The Review *of* Economics *and* Statistics

Vol. CV | July 2023 | Number 4

LONG-TERM CARE HOSPITALS: A CASE STUDY IN WASTE

Liran Einav, Amy Finkelstein, and Neale Mahoney*

Abstract—There is substantial waste in U.S. healthcare but little consensus on how to combat it. We identify one source of waste: long-term care hospitals (LTCHs). Using the entry of LTCHs into hospital markets in an event study design, we find that most LTCH patients would have counterfactually received care at Skilled Nursing Facilities—facilities that provide medically similar care but are paid significantly less—and that substitution to LTCHs leaves patients unaffected or worse off on all dimensions we can objectively measure. Our results imply Medicare could save about $4.6 billion per year by not allowing discharge to LTCHs.

I. Introduction

HEALTHCARE spending is one of the largest fiscal challenges facing the U.S. federal government. In 2014, the U.S. federal government spent $1.1 trillion on public healthcare programs (BEA, 2016), and the Congressional Budget Office (CBO) projects that spending will grow to $2 trillion by 2026 (CBO, 2016).

An *idée fixe* in health policy is that there is significant "waste" in the U.S. healthcare system, with the widely repeated claim that 30% of U.S. healthcare spending is wasteful (e.g., Orszag, 2009; McGinnis et al., 2013).[1] One prominent, stylized fact in support of this view is that the U.S. spends a much higher fraction of GDP on healthcare relative to other Organization for Economic Cooperation and Development (OECD) countries but obtains only middling health outcomes (e.g., OECD, 2017; Anderson et al., 2005; Papanicolas et al., 2018). Another is the Dartmouth Atlas evidence of large, unexplained differences within the U.S. in Medicare spending per capita, with no positive correlation between higher spending areas and better health outcomes (e.g., CBO, 2008; Skinner, 2011). While there is no universal definition, commentators typically use the term "waste" to refer to healthcare spending that does not improve patient health. Waste thus includes both transfers (e.g., excess payments to drug manufacturers) and deadweight loss (e.g., from use of an expensive technology that does not improve health).

The near-consensus on the existence of waste is, unfortunately, not matched by any agreement on how to reduce that waste. For example, Doyle et al. (2015) write, "There is widespread agreement that the United States wastes up to one-third of health care spending, yet pinpointing the source of the waste has proven difficult." In a similar spirit, Cutler (2010) notes, "Analysts from the left and right sides of the political spectrum agree that health care costs could be greatly reduced. There is, however, less agreement about the best strategy for reducing them."

Cutting healthcare spending is easy—closing down hospitals would do the trick. Cutting healthcare spending without harming patient health or well-being, however, has proved a much more elusive goal. In this paper, we provide a case study where, our evidence suggests, a substantial amount of healthcare spending—almost $5 billion per year in Medicare spending—could be saved without harming patient outcomes. While this is "only" about 1% of annual Medicare spending, a series of policies that save 1% of Medicare spending can add up to a sizable amount, as Cooper and Scott Morton (2021) emphasize.

Our case study is of a specific healthcare institution: long-term care hospitals (LTCHs).[2] LTCHs are one of several types of healthcare institutions that provide postacute care (PAC)—formal care provided to help patients recover from a surgery or other acute care event.

PAC is an understudied sector, with large stakes for both federal spending and patient health. Federal spending on PAC through the Medicare program is substantial, about $59 billion in 2014. A recent Institute of Medicine report found that, despite accounting for only 16% of Medicare spending, PAC contributed to a striking 73% of the unexplained geographic variation in Medicare spending (IOM, 2013), suggesting that there may be inefficiency in the sector.

Traditionally, PAC was provided at skilled nursing facilities (SNFs) or at home by home health agencies (HHAs). LTCHs were administratively created in the early 1980s to protect 40 chronic disease hospitals from the new Prospective

Received for publication August 26, 2020. Revision accepted for publication June 21, 2021. Editor: Benjamin R. Handel.

*Einav: Stanford University and NBER; Finkelstein: MIT and NBER; Mahoney: Stanford University and NBER.

We thank Jeremy Kahn, Mark Miller, Hannah Wunsch, and many seminar participants for helpful comments. We are grateful to Abby Ostriker, Anna Russo, and Connie Xu for excellent research assistance. Einav and Finkelstein gratefully acknowledge support from the NIA (R01 AG032449). Mahoney acknowledges support from the Becker Friedman Institute at the University of Chicago and the National Science Foundation (SES-1730466).

A supplemental appendix is available online at https://doi.org/10.1162/rest_a_01092.

[1]McGinnis et al. (2013) in turn was picked up by many major media outlets. See https://khn.org/morning-breakout/iom-report/ for a summary.

[2]The acronym LTCH is typically pronounced"el-tack," presumably reflecting the fact that LTCHs are sometimes referred to as long-term acute care hospitals (LTACs), which is phonetically pronounced in this manner.

The Review of Economics and Statistics, July 2023, 105(4): 745–765

https://doi.org/10.1162/rest_a_01092

Payment System introduced for acute care hospitals. What began as a regulatory carve-out for a few dozen specialty hospitals subsequently expanded into an industry with over 400 LTCHs and $5.4 billion in annual Medicare spending in 2014 (MedPAC, 2016).

The institutional history of LTCHs—which we discuss in detail below—suggests that they may be primarily cost-increasing institutions. LTCHs are administrative—not medical—constructs. They are unique to the U.S. healthcare system, and, to the best of our knowledge, they do not exist in any other country. LTCHs are reimbursed at substantially higher rates than other PAC facilities, and they are run primarily by large for-profit chains. They have also been the subject of several decades' worth of a regulatory game of whack-a-mole; in a series of reforms, the Centers for Medicare and Medicaid Services (CMS) has made multiple attempts to eliminate the loopholes that LTCHs offer for excess reimbursement, and to limit the growth of the sector as a whole.

We analyze the impact of a patient being discharged to an LTCH (hereafter, "LTCH discharge") on various outcomes. Our empirical strategy is to assess LTCH discharge with an event study design based on the first entry of an LTCH into a local hospital market. We define hospitals markets based on Hospital Service Areas (HSAs), of which there are about 3,400 in the United States. We analyze 17 years of data, from 1998 to 2014. During this period, 186 hospital markets experienced their first LTCH entry. Another 152 markets already had an LTCH at the start of our sample period, and over 3,000 markets still had no LTCH at the end of our sample period. Markets with LTCHs are disproportionately large, accounting for 34% of the Medicare enrollees by the end of our sample period.

We estimate that about four-fifths of discharges to LTCHs represent substitution from SNFs, while the others substitute mostly from discharges home. SNFs are reimbursed by Medicare at substantially lower rates than LTCHs; on a per day basis, LTCHs in 2014 were reimbursed about $1,400, compared to about $450 for SNFs (authors' calculation based on Medicare data described below). We estimate that a discharge to an LTCH increases net Medicare spending by about $30,000.

Patients, however, do not measurably benefit from this increased spending. We estimate that patients discharged to an LTCH owe more money out of pocket, and we find no evidence that they spend less time in institutional care. Strikingly, despite an almost 30% 90-day mortality rate, we also find no evidence that discharge to an LTCH improves mortality.

We do find that the discharging acute care hospitals benefit from sending a patient to an LTCH. Specifically, we estimate that discharge to an LTCH reduces the patient's length of stay in the originating acute care hospital by, on average, over 8 days. This generates savings for the originating hospital because they are typically paid a fixed amount per patient, regardless of the patient's length of stay, thus they benefit financially from being able to reduce the patient's length of stay. However, discharges to an LTCH increase overall costs for Medicare. Taken together, our findings indicate that Medicare could save roughly $4.6 billion per year with no harm to patients by not allowing for discharge to LTCHs.

Our strategy allows us to look not only at aggregate effects of LTCHs but also at whether there is a subset of patients or LTCHs for whom the benefits of LTCH discharge are higher and/or the costs of LTCH discharge are lower. We explore potential heterogeneity across a number of natural patient and LTCH characteristics, and we find little evidence of heterogeneous effects. Perhaps most interestingly, we examine heterogeneity across LTCH patients affected by a recent policy change that occurred shortly after the last year of our sample. To try to reduce expenditures and limit LTCH care to only the most clinically complex patients, in 2016 CMS announced a "dual payment structure" under which LTCHs are only reimbursed as LTCHs if the patients meet certain clinical criteria (MedPAC, 2017a). We find no evidence of lower spending impacts or of mortality benefits for these more complex patients who would continue to qualify for LTCH reimbursement under these new rules.

In interpreting our results, it is important to note that despite high short-term mortality rates in the affected population, the confidence intervals on our mortality results do not allow us to conclusively reject economically meaningful improvements in health; this is a common feature of nearly all research that considers mortality as an outcome. In addition, we are not able to measure nonmortality dimensions of health (such as pain, functional limitations, and other quality-of-life metrics) or non-health dimensions of utility (such as the quality of the room and board provided). Again, this is a common feature of nearly all health economics research on patient outcomes.

Another way to interpret our findings, therefore, is to note that if the excess spending on LTCHs provides unmeasured health benefits or non-health "amenity benefits," they would need to be valued (by the social planner) at about $1,000 per day in the LTCH to "justify" the incremental Medicare spending. While it is difficult—if not impossible—to definitively reject the presence of such unmeasured health and amenity benefits, we argue that the institutional history of the LTCH sector as a regulatory carve-out—rather than an institution created to serve a medical need—suggests that the "burden of proof" should be to show that LTCHs provide medical or nonmedical benefits that justify their costs. Consistent with CMS' various attempts to limit the growth of LTCHs, we cannot reject the null hypothesis that the medical care LTCHs provide is not better than the alternative.

Our paper relates to several distinct literatures. Most narrowly, it complements recent work suggesting that the PAC sector is a fruitful part of the healthcare system in which to look for inefficiencies in Medicare spending (IOM, 2013; Doyle et al., 2017); relatedly, Curto et al. (2019) note that hospital patients enrolled in Medicare Advantage are much less likely to be discharged to PAC, and particularly institutional—that is, facility-based—PAC (such as SNFs or

Table 1.—Correlates of LTCH Location

	HSAs w/ pre-1998 LTCH (1)	HSAs w/ 1998–2014 entry (2)	HSAs w/ no LTCH by 2014 (3)	Correlation[a] (4)
Number of HSAs	152	186	3,098	
HSA demographics:				
Population (1000s)	540.7	233.5	59.1	0.47
% Urban	0.84	0.76	0.50	0.28
% Black	0.16	0.15	0.07	0.18
Median age	39.6	40.9	43.2	−0.16
Median income ($, 1000s)	56.0	49.9	49.9	0.05
% < Federal Poverty Line	0.16	0.17	0.16	0.02
% Uninsured	0.14	0.15	0.14	0.03
% Dual Eligible	0.20	0.19	0.18	0.04
HSA hospital system:				
Acute Care Hospital beds per 1,000 people	4.2	4.5	3.6	0.05
% For profit	0.25	0.25	0.13	0.11
% Skilled Nursing Facility discharges	0.20	0.19	0.12	0.21
% Post-Acute Care discharges	0.41	0.39	0.21	0.27
Medicare spend per beneficiary ($US) (000s)	10.17	9.92	9.59	0.09
HSA region:				
% HSAs with LTCH in census division[b]	0.12	0.13	0.10	0.13
% HSAs with LTCH in state in 1984[c]	0.50	0.34	0.39	0.02
% in states with CON law[d]	0.40	0.41	0.49	−0.05

"Pre-1998 Entry" is the set of HSAs that ever had an LTCH from 1984–1997. "1998–2014 Entry" refers to HSAs where a first LTCH entered from 1998 to 2014. "Never Enter" is the set of HSAs that never had any LTCHs from 1984–2014. Population, share urban, and share black are determined from the 2010 census. Median age, income, the share below the poverty line, and the share uninsured are from the 2010–2014 ACS. ACH beds per capita, share for-profit, share discharged to SNF/IRF, share discharged to any PAC (including LTCH, SNF, IRF, HHA or hospice), and Medicare spending were calculated for 2014, the final year of observation in our event study.

[a] The bivariate correlation column lists the bivariate correlation between the outcome variable and an indicator for whether an HSA ever had an LTCH from 1984–2014 (i.e. the union of the HSAs in column 1 and column 2).

[b] Census Division's share of HSAs with an LTCH calculates the share of HSAs in the same Census division as that reference HSA that have an LTCH in 2014 (leaving out the reference HSA).

[c] Share with an LTCH in state in 1984 calculate the share of HSAs in each group (pre-1998 entry, 1998-2014 entry, and never entry) that had an LTCH in the state in 1984.

[d] Share in a state that ever had a Certificate of Need (CON) law: This is the share of HSAs in each group that is in a state that had a CON law at any point from 2002–2010. State CON laws for 2002–2010 are reported in AHPA (2003–2011).

LTCHs). Our results are consistent with this existing impression and point to a particular PAC institution—the LTCH—whose elimination could save money without any apparent harm to patients.

Our paper also contributes to a small but growing literature on the impact of providers on the healthcare sector. Much of this literature has focused on the effect of financial incentives on provider behavior (e.g., Cutler, 1995; Clemens & Gottlieb, 2014; Ho & Pakes, 2014; Eliason et al., 2018; Einav et al., 2018), or more broadly on the role of the physician in affecting healthcare decisions (e.g., Barnett et al., 2017; Molitor, 2018). Our study is unusual in that it examines the impact of a specific institution (or organizational form) on the efficiency of the healthcare sector. Most closely related to our analysis is Kahn et al. (2013), who look cross-sectionally at how outcomes for chronically ill, acute care hospital patients differ in markets with differential LTCH penetration. Like us, they conclude that increased probability of LTCH transfer is associated with lower use of SNFs, higher overall Medicare payments, and no improvement in survival; however, our empirical analysis below suggests that there are likely confounders to such cross-sectional analysis (see table 1).

Finally, and most broadly, our identification of a specific healthcare institution that appears to be wasteful is an illustration, in the context of healthcare, of the role Duflo (2017) advocates for economists in general: "the economist as plumber . . . she installs the machine in the real world, carefully watches what happens, and then tinkers as needed." In contrast to this "plumbing" approach, past efforts at reducing waste in U.S. healthcare have typically emphasized broad-based reforms to delivery models, often motivated by economic theory—price regulation and certificate of need laws in the 1970s (Joskow, 1981), Prospective Payment and managed care systems in the 1980s and 1990s (Newhouse, 1996), and most recently, the move to Alternative Payment Models such as Accountable Care Organizations and bundled payments (Berwick, 2011). These efforts have consistently failed to fulfill the high expectations set for them, and they have often produced unintended, negative consequences.

Our analysis of LTCHs provides an illustration of how the health economist might fruitfully transform into the health plumber. In this, our paper joins a small but growing number of "case studies" of specific waste in healthcare—from out-of-network billing (Cooper et al., 2020) to financial barriers to living kidney donation (Macis, 2021), to lack of real-time adjudication of health insurance claims (Orszag & Rekhi, 2021). This body of work, together with other projects compiled in Cooper and Scott Morton (2021), suggests that successfully reducing waste in the healthcare sector may involve more forensic investigation than health economists and health policy experts typically engage in.

The rest of our paper is organized as follows. Section II provides background on post-acute care and LTCHs. Section III describes our data and presents summary statistics. Section IV describes our empirical strategy, and section V reports the results. Section VI concludes.

II. Setting

A. *Post-Acute Care*

LTCHs are part of the post-acute care (PAC) sector, which provides patients with rehabilitation and palliative services following an acute care hospital (hereafter, ACH or "hospital") stay. PAC includes both facility-based care—skilled nursing homes (SNFs), inpatient rehabilitation facilities (IRFs), and long-term care hospitals (LTCHs)—and home-based care, provided by home health agencies (HHAs). About two-fifths of Medicare hospital patients are discharged to PAC, of which about 60% are sent to PAC facilities (70% of PAC spending) and about 40% are sent to home health care (30% of PAC spending) (MedPAC, 2015b). Because IRFs are institutionally similar to SNFs, but are much smaller in number, we lump them together with SNFs in our discussion and the empirical analysis that follows.[3]

Spending on PAC is substantial. In 2014, Medicare spent \$59 billion on PAC. This is approximately 16% of the \$376 billion in total Traditional Medicare (hereafter, "Medicare") spending and about 20% more than the much-studied Medicare Part D program spending.[4] PAC patients are high-risk, with 15% of Medicare deaths involving a PAC stay in the prior 30 days (Einav et al., 2018). Medicare spending on PAC is growing at two percentage points faster per year than overall Medicare spending, and it more than doubled between 2001 and 2013 (Boards of Trustees for Medicare, 2002, 2014). This spending growth has not been associated with any measurable improvements in patient health or quality of care (MedPAC, 2015a).

Within the PAC landscape, LTCHs generally provide the most intensive care, SNFs provide intermediate levels of care, and HHAs provide the least intensive care. Patient health follows a similar ordering, with 90-day postdischarge mortality declining from 28% for patients discharged to LTCHs, to 17% for SNF and IRF patients, and to 13% for patients discharged to home health care in 2014. Patients discharged to LTCHs look correspondingly less healthy on many dimensions. For example, compared to those discharged to SNFs, they are six times more likely to have been on a ventilator at the acute care hospitals, about three times more likely to be suffering from respiratory failure when admitted to the acute care hospitals, and about three times more likely to be suffering from septicemia (bloodstream infection).

Medicare reimbursement differs greatly across PAC providers. Loosely speaking, LTCHs are paid a fixed amount per admission, SNFs are reimbursed on a per diem basis, and HHAs are reimbursed per 60-day episode of care. In 2014, the average LTCH stay was 26 days and cost Medicare \$36,000; by contrast, an average SNF stay was 25 days and cost \$12,000. On a per day basis, therefore, LTCHs are the most expensive form of PAC (\$1,436 per day), followed by SNFs (\$466 per day), and then HHAs (\$73 per day). Patient cost sharing also differs across PAC providers. Cost sharing for LTCH stays is tied to the beneficiary's inpatient cost sharing; SNF stays are covered by a separate cost-sharing schedule, with daily copays that kick in after 20 days; and cost sharing is generally not required for HHA services.

Despite these very different reimbursement regimes, physicians lack precise medical guidelines or strict requirements from Medicare on which provider is most appropriate for a given patient. As a result, discharge decisions can reflect nonclinical factors, such as geographic availability, patient or physician preferences, and familiarity between the PAC provider and the referring hospital (Buntin, 2007; Ottenbacher & Graham, 2007). This results in substantial overlap in the types of cases treated by different PAC providers, and in significant variation in PAC utilization.

B. *Whack-a-Mole: A Brief Regulatory History of LTCHs*

Our analysis focuses on the impact of discharge to an LTCH. Unlike other medical facilities, LTCHs are a purely regulatory phenomenon and are unique to the U.S. healthcare system. To be classified as an LTCH, a hospital must have an average length of stay of 25 days or more. Because there are no specific medical requirements, LTCHs provide a diverse range of services, including those to address respiratory issues, septicemia, skin ulcers, and renal failure (MedPAC, 2018). We focus the rest of this discussion on the use of LTCHs by Medicare patients who, in 2014, accounted for just over 60% of all LTCH stays.

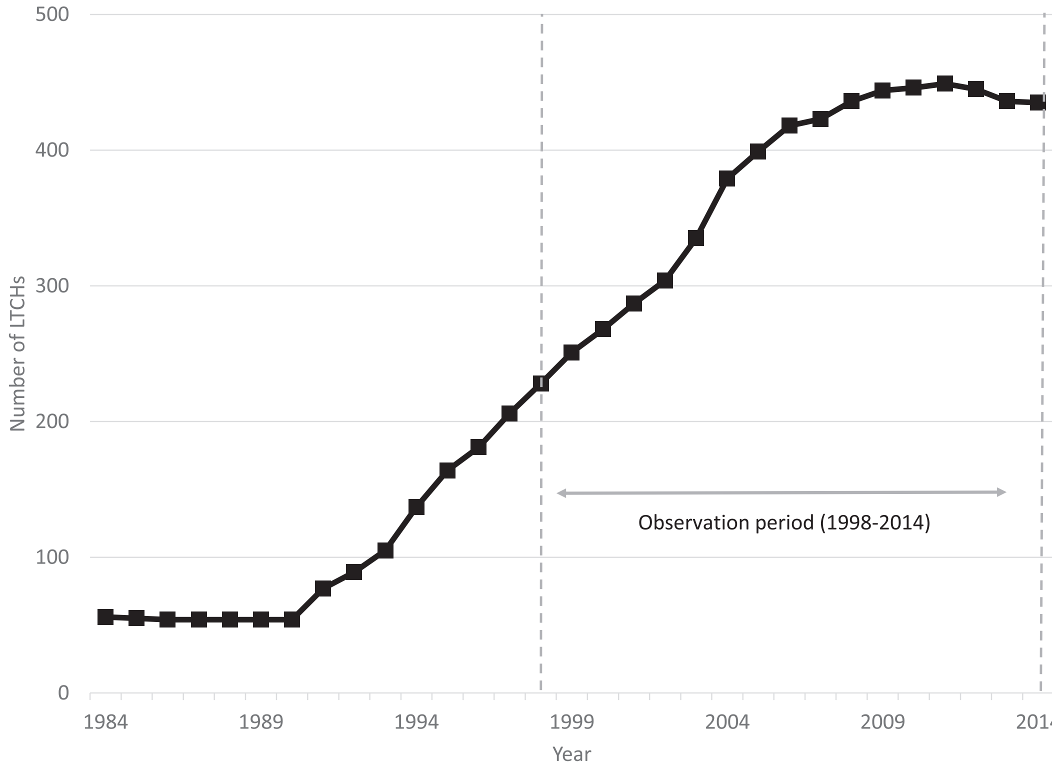
Among Medicare patients, LTCHs account for about 4% of discharges to facility-based PAC and about 12% of facility-based PAC spending (MedPAC, 2015b). As we discuss in more detail below, LTCHs exist in some hospital markets but not in others; in 2014, in markets where they exist, LTCHs accounted for 11% of discharges to facility-based PAC and 31% of facility-based PAC spending. About half of LTCHs are known as "hospitals within hospitals," meaning that they are physically located within the building or campus of a (typically larger) acute care hospital (Office of Inspector General, 2013).

The history of LTCHs reads like a whack-a-mole history of healthcare reform. In 1982, the Tax Equity and Fiscal Responsibility Act (TEFRA) established a prospective payment system (PPS) for acute care hospitals. Rather than being reimbursed on a fee-for-service ("cost-plus") basis, hospitals would be paid a predetermined, fixed amount that depended on the patient's diagnosis related group (DRG). At the time, there were about 40 hospitals—primarily former tuberculosis

[3] In 2014, there were approximately 205,000 IRF stays (\$3.3 billion in Medicare payments) and 2.5 million SNF stays (\$32.4 billion in Medicare payments). These and subsequent numbers in this section without an explicit citation are based on the Medicare data described in the next section.

[4] In particular, we estimate Part D spending for Medicare beneficiaries as the product of \$78.1 billion in total Part D spending (Boards of Trustees for Medicare, 2015) and the 62% of Part D beneficiaries enrolled in standalone PDP plans (MedPAC, 2015b), which yields \$48.4 billion in Part D spending.

FIGURE 1.—LTCH FACILITIES OVER TIME



Data are from the Provider of Service File from 1984–1998, and from the Medicare Provider and Analysis Review (MedPAR) data from 1998 forward. Figure only includes pre-1998 LTCHs if they also appear in the MedPAR data. Both data sets are described in section IIIA.

and chronic disease facilities—that specialized in clinically complex patients who required long hospital stays; regulators were concerned that the fixed payments under a PPS would be insufficient to cover costs at these hospitals. To keep these hospitals afloat, CMS excluded hospitals with an average length of stay of at least 25 days from PPS and continued to pay them based on their average per-diem cost (Liu et al., 2001). These 40 hospitals were the original LTCHs.

Figure 1 plots the number of LTCHs over time. Since 1982, there has been a rapid growth in the LTCH sector, with the number of facilities rising from 40 to over 400. Because new entrants did not have prior cost data, payments for new entrants were determined by costs in their initial years of operation. This encouraged new entrants to be inefficient when they first opened and to earn profits by increasing their efficiency over time.[5]

The majority (72% in 2014) of LTCHs are for-profit (21% are nonprofit and 7% are government-run).[6] According to recent financial statements of the two largest LTCH operators, Kindred Health Systems and Select Medical, LTCHs generate profit margins between 16% and 29%.[7]

Since the creation of LTCHs in 1982, a series of policies have been enacted to try to curb rising LTCH expenditures. The 1997 Balanced Budget Act (BBA) and the 1999 Balanced Budget Refinement Act (BBRA) established a prospective payment system for LTCHs. From 2002 to 2007, LTCHs were transitioned to a payment system in which, similar to the PPS for acute care hospitals, they were paid a fixed amount per patient-DRG. However, much like LTCHs were originally created as a necessary "carve-out" to PPS, the LTCH PPS in turn featured what was seen as a necessary carve-out: in designing the LTCH PPS, there was concern that LTCHs might discharge patients after a small number of days but still receive the large, lump-sum payments that were intended for longer stays. To address this potential perverse incentive to cycle patients briefly into an LTCH, stays in an LTCH below a certain number of days (the "threshold day") were still paid on the pre-PPS per-diem reimbursement schedule. This created a substantial (approximately $13,000) jump in Medicare payments at the threshold day, and LTCHs responded by discharging large numbers of patients right after reaching the threshold (Kim et al., 2015; Weaver et al., 2015; MedPAC, 2016; Eliason et al., 2018; Einav et al., 2018). In Einav et al.

[5]Liu et al. (2001) describe the early history and institutional features of LTCHs in greater detail.

[6]Calculated from the American Hospital Association data described in the next section.

[7]Profits are defined as EBITA (earnings before interest, taxes, and amortization). Kindred's profits have hovered between 22% and 29% of revenue based on 2009–2015 company reports. Prior to 2009, Kindred did not separate out their reporting of LTCH profits from the much larger SNF category. Select's profits have ranged between 16% and 22% of revenue based on company reports from 2004 to 2015. Kindred's annual reports are available at http://www.annualreports.com/Company/kindred-healthcare-inc and Select's are available at https://www.selectmedical.com/investor-relations/for-investors/

(2018) we explored alternative payment schedules that remove this jump in payments and generate significant savings for Medicare.

In more recent years, CMS has taken at least four distinct measures to try to reduce LTCH spending. In 2007, and again in 2014, CMS established a 3-year moratorium on the certification of new LTCHs or increases in LTCH beds (CMS, 2008, 2014). In 2005, CMS established a policy known as the "25-percent rule," which penalizes LTCHs for admitting more than 25% of patients from a single hospital, although Congress has delayed the full implementation of the law (42 CFR § 412.534, 2014). In 2011, in order to address incentives for hospitals-within-hospitals to "ping pong" patients between the ACH and the LTCH, a regulation known as the "5 percent rule" went into effect, which established that if more than 5% of patients discharged from an LTCH to a given hospital are later re-admitted to the LTCH, the LTCH will be compensated as if the patient had a single LTCH stay (42 CFR § 412.532, 2011).

In 2016, CMS phased in a dual payment structure for LTCHs to try to reduce expenditures and incentivize LTCHs to better target the clinically complex patients they were initially designed to serve. Under this new payment structure, LTCHs are reimbursed under the LTCH PPS only if the patient had an immediately preceding ACH stay with either (i) 3 or more days in an intensive care unit (ICU) or coronary care unit (CCU), or (ii) mechanical ventilation for at least 96 hrs. at the ACH. All other LTCH cases are reimbursed at the lower of the inpatient PPS comparable per diem rate and the total estimated cost incurred by the LTCH to treat the patient (MedPAC, 2017b). Irace (2018) studies this reform. Most recently, beginning in 2018, a payment reform went into effect that eliminated the jump in payments at the threshold (80 FR 37990, 2017). While it is too soon to be sure, if history is to guide us, the most recent round of reforms will generate new, unintended opportunities for LTCHs to earn profits, and the game of whack-a-mole will continue.

We have dwelled at some length on the institutional and regulatory history of LTCHs because we believe it is important for setting our priors and the appropriate null hypothesis: namely, that LTCHs are cost-increasing institutions with no clear benefits to patients. While suggestive, this qualitative history is of course by no means definitive. As noted, existing empirical evidence is limited to cross-sectional comparisons of patient outcomes in markets with differential LTCH penetration. We turn now to our data and empirical strategy that will allow us to estimate the impact of LTCHs on average, as well as on particular subsets of patients.

III. Data and Summary Statistics

A. *Data and Variable Definitions*

Our primary data source is the 100% Medicare Provider and Analysis Review (MedPAR) data from 1998–2014. These data contain claim-level information on all (fee-for-service) Medicare patient stays at acute care hospitals, LTCHs, SNFs, and IRFs. For each stay, the data contain admission and discharge dates, and information on procedures, diagnoses (DRGs), and Medicare payments.

We merge the MedPAR data with three supplementary datasets. The Medicare Annual Beneficiary Summary File provides us with basic patient demographic information, including age, sex, race, and ZIP code of residence, as well as date of death (if any) through 2014. The beneficiary summary file also includes eligibility and enrollment information, which we use to determine whether a patient is dually eligible for Medicare and Medicaid or enrolled in Medicare Advantage. We exclude approximately 12% of the beneficiary-years that have at least one month of enrollment in Medicare Advantage (MA) because claim-level information is not available for MA enrollees. The Provider of Service (POS) dataset contains annual characteristics for all Medicare-approved providers, which allows us to identify each provider's ZIP code as early as 1984. Finally, we use the American Hospital Association's (AHA) annual survey from 1998 to 2014 to classify providers as for-profit, nonprofit, or government-run, and to obtain provider latitude and longitude, which allow us to calculate distances between facilities.

Our baseline analysis focuses on the entry of the first LTCH into a Hospital Service Area (HSA). HSAs are a standard geographic measure of a healthcare market. HSAs were originally defined by the National Center for Health Statistics as a collection of contiguous ZIP codes whose residents receive the majority of their hospitalizations from hospitals in the area. Since the geographic unit's creation in the early 1990s, HSA boundaries have remained constant regardless of changes to the hospital systems in those regions. There are 3,436 HSAs in the United States, which is similar to the number of counties and roughly ten times the number of Hospital Referral Regions (HRRs), another common geographic unit of analysis.[8]

We use the claim-level MedPAR data to identify whether an LTCH is present in an HSA in each quarter of each year. We define entry as the earliest quarter with a patient admission to an LTCH in that HSA. Appendix A provides more detail on this measure of entry, showing that LTCHs quickly reach steady-state volume after entry; it also shows that our claims-based definition of entry is highly correlated with a measure of entry based on the year of an LTCH's first appearance in the POS file.

In our baseline analysis, our unit of observation is a patient "spell" which we define (following Einav et al., 2018) as starting on the date of a patient's admission to an acute care hospital (ACH) and consisting of the set of almost-continuous days with a Medicare payment to an acute care hospital, LTCH, SNF, or IRF. We start the spell with an ACH stay because the vast majority (84%) of LTCH patients are admitted to an

[8] See www.dartmouthatlas.org/downloads/geography/ziphsahrr98.xls and http://www.dartmouthatlas.org/downloads/methods/geogappdx.pdf for more details on defining HSAs and HRRs.

LTCH following their discharge from an ACH.[9] We end the spell if there are two consecutive days without any Medicare payments to any of these institutions. Note that by this definition, a patient may be readmitted to an ACH following a stay at a different facility without initiating a new spell. We show in appendix B that our core results are robust to defining the analysis window as a set amount of time following admission to the ACH.

We analyze a variety of outcomes over the course of a spell. All monetary outcomes are converted to 2014 dollars using the CPI-U. The first set of outcomes is the discharge destination from the ACH. The (mutually exclusive and exhaustive) discharge destinations are to death, to another ACH, to an LTCH, to a SNF, or to home/other (where other includes home health care and hospice); Appendix A provides more detail on how we code discharge destinations. We analyze total Medicare payments to and days at various postdischarge facility destinations throughout the spell, as well as total Medicare payments for the spell.[10] We also analyze total out-of-pocket payments owed for the spell, using the term out-of-pocket payments to refer to payments not covered by Medicare; these payments may be covered by the patient's supplemental insurance plan. Finally, we define indicators for whether the patient has died in the 90 days since the initiating admission to the acute care hospital, and whether the patient has ever been at home in the 90 days since the initiating admission to the acute care hospital. Again, appendix A provides details.

A potential limitation of our analysis is that the MedPAR data do not include payments to home health or hospice. We have separate data on such payments from 2002 to 2014. We show in appendix B that these destinations account for a relatively low share of spell spending (about 10% combined), and incorporating them into the analysis does not meaningfully impact our findings.

B. *LTCH Entry*

Figure 2 shows the distribution of LTCHs across HSAs in the first year that data are available (1984), the first year of our study period (1998), and the last year of our study period (2014). Prior to 1998, 152 HSAs had an LTCH. Over our study period (1998–2014), an additional 186 HSAs experienced their first entry. The figure also shows that LTCHs tend to be geographically concentrated.

Figure 3 reports the timing of LTCH entry into new HSAs over our study period. First entries occur fairly consistently over the first 12 years of our sample period but drop off in the last few years, presumably due to the moratorium on new facilities.[11]

Table 1 explores characteristics of the hospital markets with LTCHs, separately examining markets that had an LTCH before 1998, experienced their first LTCH entry between 1998 and 2014, and never had an entry. The final column shows the bivariate correlation between an indicator for whether the HSA ever had an LTCH and these characteristics.

Table 1 indicates that LTCHs are more likely to be located in urban and more populated markets, presumably because these markets have enough demand to recover their fixed costs. In 2014, although only about 10% of hospital markets had an LTCH, these markets covered 34% of Medicare beneficiaries. LTCHs tend to be located in markets with a higher rate of ACH beds per capita, a larger share of for-profit ACHs, and a higher rate of ACH patients discharged to SNF or any PAC (which includes home health care). LTCHs are more likely to enter states that had one of the original LTCHs (defined by the presence of an LTCH in 1984) and less likely to enter states with Certificate of Need (CON) laws, which regulate entry. The correlation between entry and these characteristics motivates our event study research design as a complement to prior work that has examined the cross-sectional correlation between outcomes and market-level LTCH penetration (Kahn et al., 2013).

C. *Predicted Probability of LTCH Discharge*

While the LTCH setting is high stakes both in terms of Medicare spending and patient health in a given year, many patients are simply not "at risk" of an LTCH discharge and mainly add noise to the estimates. For instance, in 2014, only about 1% of all hospital patients were discharged to an LTCH. Even in HSAs with LTCHs, only about 2% of hospital patients were discharged to an LTCH. To improve our statistical power, we generate a stay-level measure of the predicted probability of LTCH discharge, and we allow our first-stage estimate of the impact of LTCH market entry on LTCH discharge to vary with this *ex ante* stay-level probability of LTCH discharge. Intuitively, the heterogeneous first stage places more "weight" on patients with a higher *ex ante* probability of LTCH discharge. We describe our IV approach in more detail in section IV below.

Identifying a hospital stay's probability of LTCH discharge (hereafter, $\hat{p}$) from the high dimensional set of covariates available in the claims data is a prediction problem well suited to machine-learning methods. We use a regression tree as our prediction algorithm because its emphasis on interactions closely parallels the clinical complexity of LTCH patients, who often have multiple chronic illnesses or comorbidities (Liu et al., 2001; MedPAC, 2016).

We include as predictors demographics and predetermined health conditions that are plausibly exogenous to the

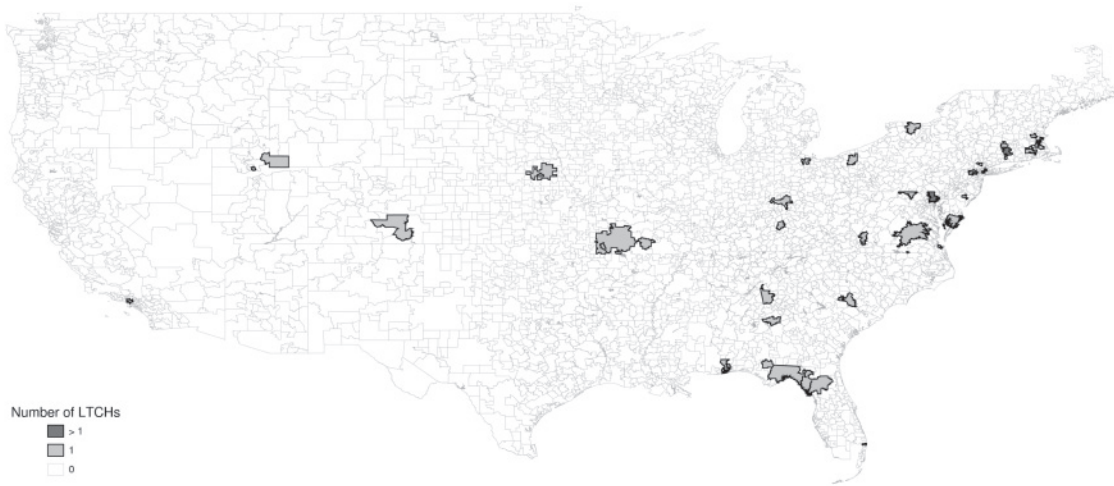
[9]Most others are admitted directly from the community via a physician referral, although a small number are admitted from other facility-based PAC.

[10]Our baseline measure includes all Medicare reimbursements except for outlier payments. In appendix B, we show that including outlier payments makes the point estimates stronger, but, because outlier payments are noisy, it reduces the precision of our results.

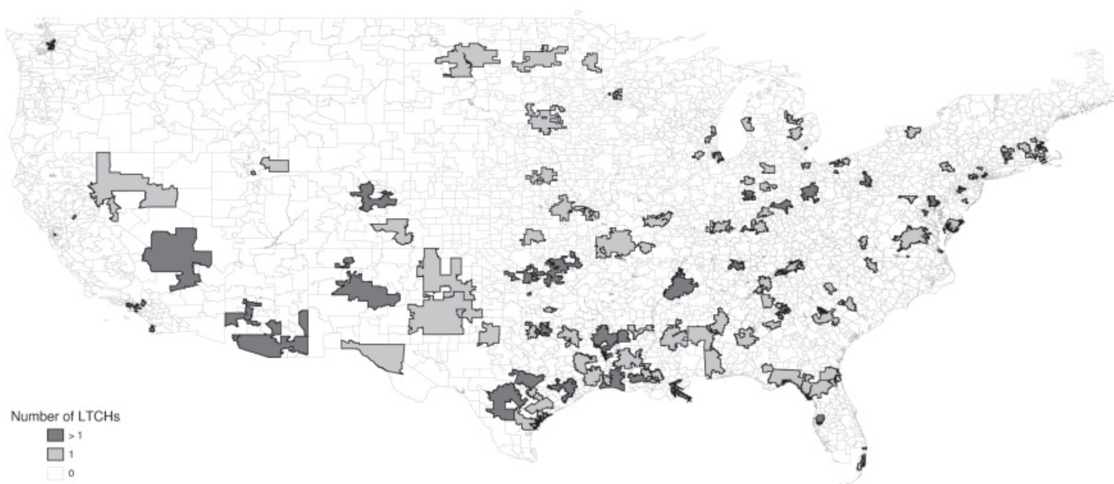
[11]As figure 3 illustrates, CMS made some exceptions to its moratorium; these are described in more detail in CMS (2008, 2014).

FIGURE 2.—LTCH CONCENTRATION OVER TIME

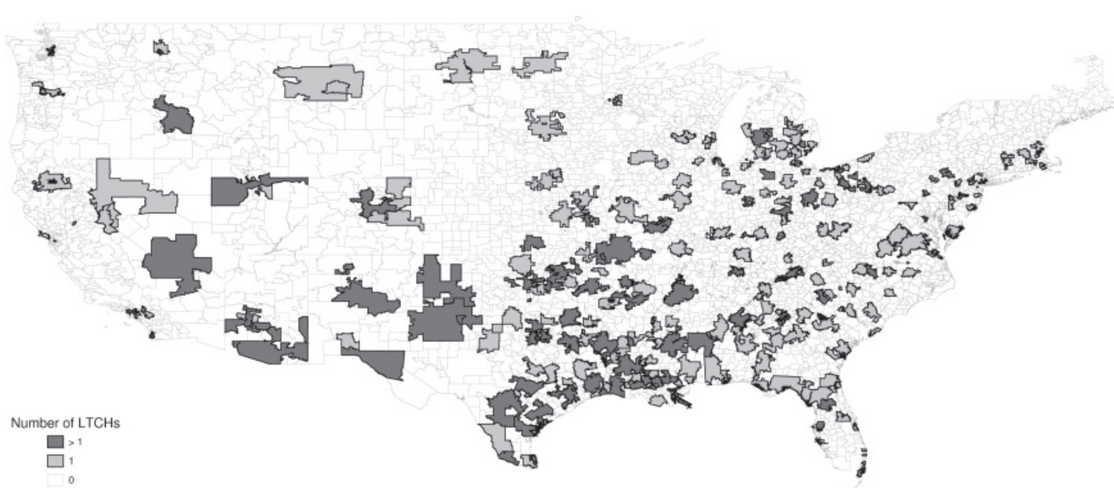
(A) 1984



(B) 1998

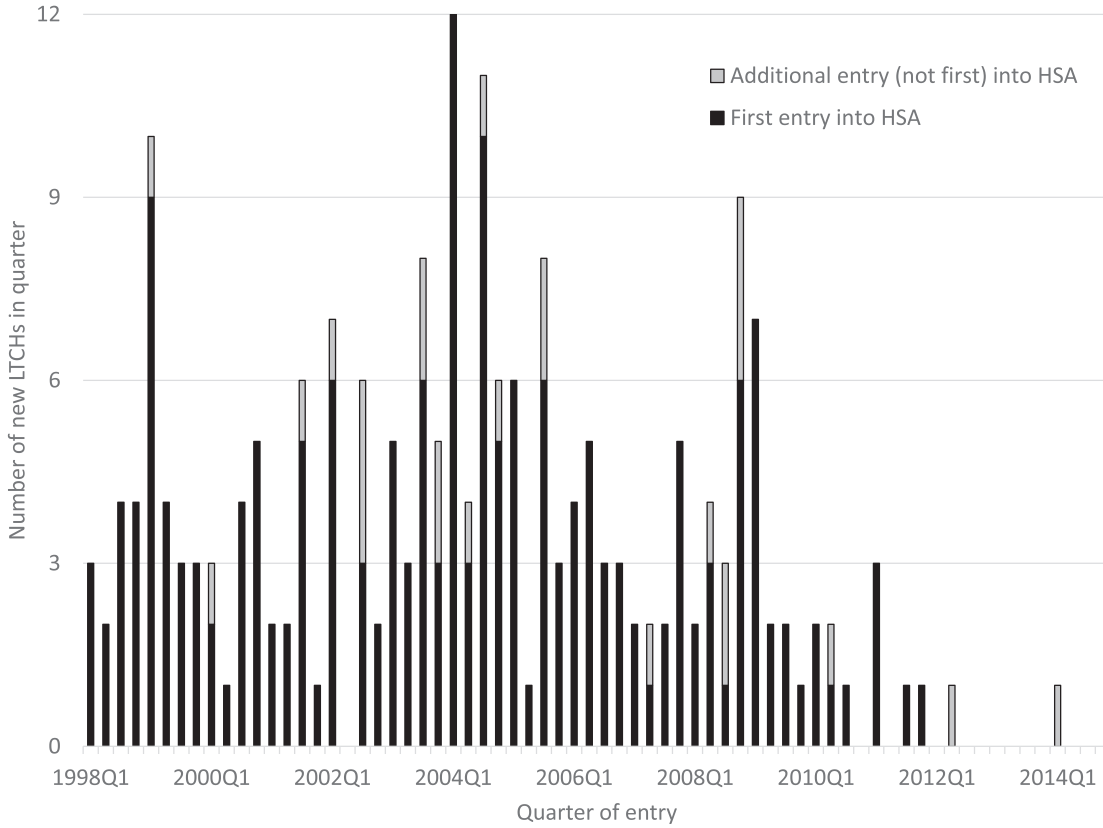


(C) 2014



Maps illustrate the number of LTCHs present in each HSA in 1984, 1998, and 2014, according to the 1984–2016 POS File and the 1998–2014 MedPAR data. White space indicates HSAs with no LTCHs.

FIGURE 3.—LTCH ENTRY QUARTERS



Histogram of LTCH entry to an HSA. First entries are defined as the first entry observed in our data (1998–2014). HSAs that had an LTCH at the start of our data period in 1998 are excluded.

discharge decision. The demographics are the calendar year of the patient admission, the patient's age, sex, race, and an indicator for dual enrollment in Medicaid. The health predictors are the ICD-9 diagnoses recorded during the patient's initiating hospital admission. Specifically, we cluster the diagnoses associated with the initiating stay (each stay can have up to nine distinct diagnoses) into 285 mutually exclusive Clinical Classification Software (CCS) codes (HCUP, 2017). CCS codes have been shown in other settings to be good predictors of health status in Medicare data (Ash et al., 2003; Radley et al., 2008).[12]

As our event study results will confirm, geographic proximity plays a central role in the probability of LTCH discharge. To determine the likelihood of LTCH discharge without geographic constraints, we predict probabilities conditional on having an LTCH in close proximity. To do so, we create a training set consisting of all ACH stays within 5 kilometers of the nearest LTCH, with distance measured as spherical distance based on the provider's latitude and longitude coordinates reported in the AHA provider survey. We train the regression tree on a 10% sample of these stays using fivefold cross-validation. We then use the estimated prediction model to generate $\hat{p}$'s for all initiating hospital stays (including those further than 5 kilometers away from an LTCH). Thus $\hat{p}$ measures the predicted probability of LTCH discharge if an LTCH were within 5 kilometers of the patient's hospital.

Appendix C provides more detail on both the construction of the prediction algorithm and its output. Because the predictions are generated under the (counterfactual) assumption that all hospital patients are within 5 kilometers of an LTCH, the mean probability of discharge to an LTCH is 2%, rather than 1% as in the general population. The distribution of $\hat{p}$ is highly right-skewed. This reflects the fact that LTCHs are designed to serve a specific type of clinically complex patients; the vast majority of hospital patients have a very low probability of LTCH discharge, even conditional on having an LTCH in the patient's HSA.

To reduce noise, we construct a "baseline" sample that focuses on all patients with a nontrivial probability of LTCH discharge. Specifically, we drop the 73 million hospital stays (45%) with a $\hat{p} \leq 0.004$, which is the "leaf" with the lowest value in the regression tree. This restriction excludes only 8% of LTCH discharges. For some of our analyses, we also focus on a "high $\hat{p}$" sample, where we restrict to stays with $\hat{p} > 0.15$. This sample keeps 16% of LTCH discharges.

Table 2 presents summary statistics for the full sample stays, the baseline sample, and the high $\hat{p}$ subsample of the

[12]We exclude procedures in the initial hospital stay from our set of predictors as the propensity to perform certain procedures could be affected by the presence of an LTCH. And, indeed, we provide suggestive evidence of this in appendix C.

Table 2.—Summary Statistics: Predictors of LTCH Discharge

	All ACH admissions (1)	Baseline sample (2)	High $\hat{p}$ sample (3)
$\hat{p}$	0.020	0.033	0.189
Number of obs. (1000s)	163,649	90,384	2,338
Demographics			
Age	73.9	75.6	71.1
Female	0.57	0.57	0.49
White	0.83	0.83	0.77
Black	0.12	0.12	0.17
Hispanic	0.02	0.02	0.02
Asian	0.01	0.01	0.01
Dual-Eligible for Medicaid	0.26	0.28	0.34
Selected Features			
Respiratory failure; insufficiency; arrest	0.07	0.14	0.71
Septicemia	0.06	0.11	0.59
Chronic skin ulcer	0.04	0.08	0.31
Nutritional deficiencies	0.05	0.09	0.44
Infective arthritis and osteomyelitis	0.01	0.02	0.15
Complications of surgical procedures or medical care	0.06	0.10	0.27
Shock	0.01	0.02	0.17
Pneumonia	0.11	0.20	0.44
Acute cerebrovascular disease	0.03	0.06	0.10
Aspiration pneumonitis; food/vomitus	0.02	0.04	0.15
Other aftercare	0.06	0.05	0.01
Skin and subcutaneous tissue infections	0.04	0.07	0.09
Bacterial Infection	0.05	0.10	0.08
Intracranial injury	0.01	0.01	0.02
Gangrene	0.01	0.02	0.05
Paralysis	0.02	0.03	0.07
Pleurisy; pneumothorax; pulmonary collapse	0.05	0.06	0.18
Excluded Features			
ICU	0.14	0.17	0.53
Mechanical ventilation	0.04	0.08	0.45
Over 3 days in ICU/CCU	0.20	0.26	0.64
Over 8 days in ICU/CCU	0.10	0.14	0.45

Each observation is a unique acute care hospital (ACH) stay. The baseline sample excludes all observations with $\hat{p} \leq 0.004$. High $\hat{p}$ stays refer to ACH stays with a predicted probability of LTCH discharge ($\hat{p}$) greater than 0.15. The CCS (Clinical Classification Software) health predictors are those that are among the 18 most important selected features used as predictors in the LTCH discharge model, where variable importance is measured by ranking the additional R^2 each of the variables adds, summed across all the leaves of the tree. Note that 17 CCS categories are chosen; the 20th important variable is age. ICU stands for intensive care unit and CCU stands for critical care unit. ICU is determined using the MedPAR ICU indicator code, and mechanical ventilation is defined using the CCS procedure code for respiratory intubation and mechanical ventilation. Age enters the regression tree continuously. Race categories not listed include "other," "unknown," and "Native American."

baseline sample. Specifically, we report means of patient demographics and our model's "most important" selected health status features, where variable importance is measured by ranking the variables by the additional R^2 provided at each leaf of the tree. We find that patients with a high probability of LTCH discharge are nearly 10 times as likely to have experienced some sort of respiratory failure and over 10 times as likely to be diagnosed with septicemia (blood poisoning) than the overall acute care population. This is consistent with previous work that finds a high prevalence of patients with sepsis or respiratory failure in LTCHs (MedPAC, 2016; Chen et al., 2011; Koenig et al., 2015). To further assess our model and square our predictions with the existing literature on LTCH patients, the bottom panel of table 2 reports rates of ICU stays and mechanical ventilation in the initial ACH stay, two common features of LTCH patients that have consistently been reported in the literature (Kahn & Iwashyna, 2010; Koenig et al., 2015) but that we excluded from our prediction algorithm due to concerns about potential endogeneity. Encouragingly, we find that over 50% of high $\hat{p}$ stays spent time in an ICU and over 45% were on a mechanical ventilator.

D. *Summary Statistics*

Table 3 presents means and standard deviations for our primary outcomes for our three event study samples. Column 1 reports results for all acute care admissions. Column 2 shows the baseline sample, which excludes all observations with a $\hat{p} \leq 0.004$, and also restricts attention to the 186 first-entry HSAs and drops quarters following subsequent LTCH entries or exits; this mimics the sample restrictions we use in the baseline event study analyses below. As a result, the event study samples are roughly one-seventh the size of the "baseline" sample sizes reported in table 2, which included the universe of hospital stays with a $\hat{p} \leq 0.004$. Finally, column 3 shows the high $\hat{p}$ subsample of the baseline sample.

A comparison of outcomes in column 2 and column 3 provides a characterization of how patients likely to be discharged from an LTCH differ from other patients. Patients in the high $\hat{p}$ sample require far more intensive, lengthy, and expensive care. High $\hat{p}$ patients have a 13% probability of being discharged to an LTCH (versus 1.8% in the baseline sample), an average spell length of 36 days (compared to 18 in the baseline sample), and average spell Medicare expenditure of over $42,000 (versus roughly $17,500 in the baseline

TABLE 3.—SUMMARY STATISTICS: OUTCOMES

	All ACH admissions		Baseline sample		High $\hat{p}$ sample	
	(1)		(2)		(3)	
Discharge destination						
LTCH	0.010	(0.101)	0.018	(0.133)	0.126	(0.332)
Skilled Nursing Facility	0.166	(0.372)	0.220	(0.414)	0.252	(0.434)
Home/Other	0.736	(0.441)	0.646	(0.478)	0.334	(0.472)
LTCH-in-training	0.000	(0.011)	0.000	(0.014)	0.001	(0.036)
(Other) Acute Care Hospital	0.052	(0.221)	0.056	(0.230)	0.063	(0.243)
Death	0.036	(0.186)	0.059	(0.236)	0.224	(0.417)
Spell days						
LTCH	0.4	(4.0)	0.7	(5.1)	4.3	(13.1)
Skilled Nursing Facility	7.0	(19.1)	9.0	(21.5)	12.4	(25.9)
Initiating ACH	5.4	(5.6)	6.9	(6.7)	16.2	(14.0)
Total	14.1	(23.3)	18.0	(26.5)	35.8	(38.3)
Spell spending ($)						
LTCH	530	(5,254)	843	(6,657)	5,869	(18,115)
Skilled Nursing Facility	2,692	(7,222)	3,404	(8,078)	4,782	(10,189)
Initiating Acute Care Hospital	10,079	(10,466)	11,201	(12,342)	27,583	(30,116)
Total	14,992	(17,665)	17,519	(20,713)	42,202	(44,769)
Patient outcomes						
Out-of-pocket spending ($)	1,507	(2,602)	1,716	(3,111)	3,334	(6,431)
Home within 90 days	0.82	(0.39)	0.73	(0.44)	0.42	(0.49)
Died within 90 days	0.14	(0.34)	0.20	(0.40)	0.44	(0.50)
Mean $\hat{p}$	0.020	(0.032)	0.034	(0.039)	0.189	(0.034)
Number of Obs. (1000s)	24,251		13,093		373	

Each observation is a unique acute care hospital (ACH) stay. All ACH admissions (column 1) includes all HSAs that experience a first entry from 1998–2014, dropping observations at and after the quarter of subsequent entry or LTCH exit. Baseline sample (column 2) further excludes all observations with $\hat{p} \leq 0.004$. High $\hat{p}$ sample (column 3) refers to ACH stays in the baseline sample with $\hat{p} > 0.15$.

sample).[13] Ninety-day mortality rates are high in the baseline sample (20%) and even higher in the high $\hat{p}$ subsample (over 40%).

IV. Empirical Strategy

We estimate the effect of LTCH discharge on patient outcomes using variation in LTCH discharges caused by the entry of the first LTCH into a hospital market. Our approach allows outcomes to differ across markets (as suggested by table 1) but assumes that, in the absence of entry, trends in outcomes would be similar across markets. We examine this assumption by examining trends in outcomes prior to entry.

In our baseline specification, we focus on the entry of the first LTCH in an HSA because this is where we expect to see the sharpest effects. Specifically, we restrict our sample to the 186 HSAs with a first entry during our 1998–2014 sample period. We exclude the 152 HSAs that, based on the POS annual 1984–1998 files, had an LTCH prior to 1998, and we exclude the over 3,000 HSAs that had no LTCH entry as of 2014. The markets we study are disproportionately large, accounting for 14% of the Medicare patients and 24% of LTCH discharges at the end of our sample period. Within the 186 HSAs we study, we truncate the data just before the quarter of second LTCH entry or LTCH exit so that the postentry results are not contaminated by further shocks to LTCH discharges. Among our 186 HSAs, 24 experience a second entry and 23 an exit. Since the restricted sample is unbalanced, the combination of heterogeneous treatment effects and changes in sample composition might generate spurious time trends in our estimates. We conduct robustness analysis where we restrict the sample to a balanced panel and show that these types of effects are not driving our results.

To qualify as an LTCH, a facility must first document that it meets the minimum average length of stay requirement of 25 days for a six-month period (42 CFR § 412.23, 2011).[14] Most LTCHs therefore begin as an ACH and are subsequently reclassified as an LTCH. These facilities are neither an LTCH nor an ACH; they are operationally an LTCH but are not reimbursed as such. To address this, we classify a facility that initially opens as an ACH for a brief period before being deemed an LTCH as an "LTCH-in-training." Appendix A describes in more detail how we identify them. Our methodology is conservative; as we discuss below, there are likely some LTCHs-in-training that we do not categorize as such.

We define time relative to the quarter of LTCH entry as relative time (r). We consider three distinct periods in relative time: a preperiod ($r < -5$, denoted P_{pre}), a postperiod ($r > 0$, denoted P_{post}), and a transition period ($r \in [-5, 0]$), in which an LTCH-in-training may have entered prior to the "true" LTCH entry at $r = 0$. We draw these distinctions based on patterns in the raw data. In appendix B, we show the results are robust to alternative plausible time windows for this transition period. The patterns in the raw data also motivate us to allow for separate trends in the outcomes pre- and postentry, and to drop from our event study estimates all observations that are associated with the transition period.

[13]Because $\hat{p}$ is the probability of LTCH discharge conditional on having one nearby, the true probability of LTCH discharge is lower than the average $\hat{p}$.

[14]To retain its LTCH reimbursement rate, a hospital must continue to report a 25-day average length of stay in each cost-reporting period.

The unit of observation is a spell, indexed by i. Each spell i is associated with an HSA j_i, a calendar time (in quarters) t_i, and a relative time $r_i = t_i - t_j^{entry}$, where t_j^{entry} is the time (in calendar quarters) of LTCH entry into HSA j_i. Our reduced form specification for outcome y_i takes the form

$$y_i = \alpha \cdot 1(r_i \in P_{post}) + 1(r_i \in P_{pre}) f(r_i) + 1(r_i \in P_{post}) g(r_i) + \gamma_{j_i} + \tau_{t_i} + \epsilon_i, \quad (1)$$

where γ_j are HSA fixed effects, τ_t are calendar quarter fixed effects, and $f(r)$ and $g(r)$ are linear functions in r, normalized such that $f(0) = g(0) = 0$.[15] Our parameter of interest α captures the average impact of LTCH entry on patient outcomes. We calculate heteroskedasticity-robust standard errors clustered at the HSA level.

Our identifying assumption is that in the absence of LTCH entry, any trends in the outcome across markets would have been similar. While we cannot test this assumption directly, we present graphical evidence of the time pattern of outcomes prior to LTCH entry that is consistent with the identifying assumption.

The parameter α in equation (1) measures the impact of LTCH entry into the market on the outcome. To study the impact of a patient's discharge to an LTCH on outcomes, we estimate instrumental variable (IV) specifications where we use LTCH entry as an instrument for LTCH discharge. Specifically, we estimate the equations

$$LTCH_i = \alpha^L \cdot 1(r_i \in P_{post}) + 1(r_i \in P_{pre}) f^L(r_i) + 1(r_i \in P_{post}) g^L(r_i) + \gamma^L_{j_i} + \tau^L_{t_i} + \epsilon^L_i, \quad (2)$$

$$y_i = \beta^y \cdot LTCH_i + 1(r_i \in P_{pre}) f^y(r_i) + 1(r_i \in P_{post}) g^y(r_i) + \gamma^y_{j_i} + \tau^y_{t_i} + \epsilon^y_i, \quad (3)$$

where $LTCH_i$ is an indicator for discharge to an LTCH, and the first line shows the "first stage" equation that relates LTCH entry in a market to discharge to an LTCH. The second line shows the "second stage" equation that relates LTCH discharge to patient outcome y_i. Both equations include the same controls as the reduced form specification [equation (1)], with the parameters allowed to vary across equations. The parameter of interest β^y can be interpreted as the impact of being discharged to an LTCH on outcome y_i. We calculate heteroskedasticity-robust standard errors clustered at the HSA level.

In the LTCH setting, an additional challenge is that, as discussed in section III, the probability of discharge to an LTCH is highly heterogeneous, and near zero for many patients (even if an LTCH exists nearby). To improve statistical power, we therefore estimate specifications where we allow the first-stage coefficient (α^L) to vary with $\hat{p}$, the predicted probability of LTCH discharge. Technically, $\hat{p}$ can be interpreted as a compliance propensity score in the spirit of Follmann (2000), which we use to determine heterogeneity in first-stage effects.

To allow for a heterogeneous first stage within our event study framework, we divide our baseline sample into five groups indexed by $k = \{1, 2, 3, 4, 5\}$. Groups 1 to 3 are quartiles 1 to 3 of the $\hat{p}$ distribution, and groups 4 and 5 are based on splitting the top quartile into two groups ($\hat{p} < 0.15$ and $\hat{p} > 0.15$). Appendix table A1 summarizes these five $\hat{p}$ groups. To account for heterogeneity, we denote by k_i the group associated with each spell i, and we estimate a modified version of our IV specification:

$$LTCH_i = \alpha^L_{k_i} \cdot 1(r_i \in P_{post}) + 1(r_i \in P_{pre}) f^L_{k_i}(r_i) + 1(r_i \in P_{post}) g^L_{k_i}(r_i) + \gamma^L_{k_i,j_i} + \tau^L_{k_i,t_i} + \epsilon^L_i, \quad (4)$$

$$y_i = \beta^y \cdot LTCH_i + 1(r_i \in P_{pre}) f^y_{k_i}(r_i) + 1(r_i \in P_{post}) g^y_{k_i}(r_i) + \gamma^y_{k_i,j_i} + \tau^y_{k_i,t_i} + \epsilon^y_i, \quad (5)$$

which is identical to equations (2) and (3), except that the first-stage coefficient and all of the controls are allowed to vary flexibly by k.

We continue to assume that the coefficient of interest β^y is homogenous across groups, and we calculate heteroskedasticity-robust standard errors clustered at the HSA-$\hat{p}$ group level. In the results that follow, we show that, consistent with our homogeneity assumption, our IV point estimates for β^y are very similar, but less precisely estimated, if we restrict the sample to patients with the highest *ex ante* probability of LTCH discharge ($\hat{p} > 0.15$). In appendix B, we also show results separately for the other $\hat{p}$ groups, and we find that the results are consistent with our homogeneity assumption; we also show that imposing a first-stage specification with a homogenous first-stage coefficient (α^L) results, as expected, in substantially less precise IV estimates.

V. Results

A. *Reduced Form Graphical Results for the High $\hat{p}$ Sample*

Figures 4–8 present graphical evidence of the reduced form effects of LTCH entry into the market. In each plot, the horizontal axis shows the relative event time r in quarters and the vertical axis shows the outcome variable. The dots show quarterly averages of the outcome, net of HSA, and calendar quarter fixed effects from estimating equation (1). The solid lines show linear trends, $f(r)$ and $g(r)$, which, as shown in equation (1), are separately estimated on the pre- and posentry periods. For visual effect, the dashed line extends the preperiod trend into the transition period. The reduced form

[15] Outside of the four-year window around entry, we model $f(r)$ and $g(r)$ as constant in relative time. Specifically, we define

$$f(r) = \begin{cases} a & \text{if } r < 16 \\ -br & \text{if } r \geq -16 \end{cases} \quad \text{and} \quad g(r) = \begin{cases} cr & \text{if } r \leq 16 \\ d & \text{if } r > 16 \end{cases}.$$

We define these functions in this way because it allows us to focus on LTCH entry inside a four-year window while still preserving observations outside the window to pin down HSA and calendar-time fixed effects.

FIGURE 4.—PREDICTED PROBABILITY OF LTCH DISCHARGE

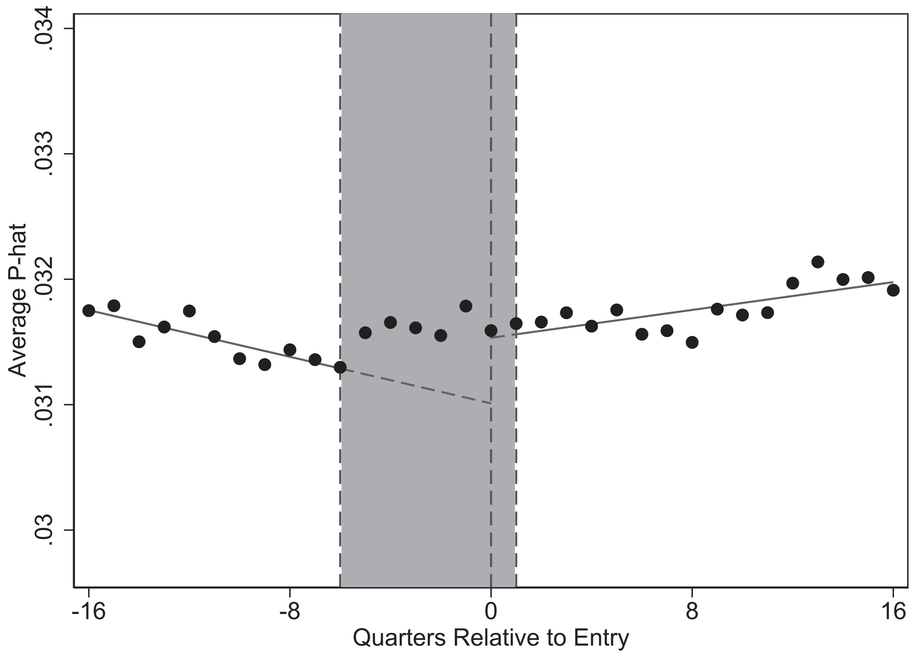


Figure reports estimates of equation (1), the reduced form impact of LTCH entry, estimated on the baseline event study sample. The figure displays our estimated function of relative quarter, r, and a scatter plot of the average residualized values of $\hat{p}$. Quarters $-6 < r < 1$ are greyed out because we drop all observations in these quarters. The y-axis reports the average $\hat{p}$ and is scaled so that the mean at $r = -1$ is equal to the mean at $r = -1$ among HSAs.

effect of LTCH entry on a given outcome, α, captures the gap between the linear trends at $r = 0$.

We start by examining the effect of LTCH entry into a market on $\hat{p}$, our predicted probability of LTCH discharge. Recall that $\hat{p}$ is constructed using demographics and predetermined health conditions of patients with ACH stays. If there was an effect of LTCH entry on $\hat{p}$, it would indicate that hospitals are responding endogenously to LTCH entry, for example by changing what patients they admit, which would raise concerns for the interpretation of our empirical results. Reassuringly, figure 4 shows no evidence of an effect of LTCH entry on $\hat{p}$ in the baseline sample. The estimated reduced form effect of LTCH entry on $\hat{p}$ (α in equation 1) is 0.00050 (standard error = 0.00027), relative to a base of 0.033 preentry.

In figures 5–8, we show the reduced form effects of LTCH entry into a market, limited to the high $\hat{p}$ subsample of our baseline sample. The first column of table 4 summarizes the point estimate (and standard error) of the impact of LTCH entry into a market on the outcome (α in equation 1). Figure 5 shows the impact of LTCH entry into a market on the fraction of patients discharged to an LTCH. This will be the first stage in our IV specification. The figure shows that LTCH entry has a sharp impact, raising the probability of discharge to LTCH by 9.2 percentage points (standard error of 0.9), a tripling of the preentry probability. The figure also shows evidence of a slight linear trend in LTCH discharges both pre- and post-LTCH entry, which is consistent with LTCHs choosing to enter more rapidly growing markets.

Figure 5 also provides support for our functional form assumptions. The sharp jump at $r = 0$ supports our decision to model LTCH entry with a discontinuous jump in the outcome rather than a gradual increase over time. The linear trend fits the data extremely well in the preperiod ($r < -5$), supporting our identifying assumption that, conditional on controls, the timing of entry is uncorrelated with deviations in the outcome from a linear trend. The linear trends fit well, but with somewhat less precision, in the postperiod ($r > 0$), perhaps reflecting heterogeneous treatment responses. The decline in discharges to LTCH during the transition period ($r \in [-5, 0]$) is consistent with the entry of LTCHs-in-training, which admit patients that would otherwise have gone to an LTCH in the quarters leading up to entry. We see this more directly in figure 6 discussed below.

Figure 6 shows the effect of LTCH entry into a market on discharges to a set of mutually exclusive and exhaustive non-LTCH discharge destinations. Panel (A) indicates that LTCH entry causes a substantial decline in the fraction of patients discharged to a SNF, suggesting that substitution away from SNFs is the primary margin of adjustment. Panel (B) shows a smaller, but non-negligible, decline in discharges to home/other, suggesting more modest substitution on this margin. Panel (C) shows a sharp increase in discharges to LTCHs-in-training during the transition period only, which is what we would expect given the institutional requirements to qualify as an LTCH. Panel (D) also shows some evidence of an increase in discharges to ACHs during the transition period only, which may reflect discharges to LTCHs-in-training that

FIGURE 5.—DISCHARGE TO LTCH

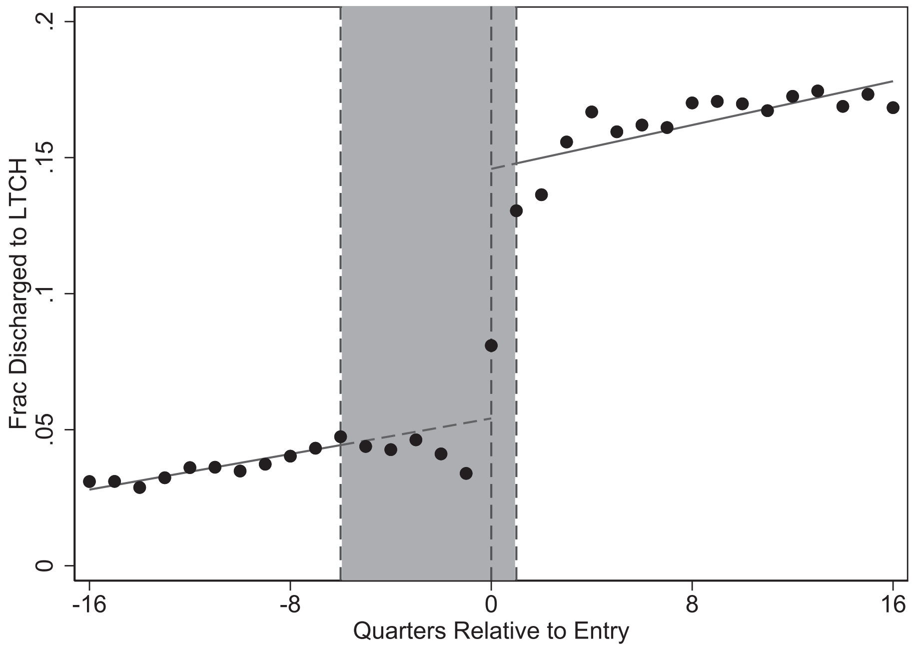


Figure reports estimates of equation (1), the reduced form impact of LTCH entry, estimated on the high $\hat{p}$ subsample of the baseline event study sample. The figure displays our estimated function of relative quarter, r, and a scatter plot of the average residualized values of the discharged to LTCH indicator. Quarters $-6 < r < 1$ are greyed out because we drop all observations in these quarters. The y-axis reports the share discharged to LTCH and is scaled so that the mean at $r = -1$ is equal to the mean at $r = -1$ among HSAs.

TABLE 4.—EVENT STUDY ESTIMATES

	High $\hat{p}$ sample Reduced form		High $\hat{p}$ sample I.V.		Baseline sample I.V.	
	(1)		(2)		(3)	
Discharge destination						
LTCH	0.092	(0.009)				
Skilled Nursing Facility	−0.062	(0.010)	−0.674	(0.103)	−0.791	(0.075)
Home/Other	−0.022	(0.010)	−0.244	(0.105)	−0.236	(0.073)
LTCH-in-training	0.001	(0.001)	0.007	(0.006)	0.007	(0.003)
(Other) Acute Care Hospital	−0.003	(0.006)	−0.035	(0.064)	0.044	(0.040)
Death	−0.005	(0.009)	−0.054	(0.101)	−0.024	(0.051)
Spell days						
LTCH	2.8	(0.4)	30.0	(1.9)	28.9	(1.0)
Skilled Nursing Facility	−1.5	(0.5)	−16.2	(6.3)	−14.3	(3.9)
Initiating Acute Care Hospital	−1.4	(0.4)	−15.5	(4.8)	−8.6	(2.1)
Total	0.1	(0.9)	1.5	(9.4)	6.6	(5.1)
Spell spending ($)						
LTCH	3,138	(592)	34,210	(4,079)	34,569	(1,708)
Skilled Nursing Facility	−513	(246)	−5,593	(2,714)	−3,024	(1,572)
Initiating Acute Care Hospital	−1,124	(844)	−12,256	(9,340)	−2,016	(3,800)
Total	1,894	(1,088)	20,649	(11,065)	29,583	(4,810)
Patient outcomes						
Out-of-pocket spending ($)	360	(133)	3,928	(1,381)	2,420	(640)
Home within 90 days	−0.004	(0.010)	−0.039	(0.110)	−0.172	(0.088)
Died within 90 days	0.014	(0.010)	0.150	(0.109)	0.101	(0.065)
Number of Obs. (1000s)	343		343		11,824	

Column 1 reports estimates and standard errors of α in equation (1) and column 2 reports the IV estimate and standard errors of β^y from equations (2) and (3), both estimated on the high $\hat{p}$ sub-sample of the baseline event study sample. Column 3 reports IV estimates and standard errors of β^y from equations (4) and (5), estimated on the baseline event study sample. Standard errors are clustered at the HSA level (186 clusters) for the high $\hat{p}$ sample (columns 1 and 2), and at the HSA-bin level (930 clusters) for the baseline specification (column 3).

we did not classify using our algorithm. Panel (E) shows no evidence of a change in the probability of discharge to death (i.e., in-hospital death) following the entry of an LTCH.

Figure 7 shows the effect of LTCH entry into a market on total spell days and total Medicare spending during the spell. Recall that the main effect of LTCH entry was substitution from SNFs to LTCHs. Panel (A) shows little effect on total spell days, suggesting that the marginal patients have similar lengths of stay at SNFs and LTCHs. Panel (B), on the other hand, shows that LTCH entry into a market leads to a fairly

FIGURE 6.—ALTERNATIVE DISCHARGE DESTINATIONS

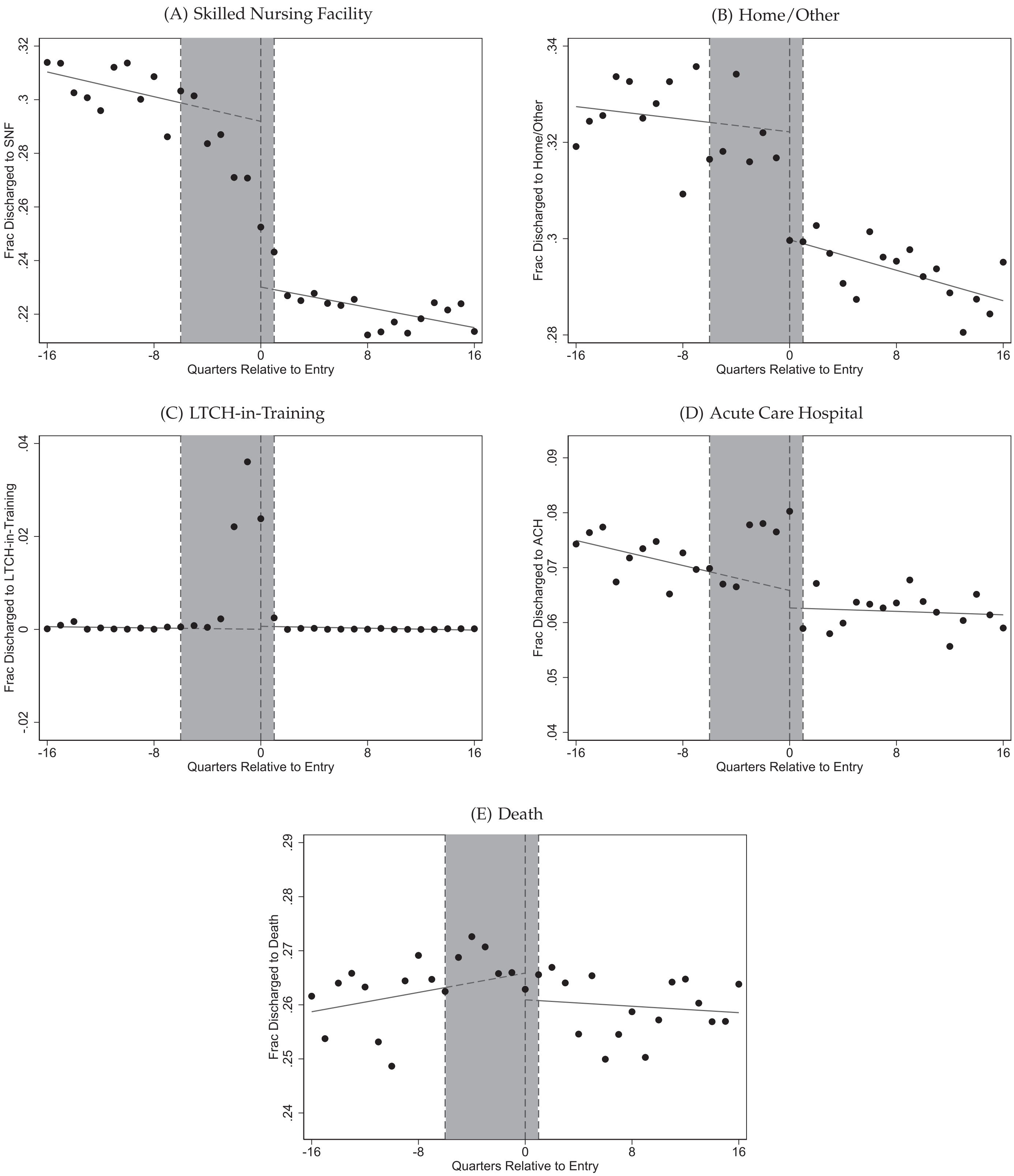


Figure reports estimates of equation (1), the reduced form impact of LTCH entry, estimated on the high $\hat{p}$ subsample of the baseline event study sample. The figure displays our estimated function of relative quarter, r, and a scatter plot of the average residualized values of each of the discharge destination indicators. Quarters $-6 < r < 1$ are greyed out because we drop all observations in these quarters. The y-axis reports the share discharged to the location indicated and is scaled so that the mean at $r = -1$ is equal to the outcome mean at $r = -1$ among HSAs.

FIGURE 7.—TOTAL SPELL UTILIZATION

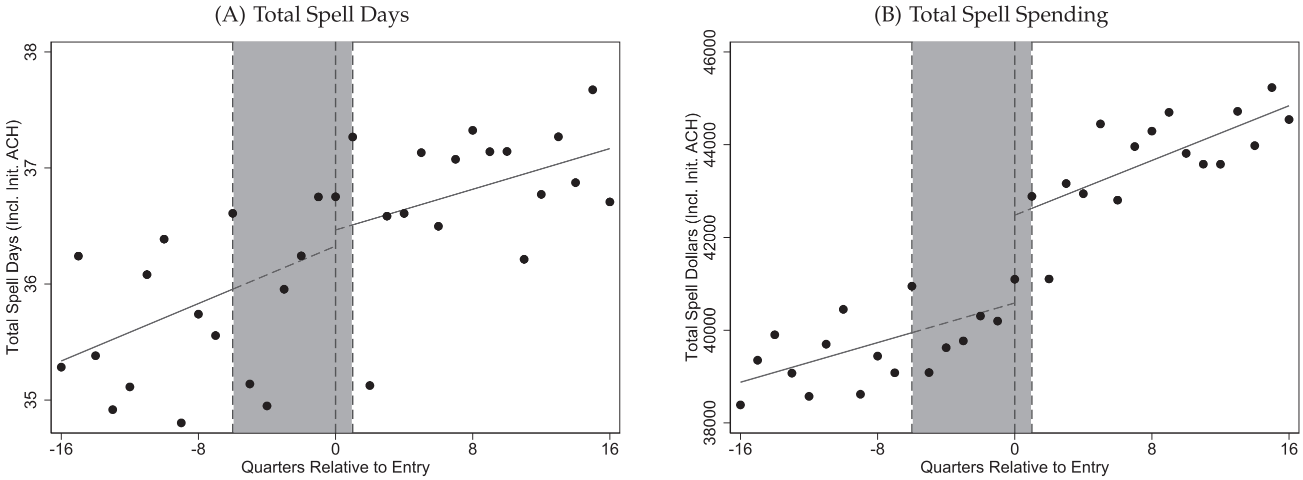


Figure reports estimates of equation (1), the reduced form impact of LTCH entry, estimated on the high $\hat{p}$ sub-sample of the baseline event study sample. The figure displays our estimated function of relative quarter, r, and a scatter plot of the average residualized values of spell days and spell spending. Quarters $-6 < r < 1$ are greyed out because we drop all observations in these quarters. The y-axis reports the utilization measure indicated and is scaled so that the mean at $r = -1$ is equal to the outcome mean at $r = -1$ among HSAs.

large increase in total Medicare spending, which is consistent with LTCHs receiving larger daily reimbursements than SNFs.[16]

Finally, figure 8 shows the impact of LTCH entry into a market on three measures of patient well-being: total out-of-pocket spell spending, the probability the patient is ever back home within 90 days after the initial hospital admission, and 90-day mortality (also measured from the date of the initial hospital admission). The graphical results suggest a clear increase in out-of-pocket spending. There is some suggestive evidence of a slight decrease in the probability of being at home at any point within 90 days. Despite the high 90-day mortality rate (44% in the high $\hat{p}$ sample), the 90-day mortality plot shows no evidence of any obvious pattern, and is quite noisy.[17]

B. IV Estimates

Columns 2 and 3 of table 4 show the IV estimates of the effect of discharge to an LTCH. Column 2 shows point estimates and standard errors in the high $\hat{p}$ sample, and column 3 shows the average impact of discharge to LTCH on patient outcomes for the whole baseline sample, allowing for a heterogeneous first stage to improve power. In the baseline sample, the share of patients discharged to LTCH increases from 0.5% in $r = -6$ (just before the transition period) to 2.4% in $r = 2$ (just after the transition period). This implies that about 20% (0.5 out of 2.4) of the patients who are discharged to LTCHs after the LTCH entry would have been discharged to LTCHs even prior to the entry. Our effects are thus identified off the remaining 80% of the patients in the baseline sample who are marginal to LTCH entry. Consistent with our assumption that the impact of discharge to LTCH on patient outcomes is constant across patients with different $\hat{p}$'s, the IV estimates in the high $\hat{p}$ subsample and the baseline sample are usually quantitatively very similar, and are never statistically distinguishable. We therefore focus our discussion below on the IV results for the full baseline sample (column 3).[18]

The top panel of table 4 show IV estimates of the effect of LTCH discharge on non-LTCH discharge locations. The results indicate that about four-fifths of patients discharged to an LTCH would have otherwise been discharged to a SNF; the remaining one-fifth would have otherwise been discharged to home without home care or other (which includes home with home health care, hospice, and other facility care). More specifically, we estimate that each patient discharged to an LTCH reduced the probability of discharge to a SNF by 0.791 (standard error of 0.075) and to home/other by 0.236 (standard error of 0.073).

A limitation to our baseline data is that we cannot see any finer granularity on the discharge destination of "home/other." However, for a subset of our study period (2002–2014), additional data allow us to further decompose this discharge destination; Appendix B shows the results. We find that about half of the impact on the discharge destination

[16] Appendix figure A5 provides a more detailed perspective, showing the effect of LTCH entry on days and spending separately by type of facility (LTCH, SNF, initiating ACH).

[17] Appendix figures A1–A4 show versions of these plots for the whole baseline sample. While the patterns are qualitatively similar to those for the high $\hat{p}$ subsample, we note that these plots do not directly correspond to the reduced form of the IV estimates for the whole sample discussed below. Specifically, our IV specification allows for a heterogeneous first stage across $\hat{p}$ groups, while appendix figure A1 shows a pooled effect of LTCH entry across $\hat{p}$ groups.

[18] For completeness, appendix table A2 presents first stage and IV estimates for the five $\hat{p}$ groups. Consistent with the interpretation of $\hat{p}$ as an estimated compliance propensity score, the first stage increases monotonically with $\hat{p}$ group. Although the results are, as expected, less precise in the lower $\hat{p}$ bins, the broad similarity in estimates across groups is consistent with our assumption that the impact of discharge to an LTCH on patient outcomes is the same across patients in different groups.

FIGURE 8.—PATIENT WELFARE OUTCOMES

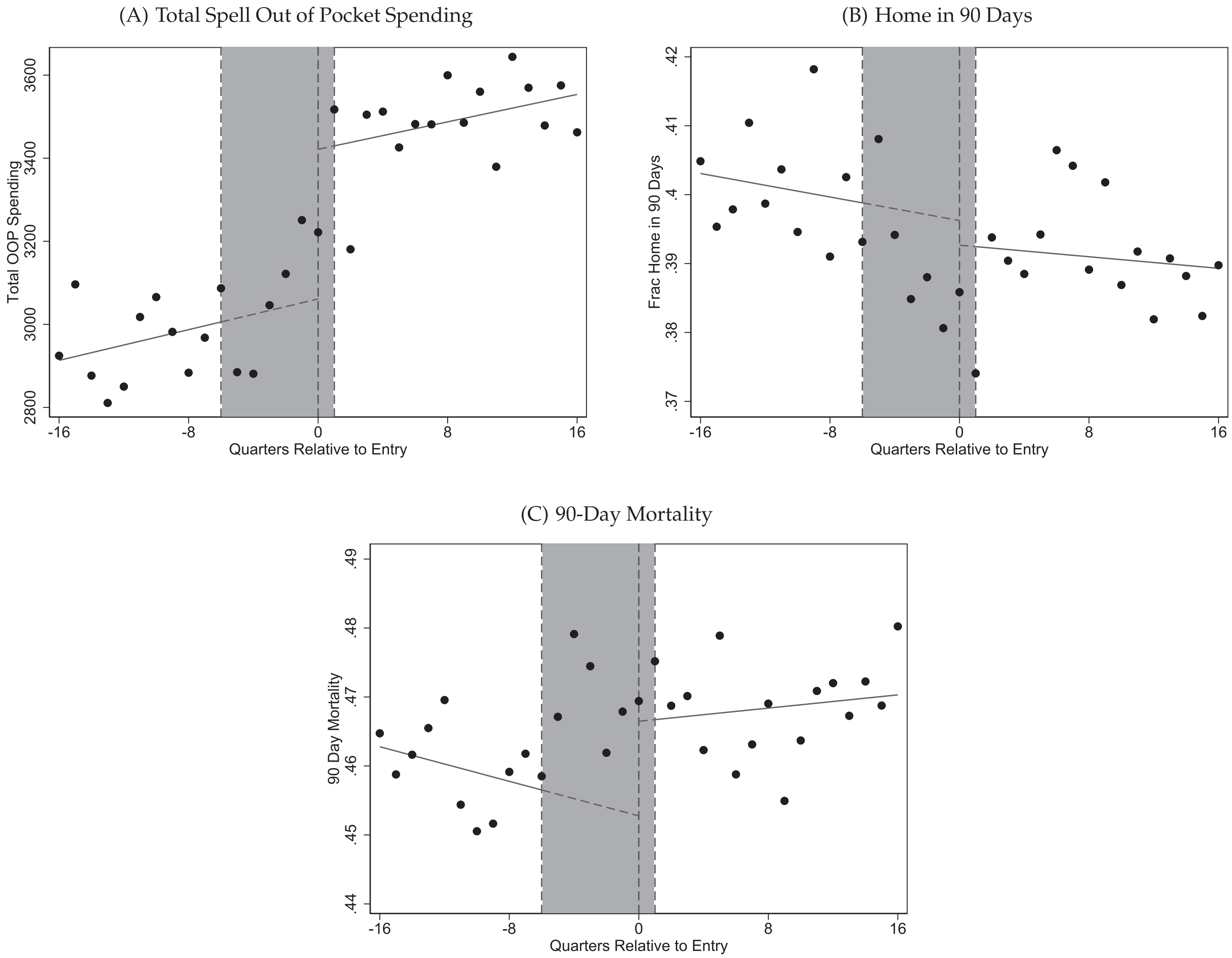


Figure reports estimates of equation (1), the reduced form impact of LTCH entry, estimated on the high $\hat{p}$ sub-sample of the baseline event study sample. The figure displays our estimated function of relative quarter, r, and a scatter plot of the average residualized values of each of the patient welfare outcomes. Quarters $-6 < r < 1$ are greyed out because we drop all observations in these quarters. The y-axis reports the utilization measure indicated and is scaled so that the mean at $r = -1$ is equal to the outcome mean at $r = -1$ among HSAs.

"home/other" reflects a decline in discharges home without home health care, and the rest stems from a decline in discharges to a residual "other" category; there is no evidence of any decline in discharges to home with home health care or in discharges to hospice.

The next two panels of table 4 show results for spell days and spell spending. Focusing again on the IV estimates for the baseline sample in column 3, our results indicate that discharge to an LTCH increases total spell days by a statistically insignificant 6.6 days (standard error of 5.1); days in both SNF and the initiating ACH decrease, while days in LTCH increase. The 8.6 day average decline in length of stay at the initiating ACH is consistent with the claim that LTCHs in some cases provide care to patients that they could not receive at other forms of institutional PAC (NALTH, 2018); when the patient is not discharged to an LTCH, she spends, on average, considerably longer in the ACH. Given that ACHs are paid a lump sum per patient that is (largely) independent of length of stay, the decline in length of ACH stay associated with LTCH discharge suggests that not only LTCHs, but also ACHs, may benefit financially from discharge to LTCH. We return to this point in the conclusion.

Discharge to an LTCH increases total spell spending by \$29,583 (standard error of \$4,810). This represents about 169% increase in total spell spending relative to the average spell spending of \$17,519 (see table 3). The increase in spending reflects a \$34,569 increase in LTCH spending, which is only slightly offset by a decline in SNF spending.[19]

The final panel of table 4 shows results for three measures of patient welfare. There is no evidence of discharge to LTCH improving patient welfare on any of these measures. Discharge to LTCH is associated with increased amounts owed

[19]We omit from the table two other possible sources of institutional days and spending: days and spending at an LTCH-in-training and data at another ACH. The effects are substantively small and statistically insignificant: LTCH-in-training utilization increases by 0.16 days (standard error of 0.09) and \$113 in spending (standard error of 50), and ACH utilization increases by 0.71 days (standard error of 1.29) and \$629 (standard error of \$1,930).

TABLE 5.—EVENT STUDY ESTIMATES: HETEROGENEITY

	High $\hat{p}$ sample First stage		Baseline sample I.V.						
	Discharge to LTCH (1)		Discharge to SNF (2)		Total spell spending ($) (3)		Died within 90 days (4)		Number of Obs. (000s) (5)
Panel A: Days in ICU/CCU									
Over 3 days	0.105	(0.011)	−0.689	(0.069)	31,935	(6,472)	0.176	(0.070)	3,297
Under 3 days	0.067	(0.008)	−1.015	(0.137)	25,818	(5,345)	−0.015	(0.120)	8,527
Panel B: Mechanical ventilator									
On a ventilator	0.094	(0.012)	−0.673	(0.074)	40,788	(2,593)	0.221	(0.097)	924
Not on a ventilator	0.091	(0.009)	−0.851	(0.098)	31,624	(1,531)	−0.002	(0.077)	10,900
Panel C: Preentry LTCH discharge rate									
Above median	0.072	(0.015)	−0.765	(0.121)	30,983	(3,167)	0.276	(0.111)	5,551
Below median	0.113	(0.011)	−0.713	(0.085)	36,363	(1,582)	0.014	(0.077)	4,590
Panel D: For-profit status									
For-profit LTCH	0.091	(0.011)	−0.745	(0.101)	34,447	(2,118)	0.192	(0.080)	7,599
Not-for-profit LTCH	0.095	(0.015)	−0.824	(0.113)	35,546	(3,383)	−0.062	(0.109)	4,225

Column 1 reports first-stage estimates and standard errors of α in equation (1) in the high $\hat{p}$ sample. Columns 2–4 report the IV estimate and standard errors of β^y from equations (4) and (5), estimated on the baseline event study sample. Standard errors are clustered at the HSA level (186 clusters) for the high $\hat{p}$ sample (columns 1), and at the HSA-bin level (930 clusters) for the baseline specification (column 3). ICU stands for intensive care unit and CCU stands for critical care unit. In Panel C, the preentry discharge rate is based on the rate in period $r = -6$. For this panel, we exclude 30 of the 186 HSAs where we do not observe outcomes in period $r = -6$.

out of pocket of $2,420 (standard error $640).[20] There is no evidence that LTCHs increase the probability of being at home at any point in the 90 days postadmission to the initial acute hospital admission; indeed the point estimates suggest a statistically insignificant decline (consistent with the statistically insignificant increase in institutional days and in mortality). The final measure of patient welfare we look at is 90-day mortality; this is quite high in our baseline sample (20%; see table 3). However, we find no evidence that discharge to LTCH reduces mortality. Indeed, the point estimate suggests that discharge to LTCH is associated with a statistically insignificant increase in 90-day mortality of 10.1 percentage points; the 95% confidence interval allows us to rule out mortality declines greater than 2.6 percentage points.

Appendix table A3 explores these mortality results in more detail, examining results over different horizons from 30 days to a year; at all these horizons we are unable to reject the null hypothesis of no impact of discharge to LTCH on mortality. We are unable to measure other potential nonmortality health benefits or non-health utility benefits from an LTCH stay. Our estimates in table 4, however, indicate that any such unmeasured benefits would need to be valued at over $32,003 per LTCH stay (increased Medicare spending of $29,583 plus increased out-of-pocket spending of $2,420) in order to cover the incremental healthcare spending associated with LTCH discharge. With an increase in length of stay of 28.9 days on average, this would require LTCHs to provide an incremental $1,107 in daily value.

[20]LTCH stays are covered under inpatient cost-sharing. In practice, 95% of LTCH stays involve no deductible. However, patients are exposed to per-day coinsurance that applies starting on day 61 of the benefit period. In 2014, LTCH stays resulted in an average $2,250 in coinsurance owed out-of-pocket. By contrast, the first 20 days in a SNF have no patient cost-sharing.

C. *Heterogeneous Impacts and Robustness*

We examine potential heterogeneity in the impact of LTCHs on a number of dimensions. Table 5 summarizes these results; Appendix tables A4 and A5 provide additional details on the heterogeneity results, while appendix figures A6 and A7 show the first-stage figures for the high $\hat{p}$ samples for each cut of the data.

Panels A and B of table 5 explore whether the impact of LTCHs differs for patients who—under the 2016 payment reform described in section II—will still be reimbursed under LTCH reimbursement rules. As discussed, this requires that the patient's immediately preceding ACH stay have either 3 or more days in an intensive care unit (ICU) or coronary care unit (CCU), as analyzed in panel A, or mechanical ventilation for at least 96 hrs. at the ACH, as proxied in Panel B by an indicator for whether or not the patient was ventilated at the initiating ACH. We estimate that about 30% of LTCH patients in our sample would meet one or both of these conditions. Consistent with the idea that these reforms were designed to exclude patients for whom other forms of PAC are a reasonable substitute, patients whose reimbursement at LTCH rates was subsequently excluded under the 2016 reform show more substitution away from SNF in response to LTCH discharge. However, there is no evidence that those patients who would still qualify for LTCH reimbursement under the new policy experience lower spending effects or greater patient welfare from LTCH discharge; indeed, if anything the point estimates are suggestive of the opposite, although we are unable to reject the null hypothesis that effects are the same across groups. Appendix table A4 considers a more stringent regulation, originally proposed by CMS but weakened when enacted into law by Congress: that patients must stay more than 8 days (rather than 3) in an ICU or CCU in order to be reimbursed using the LTCH rates (MedPAC, 2014). The results for this split of the data are again quite similar.

Panels C and D explore whether the impact of LTCHs differs across markets and providers. Our analysis thus far of LTCH entries has not captured the effects for infra-marginal patients who would have traveled outside of their HSA to receive care in an LTCH if there had not been an LTCH entry in their HSA. To shed some light on the effects for these types of patients, panel C of table 5 compares impacts of LTCHs across markets that had a higher or lower preentry LTCH discharge share. Specifically, we compare results for those markets below and above the median share of patients discharged to LTCHs in relative quarter $r = -6$, where the average share was 0.27% and 0.89% respectively. The results seem mostly similar between the two groups, with some evidence that LTCHs that enter higher preentry LTCH discharge markets may have worse impacts on patients (who are less likely to go home and more likely to die within 90 days). In Panel D, we compare results across for-profit and nonprofit LTCHs, and we see no evidence of differential impacts.

We also explored the robustness of our findings to a number of alternative specifications. Appendix B presents the results, which are reassuring. Our baseline analysis allowed for a transition period from relative quarter −5 to 0, in which an LTCH-in-training may have entered prior to the "true" LTCH entry at $r = 0$. We explore alternative transition periods, both shorter (−2 to 0) and longer (−5 to 5). Our baseline analysis is limited to the 186 markets where LTCHs entered for the first time during our study period (1998–2014). We show the results are robust to including the 152 markets with preexisting LTCHs as controls, to using an alternative geographic definition of healthcare markets (specifically, county rather than HSA), and to including entries of additional LTCHs after the first in the market. We also show the results are robust to a balanced panel, to excluding Medicaid dual eligibles from the analysis, to defining a spell as 1-year post admission to the ACH, and to including additional data on home health and hospice payments.

D. *Implications*

We briefly explored the implications of our estimates for aggregate Medicare spending and for the much-studied geographic variation in Medicare spending. In 2014, Medicare spending on LTCHs was \$5.4 billion (MedPAC, 2016). Our estimates in table 4 indicate that about 85% of LTCH spending (i.e., \$29,583/\$34,569) represents incremental spending. This suggests that the elimination of LTCHs would reduce Medicare spending by about \$4.6 billion per year, with no measurable adverse impact on patient welfare.

Relatedly, we can use our estimates to ask what share of the large, and much-discussed, geographic variation in Medicare spending would be eliminated if Medicare patients were no longer sent to LTCHs. The finding of substantial differences across areas in Medicare spending per enrollee—without correspondingly better health outcomes—has been widely touted as suggestive of waste and inefficiency in the U.S. healthcare system (e.g., CBO, 2008; Gawande, 2009; Skinner, 2011). As noted earlier, an influential report by the Institute of Medicine estimated that almost three-quarters of the unexplained geographic variation in Medicare spending could be explained by spending on PAC (IOM, 2013). This analysis, however, assumed that there would be no behavioral response to the removal of PAC. We can use our estimates of the behavioral response to LTCHs—that is, how much of LTCH spending is incremental as opposed to substitution from SNFs—to ask how much geographic variation in spending would be reduced if LTCHs were removed. We closely replicate the IOM (2013) finding—specifically, we find that eliminating PAC would reduce residual variance by 69% (compared to their 73% reported estimate). We find that eliminating LTCHs—which are only 1% of Medicare spending—would remove 13% of the residual variance, in the absence of a behavioral response, and about 10% given the substitution to SNFs. Consistent with the Dartmouth Atlas interpretation of the geographic variation as evidence of waste and inefficiency, our estimates suggest that this reduction in geographic variation would come without any adverse effects on patient well-being.

VI. Conclusion

LTCHs were originally intended as a small administrative carve-out to the new inpatient prospective payment system designed in 1982. Inadvertently, however, their designation created a regulatory loophole for post-acute care facilities to receive substantially higher reimbursements. Over the ensuing decades, CMS has endeavored, through a series of legislative and regulatory reforms, to close this loophole. Its continued attempts suggest that is has not yet been successful, and real questions have been raised about whether incremental reforms will ever achieve their goals.

Our empirical estimates suggest that by simply eliminating the administratively created concept of LTCHs as an institution with its own reimbursement schedule—and reimbursing them instead like SNFs—Medicare could save \$4.6 billion per year with no harm to patients. Moreover, despite accounting for only about 1% of Medicare spending, we estimate that eliminating LTCHs would reduce 10% of the unexplained geographic variation in Medicare spending. As is the case with any counterfactual, one must always be careful to not go too far out of sample. From this perspective, a strength of our analysis is that it provides the rare opportunity to study a nonmarginal change: the entry of a new healthcare institution into a healthcare market.

Nonetheless, there are (at least) two potential caveats to keep in mind in generalizing from our estimates to the impact of changing LTCH reimbursement to that of SNFs. First, we study the impact of LTCHs at the time of their creation. It is of course possible that the longer-run impacts of LTCHs on either spending or patient well-being are different (with unknown sign) from what we estimate here, although the graphical analysis we present in figures 5–8 do not suggest any obvious differences in the first four years of the LTCH's existence.

Second, our estimates of the impact of LTCHs are not based on all LTCH patients. Our baseline sample excludes the approximately 15% of LTCH patients who are not admitted from an ACH and the approximately 8% of LTCH admissions from an ACH that involve patients whose *ex ante* probability of discharge to an LTCH is less than 0.4%. Our estimates also do not speak to the effects for the 20% of patients who would have counterfactually been discharged to LTCHs in the absence of LTCH entry into their HSA. In this respect, we find it reassuring that we were unable to detect any evidence of heterogeneous impacts of LTCHs across patients, markets, or outcomes; in particular, we find no evidence of differential effects across markets with different shares of patients who would have counterfactually been discharged to LTCHs in the absence of LTCH entry into their HSA, for-profit, and nonprofit LTCHs, and patients whose LTCH stays are or are not eligible for LTCH reimbursement rates under the 2016 dual payment reform (MedPAC, 2017b).

We finish with a note of caution: There is little reason to expect our proposed change to the reimbursement of LTCHs will be politically easy. The $4.6 billion of incremental spending generated by LTCHs every year may look like "waste" to the health economist, but to the (largely for-profit) LTCH industry it might more accurately be referred to as "rents." In addition, the much larger number of acute care hospitals likely also benefit from the presence of LTCHs since we found that discharges to LTCHs reduce length of stay at the initiating hospital, which bears the incremental costs of additional days. This suggests a large financial incentive on the part of LTCHs as well as acute care hospitals to preclude major regulatory changes, and it may help to explain their continued survival.

REFERENCES

42 CFR §412.23, "Excluded Hospitals: Classifications," Code of Federal Regulations, Technical Report (2011).

42 CFR §412.532, "Special Payment Provisions for Patients Who are Transferred to Onsite Providers and Readmitted to a Long-Term Care Hospital," Code of Federal Regulations, Technical Report (2011).

42 CFR §412.534, "Special Payment Provisions for Long-Term Care Hospitals-Within-Hospitals and Satellites of Long-Term Care Hospitals, Effective for Discharges Occurring in Cost Reporting Periods Beginning on or Before September 30, 2016," Code of Federal Regulations, Technical Report (2014).

80 FR 37990, "A Rule by the Centers for Medicare & Medicaid Services," Federal Register, Technical Report (2017).

AHPA, "National Directory of Health Planning, Policy and Regulatory Agencies," American Health Planning Association, Technical Report (2003–2011).

Anderson, Gerard F., Peter S. Hussey, Bianca K. Frogner, and Hugh R. Waters, "Health Spending in the United States and the Rest of the Industrialized World," *Health Affairs* 24:4 (2005), 903–914. 10.1377/hlthaff.24.4.903

Ash, Arlene S., Michael A. Posner, Jeanne Speckman, Shakira Franco, Andrew C. Yacht, and Lindsey Bramwell, "Using Claims Data to Examine Mortality Trends Following Hospitalization for Heart Attack in Medicare," *Health Services Research* 38:5 (2003), 1253–1262. 10.1111/1475-6773.00175

Barnett, Michael L., Andrew R. Olenski, and Anupam B. Jena, "Opioid-Prescribing Patterns of Emergency Physicians and Risk of Long-Term Use," *New England Journal of Medicine* 376:7 (2017), 663–673. 10.1056/NEJMsa1610524

BEA, "Download NIPA Tables: Government Current Receipts and Expenditures (Section 3)" (2016). https://apps.bea.gov/iTable/?reqid=19&step=2&isuri=1&categories=survey

Berwick, Donald M., "Launching Accountable Care Organizations—The Proposed Rule for the Medicare Shared Savings Program," *New England Journal of Medicine* 364:16 (2011), e32. 10.1056/NEJMp1103602

Boards of Trustees for Medicare, "The 2002 Annual Report of the Boards of Trustees of the Federal Hospital Insurance Trust Fund and the Federal Supplementary Medical Insurance Trust Fund," Federal Hospital Insurance and Federal Supplementary Medical Insurance Trust Funds, Technical Report (2002).

——— "The 2014 Annual Report of the Boards of Trustees of the Federal Hospital Insurance Trust Fund and the Federal Supplementary Medical Insurance Trust Fund," Federal Hospital Insurance and Federal Supplementary Medical Insurance Trust Funds, Technical Report (2014).

——— "The 2015 Annual Report of the Boards of Trustees of the Federal Hospital Insurance Trust Fund and the Federal Supplementary Medical Insurance Trust Fund," Federal Hospital Insurance and Federal Supplementary Medical Insurance Trust Funds, Technical Report (2015).

Buntin, Melinda Beeuwkes, "Access to Postacute Rehabilitation," *Archives of Physical Medicine and Rehabilitation* 88:11 (2007), 1488–1493. 10.1016/j.apmr.2007.07.023

CBO, "Geographic Variation in Health Care Spending," Congressional Budget Office, Technical Report (2008).

——— "Updated Budget Projections: 2016 to 2026," Congressional Budget Office, Technical Report (2016).

Chen, Han-Yang, David J. Vanness, and Ellie Golestanian, "A Simplified Score for Transfer of Patients Requiring Mechanical Ventilation to a Long-Term Care Hospital," *American Journal of Critical Care* 20:6 (2011), e122–e130. 10.4037/ajcc2011775

Clemens, Jeffrey, and Joshua D. Gottlieb, "Do Physicians' Financial Incentives Affect Medical Treatment and Patient Health?" *American Economic Review* 104:4 (2014), 1320–1349. 10.1257/aer.104.4.1320

CMS, "Moratorium on Classification of Long-Term Care Hospitals (LTCH) or Satellites/Increase in Certified LTCH Beds," Centers for Medicare & Medicaid Services, Technical Report (2008).

——— "Long-term Care Hospital (LTCH) Moratorium–Preliminary Instructions," Centers for Medicare & Medicaid Services, Technical Report (2014).

Cooper, Zack, and Fiona Scott Morton, "Health Care Reform: One (Percent) Step At A Time," *Health Affairs Blog* (2021). https://www.healthaffairs.org/do/10.1377/forefront.20210209.381915/full/

Cooper, Zack, Fiona Scott Morton, and Nathan Shekita, "Surprise! Out-of-Network Billing for Emergency Care in the United States," *Journal of Political Economy* 128:9 (2020), 3626–3677. 10.1086/708819

Curto, Vilsa, Liran Einav, Amy Finkelstein, Jonathan D. Levin, and Jay Bhattacharya, "Healthcare Spending and Utilization in Public and Private Medicare," *American Economic Journal: Applied Economics* 11:2 (2019), 302–332. 10.1257/app.20170295

Cutler, David, "How Health Care Reform Must Bend The Cost Curve," *Health Affairs* 29:6 (2010), 1131–1135. 10.1377/hlthaff.2010.0416

Cutler, David M., "The Incidence of Adverse Medical Outcomes Under Prospective Payment," *Econometrica* 63:1 (1995), 29–50. 10.2307/2951696

Doyle, Joseph J., John A. Graves, and Jonathan Gruber, "Uncovering Waste in US Healthcare: Evidence from Ambulance Referral Patterns," *Journal of Health Economics* 54 (2017), 25–39. 10.1016/j.jhealeco.2017.03.005

Doyle, Joseph, John Graves, and Jonathan Gruber, "In Hospital Care Saves Money–and Lives," *Boston Globe* (2015). https://www.bostonglobe.com/opinion/2015/03/30/hospital-care-saves-money-and-lives/3QEgafleCxuxzqV6rcdliK/story.html

Duflo, Esther, "Richard T. Ely Lecture: The Economist as Plumber," *American Economic Review* 107:5 (2017), 1–26. 10.1257/aer.p20171153

Einav, Liran, Amy Finkelstein, and Neale Mahoney, "Provider Incentives and Healthcare Costs: Evidence from Long-Term Care Hospitals," *Econometrica* 86:6 (2018), 2161–2219. 10.3982/ECTA15022

Eliason, Paul J., Paul L. E. Grieco, Ryan C. McDevitt, and James W. Roberts, "Strategic Patient Discharge: The Case of Long-Term Care

Hospitals," *American Economic Review* 108:11 (2018), 3232–3265. 10.1257/aer.20170092

Follmann, Dean A., "On the Effect of Treatment Among Would-Be Treatment Compliers: An Analysis of the Multiple Risk Factor Intervention trial," *Journal of the American Statistical Association* 95:452 (2000), 1101–1109. 10.1080/01621459.2000.10474306

Gawande, Atul, "The Cost Conundrum: What a Texas Town Can Teach Us about Health Care," *New Yorker* (2009). https://www.newyorker.com/magazine/2009/06/01/the-cost-conundrum

HCUP, "Clinical Classifications Software (CCS) for ICD-9-CM," Healthcare Cost and Utilization Project, Technical Report (2017).

Ho, Kate, and Ariel Pakes, "Hospital Choices, Hospital Prices, and Financial Incentives to Physicians," *American Economic Review* 104:12 (2014), 3841–3884. 10.1257/aer.104.12.3841

IOM, *Variation in Health Care Spending: Target Decision Making, Not Geography* (Washington, DC: National Academies Press, 2013).

Irace, Mariano, "The Impact of Payment Reform on the Behavior of Long-Term Care Hospitals," PhD Dissertation, Northwestern University, Chapter 3 (2018).

Joskow, Paul L., *Controlling Hospital Costs: The Role of Government Regulation* (Cambridge, MA: MIT Press, 1981).

Kahn, Jeremy M., and Theodore J. Iwashyna, "Accuracy of the Discharge Destination Field in Administrative Data for Identifying Transfer to a Long-Term Acute Care Hospital," *BMC Research Notes* 3:1 (2010), 205. 10.1186/1756-0500-3-205

Kahn, Jeremy M., Rachel M. Werner, Guy David, Thomas R. Ten Have, Nicole M. Benson, and David A. Asch, "Effectiveness of Long-Term Acute Care Hospitalization in Elderly Patients with Chronic Critical Illness," *Medical Care* 51:1 (2013), 4. 10.1097/MLR.0b013e31826528a7

Kim, Yan S., Eric C. Kleerup, Patricia A. Ganz, Ninez A. Ponce, Karl A. Lorenz, and Jack Needleman, "Medicare Payment Policy Creates Incentives for Long-Term Care Hospitals to Time Discharges for Maximum Reimbursement," *Health Affairs* 34:6 (2015), 907–915. 10.1377/hlthaff.2014.0778

Koenig, Lane, Berna Demiralp, Josh Saavoss, and Qian Zhang, "The Role of Long-term Acute Care Hospitals in Treating the Critically Ill and Medically Complex: An Analysis of Nonventilator Patients," *Medical Care* 53:7 (2015), 582. 10.1097/MLR.0000000000000382

Liu, Korbin, Cristina Baseggio, Douglas Wissoker, Stephanie Maxwell, Jennifer Haley, and Sharon Long, "Long-Term Care Hospitals Under Medicare: Facility-Level Characteristics," *Health Care Financing Review* 23:2 (2001), 1.

Macis, Mario, "Removing All Financial Disincentives to Living Kidney Donation," 1% Steps for Health Care Reform, Technical Report (2021), https://onepercentsteps.com/policy-briefs/removing-all-financial-disinc entives-to-living-kidney-donation/.

McGinnis, J. Michael, Leigh Stuckhardt, Robert Saunders, Mark Smith, *Best Care at Lower Cost: The Path to Continuously Learning Health Care in America* (Washington, DC: National Academies Press, 2013).

MedPAC, "Chapter 11: Long-Term Care Hospital Services," Medicare Payment Advisory Commission, Technical Report (2014).

——— "A Data Book: Health Care Spending and the Medicare Program," Medicare Payment Advisory Commission, Technical Report (2015a).

——— "Report to the Congress," Medicare Payment Advisory Commission, Technical Report (2015b).

——— "Chapter 10: Long-Term Care Hospital Services," Medicare Payment Advisory Commission, Technical Report (2016).

——— "Long-Term Care Hospitals Payment System," Medicare Payment Advisory Commission, Technical Report (2017a).

——— "Report to the Congress: Medicare Payment Policy, Chapter 11: Long-Term Care Hospital Services," Medicare Payment Advisory Commission, Technical Report (2017b).

——— "Report to the Congress: Medicare Payment Policy, Chapter 11: Long-Term Care Hospital Services," Medicare Payment Advisory Commission, Technical Report (2018).

Molitor, David, "The Evolution of Physician Practice Styles: Evidence from Cardiologist Migration," *American Economic Journal: Economic Policy* 10:1 (2018), 326–356. 10.1257/pol.20160319

NALTH, "A Response to the National Bureau of Economics Research Working Paper, "Long-Term Care Hospitals: A Case Study in Waste" A Response to National Bureau of Economics Research Working Paper, "Long-Term Care Hospitals: A Case Study in Waste," National Association of Long Term Hospitals, Technical Report (2018).

Newhouse, Joseph P., "Reimbursing Health Plans and Health Providers: Efficiency in Production Versus Selection," *Journal of Economic Literature* 34:3 (1996), 1236–1263.

OECD, "Health at a Glance 2017: OECD Indicators," OECD, Technical Report (2017).

Office of Inspector General, "Early Alert Memorandum Report: Co-Located Long-Term Care Hospitals Remain Unidentified, Resulting in Potential Overpayments," Department of Health and Human Services, Technical Report (2013).

Orszag, Peter, and Rahul Rekhi, "Real-Time Adjudication for Health Insurance Claims," 1% Steps for Health Care Reform, Technical Report (2021), https://onepercentsteps.com/policy-briefs/real-time-adjudication-for-he alth-insurance-claims/.

Orszag, Peter R., "Heath Costs Are the Real Deficit Threat," *The Wall Street Journal* (2009).

Ottenbacher, Kenneth J., and James E. Graham, "The State-of-the-Science: Access to Postacute Care Rehabilitation Services. A Review," *Archives of Physical Medicine and Rehabilitation* 88:11 (2007), 1513–1521. 10.1016/j.apmr.2007.06.761

Papanicolas, Irene, Liana R. Woskie, and Ashish K. Jha, "Health Care Spending in the United States and Other High-Income Countries," *Journal of the American Medical Association* 319:10 (2018), 1024–1039. 10.1001/jama.2018.1150

Radley, David C., Daniel J. Gottlieb, Elliot S. Fisher, and Anna N. A. Tosteson, "Comorbidity Risk-Adjustment Strategies Are Comparable Among Persons with Hip Fracture," *Journal of Clinical Epidemiology* 61:6 (2008), 580–587. 10.1016/j.jclinepi.2007.08.001

Skinner, Jonathan, "Causes and Consequences of Regional Variations in Health Care," In *Handbook of Health Economics*, Vol. 2 (Amsterdam, Netherlands: Elsevier, 2011, pp. 45–93). 10.1016/B978-0-444-53592-4.00002-5

Weaver, Christopher, A. W. Mathews, and Tom McGinty, "Hospital Discharges Rise at Lucrative Times," *Wall Street Journal* (2015).