The Effects of Skilled Nursing Facility Care: Regression Discontinuity Evidence from Medicare

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Abstract

Among the elderly population that is hospitalized, about 20 percent are discharged to skilled nursing care facilities (SNFs), at a cost of over $30 billion annually. SNFs provide high-level care in an outpatient setting with the intent of reducing individuals' time in the hospital and preventing readmissions. I leverage a Medicare policy that induces a discontinuity in the probability of being transferred to a SNF to estimate the effectiveness of SNF care. I find that SNF care reduces the probability of readmission to the hospital within 30 days by 33 percent, suggesting that SNF care substantially improves patient outcomes.

Keywords: Post-Acute Care, Readmissions, Skilled Nursing Care

I INTRODUCTION

Nursing-care and continuing-care facilities account for about 5 percent of all health care costs in the United States, amounting to nearly $150 billion annually (CDC, 2014). A substantial portion of this spending is on post-acute care following an inpatient stay in the hospital. Among Medicare beneficiaries, 20 percent of hospitalizations result in a discharge to a SNF, and about 6 percent of Medicare's expenditures go toward SNF care (MedPac 2013). These facilities provide comprehensive, around-the-clock care in an outpatient setting, allowing patients that are unable to return to their homes to receive advanced care in a less costly manner. While in these facilities, individuals receive care to recover from surgeries and medical events that require regular skilled care and rehabilitation.

The additional care is intended to improve patient outcomes during short- to medium-term recovery from an injury or illness. Because of this, Medicare covers the majority of the initial cost of the SNF stay if the inpatient stay meets certain minimal requirements. Nevertheless, it has been established that up to 23 percent of these post-acute beneficiaries face hospital readmission within 30 days of being discharged to a SNF (Mor et al. 2010). These readmissions are costly both in terms of adverse patient outcomes — with patients at increased risk for otherwise avoidable complications — and financial burden, with the cost of the readmissions estimated at over $4 billion per year (Ouslander et al. 2010, Segal 2011). As a result, the Centers for Medicare and Medicaid Services (CMS) have pushed policy proposals that would take readmission rates into account as part of payment rates to skilled nursing facilities, and bundled payment programs that would shift financial responsibility for post-acute care to hospitals.[1]

Despite their integral and significant part of the health care system, evidence on the effectiveness of this type of care is limited, primarily due to selection issues among patients that utilize these services. Because of the intensity of care and high costs, patients discharged

[1]CMS already implemented the Hospital Readmissions Reduction Program (HRRP) in 2012, which reduces payments to hospitals with excess readmissions. A similar program for SNFs is set to go into effect in fiscal year 2019 (CMS 2015).

to SNFs are typically in poorer health. The decision to discharge to a SNF is associated with a number of patient-specific and region-specific characteristics; age, hip fractures, strokes, and having secondary insurance are all associated with an increase in the likelihood of a SNF discharge, while more income, more children, and more hospital competition are all negatively associated (Picone et al. 2003, Bowles et al. 2003). Yet it is not known how beneficial this additional care is, especially to patients on the margin when a discharge decision is made at the end of an inpatient stay. Consequently, it is unclear if this type of care is over- or under-priced by insurers and other providers. Overpriced care may prevent financially constrained individuals from receiving care, while underpricing may induce the moral hazard that has been shown to exist in other sectors of the U.S. health care market.[2] This is counteracted by many patients' desire to remain in their homes, and there is some evidence that the demand for this type of care is inelastic (Grabowski and Gruber 2007).

This paper attempts to answer the question of how being discharged to a nursing home affects patient outcomes. Medicare requires a patient spend a minimum of three days as an inpatient before subsidizing the cost of SNF care. For patients that qualify, Medicare will cover about 80 percent of all costs for an average duration stay.[3] Utilizing a regression discontinuity approach, I compare patients that qualified for SNF coverage against those that narrowly missed the necessary length of stay. This allows for the comparison of beneficiaries that differ only on the generosity of insurance coverage of post-acute care, with patients that do not go to a SNF left with either no formal care or intermittent care. Most discharges occur during the daytime when patients are awake and the hospital has more support staff available. Then, because length-of-stay days are computed based on the number of midnights in the hospital, people admitted just before or just after midnight spend a similar number of hours in the hospital, but individuals admitted just prior to midnight are more likely to qualify

[2] Newhouse et al. 1993, Finkelstein and McKnight 2008, Card et al. 2009, as examples.

[3] Medicare completely covers the first 20 days of a stay, then requires a coinsurance payment of $164.50 per day for the next 80 days of the stay. The average length of stay is 28 days and the average cost per day is $228.

for Medicare coverage of the SNF stay.[4] I use administrative hospital records covering both emergency department visits and inpatient admissions from several large states, ensuring the sample sizes are large enough to precisely estimate effects for patients most affected by the Medicare restrictions.

I find that patients that are admitted just before midnight and are therefore more likely to qualify for Medicare coverage of their SNF care are 22 percent more likely to be discharged to a SNF. About two-thirds of these patients instead experience routine home discharges, with the remaining portion in managed home healthcare. Patients that were more likely to go to a SNF upon discharge were 1.1 percentage points less likely to readmitted for any cause within the next 30 days. This suggests that SNF care reduces the probability of 30-day readmission by 33 percent for the affected population. Furthermore, I find suggestive evidence that this group is also less likely to return for treatment to the emergency department without an inpatient admission in the same time frame.

Along with Jin et al. (2018), these results comprehensively document the effects of SNF care on patient outcomes using quasi-experimental methods, and suggest that this care improves outcomes even for patients on the margin. My results present evidence that not only does the additional subsidized care induce patients and providers to change discharge plans, but also that both groups substantially benefit when restrictions on SNF care are eased. Simple calculations indicate that these benefits could occur with extremely modest costs to Medicare, with the reduction in readmissions offsetting the majority of the costs associated with the additional SNF care. This suggests that SNF care is a far more cost-effective form of post-acute care than long-term care hospitals, which recent work has shown to be wasteful (Einav, Finkelstein, and Mahoney 2018a, 2018b).

The paper is organized into five sections. Section 1 provides background information on Medicare rules regarding skilled nursing facility care and a review of the literature on patient readmissions. Section 2 describes the datasets used in the analysis. Section 3 outlines the

[4] This approach is somewhat similar to that of Almond and Doyle (2011), who leverage the midnight discontinuity with mandatory stay lengths for childbirth to examine newborn health.

estimation strategy and Section 4 provides the estimated effects of being discharged to a skilled nursing facility for a Medicare beneficiary. Section 5 concludes.

II BACKGROUND & POLICY SIGNIFICANCE

Post-acute care has been targeted as the next dimension of potential savings for Medicare cost savings (Mechanic 2014). Approximately 1.4 million Americans reside in one of the country's 15,700 nursing homes at a given time, at a cost of $143 billion in 2013 (Harris-Kojetin et al. 2013). A portion of this goes to skilled nursing facility care rather than long-term nursing care. While Medicare does not cover long-term nursing care and not all nursing facilities are eligible or willing to take Medicare patients, it will cover skilled nursing facilities care for a limited amount of time and under certain conditions. Medicare is the primary payer for 14.5 percent of all nursing home residents, and spending on SNFs amounted to $31.3 billion in 2011, or about 6 percent of Medicare's total expenditures (Kaiser Family Foundation 2013, MedPac 2013). Nursing care facility expenditures increased to $155 billion in 2014, which was strongly driven by the 4.1 percent growth in Medicare spending (National Health Expenditure Accounts 2015).

In general, Medicare beneficiaries are discharged to a SNF when a physician decides the patient needs daily skilled care following an inpatient stay in the hospital. Medicare will only subsidize these services when the inpatient stay meets the conditions to be a "qualifying hospital stay." For this, the most stringent criterion is that the patient spend three midnights as an inpatient, which includes the day of admission but does *not* include the day of discharge.[5] Additionally, time spent as an outpatient — including time in the emergency room or time in observation services — does not count toward this three-day minimum.

Beyond rare examples to examine insurance coverage experimentally, researchers have

[5] The other criteria are simply that the physician prescribes SNF care and that skilled services are required to treat a medical condition that was also treated during the inpatient stay.

exploited insurance rules to find plausibly exogenous changes in coverage generosity.[6] These studies generally find that health care services are price sensitive, and that the benefits of the additional services are either absent or difficult to detect. Perhaps most significant to this study, however, Grabowski and Gruber (2007) find no evidence of increases in nursing facility utilization when Medicaid financial means restrictions become less severe, concluding that nursing home care is inelastic with respect to coverage generosity. However, this comes entirely from the Medicaid population, who are far more likely to use nursing homes for long-term care of chronic diseases.

Medicare does not cover long-term care for patients, and SNF coverage can only last for a maximum of 100 days per benefit period. A benefit period measures a beneficiary's use of hospital and skilled nursing services, and begins the day the patient is admitted as an inpatient. The benefit period ends when the patents has not received inpatient or SNF care for 60 consecutive days, and there is no limit to the number of benefit periods a beneficiary may receive. Following the start of a benefit period, Medicare beneficiaries pay nothing for the first 20 days in the skilled nursing facility, then pay daily coinsurance for the 21-100th day. This coinsurance amount was \$133.50 in 2009, increasing to \$164.50 in 2017. After that point, the patient is responsible for the full costs of the facility. Survey estimates of the median daily costs range from \$225-\$248 (Genworth Cost of Care Survey 2016, Lincoln Financial Group "What Care Costs" Study 2017, Metlife Market Survey of Long-Term Care Costs of 2012). However, Medicare data put this amount at \$354 net of the deductible and coinsurance (Medicare SNF Fee-for-Service Claims Data, 2014).

The 3-day policy policy may create unnecessary costs for both Medicare and for beneficiaries, as it is possible for patients to be left without coverage for their physician's first-choice discharge plan (Lipsitz 2013). The rule was implemented in 1965, when it took about three days for a Medicare patient to be admitted, evaluated, and discharged, but this process has

[6] These studies include policy changes in patient cost-sharing (Chandra et al. 2007), the price elasticity of prescription drugs (Goldman et al. 2006), the advent of Medicare (Finkelstein and McKnight 2008), and the transition into Medicare at age 65 (Card et al. 2009).

been streamlined to 1 to 2 days for many patients (Lipsitz 2013). There have been attempts to modify the rule, and the Health Care Financing Administration (now CMS) ran pilot studies that eliminated the three-midnight requirement but decided against permanent implementation after it was deemed to have little effect on costs and the quality of patient care. The three-night stay requirement was also waived by the Medicare Catastrophic Coverage Act (MCCA) of 1988, but the act was repealed after just one year following a 243 percent increase in Medicare expenditures for SNF care in an evaluation study (Aaronson et al. 1994). Grebla et al. (2015) find that there is a small decrease in the average length of inpatient stay when the three-day restriction is relaxed for select Medicare Advantage plans, although the majority of this effect is driven by an increase in average length of stay for the control group during the study period.

With about 20 percent of Medicare patients discharged to a skilled nursing facility, the effect of this type of post-acute care has been surprisingly understudied. Because SNFs provide intensive, around-the-clock care, alternative discharge plans represent significant reductions in the amount of care provided to individuals. These patients face difficulties with follow-up appointments and tests, medications, and trips to the emergency department (Arora et al. 2010). Elderly patients often struggle with housekeeping tasks and need for more information about their discharge plan (Mistiaen et al. 1997). Shorter hospital stays often necessitate more intensive post-discharge follow-up, and home services and families are often required to act as safety nets with more comprehensive discharge planning (Naylor et al. 1999). However, it is often the case that the primary care physician is unaware of the hospitalization entirely, despite recommendations by major medical societies that the PCP be informed during all care transitions (Arora et al. 2010). Most recently, Jin et al. (2018) leveraged the three-day rule with an instrumental variables approach, using the interaction of the three-day threshold and having Medicare to show some benefits to SNF care, although not for hip and knee replacement patients. [7]

[7] The identification strategy compares patients with day 3 discharges and Medicare as the primary payer to non-Medicare day 2 discharges, relying on the assumption that patient and hospital characteristics along

Of course, patients discharged to a SNF are generally in poorer health, and it is difficult to compare them to patients discharged to home care (Allen et al. 2011). The decision to discharge to a SNF is associated with a number of patient-specific and region-specific characteristics; age, hip fractures, strokes, and having secondary insurance are all associated with an increase in the likelihood of a SNF discharge, while more income, more children, and more hospital competition are all negatively associated (Picone et al. 2003, Bowles et al. 2003). Policies that penalized hospitals for overly short inpatient stays gave inconsistent effects on rehospitalization rates among patients that were discharged to a SNF, with only some diagnoses groups showing improvements in rehospitalization rates (Unruh et al. 2013). Patients face substantial risk when transitioning between care settings, as communication between practice settings can be fragmented (Coleman 2003). Toward the end of an inpatient stay, hospital-based physicians often create discharge plans that detail a medication regimen, future tests and appointments for the patient to undertake, and/or pending test results to be followed up by an outpatient physician. Many of these plans are not diligently followed, and these errors are associated with higher rates of rehospitalization (Moore et al. 2003).[8] In some cases, the discharge summary and the patient care referral form simply do not match up. Tjia et al. (2009) found that this resulted in medical discrepancies in medications in nearly three quarters of SNF admissions, while Wong et al. (2008) found remarkably similar figures for home discharges. Interventions to improve this have typically been targeted at long-term SNF occupants rather than those receiving the Medicare short-term rehabilitation services examined in this paper (LaMantia et al. 2010).

with the day 3 discharge and Medicare interaction capture all health conditions relating to discharge location. The advantage of this strategy is that it does not rely on admissions near midnight, which are less common than day or evening admissions. However, the drawback is that capturing all observable and non-observable characteristics a difficult task, and the identification strategy used in this paper does not rely on non-Medicare patients. This is important both because Medicare eligibility has been shown to change behavior (e.g. Card et al. 2009) and because non-Medicare patients over the age of 65 have selected out of Medicare, making them substantially different than the typical over 65 Medicare beneficiary.

[8] Doyle et al. (2015) show that patients that go to hospitals that are more likely to discharge to a SNF have increased one-year mortality rates, and that these hospitals have relatively lower spending. It is unclear if this result is driven by hospital heterogeneity or the impact of SNF care, as the identification strategy has patients quasi-randomly assigned to hospitals rather than identifying variation in discharge plans.

Outside of SNF care, recent work has examined long-term care hospitals (LTCHs) as another form of post-acute care. Einav, Finkelstein, and Mahoney (2018a) show that the Medicare reimbursement rules drive more patients and healthier patients to LTCHs, and these authors also show that new facility openings take patients away from SNFs, which cost far less (Einav, Finkelstein, and Mahoney 2018b). LTCH patients are typically in very poor health, even worse than the typical SNF patient — 30 percent die within 90 days of admission. However, SNF care is generally seen as the closest substitute, and evidence on SNF care is even more crucial if the effectiveness of LTCHs is questionable.

In this study, I leverage the time of admission to identify the impact of SNF care. In other words, I do not compare patients by discharge status. This avoids the selection bias issue by leveraging variation in the probability of going to a SNF that results from Medicare coverage rules. The medical literature has established no link between time of hospital inpatient admission and medical outcomes.[9]

Finally, there is an ongoing policy debate as to which beneficiaries qualify as a "marginal" patient. While some services are regarded as "inpatient only," hospitals are given considerable discretion on the admission decision, and similar patients may be admitted for a short hospital stay at one hospital and kept for outpatient observation services at another. This decision affects both Medicare payouts to the hospital and out-of-pocket costs for beneficiaries. CMS has attempted to standardize this decision, proposing that patients should move to inpatient care if the physician believed they should be in the hospital for at least two midnights. But the proposed "two-midnight rule" was immediately controversial when proposed and implementation was delayed (Health Affairs 2015). Although the primary interest of this paper is the impact of access to SNF care, it also sheds light on the 2-midnight rule more generally, and underlines the consequences of when a patient is given inpatient status.

[9] Some studies have focused on day of admission, most often finding no association between mortality rates and weekend admission (Ensminger et al. 2004). Further, others have concluded that there is no association with off-hour admission, regardless of the day of the week (Meynaar et al. 2009).

III DATA

A. *Data Description*

I use data detailing individual-level hospital inpatient stays and emergency department visits to examine the impact of a slight difference in admission time on downstream medical outcomes. The Healthcare Cost and Utilization Project (HCUP) centralizes data provided voluntarily by participating states, and the databases are derived from administrative records. HCUP is a Federal-State-Industry partnership funded by the Agency for Healthcare Research and Quality (AHRQ), which is itself a branch of the U.S. Department of Health and Human Services.

The State Inpatient Databases (SID) gives information on the universe of inpatient stays for a participating state in a given year. The State Emergency Department Databases (SEDD) provide information on the universe emergency department admissions that do *not* result in an inpatient admission. These two databases include an identifier which allows me to track individuals across datasets over time. This allows the data to be longitudinal for all hospital-related encounters for a patient, even across years, with the only restriction being to this is that patients cannot be tracked across states.

HCUP gathers health care data from 47 states and the District of Columbia, which covers 97 percent of all inpatient discharges annually. Databases are standardized for comparability, such that AHRQ transforms the administrative health care data into uniform databases with common data elements. However, states are given the freedom to decide which variables they wish to provide to HCUP in both the inpatient and emergency department databases. Further, states can change what information they provide from year to year. This study uses data from states with large populations that also provide hour of admission. The sample consists of data from Florida and New York from 2009-2013, resulting in a dataset containing 20 million inpatient admissions and more than 55 million emergency department visits. I am left with just over 15 million encounters once only Medicare beneficiaries are considered.[10] The discharge data include patient demographics, procedure and diagnosis codes, primary payer, and admission and discharge time. The data are extremely rich, and give a comprehensive picture of a patient's medical conditions and treatments received in the emergency department or as an inpatient. Summary statistics are provided in Table A6.

For general statistics on Medicare utilization of SNF care, I use provider-level data from the Skilled Nursing Facility Utilization and Payment Public Use File. This database gives details on services and charges to Medicare beneficiaries residing in skilled nursing facilities, with all information from calendar year 2013.

B. *Analysis Sample*

One limitation of the hospital database records is that only the hour of admission is reported, with the minutes imputed to zero.[11] While this does not create any bias in the estimates of the discontinuity, it is somewhat limiting in efforts to present results visually. Additionally, the lumping makes the smoothness of the density of admissions across midnight slightly harder to assess. Admissions will clearly be decreasing as the volume of patients decreases throughout the night, but some hospitals show a larger decrease at midnight. The question is whether there is a drop at midnight due to hospital shift times resulting in staffing changeovers or systematic misreporting of admission time in order to increase charges or qualify some patients for SNF care through Medicare. This is a concern for this analysis, as hospitals may alter admission time for different types of patients. If healthier patients are more likely to be admitted before midnight (making them more likely to be SNF eligible), then RD estimates will be biased towards finding a positive impact on readmissions. Conversely, if sicker patients are more likely to be admitted before midnight in order to ensure SNF

[10] I additionally use data from 2009-2011 for Washington in some summary statistics, robustness checks, and balance checks. Because the state does not submit data to the emergency department database, I exclude it from the main analysis to provide consistency between inpatient outcomes and any hospital-based care outcomes.

[11] Two states, New Mexico and Nebraska, actually do provide admission times in hours and minutes along with linkage variables, but the population sizes of these states prevents them from being particularly useful for this analysis given clear round-number bias in admission times.

eligibility at the end of the inpatient stay, then estimates will be biased downward. While shift changes are a plausible explanation, I cannot rule out that hospitals are sensitive to the three-day rule, and some in fact appear to respond to the incentive more strongly than others.[12] More specifically, these hospitals display a sharp drop in the number of patients admitted at midnight. I restrict my sample to hospitals that do not display this phenomenon, detected by estimating the change in the volume of admissions at midnight by hospital. While this is a less than ideal outcome from an analysis perspective, Table A2a shows first stage estimates with all hospitals included that are nearly identical to those derived from the main analysis sample.[13] Appendix A goes into more detail on how hospitals were chosen to be included in the sample.

With the included hospitals, Figure 1 plots the number of admissions by hour of the day. The change at midnight is larger than the change at 1 a.m. (19 percent decrease against 11.5 percent decrease), but is smaller than changes at other areas of the distribution (up to a 32 percent increase in the morning hours).[14]

Data trimming presents an interesting econometric problem in this context. In a normal regression discontinuity setup, the primary trimming can be done by choosing the correct bandwidth, often through a packaged procedure.[15] In this setting, the maximum bandwidth is limited by the 24-hour clock. Instead, the difficulty is isolating the group that faces the Medicare 3-day rule without inducing a compositional change. There are two reasons for this. First, patients with length of stays that are very short or very long are not affected by the three-day Medicare rule. Including them in the analysis reduces the precision of the estimates by stacking individuals, who, for example, had similar admission times but had length of stays that differed by several days or even weeks. Second, the vast majority of

[12]A small subset of hospitals was contacted to attempt to get a better understanding of the effect of shift structure. Of these, it was more common among dropped hospitals to have shifts beginning at 11 or 12 for some personnel, although these hospitals were not able to verify that these shift structures were in place during the time period included in this analysis.

[13]Readmissions results (available on request) are similarly close to those derived from the main analysis sample.

[14]A McCrary-style test gives a p-value of 0.46 at midnight (McCrary, 2008).

[15]For example, the popular optimal bandwidth procedure detailed in Imbens and Kalyanaraman (2012).

discharges take place during daylight hours. Hence, the simplest solution of truncating by length of stay in days can increase the variance of results quite significantly.

With this in mind, the dataset is trimmed in the following ways. First, only patients that list Medicare as the primary or secondary payer are included.[16] Next, elective admissions — signified by patients that do not come through the ED — are dropped, although this has negligible impact as these individuals are unlikely to be admitted close to midnight. I concentrate on the group most susceptible to the Medicare rule by examining patients that had inpatient stays close to the 3-day threshold. Because the day of discharge does not count toward the tally needed for SNF eligibility, I exclude patients that stayed less than 60 or more than 84 hours as an inpatient, i.e. 12 hours on either side of the 72 hour mark. Appendix B gives density figures and first stage results after each of these trimming steps is made. While these results are clearly heavily attenuated, they do highlight that the effects are present in the larger Medicare population. Results are also similar when only examining diagnosis codes that have a median stay length in this range, but the stay length is not truncated explicitly.[17]

To provide further evidence that this particular hour truncation is not crucial to the analysis, Figure A7 shows the change in eligibility for SNF coverage from Medicare at midnight (shown in orange) and the change in proportion discharged to a SNF at midnight (shown in green) for a range of possible hour trimmings. Each point is a regression discontinuity estimate of the change at midnight, and at the largest range 55 percent of all discharges are represented. The change in SNF eligibility is increasing as the range of included hours becomes smaller, approaching 100 percent of patients when the range is very small. However, it is not monotonically increasing, reflecting the bunching in discharges. The change in the SNF discharge rate at midnight is relatively more constant, although again increasing in

[16] Florida does not provide a secondary payer, and as such I only include patients with Medicare as the primary payer. Additionally, I drop patients that were "discharged" to other sections of a hospital. Finally, many individuals have multiple forms of insurance coverage, and the sample only restricts to Medicare as a primary or secondary payer of the inpatient stay rather than requiring Medicare to be the only payer.

[17] The point estimate for the first stage is 0.02 (standard error of 0.004) and the estimate for the 30-day hospital readmission probability is -0.012 (standard error of 0.003).

when the included range is very small. The blue points represent the ratio between these two to form the IV estimate, where the change in SNF eligibility can be seen as a first stage and actual SNF discharge as the reduced form. This ratio is relatively flat across all trimming ranges, indicating that the trimming range chosen for analysis will not be a key driver of results. Further, I show a number of falsification tests for these choices. There is no change in the SNF discharge rate for non-Medicare patients aged 60-64 in Table A1a, and similarly there is no change for individuals with inpatient stays that were less than 60 hours or greater than 84 hours in Table A1b.[18] Getting away from the the three-midnight mark produces little movement in discharge location, as shown in Table A1c and Figure A1d for inpatient stays between 108 and 132 hours.

It is possible that patients and providers manipulate length of stay on the discharge end of the stay. Such manipulation is likely minimal given the large costs to the hospital of an extra night of stay, as Medicare reimburses hospitals according to patient condition (prospective payment system) rather than for services received (fee for service). Conversations with several physicians and hospitalists indicated that while most would not be willing to alter stay lengths for insurance purposes, some individuals may be willing to do so when the change is marginal and beneficial to the patient substantial.[19] As such, I check this in two ways. First, figure A10a shows a histogram of stay lengths for all non-elective Medicare admissions. If patients and providers were engaging in this manipulation, there would be a substantial increase in the number of three-day — and hence SNF-coverage eligible — stays over two-day stays for this population. Here, the number of two-day stays is nearly equal to the number of three-day stays. Second, I examine the probability that a patient is still in the

[18] Medicare Advantage plans and Accountable Care Organizations have the option of waiving the three-day requirement, and patients with these plans would provide another useful falsification test. However, the data do not provide the specific Medicare Advantage plan or ACO that a patient is enrolled in, and Grebla et al. (2015) found that only a small proportion of Medicare Advantage plans had actually waived the requirement. Falsification tests using Medicare Advantage plans only (not shown, available on request) do not alter results significantly, and as such, Medicare Advantage patients are included in the analysis sample, with the small fraction of patients on plans that waived the requirement likely attenuating estimates.

[19] This answer is difficult to elicit, as it also ties in to the proposed "two-midnight rule" with Medicare's increased scrutiny of short inpatient stays.

hospital at 4 A.M. on the fourth day after their admission; for midnight admits, for example, this would be the probability the individual is still in the hospital 76 hours after she was admitted. This time is chosen because of the low probability of any discharges occurring at that point. Figure A10b shows these probabilities by admission time for patients with the restrictions listed above except for the length of stay trimming. This shows a bump in the probability of staying until 4 A.M. on the fourth day for patients admitted at midnight, with the probability returning to the previous trajectory for patients admitted at other times.[20] This indicates any effects I find of SNF care are actually somewhat attenuated, as a fraction of patients admitted just after the midnight threshold — and thus less likely to be SNF eligible — are given an extra day of high-level inpatient care in the hospital.

IV ESTIMATION STRATEGY

Consider a simple reduced-form model of the effect of being discharged to a skilled nursing facility on medical outcomes:

$$Y_i = \alpha_0 + \alpha_1 SNF_i + \varepsilon_i \tag{1}$$

Here, Y_i can be taken to be 30-day readmission probability for individual i, and SNF_i is a dummy variable indicating if the individual was discharged to a SNF.[21] It is unreasonable to expect to obtain consistent estimates of α_1 because of the correlation between SNF discharge status (SNF_i) and the many unobserved factors that determine an individual's likelihood of returning to the hospital. The inpatient physician has considerable influence on the discharge decision, and will generally make this decision based on the patient's recent medical history,

[20] RD estimates for this bump are estimated to be around two percentage points, but only with a local polynomial regression.

[21] Readmissions have been of upmost importance to Medicare for well over a decade, especially after the HRRP was recommended in 2007 (MedPac 2007). While readmissions are less directly linked to patient welfare outcomes such as mortality, they are far more frequent, sensitive to low-cost interventions (e.g. Naylor et al. 1999), and have a long history of being used as a measure of adverse medical events (e.g. Cutler 1995).

test results, and disposition. Further, the patient's or patient advocate's wishes may influence the decision as well, as the individual must cope with additional time out of their home in addition to the financial obligations.

In general, patients that are discharged to a SNF instead of to their homes are in poorer health. Table 1 shows differences in means between patients discharged to a SNF and those discharged under any other status code for Medicare beneficiaries that stayed between 60 and 84 hours as an inpatient. Beneficiaries with SNF discharges have more diagnoses and chronic conditions on their record, were discharged later, and were nearly nine years older. Interestingly, patients discharged to a SNF actually have slightly lower total charges than patients discharged elsewhere. Clearly, patients discharged to a SNF had different dispositions and inpatient experiences, on average.

To avoid the confounding effect of omitted variables, I rely on a sharp discontinuity in the probability being discharged to a skilled nursing facility. Let $Z_i = 1\{LOS \geq 3\}$ be a dummy variable that indicates if an individual stayed three or more calendar days as an inpatient. The length of stay is measured as the number of midnights spend in the hospital. This means that people with nearly identical amounts of time in the hospital can have a one day difference in length of stay if they are admitted right before or after midnight. Figure 2 plots the time of admission profile of stay lengths in both days and hours. This shows that the length of stay in hours is continuous around midnight admission, but the length of stay in days changes discretely. While beneficiaries admitted before midnight all stayed three days or more, the probability of staying three or more days — and thus being eligible for SNF coverage from Medicare — drops to under 25 percent for those admitted after midnight.

Fundamentally, an individual admitted as an inpatient just before midnight is very similar to an individual admitted just after midnight. With the Medicare coverage rules, however, the individual admitted just before midnight has a longer length of stay and is suddenly eligible for SNF coverage. This fuzzy RD design allows for identification of α_1 assuming that no other variables change discretely at midnight, i.e. that $\mathbb{E}[\varepsilon_i | LOS_i = a]$ is continuous at admission time a equal to midnight. This assumption could be violated if, for example, patients admitted after midnight are less healthy, or are less likely to receive an operating room procedure. Column (2) of Table 2 gives RD estimates for these measures, along with associated p-values in column (3). A health index was created to include the number of procedures, the number of chronic conditions, number of diagnoses, and number of comorbidities. Crucially, this index does not vary significantly across the midnight threshold, indicating that health does not change discontinuously by admission time. This is also true for the average arrival time to the emergency department and discharge hour, as well as individuals' age and gender. There is a slight change in the racial composition at midnight with patients about 7 percent more likely to be black, although there is not a significant change in any other race.[22] Not shown in this table are total hospital charges, which mechanically are $2000 cheaper on average for those admitted after midnight, with the hospital billing based on the length of stay in days rather than hours. Thus, due to hospital billing practices, a beneficiary admitted before midnight would have a more expensive stay if Medicare did not cover these costs.[23]

I estimate the reduced form effect of being discharged to a nursing home on outcome Y_i using regressions of the form:

$$Y_i = \beta_0 + \beta_1 Midnight_i + g(AdmitTime_i) + \beta_2 X_i + \xi_i \tag{2}$$

where $Midnight_i$ is a dummy variable equal to 1 if the individual was admitted as an inpatient before midnight or 0 otherwise. Note that this is the reverse of a typical "left-to-right" RD notation. This is done to make estimates easier to interpret, as the group in the before midnight side of the discontinuity are the individuals more likely to be satisfy

[22]It is unclear what is driving the imbalance in race, but this difference appears to be entirely driven by the state of New York with insignificant point estimates from Florida alone. Further, the point estimates are weaker if a more flexible cubic specification is used. In the interest of transparency, the time of admission profiles for race and age are presented in Appendix E. The figure for *proportion white* suggests some "non-elective" may be miscategorized, with a sharp uptake in the morning hours when planned admissions are often scheduled.

[23]Medicare does have a deductible for inpatient stays, but it does not vary with length of stay.

the requirements for SNF coverage. The $g(AdmitTime_i)$ term is a quadratic polynomial in time of admission, although results are robust to this choice.[24] A vector of observable characteristics X_i is included in some regressions, and includes flexible controls for age, number of procedures as an inpatient, and number of diagnoses on record.[25] I generally use a bandwidth of 8 hours, and cluster standard errors by hour of admission. Because this a relatively low number of clusters (Cameron et al. 2008), key results with alternative handling of standard errors is presented in Table A8. This equation is used to estimate both the first stage — the change in the composition of discharges related to admission time — and the reduced form, which is the change in the share of people that return to the hospital in a defined period of time. The causal effect of nursing facility use on outcome Y_i is reached by combining the first stage and reduced form results. Specifically, I divide the effect of being admitted after midnight on outcome Y_i by the effect of being admitted after midnight on likelihood of being discharged to a nursing facility, SNF_i. Thus, the midnight discontinuity is used as an instrument to identify the causal effect of care at a skilled nursing facility (Hahn et al. 2001).

Finally, I back out the characteristics of the compliers, i.e. those induced to going to a SNF by being admitted before midnight. These beneficiaries behave differently than the "always takers" — who go to SNF regardless of time of admissions — and "never takers", who are not discharged to a SNF regardless of admission time. While is it not possible to identify individual compliers, their characteristics can be described in order to give a sense of the types of beneficiaries that respond to the Medicare incentive. To do this, I first estimate the change at midnight for a vector of individual characteristics twice, first while restricting the sample to only patients that go to a SNF and again for only those that did not go to a SNF:

[24] See Table A5 for robustness checks on key results with a linear specification and different bandwidth choices.

[25] Because patients and the discharge decision could potentially vary by hospital and the day of the week of the admission, I further show robustness to including hospital fixed effects, weekend fixed effects, and hospital-by-weekend fixed effect in Table A5.

$$X_i = \alpha_0 + \alpha_1 Midnight_i + g(AdmitTime_i) + \epsilon_i \quad \text{SNF} \tag{3}$$

$$X_i = \delta_0 + \delta_1 Midnight_i + g(AdmitTime_i) + \epsilon_i \quad \text{non-SNF} \tag{4}$$

Then, the means can be estimated from both the SNF-going group and the non-SNF-going group:

$$\bar{X}_{C,\text{ SNF}} = \frac{\hat{\beta}_0}{\hat{\beta}_1}\hat{\alpha}_1 + \hat{\alpha}_0 + \hat{\alpha}_1 \tag{5}$$

$$\bar{X}_{C,\text{ non-SNF}} = \hat{\delta}_0 + \hat{\delta}_1 + \frac{\hat{\beta}_0 - 1}{\hat{\beta}_1}\hat{\delta}_1 \tag{6}$$

where $\hat{\beta}_0$ and $\hat{\beta}_1$ are from the first stage regression estimating the change in the SNF-going rate at midnight. (5) and (6) can then be combined — weighted by the variances of $\hat{\alpha}_1$ and $\hat{\delta}_1$ — giving estimates of the means of the complier group, $\bar{X}_C$. The means of the characteristics of the never-takers can be estimated from the group admitted just before midnight in (4), and the characteristics of the always-takers from the group admitted just after midnight in (3).

V RESULTS

A. *Discharge Location*

Figure 3 presents the time of admission profile for being discharged to a skilled nursing facility. Specifically, the plot shows the proportion of people discharged to a SNF for each hour of admission with fitted values from equation 2 superimposed. Midnight is centered at 0 on the x-axis.

Figure 3 reveals a discrete drop in the proportion of Medicare beneficiaries discharged to a nursing facility at the midnight admission hour. The estimate of this jump is shown in the first column of Table 3, with the estimated change given at 3.37 percentage points. In the table, standard errors — clustered by hour of admission — are listed below the point estimates, and means for beneficiaries admitted just before midnight are given in italics. The proportion of the sample population that is discharged to a SNF just before midnight is estimated to be 14.86 percent, meaning that there is a 22 percent increase in SNF discharges for people that were admitted before midnight and were hence more likely to have Medicare coverage for the SNF stay. Columns 3 and 4 give estimates for the proportion of people that are discharged to their homes without further care — in other words, a routine discharge — and the proportion of beneficiaries discharged to their home with the expectation of receiving organized home healthcare. This latter category indicates that the individual is being sent home, but under the care of a home health service organization in anticipation of receiving skilled care such as a home attendant or nursing aide. The final column represents all other discharge codes.[26]

These two categories are being examined here to demonstrate where post-midnight beneficiaries are going in lieu of being discharged to a nursing home. From Table 3, it is evident that there is a decrease in routine discharges of about 2.5 percentage points, with the pre-midnight estimate at 61.3 percent. This means that the majority of the change in skilled nursing discharges is being absorbed by home discharges. However, organized home health care also decreases significantly at the midnight threshold, implying that some patients that would have gone to a nursing facility if Medicare coverage was provided to them were instead scheduled to have in-home visits. Medicare describes this form of post-acute care as the "Medicare home health benefit", and consists of a Medicare-approved health care professional intermittently visiting the home of the patient to provide one or more of skilled nursing care, physical therapy, speech-language pathology, or continued occupational therapy. This form of care has a lower barrier to entry than SNF care — as it is less costly to Medicare — and there is no minimum inpatient stay requirement. However, patients must only need "intermittent" skilled care, defined as care that is needed fewer than seven days each week or less

[26] There are over 20 patient discharge status codes; the three enumerated categories make up about 90 percent of all discharges.

than eight hours each over a period of 21 days. As such, this option much less medical care and supervision than being discharged to a SNF.[27] Finally, the other discharges category shows an increase that is a small but statistically significant, although not with additional controls included.

Medicare beneficiaries respond to the reduced costs for skilled nursing care by increasing their use of these services. This is perhaps unsurprising, as the cost of SNF care (about $250-350 per day) is often prohibitively expensive to patients and their families. Further, the alternative choices could leave some patients needing to fill in the gaps via a caregiver ($20-$30 hour), with Medicare home health care services not providing homemaker services or personal care, such as cooking, bathing, and dressing. Consistent with this result, CMS Skilled Nursing Facility Transparency Data show that the average stay in a skilled nursing facility is just 28 days for Medicare beneficiaries, which leaves the average beneficiary with a bill of just $1288 for nearly a month of care, significantly less than the median cost of $6500 if paid out of pocket. Despite inconveniences associated with temporary SNF care, patients on the margin have a clear incentive to opt in to a more intensive level of care at a steeply discounted cost.

B. *Patient Outcomes*

Next, I examine the effect of a discharge to a SNF on the probability of readmission to the hospital. The Centers for Medicare and Medicaid Services has become increasingly concerned with the rate at which beneficiaries return to the hospital, and uses a 30-day risk standardized readmission measure as a key benchmark in hospital performance. More recently, CMS has made these numbers public and reduced payments to hospitals with excess readmissions. The Hospital Readmissions Reduction Program (HRRP) began in fiscal year 2013, and initially encompassed only patients with one of three diagnosis codes: acute myocardial infarction, heart failure, and pneumonia. Here, I focus first on the likelihood of patients to return to the

[27] Even in in this setting, however, longer visits have been shown to reduce the risk of readmission (Andreyeva et al., 2018).

hospital — either as an inpatient or only to the emergency department — for any cause.[28]

Table 4 presents estimates on the change in readmission and revisitation rates as an inpatient for beneficiaries admitted before midnight, i.e. those that were more likely to be eligible for SNF coverage. Following Medicare's standard, readmission times are calculated from the point the patient is discharged to the next admission, rather than from the initial admission. "ED only" signals that the individual returned to the emergency department but was not readmitted, while a "revisit" indicates that the patient returned to the emergency department *or* was readmitted.

The first set of estimates reveal that the chance of being readmitted to the hospital within 30 days decreases by approximately 1.1 percentage points for this group, representing a change of about 7.5 percent. This effect is also present and statistically significant at 14 days (0.83 percentage points, 9.2 percent) and 100 days (0.96 percentage points, 3.8 percent). This indicates that the group that was more likely to go to a SNF due to having it covered by Medicare is less likely to experience readmission. All of these estimates in Table 4 remain significant whether or not the additional controls are included in the regressions, with the point estimates only altered slightly, if at all.[29]

The second set of estimates examine the change in the chances of returning only to the emergency department. Unlike readmittance, the group with a higher SNF-discharge rate do not have ED-only visits in lower rates after two weeks, and the coefficients on the 30-day interval are very small and only significant at the 90 percent level. The third set of estimates measures the chances of having any visit to the emergency department on return, whether or not the patient was later admitted. This is similar to revisits, but records explicitly

[28] Appendix D explores the effect the HRRP may have had on SNF readmissions by contrasting patients with the codified diagnosis codes to those with other illnesses and injuries. In line with other recent work on the program (e.g. Gupta (2017) and Ziedan (2018)), this analysis shows that hospitals respond to the HRRP, and shows suggestive evidence that the HRRP may be attenuating the main results shown here.

[29] To give a clearer picture of the timeline on returning to the emergency department or being readmitted, Figure A11 shows the relevant portion of the CDF of hospital revisits. The distribution is nearly identical between the higher-SNF group (before midnight admits) and the lower-SNF group (after midnight admits) over the first seven days after discharge. The functions then diverge, and maintain roughly the same separation well beyond the 35 days shown.

if the patient visited the emergency department on return to the hospital. Estimates show coefficients that are negative and similar in magnitude to being readmitted. This is consistent with evidence that patients without insurance or public insurance are more likely to return to the emergency department for follow-up care that could have been handled in an outpatient setting (Ladha et al. 2011). Finally, the "revisit" category shows that the the chance of returning to the ED or being readmitted within two weeks decreases by approximately 1.25 percentage points for the group more likely to go to a SNF, and the risk of returning within 30 days decreases by about 1.3 percentage points. The change is also present 100 days after discharge, but is no longer statistically significant.

Figures 4 and 5 give the complementary visual representation of these estimates, with centered time of admission plotted against readmission rate and ED-return rate for a given length of time. In Figure 4 there is a clear increase for both the 14- and 30-day probabilities of being readmitted, and a smaller jump for the 100-day measure. Again, this shows that for patients in the group more likely to go to a SNF, the likelihood of returning to the hospital and being readmitted is reduced. Figure 5 shows the change for midnight admits of returning to the ED but not being readmitted, with the group more likely to be SNF-eligible showing a general decrease but not as clear of a discrete jump.

This finding implies skilled nursing facilities are better at keeping patients from being readmitted in a relatively short period of time. The effect is strongest in the very short term — including the 30-day mark used for Medicare policymaking — and tapers off as the length of time from the initial inpatient stay increases.

Combining these estimates with those from the first stage gives an IV estimate of the change in the likelihood of returning to the hospital for those that were discharged to a SNF. For the 30-day timeframe, the estimate for being readmitted is quite large at -33.1 percent (standard error of 8.1 percent).[30] The corresponding estimate for 30-day emergency department only is smaller and statistically significant at the 90 percent level (-7.9 percent,

[30] IV standard errors calculated via the delta method.

standard error of 4.6 percent).

This finding leads to two obvious and related questions: Why are patients who go to a SNF upon discharge less likely to return to the hospital, and why are they less likely to be readmitted? Clearly, these questions cannot be addressed completely with this identification strategy, but I am able to provide evidence for answers to both inquiries.

I investigate the first question by examining the specific health problems of patients upon returning to the hospital. With this, I can examine if the hospital returns are concentrated in causes that are most sensitive to the quality of post-hospital discharge care. Specifically, beneficiaries in a skilled nursing facility may be less vulnerable to adverse events related to medication, follow-up care, or infections (Office of Inspector General, 2014). Table 5 breaks down ED-return and readmission 30-day rates by diagnosis when the patient returns. Here, each dependent variable is a dummy variable indicating whether or not a patient had that diagnosis listed as their primary diagnosis when she returned to the hospital, such that the entire sample is still used. The categories were formed from ICD-9 Codes truncated to two digits to make the categories more general. The specific 18 categories in the table were formed by looking at the most common diagnoses in the analysis sample as well as categories — such as congestive heart failure, pneumonia, urinary tract infections, and chronic obstructive pulmonary disease — that should be manageable in a nursing home. Note that the categories are exhaustive, such that the variable "Other" accounts for all other diagnoses not explicitly listed.

For readmission, the probability of being readmitted with a specific diagnosis changes discretely for only one specific category: heart disease (includes heart failure and diseases of pericardium). This is a large and significant category, with nearly two percent of individuals admitted just before midnight with this diagnosis getting readmitted within 30 days. For those that were more likely to go to a SNF, the probability of being readmitted with a heart disease primary diagnosis drops significantly by about 10 percent.

However, for returning to the emergency department without inpatient admission, there are diagnoses categories with opposing signs. When patients are in the group more likely to go to a SNF, they are more likely to return to the emergency department for heart disease (including dysrhythmias and pericarditis and myocarditis), and this same group is less likely to return to the ED for general symptoms (including syncope) and intestinal disorders. Importantly, the high SNF-going group is also more likely to return to ED for complications from care.

One explanation for the results presented here would be that SNFs are more able to treat minor issues with patients, and patients avoid having their condition degrade to the point that a readmission is necessary. Some of these patients would then be treated at the SNF without going to the hospital. Another explanation is that SNFs could catch symptoms sooner, thus explaining the lack of congruity between emergency department visits and readmission rates. As evidence, some categories show that the patients in the group less likely to go to a SNF face a higher probability of returning to the ED, but are no more likely to be readmitted. Diagnoses that fit this description include general symptoms and intestinal disorders. These diagnoses should not be associated with the quality of care, suggesting that the facilities are able to treat patients and prevent readmissions for some conditions.[31]

Because the identification strategy of this study identifies a local average treatment effect, the estimated effects are for those induced to change their discharge location by being admitted after midnight. Compliers will likely differ from the general population, especially in this setting where the treatment can change the living situation of the individual. Always-takers — those who enter the nursing facility regardless of discharge time — are likely to be sicker on average, while never-takers will be more healthy on average.

Mean observable characteristics of all three groups are shown in Table 6. These calculations are for patients admitted at midnight — such that the treatment here is defined as *not* going to a SNF — with this group less likely to eligible for a Medicare-covered SNF

[31] Of course, it is possible that the primary diagnosis may mask lapses in care, such that the primary diagnosis remains from a previous adverse event, but was subsequently exacerbated by less than ideal care. Unfortunately, the identification strategy used here does not allow me to investigate this further.

stay. Statistics for the general over 65 Medicare population in this sample are also shown for reference. On average, compliers appear to be slightly more healthy, with fewer chronic conditions and procedures as an inpatient than both always takers and never takers. However, this group experiences more procedures than the never takers on average, but fewer than the always takers. The complier group is also much more likely to be female, and is younger than the always-takers but nearly seven years older than the never-takers. These calculations further reinforces that the complier group — i.e. those that do not go to the SNF because it is not covered by Medicare — are on the margins of where to be discharged, such that it is the lack of Medicare coverage that becomes the deciding factor.

VI CONCLUSION

Little has been documented about the effect of skilled nursing facility care in previous literature. Difficulties in estimating effects stem from selection bias among patients, in which sicker and/or better off patients are much more likely to be discharged to a SNF. In this paper, I use Medicare's eligibility rules for skilled nursing facility care coverage in a quasi-experimental design. I document that Medicare's restrictions have a considerable effect on both the likelihood of being discharged to a SNF after an inpatient stay and on the likelihood of being readmitted to the hospital in a relatively short period of time. Medicare beneficiaries admitted just before midnight are more likely to receive SNF care after discharge than those admitted just after midnight. The majority of this change is absorbed by routine discharges to the patients' homes, but I also find decreases in managed home health care. I then find that this increase in SNF care makes these beneficiaries somewhat less likely go back to the hospital by way of the emergency department, but substantially less likely to be readmitted to the hospital. This result holds for very short time periods (2-4 weeks), with evidence that the effect shrinks slightly as the duration from the initial inpatient stay increases.

These results have several implications for both Medicare's reimbursement rules and for skilled nursing facility care in general. First and foremost, it is clear that patients are responding to incentives by taking the Medicare-subsidized SNF care when it becomes available. Ex ante, this result may be surprising, given that many beneficiaries would prefer to return home after a hospital stay.[32] However, SNF care is very expensive for a reason, with around-the-clock care given by a highly-trained staff. Given that the next most intensive option for beneficiaries — home health care — provides significantly fewer medical and personal services, it is reasonable that some patients on the margin are induced into being discharged to a SNF. As mentioned previously, this is consistent with average length of stay in a SNF being just over a week longer than the period completely covered by Medicare. Medicare considers 30-day readmission to be a key measure of patient health, and reduces payments to hospitals with excess readmissions. With the previous lack of evidence on the effectiveness of SNF care, Medicare has pushed for cost savings in post-acute care with a soon-to-be implemented readmissions reduction program as well as bundling of Medicare payments. Zhu et al. (2018) qualitatively found that hospitals respond to these bundled payment programs by either reducing SNF referrals or increasing networks with SNFs to increase control over quality and costs. While results from Doyle et al. (2015) suggest that excessive SNF usage may be an indicator of poor hospital quality, the results presented here indicate non-inelastic preferences for this type of care, and give evidence that a portion of the population can benefit substantially from SNF care.

There are several limitations to this study. First, some hospitals were excluded from the sample because they had discontinuous counts of inpatient spells across the midnight threshold. This may be due to shift changes, hospital billing, the three-midnight rule, or other factors, but it is difficult to find a universal reason. However, including these hospitals only marginally affects first-stage results, as shown in Table A2a, and readmissions reductions results for these hospitals (available on request) are close to the main results presented here.

[32] The University of Michigan Health and Retirement Study (HRS) even leads the question of expected future nursing facility use with: "Of course nobody wants to go to a nursing home, but sometimes it becomes necessary."

The second major limitation is that the results here are for Medicare patients, and it is less clear if there are differences in how SNF care may affect much younger patients.

The results presented here show that patients substantially benefit from this post-acute care. Going to a SNF helped reduce hospital readmissions by as much as 33 percent. This suggests that compared to the high costs of SNF care, the burden is offset by preventing readmissions, with the cost of readmissions for Medicare exceeding $24 billion annually (AHRQ 2014).

Medicare cost reports indicate that CMS spends $354 per day for SNF care for beneficiaries. This is dwarfed by the average cost of a day as an inpatient at $2346 (HCUP Statistical Brief #180, 2014). As such, relaxing the 3-day rule for SNF care may be sensible from a policy standpoint despite the increased costs of SNF care. With an all-cause 30-day readmission rate of 17.2 per 100 admissions, patients with Medicare as the primary payer are the most likely to return to the hospital of any insurance type (AHRQ 2014). The complier group in my sample — taken to be be beneficiaries with an average age of 79 and 10.5 diagnoses on record — has a slightly higher rate at 17.38 per 100 admissions. Each readmission costs Medicare, on average, $13,800 (HCUP Statistical Brief #199). From my results, the 3.3 more people per 100 going to SNFs cost an estimated $32,700, calculated by multiplying by the average SNF stay that lasts 28 days and average costs to Medicare of $354 per day.[33] The is slightly more than the savings from a reduction of 1.1 per 100 beneficiaries reduction in readmissions, calculated to be $15,373.[34] Therefore, for the complier group that has the SNF coverage made available to them, the increase to Medicare costs would be about $17,300 per 100 individuals. In 2012, there were 354,637 Medicare-covered

[33]CMS Skilled Nursing Facility Transparency Data report the total number of stays, average length of stay in days, and total charges for each nursing home. For the average stay length, I calculated a weighted average weighted by the number of stays in that facility. For the average cost to Medicare, I divided the "Total SNF Medicare Standard Payment Amount" — documented as the total amount that Medicare paid for all Medicare stays in the year after deductible and coinsurance amounts have been deducted, adjusted for geographic differences in payment rates — by the number of stays, and again calculated a weighted average. Then, 28 days * $354 * 3.3 = $32,700.

[34]This is calculated from the point estimate in Table 4 of 1.114 multiplied by the average cost of a readmission to Medicare of $13,800 (1.114*13800 = $15373).

hospital stays that lasted at least three days (including time in the emergency department) but had fewer than three inpatient nights (Office of the Inspector General 2013). Given this amount, a modest relaxation of the Medicare three-night requirement for SNF coverage has the potential to improve health outcomes and costs just $61 million, or about two-tenths of one percent of Medicare's current spending on skilled nursing facilities. As such, this analysis suggests CMS would incur modest costs by removing the length-of-stay requirement on inpatient stays before providing coverage for skilled nursing facility care.

This cost-benefit analysis has a few caveats. First, the analysis of the complier group shows that those kept away from SNF care by the three-day rule are slightly healthier than average SNF patients. This suggests that removing this rule would bring healthier, lower-cost patients into SNFs — for whom readmissions may be less frequent and less costly — and the benefits may not be as stark. However, patients are generally readmitted because of deteriorating health, and it is difficult to measure the long-term health impacts of reducing these events. Further, a less conservative analysis would encapsulate the decrease in home health services instead of assuming a routine discharge. The average Medicare payment for home health agency claims was $3,037 in 2013 (Home Health Agency Utilization and Payment Public Use File), and the results shown here would indicate a savings of $2,125 per 100 people. Finally, these calculations do not include benefits of SNF care that are difficult to capture — such as reduced expenditure outside of Medicare on at-home care and the reduction in the burden on family caretakers — nor costs that are similarly difficult to calculate, such as increased home-to-home time for some patients.

These results suggest that the policymakers concerned about excess Medicare readmissions should consider these restrictions to SNF care carefully, as they offer an effective way forward for further readmission reduction programs.

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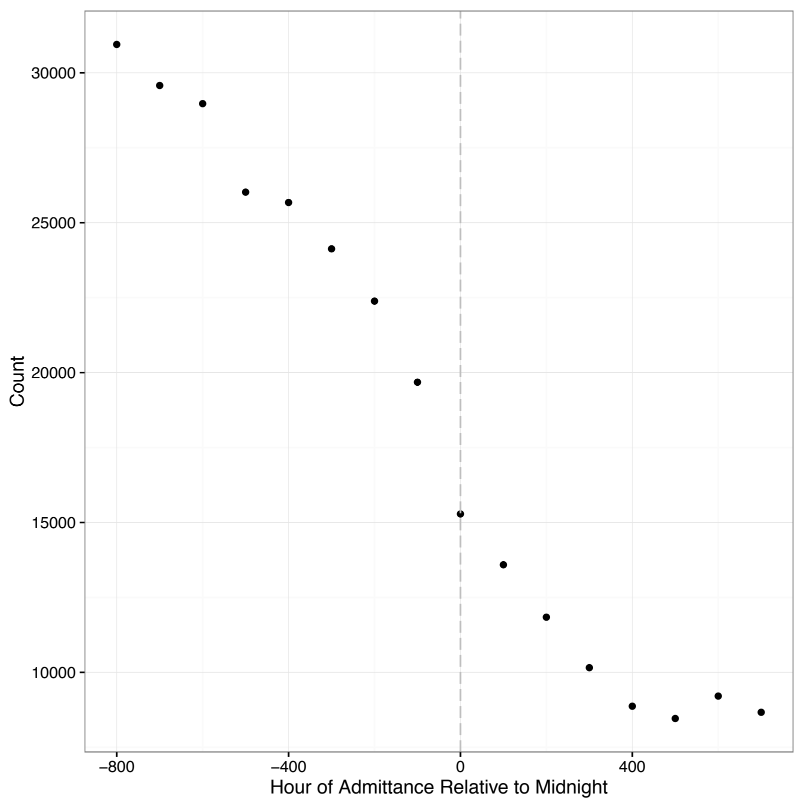
Figure 1: Frequency of Admission by Hour

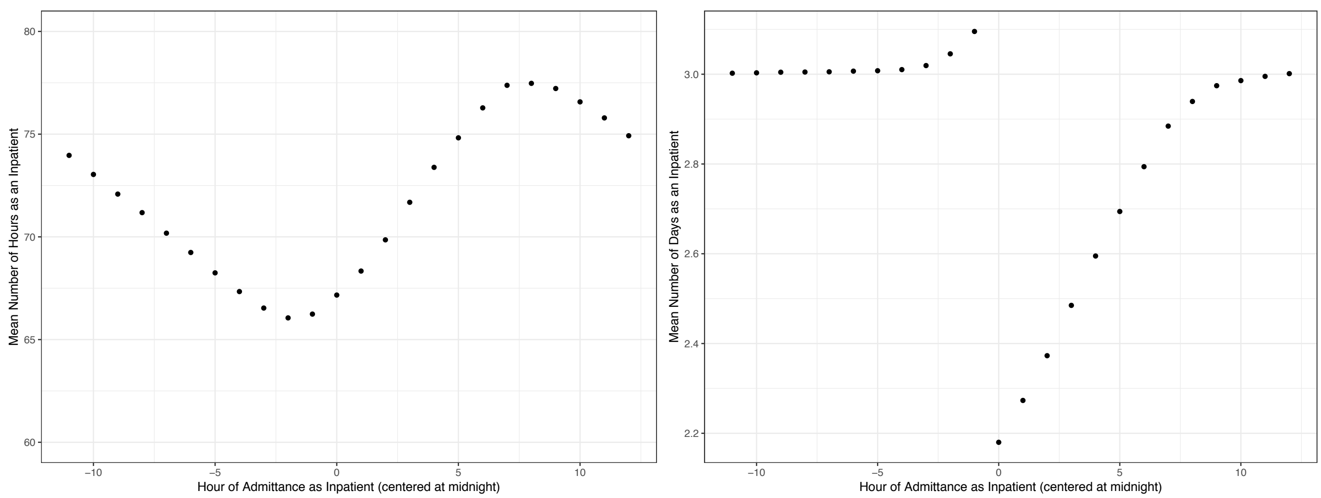


Notes: Counts of inpatient admissions by hour of admission for the final sample, with data from included hospitals in New York, Washington, and Florida from 2009-2013 for Medicare beneficiaries that stayed between 60 and 84 hours as an inpatient.

Figure 2: Time of Admission Profile of Length of Stay in Days and Hours

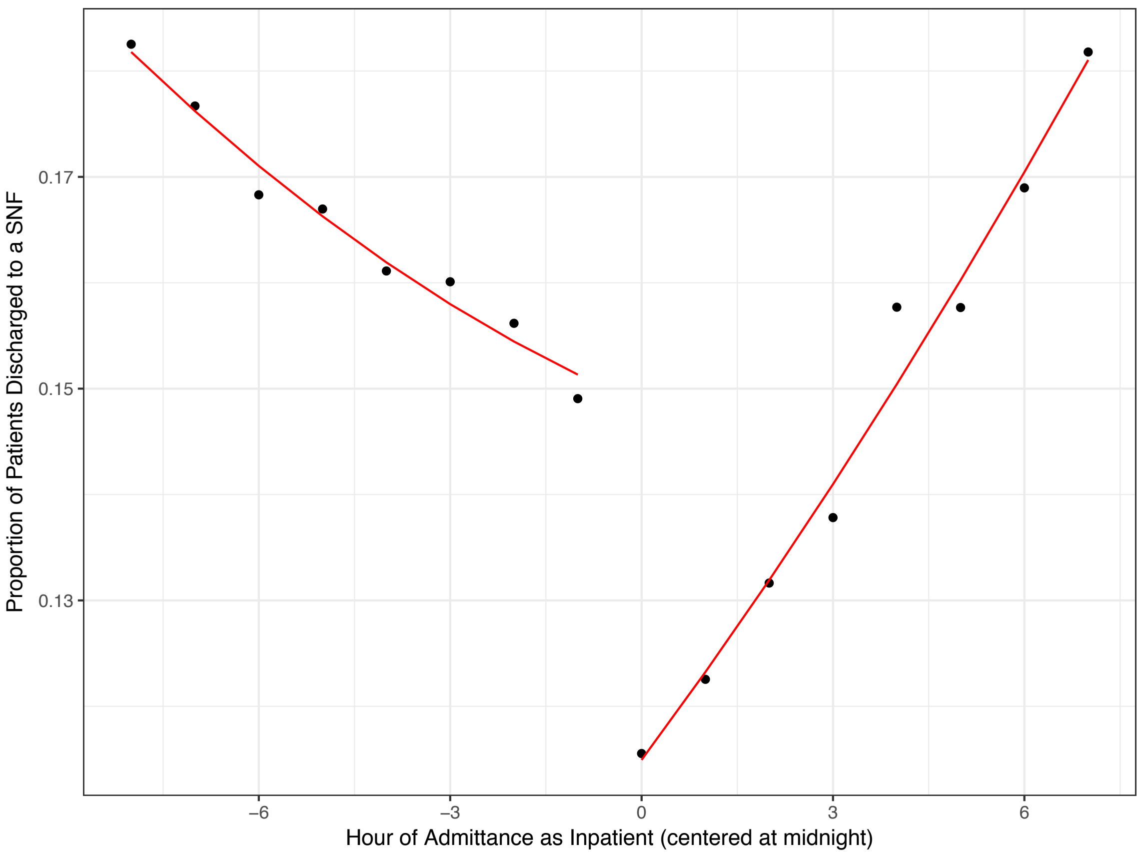
(a) Length of Stay in Hours

(b) Length of Stay in Days



Notes: The time of admission as inpatient profile for the length of stay in hours (Panel 2a) and days (Panel 2b), with data from a near census of inpatient visits in New York, Washington, and Florida from 2009-2013 for Medicare beneficiaries that stayed between 60 and 84 hours as an inpatient.

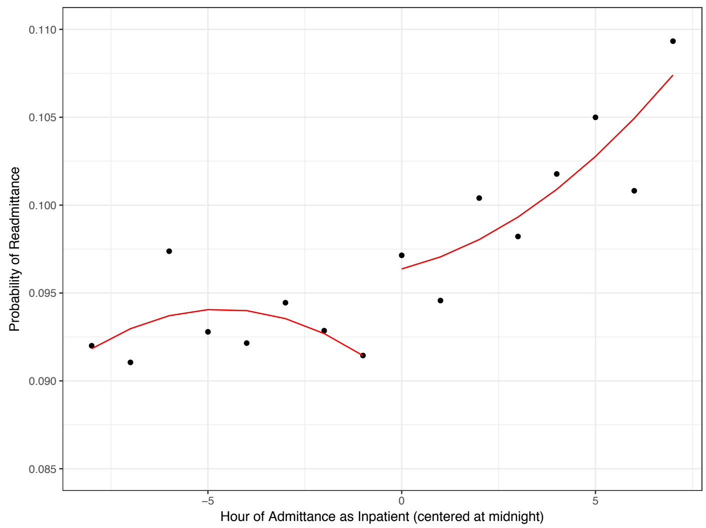
Figure 3: Time of Admission Profile of Likelihood of Being Discharged to a SNF



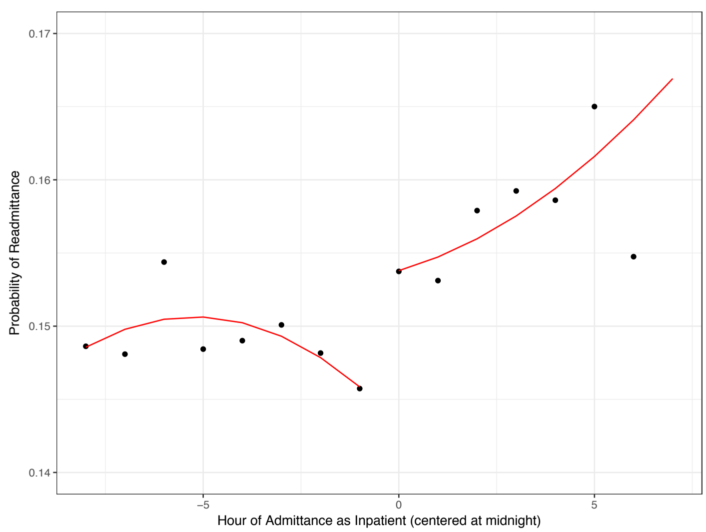
Notes: The time of admission as inpatient profile for the likelihood of being admitted to a skilled nursing facility is shown, with data from a near census of inpatient visits in New York and Florida from 2010-2013. The fitted values (red line) are from equation (2) with a quadratic polynomial in time of admission.

Figure 4: Time of Admission Profile of Likelihood of Readmission as an Inpatient

(a) 14 Days



(b) 30 Days



(c) 100 Days

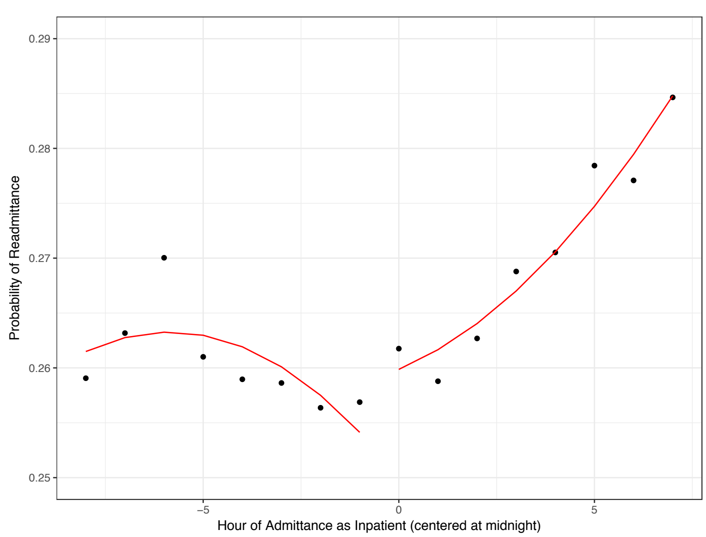
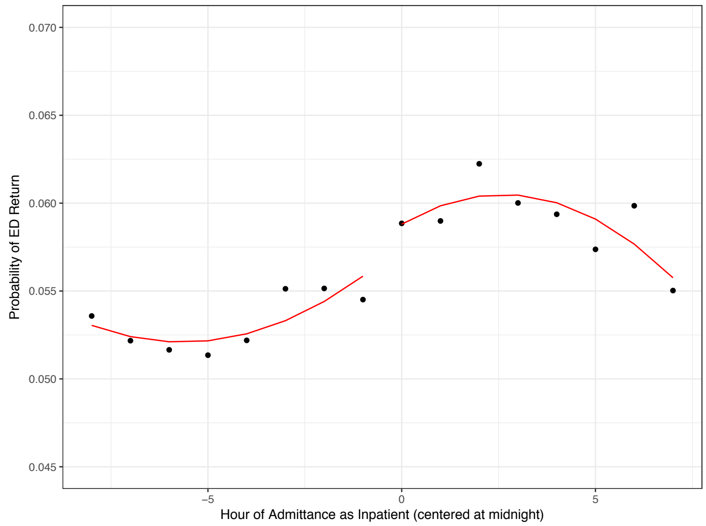
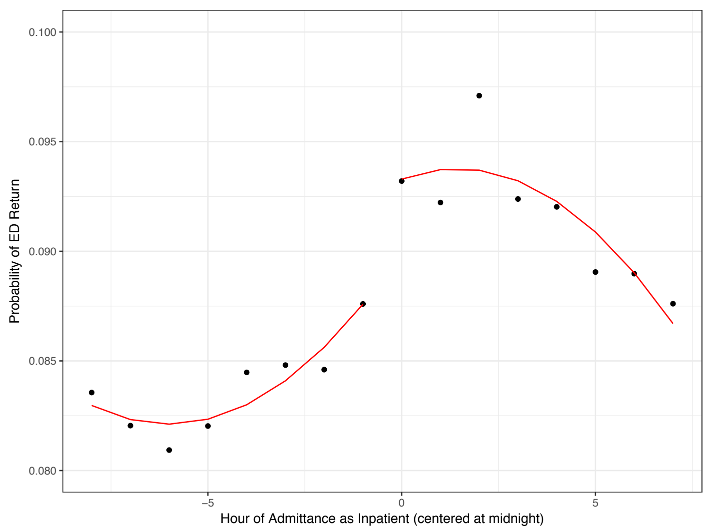


Figure 5: Time of Admission Profile of Likelihood of Emergency Department Revisit (Not Later Admitted)

(a) 14 Days



(b) 30 Days



(c) 100 Days

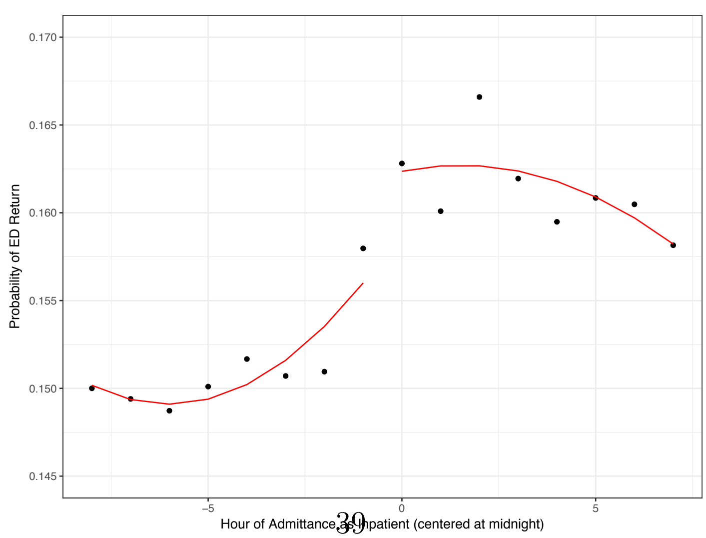


Table 1: Differences Between Patients By Discharge Location

	Other Discharge		SNF Discharge			
	Mean (1)	SD (2)	Mean (3)	SD (4)	Difference (5)	p-value (6)
NPR	1.175	1.246	0.742	1.807	-0.433***	<0.001
NDX	10.426	4.532	11.228	4.597	0.802***	<0.001
NChronic	5.873	2.797	6.25	2.772	0.377***	<0.001
EDHour†	1315.655	530.739	1278.562	558.213	-37.093***	<0.001
Age	73.065	10.27	81.812	13.74	8.747***	<0.001
Died	0.024	0.00	0.000	0.153	-0.024***	<0.001
Discharge Hour	1486.627	278.062	1540.862	319.389	54.235***	<0.001
Female	0.542	0.475	0.657	0.498	0.115***	<0.001
Hispanic	0.133	0.266	0.077	0.339	-0.056***	<0.001
Black	0.133	0.302	0.101	0.34	-0.032***	<0.001
White	0.68	0.409	0.787	0.466	0.107***	<0.001
OR Procedure	0.074	0.282	0.088	0.261	0.014***	<0.001
Median Income	2.464	1.114	2.55	1.132	0.086***	<0.001
Total Charges	25010.063	14046.803	22602.586	17768.687	-2407.477***	<0.001

Notes: Differences in means for patient characteristics and experiences for non-elective admissions with stay lengths between 60 and 84 hours, with "SNF Discharge" means subtracted from "Other Discharge" means. All estimates come from hospital inpatient administrative records from New York and Florida from 2010-2013. Sequentially, the dependent variables are: Number of ICD-9 procedures as an inpatient, number of diagnoses on record, number of chronic conditions on record, emergency department arrival time, age at time of admission, whether the patient died, discharge hour, patient gender, patient race (Hispanic, Black, and White), an indicator for one or more major operating room procedures, median income by state for the patient's ZIP code, and total charges. Coefficients that are significantly different from zero are denoted by: *10%, **5%, and ***1%. †Only Florida provides information on ED arrival time.

Table 2: Differences Between Patients Admitted Before and After Midnight

	Constant (1)	RD Estimate (2)	p-value (3)
Health Index	0.494	0.0196	0.1218
ED Hour†	19:52	43.2	0.6668
Age	72.3929	−0.3095	0.2600
Died	0.0189	0.0018	0.6604
Discharge Hour	14:48	−6.528	0.1826
Female	0.5613	−0.0127	0.1131
Hispanic	0.1265	0.0034	0.6207
Black	0.1254	0.0094	0.0011***
White	0.7005	−0.0152	0.1072
Other Race	0.0476	0.0024	0.3486
OR Procedure	0.0689	0.0001	0.9798
Median Income	2.4129	0.0166	0.3477
DRG Payment	5,978.16	12.1299	0.4371

Notes: RD estimates for patient characteristics and experiences for non-elective admissions with stay lengths between 60 and 84 hours. All estimates come from hospital inpatient administrative records from New York and Florida from 2010-2013. Estimates are from collapsed data. The constant gives the estimate for each dependent variable just before midnight. Sequentially, the dependent variables are: A scaled health index that includes the number of ICD-9 procedures as an inpatient, number of diagnoses on record, number of chronic conditions on record, and total comorbidities; emergency department arrival time; age at time of admission; whether the patient died; discharge hour; patient gender; patient race (Hispanic, Black, and White, or other); an indicator for one or more major operating room procedures; median income by state for the patient's ZIP code; and the average Medicare payment for the patient
s listed DRG code. Coefficients that are significantly different from zero are denoted by: *10%, **5%, and ***1%. †Only Florida provides information on ED arrival time.

Table 3: Change in Discharge Location for Midnight Admissions

	Skilled Nursing Facility		Home (Routine)		Organized Home Healthcare		Other	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Change at Midnight	0.0337***	0.0309***	−0.0254***	−0.0204***	−0.0070***	−0.0096***	−0.0025**	−0.0011
	(0.0030)	(0.0023)	(0.0036)	(0.0024)	(0.0025)	(0.0023)	(0.0013)	(0.0016)
	0.1486		*0.6134*		*0.1775*		*0.0309*	
Controls	No	Yes	No	Yes	No	Yes	No	Yes
n	257,703	257,703	257,703	257,703	257,703	257,703	257,703	257,703

Notes: Estimates from equation (2) with a dummy variable for discharge status as the respective dependent variables. Standard errors clustered by hour of admission are shown below coefficient estimates in parenthesis. The proportion of the people admitted just before midnight with a given discharge status is shown in italics below the point estimates and standard errors. Coefficients that are significantly different from zero are denoted by: *10%, **5%, and ***1%.

Table 4: Change in Revisits and Readmissions for Midnight Admissions

Timeframe:	14 Days		30 Days		100 Days	
	(1)	(2)	(3)	(4)	(5)	(6)
Readmission	-0.0083^{***}	-0.0085^{***}	-0.0112^{***}	-0.0114^{***}	-0.0096^{***}	-0.0103^{**}
	(0.0027)	(0.0026)	(0.0025)	(0.0023)	(0.0038)	(0.0041)
	0.0898		*0.1455*		*0.2527*	
ED Visit Only	-0.0039	-0.0037	-0.0027^{*}	-0.0024^{*}	0.0009	0.0011
	(0.0028)	(0.0027)	(0.0015)	(0.0014)	(0.0027)	(0.0028)
	0.0567		*0.0913*		*0.1628*	
Any ED on Return	-0.0092^{**}	-0.0093^{**}	-0.0089^{***}	-0.0091^{***}	-0.0046	-0.0054
	(0.0045)	(0.0043)	(0.0028)	(0.0024)	(0.0049)	(0.0053)
	0.1372		*0.2158*		*0.3731*	
Revisit	-0.0122^{**}	-0.0122^{**}	-0.0138^{***}	-0.0138^{***}	-0.0087	-0.0092
	(0.0051)	(0.0049)	(0.0031)	(0.0027)	(0.0055)	(0.0059)
	0.1465		*0.2368*		*0.4156*	
Controls	No	Yes	No	Yes	No	Yes
n	257,708	257,708	257,708	257,708	257,708	257,708

Notes: Estimates from equation (2) with a dummy variable for returning to the hospital as the respective dependent variables. The first two dependent variables indicate if the patient was readmitted as an inpatient and if the event was an ED visit only, respectively. The next dependent variable takes on a value of 1 if the patient returned to the ED within the indicated amount of time, whether or not they were later admitted. For "revisit", a value of 1 for the dependent variable means that the patient returned to the hospital within the indicated amount of time in any capacity. The first set of estimates correspond to the plots shown in Figure 4 , and the second set of estimates correspond to the plots in Figure 5. Standard errors clustered by hour of admission are shown below coefficient estimates in parenthesis. The estimates from just before midnight are listed in italics below the standard errors. Coefficients that are significantly different from zero are denoted by: *10%, **5%, and ***1%.

Table 5: Readmission and Revisit for Specific Diagnoses for Midnight Admissions (Within 30 Days)

Next Visit:	Heart Disease (1)	General Symptoms (2)	Pneumonia & Flu (3)	COPD (4)	UTI (5)	Renal Failure (6)
Readmit	−0.0017***	−0.0008	−0.0007	0.0002	−0.0009	−0.0005
	(0.0005)	(0.0010)	(0.0005)	(0.0009)	(0.0008)	(0.0003)
	0.0172	*0.0094*	*0.0049*	*0.0081*	*0.0040*	*0.0035*
ED Only	0.0011**	−0.0037***	−0.0002	0.0008	−0.0005	0.0003
	(0.0004)	(0.0007)	(0.0002)	(0.0007)	(0.0006)	(0.0001)
	0.0037	*0.0257*	*0.0002*	*0.0037*	*0.0041*	*0.0004*
	Ischemic Heart Disease (7)	**Intestinal Disorders (8)**	**Complications From Care (9)**	**Lower Body Fractures (10)**	**Upper Body Fractures (11)**	**Drugs & Poisons (12)**
Readmit	0.00004	−0.0004	−0.0002	0.0001	−0.000005	−0.0002
	(0.0004)	(0.0008)	(0.0004)	(0.0002)	(0.0002)	(0.0003)
	0.0080	*0.0060*	*0.0060*	*0.0014*	*0.0005*	*0.0009*
ED Only	0.0001	−0.0012***	0.0004**	−0.0002**	0.0002	0.0001
	(0.0001)	(0.0003)	(0.0002)	(0.0001)	(0.0002)	(0.0001)
	0.0006	*0.0017*	*0.0028*	*0.0003*	*0.0006*	*0.0006*
	Skin Diseases (13)	**Ear Diseases (14)**	**Psychoses (15)**	**Dorsopathies & Rheumatism (16)**	**Cerebro-vascular (17)**	**Other (18)**
Readmit	0.0001	0.0003	−0.0008	0.0001	−0.00005	−0.0057***
	(0.0002)	(0.0006)	(0.0009)	(0.0001)	(0.0007)	(0.0018)
	0.0022	*0.0066*	*0.0062*	*0.0018*	*0.0045*	*0.0541*
ED Only	0.00001	−0.0001	−0.0003	−0.0004	−0.0001	0.0010
	(0.0003)	(0.0002)	(0.0004)	(0.0004)	(0.0001)	(0.0021)
	0.0016	*0.0004*	*0.0013*	*0.0039*	*0.0004*	*0.0393*

Notes: Estimates from equation (2) with dependent variables above each of the 18 cells, with "Readmit" referring to a readmission for that specific cause and "ED Only" meaning an ED visit without admission for that cause. Return categories are exhaustive. Standard errors clustered by hour of admission are shown below coefficient estimates in parenthesis. The estimates from just before midnight are listed in italics below the standard errors. Coefficients that are significantly different from zero are denoted by: *10%, **5%, and ***1%.

Table 6: Mean Characteristics Compliers, Always Takers, and Never Takers

	Compliers	Bootstrap SE	Always Takers	Never Takers	Medicare, 65+
Age	79.36	(2.9187)	80.21	71.56	78.28
Diagnoses	10.74	(1.0339)	11.28	10.28	11.56
Procedures	0.54	(0.3411)	0.72	0.99	1.98
Chronic	5.52	(0.6501)	6.26	5.76	6.24
Median Income Quartile	2.53	(0.2502)	2.34	2.31	2.48
Female	0.73	(0.1183)	0.65	0.54	0.56
White	0.76	(0.1011)	0.74	0.68	0.73
Hispanic	0.10	(0.0710)	0.10	0.14	0.11
Black	0.11	(0.0736)	0.12	0.15	0.11

Notes: Compliers are individuals that are induced *not* to go to SNF when they are admitted after midnight. Means are calculated as described in the text. The final column contains means for the over 65 Medicare population in this sample.

Appendix

A Hospital Inclusion Criteria

Capacity and staffing normally dictate the movement of patients from the ED to inpatient wards, and some hospitals may be affected by a not uncommon shift structure that sees a shift change at 11PM. However, when an admission decision is made close to midnight, insurance and billing practices may present some hospitals with an incentive to ensure a patient is admitted before midnight. This depends on the insurance coverage of the patient as well as the length of the time the patient was in the emergency department. Many insurance plans will accept emergency room and observation charges or inpatient room and board charges on a given calendar day, but not both, with the higher cost option depending on the patient's insurance coverage as well as the amount of time and care received prior to being admitted. This consideration would not be relevant for Medicare beneficiaries without secondary coverage or Medicare Advantage, as CMS uses a prospective payment system (PPS).

To provide evidence that some hospitals engage in more gaming than others, I first establish that the flow into inpatient wards is not discontinuous. Figure A1 shows that emergency department arrivals do not vary discretely over time, with the natural inflow of patients increasing during the day and falling off in the early hours of the morning. Figure A1a plots the mean time of ED arrival for patients that were later admitted as inpatients, and Figure A1b shows the count of ED arrivals whether or not the patient was admitted, with neither of these changing dramatically at midnight. Together, these suggest that the arrival rate of patients does not decrease abruptly after midnight. Figure A2 then plots the admission probability by ED arrival time, and again there is no significant change at midnight.[35]

[35] Note that data for Figures A1a and A2 come only from Florida, as other states do not disclose ED arrival time for patients that were later admitted.

These plots show no substantial difference in patient experience for included and excluded hospitals. Figure A3, however, shows that there is a drop in inpatient admissions for excluded hospitals at midnight, while the density is much smoother for included hospitals.[36]

Figure A4 provides insight into the largest difference between included and excluded hospitals by plotting time spent waiting in the ED by admission time, as well as the complementary figure showing ED charges by admission time.[37] This shows that for excluded hospitals there is a spike in the average time between ED arrival and inpatient admission at midnight, and that there is a corresponding spike in the billed amount for ED and observation services. One explanation for this is that these hospitals encounter some degree of backup due to a shift change at 11PM or 12AM, and patients are forced to wait longer before being transferred. However, it may also be the case that excluded hospitals have a more forceful response to the payment incentives outlined above, and as such are not included in the analysis sample.

Table A3 shows the differences between included and excluded hospitals. There is no statistically significant difference in number of beds or discharges, and there is no clear difference in owner type. Further, there are no obvious trends among service types or urban/rural distinctions.

Table A2a gives the first stage estimates with all hospitals included. The point estimate for the increase in the SNF discharge rate for before midnight admissions is only slightly larger than before at 3.7 percentage points, and the other categories are similarly narrowly affected. Table A2b shows first stage results for non-Medicare patients aged 60-64, and with no other sample restrictions. This demonstrates that the difference between Medicare and non-Medicare patients exists in the full sample and is not a product of imposed sample restrictions.

[36] A very small number of hospitals displayed large *increases* at midnight, and these hospitals were similarly excluded.

[37] The lag between ED arrival time and inpatient admission time are underestimates, as the data do not allow me to know if this lag was greater than 24 hours. As such, all individuals are treated as if they spent less than 24 hours receiving observation services.

B Data Trimming Strategies & Robustness

The data used in this paper are comprehensive and include all emergency department visits and inpatient stays in a given state and year. The majority of these encounters involved patients whose conditions would not have warranted going to a SNF, regardless of coverage for that type of care. Here, I describe the steps I took to trim the data in order to focus on the patients that may have been affected by Medicare's SNF coverage policy. I also provide accompanying density figures to demonstrate that these trimming steps do not induce bias into estimated outcomes.

Starting with the entire sample, I first trim observations that come from hospitals that displayed signs of discrete change in admission policy at midnight, as previously described. The initial density and the density with these hospitals removed are presented in Figures A5a and A5b.

I next remove patients that did not come through the emergency department in order to exclude patients that had planned or scheduled admissions and transfers, along with patients that were transferred from other units of the same hospital. In the density for this trimming step shown in Figure A5c, the irregular spikes in the morning hours are no longer present. Following this, I remove all patients that do not have Medicare listed as either a primary or secondary payer for their inpatient stay, and Figure A5d shows that the density is mostly unaffected.

Finally, I trim on length of stay in hours to focus on the three-day threshold required by Medicare. For this, my primary analysis sample includes patients that stayed between 60 and 84 hours as an inpatient, or 12 hours either side of the 72-hour mark. In order to show that this particular trimming is robust, I plot the change in SNF eligibility at midnight and the change in SNF discharge at midnight for a range of possible hour trimmings, along with the ratio of the two in Figure A7. The change in SNF eligibility approaches 100 percent as the range of hours stayed is narrowed close to 72, with local maxima around +/- 27 hours and +/- 52 hours reflecting bunching in discharge times. The change in the SNF discharge rate shows a slight increase, going from about 0.5 percentage points to over 7 percentage points when only an extremely narrow range of hours is considered. Combining these, the ratio gives the change in SNF-going rate for the patients that were eligible for SNF discharge. This estimate is relatively constant for any trimming range, suggesting that the range used for analysis has a relatively small impact on estimates of outcomes. To further this point, Figure A8 gives the first stage estimate, reduced form estimate, and IV estimate for different length of stay trimming lengths. The IV estimate is relatively stable, and is statistically significant for nearly all hour trimming lengths.

The main analysis sample examines Medicare beneficiaries who stayed between 60 and 84 hours as an inpatient. To provide evidence that these trimming decisions were sensible, I calculate the first stage effects for non-Medicare patients with ages 60-64 as a falsification exercise. Table A1a shows that there is no change in the proportion of people discharged to a SNF around midnight for this population, and SNF-going rates are low overall.

Figure A6 shows the density for the analysis sample with the length of stay trimming along with all previous steps as described. It can be seen that the density is similar to that shown in previous steps.

Table A4 shows first stage results of the change in the SNF-going rate at midnight for each step of the trimming process. Estimates all have the same direction, with a small but discernible drop the proportion of the population going to a SNF for midnight admits. This effect is still present and significant when stays up to 10 days are included, which represent 87 percent of all discharges. The magnitude, however, is heavily attenuated until the final step of the trimming process, when the length of stay restriction around the three-day rule is imposed.

C Summary Statistics

Summary statistics are listed in Table A6. The first two columns come from the full sample, which is a near census of emergency department and inpatient admissions from New York, Florida, and Washington from 2009-2013. On average, patients that are admitted are older, have nearly four times as many diagnoses on record, and are more likely to have multiple procedures on their record for that stay. Once the data are limited to Medicare beneficiaries in the third column, the average patient is 70 years old, which is nearly 20 years older than the average inpatient in the full sample. Beneficiaries have more chronic conditions on their record, but actually have fewer diagnoses and procedures. Finally, the fourth column presents statistics from the trimmed sample used in the primary analysis. The average patient is nearly four years older than the average Medicare beneficiary, and has over ten diagnoses on her record.

D Hospital Readmissions Reduction Program (HRRP)

I investigate whether the disparity between returning to the emergency department only and being readmitted is related to financial incentives faced by the hospitals. As mentioned previously, starting in the 2013 fiscal year hospitals faced reduced payments for excess readmissions, defined as a risk-adjusted measure compared to the national average. The Hospital Readmissions Reduction Program reduces payments at the hospital level, rather than at the patient level. However, the penalty lasts the entire fiscal year, and is between 1 and 3 percent for *all* Medicare payments. As such, hospitals have a strong incentive not to readmit Medicare beneficiaries with one of the three diagnosis codes on record.[38]

Because patients admitted just after midnight are proportionally more likely to return to the hospital in any capacity, it should be the case that this group is more likely to return to the emergency department only as well as be readmitted. If, however, hospitals

[38] In subsequent years, CMS has made minor adjustments to the program by accounting for planned readmissions and expanding the list of diagnosis codes.

are responding to the incentives of the HRRP, the expected result could be neutralized. Table A7 presents 30-day readmission probabilities around the midnight discontinuity for two groups: those with a diagnosis that Medicare considers for the HRRP, and those with other diagnoses. This is further split into two time periods, corresponding to roughly before and after the program began. This analysis only considers the primary diagnosis, and as such should be considered a lower bound.

Column (1) shows that from 2009-2012, Medicare beneficiaries with heart failure, acute myocardial infarction, or pneumonia that were initially admitted at midnight were not more or less likely to be readmitted within 30 days. However, column (2) shows a significant difference across midnight for patients with other diagnosis codes. Columns (3) and (4) — corresponding to calendar year 2013 — state a different effect. There is significantly positive decrease of 1.3 percentage points across midnight for patients with other diagnosis codes. For patients with one of the three monitored diagnosis codes, the effect is small but significant at 0.22 percentage points. These results could indicate that hospitals are responding to the HRRP and were more reluctant to readmit patients with one of the monitored diagnoses after the rule took effect. Of patients that are discharged to a SNF, only 5.5 percent have one of the three diagnosis codes considered for the HRRP, compared to over 9 percent of non-SNF dischargees. With SNF patients less likely to have one of the targeted diagnosis codes, those in the high SNF-going group should be more likely to be readmitted. This suggests that the HRRP is actually attenuating the effect of post-acute SNF care, and the discontinuity in readmission rates exists in spite of hospitals responding to Medicare payment incentives and abstaining from readmitting some patients.[39]

E Additional Tables and Figures

[39] This does not necessarily mean patients are not receiving health care at all. As mentioned previously, there has been a dramatic rise in both the volume and length of observation stays, in which patients are kept overnight (or longer) while the hospital continues to evaluate the patient before making an admission decision. Efforts by CMS to clarify who qualifies as an inpatient are ongoing.

Table A1: Falsification Tests

(a) Change in Discharge Location for Non-Medicare Patients

	Skilled Nursing Facility (1)	Home (Routine) (2)	Organized Home Healthcare (3)	Other (4)
Change at Midnight	−0.00002	−0.0003	0.0012	−0.0012
	(0.0013)	(0.0012)	(0.0023)	(0.0023)
n= 540274	*0.0089*	*0.9137*	*0.0429*	*0.0233*

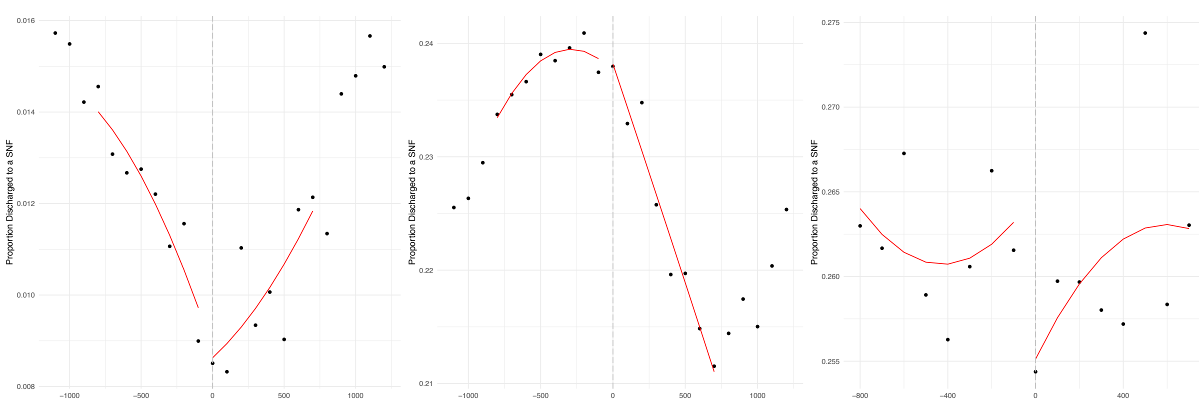
(b) Outside of Three-Day Stay Falsification Test

	Skilled Nursing Facility (1)	Home (Routine) (2)	Organized Home Healthcare (3)	Other (4)
Change at Midnight	−0.0012	−0.0003	−0.0003	0.0006
	(0.0022)	(0.0026)	(0.0017)	(0.0012)
n= 2555135	*0.2373*	*0.4613*	*0.1916*	*0.0614*

(c) Five-Day Stay Falsification Test

	Skilled Nursing Facility (1)	Home (Routine) (2)	Organized Home Healthcare (3)	Other (4)
Change at Midnight	0.0100*	−0.0172***	0.0015	0.0015
	(0.0051)	(0.0033)	(0.0052)	(0.0023)
n= 298960	*0.2650*	*0.4375*	*0.2273*	*0.0292*

(d) SNF Discharge Profiles



Notes: Changes in discharge location for patients aged 60-64 without Medicare (a), changes in discharge location for patients with length of stays less than 60 hours or more than 84 hours (b), and changes in discharge location focusing for patients with length of stays less than 132 hours and more than 108 hours. Estimates from equation (2) with a dummy variable for discharge status as the respective dependent variables. Robust standard errors in parentheses. The proportion of the people admitted just before midnight with a given discharge status is shown in italics below the point estimates and standard errors. Coefficients that are significantly different from zero are denoted by: *10%, **5%, and ***1%. The figures in (d) gives the time of admission profile associated with column (1) of (a), (b), and (c).

Table A2: All Hospitals

(a) Change in Discharge Location with All Hospitals Included

	Skilled Nursing Facility (1)	Home (Routine) (2)	Organized Home Healthcare (3)	Other (4)
Change at Midnight	0.037***	−0.0307***	−0.0071***	−0.0003
	(0.0010)	(0.0021)	(0.0008)	(0.0010)
n = 691,009	*0.1505*	*0.5987*	*0.1792*	*0.0339*

Notes: Changes in discharge location with primary analysis sample but with all hospitals included. Estimates from equation (2) with a dummy variable for discharge status as the respective dependent variables. Standard errors clustered by hour of admission are shown below coefficient estimates in parenthesis. The proportion of the people admitted just before midnight with a given discharge status is shown in italics below the point estimates and standard errors. Coefficients that are significantly different from zero are denoted by: *10%, **5%, and ***1%.

(b) Change in Discharge Location with All Hospitals Included, Non-Medicare Patients Aged 60-64

	Skilled Nursing Facility (1)	Home (Routine) (2)	Organized Home Healthcare (3)	Other (4)
Change at Midnight	0.0011	0.0007	−0.0117	0.0091
	(0.0022)	(0.0119)	(0.0196)	(0.0105)
n = 1,146,331	*0.0612*	*0.7092*	*0.1091*	*0.0765*

Notes: Changes in discharge location with all hospitals included and only non-Medicare patients aged 60-64. No other sample restrictions from the main analysis are imposed. Estimates from equation (2) with a dummy variable for discharge status as the respective dependent variables. Standard errors clustered by hour of admission are shown below coefficient estimates in parenthesis. The proportion of the people admitted just before midnight with a given discharge status is shown in italics below the point estimates and standard errors. Coefficients that are significantly different from zero are denoted by: *10%, **5%, and ***1%.

Table A3: Characteristics of Hospitals Included in Analysis Sample

A. Balance

Variable	Not Included Mean	SD	Included Mean	SD	Difference	p-value
Hospital Beds	367.609	428.894	350.722	445.022	16.887	0.674
Discharges	36737.972	35971.297	41080.067	34183.027	-4342.095	0.180

B. Distribution of Characteristics

Owner Type:	Gov't, Non-Federal	Not-For-Profit	For-Profit	Gov't, Federal		
Included	22	17	119	54		
Not Included	31	21	140	66		

Service Type:	General Med & Surgical	Psychiatric	OB/GYN	Rehabilitation	Orthopedic	Other
Included	180	1	0	9	2	23
Not Included	232	10	0	8	0	13

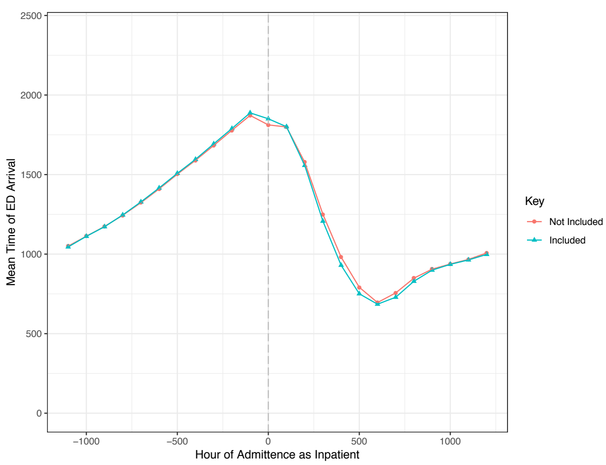
Urban/Rural:	Division	Metro	Micro	Rural		
Included	83	94	25	13		
Not Included	90	138	21	14		

Included $n = 215$, Not Included $n = 263$

Notes: Panel A gives the differences in means for number of annual discharges and number of hospital beds between hospitals included and not included in the analysis sample. Panel B gives the distribution of owner type, service type, and urban/rural designation for these hospitals. Coefficients that are significantly different from zero are denoted by: *10%, **5%, and ***1%.

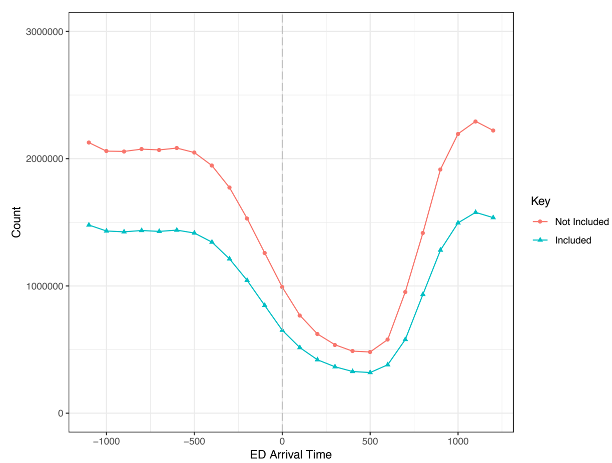
Figure A1: Emergency Department Arrival

(a) Average ED Arrival Time for Admitted Patients



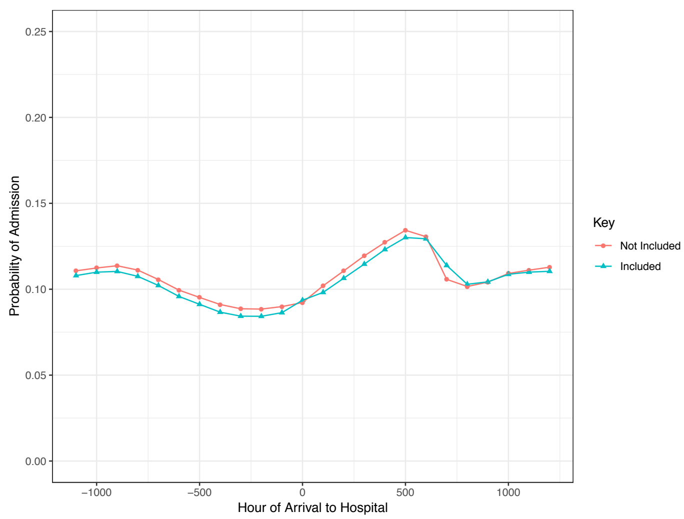
Notes: Average ED arrival time (shown on 24-hour clock) by hour of admittance as an inpatient and hospital inclusion. Included hospitals are shown in blue, while non-included hospitals are shown in red.

(b) Density of ED Arrival for All Patients



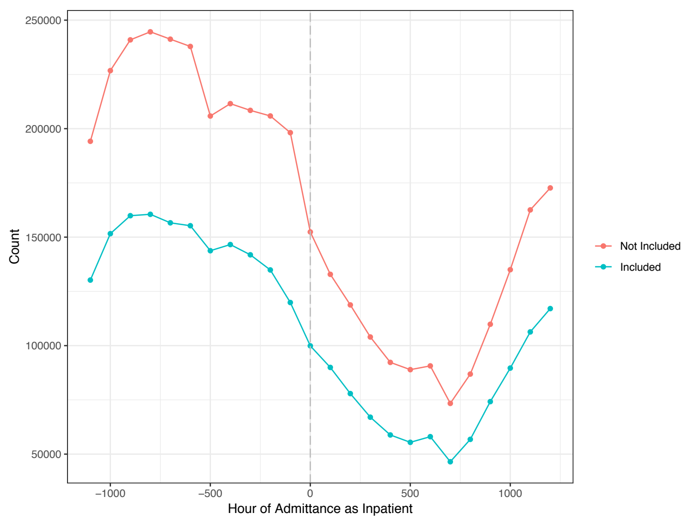
Notes: Density of ED arrival time by hour of admittance as an inpatient and hospital inclusion. Included hospitals are shown in blue, while non-included hospitals are shown in red.

Figure A2: Admission Probability by ED Arrival Time



Notes: Probability of inpatient admission by ED arrival time (shown relative to midnight on the x-axis) and hospital inclusion. Included hospitals are shown in blue, while non-included hospitals are shown in red.

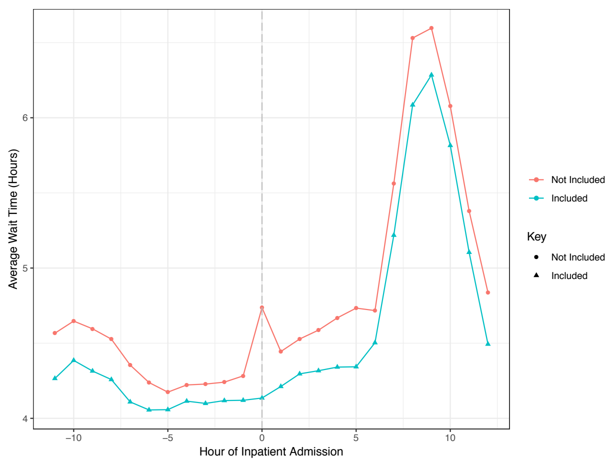
Figure A3: Density of Inpatient Admissions by Admission Time



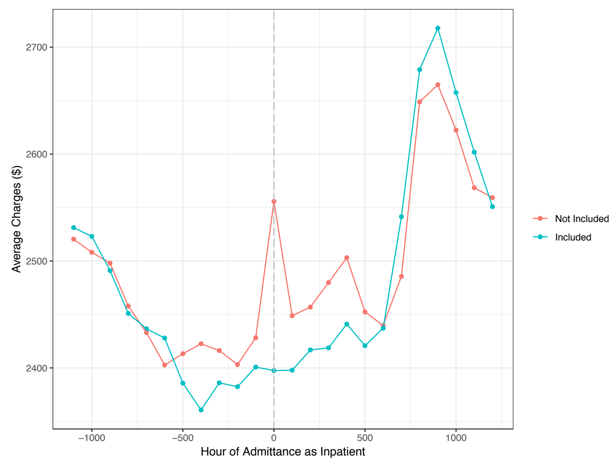
Notes: Density of inpatient admission by admission time and hospital inclusion. Included hospitals are shown in blue, while non-included hospitals are shown in red.

Figure A4: Waiting Time to Hospital Admission and ED Charges

(a) By Admission Time



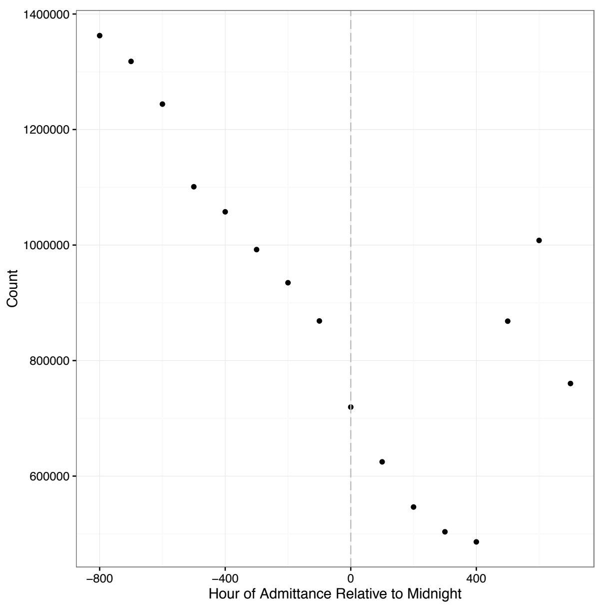
(b) By ED Arrival Time



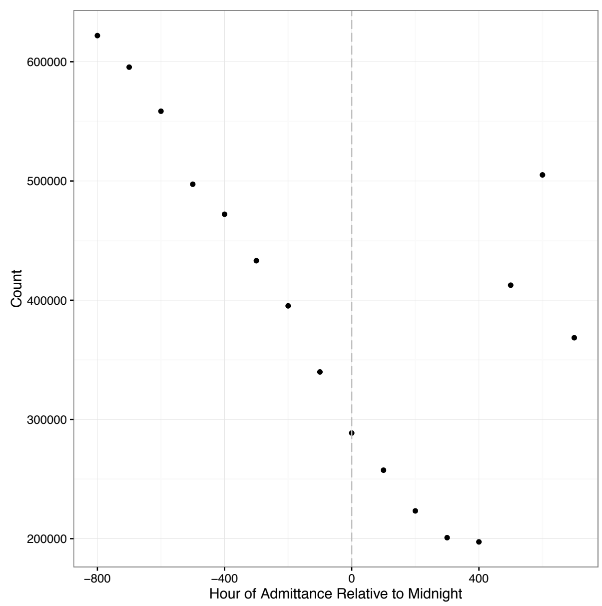
Notes: (Left) Average time from arrival at the emergency room until admission plotted by time of admission as an inpatient. (Right) Observation and ED charges by time of admission as an inpatient. Included hospitals are shown in blue, while non-included hospitals are shown in red.

Figure A5: Hospital Admission Counts by Admission Time at Each Trimming Step

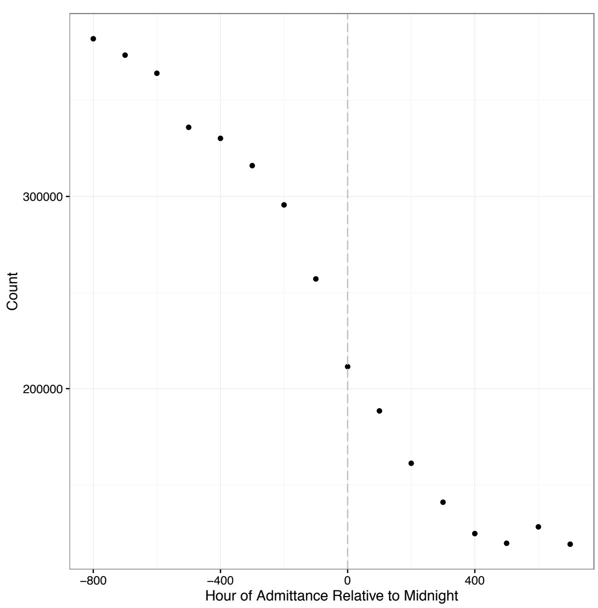
(a) Untrimmed



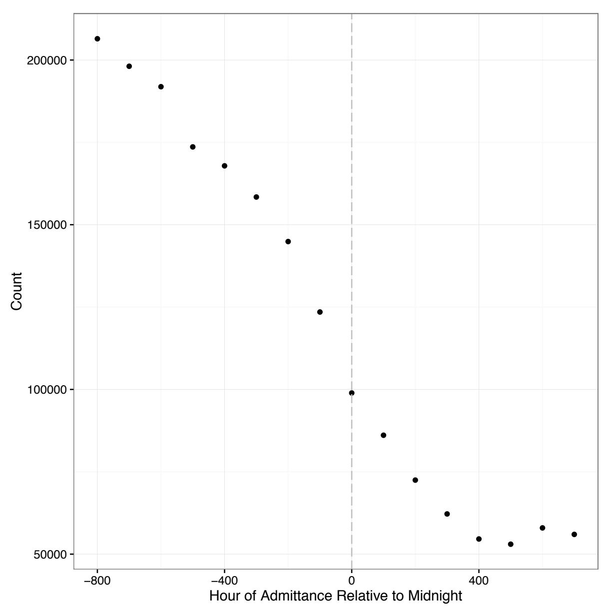
(b) With Included Hospitals



(c) With Included Hospitals and Patients from ED

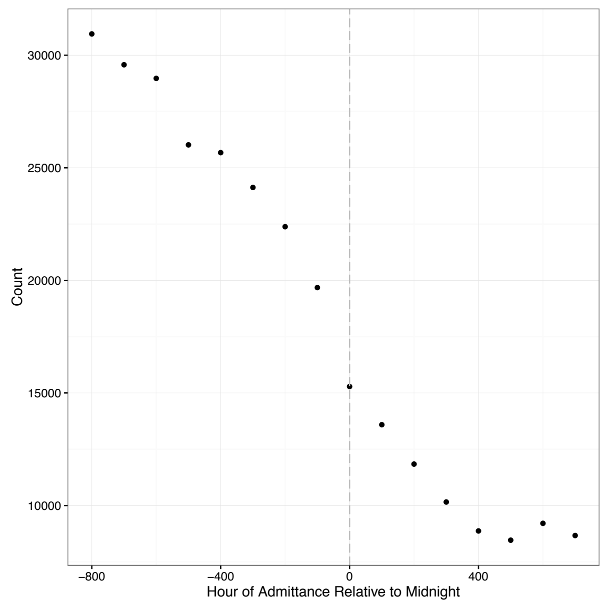


(d) With Included Hospitals, Patients from ED, and Medicare Beneficiaries



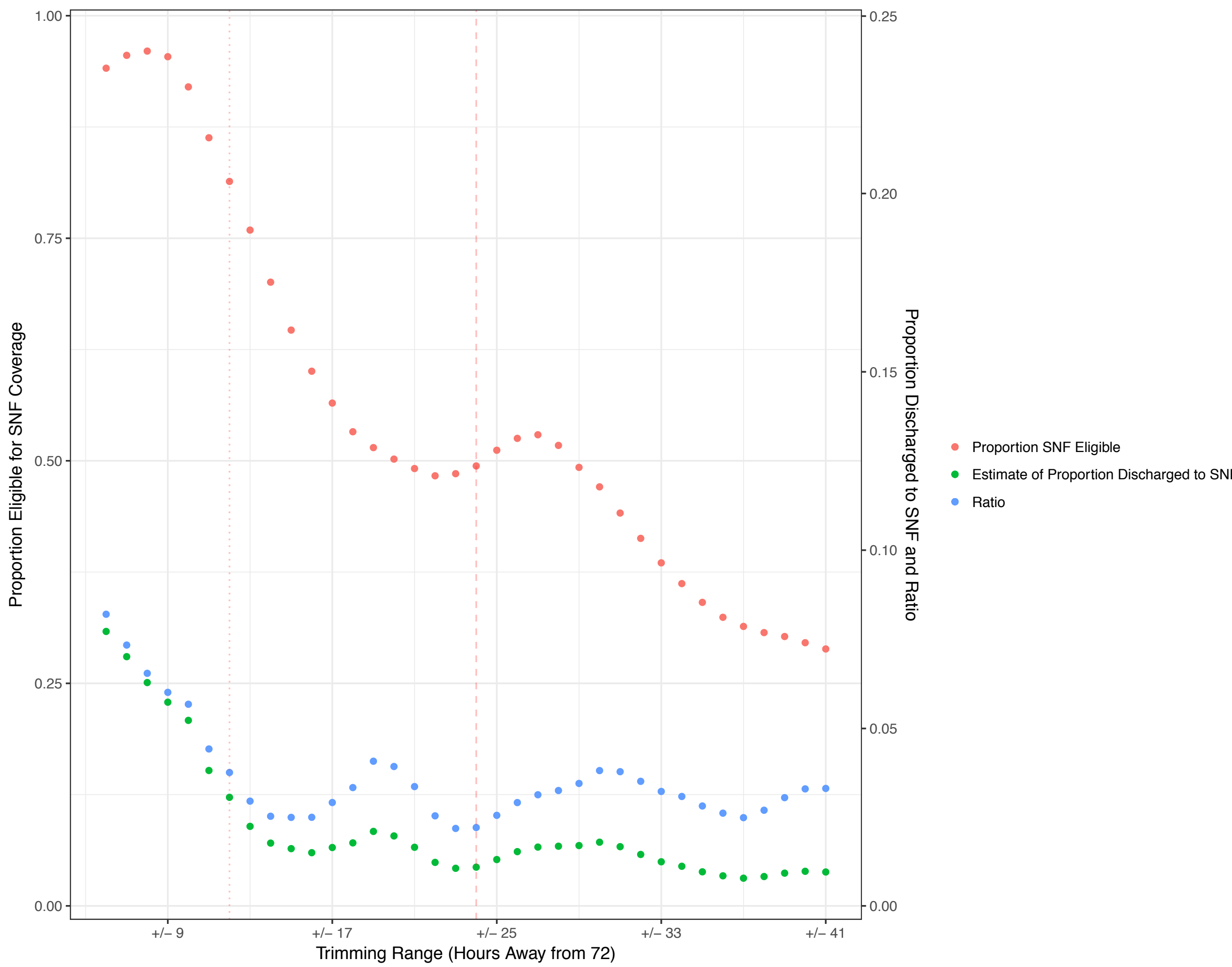
Notes: Clockwise from top left: The density of hospital admissions by hour for all patients in the untrimmed dataset, the density of hospital admissions by hour for all patients from an included hospital, the density of hospital admissions by hour for all patients from an included hospital that went through the emergency department and were not transferred from another unit of the same hospital, and the density of hospital admissions by hour for all Medicare patients from an included hospital that went through the emergency department and were not transferred from another unit of the same hospital.

Figure A6: Density with Included Hospitals, Patients from ED, Medicare Beneficiaries, and Length of Stay Trimming



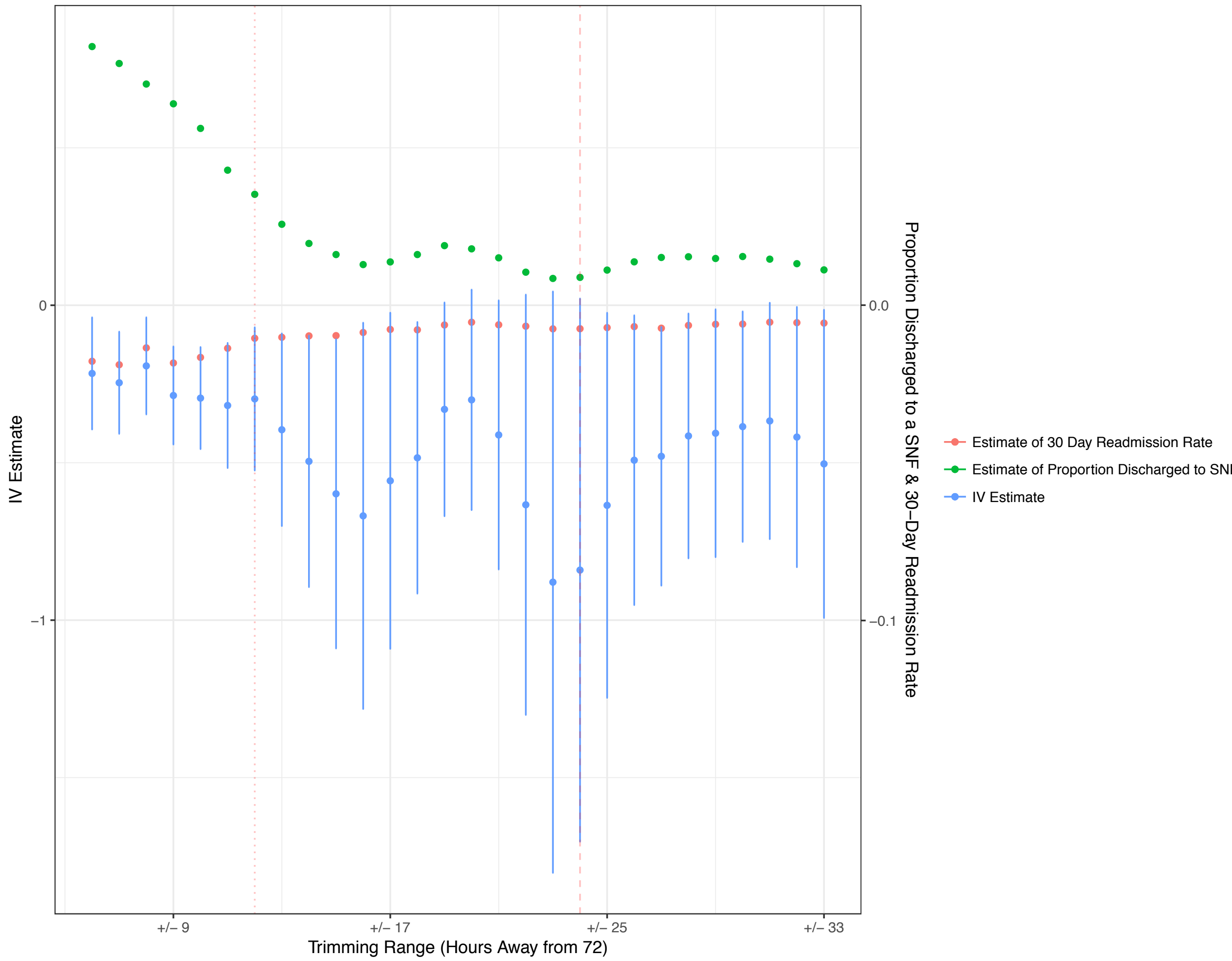
Notes: The density of hospital admissions by hour for all Medicare patients from an included hospital that went through the emergency department and were not transferred from another unit of the same hospital, and stayed between 60 and 84 hours as an inpatient.

Figure A7: Length of Stay Trimming Robustness, First Stage



Notes: Plot of the change in SNF eligibility at midnight (shown in orange, left axis), the change in SNF-going rate at midnight (shown in green, right axis), and the ratio between the two (shown in blue, right axis) for different trimming ranges of length of stay in hours (shown on the x-axis). Each point comes from an RD regression around midnight with 4-hour bandwidth using the data trimming as described in the text.

Figure A8: Length of Stay Trimming Robustness, IV Estimate



Notes: Plot of the change in SNF-going rate at midnight (shown in green), the change in the 30-day readmission rate (shown in orange), and the IV estimate formed with the previous two estimates with confidence intervals (shown in blue) for different trimming ranges of length of stay in hours (shown on the x-axis). Each point comes from an RD regression around midnight with 4-hour bandwidth using the data trimming as described in the text. The left-side axis corresponds to the IV estimate, while the right-side axis is for the first stage and reduced form.

Table A4: Change in SNF-going Rates at Midnight by Trimming Step

	Untrimmed	Included Hospitals	From ED	Medicare	Length of Stay <10 day
Change at Midnight	0.0068***	0.0045**	0.0022**	0.0023	0.005***
p-value	0.0000	0.0013	0.0438	0.1977	0.0144
Before Midnight	*0.0972*	*0.0959*	*0.1131*	*0.2148*	*0.1983*
n	23,441,389	10,680,806	6,144,715	3,144,813	1,579,202

Notes: Estimates from equation (2) with a dummy variable for SNF discharge status as the dependent variable, with each column representing a sequential step in the trimming process. The proportion of the people admitted just before midnight with a SNF discharge status is shown in italics below the point estimates and p-values. Coefficients that are significantly different from zero are denoted by: *10%, **5%, and ***1%.

Table A5: Robustness to Bandwidth, Polynomial Choice, and Hospital and Weekend Fixed Effects

	Skilled Nursing Facility (1)	Home (Routine) (2)	Organized Home Healthcare (3)	Other (4)	Readmission (30 Day) (5)
			Linear Polynomial		
Change at Midnight	0.0314***	−0.0265***	−0.0025	−0.0022*	−0.0052***
	(0.0017)	(0.0037)	(0.0029)	(0.0012)	(0.0018)
	0.1139	*0.6424*	*0.1812*	*0.0341*	*0.1529*
			Bandwidth = 4 Hours		
Change at Midnight	0.0236***	−0.0112**	−0.0088**	−0.0078***	−0.0173***
	(0.0003)	(0.0048)	(0.0043)	(0.0008)	(0.0008)
	0.1153	*0.6383*	*0.1847*	*0.0338*	*0.1392*
			Bandwidth = 12 Hours		
Change at Midnight	0.0386***	−0.0311***	−0.0064**	−0.0012	−0.0079***
	(0.0053)	(0.0065)	(0.0030)	(0.0015)	(0.0026)
	0.1077	*0.6472*	*0.1830*	*0.0334*	*0.1476*
			With Weekend Fixed Effects		
Change at Midnight	0.0337***	−0.0253***	−0.0071***	−0.0025**	−0.0111***
	(0.0030)	(0.0036)	(0.0025)	(0.0013)	(0.0025)
			With Hospital Fixed Effects		
Change at Midnight	0.0330***	−0.0249***	−0.0058**	−0.0021	−0.0107***
	(0.0028)	(0.0035)	(0.0025)	(0.0013)	(0.0026)
			With Hospital x Weekend Fixed Effects		
Change at Midnight	0.0330***	−0.0251***	−0.0058**	−0.0021	−0.0106***
	(0.0029)	(0.0036)	(0.0025)	(0.0013)	(0.0026)

Notes: Estimates from equation (2) with a dummy variable for discharge status (columns 1-4) or 30-day readmission (column 5) as the respective dependent variables. Standard errors clustered by hour of admission are shown below coefficient estimates in parenthesis. The proportion of the people admitted just before midnight with a given discharge status is shown in italics below the point estimates and standard errors. Coefficients that are significantly different from zero are denoted by: *10%, **5%, and ***1%.

Table A6: Summary Statistics

	Full Sample			
	ED Only	Inpatient	Medicare	Trimmed
	$n = 55,010,734$	$n = 20,780,379$	n =10,587,472	$n = 700,934$
	(1)	(2)	(3)	(4)
Age	35.06	50.43	70.59	74.10
Discharge Hour	13:49	14:41	14:28	15:02
Diagnoses	2.50	8.47	7.892	10.583
Procedures	0.16	1.82	1.43	1.006
Chronic	-	4.11	4.08	6.03
Admission Hour	13:32	12:43	13:08	13:35
Female	0.55	0.56	0.56	0.56
Length of Stay	0.13	5.15	3.20	2.91

Notes: Summary statistics for the full sample (emergency department and inpatient separately), Medicare beneficiaries, and the trimmed sample used in the primary analysis.

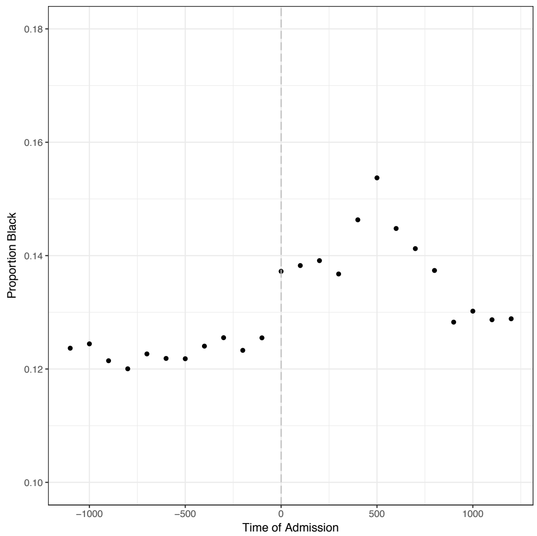
Table A7: Change in 30-Day Readmissions for Midnight Admissions By Year and Diagnosis Group

	2010-2012		2013	
	In DRG	Not In DRG	In DRG	Not In DRG
	(1)	(2)	(3)	(4)
Readmission	-0.0010	-0.0086^{*}	-0.0022^{*}	-0.0138^{*}
(30 Day)	(0.0009)	(0.0051)	(0.0013)	(0.0081)
	0.0151	*0.1373*	*0.0125*	*0.1123*
n	193,004		64,704	

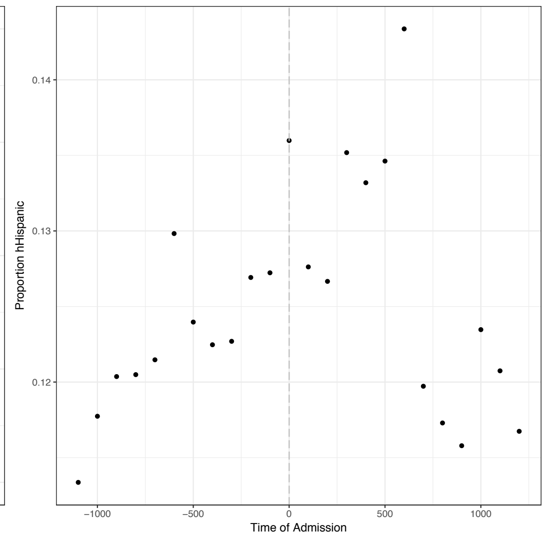
Notes: Estimates from equation (2), where the dependent variables are whether or not a patient was readmitted to the hospital within 30 days and whether the patient has a principal diagnosis that is one of the ICD-9 codes that Medicare considers for the Hospital Readmissions Reduction Program (HRRP). These diagnoses are acute myocardial infarction, pneumonia, and heart failure. The first two columns correspond to data pooled from the years 2010-2012, while the second two correspond to calendar year 2013. Standard errors clustered by hour of admission are shown below coefficient estimates in parenthesis. The estimates from just before midnight are listed in italics below the standard errors. Coefficients that are significantly different from zero are denoted by: *10%, **5%, and ***1%.

Figure A9: Time of Admission Profiles of Race and Age

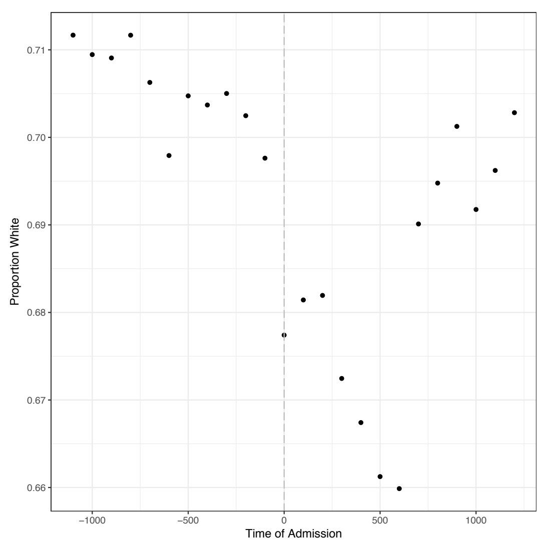
(a) Proportion Black



(b) Proportion Hispanic



(c) Proportion White



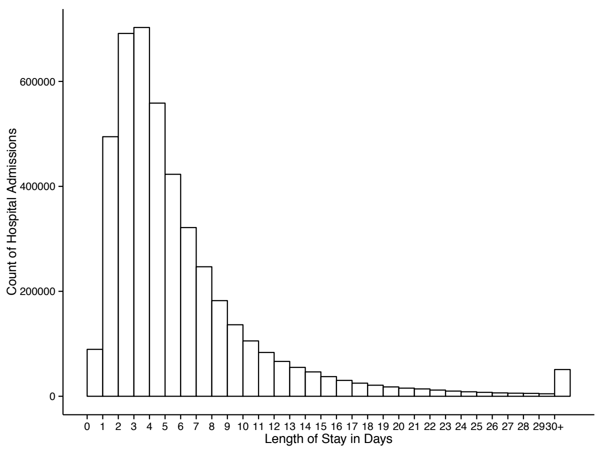
(d) Estimates With Cubic Polynomial

	Proportion Black	Proportion Hispanic	Proportion White
RD Estimate	0.0094***	−0.0001	−0.0046
	(0.0028)	(0.0042)	(0.0058)

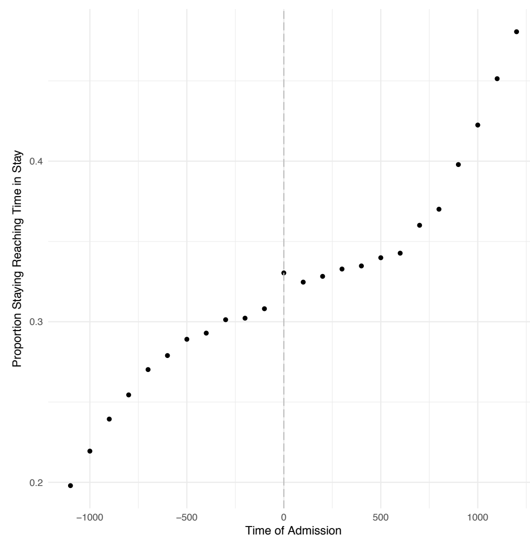
Notes: Time of admission profiles by race and profile of age, as well as estimates when using a cubic polynomial.

Figure A10: Probability of Long Hospital Stay

(a) Histogram of Stay Lengths

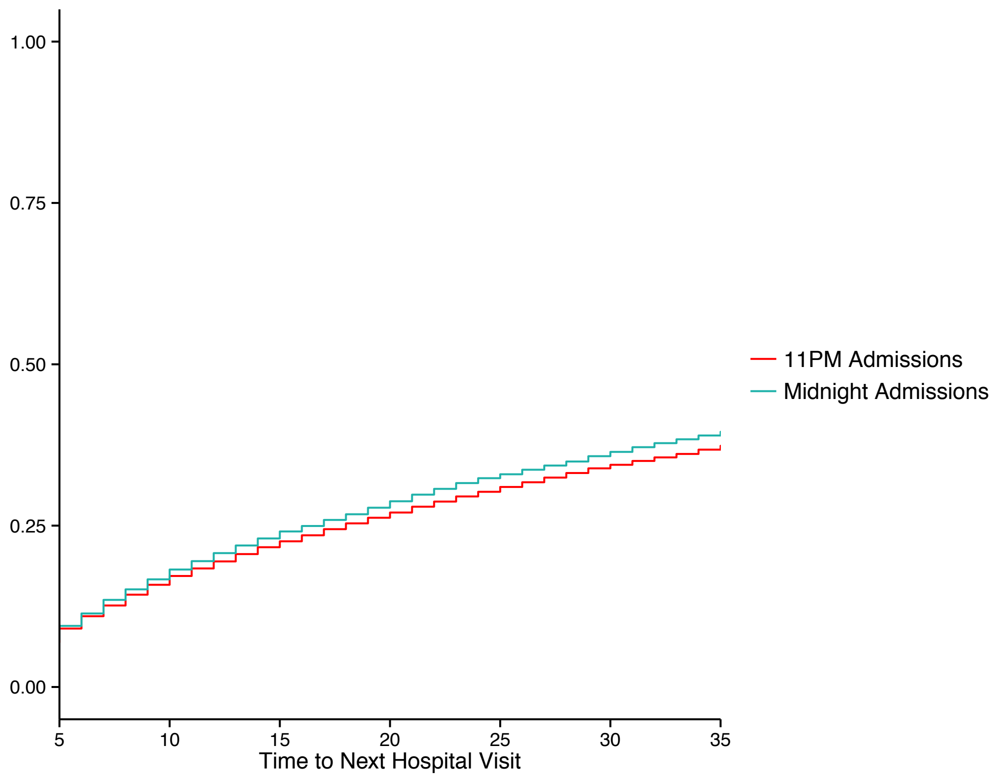


(b) Probability of Staying at Least Until 4 A.M. on Fourth Day of Inpatient Stay by Admission Hour



Notes: On left, the histogram of length of stay in days truncated at 30 days. Data come from all non-emergent Medicare admissions. On right, the probability that a patient admitted at a given time stays at least until 4 A.M. on the fourth day of their stay (e.g. stays at least 76 hours as an inpatient for an individual initially admitted at midnight)

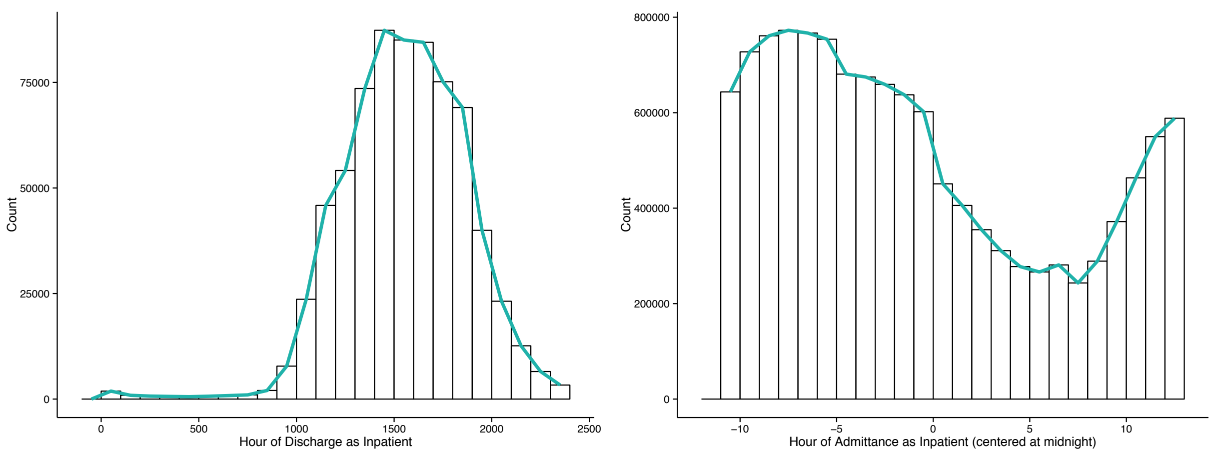
Figure A11: CDF of Hospital Revisit (5-35 Days)



Notes: CDF of return zoomed in to 5 to 35 days. "Revisit" means the patient came back to the emergency department or was readmitted. The red line is the CDF for patients admitted just before midnight, while the blue line is the CDF for patients admitted just after.

Figure A12: Additional Densities

(a) Discharge Density (b) Full Sample Time of Admission Density



Notes: Histogram of the time of day patients are discharged in the analysis sample (Figure A12a) and histogram of the time of day patients are admitted in the full sample without hospital trimming (Figure A12b).

Table A8: Results with Alternative Standard Error Approaches

	Wild Bootstrap	Collapsed	Clustered
SNF-going rate	-0.033***	-0.033***	-0.033***
	(0.014)	*(0.000)*	*(0.003)*
Readmission (30 days)		0.011***	0.011***
		(0.001)	*(0.002)*

Notes: Key results with alternative approaches for handling standard errors. P-values are listed below coefficients in parentheses and italics. The first column uses wild bootstrap clustered standard errors (Cameron et al., 2008). The second column estimates equation 2 on collapsed data, using the means at each hour of admission for each outcome. Standard errors are then standard Huber-White standard errors. The third column simply reproduces results from the main analysis for reference, using standard errors clustered by hour of admission.