Kindred and Select's LTCHs, the behavior of co-located LTCHs, and the different treatment of African-American patients.

In related work, developed independently from our own, Einav et al. (2018) also look at the discharge practices of LTCHs. Although the findings of Einav et al. (2018) and our paper are largely in agreement, our respective focuses are somewhat different. Both papers present evidence that LTCHs strategically discharge patients in response to the PPS and estimate a dynamic structural model to simulate the impact of alternative reimbursement policies on LTCH behavior, the results of which, where comparable, are very similar. Distinguishing our two papers, Einav et al. (2018) place a greater emphasis on the impact of strategic behavior on patient outcomes and find that the practice does not meaningfully affect patients' mortality rates after they leave the facility. Our paper, by contrast, places a greater emphasis on the heterogeneity of strategic discharging across different types of patients and facilities.

One key example of this heterogeneity is the new evidence we contribute to the extensive 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 non-profits do, we bolster similar findings in this vein, such as those in Silverman & Skinner (2004). Others, such as Grieco & McDevitt (2017), have found that for-profit health-care providers often deliver lower-quality care. This may also be the case for LTCHs given previous reports 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 (Berenson 2/9/2010).

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 discharging 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 two other schemes. Section 7 concludes. The

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

online 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 for LTCHs, and several figures relevant for our counterfactual analysis.

2 Overview of Long-term Care Hospitals

Long-term care hospitals provide inpatient care for patients with prolonged, post-acute medical needs. To qualify as an LTCH, a facility must meet Medicare's qualifications for being a general acute-care hospital and also have 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 a 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 lengths of stay from the new PPS due to concerns that they would not be financially viable under this system. In 2002, Medicare further adjusted the LTCH reimbursement scheme to what is now 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). From fewer than 10 such facilities in the 1980s, the number of Medicare-certified LTCHs in the U.S. has now grown to more than 420, with payments from Medicare accounting for about two-thirds of overall revenue and totaling \$5.5 billion (Medicare Payment Advisory Commission 2014). Most LTCHs operate as for-profit entities, and coinciding with industry growth, the market has consolidated to the point where two leading firms, Kindred Healthcare (Kindred) and Select Medical (Select), now operate 38 percent of all LTCHs, having expanded largely through acquisitions.

LTCHs receive payments from both patients and their insurers. For Medicare patients, who are 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 occurring in only 4.7% of all LTCH stays from 2004-2013).[7] 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 occurring in just 0.17% of all LTCH stays from 2004-2013), 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 therefore pays no deductible) and stays for less than 60 days, Medicare is the sole source of revenue for the LTCH.

[7]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.

Before 2002, Medicare paid LTCHs 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 treatment, which we detail in Online Appendix C. The LTCH PPS uses the same DRG groups as the acute inpatient PPS but accounts for differences in the costs of treating regular inpatient and long-term care cases because the afflictions of patients requiring longer stays are typically more severe, and hence more costly to treat. Reflecting this, full LTCH payments are usually much larger than Medicare payments for similar patients being treated in other types of facilities, such as the inpatient prospective payments (IPPS) received by general acute-care hospitals. As an example, DRG 207, respiratory system diagnosis with prolonged mechanical ventilation, had a standard IPPS payment of $30,480 in 2014 compared to an LTCH payment of $80,098.[8]

To discourage needless transfers between facilities and to ensure that only those patients who truly require 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 (SSOs), 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.[9]

Under Medicare's modified PPS, LTCHs receive payments that increase linearly with a patient's length of stay for short-stay outliers before culminating in a discrete jump in reimbursements on the magic day. The discontinuity in Medicare's reimbursement of LTCHs creates a strong financial incentive to keep patients just past the SSO threshold. As an example, consider Figure 1 that includes patients with DRG 207 discharged to a nursing facility, the most common discharge destination (although the findings are the same for other discharge destinations). Here the estimated average costs (dashed line) and the average Medicare payments (solid line) are broken down by length of stay for years 2005-2010, with the gray bands indicating the 25th and 75th percentiles.[10] In these years, the SSO threshold was 29 days, and the jump in payments just beyond this point is immediately evident.

The quotes from industry sources in the Introduction describe the pressure put on LTCH employees to maximize profits by keeping patients longer than medically necessary and then discharging them shortly after they pass the SSO threshold. Figure 1 clearly illustrates the financial stakes underpinning this pressure: the average payment the day before the SSO threshold for

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

[9]See Online Appendix C for full details of this payment schedule and an example calculation.

[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 upwards for the shorter stays and downwards for the longer stays.

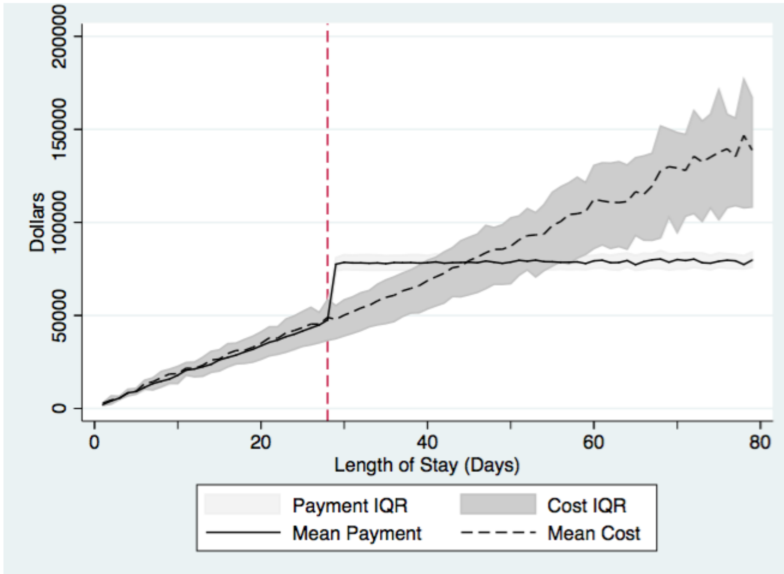

Figure 1: Revenues and Costs for DRG 207 Patients by Length of Stay, 2005-2010

DRG 207 is $47,537.56, but then jumps to $78,529.82 once the patient reaches the threshold. If we impute daily costs from hospital charges and cost-to-charge ratios (see footnote 10), this corresponds to the average profit per patient jumping from $-1,406.03 on the day before the SSO threshold to $28,327.78 on the day after. After reaching the SSO threshold, the LTCH receives no further payments for the patient, so profits begin to fall as the hospital continues to incur costs during her stay. In the case of DRG 207, Figure 1 shows that additional costs completely exhaust profits after day 45, leading to a roughly 2 week window of profitability for the hospital.

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 costs like laboratories and cleaning services. More controversially, this arrangement also makes it easier to transfer patients between the co-located hospitals, by which both hospitals stand to gain: a transfer allows the LTCH to receive a separate payment from Medicare and 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 much 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, and 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]

[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-

3 Data Description and Motivating Facts

We use a claims dataset from CMS linked to data on hospital characteristics from CMS and the American Hospital Association (AHA). 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 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 payments, covered costs, length of stay, diagnosis and procedural codes, race, age, gender, the type of hospital admission, whether the patient was discharged alive, and, if so, the discharge destination (i.e., discharged to home care, to a general hospital, etc). The CMS certification number of the hospitals allows us to link the claims data to data on hospital characteristics, although the de-identification of patients means we cannot measure some patient-level outcomes, such as readmissions.

The hospital data come from two sources, the 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. Because hospitals are added to the POS file when they are certified as Medicare and Medicaid providers, in principle one could use historical versions of these reports to construct a panel dataset of all eligible providers. Once a hospital becomes a part of the POS file, however, CMS regional offices only intermittently administer surveys and update the dataset, meaning that we may not observe precisely 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, and bed count. We used the guide's data on hospital ownership, ownership changes, affiliation, and co-location for LTCHs.

Much of our analysis focuses on hospital stays coded as DRG 207 for patients ultimately

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located hospital, then the net payment amount for those discharges beyond the 25 percent mark became the lesser of the LTCH PPS 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`.

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 as DRG 207, with 90,755 terminating in a discharge to home or a nursing facility.

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
Male	0.484	0.5
White	0.746	0.435
African-American	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 re-admissions 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 drop them.

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 until the SSO threshold. The average total payment to hospitals is $71,108; most of this, $70,530, comes from Medicare, with the rest

[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 magnitude of the discontiuity upon reaching the SSO threshold 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 Online 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.

paid as a deductible, as co-insurance, or by a third party. 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 (i.e., bed count). As mentioned above, the largest two firms are Kindred and Select, which together operate almost 40 percent of facilities. Nearly one-third of LTCHs are HwH. For-profits comprise two-thirds of LTCHs, while 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, LTCHs have an average bed count of 70.

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
Non-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
Non-profit	0.275	0.446
Government owned	0.166	0.372
Affiliated with medical school	0.180	0.384
$N = 4,108$		

4 Evidence of Strategic Discharging

We now consider whether the financial incentives created by Medicare's PPS influennce LTCHs' discharge decisions. The crux of our analysis is that the discontinuous jump in payments at the SSO threshold 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 within the same year, (iii) variation in the existence of an SSO threshold given Medicare's policy change in 2002, (iv) variation in the size of the payment discontinuity at the SSO threshold across DRGs, (v) variation in the ease of manipulating discharges across discharge destinations, and (vi) variation in the incentives faced by different types of hospitals to engage in strategic discharge (e.g., for-profit vs. non-profit). These different sources of variation bring the central message of our analysis into sharp focus: 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 they pass the SSO threshold. In Section 4.1, we use histograms to provide visual evidence in support of our arguments. In Section 4.2, we quantify the extent of strategic discharging in a difference-in-differences regression that exploits variation in the SSO discontinuity across DRGs and over time.

4.1 Graphical Evidence

We first examine the distribution of discharges to home or a nursing facility for a single DRG, DRG 207 (Respiratory System Diagnosis with Ventilatory Support > 96 Hours), relative to its SSO threshold. The discontinuity in discharges at the SSO threshold is immediately apparent in Figure 2, which has a distinct spike on the SSO threshold day along with a pronounced dip for the days immediately preceding it.[18] Typically, one would expect a smooth distribution of discharges absent any deliberate manipulation by LTCHs; the spike in discharges on the days immediately after the SSO threshold suggests that LTCHs base their decisions on factors other than just clinical guidelines.

Given that Medicare sets the SSO threshold based on the historical discharge rates for each DRG, we cannot immediately rule out the possibility that the underlying treatment regimen for DRG 207 just happens to result naturally in a mass of discharges following the threshold day. To link the spike in discharges to facilities' financial incentives, we will therefore use several sources of variation in the data to identify a consistent pattern of strategic behavior, starting in this subsection with a series of suggestive histograms. We also supplement these charts with Table A3 in the online appendix that summarizes the key statistics from the histograms, such as the percentage of patients discharged on the threshold day, which we refer to often throughout our discussion.

We first show how the distribution of patients' lengths of stay has evolved over time. Figure 3 presents the distributions for the years 2002, 2004, and 2013. The solid vertical line denotes the threshold day in 2004, the 30th day after admission, and the dashed vertical line denotes the

[18] The x-axis in Figure 2 has been normalized to show the day of discharge relative to the threshold day, as it changes by year.

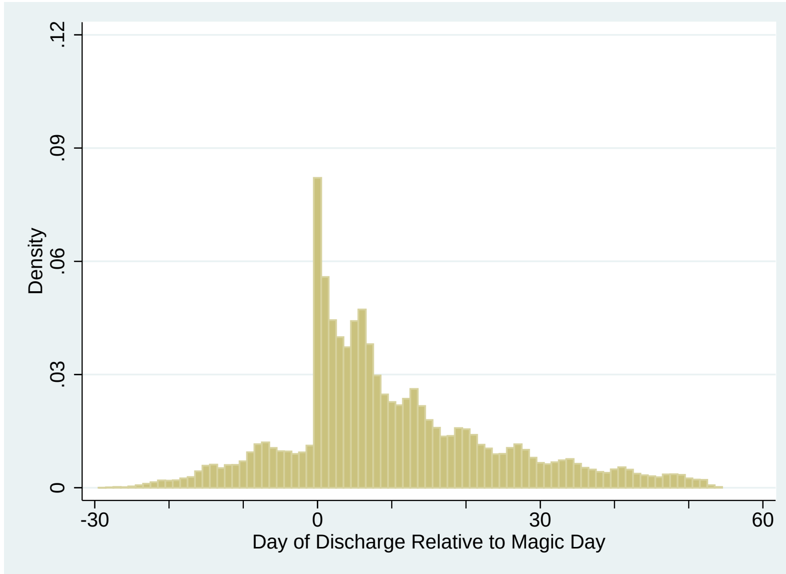


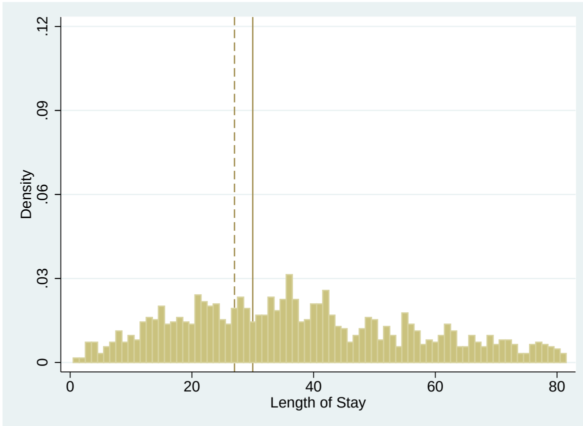
Figure 2: Distribution of Length of Stay Relative to Magic Day, FY 2004-2013

threshold day in 2013, the 27th day after admission. In panel (a), we see that in 2002, when Medicare's reimbursement schedule did not include a lump-sum payment, there is no discernible 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 were discharged on the day immediately before the magic day compared to 4.6 percent on the magic day itself, a 2.2-fold increase. In 2013, by contrast, 1.4 percent of patients were discharged on the day before the magic day compared to 10.2 percent on the magic day, a substantially larger 7.3-fold increase.

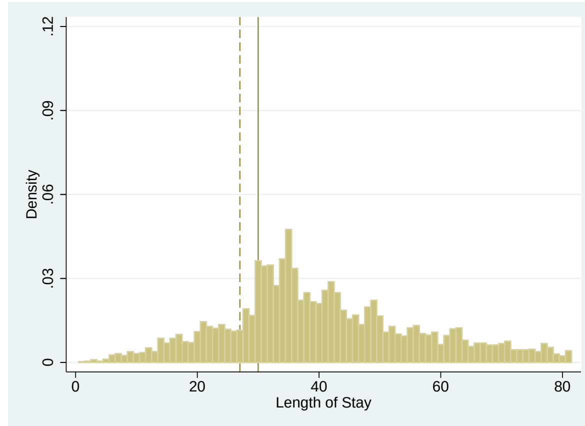
In comparing panel (a) with panels (b) and (c), it is clear that when there is no discontinuity in the reimbursement scheme, there is also no spike in discharges around what would subsequently become magic days. In addition, comparing panels (b) and (c), we see that in 2004 the spike in discharges occurs on day 30, the magic day for that year, while in 2013 this spike occurs on day 27, the magic day for that year.[19] Although 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, and the lack of a similar spike in 2002 further bolsters this claim. Moreover, we show in the online appendix that the same distinct pattern emerges across the other most-common DRGs (see Figure A1 in Online Appendix B). It is even more unlikely that several independent medical advances occurred for each of these different DRGs in a way that coincidentally shifted discharges to precisely after their DRGs' thresholds.[20]

[19] We also note 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 a gradual rollout of the PPS or LTCHs learning how to best maximize profits, as interesting but beyond the scope of our current paper.

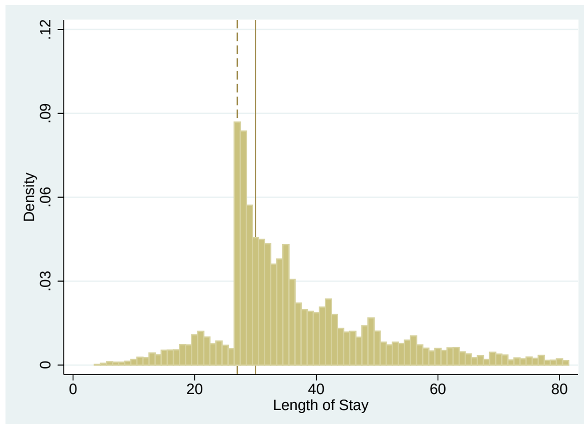
[20] In Section 4.2, we relate the likelihood of strategically discharging a patient to that patient's DRG's lump-sum



(a) Absolute Length of Stay, FY 2002



(b) Absolute Length of Stay, FY 2004



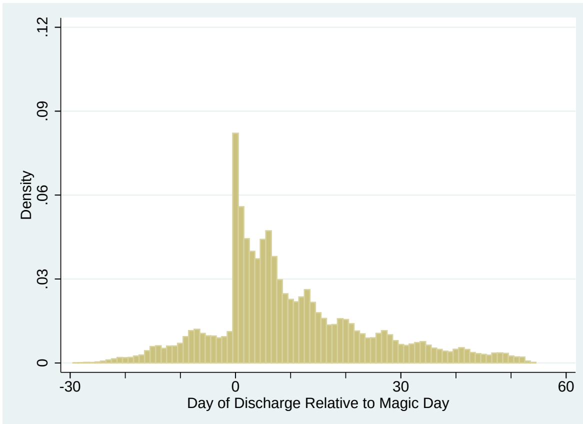
(c) Absolute Length of Stay, FY 2013

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

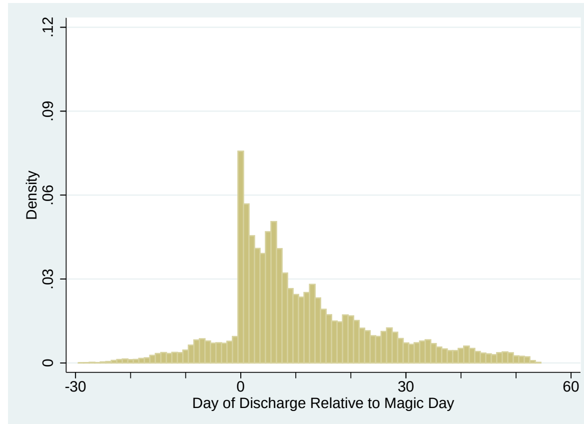
Next, we examine differences in discharge patterns by destination, categorized by how easily an LTCH could alter a patient's treatment plan based on financial incentives. Discharges to home are the easiest type for LTCHs to manipulate because they have the least subsequent oversight and these patients' conditions have stabilized enough so that they can be sent home. Discharges to skilled nursing facilities are slightly more difficult to manipulate because trained medical staff evaluate a patient following the transfer and these patients still have many lingering health issues. Discharges to acute-care hospitals will then be even harder to manipulate because they have more extensive admission screening and these patients have a comparatively worse health status. 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 has no spike at all on the threshold day. For patients discharged to home, LTCHs discharge 6.1

payment to build the argument that strategic discharges are most likely for those DRGs where the discontinuity is greatest.

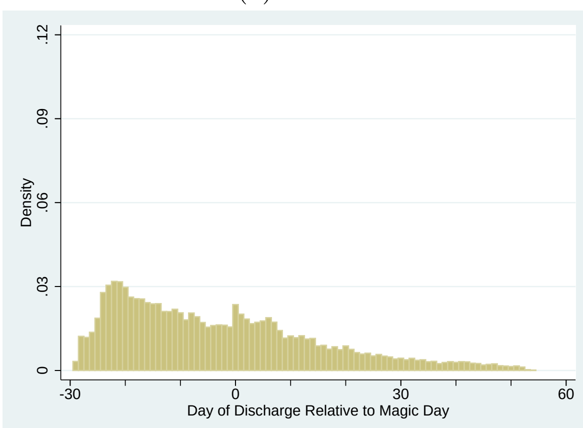
times as many patients on the theshold day relative to the day before it, whereas for patients discharged due to death the corresponding ratio is a flat 1.0.



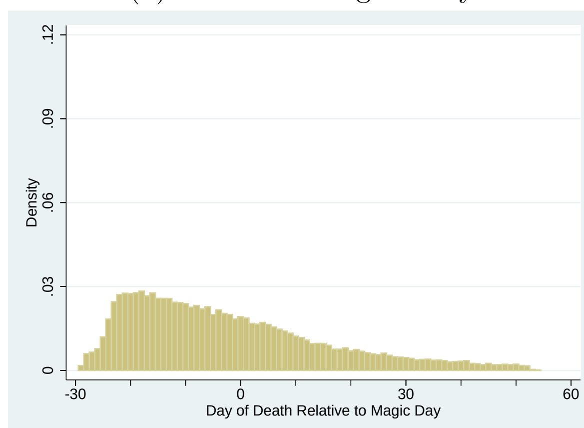
(a) Home



(b) Skilled Nursing Facility



(c) Acute-care Hospital

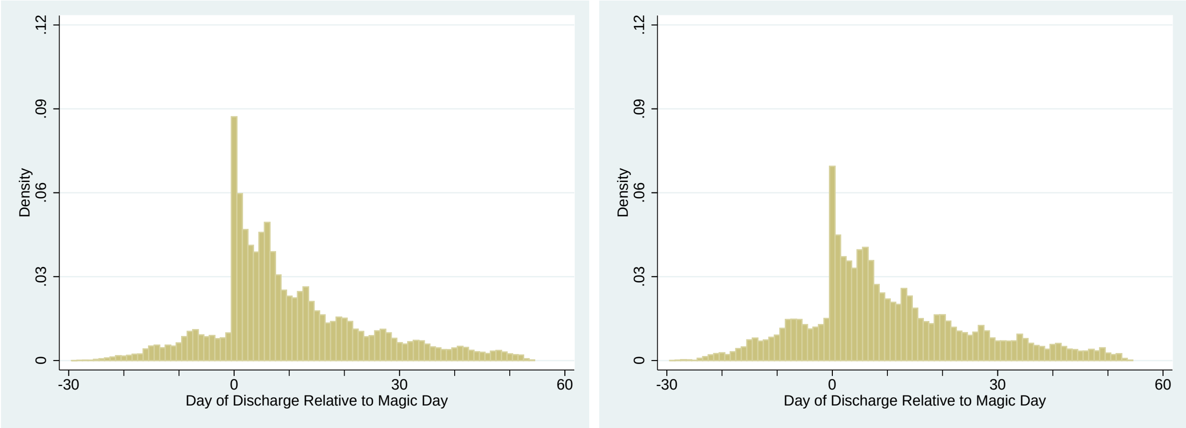


(d) Death

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

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 presssure to strategically discharge patients are consistently more likely to do so. 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, whereas non-profit LTCHs have a spike about half as large, at 4.6 times.

For-profit LTCHs also behave differently after being acquired by one of the two major for-profit LTCH chains, which allows us to isolate the role of corporate strategy from many other confounding factors that might explain differences in discharge patterns (e.g., the demographics of patients in the LTCH's market). The two dominant chains, Kindred and Select, have grown considerably 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 —

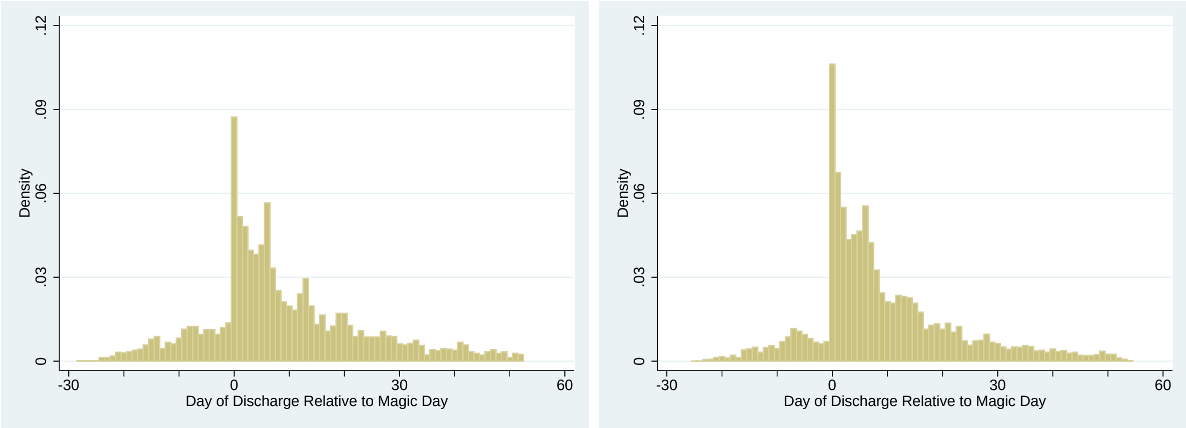


(a) For-Profit LTCHs

(b) Non-profit LTCHs

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

and thus may be a central component of their growth strategies — it is possible that Kindred and Select acquire LTCHs specifically to implement their more-lucrative discharge policies. 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 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 or Select acquire an LTCH, the ratio of discharges on the threshold day relative to the day before it increases on average from 8.7 to 15.1, suggesting that the acquired LTCHs subsequently adopt their acquirers' discharge policies.[21]

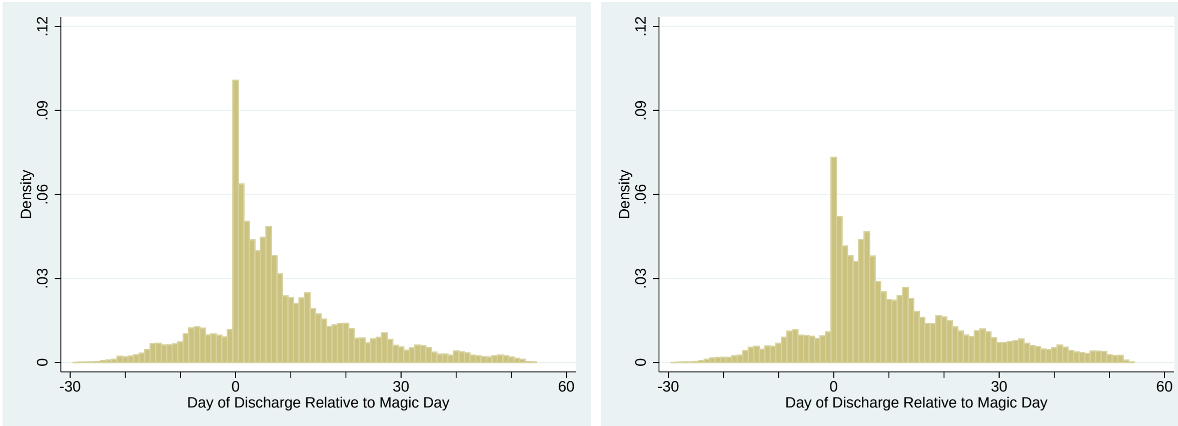


(a) Before Acquired by Select or Kindred

(b) After Acquired by Select or Kindred

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

[21]We also show below that Kindred and Select's 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 to strategically discharge patients than it was before being acquired.



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

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

Finally, we consider whether an 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 in discharges on the magic day. Officially, hospitals have little control over such facilities and patients can choose where to go. In practice, however, hospital discharge teams often steer patients to a favored facility. Consistent 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 threshold day relative to the day before it, whereas standalone LTCHs discharge 6.6 times as many.

4.2 Quantifying the SSO Threshold Effect

The preceding figures provide strong visual evidence that discharges spike 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 3 shows the results from a series of probit regressions that estimate the probability of discharge given a patient's length of stay in relation to her particular SSO threshold:

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

where t is the absolute day of the hospital stay and s is the day relative to the threshold day ($s = 0$ indicates the day is the threshold day, $s < 0$ indicates days prior to the threshold day, and $s > 0$ indicates days after the threshold day). We present the results for DRG 207 in the main text and the analogous results for the next three most common DRGs in Online Appendix

B.[22]

This simple model relies on variation in the SSO threshold across years to identify how the lump-sum payment influences discharges, assuming that any time spent in an LTCH affects patients' health in a continuous manner — that is, a patient's condition changes smoothly over the course of a stay in contrast to the payments that jump discretely. We include a quadratic function of a patient's length of stay 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. For example, 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 SSO threshold in one year but not in another, then the year in which it coincides with the SSO threshold should have a greater likelihood of discharge if LTCHs are acting strategically to maximize reimbursements. The parameter μ_s captures this strategic behavior in our analysis.

Table 3 presents the estimated discharge probabilities from this model for DRG 207.[23] The sample we use here is based on stays that ended in a discharge to home care or a nursing facility because these are the discharges for which hospitals have the most discretion. In all cases, we see a sharp jump in discharges on the threshold day relative to the day before, and this pattern is remarkably consistent across years. For instance, in 2010 when the SSO threshold was 29 days, the probability of discharge increases from 1.11 percent on the day before the magic day to 8.86 percent on the day of the threshold, a nearly eightfold increase. In 2013, when the threshold day was two days earlier, on day 27, the rate increased from 1.3 percent to 9.7 percent, a similar order of magnitude as in 2010.[24]

Given the finding above that financial incentives influence the timing of LTCHs' discharges, we would expect this response to vary based on the amount of potential profit at stake. To this point, we show in Online Appendix B that among the four most common DRGs, the effect is strongest for DRG 207, which has the highest payment/cost ratio on the magic day. For DRG 207, profits increase approximately $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. By contrast, DRG 189 and DRG 871 have smaller payment bumps of $12,000 and $11,000, respectively, that correspond to likewise similar and smaller median magic day effects of 6.29 and 6.55. Finally, DRG 177 has an even smaller payment bump of $9,000 to go along with its smaller median threshold day effect of 3.77.

[22] We estimate this regression separately for each DRG to isolate the strategic effect of discharge from any other differences that may exist across diagnoses.

[23] The parameter estimates for the probit model appear in Table A8 in Online Appendix D for DRG 207. Estimates for other DRGs are available upon request.

[24] Even though we condition on a patient's DRG in this analysis, one still might be concerned that there is additional variation in patient health within a DRG that could contaminate our findings. Although we do not observe patient health directly, to explore this possibility we have confirmed that the results in Table 3 are robust to including controls for the type of admission, a proxy for patient health (e.g, ER vs. elective).

Table 3: Marginal Effects on Probability of Discharge
DRG 207

Day of stay (t)	Probability of Discharge on Threshold Day[1]	Probability of Discharge on Day Preceding Threshold 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 A9

[1] $\Phi(\gamma_0 + \gamma_1 t + \gamma_2 t^2 + \mu_0) * 100$

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

[3] Hazard ratio: $\frac{\Phi(\gamma_0+\gamma_1 t+\gamma_2 t^2+\mu_0)}{\Phi(\gamma_0+\gamma_1 t+\gamma_2 t^2+\mu_{-1})}$. Square brackets contain the p-value from a Wald test for $H_0 : HR = \frac{\Phi(\gamma_0+\gamma_1 t+\gamma_2 t^2+\mu_0)}{\Phi(\gamma_0+\gamma_1 t+\gamma_2 t^2+\mu_{-1})} = 1$.

In addition, different types of LTCHs may respond more strongly to financial incentives. To see this, we next interact the SSO threshold effects with various LTCH characteristics, which allows discharge practices to vary by hospital type. The estimating equation for these models has the form

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

where $x(i)$ is an indicator variable for whether observation i is of type x, such as whether it is a for-profit LTCH, a HwH, owned by Select or 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 a stay, t, the relative day of a stay, s, and the hospital's characteristics. We limit the hospital characteristics to create a single partition of hospitals into types, as allowing for overlapping types would muddle the interpretation of the marginal effects.

Table 4 contains estimates for the marginal effects from six interacted probit models, with each model separated by a line in the table. We find that the magic day effect is nearly twice as large at for-profit LTCHs compared to non-profits, 9.60 relative to 4.99. For Kindred and Select, we estimate a magic day effect of 10.01, whereas it is only 6.12 for other LTCHs. Similarly, just as Kindred and Select are more likely to strategically discharge patients than other hospitals in our second estimated model, in our third model individual LTCHs increase their strategic discharge behavior after being acquired by these chains from 6.70 to 16.82. Lastly, the threshold day effect for co-located LTCHs is almost 30 percent higher than for standalone facilities, 9.42

compared to 7.34.[25,26]

We also investigate the prevalence of strategic discharge across patient types, as hospitals may treat patients differently if they have less influence over their own care. We examine two characteristics that may proxy for a patient's vulnerability in this regard, race and age. In the last panels of Table 4, we present results that include LTCH fixed effects to control for sorting of patients into hospitals and find that African-American patients are more likely to be strategically discharged than other patients: the magic day effect for African-American patients is nearly 30 percent larger.[27] For age, however, we do not find evidence that the elderly have a different likelihood of being discharged strategically. In Section 6, we will return to this analysis in our structural model.[28]

5 Quantifying the Response to Financial Incentives

The results above show that LTCHs respond to the financial incentives created by the PPS when making discharge decisions. In this section, we propose a dynamic model to isolate the effect of Medicare's payment policy on discharges, which then allows us to consider how changes to the reimbursement scheme would affect hospitals' behavior.

Before introducing the model, we should note that it is just one of several components that would be required to conduct a full welfare analysis of Medicare's payment policies. At least two key ingredients are missing. First, we cannot recover the marginal benefit patients get from an additional day of care because we lack the necessary data on patients' medical histories to do so. Second, we do not have clear information on the marginal costs of providing an additional day of treatment. Although we do have data on hospitals' cost-to-charge ratios that 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 differences in costs across hospitals rather than as a direct measure of marginal costs.

[25] The results in Table 4 are also robust to including controls for the type of admission to address the same concerns outlined in Footnote 24.

[26] We have also explored how strategic discharge depends on capacity constraints. Despite the challenge of reliably measuring capacity utilization, we find some suggestive evidence that more capacity constrained hospitals engage in more strategic discharge. The results are in Appendix E.

[27] The results from the first four models are robust to geographic controls like state fixed effects.

[28] We also investigated whether LTCHs are less likely to engage in strategic discharge for sicker patients, though the evidence is inconclusive. First, we compared patients with DRG 207 (the main DRG we focus on in the paper) admitted from the emergency room to those admitted based on an elective decision. Although both types of patients experience strategic discharge, the magnitude of strategic discharge (measured by the hazard ratio) is greater for those patients with elective admission; however, we cannot reject the null that they experience the same level of strategic discharge (p-value 0.47). Second, we examined the DRGs for Osteomyelitis, which are explicitly broken out based on the severity of complicating conditions. Again, although we found that the magnitude of strategic discharge was lower for patients with major complication conditions, the result was not statistically significant (p-value 0.44). Results are available from the authors upon request.

Table 4: Probit Marginal Effects by LTCH Type, DRG 207 at Day 29

Model #/Partition	Predicted Prob. of Discharge: SSO Threshold Day	Predicted Prob. of Discharge: Preceding Day	Hazard Ratio[1]	Ratio of Hazard Ratios[2]
Model #1:				
For-profit	9.28	0.967	9.60	1.92
	(0.363)	(0.052)	[0.000]	[0.000]
Non-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	1.64
	(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	2.51
	(0.662)	(0.089)	[0.000]	[0.000]
Before Acquisition[7]	9.94	1.48	6.70	0.89
	(0.778)	(0.172)	[0.000]	[0.000]
Never Acquired	8.53	1.13	7.54	
	(0.357)	(0.067)	[0.000]	
Model #4:				
HwH	11.31	1.20	9.42	1.28
	(0.508)	(0.099)	[0.000]	[0.000]
Not HwH	7.73	1.05	7.34	
	(0.344)	(0.066)	[0.000]	
Model #5, includes LTCH FEs:				
African-American[5]	8.43	0.84	9.94	1.27
	(0.383)	(0.080)	[0.000]	[0.047]
Other	8.62	1.17	7.38	0.94
	(0.328)	(0.149)	[0.000]	[0.686]
White	8.77	1.12	7.82	
	(0.281)	(0.067)	[0.000]	
Model #6, includes LTCH FEs:				
65 and over	8.08	0.99	8.19	1.06
	(0.353)	(0.059)	[0.000]	[0.454]
Under 65	10.65	1.38	7.73	
	(0.353)	(0.010)	[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. See also table notes from Table 3.

[1] Square brackets contain the p-value from a Wald test for $H_0 : HR = \frac{\Phi(\gamma_0+\gamma_1 t+\gamma_2 t^2+\mu_0)}{\Phi(\gamma_0+\gamma_1 t+\gamma_2 t^2+\mu_{-1})} = 1$.

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

[3] Ratio of hazard ratio for acquisition LTCHs and pre-acquisition LTCHs.

[4] Ratio of hazard ratio for pre-acquisition LTCHs and "never acquired" LTCHs.

[5] Ratio of hazard ratio for both "African-American" and "Other" patients are relative to "White" patients.

Because we cannot directly measure hospitals' costs or patients' benefits, we rely on a structural model to recover the effect of payment policies on discharges. In the model, we will allow for a flexible DRG-specific length-of-stay effect that, under reasonable assumptions, controls for the impact of both marginal costs and patients' benefits on hospitals' discharge decisions. If our model shows that the distribution of discharges and its key moments, such as the average length of stay, vary in response to alternative payment schemes, then determining the optimal payment scheme represents an important policy goal because of its influence on hospitals' choices. Moreover, our analysis gives us a precise understanding of how the PPS affects a patient's length of stay. Under the reasonable assumption that treatment costs rise as a patient stays longer in the hospital, the length of stay itself can be used as a useful measure of how payment policies affect hospital costs.

5.1 A Model of Hospital Discharge Decisions

We model the daily decision of an LTCH to discharge a patient.[29] 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.[30] 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. Given Medicare's PPS, payments are defined according to the following piecewise function,

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

where p represents the per-diem payment for stays shorter than the SSO threshold, t^m. We estimate p from patient-level payment data and allow it to depend on hospital and patient characteristics. The variable P is the payment governed by the LTCH 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.

[29]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.

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

The LTCH decides each day whether or not to discharge the patient. In so doing, it weighs the financial incentives of discharging today against the costs of providing further treatment and 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). If the patient is discharged, then treatment ends and the LTCH can use the bed to treat other patients. We normalize the value of an open bed to 0, so that the flow value of treating a patient on day t is relative to the value of having an open bed. Otherwise, the patient continues to be treated and the LTCH faces a new discharge decision the next day.

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 $t+1$. Because the model is non-stationary, we assume a finite time horizon and define a parameter $\Omega = EV_{T+1}$ that represents the termination value of treating a patient beyond day T (i.e., not discharging on day T). We then estimate this value as a part of the model, allowing a distinct Ω 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, so the probability that the patient is discharged on day t (given no earlier discharge) is

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

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

$$EV_t = u_{t+1} + \log(\exp(\delta EV_{t+1}) + 1).[31] \tag{6}$$

We then solve the model 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 for each day.

In contemporaneous work, Einav et al. (2018) also propose a structural discrete choice model of LTCH discharges. Before turning to estimation, it is worth comparing the two approaches,

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

which differ substantially in the details of implementation. First, we explicitly incorporate observable information on patient demographics, DRG, hospital type, and payment policy into the model, whereas Einav et al. (2018) pool the discharge data to estimate the average impact of the payment threshold on the average patient. Second, we assume that hospitals face a non-stationary dynamic problem where patient health can be captured through DRG-specific length-of-stay effects. After conditioning on patient and hospital characteristics, as well as length of stay, any remaining heterogeneity is captured by idiosyncratic choice-specific shocks. By contrast, Einav et al. (2018) assume that a patient's unobserved health status evolves according to a stationary process, with the only source of non-stationarity in the hospital's problem coming from the payment policy itself. They estimate this unobserved process using a fixed-point procedure that likely would be intractable with our richer conditioning set. Finally, while we focus on so-called "downstream" discharges to home care and nursing facilities, treating "upstream" discharges to acute-care hospitals as exogenous, Einav et al. (2018) explicitly model both an upstream and a downstream discharge choice.[32] These different modeling choices are complementary. Whereas our model allows us to condition on a richer set of hospital, patient, and treatment characteristics to exploit variation that is useful in determining the marginal impact of payment policies, theirs is more parsimonious in capturing unobserved heterogeneity in patients' health status. Overall, we find it reassuring that these two distinct approaches for modeling the discharge process produce broadly similar results, which we establish in the following section.

5.2 Estimation

We estimate the model using the nine most common DRGs in the data for the years after the SSO threshold was implemented, 2004-2013. Our estimation sample is summarized in Table A4 in Online 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 it keeps a patient 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, which we estimate using data on total payments, length of stay, and hospital characteristics.[33]

[32] Our choice is motivated by our finding that the vast majority of strategic discharging appears to be associated with downstream discharges (Figure 4).

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

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

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

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 estimation sample includes only those observations such that $d_{yhi} < t_y^m$, where t_y^m is the SSO threshold for year y (this will also vary with the specific DRG for patient i). The ζ parameter represents a per-diem payment for short stays — using the notation of (3), $p = \hat{\zeta}$ — and is allowed to vary by patient characteristics, Z_i, and hospital characteristics, X_h. Our specification allows ζ 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, resulting in the functional form

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

In choosing this form, we have tried to allow for a great deal of flexibility in estimating the payment policy. There is a distinct ζ^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 ζ^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 ζ^3 for each year and LTCH type;[34] this allows for the possibility that different types of hospitals have different cost-reporting policies or strategies for extracting Medicare payments. Per-diem payments for short stays, p, are then set equal to $\hat{\zeta}^1_{y,DRG_i} + \hat{\zeta}^2_{y,MSA} + \hat{\zeta}^3_{y,type}$ for each day up to the SSO threshold.

Our data contain 61,590 patients who were discharged prior to the SSO threshold, and we include 1,874 parameters in Specification (8) to flexibly estimate a payment rate for each observation based on patient and hospital characteristics. Including this degree of heterogeneity allows us to explain most of the variation in payments: the OLS model has an R^2 of 0.964 and an adjusted R^2 of 0.963. In panel (a) of Table A5 in Online Appendix A, we report the mean, median, 25th percentile, and 75th percentile for the distribution of per-diem payment rates by hospital type. For-profit standalone LTCHs have, on average, per-diem rates \$89 lower than non-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 A5, however, shows considerable heterogeneity in the per-diem rates within hospital types. Much of this het-

[34]LTCH type refers to the interaction between for-profit status and HwH status. Thus, there are four types: for-profit HwH, for-profit standalone, non-profit HwH and non-profit standalone.

erogeneity is explained by differences in per-diem payments across DRGs, as shown in Online Appendix Table A4.

The full PPS payment, P, is paid out if the patient stays past the SSO threshold, which we compute directly from the payment policy, as explained in Section 2 and Online Appendix C. The policy adjusts the full 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 discontinuity in payments 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 A5 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 mix of DRGs admitted to each hospital. Among non-profit hospitals, the difference in mean full PPS payments at HwH and standalone LTCHs is \$1,079, 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 mix of DRGs varies across hospitals.

Table A4 illustrates how the DRG 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 therefore have a higher mean full PPS payment. Table A4 also shows that there is some variation in the mix of DRGs across LTCH types. For example, for-profit HwH LTCHs account for just 17 percent of total hospital stays but have 23 percent of DRG 207 stays. By contrast, for-profit standalone LTCHs account for 57 percent of hospital stays but have only 50 percent of DRG 207 stays.

Finally, Panel (c) of Table A5 contains the resulting threshold day payments. Threshold day payments are highest, on average, at for-profit HwHs. This is partly because they have more DRG 207 cases. Once again, there is substantial variation in threshold day payments, largely due to differences across DRGs. Among for-profit HwHs, the 25th percentile threshold day payment is \$8,965, while the 75th percentile is \$29,478. As with our discussion above, all of this variation will be useful for identifying how financial incentives affect discharges.

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 to capture heterogeneity across hospitals. Our estimate of average daily costs comes from 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 shorter than the SSO threshold. Our cost estimates appear in Online Appendix Table A6.

In the data, we observe a weekly cycle in the probability of discharge, with discharges dropping off precipitously on Saturdays and Sundays. We account for this in the model by including a series of dummy variables for each day of the week. Our final specification of λ_t thus takes the form

$$\lambda_{i,t} = \gamma_{0,DRG} + \gamma_{1,DRG}t + \gamma_{2,DRG}t^2 + \gamma_{3,DRG}t^3 - \beta\hat{c}_h + \psi_{\text{day of week}}. \quad (9)$$

The presence of $\gamma_{3,DRG}$ guarantees that this form of λ is flexible enough to generate even increasing patterns of discharges if the data support them.[35]

In a final parameterization, we allow α to vary by hospital and patient characteristics to capture any potential heterogeneity in how revenue affects discharges. Specifically, we allow for a different α for each of four LTCH types (for-profit HwH, for-profit standalone, non-profit HwH, and non-profit standalone), indexed by k, and include an additive term for the patient type (African-American and under 65 years of age), indexed by z:

$$\alpha = \alpha_k + \alpha_z. \quad (10)$$

5.2.3 Likelihood

We use the dynamic model to estimate $\theta = \{\lambda, \alpha\}$.[36] 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,

$$\Pr(d_{hi}|p_{hi}, \theta) = D_t(p_{hi}; \theta) \prod_{\tau=1}^{d_{hi}-1} (1 - D_\tau(p_{hi}; \theta)) \ , \quad (11)$$

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). Because optimal decisions are independent across patients, the likelihood function is then

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

[35]The results are robust to using a quadratic specification, and also a less parametric specification where we remove the cubic specification for patient health and simply allow for a different fixed effect for each week after a patient is admitted to the LTCH.

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

6 Estimation Results and Counterfactual Policy Analysis

We begin this section by presenting our estimates of the model outlined above. We then use the recovered parameters from our model to explore how alternative payment policies would affect discharges and, consequently, Medicare expenditures.

6.1 Estimation Results

Table 5 presents estimation results for two specifications of the model that differ based on the form of λ in equation (9) and α, the payment effect. The model fits the observed discharge patterns quite closely (see Figure A3 in Online Appendix F). The key parameter of interest, α, shows how payments influence discharge decisions. For all hospital types, α is positive and statistically significant, indicating that the prospect of future payments reduces the probability of discharge on any given day. Our results also show that hospital types differ in how they respond to financial incentives, with for-profit HwHs being the most responsive and non-profit standalones the least. The differences between every possible pair of α coefficients are statistically significant at the 1 percent level, and the magnitudes suggest the differences are economically meaningful as well. The α coefficient for for-profit HwHs is as much as 55 percent larger than for non-profit standalone LTCHs, depending only slightly on the specification.

In column (2), we add controls for patients' race and age in the functional form of α. These results suggest that payments play a larger role in the timing of discharges for African-American and older patients. To put these numbers in context, simulations of the model show that for the nine pooled DRGs in our analysis, the average length of stay for African-American patients is 28.8 days, whereas the average length of stay for other patients is 1.4 days shorter. Coupled with these longer stays is a greater probability of an African-American patient remaining at the hospital until the magic day: 83 percent of African-American patients remain in the hospital until the SSO threshold compared to only 78 percent for other patients.

6.2 Simulating Alternative Reimbursement Schemes

We consider three separate counterfactual payment policies. The first makes hospital payments independent of a patient's length of stay, which illustrates the extent to which the current payment policy affects discharges. In the second counterfactual, we consider a recent proposal that would remove the discontinuity associated with the SSO threshold but still provide smaller payments for short-stay visits. Finally, we analyze a cost-plus policy that is similar to how Medicare reimbursed LTCHs prior to 2003. In Figure 8, we compare simulated discharge patterns from the baseline model to those simulated for the three alternative payment policies. The analysis that follows focuses on the pooled DRGs, shown in the left-hand column of Figure 8, while the right-hand column isolates DRG 207 in order to facilitate comparisons with Section 4. Table 6 then contains key comparisons between the baseline and counterfactual outcomes.

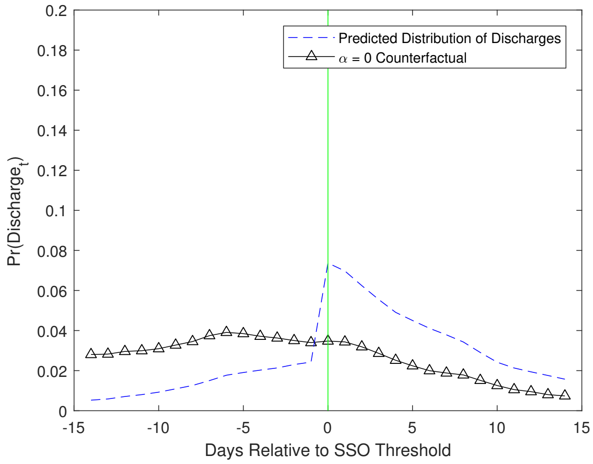
Our analysis flexibly controls for changes in patient health during treatment by controlling for diagnosis and length of stay. Hence, it captures how hospital discharge decisions are affected by changes in payment policies assuming other treatment protocols remain fixed. This raises an important caveat: if hospitals respond to a different payment policy either by substantially changing their treatment intensity or by altering how unobservable patient characteristics affect discharge policies, our approach would be unable to capture these effects, making our findings conservative. We believe these effects are likely to be second-order, however, given that we find a relatively smooth length-of-stay effect in both our descriptive work and the structural model.[37]

Additionally, when interpreting the counterfactuals, it is important to note that our model takes the inflow of patients and the continued operation of hospitals as given, whereas if these policies were actually implemented, hospitals may respond by either changing the rate of admissions, the composition of admissions, or the decision to operate altogether. Because we have little evidence that patient characteristics have changed over our ten year sample of data, especially following the change to the very-short-stay-outlier payment policy in 2013 when hospitals potentially faced a strong impetus to screen patients more selectively, we do not believe selection bias undermines our results.

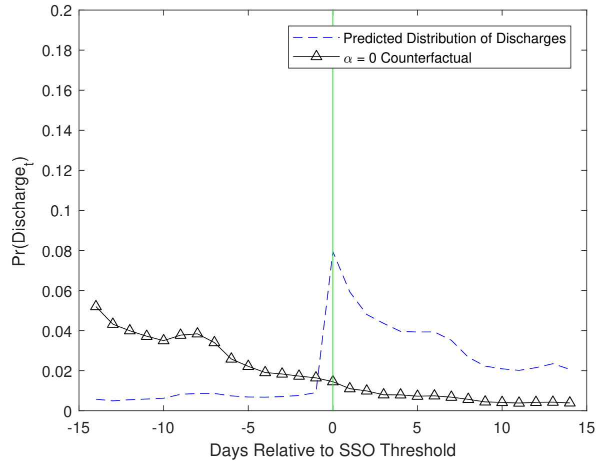
For our first counterfactual, we consider the case where payments do not depend on a patient's length of stay, meaning that the marginal payment for an additional day of treatment is zero. In principle, this could be accomplished by paying LTCHs a lump sum for each admission, as with a traditional PPS. In practice, the temptation for LTCHs to game the system by admitting and quickly discharging healthy patients would still remain, so a feature like the current very-short-stay adjustment discussed in Online Appendix C would probably also have to be in place. The policy could also be implemented by nationalizing LTCHs and funding them independently of patient stays, similar to a VA hospital. Although neither of these options seem feasible in the short run, we view this scenario as a useful benchmark for examining how the distribution of discharges is affected by Medicare's reimbursement scheme and hospitals' incentives.

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 (2) of Table 5, while panel (b) shows the predicted discharges for just DRG 207. In each of these figures, we normalize the horizontal axis to display the day of discharge relative to the SSO threshold, which varies over time. As expected, removing the incentive to keep patients past the SSO threshold eliminates the spike in discharges around the magic day. It is clear in the figure, however, that in addition to smoothing out discharges around the threshold, there is a substantial leftward shift in the

[37] Moreover, our finding that strategic discharging is not more prevalent among relatively healthy patients (see footnote 28), while only suggestive, appears to indicate that hospitals are unlikely to substantially change their treatment regimens for their least healthy patients.

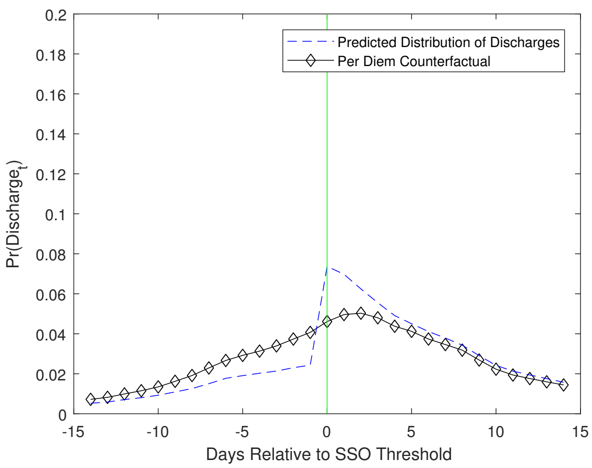


(a) Counterfactual 1, all DRGs

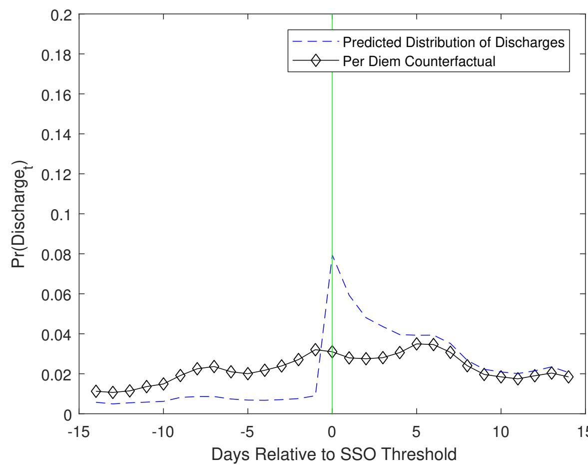


(b) Counterfactual 1, DRG 207

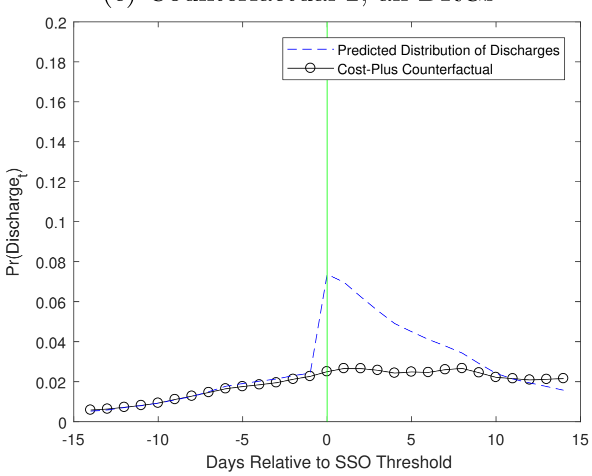
0



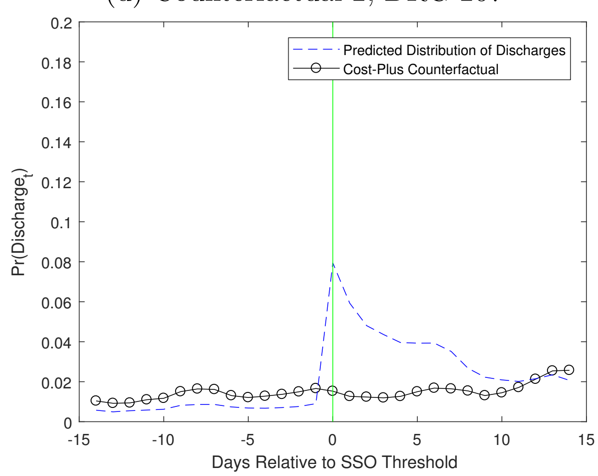
(c) Counterfactual 2, all DRGs



(d) Counterfactual 2, DRG 207



(e) Counterfactual 3, all DRGs



(f) Counterfactual 3, DRG 207

Figure 8: Predicted discharge probabilities for baseline model counterfactual scenarios

Table 5: Model Estimates

		(1)	(2)
Hospital Types			
	For-profit, HwH	0.909	0.891
		(0.004)	(0.004)
	For-profit, standalone	0.789	0.769
		(0.002)	(0.002)
	Non-profit, HwH	0.707	0.678
		(0.005)	(0.005)
	Non-profit, standalone	0.598	0.575
		(0.003)	(0.004)
Patient Types			
	African-American		0.157
			(0.004)
	Under 65 years old		-0.138
			(0.003)
Day of week dummies			X
Average daily cost (β), interacted with four hospital types		X	X
DRG specific λ		X	X
DRG specific Ω		X	X
$N = 377,513$			

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

entire distribution: the discharge probability 10 days prior to the threshold is 3.5 times higher. Overall, patients are released much earlier when the financial incentives to delay discharge are eliminated, with the average length of stay declining by 8.3 days relative to the baseline model, an average reduction of 26 percent.

Given that LTCHs cannot be reimbursed based on length of stay in this counterfactual, it is difficult to gauge the full impact it would have on Medicare's costs. To still provide some informative estimates along this dimension, however, we assume Medicare reimburses hospitals with a lump-sum payment that equals their expected costs. This should make hospitals indifferent between operating and not operating without giving them an incentive to manipulate discharges in order to receive higher payments.[38] If we assume these payments are equal to our average cost-per-day estimates for each hospital-DRG-year, Medicare would save, on average, $14,779 per patient. Over our entire sample of patients with the nine most-common DRGs that were discharged to home or a nursing facility, the aggregate savings per year would be $558 million.

[38]Of course, if hospitals were aware that their lump-sum payment were being calculated in this way, it would provide a potential incentive to lengthen treatments in order to increase future lump-sum payments. These concerns are outside the scope of our model.

Table 6: Counterfactual Outcomes

	Baseline model	Counter.1: $\alpha = 0$	Counter. 2: Per-diem	Counter. 3: Cost-plus
Share of patients discharged before SSO threshold	0.21	0.62	0.33	0.21
Share of patients discharged after SSO threshold	0.79	0.38	0.67	0.79
Share of patients with longer stay compared to baseline		0.00	0.04	0.40
Share of patients with shorter stay compared to baseline		0.47	0.12	0.05
Mean day of discharge relative to SSO threshold	3.31	-4.10	2.11	5.60
St. dev. day of discharge	7.82	9.93	8.28	10.44
Mean length of stay	27.64	19.35	26.39	32.36
Mean percent change in length of stay relative to baseline		-26	-3	27
Of patients in the hospital 3 days prior to the magic day:				
Percent held until the magic day	90	73	82	91
Percent discharged within 3 days after the SSO threshold	30	25	24	12
Mean payments ($1000s)	40.13	25.35	38.90	45.70
St. dev. payments	22.27	15.87	20.13	23.55
Percent change in payments relative to baseline		-29	-3	32
Mean Costs ($1000)	37.10	25.35	35.39	43.50
St. dev. payments	19.61	15.87	19.41	22.44
Percent change in costs relative to baseline		-26	-3	26

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

Our second counterfactual simulates a reimbursement formula recently proposed by MedPAC to stem strategic discharges.[39] The proposed payment system consists of a per-diem payment rate based on the full LTCH payment divided by the geometric mean length of stay, so we refer to this scheme as the "per-diem counterfactual." Under this system, 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 length of stay. As a result, the reimbursement policy is completely linear until the mean length of stay is realized, at which

[39]See Medicare Payment Advisory Commission (2014), Chapter 11, for a detailed description of the proposal. Although this policy has not yet been adopted, it remains under consideration. CMS did alter the LTCH-PPS policy in FY 2018 to offer more generous payments for discharges prior to the SSO threshold, although a discontinuity in payments at the threshold remains. See Online Appendix C for details.

point the reimbursement ceases, as we illustrate in panel (a) of Figure A4 in Online Appendix F. The goal of this policy is to discourage very short stays while dampening the incentive to hold patients in the hospital as they approach the threshold. At the same time, the new per-diem rates will be higher than the old rates, which may prompt LTCHs to keep some patients longer than they would have under the old system, particularly if they were very unlikely to remain in the hospital until the SSO threshold.

Panels (c) and (d) of Figure 8 show the predicted probability of discharge for any given day under this counterfactual compared to the baseline model. The policy is clearly effective at removing the spike in discharges at the SSO threshold. Comparing this counterfactual to the "lump-sum" counterfactual in panel (a), we see that, due to the offsetting effect of higher per-diem payments, far fewer discharges occur well in advance of the SSO threshold — discharges under this policy closely resemble the baseline discharge pattern ten days before and five days after the threshold. Rather than a general leftward shift in the distribution, we see a more localized shift in patients being discharged from just after the threshold to the days just before it. In this case, the impact of the policy is strongest for those patients likely to be discharged near the SSO threshold — for these patients, the looming lump-sum payment in the present scheme provides a strong incentive for LTCHs to hold them longer because the payoffs from delaying discharge are highest. Highlighting the policy's impact on strategic discharge behavior, patients that are still in the hospital three days before the threshold day are now 8.8 percent less likely to remain there until the SSO threshold than in the baseline model, and 20 percent less likely to be discharged during the three days after it. Overall, however, the impact of this payment scheme is more modest than the "lump-sum" scenario. Compared to the baseline model, the per-diem counterfactual has a 1.25-day shorter mean length of stay for the nine pooled DRGs, a three percent decrease.

It is likely that removing the spike in discharges would benefit patients who were being held in the hospital solely so the LTCH could secure a larger payout. Nevertheless, the new policy may have opposing effects on overall Medicare payments: although shorter stays yield savings, the increased per-diem rate partially offsets them. Taking this into account, we find that the MedPAC proposal does offer considerable savings for Medicare, reducing payments by four percent. On average, the per-diem payment scheme saves about $1,230 per hospital stay compared to the current policy, which would amount to an annual aggregate savings of $46.4 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, referring to it as the "cost-plus" counterfactual and presenting it in panel (b) of Figure A4 in Online Appendix F.

This counterfactual also successfully removes the spike in discharges, but does so by shifting discharges later. Here, 79 percent of patients are held past the SSO threshold, which is similar to the baseline model. Focusing only on patients remaining in the hospital until at least three days prior to the magic day yields an important insight: of these patients, many fewer are discharged during the three days following the magic day (12 percent instead of 30 percent). As a result, the average length of stay under the counterfactual is nearly five days longer than in the baseline. Implementing this policy would lead to a 32 percent increase in payments to LTCHs, due to both longer stays and more-lucrative payments for long-staying patients.

Given the similarity of our paper to Einav et al. (2018), it is instructive to compare our counterfactual analysis with theirs. Both of our dynamic models of patient discharge have LTCHs receiving a daily flow payoff that takes into account their revenue, cost of treatment, and patient's utility from staying in the facility, with the LTCH making a binary decision each day of whether to discharge the patient or not. Furthermore, in their counterfactual analysis, Einav et al. (2018) assume, as we do, that both the set of LTCHs and the distribution of patients admitted to the LTCHs remain the same under alternative counterfactual reimbursement policies. In estimating their model, however, Einav et al. (2018) use both the pre-PPS and PPS periods, whereas we only use the PPS period.[40]

The exact counterfactuals considered in Einav et al. (2018) are, for the most part, different than the ones we consider, although based on the similarity of the two models, in principle each paper's model could analyze the other's hypothetical policies. For example, Einav et al. (2018) consider what they call "win-win" payment schedules that hold LTCH revenue fixed under the observed discharge patterns but wherein the LTCHs receive a constant per-diem amount up to a threshold length of stay, at which point the payments are capped and per-diem payments drop to zero. Einav et al. (2018) demonstrate that there exists a set of contracts that reduce total Medicare payments for the episode of care but do not reduce LTCH profits.

Although most of the counterfactual payment policies analyzed in Einav et al. (2018) are different than the ones we investigate, they do consider one that is similar to our second counterfactual, what we call our "per-diem counterfactual." In this analysis, Einav et al. (2018) consider a counterfactual that "removes the jump" in payments by choosing a reimbursement scheme that eliminates the jump in payments at the SSO threshold, but, like the current scheme, provides no extra payments for days beyond this threshold.[41] They show that, by removing the jump in payments, LTCHs are less likely to hold patients until the magic day and estimate that the average length of stay falls by 1.9 days. In our "per-diem counterfactual," we find that the av-

[40]We have checked, however, that our model can generate similar patterns to those observed during the pre-PPS period by comparing the results of our "cost-plus" counterfactual to the discharge patterns in 2002, when the reimbursement process was similar to a cost-plus type scheme. Results are available upon request.

[41]We are referring to what Einav et al. (2018) call the "higher rate per day" counterfactual. In this analysis they increase the per-diem payment prior to the SSO threshold but hold the post-threshold payment fixed.

erage length of stay falls by a similar magnitude of 1.3 days. Neither paper finds a large change in costs for Medicare: we predict that Medicare costs will fall by about three percent, whereas Einav et al. (2018) predict that costs will increase by about 1 percent. We suspect that our different predictions about costs stem from the fact that neither the samples nor the policies are exactly the same in the two papers. For example, in our paper the full payment is reached at the mean length of stay, whereas in Einav et al. (2018) the full payment is still reached at the SSO threshold (5/6 of the geometric mean length of stay).[42]

7 Conclusion

Medicare's prospective payment system for long-term care hospitals influences hospitals' discharge decisions. Because the current reimbursement formula provides a large lump-sum payment for patients who stay past a certain threshold, LTCHs respond to these financial incentives by holding patients until right after they reach this point. Our findings suggest that LTCHs respond to this payment scheme by manipulating discharges for financial reasons, resulting in needless costs for Medicare and potentially a greater risk of adverse events 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 threshold 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.

We also consider several institutional details of the LTCH market. Consistent with reports from industry insiders, we find that for-profit LTCHs are much more likely to discharge patients immediately 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 discharge patients strategically, perhaps because they can easily transfer patients across floors to secure larger payments from Medicare.

Finally, our dynamic structural model of LTCHs' discharge behavior allows us to evaluate MedPAC's recently proposed changes to the 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 provide substantial savings for Medicare as LTCHs respond to the new policy by discharging patients sooner.

[42] Furthermore, Einav et al. (2018) show in a separate "remove the jump" counterfactual analysis, which they term the "lower cap" payment policy, that both length of stay and Medicare reimbursements can decline.

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Online Appendix — Not For Publication

A Complete Summary Statistics

Table A1: 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
African-American	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 A2: 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
African-American	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 A3: 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
Non-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		

Note: 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.

Table A4: 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
Non-profit, HwH	0.07	0.08	0.05	0.06	0.09	0.10	0.07	0.06	0.03	0.07
Non-profit, standalone	0.17	0.18	0.23	0.18	0.18	0.18	0.18	0.16	0.14	0.24
N^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 A7 for the descriptions on these DRGs.

Table A5: 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
Non-profit, HwH	1,280	1,055	1,220	1,503
Non-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
Non-profit, HwH	44,177	33,746	33,746	68,396
Non-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
Non-profit, HwH	14,437	7,018	11,352	23,111
Non-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				

Table A6: Average daily cost estimates (in $)

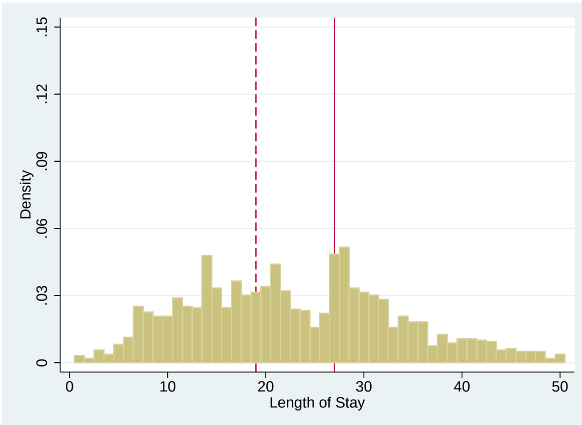
	Mean	**25th Percentile**	**Median**	**75th Percentile**
Overall	1,319	1,075	1,280	1,526
For-profit, HwH	1,266	1,003	1,237	1,501
For-profit, standalone	1,300	1,078	1,267	1,488
Non-profit, HwH	1,398	1,100	1,365	1,640
Non-profit, standalone	1,401	1,135	1,372	1,631
Select	1,279	1,028	1,267	1,497
Kindred	1,293	1,078	1,253	1,487
Other	1,348	1,089	1,301	1,558
N = 377,513				

B Other DRGs

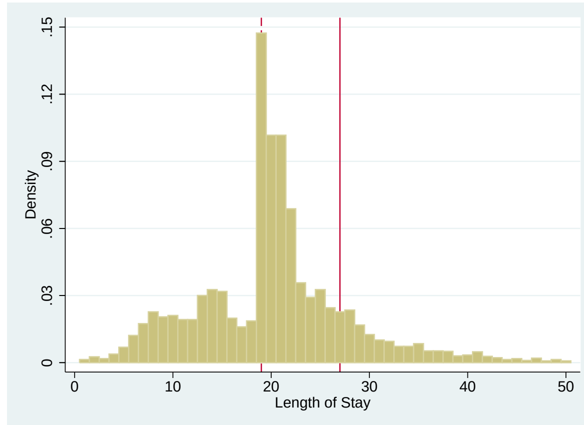
While our paper at times focuses on DRG 207, in this appendix we extend the analysis to other DRGs, summarized above in Appendix A. Our structural estimation uses the nine most common DRGs in order to increase the variation in magic days in the data. Table A7 describes each of these DRGs. Figure A1 plots discharge patterns for the next three most common DRGs after DRG 207 in 2004 and 2013, along with their respective SSO thresholds. Figure A2 plots realized Medicare payments and discharge patterns that suggest other DRGs have similar discharge practices.

Table A7: DRG Descriptions

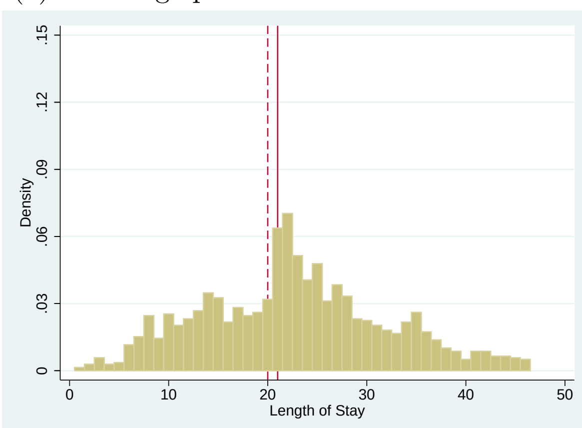
DRG	Description
177	Respiratory infections and inflammations with major complicating conditions
189	Pulmonary edema and respiratory failure
190	Chronic obstructive pulmonary disease with major complicating conditions
193	Simple pneumonia and pleurisy with major complicating conditions
207	Respiratory 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



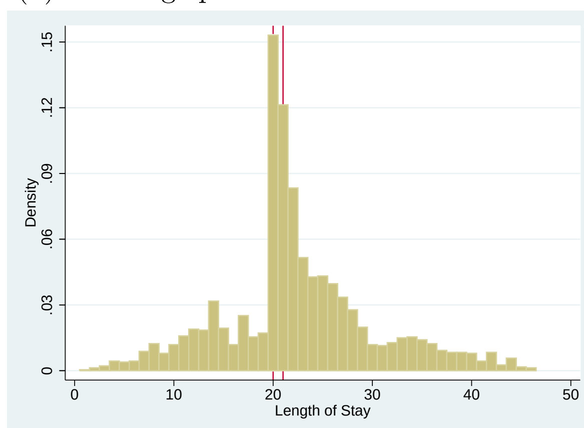
(a) Discharge practices for DRG 189 in 2004



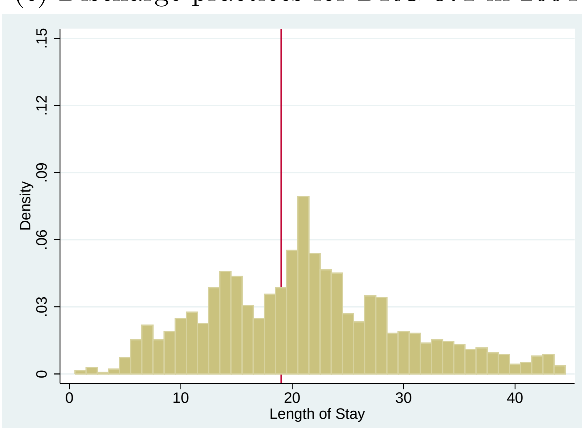
(b) Discharge practices for DRG 189 in 2013



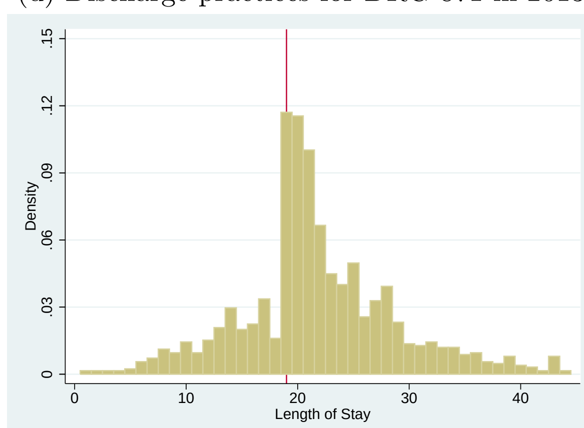
(c) Discharge practices for DRG 871 in 2004



(d) Discharge practices for DRG 871 in 2013

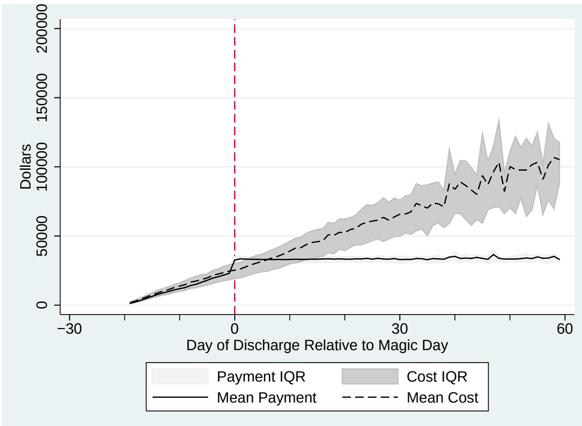


(e) Discharge practices for DRG 177 in 2004

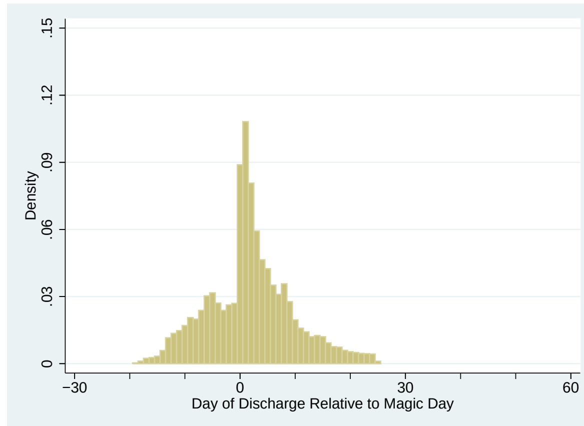


(f) Discharge practices for DRG 177 in 2013

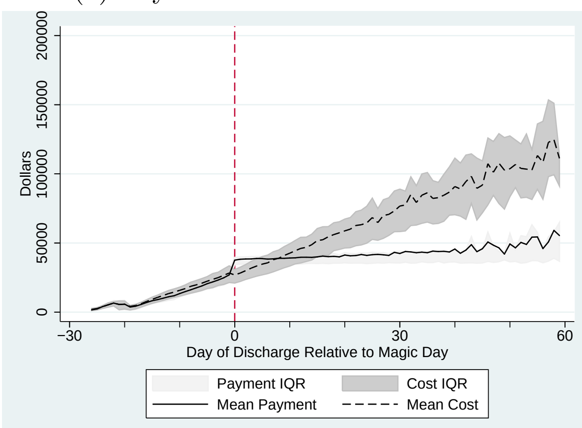
Figure A1: Discharge timing across DRGs and years



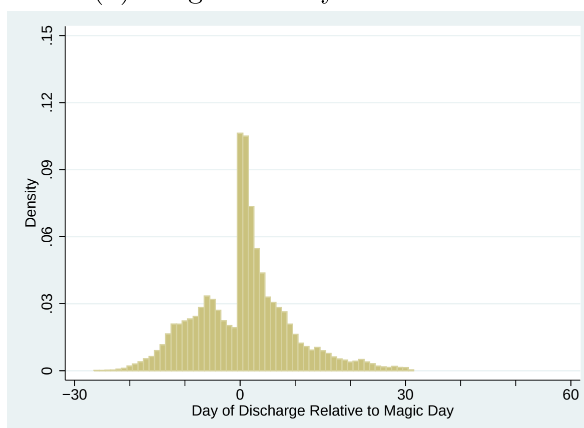
(a) Payoffs and Costs for DRG 177



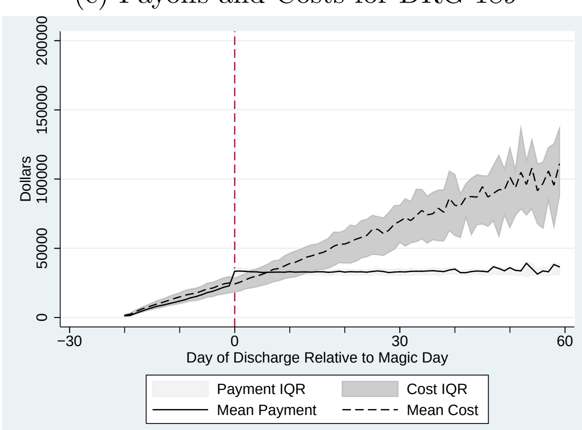
(b) Lengths of stay for DRG 177



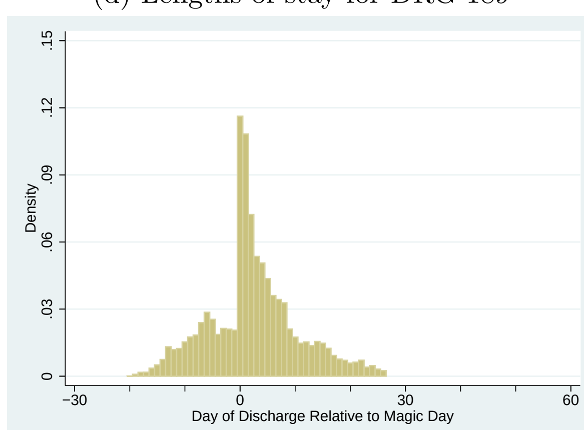
(c) Payoffs and Costs for DRG 189



(d) Lengths of stay for DRG 189



(e) Payoffs and Costs for DRG 871



(f) Lengths of stay for DRG 871

Figure A2: Costs, payoffs and discharge patterns for other DRGs

C Payment Policy Details & Example

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 known as the full LTCH payment.

For 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.

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.[43]

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`.

[43] 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.

100 percent of cost of case

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

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.

After our data period, CMS has continued to make changes to the LTCH-PPS. In FY 2018, the "very short stay outlier" payment was eliminated. In addition, CMS began calculating payments for discharges prior to the SSO threshold according to the "blended" formula described in option 4 above rather than the lowest payment of all four options. This change, which effectively raised payments for discharges prior to the SSO threshold, was implemented in part due to concerns that hospitals were delaying discharges in response to the SSO policy.[44] However, the revised policy still results in a discontinuity in payments at the SSO threshold.

[44]See `http://www.cms.gov/Outreach-and-Education/Medicare-Learning-Network-MLN/MLNMattersArticles/downloads/MM10273.pdf` for a detailed list of recent policy changes regarding LTCH payments.

D Probit Model: Coefficient Estimates and other DRGs

Table A8 contains the estimated coefficients from the probit model for DRG 207. Table A9 presents the estimated marginal effects of the baseline probit model for other DRGs. Table A10 shows (a sample of) the estimated probit coefficients for the interacted models for DRG 207.

Table A8: 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 A9: 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] $\Phi(\gamma_0 + \gamma_1 t + \gamma_2 t^2 + \mu_0) * 100$

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

[3] Hazard ratio: $\frac{\Phi(\gamma_0+\gamma_1 t+\gamma_2 t^2+\mu_0)}{\Phi(\gamma_0+\gamma_1 t+\gamma_2 t^2+\mu_{-1})}$. Square brackets contain the p-value from a Wald test for $H_0 : HR = \frac{\Phi(\gamma_0+\gamma_1 t+\gamma_2 t^2+\mu_0)}{\Phi(\gamma_0+\gamma_1 t+\gamma_2 t^2+\mu_{-1})} = 1$.

Table A10: Selected Probit Coefficients by Subgroup, DRG 207 at $day = 29$

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

Note: Standard errors in parentheses.

E Strategic Discharge and Capacity Constraints

This appendix considers whether capacity constraints affect LTCHs' decisions to strategically discharge patients. Measuring the capacity utilization of LTCHs is difficult because we only have data for their Medicare patients, and even then we only observe the quarter of the year in which their stays began. Nevertheless, we can create a rough proxy for capacity utilization by constructing a variable for each LTCH-quarter that gives the number of Medicare patient-days per LTCH bed per quarter across all the DRGs in our data. We use this variable to gauge how the probability of discharge varies across our measure of capacity utilization, with the idea being that hospitals that routinely have more patients per bed would also be more likely to be capacity constrained.[45] Table A11 shows the probability of being discharged on the magic day and the day before it for DRG 207, the main DRG we analyze in the paper. Broken down by decile based on the number of Medicare patient-days per LTCH bed per quarter (so the 10th decile is the set of hospitals that have the most Medicare patient-days per LTCH bed per quarter, i.e., the hospitals that are the most capacity constrained according to this rough measure of capacity utilization), the ratio of the discharge probabilities for the magic day over the day before it clearly shows that the probability of engaging in strategic discharge initially increases in the LTCH's capacity utilization, but then flattens out.

Table A11: Strategic Discharge by Capacity Utilization

Medicare Patient Days	Probability of Discharge			P-value of difference
Per Bed Decile	SSO Threshold Day	Preceding Day	Ratio	with lower decile
1	0.048	0.016	2.99	-
2	0.066	0.013	5.23	0.000
3	0.078	0.011	7.29	0.000
4	0.081	0.01	8.17	0.250
5	0.09	0.01	8.8	0.001
6	0.088	0.009	9.79	0.417
7	0.095	0.009	10.79	0.022
8	0.091	0.01	9.39	0.219
9	0.091	0.011	8.65	0.980
10	0.09	0.01	8.76	0.866

Note: The proxy for capacity constraint is described in the text. Discharge results are for DRG 207.

Motivated by the summary statistics in Table A11, we further consider this issue using the same type of probit analysis as in Section 4.2. Table A12 shows that LTCHs in the first tercile of capacity utilization (i.e., the least capacity constrained) engage in less strategic discharging than hospitals in the second or third tercile (between the second and third there is no statistically significant difference).

The next two tables show the heterogeneous effects of this relationship across different hospital types. Table A13 repeats the analysis from Table A12 but interacts the extent of capacity utilization with indicators for whether the LTCH is a for-profit facility or not. The table shows that the difference in strategic discharging across for-profit and non-profit LTCHs is greatest

[45]It should be noted that this proxy for capacity utilization may suffer from non-classical measurement error, as it may be correlated with other factors such as the Medicare share of total hospital days at each LTCH.

Table A12: Probit Marginal Effects by Capacity Utilization, DRG 207

	Predicted Prob. of Discharge		Hazard	Ratio of
	SSO Threshold Day	Preceding Day	Ratio	Hazard Ratios[1]
Tercile of Capacity Utilization:				
First	7.36	1.31	5.63	
	(0.381)	(0.121)	[0.000]	
Second	9.38	1.00	9.31	1.65
	(0.435)	(0.079)	[0.000]	[0.000]
Third	9.39	0.949	9.90	1.76
	(0.481)	(0.070)	[0.000]	[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] Ratio of hazard ratios are relative to the first tercile.

within the bottom tercile of capacity utilization. Furthermore, only non-profit LTCHs become more likely to strategically discharge patients as they become more capacity constrained.

Table A14 repeats the analysis from Table A12 but interacts the extent of capacity utilization with indicators for whether the LTCH is owned by a chain or not. The table shows that chain-owned LTCHs engage in more strategic discharging than non-chain-owned LTCHs, but this difference is mainly at lower levels of capacity utilization. Finally, while chain-owned LTCHs do not increase their use of strategic discharge until they become very capacity constrained (third tercile), non-chain-owned LTCHs do so at lower levels of capacity utilization.

Table A13: Probit Marginal Effects by Capacity Utilization by For-Profit Status, DRG 207

	Predicted Prob. of Discharge		Hazard	Within Ratio of	Across Ratio of
	SSO Threshold Day	Preceding Day	Ratio	Hazard Ratios[1]	Hazard Ratios[2]
Tercile of Capacity Utilization:					
First:					
For-Profit	8.48 (0.482)	1.03 (0.110)	8.14 [0.000]		
Non-Profit	5.54 (0.520)	1.79 (0.260)	3.09 [0.002]		2.63 [0.005]
Second:					
For-Profit	9.60 (0.480)	0.91 (0.079)	10.55 [0.000]	1.30 [0.126]	
Non-Profit	8.76 (0.730)	1.29 (0.200)	6.79 [0.000]	2.19 [0.026]	1.55 [0.104]
Third:					
For-Profit	9.31 (0.526)	0.86 (0.066)	10.83 [0.000]	1.33 [0.121]	
Non-Profit	9.79 (1.130)	1.39 (0.215)	7.04 [0.000]	2.28 [0.048]	1.54 [0.146]

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] Ratio of hazard ratios are relative to the first-tercile-capacity-row for the same type of hospital. That is, it compares for-profits (or non-profits) at different terciles of capacity utilization to those in the first tercile.
[2] Ratio of hazard ratios are relative to the same capacity-tercile-row for the other type of hospital. That is, it compares for-profits and non-profits within the same tercile of capacity utilization.

Table A14: Probit Marginal Effects by Capacity Utilization by Chain-Owned Status, DRG 207

	Predicted Prob. of Discharge		Hazard	Within Ratio of	Across Ratio of
	SSO Threshold Day	Preceding Day	Ratio	Hazard Ratios[1]	Hazard Ratios[2]
Tercile of Capacity Utilization:					
First:					
Chain	8.52	1.01	8.44		
	(0.576)	(0.130)	[0.000]		
Non-Chain	6.22	1.58	3.94		2.14
	(0.471)	(0.191)	[0.000]		[0.011]
Second:					
Chain	9.56	0.91	10.50	1.24	
	(0.503)	(0.091)	[0.000]	[0.243]	
Non-Chain	9.18	1.12	8.20	2.08	1.28
	(0.725)	(0.133)	[0.000]	[0.010]	[0.281]
Third:					
Chain	9.71	0.76	12.81	1.53	
	(0.650)	(0.070)	[0.000]	[0.081]	
Non-Chain	8.87	1.25	7.10	1.80	1.80
	(0.677)	(0.130)	[0.000]	[0.025]	[0.166]

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.

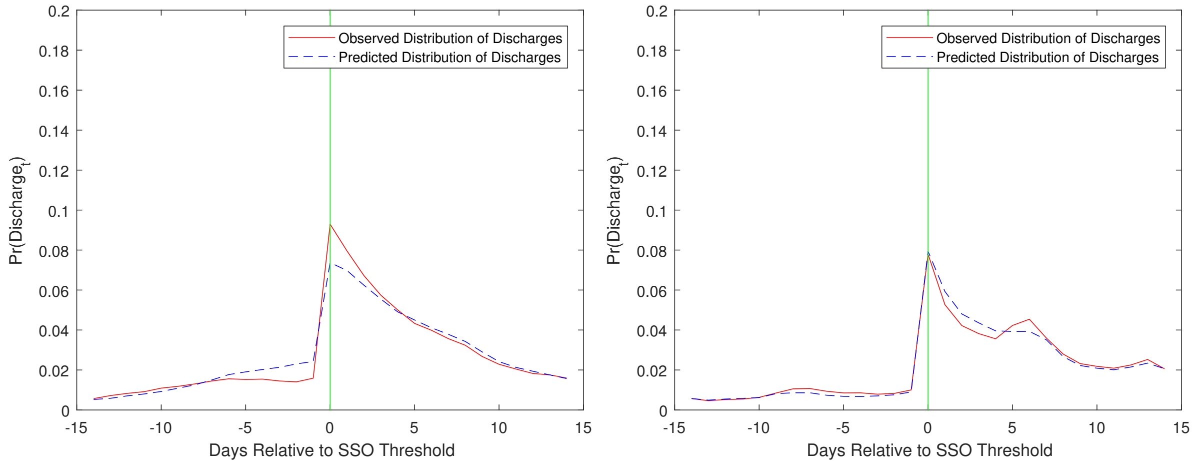
[1] Ratio of hazard ratios are relative to the first-tercile-capacity-row for the same type of hospital. That is, it compares Chain-owned (or Non-chain-owned) at different terciles of capacity utilization to those in the first tercile.

[2] Ratio of hazard ratios are relative to the same capacity-tercile-row for the other type of hospital. That is, it compares Chain-owned and Non-chain-owned within the same tercile of capacity utilization.

F Additional Figures for Counterfactual Analysis

Figure A3 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 5, where the horizontal axis in these figures is the number of days relative to the magic day (vertical line).[46] Panel (a) compares the predicted and observed discharge distributions for the entire sample of pooled DRGs while panel (b) focuses on just DRG 207.

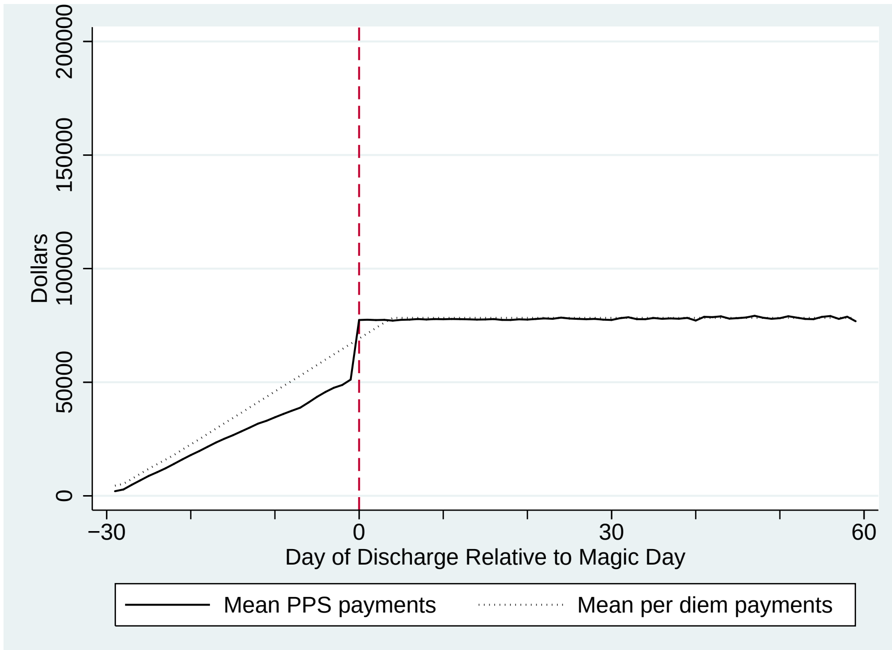
Figure A3: Observed and predicted discharge probabilities



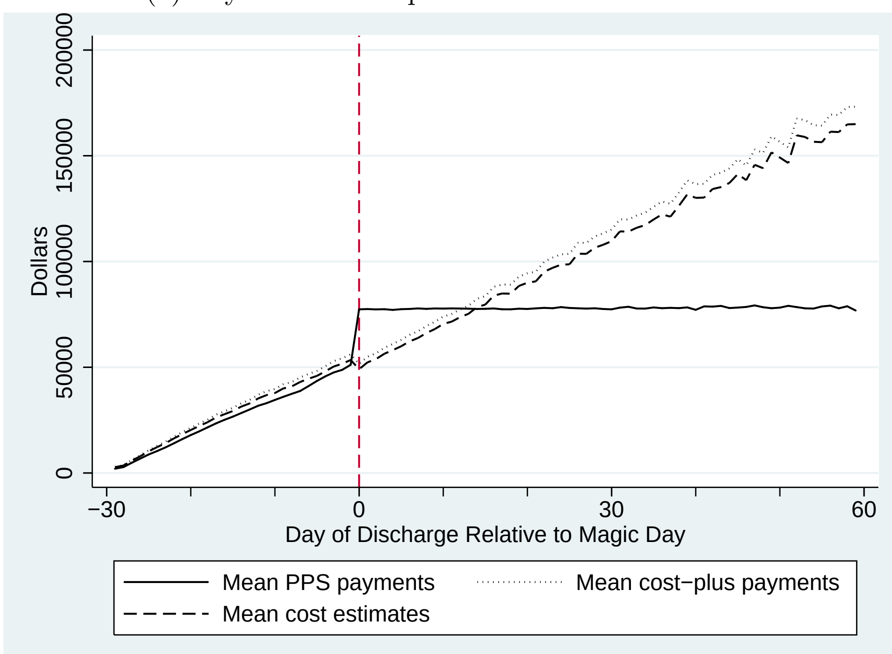
(a) Pooled DRGs (b) DRG 207

Figure A4 compares the reimbursement schemes we consider in the counterfactual analysis to the current PPS.

[46]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 A4: Counterfactual Reimbursement Policies for DRG 207.