Effect of Prospective Payment System on Health Equity in Post-acute Care Among Traditional Medicare Beneficiaries in Inpatient Rehabilitation Facilities

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Abstract: This study investigates the impact of the Medicare Prospective Payment System (PPS) on LOS and different outcomes in post-acute care (PAC) among traditional Medicare beneficiaries in Inpatient Rehabilitation Facilities (IRFs). Using an instrumental variable (IV) approach, we employ PPS-regulated expected length of stay (LOS) as an instrument to assess the causal effects of LOS on various outcomes, including functional improvements, the discharge location, and the probability of successful returning to the community. The analysis leverages data from the Inpatient Rehabilitation Facility-Patient Assessment Instrument (IRF-PAI) for 2019–2020, as well as focusing on key conditions of stroke, hip fractures, cardiac, and joint replacement issues. +In general, our results show that longer LOS is significantly associated with better outcomes. Specifically, longer LOS is significantly associated with improvements in mobility and cognitive function among all conditions. LOS is also significantly associated with a higher likelihood of returning to the community after discharge, particularly for stroke, hip fracture, and cardiac patients. These findings suggest that the PPS-regulated expected LOS indeed changes actual LOS and therefore changes outcomes. These findings highlight the effective role of PPS for optimizing PAC delivery, which can mitigate disparities and improve health equity in PAC settings.

Introduction

Post-acute care (PAC) is an essential component in the continuum of health care services. It provides tailored support for patients recovering from acute illness or injuries. By 2021, Traditional Medicare (TM) spending on PAC had doubled compared to 2001, which reached $56.8 billion.[1,2] Inpatient rehabilitation facilities (IRFs) provide the most intensive care rehabilitation care comparing to other PAC facility types such as skilled nursing facilities (SNFs) and home health agencies (HHAs). The TM expenditure for IRF also experienced a substantial increase in the past several decades, from $4.8 billion in 2001 to $8.8 billion by 2021.[1,2]

Medicare, which is administrated by the Centers for Medicare & Medicaid Services (CMS), is the primary payer for PAC. It offers two coverage types: Traditional Medicare (TM) (Part A and B) and Medicare Advantage (MA) (Part C). TM is a fee-for-service plan centrally administered by CMS, and MA plans are capitated plans individually managed by various insurance providers.[3]

Before PPS was implemented, IRFs received payments based on a cost-reimbursement model, subject to per-patient limits that varied widely across facilities. These limits were established based on each facility's historical costs, calculated as the average cost per patient during the facility's base year of operation.[4] However, this method proved ineffective in controlling healthcare costs within IRFs. Notably, between 1988 and 1997, post-acute care emerged as the fastest-growing category of Medicare expenditure, experiencing an average annual growth rate of 25%.[5] The Balanced Budget Act of 1997 and subsequent Balanced Budget Refinement Act of 1999 attempted to control the rising spending and costs by shifting payments to providers from a cost basis to prospective payment systems (PPSs). The Medicare Prospective Payment System (PPS) was implemented in Inpatient Rehabilitation Facilities (IRFs) in January 2002. This system reimburses IRFs based on a combination of the patient's case mix groups (CMGs) and comorbidity tier (Tier)—determined by the primary reason for rehabilitation, functional status, age, and number and severity of comorbidities—and factors related to the provider, such as the wage index and other characteristics. Additionally, adjustments are made for rural status, the proportion of low-income patients, and the presence of short-stay and high-cost outliers, ensuring a more nuanced and equitable reimbursement structure.

Research has demonstrated that the IRF PPS is an effective mechanism that has significantly reduced both costs and the LOS without negatively affecting health outcomes.[6,7] Under the IRF PPS, the reimbursement rates are not static. The Centers for Medicare & Medicaid

Services (CMS) annually adjusts these rates to account for changes in various factors, including wage inflation as well as variation in utilization by CMG and Tier during the previous five years across the country. Many research has investigated the policy effects in the early stage of PPS implementation.[6,8-11] However, there is scant research exploring whether these annual adjustments have effects on LOS, and therefore affect care delivery and outcomes of Post-Acute Care (PAC) within IRFs.

Based on the above literature review, this study aims to explore the consequences of annual PPS modifications on LOS. We hypothesize that annual PPS modification would induce changes in LOS and subsequently change various post-acute care outcomes for traditional Medicare beneficiaries. Specifically, we primarily focus on patients with four conditions: stroke, hip fracture, cardiac, and joint replacement. These conditions are the most common conditions for IRFs among the aging population.[12] This investigation aims to shed light on how changes in the PPS influence LOS. In turn, variations in LOS affect patient care and outcomes across different demographic and clinical groups over time.

Theoretical Framework

In this section, we build an economic model for how different factors influence the LOS in IRFs and whether these factors lead to health inequities among TM beneficiaries. We also used this model to identify whether the PPS can reduce health inequities among TM beneficiaries.

Under TM, IRFs are paid via the Prospective Payment System (PPS). This means they receive a fixed payment based on the expected LOS for a given patient type (CMGs Group and Tiers). The profit function for taking care of a single patient among TM beneficiaries can be written as:

$$\pi = P - C \ (1.1)$$

P is the reimbursement level pre-determined by the PPS, and C is the actual cost during the treatment process.

To simplify our model, the actual costs we assume to be associated with the actual LOS of a single patient staying in the hospital. Thus, we define:

$$C = C\left({LOS_{TM\ actual}}^2\right)(1.2)$$

$LOS_{TM\ actual}$ measures the number of LOS a single patient stays in IRFs during the treatment process. The square of $LOS_{TM\ actual}$ captures the increasing marginal costs associated with longer stays, according to Grossman model of health demand.[13]

When a single patient is admitted into IRFs, the PPS will pre-determine an expected LOS as the reference for IRFs. If the actual LOS is larger than the expected LOS, IRFs will lose the profit, vice versa. Moreover, the reimbursement level P is also associated with expected LOS. Thus, both P and $LOS_{TM\ actual}$ can be defined as a function of $LOS_{TM\ expected}$ as:

$$P = pLOS_{TM\ expected}\ (1.3)$$

$$LOS_{TM\ actual} = f\left(LOS_{TM\ expected}, \theta\right)\ (1.4)$$

p is the predetermined payment rate for one unit of LOS. θ captures the effect from all other non-clinical factors. If $\theta = 0$, $LOS_{TM\ actual}$=$LOS_{TM\ expected}$, so there is no health equity issue. If $\theta > 0$, $LOS_{TM\ actual} \neq LOS_{TM\ expected}$. There is a health equity issue.

If we include equation (2) (3) (4) into equation (1.1), the profit function for TM is defined as:

$$\pi = pf\left(LOS_{TM\ expected}, \theta\right) - C\left(f^2\left(LOS_{TM\ expected}, \theta\right)\right)\ (1.5)$$

To maximize the profit, I take the first order condition of Equation (5) with respect to $LOS_{TM\ expected}$:

$$\frac{d\pi_{TM}(t)}{dLOS_{TM\ expected}} = p\frac{df}{dLOS_{TM\ expected}} - \frac{dC}{df^2}\frac{df^2}{df}\frac{df}{dLOS_{TM\ expected}} = 0\ (1.6)$$

Then, we can get:

$$p\frac{df}{dLOS_{TM\ expected}} = 2f\frac{dC}{df^2}\frac{df}{dLOS_{TM\ expected}}\ (1.7)$$

If we assume that equation (1.4) is linear, $\frac{df}{dLOS_{TM\ expected}}$, will be a constant which measures the marginal effect of expected LOS on actual LOS. Since equation (1.4) is linear, $C(f^2)$ is definitely quadratic, and $\frac{dC}{df^2}$ is also constant. For example, $C = c_0 + c_1 \cdot f^2$, then $\frac{dC}{df^2} = c_1$. Since both $\frac{df}{dLOS_{TM\ expected}}$ and $\frac{dC}{df^2}\frac{df}{dLOS_{TM\ expected}}$ will be constant, we can get:

$$p = 2f\left(LOS_{TM\ expected}, \theta\right) \times \frac{dC}{df^2} = 2f\left(LOS_{TM\ expected}, \theta\right) \times \alpha\ (\alpha\ is\ constant)(1.8)$$

Then we can get:

$$\frac{p}{2\alpha} = f\left(LOS_{TM\ expected}, \theta\right) \ (1.9)$$

Invert the function of f, we can get:

$$\theta = f^{-1}\left(LOS_{TM\ expected}, \frac{p}{2\alpha}\right) \ (1.10)$$

Thus, the effect from all other non-clinical factors can be a function of expected LOS and the payment rate of PPS. Based on the economic theoretical model, the PPS can be used as an effective way to control other non-clinical factors and therefore reduce health disparity. In the following part, I will use econometric and statistical methods to test this assumption.

Methods

Data and Sample

We analyzed data from the Inpatient Rehabilitation Facility—Patient Assessment Instrument (IRF-PAI), which is provided by the Uniform Data System for Medical Rehabilitation (UDSMR) from 2019-2020.[14] The UDSMR has the world's largest independent repository of rehabilitation outcomes and IRF-PAI data. The IRF-PAI is mandated by the Centers for Medicare & Medicaid Services (CMS) for reimbursement purposes. It includes comprehensive information on patient demographics, pre-admission and post-discharge locations, medical conditions, facility characteristics, and cost factors like LOS, payment amounts, and sources of payment (e.g., TM and MA). In terms of medical conditions, we include the case-mix group (CMG) and the comorbidity tier. A CMG is a classification system used in inpatient rehabilitation facilities (IRFs) to categorize patients based on their clinical characteristics and resource needs. A comorbidity tier is a classification used in IRFs to account for the presence and severity of additional medical conditions (comorbidities) that a patient may have alongside their primary reason for rehabilitation. Additionally, the IRF-PAI captures patient functionality—assessed within 72 hours of admission and before discharge—as well as details on therapies received, care interruptions, and other key clinical practices.

Our study sample comprises TM beneficiaries aged 65 years and older who were admitted to Inpatient Rehabilitation Facilities (IRFs) for inpatient rehabilitation services. The period of study spans from January 1, 2019, to December 31, 2020, focusing on three common admission conditions prevalent among the aging population: Stroke (Impairment Group Code (IGC): 01.1-01.9), Hip Fracture (IGC: 08.11-08.12), Joint Replacement (IGC: 08.51-08.52, 08.61-08.62, 08.71-08.72), and Cardiac (IGC: 09). Excluded from the sample were those patients who were not admitted for initial rehabilitation or died during the rehabilitation stay, whose prehospitalization living settings were non-home, whose LOSs were longer than 30 days or shorter than 3 days, whose rehabilitation programs were interrupted, or who were discharged against medical advice. These patient-episodes were deemed to be different from others due to complicated clinical concerns and hence were less comparable.[15,16] Figure 1 shows the flowchart of sample derivation and the number of excluded episodes in each step. The final study sample has 184,202 patient episodes, among which 85,737 are stroke, 54,763 are hip fracture, 28,151 are cardiac, and 15,551 are joint replacement.

Variables

Our outcomes include functional improvements, discharge location, and whether the patient has successfully returned to community living after discharge (i.e. home or home with home health care). Functional improvements are measured by GC130 (Mobility score improvement) and GC170 (Cognitive score improvement), which are defined by the CMS functional assessment rules introduced in 2019. The discharge Location is a quaternary variable indicating whether the patient is discharged home with self-care, home with home health services, to a Skilled Nursing Facility (SNF), or other locations (including hospice and long-term care hospitals). Successfully Return to Community After Discharge is a binary variable indicating whether a patient was discharged home, with or without home health care (Yes = 1), or to any other location (No = 0).

Analytical approach

Empirical analysis

There is a potential issue of endogeneity of LOS when trying to identify the causal effects of LOS on care outcomes. As a result, we use the expected LOS as the instrument variable for the actual LOS. An IRF receives a pre-determined prospective payment for each admitted patient based on their Case Mix Groups (CMGs) and comorbidity tier (Tier). Each patient has an expected Length of Stay (LOS) that reflects the anticipated resource utilization for patients within that category.[17] Therefore, the actual LOS is closely related to the expected LOS, which is determined solely by CMGs and comorbidity tiers. As a result of it, the expected LOS serves as an ideal instrumental variable for the actual LOS at the patient-episode level. Moreover, expected LOS will be adjusted by CMS annually each year. Thus, it is an ideal situation to test whether outcomes will change in response to changes in LOS, which in turn result from changes in expected LOS attributable to CMS policy adjustments.

The following are the empirical two-way fixed-effect instrumental variable models (TWFE IV) I will use:

(1.1) $LOS_{itr} = \alpha_1 Expected\ LOS_{itr} + \alpha_2 X_{itr} + \gamma_{itr} + \tau_{itr} + v_{itr}$ (Stage 1)

(1.2) $Outcome_{itr} = \beta_1 LOS_{itr} + \hat{v}_{itr} + \gamma_2 X_{itr} + \gamma_{itr} + \tau_{itr} + \varepsilon_{itr}$ (Stage 2)

Where the outcome variables are functional improvements, discharge location, and whether the patient has successfully returned to the community of patient i in the administration region r in year-month t, as I mentioned before. γ_{itr} denotes regional fixed effect, which is consistent with 10 CMS administration regions. CMS has 10 regional offices: Boston, New York, Philadelphia, Atlanta, Chicago, Dallas, Kansas City, Denver, San Francisco, and Seattle. τ_{itr} denotes calendar year-month fixed effects. Model (1.1) shows the first stage of IV regression model. Since LOS is a count variable, the poison regression model is used in stage 1. Since our first stage is a non-linear regression model, the predicted LOS in the model (1.1) (first stage) cannot be used in the second stage, or we will get the forbidden regression. To avoid this, we will include the predicted residual $\hat{v}_i$ from model (1.1) (first stage) into model (1.2) (second stage) to estimate the causal effect β_1 of LOS on outcomes. Moreover, since there is a collinearity between expected LOS and CMGs and Tiers, we did not include CMGs and Tiers in the first stage to get the predicted residual $\hat{v}_i$. We assume that the expected LOS can cover all the variation from CMGs and Tiers.

Based on different outcomes, different models in stage 2 were used. Linear regressions were used in mobility score improvement and cognitive score improvement, because all their distribution were normally distributed. As for discharge location, multinomial logistic regression was used to compare the differences of different discharge locations. Regarding successfully returning to community after discharge, logistic regression is used.

Sensitivity analysis

We conducted sensitivity analyses to test the robustness of our results. In terms of the discharge location, we fitted multinomial probit models to see if the assumption of independence of irrelevant alternatives was held for the multinomial logistic regression. In terms of successfully returning to community after discharge, linear probability regression and probit regression were used to conduct the sensitivity analysis.

Results

Descriptive statistics

Figure 2 showed mobility and cognitive score improvement over months of patients among traditional Medicare Beneficiaries by different conditions. Both mobility score improvement and cognitive score improvement is constant over time among stroke, fracture, and cardiac patients. Among joint replacement patients, the cognitive score improvement shows a sharp decrease at the beginning of pandemic but later comes back.

Tables 1-1 to 1-4 present the descriptive statistics across different conditions. There are minimal differences in demographic characteristics across these groups. Among the conditions, hip fracture patients are the oldest, with an average age of around 80, while joint replacement patients are the youngest, with an average age of about 76. The percentage of female patients is higher than that of males for stroke, hip fracture, and joint replacement cases, whereas the cardiac group has a higher percentage of male patients. Hip fracture patients have the highest percentage of white individuals, while stroke patients have the lowest percentage of white individuals across conditions. Stroke patients show a nearly equal distribution between those with and without a partner, while hip fracture, cardiac, and joint replacement patients have a significantly higher percentage of individuals without a partner. Among all these conditions, the only consistent finding is that the case-mix group and comorbidity tiers differ between the pre-pandemic and during-pandemic periods, as indicated by the p-value. Other differences between these periods vary across different conditions.

Functional improvements

Tables 2-1 through 2-4 present the results of the instrumental variable (IV) regression analysis for mobility and cognitive score improvements across different conditions. For stroke patients, the first stage shows a significant association between expected LOS and actual LOS. The incident rate ratio (IRR) for expected LOS is 1.0581 (SE: 0.0003, $p < 0.01$), indicating that a 1-unit increase in expected LOS corresponds to a 5.81% increase in predicted LOS. In the second stage, LOS is significantly associated with a 4.51% increase in mobility score (Coefficient: 0.440, SE: 0.018, $p < 0.01$) and a 3.70% increase in cognitive score (Coefficient: 0.898, SE: 0.039, $p < 0.01$).

For hip fracture patients, the first stage also demonstrates a significant relationship between expected LOS and actual LOS. The IRR for expected LOS is 1.0600 (SE: 0.0003, $p < 0.01$), indicating that a 1-unit increase in expected LOS results in a 6.00% increase in predicted LOS. In the second stage, LOS is significantly associated with a 4.50% increase in mobility score (Coefficient: 0.567, SE: 0.094, $p < 0.01$) and a 2.96% increase in cognitive score (Coefficient: 0.943, SE: 0.210, $p < 0.01$).

For cardiac patients, the first stage reveals that the expected LOS is significantly associated with actual LOS, with an IRR of 1.0692 (SE: 0.0008, $p < 0.01$), meaning a 1-unit increase in expected LOS is associated with a 6.92% increase in predicted LOS. In the second stage, LOS is significantly associated with a 4.39% increase in mobility score (Coefficient: 0.475, SE: 0.149, $p < 0.01$) and a 3.16% increase in cognitive score (Coefficient: 0.832, SE: 0.309, $p < 0.01$).

For joint replacement patients, the first stage indicates a significant association between expected LOS and actual LOS. The IRR for expected LOS is 1.0825 (SE: 0.0014, $p < 0.01$), suggesting that a 1-unit increase in expected LOS corresponds to an 8.25% increase in predicted LOS. However, in the second stage, LOS is not significantly associated with mobility score improvement (Coefficient: 0.089, SE: 0.1, $p > 0.1$). LOS is, however, significantly associated with a 3.16% increase in cognitive score (Coefficient: 0.493, SE: 0.230, $p < 0.01$).

In sum, the relationship between LOS and recovery outcomes varies by condition. Stroke, hip fracture, and cardiac patients show significant associations between LOS and improvements in both mobility and cognitive scores. In contrast, for joint replacement patients, LOS is not significantly associated with mobility score improvements but does show a significant positive association with cognitive score improvements. These findings highlight the condition-specific nature of LOS effects on recovery.

The discharge location

Tables 3-1 through 3-4 present the results of the IV analysis for discharge location, highlighting trends between discharge destinations and length of stay (LOS). For stroke patients, the multinomial logistic and probit regressions show consistent patterns. Discharge to home (self-care) is set as the reference group. For discharge to home health, the relative risk ratio (RRR) in the multinomial logistic regression is 1.051 ($p < 0.01$), and the coefficient in the multinomial probit regression is 0.037 ($p < 0.01$), indicating that a longer LOS is associated with a slightly increased likelihood of discharge to home health compared to home. For discharge to a skilled nursing facility (SNF), the RRR is 1.069 ($p < 0.01$), and the probit coefficient is 0.043 ($p < 0.01$), showing a stronger association with longer LOS. This suggests that patients with a longer LOS are more likely to be discharged to SNF compared to both home and home health. Moreover, the higher RRR for SNF (1.069) compared to home health (1.051) indicates that patients with extended stays are more likely to require SNF care, which involves more intensive healthcare services. For other discharge locations, the RRR is 0.809 ($p < 0.01$), and the probit coefficient is -0.127 ($p < 0.01$), suggesting that a longer LOS is associated with a lower likelihood of discharge to other less common locations compared to home.

For hip fracture patients, both regression models again show consistent patterns, with discharge to home (self-care) as the reference group. For discharge to home health, the RRR in the multinomial logistic regression is 1.018 ($p > 0.1$), and the multinomial probit coefficient is 0.006 ($p > 0.1$). These insignificant results suggest that longer LOS is not associated with the likelihood of discharge to home health compared to home. Similarly, for discharge to SNF, the RRR is 0.956 ($p > 0.1$), and the probit coefficient is -0.012 ($p > 0.1$), showing no significant association. However, for other discharge locations, the RRR is 0.809 ($p < 0.01$), and the probit coefficient is -0.127 ($p < 0.01$), indicating that a longer LOS is associated with a lower likelihood of discharge to other less common locations compared to home.

For cardiac patients, the multinomial logistic and probit regressions also show consistent patterns. Discharge to home (self-care) is used as the reference group. For discharge to home health, the RRR in the multinomial logistic regression is 0.921 ($p > 0.1$), and the multinomial probit coefficient is -0.080 ($p < 0.05$), indicating that a longer LOS is slightly associated with a decreased likelihood of discharge to home health compared to home. For discharge to SNF, the RRR is 1.051 ($p > 0.1$), and the probit coefficient is 0.019 ($p > 0.1$), showing no significant association between LOS and the likelihood of discharge to SNF. For other discharge locations, the RRR is 0.731 ($p < 0.01$), and the probit coefficient is -0.176 ($p < 0.01$), indicating that a longer LOS is associated with a lower likelihood of discharge to other less common locations compared to home.

Finally, for joint replacement patients, the regression models again show consistent patterns. Discharge to home (self-care) is set as the reference group. For discharge to home health, the RRR in the multinomial logistic regression is 1.065 ($p < 0.1$), and the multinomial probit coefficient is 0.044 ($p < 0.1$), suggesting no significant association between LOS and the likelihood of discharge to home health compared to home. For discharge to SNF, the RRR is 1.117 ($p < 0.1$), and the probit coefficient is 0.071 ($p < 0.1$), which is also not significant. For other discharge locations, the RRR is 0.931 ($p > 0.1$), and the probit coefficient is -0.016 ($p > 0.1$), indicating that LOS is not associated with the likelihood of discharge to other less common locations compared to home.

In sum, the relationship between LOS and discharge destination varies by condition. For stroke patients, a longer LOS is strongly associated with an increased likelihood of discharge to both home health and SNF, with a stronger effect for SNF. In contrast, for hip fracture and cardiac patients, the associations between LOS and discharge destination are minimal or not significant, except for a lower likelihood of discharge to other locations. For joint replacement patients, there is no significant relationship between LOS and any discharge destination, indicating that the impact of LOS on discharge location is condition specific.

Successfully returning to the community after discharge

Tables 4-1 through 4-4 present the instrumental variable (IV) analysis results for the likelihood of returning to the community after discharge. For stroke patients, the logistic regression, linear probability model, and probit regression yield consistent findings regarding the relationship between LOS and community reintegration. In the logistic regression, the odds ratio (OR) for returning to the community is 1.073 (SE: 0.006, $p < 0.01$), indicating that a longer LOS is associated with higher odds of returning to the community compared to shorter stays. Similarly, the linear probability model shows a coefficient of 0.016 (SE: 0.001, $p < 0.01$), suggesting that a longer LOS increases the probability of a successful return to the community by 1.6 percentage points. The probit regression further supports this conclusion, with a coefficient of 0.042 (SE: 0.003, $p < 0.01$), confirming that a longer LOS positively influences the likelihood of returning to community life.

For hip fracture patients, the logistic regression, linear probability model, and probit regression also show some consistent patterns regarding LOS and the likelihood of community return. In the logistic regression, the odds ratio (OR) is 1.199 (SE: 0.037, $p < 0.01$), suggesting that a longer LOS is associated with higher odds of returning to the community. However, the linear probability model presents a different result, with a coefficient of 0.0005 (SE: 0.005, $p > 0.1$), indicating no significant association between LOS and the probability of a successful community return. Despite this discrepancy, the probit regression aligns with the logistic regression, showing a coefficient of 0.082 (SE: 0.018, $p < 0.01$), reinforcing the finding that a longer LOS positively influences the likelihood of community reintegration.

For cardiac patients, the results across the three models are inconsistent. The logistic regression indicates that a longer LOS is associated with higher odds of returning to the community, with an OR of 1.095 (SE: 0.045, $p < 0.01$). However, the linear probability model contradicts this, showing a coefficient of -0.0011 (SE: 0.005, $p > 0.1$), suggesting no significant relationship between LOS and community return. The probit regression similarly finds no significant association, with a coefficient of 0.036 (SE: 0.023, $p > 0.1$), providing no evidence to support a positive relationship between LOS and the likelihood of community reintegration for cardiac patients.

For joint replacement patients, all three models consistently indicate that LOS is not associated with the likelihood of returning to the community. In the logistic regression, the odds ratio (OR) is 1.012 (SE: 0.046, $p > 0.1$), showing no significant relationship. The linear probability model supports this finding with a coefficient of 0.0016 (SE: 0.0045, $p > 0.1$), and the probit regression also reports no association, with a coefficient of 0.003 (SE: 0.024, $p > 0.1$).

In sum, the analysis reveals that the relationship between LOS and returning to the community after discharge is condition specific. For stroke patients, a longer LOS is consistently associated with higher odds of community reintegration. Hip fracture patients show mixed results, with logistic and probit models suggesting a positive relationship, but the linear probability model showing no significant association. Cardiac patients exhibit inconsistent findings, with only the logistic regression indicating a significant positive relationship. For joint replacement patients, all models agree that LOS has no significant impact on the likelihood of returning to the community. These findings highlight the complexity and variability of the effects of LOS on post-discharge outcomes across different conditions.

Discussion and Limitation

My findings highlight the causal effect between length of stay (LOS) and various post-acute care (PAC) outcomes in inpatient rehabilitation facilities (IRFs). The association between LOS and expected LOS is statistically significant across all patient conditions. However, when expected LOS is used as an instrumental variable, the strength and significance of the association between LOS and different discharge outcomes vary by condition. In summary, longer lengths of stay (LOS) are generally associated with better outcomes, including greater functional improvement and a higher likelihood of returning to the community, particularly for stroke patients. Regarding discharge location, a longer LOS is significantly associated with a lower likelihood of discharge to other post-acute care (PAC) settings compared to home with self-care. Patients with poor outcomes generally require more health care, which has been supported by many other studies.[18-21] "Other PAC settings" include hospice and long-term care, which provide more healthcare services compared to home, home health, and skilled nursing facilities (SNFs). As a result, admission to these settings often indicates poorer outcomes. Therefore, the findings on discharge location further support the conclusion that longer LOS is associated with better outcomes. Overall, the results suggest that longer LOS is linked to greater health improvement, consistent with findings from other studies.[19,22] However, these results differ from studies conducted in other PAC settings, which suggest that SNF stays may sometimes be unnecessarily prolonged.[23]

As noted in the results section, the significance of the association between length of stay (LOS) and outcomes varies by condition. This can be explained by the differing rehabilitation needs of each patient population. Stroke patients typically require highly tailored rehabilitation to address specific impairments.[24,25] Consequently, extended LOS significantly impacts their functional recovery and discharge planning, directly influencing their ability to transition to less intensive care settings. In contrast, hip fracture and cardiac patients generally require rehabilitation focused on regaining independence and stability. These patients often achieve a functional level that enables them to avoid high-level care settings like skilled nursing facilities (SNFs).[18,19,26,27] Longer stays enhance their readiness for community discharge, but they do not necessarily alter their discharge destination. For these populations, extended LOS supports functional gains that increase their likelihood of transitioning directly to community living. However, LOS has less impact on discharge location, as these patients typically do not require care beyond the inpatient rehabilitation facility (IRF) once they achieve a stable state. Joint replacement patients, on the other hand, tend to regain mobility relatively quickly and often require less intensive or prolonged rehabilitation. Extended stays are less beneficial for this population because their needs are typically met within a shorter timeframe. Additionally, the elective and selective nature of joint replacement procedures means that LOS is less influenced by clinical recovery needs and more by individual patient factors.[28-30] These factors explain the lack of significant association between LOS and recovery outcomes for joint replacement patients.

There are several limitations to this study. First, since our dataset is national in scope, the results may not be valid for state or county-level analyses. Second, the study may not fully account for other policy changes during the study period, which could independently affect LOS and discharge outcomes. The reliance on administrative data, which may contain inaccuracies or misclassifications, could affect the measurement of key variables. Third, the study's focus on specific conditions such as strokes, hip fractures, cardiac, and joint replacements may limit the generalizability of the findings to other conditions treated in IRFs. Fourth, the impact of the COVID-19 pandemic, which significantly altered healthcare delivery and IRF operations, adds another layer of complexity to the interpretation of results. Finally, the study focuses on outcomes measured within a relatively short follow-up period (2019-2020). Long-term outcomes and sustainability of the observed effects are not assessed, limiting the understanding of the long-term impact of PPS adjustments.

Conclusion

Using expected LOS as an instrumental variable, LOS is shown to be significantly associated with various outcomes in PAC within IRFs. Additionally, longer LOS is generally linked to better outcomes; however, the strength and significance of this association vary across different conditions. These findings indicate that the PPS can play a crucial role in reducing health disparities and promoting health equity.

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Figure 1: Flow Chart

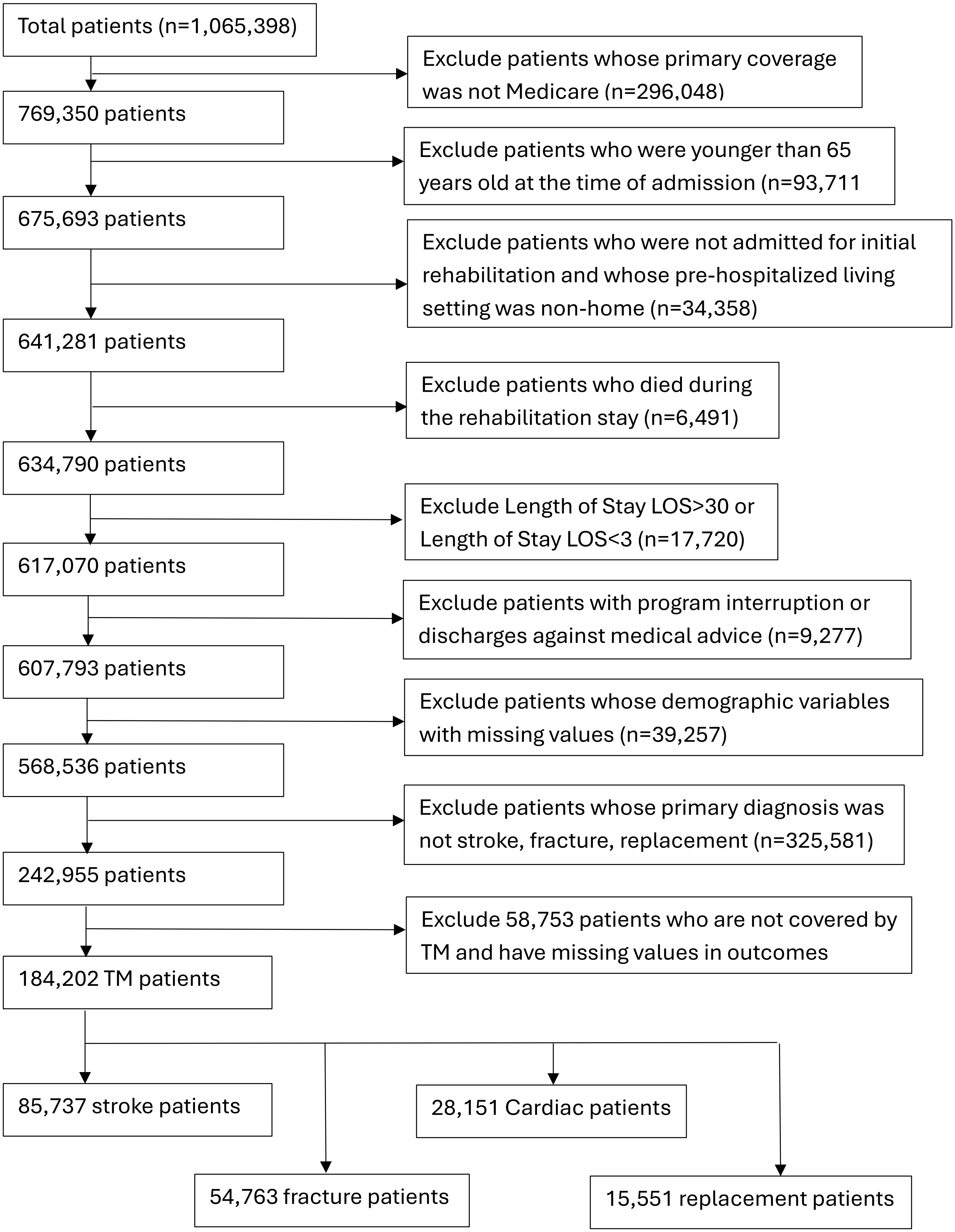

Figure 2: Mobility score and cognitive score by admission conditions over time

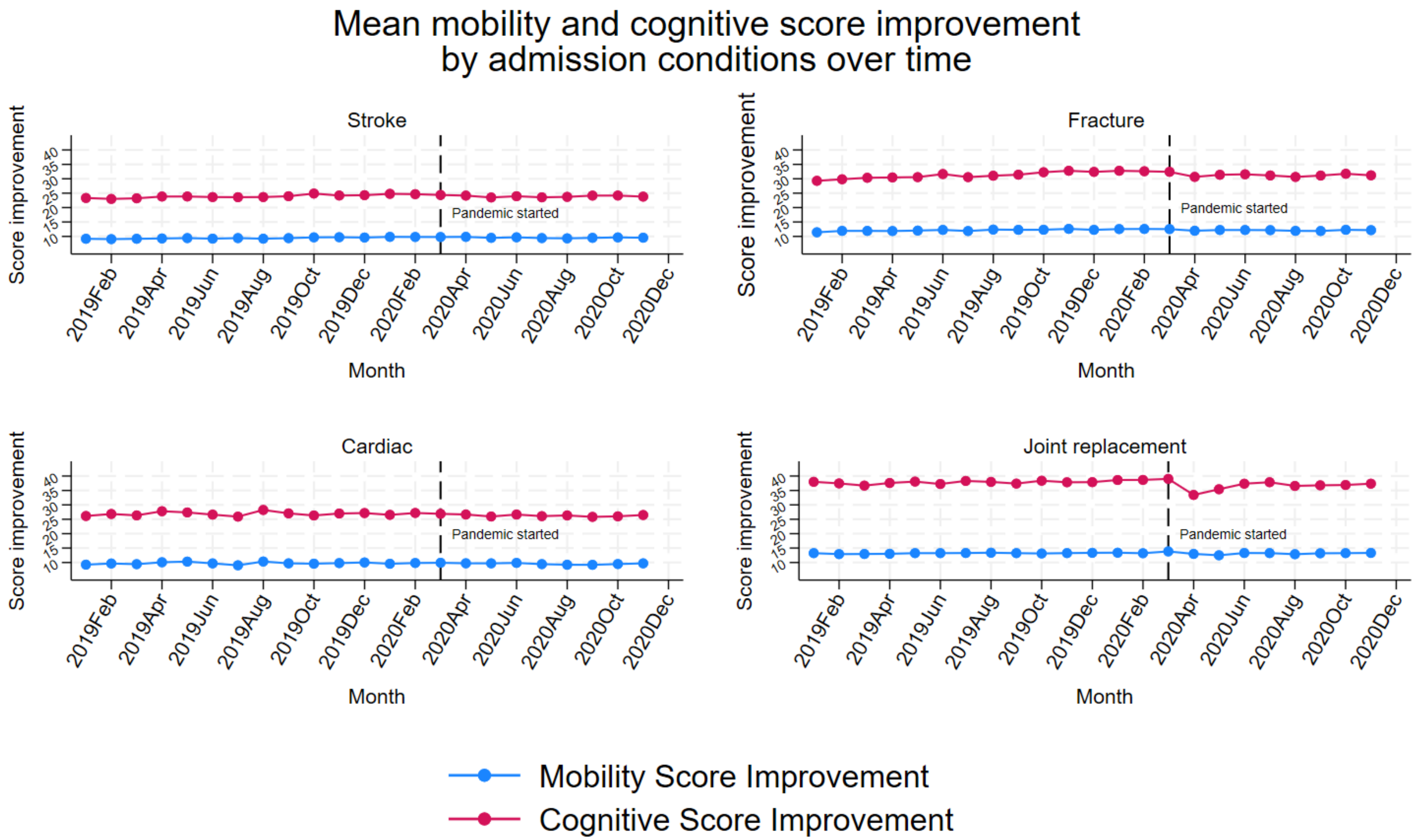

Table 1-1: Descriptive statistics of stroke patients among traditional Medicare beneficiaries

TM N=85,737	Pre-pandemic	N=53,789	During-pandemic	N=31,948	
	Mean	**SD**	**Mean**	**SD**	**P-value**
Age	77.33	0.03	77.29	0.04	0.471
Certified Beds	48.52	0.15	48.73	0.19	0.372
	N	**%**	**N**	**%**	
Gender					
Male	26,182	48.68	15,663	49.03	0.320
Female	27,607	51.32	16,285	50.97	
Race					
NH White	43,863	81.55	26,422	82.7	0.000
NH Black	5,969	11.1	3,321	10.4	
Hispanic	2,209	4.11	1,169	3.66	
Other	1,748	3.25	1,036	3.24	
Marital Status					
With a partner	26,963	50.13	15,956	49.94	0.603
Without a partner	26,826	49.87	15,992	50.06	
Dual Coverage					
No	49,203	91.47	29,269	91.61	0.000
Yes	4,586	8.53	2,679	8.39	
CMG					
101	3,786	7.04	1,676	5.25	0.000
102	8,182	15.21	4,189	13.11	
103	14,988	27.86	8,204	25.68	
104	9,283	17.26	5,630	17.62	
105	4,032	7.5	2,798	8.76	
106	13,518	25.13	9,451	29.58	
Tier					
None	28,553	53.08	15,965	49.97	0.000
Major	1,199	2.23	769	2.41	
Medium	677	1.26	474	1.48	
Minor	23,360	43.43	14,740	46.14	
Facility type					
Freestanding	30,096	55.95	17,616	55.14	0.021
Unit in hospital	23,693	44.05	14,332	44.86	
Region					
P01	3,107	5.78	1,835	5.74	0.000
P02	2,805	5.21	1,575	4.93	
P03	6,594	12.26	4,185	13.1	
P04	11,840	22.01	6,901	21.6	
P05	7,854	14.6	4,505	14.1	
P06	9,009	16.75	5,404	16.91	
P07	3,305	6.14	1,994	6.24	
P08	1,809	3.36	1,197	3.75	
P09	5,793	10.77	3,304	10.34	
P10	1,673	3.11	1,048	3.28	

Table 1-2: Descriptive statistics of hip fracture patients among traditional Medicare beneficiaries

TM N=54,763	Pre-pandemic	N=31,817	During-pandemic	N=22,946	
	Mean	**SD**	**Mean**	**SD**	**P-value**
Age	80.25	0.04	80.46	0.05	0.001
Certified Beds	47.77	0.19	47.10	0.22	0.020
	N	**%**	**N**	**%**	
Gender					
Male	9,694	30.47	7,008	30.54	0.854
Female	22,123	69.53	15,938	69.46	
Race					
NH White	29,099	91.46	21,160	92.22	0.000
NH Black	944	2.97	680	2.96	
Hispanic	1,122	3.53	665	2.90	
Other	652	2.05	441	1.92	
Marital Status					
With a partner	14,113	44.36	9,979	43.49	0.044
Without a partner	17,704	55.64	12,967	56.51	
Dual Coverage					
No	29,694	93.33	21,468	93.56	0.281
Yes	2,123	6.67	1,478	6.44	
CMG					
701	3,174	9.98	1,656	7.22	0.000
702	6,523	20.50	3,736	16.28	
703	11,300	35.52	7,856	34.24	
704	10,820	34.01	9,698	42.26	
Tier					
None	19,002	59.72	12,719	55.43	0.000
Major	782	2.46	588	2.56	
Medium	2,004	6.30	1,669	7.27	
Minor	10,029	31.52	7,970	34.73	
Facility type					
Freestanding	17,045	53.57	12,413	54.10	0.224
Unit in hospital	14,772	46.43	10,533	45.90	
Region					
P01	1,686	5.30	1,255	5.47	0.000
P02	1,551	4.87	977	4.26	
P03	3,825	12.02	2,763	12.04	
P04	8,248	25.92	5,980	26.06	
P05	2,696	8.47	2,034	8.86	
P06	7,689	24.17	5,542	24.15	
P07	1,458	4.58	1,193	5.20	
P08	915	2.88	699	3.05	
P09	3,469	10.90	2,259	9.84	
P10	280	0.88	244	1.06	

Table 1-3: Descriptive statistics of cardiac patients among traditional Medicare beneficiaries

TM N=28,151	Pre-pandemic Mean	N=17,871 SD	During-pandemic Mean	N=10,280 SD	P-value
Age	78.25	0.05	78.04	0.07	0.016
Certified Beds	50.73	0.25	49.71	0.33	0.014
	N	**%**	**N**	**%**	
Gender					
Male	9,684	54.19	5,529	53.78	0.512
Female	8,187	45.81	4,751	46.22	
Race					
NH White	15,496	86.71	9,014	87.68	0.127
NH Black	1,475	8.25	783	7.62	
Hispanic	571	3.2	301	2.93	
Other	329	1.84	182	1.77	
Marital Status					
With a partner	8,575	47.98	4,787	46.57	0.022
Without a partner	9,296	52.02	5,493	53.43	
Dual Coverage					
No	16,437	91.98	9,457	91.99	0.956
Yes	1,434	8.02	823	8.01	
CMG					
1401	2,493	13.95	1,141	11.1	0.000
1402	6,714	37.57	3,518	34.22	
1403	4,878	27.3	2,843	27.66	
1404	3,786	21.19	2,778	27.02	
Tier					
None	6,104	34.16	3,114	30.29	0.000
Major	1,028	5.75	680	6.61	
Medium	1,608	9	1,048	10.19	
Minor	9,131	51.09	5,438	52.9	
Facility type					
Freestanding	9,147	51.18	5,494	53.44	0.000
Unit in hospital	8,724	48.82	4,786	46.56	
Region					
P01	867	4.85	500	4.86	0.000
P02	656	3.67	351	3.41	
P03	2,044	11.44	1,248	12.14	
P04	5,335	29.85	2,945	28.65	
P05	2,535	14.18	1,511	14.7	
P06	3,523	19.71	1,937	18.84	
P07	898	5.02	621	6.04	
P08	257	1.44	236	2.3	
P09	1,574	8.81	828	8.05	
P10	182	1.02	103	1	

Table 1-4: Descriptive statistics of joint replacement patients among traditional Medicare beneficiaries

TM N=15,551	Pre-pandemic Mean	N=10,505 SD	During-pandemic Mean	N=5,046 SD	P-value
Age	75.87	0.07	76.18	0.10	0.008
Certified Beds	52.56	0.33	50.46	0.47	0.000
	N	**%**	**N**	**%**	
Gender					
Male	3,640	34.65	1,814	35.95	0.112
Female	6,865	65.35	3,232	64.05	
Race					
NH White	9,123	86.84	4,494	89.06	0.000
NH Black	733	6.98	306	6.06	
Hispanic	340	3.24	146	2.89	
Other	309	2.94	100	1.98	
Marital Status					
With a partner	5,117	48.71	2,442	48.39	0.713
Without a partner	5,388	51.29	2,604	51.61	
Dual Coverage					
No	9,805	93.34	4,736	93.86	0.218
Yes	700	6.66	310	6.14	
CMG					
801	2,320	22.08	748	14.82	0.000
802	2,063	19.64	793	15.72	
803	2,250	21.42	1,103	21.86	
804	2,405	22.89	1,326	26.28	
805	1,467	13.96	1,076	21.32	
Tier					
None	6,153	58.57	2,817	55.83	0.003
Major	98	0.93	56	1.11	
Medium	276	2.63	167	3.31	
Minor	3,978	37.87	2,006	39.75	
Facility type					
Freestanding	4,371	41.61	2,317	45.92	0.000
Unit in hospital	6,134	58.39	2,729	54.08	
Region					
P01	398	3.79	224	4.44	0.000
P02	662	6.3	234	4.64	
P03	1,537	14.63	760	15.06	
P04	1,896	18.05	906	17.95	
P05	858	8.17	382	7.57	
P06	3,076	29.28	1,515	30.02	
P07	494	4.7	282	5.59	
P08	351	3.34	191	3.79	
P09	1,081	10.29	455	9.02	
P10	152	1.45	97	1.92	

Table 2-1: IV regression results of the association between LOS and mobility & cognitive score improvement among stroke patients

	Mobility Score Improvement	**Cognitive Score Improvement**
2nd Stage	Coefficient (SE)	Coefficient (SE)
LOS	0.440***	0.898***
	(0.018)	(0.039)
1st Stage	IRR	95% CI
Expected LOS	1.058***	(1.058, 1.059)
Predicted Mean of functional improvement	9.756	24.268
Relative Change of functional improvement for 1 unit (day) increase in LOS	4.51%	3.70%
Observation	85,737	85,737

Models are controlled for necessary clinical factors, demographics, facility factors, and regional factors
***p < 0.01; **p < 0.05; *p < 0.10.

Table 2-2: IV regression results of the association between LOS and mobility & cognitive score improvement among hip fracture patients

	Mobility Score Improvement	**Cognitive Score Improvement**
2nd Stage	Coefficient (SE)	Coefficient (SE)
LOS	0.567***	0.943***
	(0.094)	(0.210)
1st Stage	IRR	95% CI
Expected LOS	1.060***	(1.059, 1.061)
Predicted Mean of functional improvement	12.606	31.843
Relative Change of functional improvement for 1 unit (day) increase in LOS	4.50%	2.96%
Observation	54,763	54,763

Models are controlled by necessary clinical factors, demographics, facility factors, and regional factors
***p < 0.01; **p < 0.05; *p < 0.10.

Table 2-3: IV regression results of the association between LOS and mobility & cognitive score improvement among cardiac patients

	Mobility Score Improvement	**Cognitive Score Improvement**
2nd Stage	Coefficient (SE)	Coefficient (SE)
LOS	0.475***	0.832***
	(0.149)	(0.309)
1st Stage	IRR	95% CI
Expected LOS	1.069***	(1.068, 1.071)
Predicted Mean of functional improvement	10.800	28.518
Relative Change of functional improvement for 1 unit (day) increase in LOS	4.39%	3.16%
Observation	28,151	28,151

Models are controlled for necessary clinical factors, demographics, facility factors, and regional factors
***p < 0.01; **p < 0.05; *p < 0.10.

Table 2-4: IV regression results of the association between LOS and mobility & cognitive score improvement among joint replacement patients

	Mobility Score Improvement	**Cognitive Score Improvement**
2nd Stage	Coefficient (SE)	Coefficient (SE)
LOS	0.089	0.493**
	(0.100)	(0.230)
1st Stage	IRR (SE)	95% CI
Expected LOS	1.083***	(1.080, 1.085)
Predicted Mean of functional improvement	13.818	38.267
Relative Change of functional improvement for 1 unit (day) increase in LOS	0.64%	3.16%
Observation	15,551	15,551

Models are controlled for necessary clinical factors, demographics, facility factors, and regional factors
***p < 0.01; **p < 0.05; *p < 0.10.

Table 3-1: IV analysis results of the association between LOS and the discharge location among stroke patients

2nd Stage	**Multinomial Logistic Regression** RRR (95% CI)	**Multinomial Probit Regression** Coefficient (SE)
LOS		
Home	Reference	Reference
Home Health	1.051***	0.037***
	(1.037, 1.065)	(0.005)
SNF	1.069***	0.043***
	(1.052, 1.086)	(0.006)
Others	0.809***	-0.127***
	(0.793, 0.825)	(0.007)
1st Stage	IRR	95% CI
Expected LOS	1.058***	(1.058, 1.059)
Observation	85,737	85,737

Models are controlled for necessary clinical factors, demographics, facility factors, and regional factors
***p < 0.01; **p < 0.05; *p < 0.10.

Table 3-2: IV analysis results of the association between LOS and the discharge location among hip fracture patients

	Multinomial Logistic Regression	**Multinomial Probit Regression**
2nd Stage	RRR (95% CI)	Coefficient (SE)
LOS		
Home	Reference	Reference
Home Health	1.018	0.006
	(0.948, 1.094)	(0.027)
SNF	0.956	-0.012
	(0.872, 1.049)	(0.032)
Others	0.661***	-0.240***
	(0.586, 0.746)	(0.038)
1st Stage	IRR	95% CI
Expected LOS	1.060***	(1.059, 1.061)
Observation	54,763	54,763

Models are controlled for necessary clinical factors, demographics, facility factors, and regional factors
***p < 0.01; **p < 0.05; *p < 0.10.

Table 3-3: IV analysis results of the association between LOS and the discharge location among cardiac patients

2nd Stage	**Multinomial Logistic Regression** RRR (95% CI)	**Multinomial Probit Regression** Coefficient (SE)
LOS		
Home	Reference	Reference
Home Health	0.921*	-0.080**
	(0.846, 1.002)	(0.033)
SNF	1.051	0.019
	(0.914, 1.208)	(0.045)
Others	0.731***	-0.176***
	(0.647, 0.827)	(0.041)
1st Stage	IRR	95% CI
Expected LOS	1.069***	(1.068, 1.071)
Observation	28,151	28,151

Models are controlled for necessary clinical factors, demographics, facility factors, and regional factors
***p < 0.01; **p < 0.05; *p < 0.10.

Table 3-4: IV analysis results of discharge location of joint replacement patients among traditional Medicare beneficiaries

2nd Stage	**Multinomial Logistic Regression** RRR (95% CI)	**Multinomial Probit Regression** Coefficient (SE)
LOS		
Home	Reference	Reference
Home Health	1.065*	0.044
	(0.996, 1.138)	(0.027)
SNF	1.117*	0.071*
	(0.990, 1.261)	(0.040)
Others	0.913	-0.016
	(0.786, 1.061)	(0.045)
1st Stage	IRR (SE)	95% CI
Expected LOS	1.083***	(1.080, 1.085)
Observation	15,551	15,551

Models are controlled for necessary clinical factors, demographics, facility factors, and regional factors
***p < 0.01; **p < 0.05; *p < 0.10.

Table 4-1: IV analysis results of the association between LOS and successfully returning to community after discharge among stroke patients

2nd Stage	Logistic Regression OR (95% CI)	Linear Probability Regression Coefficient (SE)	Probit Regression Coefficient (SE)
Return to community (Yes=1)			
LOS	1.073***	0.016***	0.042***
	(1.061, 1.084)	(0.001)	(0.003)
1st Stage	IRR	95% CI	
Expected LOS	1.058***	(1.058, 1.059)	
Observation	85,737	85,737	85,737

Models are controlled for necessary clinical factors, demographics, facility factors, and regional factors
***p < 0.01; **p < 0.05; *p < 0.10.

Table 4-2: IV analysis results of the association between LOS and successfully returning to community after discharge among hip fracture patients

2nd Stage	Logistic Regression OR (95% CI)	Linear Probability Regression Coefficient (SE)	Probit Regression Coefficient (SE)
Return to community (Yes=1)			
LOS	1.199***	0.0005	0.082***
	(1.129, 1.274)	(0.005)	(0.018)
1st Stage	IRR	95% CI	
Expected LOS	1.060***	(1.059, 1.061)	
Observation	54,763	54,763	54,763

Models are controlled for necessary clinical factors, demographics, facility factors, and regional factors
***p < 0.01; **p < 0.05; *p < 0.10.

Table 4-3: IV analysis results of the association between LOS and successfully returning to community after discharge among cardiac patients

2nd Stage	Logistic Regression OR (95% CI)	Linear Probability Regression Coefficient (SE)	Probit Regression Coefficient (SE)
Return to community (Yes=1)			
LOS	1.095**	-0.0011	0.036
	(1.010, 1.186)	(0.005)	(0.023)
1st Stage	IRR	95% CI	
Expected LOS	1.069***	(1.068, 1.071)	
Observation	28,151	28,151	28,151

Models are controlled for necessary clinical factors, demographics, facility factors, and regional factors
***p < 0.01; **p < 0.05; *p < 0.10.

Table 4-4: IV analysis results of the association between LOS and successfully returning to community after discharge among joint replacement patients

2nd Stage	Logistic Regression OR (95% CI)	Linear Probability Regression Coefficient (SE)	Probit Regression Coefficient (SE)
Return to community (Yes=1)			
LOS	1.012	0.0016	0.003
	(0.926, 1.106)	(0.0045)	(0.024)
1st Stage	IRR (SE)	95% CI	
Expected LOS	1.083***	(1.080, 1.085)	
Observation	15,551	15,551	15,551

Models are controlled for necessary clinical factors, demographics, facility factors, and regional factors
***p < 0.01; **p < 0.05; *p < 0.10.