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DEDICATION

To my parents.

For all your love and support.

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ABSTRACT

Health care expenditures in the United States currently exceed $3 trillion with almost 1/3rd paid by the federal government. With the rising costs of health care, policymakers are increasingly concerned about the value of expenditures. In particular, a high degree of variation in expenditures in the post-acute care setting has led many to believe that post-acute care may be the next frontier in controlling health care expenditures, and nursing homes account for about half of all post-acute care expenditures. Furthermore, policymakers are skeptical about the dramatic improvements in nursing home quality following the release of 5-star rating system in 2008, with some questioning if the improvements are real. Finally, there are concerns about health inequalities between different caste/ethnicity groups and potential repercussions in developing countries. This dissertation informs these concerns by exploring the following three specific questions: 1) do patients admitted to high-spending skilled nursing facilities (SNFs) for their post-acute care needs have improved health outcomes and expenditures?, 2) are the improvements in reported staffing quality corroborated by increases in nursing home expenditures following the release of 5-star rating system?, and 3) what are the trends in malnutrition inequalities between the marginalized communities (Dalits) and non-marginalized communities (non-Dalits) in Nepal and what factors, if any, account for the malnutrition inequalities?

We use several data sources and advanced econometric methods to answer different questions in this dissertation. In Chapter 2, we identify Medicare fee-for-service patients admitted to SNFs using Medicare claims data. Using differential distance as an instrument to account for patient selection into high-spending vs. low-spending SNFs, we estimate the causal

effect of admission to high-spending SNFs on patient outcomes and expenditures. We examined the relationship between admission to high-spending SNFs and outcomes using multivariate regressions with/without instrumental variables including two-stage least squares regressions, multinomial regressions, and generalized linear models. We find that patients admitted to high-spending SNFs are significantly less likely to be rehospitalized within 30, 90, and 180 days following the SNF admission but there is no difference in mortality. Despite a reduction in rehospitalization, total SNF and hospital expenditures during the 30, 90, and 180 days are higher for those admitted to high-spending SNFs vs. low-spending SNFs; the increased spending for the post-acute care stay more than offsets the reduction in spending from fewer hospitalizations. While there may be other outcomes of interest (for example, changes in functional status) that we may care about, from Medicare's perspective, the returns to additional expenditures on post-acute care in SNFs appear low in terms of rehospitalization and mortality.

In Chapter 3, we obtain publicly available data on nursing home expenditures and previously unreleased data on nursing home staffing from the CMS to analyze the relationship between expenditures and staffing. Using facility and year fixed-effects regressions, we estimate the relationship between changes in expenditures and changes in staffing scores within facilities pre. vs. post-5-star period. We find that the relationship between expenditures and licensed practical nurses (LPN) staffing is weaker in the post-5-star period in the overall sample, as well as across multiple subgroups. In addition, we observe a weaker relationship between expenditures and registered nurses (RN) staffing among for-profit facilities with a high share of Medicaid residents in the post-5-star period. The finding that the relationship between expenditures and staffing is weaker in the post-5-star era is concerning as it suggests the potential for gaming of self-reported staffing scores. While the Centers for Medicare and

Medicaid Services (CMS) has instituted a more robust reporting system for staffing through the payroll system in recent years to address potential gaming, our findings suggest a need to continue monitoring staffing data in nursing homes.

Finally, in Chapter 4 we use data on children below the age of 5 from the Demographic and Health Survey for Nepal for 2006, 2011, and 2016 to examine malnutrition inequalities between marginalized communities (Dalits) and non-marginalized communities (non-Dalits). We find that malnutrition inequality between Dalits and non-Dalits has declined substantially from 2006 to 2016. Furthermore, using Blinder-Oaxaca decomposition techniques, we find that the differences in family education and wealth account for most of the difference in malnutrition inequality across all years. Although it is encouraging that malnutrition inequality between these two groups has declined in recent years, differences in the levels of education and wealth remain. Policies designed to narrow the gaps in education and wealth are important if we are to further address malnutrition inequalities between Dalit and non-Dalit groups in Nepal.

The work presented in this dissertation has important policy implications for the health care system in the United States and Nepal. Although we did not analyze other outcomes including changes in functional status, a lack of substantial reduction in rehospitalization and no difference in mortality suggests that there are potentially wasteful expenditures in the post-acute care setting and policies designed to lower the length of stay for residents in skilled nursing facilities may lead to lower expenditures for Medicare without impacting patient mortality. Second, we find evidence of potential gaming by nursing homes in the staffing domain of the 5-star rating system for nursing homes. Our findings highlight the importance of continuing efforts to collect more reliable staffing data. Finally, despite reductions in malnutrition inequalities, we find that there are gaps in education and wealth between the Dalits and non-Dalits in Nepal.

Further reductions in malnutrition inequalities between Dalits and non-Dalits may require efforts to narrow the gaps in education and wealth. More specifically, focusing on reducing the gaps in modifiable factors like sanitation, electricity, and transportation services can narrow the remaining disparity in malnutrition.

CHAPTER 1

INTRODUCTION AND MOTIVATION

Rising health care costs, questionable quality improvements in the health care setting, and inequalities in health are growing concerns in the United States and around the world. We need to evaluate ways to contain rising health care costs, examine whether improvements in reported qualities in the health care setting are real, and finally, assess if all groups in society are benefiting from the improvements in health observed over the years.

With health care expenditures exceeding $3 trillion, many policymakers in the United States are focusing on ways to reduce wasteful health care expenditures. A recent study suggested that approximately 34% of the total health care spending in the United States may be wasteful [1]. Since spending patterns vary substantially across geographic and hospital markets with post-acute care services comprising much of this variation, many studies have identified post-acute care as a prime target for cost containment[2,3]. However, a careful analysis of the relationship between expenditures and outcomes in the post-acute care setting is necessary before we can make policy recommendations.

While a number of studies have evaluated the causal impact of either higher hospital spending or hospitals with higher post-acute care spending on mortality [4,5], to our knowledge, robust evidence on the relationship between expenditures and health outcomes in the post-acute care setting is lacking. Skilled nursing facilities (SNFs) take care of about half of all post-acute care residents at a cost of approximately $29.6 billion to Medicare in 2015 [6]. Hospitalization and mortality are important outcomes for individuals sent to SNFs for their post-acute care needs; about a quarter of residents discharged to nursing homes die within one year [7] while a quarter of post-acute care residents get re-hospitalized within 30 days [8] with avoidable hospitalizations costing Medicare as much as $450 million a year [9]. A comprehensive evaluation of whether hospitalizations, mortality, and Medicare expenditures differ for individuals with post-acute care needs admitted to high-spending SNFs vs. low-spending SNFs will give us with evidence to make policy recommendations.

As our health care system gets more complex, policymakers have also focused on improving quality provided in health care settings. In particular, Medicaid and Medicare cover a large portion of expenditures for nursing home residents and these programs have an incentive to promote increased efficiency and quality of care in nursing homes. As part of its effort to improve quality of care in nursing homes, the Centers for Medicare & Medicaid Services (CMS) started publicizing information on nursing home quality in 1998 through the Nursing Home Compare website. In late 2008, CMS simplified the reporting system by assigning star ratings to nursing homes (one to five stars, with five stars indicating the highest level of quality). These included both overall ratings and ratings specific to regulatory deficiencies, clinical quality, and staffing ratios.

After 2008, there was a rapid increase in the number of higher-rated nursing homes. For instance, there was a considerable increase in the number of facilities with a 4-star rating for staffing, increasing from 31% to 38% between 2008 and 2010 while those with a 1-star rating for staffing decreased dramatically from 23% to 15% during the same period[10]. The rapid improvements in reported quality following the release of 5-star system, particularly in the staffing and clinical quality domains that are based on self-reported data, have raised some concerns as to whether the quality improvements are real. An article published in The New York Times suggested that nursing homes are not only able to manipulate self-reported quality measures but that they also often anticipate and can better prepare themselves for inspections, potentially temporarily adding staff [10]. Although The New York Times article pointed to potential gaming, more robust evidence on gaming by nursing homes is lacking. An assessment of presence or lack of gaming in the 5-star rating system will allow us to come up with policies to enhance the reliability and validity of the 5-stars rating system for nursing homes.

Finally, countries around the world have seen tremendous improvements in health over the last several decades. However, policymakers are worried that the distribution of the improvements in health may not be equal across different groups of people. In particular, developing countries like Nepal have undergone a rapid improvement in health over the years but also face inequalities in health across caste/ethnic groups. Marginalized communities in Nepal, often known as "Dalits", have been excluded from the socio-political system for a long time and lag behind in key markers of progress including education and wealth when compared with non-marginalized communities. These gaps in education and wealth have real implications for health. One of the consequences of such marginalization of some caste groups is evident in child health outcomes. Although Nepal has seen a decline in the prevalence of child malnutrition, about 41% of children under the age of 5 still suffer from stunting in 2011 [11] and stunting prevalence is about 31% for the hill Brahmins, a more privileged class in Nepali society, compared with 51% for the hill Dalits, a traditionally marginalized group [11].

In order to design appropriate policies to reduce health inequalities, we need to understand the determinants of health inequality. Health inequality is not only about income; redistribution of income from the rich to the poor will not remove all the inequality [12]. For example, the marginalized communities not only have low income but also lack good education. The marginalized communities face worse health not only because they are disadvantaged in the determinants of health but also because the returns to determinants like education might be lower. Furthermore, there is a concern that the gap between marginalized communities and others may be growing over time. It is important to observe the changes in health inequalities over time and the contributing factors in order to design policies to address inequalities in health.

The work presented in this dissertation uses advanced econometric methods to evaluate the problems related to rising health care costs in the United States, questionable quality improvements in nursing homes in the United States, and health inequalities between Dalits and non-Dalits in Nepal. Three chapters of the dissertation will delve into each of these questions. More specifically, in Chapter 2, we evaluate whether patients admitted to high-spending skilled nursing facilities (SNFs) for their post-acute care needs have better health outcomes and expenditures. In Chapter 3, we examine whether the improvements in reported staffing quality are corroborated by increases in nursing home expenditures following the release of 5-star rating system. Finally, in Chapter 4, we assess the trends in malnutrition inequalities between marginalized communities (Dalits) and non-marginalized communities (non-Dalits) in Nepal and identify important factors that account for the malnutrition inequalities.

CHAPTER 2

DOES SPENDING MORE ON POST-ACUTE CARE IN SKILLED NURSING FACILITIES IMPROVE PATIENT OUTCOMES?

ABSTRACT

Policymakers in the United States are increasingly concerned about growth in health care expenditures, especially expenditures that are potentially wasteful. Post-acute care has been identified as a key target for cost containment given the substantial geographic variation in post-acute care expenditures; some reports suggest that geographic variation in Medicare spending would decrease by 73% if we were to eliminate variation in post-acute care spending. In particular, policymakers acknowledge that current payment policies to skilled nursing facilities (SNFs) may incentivize higher therapy use and longer patient stays. Increased spending may or may not be wasteful depending on the resulting level of improvement in health outcomes. Evaluation of the returns to higher spending are essential, yet comparison of patient outcomes among high-spending vs. low-spending SNFs may be biased by unmeasured differences in patient need.

In this paper, we use differential distance as an instrument to account for patient selection into high-spending vs. low-spending SNFs to estimate the causal effect of admission to high-spending SNFs on patient outcomes and expenditures. We find that patients admitted to high-spending SNFs are significantly less likely to be rehospitalized within the 30, 90, and 180 days following the SNF admission but there is no difference in mortality. Despite a reduction in rehospitalization, total SNF and hospital expenditures during the 30, 90, and 180 days are higher for those admitted to high-spending SNFs vs. low-spending SNFs; the increased spending for the post-acute care stay more than offsets the reduction in spending from fewer hospitalizations.

While there may be other outcomes of interest (for example, changes in functional status) that we may care about, from Medicare's perspective, the returns to additional expenditures on post-acute care in SNFs appear low in terms of rehospitalization and mortality.

INTRODUCTION

There is growing concern about wasteful spending in health care in the United States as total health care expenditures soared to $3 trillion in 2014, with 28 percent of this expenditure borne by the federal government[13]. A recent study suggested that approximately 34% of the total health care spending in the United States may be wasteful [1]. However, spending patterns vary substantially across geographic and hospital markets. Post-acute care services comprise much of this variation [14]; a recent IOM report claimed that Medicare spending variation would decrease by 73% if there was no geographic variation in post-acute care spending [15]. Accordingly, several studies have identified post-acute care as a prime target for cost containment [2,3].

Although Medicare pays for fewer than 20% of nursing home residents at any given point in time, it is a major source of payment for the initial three months of a nursing home stay following a hospitalization; approximately 40% of the Medicare beneficiaries discharged from acute care hospitals use some type of post-acute care services in the 30 days after discharge, and about half of these go to skilled nursing facilities (SNFs) [8]. Medicare pays 100% of costs on a per diem basis adjusted for case-mix for the first 20 days in a nursing facility following a qualified hospital stay after which there is a coinsurance for the next 80 days; coinsurance was about $157 per day for 2015. [16] After 100 total days in a nursing facility, the patient is responsible for financing the additional time spent on a nursing home. Certain therapies and other ancillary services are paid separately by Medicare. Medicare spent approximately $29.6 billion on post-acute care in about 15,000 SNFs in 2015 [6]. In order to design appropriate policies to contain growing post-acute care expenditures, causal evidence on the value of health care expenditures in the post-acute care setting is needed. Furthermore, current payment reforms including bundled payments and the Hospital Readmission Reduction Program (HRRP) give hospitals and Accountable Care Organizations (ACOs) increasingly greater incentive to seek SNFs with lower spending and/or lower readmission rates. Hospitals and ACOs need to understand the relationship between post-acute care spending and health outcomes to identify SNFs that best meet their needs.

A number of studies have evaluated the causal impact of either higher hospital spending or hospitals with higher post-acute care spending on mortality [4,5]. However, to our knowledge, there are no studies in the literature that have evaluated the outcomes of patients admitted to SNFs with respect to the spending levels of the SNFs themselves. In particular, hospitalization and mortality are important outcomes for individuals sent to SNFs for their post-acute care needs; about a quarter of residents discharged to nursing homes die within one year [7] while a quarter of post-acute care residents get re-hospitalized within 30 days [8] with avoidable hospitalizations costing Medicare as much as $450 million a year [9]. In this paper, we begin to fill this gap by evaluating whether hospitalizations, mortality, and Medicare expenditures differ for individuals with post-acute care needs admitted to high-spending SNFs vs. low-spending SNFs.

There are two main ways that patients in a high-spending SNF could have higher average Medicare spending than similar patients in a low-spending SNF: longer length of stay, and higher reimbursement per day.[1] Resource utilization groups (RUGs) based on clinical severity and therapy need determine reimbursements per day. Since SNFs are paid a fixed amount per day based on RUGs, they have an incentive to keep patients longer. Longer length of stay, when appropriate, could better prepare patients for post-discharge life in the community and might

[1] Here, we are assessing Medicare reimbursements to SNFs rather than the actual cost of care to the SNFs.

improve health outcomes. Similarly, higher intensity therapy may result in better outcomes if patients need the therapy. However, higher intensity therapies have higher profit margins [17] which may incentivize SNFs to provide higher intensity therapy even when patients don't need it; such practices may not lead to improved outcomes. In a study conducted by the Office of the Inspector General, 22 percent of the RUG groups assigned by nursing homes were associated with higher payments than those that were determined based on the medical record resulting in approximately $542 million in additional expenditures to Medicare in 2002 [18]. Given these payment incentives, which may lead to wasteful spending, it is unclear whether individuals admitted to high-spending SNFs will have better outcomes in terms of lower rehospitalizations, mortality, and Medicare expenditures.

In order to estimate the causal impact of admission to high-spending SNFs for post-acute care on patient outcomes, we classify SNFs into high-spending or low-spending status based on the ratio of average observed spending over average expected spending; expected spending is based on patient and prior hospital characteristics as well as geographical differences in wages. Our method identifies SNFs that are high-spending or low-spending given its mix of patients. We use an instrumental variables approach to "pseudo-randomize" individuals to high- and low-spending SNFs to address potential endogeneity concerns. Finally, we use different estimation techniques with and without instrumental variables including least squares and multinomial logit models to evaluate rehospitalization and mortality risk, and generalized linear models to estimate Medicare expenditures.

We find that individuals admitted to high-spending SNFs have fewer rehospitalizations at 30, 90, and 180 days post-admission, but there is no difference in mortality. In addition, we find that individuals admitted to high-spending SNFs have significantly higher Medicare expenditures (hospital and SNF combined) relative to those admitted to low-spending SNFs in 30, 90, and 180 days following admission to the SNFs; the increased spending in post-acute care stay more than offsets any reductions in spending associated with fewer rehospitalizations. These findings have several policy implications including the need for payment reforms to better align Medicare and provider incentives, such as bundled payments that create accountability for Medicare expenditures throughout the health care system. Furthermore, the difference in spending is much larger at 90 days and 180 days than at 30 days following admission to the SNFs suggesting that 30-day episodes for payments and penalties may not be optimal.

LITERATURE AND CONCEPTUAL FRAMEWORK

Related Literature

There is a growing interest in the relationship between spending and health outcomes, but the evidence is mixed. Furthermore, most studies of this issue evaluate spending status at the geographic level or hospital level. Using spending variation at the geographic level, a national study of Medicare beneficiaries found no evidence that Medicare beneficiaries in high spending areas have better quality of care, access, or health outcomes [19,20]; the authors used the end-of-life expenditures to define high-spending vs. low-spending areas. In contrast, using hospital spending variation, several other studies found that high-spending hospitals are associated with lower mortality, readmissions, and cardiac events [21,22]; both of these studies used end-of-life expenditure to determine the spending status of hospitals. It is important to note that these studies are based on the assumption that area-level or hospital-level end-of-life expenditures are unrelated to illness levels of patients.

Similarly, a recent study evaluated differences in patient access, quality, and total spending between high-price physician practices vs. low-price physician practices and found that the high- vs. low-price physician practices did not differ on the use of acute care services and total Medicare spending [23]. They used the prices negotiated with commercial insurers to identify high- vs. low-price physician practices. This study was cross-sectional in nature and compared physician practices within the same geographic area but may not have been able to adjust for unobserved differences in patients.

Although not directly related to nursing home spending, two key studies in this growing literature used instrumental variables to obtain plausibly unbiased estimates of the impact of hospital spending or hospitals with high post-acute care spending on mortality and readmissions. In a study using ambulance referral patterns to "pseudo-randomize" patients going to high-spending hospitals, the authors found that high-spending hospitals had lower mortality for emergency conditions [4]. The validity of ambulance referral patterns as an instrumental variable relies on the exogeneity in the assignment of ambulance companies and the notion that ambulance companies take their patients to specific hospitals based on their preferences, irrespective of the patient's condition/severity. In another study using ambulance referral patterns, hospitals with higher inpatient spending had lower mortality but hospitals with higher SNF spending were found to have higher mortality [5], raising questions about the value of post-acute care expenditures. Both of these studies underline the important role hospitals and hospital spending plays on patient outcomes. Since the authors evaluated outcomes for hospitals associated with high- vs. low-SNF spending rather than "randomizing" patients into high- vs. low-spending SNFs, the authors are unable to disentangle the underlying mechanisms for higher mortality. It is unclear whether the hospitals with high post-acute care spending are of lower quality or that post-acute care stay in SNFs is harmful. In addition, the authors use data from patients who were hospitalized via ambulance, which may or may not be representative of the broader sample of patients.

Given these findings, it is important to consider why higher spending may or may not improve patient outcomes. In a recent study, researchers sought to obtain the prevalence and factors determining the excessive use of low-value services and found that the use of low-value services was as high as 46.5% for preoperative cardiac testing for low-risk, non-cardiac procedures [24]. Use of more low-value services in some settings (hospitals, nursing homes), areas, or among some providers but not others probably explains part of the reason why estimates of the relationship between spending and health care quality and outcomes appear inconsistent.

Conceptual Framework

The relationship between spending and patient outcomes depends on how much is spent on appropriate patient care. Higher spending on appropriate patient care can result in higher quality of care and subsequently better patient outcomes [25]. In particular, a longer length of stay in a SNF may allow patients to be discharged in a healthier state or to prepare well for self-care in the community after discharge. Similarly, post-acute care patients who are discharged following a surgery, for instance, may benefit from additional therapy. There is some evidence to show that increased therapy is associated with a higher likelihood of discharge to home for patients with hip fracture [26]. However, higher spending on unnecessary care can result in either no difference in patient outcomes or worse, a negative impact on patient outcomes.

While the link between additional spending on appropriate care and patient outcomes is clearer, the motivation behind differential spending on appropriate care by SNFs for similar patients is less clear. On one hand, SNFs have an incentive to keep patients longer and up-code patients to higher resource utilization groups (RUGs) and/or higher therapy groups for larger profits; in fact, some believe that up-coding is partially responsible for an increase in the proportion of patient days in very high therapy RUG groups in recent years [27]. On the other hand, SNFs providing poor quality of care may see a reduction in the number of patients. Since reduction in the number of patients will impact profitability, it is possible that at least part of the additional spending is appropriate. There is some suggestive evidence in this regard; a recent study found a correlation between the growth in therapy staffing in freestanding nursing homes and case-mix acuity, implying that patients were getting more care because they needed it [28]. Finally, SNFs may be unable to increase the length of stay inappropriately because of the preferences of patients and other care coordinators (hospitals, ACOs). Medicare patients face hefty copays after the first 20 days, and SNFs might have a difficult time trying to convince patients to stay longer than 20 days unless patients are unable to transition to a stay in the community. Furthermore, care coordinators, including those employed by hospitals with bundled payments and ACOs, have their own preferences and SNFs may have limited control over the length of stay.

Since the relationship between SNF spending and patient outcomes can be mixed depending on the quality of care provided by the SNFs, whether higher spending in SNFs leads to fewer rehospitalizations and lower mortality and Medicare expenditures is an empirical question. If SNFs are spending more on appropriate care, we might see a positive effect of spending on rehospitalization rates and mortality. Even with improved rehospitalization rates, whether additional spending on post-acute care will decrease combined Medicare expenditures for hospital and SNF stay depends on the amount of reduction in rehospitalization. If the reduction in rehospitalization is small, combined Medicare expenditures may actually be higher for those admitted to high-spending SNFs relative to low-spending SNFs. By comparing similar patients across the country treated at high-spending vs. low-spending SNFs, we can evaluate whether admission to high-spending SNFs improves rehospitalization and mortality rates and lowers Medicare expenditures.

EMPIRICAL FRAMEWORK AND STATISTICAL METHODOLOGY

A major challenge in analyzing the relationship between spending and health outcomes for post-acute care patients is the problem of patient selection. Patients might choose or be sent to particular SNFs based on their preferences and needs. However, many of these determinants of SNF choice are unobservable to the researcher. While some of the differences in patient severity can be adjusted using diagnosis and procedure codes, unobserved differences in patient types will likely remain resulting in biased estimates. For instance, if sicker individuals select high-spending SNFs and have higher mortality, it may appear that admission to high-spending

SNFs leads to higher mortality when we might have observed higher mortality due to their higher disease severity.

In order to evaluate whether SNFs that spend more have better outcomes (e.g., lower hospitalization rates), we need to correct for both observed and unobserved differences in patients across high-spending and low-spending SNFs using appropriate methods. Our approach in this study is to use differential distance as an instrumental variable for SNF choice. If high-spending SNFs are genuinely spending more on appropriate patient care, we should observe better outcomes for high-spending SNFs compared with low-spending SNFs. On the other hand, if most of the expenditures by high-spending SNFs are "overtreatment" or unnecessary treatments, we may not see any substantial value to these additional expenditures. In the next few sections, we describe the data, sample construction, outcome variables, independent variables, and our instrumental variable – differential distance.

Data

The key data sources for our analysis are: Medicare claims data from Medicare Provider Analysis and Review (MedPAR), Master Beneficiary Summary Files (MBSF), LTCfocus, and Medicare Cost reports. MedPAR data have information on patients including gender, race, survival status, and Medicare payments. In addition, MedPAR data has information on the date of admission to providers (SNFs, hospitals) and discharge along with up to 25 diagnostic codes. MBSF files allow for the identification of fee-for-service (FFS) Medicare patients along with information about dual eligibility status.

We obtain nursing home characteristics from LTCfocus data (www.ltcfocus.org). LTCfocus is a dataset compiled at Brown University using multiple data sources (OSCAR/CASPER, Minimum Data Set, and Residential History File). LTCfocus has nursing home level information on facility characteristics including payer mix, occupancy rate, ownership type, chain membership, and size. We obtain hospital characteristics using Medicare cost reports. In particular, we retrieve information on teaching status, receipt of DSH payments, urban location, chain membership, size, total and Medicare discharges, and total and Medicare inpatient days.

In addition to the key datasets mentioned above, we get information on ZIP-code level 5-year average income from the American Community Survey data (2011-15). We gather nursing home wage indices from annual notices in the Federal Register. We also obtain the Consumer Price Index for Medical Care from the Bureau of Labor Statistics.

Finally, we obtain geographic information from two data sources. First, ZIP code distances from the National Bureau of Economic Research (NBER) are used to construct our differential distance measure. NBER ZIP code distance data provides great-circle distances using the Haversine formula based on ZIP-code centroids. Second, we use Dartmouth Atlas data to link ZIP codes to hospital referral regions (HRRs).

Sample Construction

Our sample construction involves a series of steps to identify Medicare fee-for-service patients newly admitted to SNFs for their post-acute care needs. More specifically, we include individuals who are newly admitted to SNFs (i.e., no SNF admission in the past 1 year at the least) and are enrolled in fee-for-service Medicare for the entire period. Furthermore, we require the patients to be at least 66 years of age at the time of admission to the SNFs. All individuals are required to have at least one year of eligibility prior to the admission and at least 3 months following the admission to SNFs. Detailed sample inclusion/exclusion criteria are described in **Appendix Table 19**.

After selecting the core group of patients, we select 10 subgroups of patients identified as high-volume conditions in a recent study [29]: acute myocardial infarction (AMI), heart failure (HF), chronic obstructive pulmonary disease (COPD), gastrointestinal hemorrhage, hip and femur procedures, joint replacements, kidney and urinary tract infections, pneumonia, septicemia, and stroke. The Medicare Severity Diagnostic Related Groups (MS-DRGs) codes used to identify these subgroups are provided in **Appendix Table 20**.

Key Variables

Dependent Variables:

Rehospitalization: We evaluate any rehospitalization within 30, 90, and 180 days following admission to a SNF. A large literature studies hospital readmissions from nursing homes [30,31]. We identify both any-cause readmissions and potentially avoidable readmissions, following a methodology commonly used in the literature. In particular, we combine ambulatory care sensitive conditions with nursing home avoidable conditions to obtain potentially avoidable hospitalizations [32,33]. ICD-9 codes used to identify potentially avoidable hospitalizations are provided in **Appendix Table 21**.

Mortality: Mortality is a particularly important outcome in the nursing home setting given the age and vulnerability of the nursing home population. In our study, we evaluate all-cause mortality in the 30, 90, and 180 days following an admission to the SNFs.

Medicare spending: If a patient's length of stay in high-spending SNFs is longer but leads to reduced rehospitalizations, it is possible that high-spending SNFs save money for Medicare. However, the net effect depends on how much is spent on additional post-acute care and how much is saved from lower rehospitalizations. We generate a measure of Medicare spending by combining post-acute care spending in SNFs with hospital spending in 30, 90, and 180 days following an admission to the SNFs. While our measure of Medicare spending does not capture all Medicare expenditures (e.g., home health expenditures are not available), SNF stay and hospital readmissions account for most of the Medicare expenditures among patients admitted to SNFs following a hospitalization. For instance, SNF stay and hospital readmissions account for approximately 86% of total Medicare expenditures for hip fracture and stroke patients initially admitted to SNFs during the 120 days following discharge from the hospital [31].

Independent Variables:

High-spending vs. low-spending SNFs: As described in the introduction, there are two main ways through which some SNFs spend more than others for similar patients: longer length of stay, and higher reimbursements per day. Medicare pays nursing homes on a per diem basis, incentivizing SNFs to extend patient stays longer. In addition, therapy resource utilization groups (RUG) are generally reimbursed at higher rates than non-therapy RUGs, and high intensity therapies pay more than low-intensity therapies. The margins are higher for the high-therapy groups than low-therapy groups, giving an incentive for SNFs to provide patients with higher therapy intensity.

To capture the variations in spending partly attributable to these incentives, we use the ratio of observed over expected SNFs episode spending to define high-spending vs. low-spending SNFs. Studies commonly use observed/expected ratios to identify different provider types in the literature [34,35]. In our study, we chose Medicare SNF episode spending instead of costs primarily for two reasons: for policy considerations, evaluation of the value of Medicare spending allows us to design alternative payment policies but costs would not, and while Medicare cost reports provide aggregate costs, we do not have disaggregated data on actual costs per patient.

Observed Medicare spending for a given episode in SNFs is obtained directly from the Medicare claims. To obtain expected spending per stay, we use an OLS regression model to predict average spending per-stay in a given SNF after adjusting for the wage index, year, patient case-mix, and discharging hospital characteristics. We adjust for demographic and clinical case-mix to compare spending among Medicare beneficiaries who have similar needs in terms of clinical resources. Patient related variables adjusted in the regression include: demographic variables – age, gender, race, dual eligibility; clinical variables – Elixhauser comorbidities in the prior hospital stay as well as in the past one year; all level two comorbidities and procedures in the prior hospitalization that are 1% or higher in prevalence based on Clinical Classifications Software (CCS) available as part of the Healthcare Cost and Utilization Project (HCUP) sponsored by the Agency for Healthcare Research and Quality (downloaded from: https://www.hcup-us.ahrq.gov/toolssoftware/ccs/ccs.jsp); broader categories of surgeries relevant to the population of interest in the prior hospitalization and the prior year: operations related to the nervous system, respiratory system, cardio-related surgeries, hip and other fracture related surgeries, and amputation; and resource utilization in terms of the number of hospital days in the past one year, and Medicare payment for prior hospitalization. Finally, we also incorporate acute care hospital characteristics as an additional proxy for the patient's potential resource needs – size, teaching status, chain membership, receipt of DSH payments, hospital location, total and Medicare inpatient days, total and Medicare hospital discharges.

After estimating the expenditure regression, we follow standard techniques to exclude outliers and to normalize predictions [5]. In particular, we truncate the predicted expenditures at the 0.5th and 99.5th percentile and normalize the predicted expenditures to ensure that the average expenditures are the same before and after truncation. To exclude outliers, we obtain the difference between observed spending and predicted spending and exclude observations with the difference above 99th and below 1st percentile. Finally, we calculate the ratio of observed over expected spending at the facility level.

In order to create a clear distinction between the high-spending vs. low-spending SNFs, our base analysis removes the SNFs in the middle 20% of the ratio (40th to 60th percentile) and defines high-spending SNFs as those above the 60th percentile and low-spending SNFs as those below the 40th percentile. We conduct sensitivities around this definition by using two alternative samples: all SNFs (over/under 50th percentile), and excluding SNFs in the middle 10% of the ratio (over 55th/under 45th percentile).

Instrumental variable – Differential distance: Differential distance has been used as an instrument to identify the effects of different types of providers in numerous studies in health economics literature [30,31,36,37]. In our study, differential distance measures the distance from the nearest high-spending SNF to the nearest low-spending SNF. Patients may be sent to a SNF based on patient needs, preferences, and some knowledge of the quality of a SNF that is not observed in the data. Thus, there might be unobservable differences in the type of patients going to high-spending vs. low-spending SNFs. However, most families and hospitals are not well-prepared to choose a post-acute care facility that best matches a patient's needs following discharge [38], and the convenience of the nearest SNF often plays a dominant role in patient choice [39].

Several assumptions must be satisfied to ensure instrument validity: stable unit treatment value assumption (SUTVA), independence of outcome, monotonicity, non-zero effect of instrument on treatment, and exogeneity of the instrument [40]. SUTVA requires that there is no interference between units. We have no reason to believe that outcomes for any individuals admitted to high- or low-spending SNFs are affected by other individuals. The independence assumption implies that potential outcomes are independent of the instrument. We have little reason to believe that potential hospitalizations, mortality, and Medicare expenditures are related to our instrument, differential distance. The monotonicity assumption requires that there are no individuals who would attend a high-spending SNF if they have a higher differential distance but would not if they have a lower differential distance. Individuals have a strong preference for closest SNFs and thus, we believe that this assumption should hold in our context. The next assumption- a non-zero effect of instrument on treatment is extremely important. In our context, differential distance should be a strong predictor of whether someone goes to a high-spending SNF since people prefer to go to facilities close to their residence. This assumption about non-zero effect of the instrument on treatment can be tested empirically and we provide the first-stage F-statistics for our instrument. The exclusion restriction implies that any effect of the instrument on outcome should be only through the treatment. In our case, the effect of differential distance on hospitalization, for example, should only come through the treatment in a high-spending SNF. We do not believe that differential distance in itself or through factors other than the treatment facility causes hospitalization of patients living in a SNF. Although we cannot empirically test the validity of the instrument, we can examine the observable characteristics by differential distance. If the characteristics are similar, this lends credibility to the ability of our instrument to "pseudo-randomize" patients to high-spending and low-spending facilities.

Other independent variables: In addition to the independent variables listed earlier in the regression model to identify high-spending and low-spending SNFs, we additionally control for variables that may be related to both spending status and health outcomes. To control for confounding due to SNF characteristics that may be related to their high-spending status and patient outcomes, we include the following nursing home characteristics – profit status, chain membership, occupancy percentage, size, payer mix. Similarly, patient income may be related to where they go for post-acute care and outcomes. So, we additionally control for ZIP-code level income. These control variables, in addition to those described earlier, largely capture the potential confounders identified in a recent study with reference to the use of distance to a facility as an instrumental variable [41].

Statistical Analyses

We begin with a descriptive analysis of facilities and patient characteristics. We report SNF characteristics, hospital characteristics, as well as average length of stay and spending by high-spending status and differential distance. We also summarize patient characteristics including age, race, gender, and comorbidities by high-spending status and differential distance. In order to assess the differences in SNF, hospital, and patient characteristics between the two groups (e.g., high-spending vs. low-spending), we calculate standardized differences between the two groups as the difference in mean divided by the pooled standard deviation.

$$Standardized\ difference = \frac{\overline{\mathrm{Group}_{highspending}} - \overline{Group_{lowspending}}}{Std_{pooled}}$$

Next, we use a variety of estimation techniques and specifications to assess the impact of admission to high-spending SNFs on readmissions, mortality, and Medicare expenditures. We use different versions of our basic specification given below:

$$Y_i = \alpha + \beta High_j + \delta X_i + \gamma NF_k + \mu Hosp_l + \tau Year_t + \theta FE_f + \varepsilon_i \quad (1)$$

In this model, Y_i represents patient outcome (hospitalization, mortality, and Medicare expenditures); $High_j$ equals 1 if facility j is a high-spending facility, X_i represents a vector of patient level characteristics including age, gender, comorbidities etc., NF_k represents a vector of nursing home characteristics, $Hosp_l$ represents a vector of hospital characteristics, and $Year_t$ represents year fixed effects; FE_f represents hospital or HRR fixed effects; ε is a random error term.

Our base model fits hospital fixed effects regressions with instrumental variables (IV) and without IV (non-IV) for hospitalization and mortality. Even though hospitalization and mortality are binary outcomes and non-linear models are appropriate for such outcomes, estimating non-linear models with a large number of fixed effects leads to the incidental parameters problem [42]. Given that our outcomes are not close to zero, the estimated effects should be similar to the marginal effects from non-linear models. For our base models, we prefer to use hospital fixed effects regressions for non-IV and two-stage least squares (2SLS) with differential distance as the instrumental variable combined with hospital fixed effects for IV regressions. We cluster the standard errors at the hospital level.

Since expenditures tend to be skewed, estimating Medicare expenditures using least squares regressions with fixed effects presents a different problem; linear regressions can result in negative predicted expenditures and large variability in residuals due to the skewness of the data. Generalized linear models (GLM) are commonly used to estimate health care expenditures [43]. We use GLM with log link and hospital referral region (HRR) fixed effects to estimate the impact of admission to high-spending facilities on Medicare expenditures. GLM models can address issues related to heteroscedasticity as well. GLM models without IV can be estimated in a single model but we use 2-stage residual inclusion (2SRI) approach for IV models [44]. For GLM models with IV, we first estimate the first stage with SNF spending status (high or low) as the dependent variable as a function of differential distance as the instrument and all other control variables. From this regression, we obtain the residuals to be used in the second stage. In the second stage, we estimate the expenditures as a function of high-spending status and all other control variables including the residuals from the first stage. We obtain standard errors using the delta method.

Even though we used 2SLS regressions in our base models, estimation of hospitalizations using such regressions ignores mortality as the competing risk. High-spending nursing homes may keep patients alive longer and thus, might give patients more time to get hospitalized. Death is a potential outcome that leads to censoring of patients and failure to account for it can lead to a bias in our estimation [30]. Furthermore, when patients have multiple potential outcomes, separate estimations of these outcomes using logistic regressions can lead to a situation where the total probability exceeds one. In addition, we also have the usual problem of estimating binary outcomes with a linear regression, although this issue may not be problematic given that our outcome mean is much higher than zero. In order to address both issues, we estimate hospitalizations using multinomial logistic regressions with and without IV using hospitalization, death, and neither as three potential outcomes. Again, our basic framework for multinomial logit regression is given below:

$$Y_i = \alpha + \beta High_j + \delta X_i + \gamma NF_k + \mu Hosp_l + \tau Year_t + \theta FE_f \quad (2)$$

Here, Y_i represents one of the three potential outcomes (hospitalization, death, and neither) for individual i. Rest of the variables are as described earlier. In addition, we replace hospital fixed effects with HRR fixed effects. When we have three potential outcomes, equation (2) above involves the estimation of the following two equations:

$$\log\left(\frac{\pi_i^{hosp}}{\pi_i^{neither}}\right) = \alpha^{hosp} + \beta^{hosp} High_{jk} + \cdots \quad (2a)$$

$$\log\left(\frac{\pi_i^{death}}{\pi_i^{neither}}\right) = \alpha^{death} + \beta^{death} High_{jk} + \cdots \quad (2b)$$

Where, π_i^{hosp} is the probability of rehospitalization.

Estimation of multinomial logit models without endogenous variables is straightforward. However, to estimate multinomial logit models with IV, we follow a control function approach using 2-stage residual inclusion method (2SRI). In the literature, 2SRI regressions have become common approaches to handling instrumental variables regressions with binary outcomes and binary endogenous variables [44,45]. In these regressions, instead of predicted values of the dependent variable, residuals from the first stage are replaced in the second stage of the regression.

To explore the timing and type of rehospitalization, we further estimate equation (2) with two types of rehospitalizations: direct vs. after discharge and potentially avoidable vs. potentially unavoidable. These estimations will have 4 categories of potential outcomes for an individual: two categories of rehospitalizations along with death and neither.

Specification Checks

In order to check if the findings from our analyses are sensitive to some of the choices made in our analyses, we conduct a number of robustness checks. These estimations are designed to assess the robustness across time, sample, identification of high-spending status, and definitions of differential distance as an instrumental variable. To see if our findings are sensitive to our choice of 90 days for the outcome measurement, we replicate our main analysis for hospitalizations, mortality, and Medicare expenditures using 2SLS (or GLM for expenditures) framework for outcomes in 30 and 180 days.

Next, we repeat our main analysis using different samples. First, exclude patients from Maryland since the hospitals in Maryland are subject to a different payment system. While evaluation of hospitalization and mortality outcomes may not be problematic, assessment of Medicare expenditures in Maryland vs. rest of the country is not comparable. Second, we evaluate the outcomes for the individuals that are eligible for both Medicare and Medicaid (often known as duals) vs. those that are eligible for only Medicare (non-duals) separately to see if the impact of admission to a high-spending SNF is different in these groups. It is possible that duals may not have the same level of support system at home to continue recovery following discharge from a SNF and a longer SNF stay may be more beneficial for this group than the non-duals. Third, we evaluate the ten common conditions identified using MS-DRGs separately and as a combined group: acute myocardial infarction (AMI), heart failure (HF), chronic obstructive pulmonary disease (COPD), gastrointestinal hemorrhage, hip and femur procedures, joint replacements, kidney and urinary tract infections, pneumonia, septicemia, and stroke.

We also evaluate sensitivities around the identification of high-spending SNFs. First, we exclude SNFs whose observed over expected spending ratio was in the middle 10% (45^{th} to 55^{th} percentile) and repeat our analysis for 90-day outcomes. We expect the impact to be lower in this approach given that the difference in spending ratio is now lower than in our original sample where we exclude the middle 20%. Second, we include all facilities irrespective of their spending ratio. We expect the impact of admission to high-spending facilities to be even lower in this sample. Third, we exclude all patients who stayed in the nursing home beyond 90 days and estimate the ratio of observed over expected spending. In this specification, we further exclude the SNFs that have the ratio in the middle 20% (40^{th} to 60^{th} percentile) to define high-spending status. This approach is similar to our base model but will exclude the patients that are potentially transitioning from post-acute care stay to long stay.

Finally, we estimate two additional sensitivities that change the level of fixed effects and alter the definition of the instrument. First, we analyze our main outcomes using fixed effects at the hospital referral regions (HRR) instead of hospitals. This will allow us to evaluate outcomes for patients admitted to high-spending vs. low-spending SNFs within HRRs. Second, to assess if our definition of instrumental variable on a continuous scale is robust, we create a binary version of the instrument using the median for differential distance as the cut-off point. This approach will minimize the impact of large values of differential distance in the estimation.

RESULTS

Table 1 describes the average patient characteristics and standardized differences by SNF spending status as well as by differential distance above or below the median. We have a total of 1,961,927 individuals in our analytical sample. About 67% of the observations with differential distance below the median are high-spending facilities whereas only 21% of observations with differential distance above the median are high-spending; this implies that our instrument will be highly predictive of high-spending status, a necessary condition for IV analysis to be valid. Average age is approximately 82 years in both groups. The percentage of individuals who are white, female, had dual eligibility, and average ZIP-code level income are largely similar between the two groups as shown by the standardized differences which are all below 0.1. Average difference in SNF episode spending is approximately $2,500 with a standardized difference of 0.25. The difference in spending seems to be largely driven by longer patient stay as reflected by a difference of approximately 5 days between observations with differential distance below the median vs. above the median. Spending for individuals at the originating hospital appears to be similar. The patient characteristics by SNF spending status also appear similar with the exception of dual eligibility and ZIP code level income. These differences, however, appear similar when we look at the groups stratified by our instrument, differential distance.

Table 1: Select Patient Characteristics by SNF Spending Status & Differential Distance (DD) (N=1,961,927)

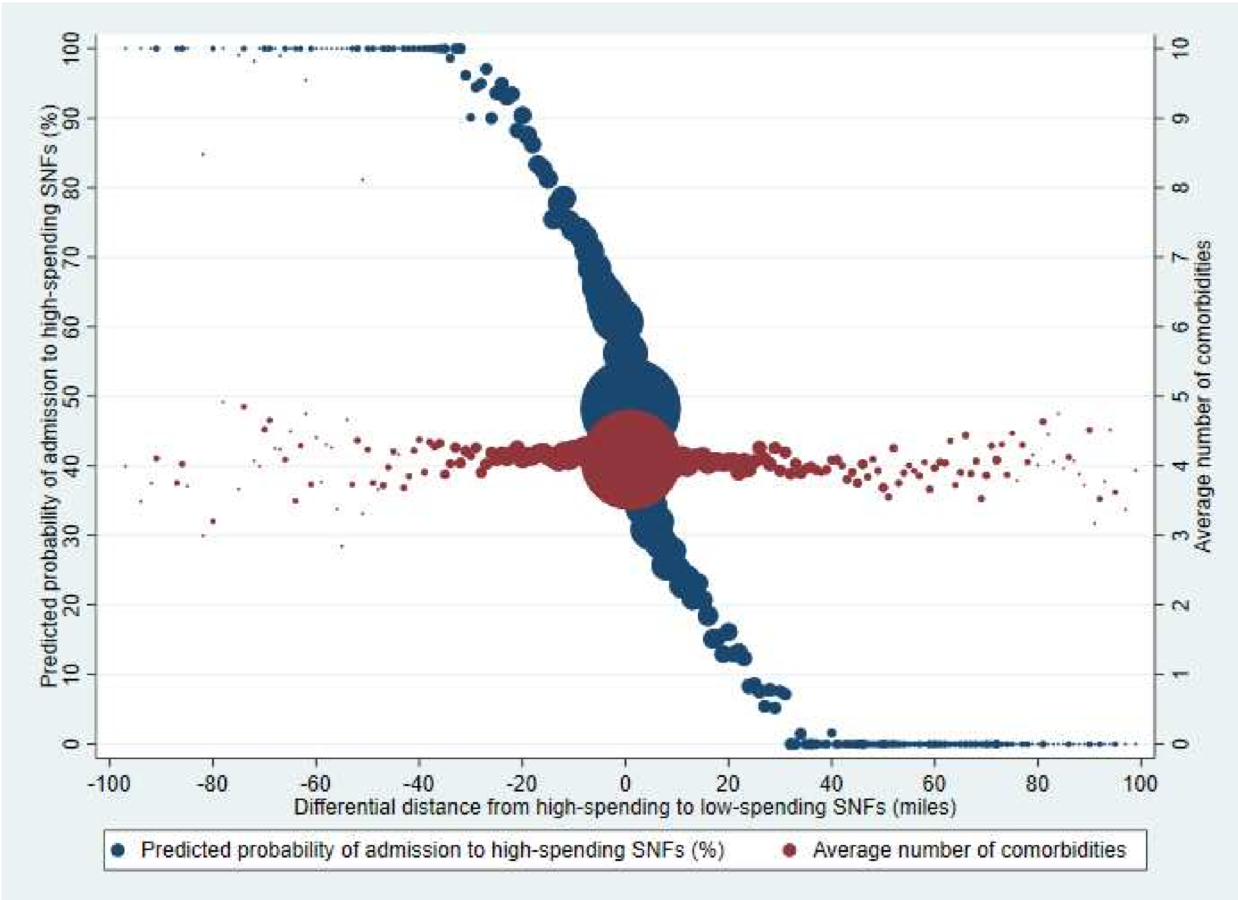
	High Spending	Low Spending	Standardized Difference	Differential Distance >Median	Differential Distance ≤Median	Standardized Difference
High-spending	-	-	-	0.21	0.67	-0.91
Age	82.09	82.29	-0.03	82.18	82.20	-0.00
White	0.88	0.90	-0.07	0.90	0.89	0.06
Female	0.63	0.64	-0.02	0.64	0.64	-0.00
Dual eligible	0.25	0.19	0.15	0.20	0.23	-0.08
Average ZIP-code income	73297.23	78188.62	-0.15	77528.64	74669.13	0.09
SNF episode spending	15377.69	10461.77	0.50	11364.80	13838.19	-0.25
SNF length of stay	38.33	27.59	0.28	29.72	34.86	-0.13
SNF expenditure per person/day	431.61	412.22	0.15	415.53	425.71	-0.08
Hospital episode spending	13675.34	13736.06	-0.00	13741.83	13683.01	0.00
Joint replacements	0.10	0.13	-0.09	0.12	0.11	0.04
Hip & femur procedures	0.05	0.06	-0.02	0.06	0.06	0.01
Pneumonia	0.03	0.03	-0.00	0.03	0.03	0.00
Stroke	0.04	0.03	0.01	0.03	0.04	-0.00
Heart failure	0.03	0.03	-0.00	0.03	0.03	-0.00
Kidney and UTI	0.03	0.03	0.02	0.03	0.03	-0.01
AMI	0.01	0.01	0.00	0.01	0.01	-0.00
GOPD	0.02	0.02	0.01	0.02	0.02	-0.01
GI	0.01	0.01	0.00	0.01	0.01	-0.00
Septicemia	0.05	0.05	0.02	0.05	0.05	-0.01

Notes: Means along with standardized differences (Std. diff) are provided. Standardized difference is obtained as the difference in group means divided by pooled standard deviation. For example:

$$Standardized\ difference = \frac{\overline{Variable_{dist<median}} - \overline{Variable_{dist>median}}}{Std_{pooled}}.$$

Figure 1 shows the distribution of average number of Elixhauser comorbidities and predicted probability of admission to a high-spending SNF based on the first stage of our 2SLS regression across different values of differential distance. The average number of Elixhauser comorbidities is roughly the same across different values of differential distance but the predicted probability (from the first stage of our 2SLS regression) of admission to high-spending SNF increases as we move closer to high-spending SNF, i.e., negative differential distance. These two observations suggest that differential distance is a strong predictor of whether someone gets admitted to a high-spending SNF and at the same time, may be unrelated to underlying patient illness level. Patient comorbidities identified using ICD-9 codes also appear similar between the two groups classified using differential distance (Appendix Table 22).

Figure 1: Distribution of Average Number of Elixhauser Comorbidities and Predicted Probability of Admission to a High-spending SNF by Differential Distance



Note: Negative differential distance implies that high-spending SNF is closer. Positive differential distance suggests that low-spending SNF is closer. The figure shows that the average number of Elixhauser comorbidities during the past one year is roughly the same across different values of differential distance but the predicted probability (from the first stage of our 2SLS regression) of admission to high-spending SNF increases as we move closer to high-spending SNF, i.e., negative differential distance. These two observations suggest that differential distance is a strong predictor of whether someone gets admitted to a high-spending SNF and at the same time, may be unrelated to underlying patient illness level.

We report SNF and hospital characteristics by high-spending status and differential distance in Table 2. These results show that high-spending SNFs tend to be for-profit, affiliated with a chain, have a higher share of Medicaid residents, and are slightly larger in size. The size and type (teaching vs. not) of originating hospital appear to be similar between the individuals admitted to high-spending vs. low-spending SNFs. Although our instrument is not designed to randomize SNFs, the differences in SNF characteristics by differential distance above and below the median are much lower than those reported by spending status.

Table 2: Characteristics of SNFs & Hospitals by SNF Spending Status & Differential Distance (DD) (N=1,961,927)

	High Spending	Low Spending	Standardized Difference	Differential Distance >Median	Differential Distance ≤Median	Standardized Difference
SNF Characteristics						
For-profit	0.82	0.61	0.47	0.67	0.74	-0.17
Chain	0.63	0.53	0.20	0.56	0.59	-0.05
Occupancy %	84.76	84.02	0.06	84.48	84.30	0.01
Medicaid Pay %	51.87	48.42	0.15	49.80	50.30	-0.02
Total beds	133.97	126.46	0.11	126.35	132.62	-0.09
Hospital Characteristics						
Teaching hospital	0.49	0.51	-0.05	0.50	0.50	0.00
Hospital beds	339.58	332.04	0.02	323.49	343.88	-0.06

Note: Means along with standardized differences are provided. Standardized difference is obtained as the difference in group means divided by pooled standard deviation. For example: $Standardized\ difference = \frac{\overline{Variable_{dist<median}} - \overline{Variable_{dist>median}}}{Std_{pooled}}$.

The results from our base model using two-stage least squares for hospitalization and mortality, and GLM with log link for Medicare expenditures are presented in Table 3. The F-statistic for our instrument, differential distance, varies slightly across the models since we use slightly different specifications in some models but in all cases, our instrument far exceeds the typical threshold of 10 suggested in the literature. For instance, in the hospitalization regressions, our first-stage F-statistic for differential distance is 1864.5. Average rehospitalization and mortality rates during the 90-day period following admission to SNFs in the sample were 32%, and 17%, respectively. Results without instrumental variables obtained using linear regressions with hospital fixed effects show that individuals admitted to high-spending SNFs are about 2.0 percentage points less likely to be rehospitalized in 90 days but there is no difference in mortality relative to low-spending SNFs. Medicare spending is about $4,140 higher for individuals admitted to high-spending SNFs. The results from IV regressions are broadly similar to non-IV regressions, although the magnitudes are slightly different; individuals admitted to high-spending facilities are 1.5 percentage points less likely to be rehospitalized but cost about $5,205 more to Medicare. Since our base rehospitalization rate is 32%, a 1.5 percentage point reduction is equivalent to about 4.7% reduction in rehospitalization. There was no difference in mortality between the two groups in the IV regressions as well.

Table 3: Effect of Admission to High-Spending SNFs on 90-day Hospitalization, Mortality, and Medicare Expenditures

	Outcome mean	No IV	With IV
Hospitalization	0.32	-0.020***	-0.015***
		(0.0010)	(0.0042)
Mortality	0.17	-0.00032	-0.000066
		(0.00077)	(0.0032)
Medicare expenditures	$20,034	$4,140***	$5,205***
		($91)	($195)
Observations		1,961,927	1,961,927

Notes:
a. Regression coefficients without IV are obtained using hospital fixed effects while those with IV are obtained using 2SLS framework with differential distance as the instrument and hospital fixed effects. Standard errors provided in parentheses are clustered at the hospital level.
b. Generalized linear models with log link and HRR fixed effects are used to estimate Medicare expenditures (hospital and SNF). Standard errors provided in parentheses are clustered at the HRR level. IV models use 2SRI approach.
c. *p<0.1, ** p<0.05, *** p<0.01

Table 4 presents average marginal effects from multinomial logistic regressions with and without IV. Overall rehospitalization rates are similar to those obtained using two-stage least squares approach. The results from non-IV and 2SRI approaches are qualitatively similar with some differences in magnitudes for rehospitalizations. In the 2SRI approach, individuals admitted to high-spending facilities are about 1.8 percentage points less likely to be rehospitalized in 90 days following admission to the SNFs.

Table 4: Effect of Admission to High-Spending SNFs on 90-day Hospitalization and Mortality–Results from Multinomial Logit Regressions

	No IV	With IV
Aggregate hospitalization	-0.020^{***}	-0.018^{***}
	(0.0011)	(0.0042)
<u>Direct vs. after discharge</u>		
Direct hospitalization	0.0088^{***}	0.012^{***}
	(0.00097)	(0.0035)
Hospitalization after discharge	-0.029^{***}	-0.030^{***}
	(0.00080)	(0.0029)
<u>Avoidable vs. unavoidable</u>		
Avoidable hospitalization	-0.010^{***}	-0.0090^{***}
	(0.00092)	(0.0031)
Unavoidable hospitalization	-0.0099^{***}	-0.0086^{***}
	(0.00064)	(0.0022)
Mortality	0.0016^{*}	0.00095
	(0.00091)	(0.0024)
Observations	1,961,927	1,961,927

Notes:
a. Average marginal effects from multinomial logit regressions with and without differential distance as the instrument and hospital referral region fixed effects are reported. Multinomial logit regressions for hospitalization outcome include death, hospitalization measure(s), and neither of those two as potential outcomes in the regression. For mortality outcome, a standard logistic regression is estimated. Standard errors provided in parentheses are clustered at the HRR level.
b. *p<0.1, ** p<0.05, *** p<0.01

In Table 4 above, a decomposition of overall rehospitalization shows that individuals admitted to high-spending SNFs are 1.2 percentage points more likely to be directly rehospitalized from the SNFs but 3.0 percentage points less likely to be rehospitalized following discharge. Furthermore, individuals admitted to high-spending SNFs are about 0.90 percentage points less likely to have potentially avoidable rehospitalizations and 0.86 percentage points less likely to have potentially unavoidable rehospitalizations. These reductions represent about 2.8% and 2.7% reduction in rehospitalizations from our base rehospitalization rate of 32%. Interestingly, mortality results are significant in the non-IV regressions but the magnitude is lower and significance disappears in the 2SRI regressions.

We present the results from our robustness checks using 30- and 180-day rehospitalizations, mortality, and Medicare expenditures in Table 5.

Table 5: Effect of Admission to High-Spending SNFs on 30-day and 180-day Hospitalization, Mortality, and Medicare Expenditures

	No IV	With IV
30-day		
Hospitalization	-0.019***	-0.0099***
	(0.00082)	(0.0036)
Mortality	-0.00016	-0.00039
	(0.00053)	(0.0024)
Medicare expenditures	$1,228***	$1,667***
	($38)	($93)
180-day		
Hospitalization	-0.016***	-0.0089**
	(0.0011)	(0.0044)
Mortality	0.0016*	0.0014
	(0.00086)	(0.0036)
Medicare expenditures	$4,525***	$5,824***
	($130)	($274)
Observations	1,961,927	1,961,927

Notes:
a. Regression coefficients without IV are obtained using hospital fixed effects while those with IV are obtained using 2SLS framework with differential distance as the instrument and hospital fixed effects. Standard errors provided in parentheses are clustered at the hospital level.
b. Generalized linear models with log link and HRR fixed effects are used to estimate Medicare expenditures (hospital and SNF). Standard errors provided in parentheses are clustered at the HRR level. IV models use 2SRI approach.
c. *p<0.1, ** p<0.05, *** p<0.01

The rehospitalization results are qualitatively similar to the 90-day results but the magnitudes are much lower in 30 and 180 days. Individuals admitted to high-spending SNFs are about 1.0 percentage points and 0.89 percentage points less likely to be rehospitalized in 30 days and 180 days, respectively. Again, there are no differences in mortality between individuals admitted to high-spending SNFs vs. low-spending SNFs. The results from the expenditure regressions show that individuals admitted to high-spending facilities have higher Medicare expenditures but that the difference in expenditures is much lower in 30 days ($1,667) while the difference in expenditures in 180 days ($5,824) is statistically similar to that observed in 90 days ($5,205).

Table 6 presents results from different specification checks for our IV models from Table 3. The results across different specifications for 90-day hospitalization, mortality, and Medicare expenditures are largely consistent, with some differences in the magnitudes of the effects. When we include HRR fixed effects instead of hospital fixed effects, the results are similar to our base models. The results using binary version of the differential distance as IV show that individuals admitted to high-spending SNFs are about 2.6 percentage points less likely to be rehospitalized, an effect slightly higher than in our base model. The magnitudes of effects are similar to our main effects when we exclude all patients from Maryland which has a different payment system for hospitals. Duals tend to benefit more from admission to high-spending SNFs in terms of fewer rehospitalizations but they also incur higher Medicare expenditures relative to non-duals. The magnitudes are lower when we include all observations or exclude only the SNFs in 45^{th} to 55^{th} percentiles in the observed over expected spending ratio. The findings are similar when we exclude discharges after 90 days.

Table 6: Effect of Admission to High-Spending SNFs on 90-day Hospitalization, Mortality, and Medicare Expenditures – Specification Checks (IV Regressions Only)

	Hospitalization	Mortality	Medicare Expenditures
Baseline model (N=1,961,927)	-0.015***	-0.000066	$5,205***
	(0.0042)	(0.0032)	($195)
HRR fixed effects (N=1,961,927)	-0.018***	0.0015	$5,205***
	(0.0041)	(0.0025)	($195)
Binary IV (N=1,961,927)	-0.026***	0.000041	$4,431***
	(0.0041)	(0.0031)	($179)
Exclude Maryland (N=1,912,424)	-0.015***	-0.0002	$5,229***
	(0.0042)	(0.0032)	($193)
Duals (N=430,254)	-0.023***	0.0016	$6,734***
	(0.0077)	(0.0055)	($258)
Non-duals (N=1,531,673)	-0.013***	0.0016	$4,721***
	(0.0049)	(0.0036)	($249)
Exclude 45-55th percentile (N=2,264,678)	-0.0111***	-0.0032	$4,855***
	(0.0040)	(0.0029)	($199)
Include all observations (N=2,569,947)	-0.0092***	-0.0062**	$4,516***
	(0.0037)	(0.0028)	($195)
Exclude discharges>90 days (N=1,897,635)	-0.013***	-0.0035	$3,972***
	(0.0043)	(0.0032)	($183)

Notes:

a. Regression coefficients for hospitalization and mortality are obtained using 2SLS framework with differential distance as the instrument and hospital fixed effects. Standard errors provided in parentheses are clustered at the hospital level.

b. Generalized linear models with log link and HRR fixed effects are used to estimate Medicare expenditures (hospital and SNF). Standard errors provided in parentheses are clustered at the HRR level. IV models use 2SRI approach.

c. *p<0.1, ** p<0.05, *** p<0.01

We explore the heterogeneity in outcomes among the 10 common conditions in Table 7.

Table 7: Effect of Admission to High-Spending SNFs on 90-day Hospitalization, Mortality, and Medicare Expenditures - Subgroup Analyses (IV Regressions)

	Hospitalization	Mortality	Medicare Expenditures
All common conditions (N=774,785)	-0.014**	0.00027	$5,092***
	(0.0064)	(0.0048)	($219)
Joint replacements (N=221,808)	-0.0023	0.011*	$3,698***
	(0.011)	(0.0060)	($259)
Hip and femur procedures (N=111,311)	-0.035**	-0.019	$6,093***
	(0.016)	(0.012)	($415)
Septicemia (N=96,233)	0.0030	-0.0057	$5,437***
	(0.020)	(0.017)	($385)
Stroke (N=68,375)	-0.034*	-0.014	$5,542***
	(0.020)	(0.017)	($449)
Pneumonia (N=67,123)	0.014	0.037	$5,340***
	(0.025)	(0.023)	($428)
Heart failure (N=66,227)	-0.026	0.027	$5,222***
	(0.027)	(0.024)	($477)
Kidney and UTI (N=63,905)	-0.017	0.012	$6,607***
	(0.028)	(0.022)	($379)
COPD (N=32,513)	-0.036	-0.024	$4,877***
	(0.040)	(0.034)	($642)
AMI (N=23,670)	-0.032	-0.0074	$3,919***
	(0.036)	(0.031)	($798)
Gastrointestinal hemorrhage (N=23,620)	0.021	-0.013	$5,991***
	(0.038)	(0.031)	($704)

Notes:
a. Regression coefficients for hospitalization and mortality are obtained using 2SLS framework with differential distance as the instrument and hospital fixed effects. Standard errors provided in parentheses are clustered at the hospital level.
b. Generalized linear models with log link and HRR fixed effects are used to estimate Medicare expenditures (hospital and SNF). Standard errors provided in parentheses are clustered at the HRR level. IV models use 2SRI approach.
c. Patient subgroups are identified using MS-DRGs. Common conditions include all 10 conditions.
d. *p<0.1, ** p<0.05, *** p<0.01.

The rehospitalization, mortality, and Medicare expenditure results from the combined group of 10 common conditions that comprise approximately 40% of our sample are consistent with our main findings. Rehospitalization and mortality results in the subgroups are generally consistent with our main findings but statistical significance disappears in most of the cases. The expenditure results, however, remain consistent with our main findings and are statistically significant. Patients admitted to high-spending SNFs have significantly higher Medicare expenditures in the 90-day period relative to low-spending SNFs across all subgroups.

DISCUSSION

In this study, we evaluated rehospitalizations, mortality, and Medicare expenditures of individuals admitted to high-spending vs. low-spending SNFs. In our main model, we find that individuals admitted to high-spending SNFs have lower rehospitalizations but there is no difference in mortality. Furthermore, combined Medicare expenditures for SNF and hospital stay are substantially higher for individuals admitted to high-spending SNFs relative to low-spending SNFs despite lower rehospitalizations. These findings are consistent across different specifications and time periods, suggesting that the value of additional spending associated with high-spending SNFs may be low for Medicare.

Despite fewer rehospitalizations among individuals admitted to high-spending SNFs, our findings point to potentially wasteful spending in post-acute care in SNFs. As we briefly discussed in the introduction and conceptual framework, the relationship between spending and health outcomes depends on whether additional spending is appropriate or not. While it is difficult for researchers to identify what part of spending is appropriate, there is evidence in the literature that additional therapy could be beneficial to, for instance, hip fracture patients [26]. Broadly, our results suggest some benefit to increased spending in SNFs in terms of fewer rehospitalizations but there are no benefits in terms of lower mortality. The reductions in rehospitalizations are roughly the same whether we look at potentially avoidable vs. potentially unavoidable rehospitalizations, suggesting that the benefits of increased spending may translate beyond those conditions currently considered as potentially avoidable rehospitalizations. Moreover, the reductions in rehospitalizations are largely accrued after discharge from the facility, suggesting that longer length of stay in SNFs may result in healthier discharge and better prepare patients for self-care in the community after discharge. The finding that rehospitalizations are substantially lower after discharge for individuals admitted to high-spending SNFs is partly mechanical since these individuals spend fewer days in the community after discharge within the 90 days.

It is important to note that there are other outcomes of importance in this population besides rehospitalization and mortality. One of the goals of post-acute care services is to help patients gain improvements in functional status so that the patients can go back to the daily activities they used to participate in prior to the injury or illness. While we can evaluate the gains in functional status for some patients, we do not have multiple assessments to measure changes in functional status for many patients, making it difficult to assess the gains. Moreover, we are also unsure about the quality of data on functional status since nursing homes self-report changes in functional status. We focused on rehospitalization and mortality outcomes because these measures are more objective and available for all patients.

The findings from our study have several policy implications. First, our study provides causal evidence on potentially wasteful spending in post-acute care. Despite numerous studies in the literature suggesting substantial variation in post-acute care spending, our study is the first, to our knowledge, to directly document potentially wasteful spending in SNFs. Even though there are reductions in hospitalizations and we may care about other outcomes including gains in functional status, the increased spending on SNF care associated with high-spending SNFs has no impact on patient mortality. Setting aside any quality of life gains to patients from fewer hospitalizations, our findings suggest that it is possible to decrease post-acute care spending on SNFs without adversely affecting patient mortality.

Second, our finding that combined Medicare expenditures for SNF stay and rehospitalizations are higher for those admitted to high-spending SNFs suggests a need for payment reforms to better align Medicare and provider incentives, such as bundled payments that create accountability for Medicare expenditures throughout the health care system. The Centers for Medicare and Medicaid Services is currently experimenting with alternative payment models including Bundled Payments for Care Improvement (BPCI), and Value-based Purchasing (VBP) in an effort to contain growing health care costs. The goal is to make at least 50% of total Medicare payments through such alternative payment models by the end of 2018 [46]. Whether such efforts can lead to lower expenditures without worsening quality on a large scale is yet to be seen, but early evidence suggests that post-acute care is a prime target for cost containment under these programs. In a recent study that evaluated the impact of bundled payments for joint replacements at Baptist Health System (BHS) which participated in the BPCI program, researchers found that substantial reductions in expenditures came from lower use of post-acute care [47]. The study further found that there were reductions in post-acute care spending only when the post-acute care episodes were included in the bundled payments [47]. Our findings that individuals admitted to high-spending nursing homes have substantially higher Medicare expenditures with no difference in mortality, along with anecdotal evidence on the impact of bundled payments, suggest that including post-acute care stay in bundled payments is important in order to force providers to coordinate care and decrease Medicare expenditures. These findings also underscore the type of SNFs that hospitals and Accountable Care Organizations should seek out in their efforts to lower expenditures without affecting mortality.

Finally, our finding that the difference in spending between individuals admitted to high-spending vs. low-spending SNFs at 90 days and 180 days are similar but substantially larger than the difference in 30 days uncovers a different issue with existing payment models. In particular, defining a 30-day window for calculating payment episodes appears to be potentially problematic in two ways. First, the currently planned SNF value-based purchasing (SNFVBP) program slated to start in 2019 will penalize nursing homes for excess readmissions in 30 days. However, our findings show that individuals admitted to high-spending SNFs have lower rehospitalizations and most of the increased spending is due to a longer length of stay. This implies that nursing homes could simply extend the length of stay to reduce readmissions while also increasing their revenue. Any payment policy that fails to target the length of stay in a post-acute care setting may not lead to lower expenditures. Second, existing experiments with alternative payment models define payment episodes at 30, 60, and 90 days. The findings from our study show that the difference in Medicare payments is much larger in 90 days than in 30 days following admission to a SNF. Furthermore, the differences remain similar after the 90 days. These findings suggest that the 30-day period following a discharge from the hospital may not be the optimal episode definition in order to effectively coordinate care to lower Medicare expenditures. One of the challenges to designing policies with episodes longer than 30 days is that we need to know the extent to which we can attribute the patient outcomes beyond the 30-day window to the activities performed by SNFs.

The findings from our study are subject to several limitations. First, although we believe that patient selection has been accounted by the use of differential distance as an instrument in our analysis, selection on SNFs can remain. SNFs might have certain attributes that are difficult to measure but are correlated with both high-spending status and resident outcomes (e.g., skill of staff, managerial outlook or competence). However, our research goal is to identify the causal effects of admission to one type of SNF or another, regardless of the facility-level correlates of spending. This is the perspective that Medicare might take, for example, in steering patients to higher-value care. Second, the estimates from instrumental variable regressions must be interpreted as local average treatment effects and may not be generalizable to all patients. Third, the generalizability of our findings is limited by several exclusion criteria used in our study. For instance, we exclude patients admitted to SNFs more than 100 miles from their home ZIP-code. These patients are typically vacationers and/or may have specific reasons for selecting those particular SNFs. Thus, our exclusion of such patients is well justified.

Our study contributes to the existing body of knowledge on the relationship between spending and health outcomes. In particular, we find that individuals admitted to high-spending SNFs have lower rehospitalizations but there is no difference in mortality. Despite lower rehospitalizations, individuals admitted to high-spending SNFs have substantially higher

Medicare expenditures. These findings underscore the rationale for a carefully designed bundled payment system that combines acute care with post-acute care to combat growing health care expenditures without impacting patient mortality.

CHAPTER 3
THE RELATIONSHIP BETWEEN REPORTED STAFFING AND EXPENDITURES IN NURSING HOMES

ABSTRACT

Dramatic improvements in reported nursing home quality, including staffing ratios, have come under increased scrutiny in recent years because they are based on data self-reported by nursing homes. In contrast to other domains, the key mechanism for real improvement in the staffing ratios domain is clearer: to improve scores, nursing homes should increase staffing expenditures. We analyze the relationship between changes in expenditures and reported staffing quality pre vs. post the 5-star rating system. Our results show that the relationship between expenditures and LPN staffing is weaker in the post-5-star period, overall, and across subgroups; furthermore, there is a weaker relationship between expenditures and RN staffing among for-profit facilities with a high share of Medicaid residents in the post-5-star period. The weaker relationship between staffing expenditures and staffing scores in the post-5-star era underscores the potential for gaming of the self-reported staffing scores and the need for more reliable sources.

INTRODUCTION

Nursing home costs and quality are important to Medicaid and Medicare. Approximately 1.4 million residents reside in about 15,000 nursing homes in the United States [48] at a substantial cost to Medicare and Medicaid. Medicare spent approximately $28.7 billion on post-acute care in skilled nursing facilities in 2013 [16] and Medicaid paid about $50 billion to nursing facilities in 2014 for long-term care services [49]. Since Medicaid and Medicare cover a large portion of expenditures for nursing home residents, these programs have an incentive to promote increased efficiency and quality of care in nursing homes.

One potential way to improve quality is to publicly disseminate quality information. The role of information in well-functioning markets dates back to influential articles published in the 1960-70s [50,51]. In recognition of the importance of quality information for nursing homes, the Centers for Medicare & Medicaid Services (CMS) started publicizing information on nursing home quality in 1998 through the Nursing Home Compare website. The publication of quality information was aimed at promoting quality of care through consumer and provider response. Several early studies suggested that nursing homes responded to the publication of nursing home quality information by improving on at least some quality measures. For example, there were improvements in reported quality for pain and physical restraints but not on pressure ulcers following the release of quality information [52]. In a study focused on post-acute care quality measures, there were improvements in quality measures related to pain and walking but not delirium [53].

Despite these results, there was speculation that consumers had a difficult time using the vast amount of reported quality information in a meaningful way. Accordingly, in late 2008, CMS simplified the reporting system by assigning star ratings to nursing homes (one to five stars, with five stars indicating the highest level of quality). These included both overall ratings and ratings specific to regulatory deficiencies, clinical quality, and staffing ratios. The calculation of the overall rating starts with the deficiency measure, considered the most objective because it is based on inspections by state surveyors, but allows for the addition or subtraction of stars based on performance on staffing and clinical quality. For example, during the time period of our study, a nursing home with a 4-star or 5-star rating in staffing could shift up its overall rating by as much as one star. Staffing measures include separate measures for Registered Nurse (RN) staffing and total direct-care staffing (RNs, Licensed Practical Nurses (LPNs), and nurse aides). Staffing is often considered a key marker of nursing home quality, given that nurses and nurse aides provide the bulk of direct care.

Based on these star levels, average reported nursing home quality started improving dramatically after the launch of the 5-Star system. Specifically, the number of facilities rated as 5 stars increased from 12% to 15% from 2008 to 2010 while those rated as 1 star decreased from 23% to 16% during the same period [54]. These trends were driven largely by improvements in domains based on data self-reported by nursing homes, i.e. staffing ratios and clinical quality. For instance, there was a considerable increase in the number of facilities with a 4-star rating for staffing from 31% to 38% between 2008 and 2010 while those with a 1-star rating for staffing decreased dramatically from 23% to 15% during the same period. The number of facilities with a 5-star rating for staffing increased modestly from 7% in 2008 to 9% in 2010. [10]

The rapid improvements in reported quality following the release of 5-star system, particularly in the domains that are based on self-reported data, have raised some concerns as to whether the quality improvements are real. An article published in The New York Times suggested that nursing homes are not only able to manipulate self-reported quality measures but that they also often anticipate and can better prepare themselves for inspections, potentially temporarily adding staff [10]. A recent study found that some people did not trust the quality information on Nursing Home Compare, a CMS website that allows people to access quality ratings for nursing homes [55]; the reasons for distrust could be lack of awareness and/or negative publicity in the media.

When consumers use the 5-star system, the overall star rating tends to dominate [55]. A closer look at how 5-star rating for staffing affects the overall 5-star rating for a facility allows us to understand the incentives nursing homes might have to game the system. Nursing home inspections for health deficiencies are carried out by state agencies once every 12-15 months and an aggregate deficiency score is obtained based on the number and severity of deficiencies. A weighted average is calculated from the past three inspections for each facility. Five-star ratings for deficiencies are then calculated for each facility based on the distribution of these weighted averages within each state. In addition, staffing and quality 5-star ratings are calculated separately based on self-reported data from nursing homes. If the staffing rating is 4 or 5 stars, the overall rating is increased by 1 star so long as the staffing ratings exceed the deficiency ratings. For instance, if the rating based on deficiency scores is 3 stars, and staffing rating is 4 stars, the overall rating becomes 4 star; alternatively, if the staffing rating is 1 star, then the overall rating is decreased to 2 stars. Thus, staffing ratings can not only increase but also decrease the overall rating. Similarly, quality ratings can also increase or decrease the overall rating by 1 star.

The ability to shift the overall rating gives nursing homes strong incentive to achieve a high rating on staffing (and some consumers may look at the staffing ratings directly). However, while inspections are carried out by independent inspectors, data for staffing is self-reported by nursing homes based on their staffing levels during the 14 days prior to the health inspections. As suggested in The New York Times article [10], nursing homes are often able to anticipate the inspection dates and thus, increase staffing during the 14 days prior to inspections. Furthermore, they could misreport their staffing levels, although evidence on this has not been documented. Using the self-reported staffing data in OSCAR (now CASPER), case-mix adjusted RN hours per resident day and total staffing hours per resident day are obtained. Then, using fixed thresholds and percentiles on a national level, each facility gets a separate 5-star rating for RN staffing and total staffing. The star rating for staffing is obtained by giving equal weights to separate star ratings for RN and total staffing (RN+LPN+Nurse aides). For instance, to get a 5-star rating in overall staffing, a facility needs to obtain 5-star ratings for both RN staffing and total staffing [10].

A fundamental challenge facing both policymakers and consumers is that little is known about exactly how facilities improve their performance in any of the domains. When the processes for improvement are uncertain or unknown, it is difficult to assess when we should applaud dramatic improvement and when we should be skeptical that improvement is too dramatic. In this paper, we begin to address that challenge by assessing one main pathway to improved scores: increasing spending on staffing. Unlike the other domains, it is difficult to imagine genuine and sizable improvements in staffing ratios without a corresponding increase in spending. Minor improvements may be achieved through the hiring of cheaper staff, for example, either by hiring less experienced nurses of the same type or substituting among nurse types (using more LPN hours in place of RN hours).. There is some evidence for factor substitution in nursing homes from nurses to non-labor materials when nursing wages increase [56] or from non-clinical staff to clinical staff when states initiate minimum clinical staffing requirements [57]. Although we cannot rule out all these other pathways, a high correlation between improvement and additional expenditures would provide some assurance that reported improvements in staffing ratios may be genuine. Our approach is to link the raw scores for staffing measures used by CMS to Medicare cost reports as well as nursing home level information available in Online Survey, Certification, and Reporting (OSCAR) data. We use facility fixed-effects regression to assess whether better reported staffing quality scores are associated with higher nursing home expenditures, and whether this relationship is different in the post-5-star era.

New Contribution

Nursing home reported quality for staffing improved rapidly since the CMS started assigning star ratings to nursing homes in 2008. However, to our knowledge, no study has evaluated whether the improvements in reported staffing ratios in nursing home compare are corroborated by additional spending on staffing. Our study has three key contributions. First, we employ a new approach to test gaming in quality improvement efforts. Our approach to testing gaming relies on the assumption that if there is no gaming, then the relationship between quality and expenditures should be the same before and after a policy change. This approach not only applies to staffing quality in Nursing Home Compare but could be utilized in other settings including hospitals and home health agencies as long as the quality measure in question can be tied conceptually to expenditures. Second, we assess whether gaming actually occurred with respect to different types of staffing in nursing homes. We identify the relationship for each type of staff – RN, LPN, and nurse aides, allowing us to explore the staffing types that are more likely to be the subject of gaming. Assuming that the reported staffing quality measures identified by

CMS are associated with improved patient outcomes, if nursing homes are spending more to improve reported staffing ratios, it provides us with additional confidence that improvements in these reported quality measures may be real and are likely to benefit residents. If, however, the relationship between expenditures and staffing scores is weaker in the post-5-star era, it is possible that nursing homes may be engaged in strategies that do not reflect true changes in staffing, such as bending the definition of which staff should be included in the ratios or "staffing up" before an inspection. Finally, we explore the heterogeneity across different types of facilities including profit status, Medicaid share, initial quality ratings, and cross-stratified by profit status and Medicaid share to identify the types of facilities that are more likely to engage in gaming. As CMS continues to refine the 5-star system, filling this gap provides essential evidence about the validity of the measures and the underlying data as well as insights into provider response and the potential need to monitor certain types of staffing and/or facilities.

CONCEPTUAL FRAMEWORK

Nursing homes are predominantly for-profit firms, and like other firms have incentives to maximize profits by pursuing quality improvement as efficiently as possible and to the extent that it is profitable for them. Even not-for-profit nursing homes (the minority), while they may have objectives other than profits, need to balance their investment in quality improvement against the returns on their investment. Prior research has shown that improving reported quality can improve financial performance of nursing homes [58]. An increase in reported quality can increase profits if the additional costs of improving quality are lower than the increased revenue that results. Improved quality can attract high-margin patients (i.e., Medicare or private-pay residents), and also allow for higher prices to private-pay residents to reflect the increased quality; either could boost profits for nursing homes.

Despite the theoretical motivations for improving quality, whether a nursing home needs to invest more resources to improve reported quality is not clear and varies by domain. To improve staffing scores, nursing homes theoretically have to hire more staff for a given patient case-mix and in most instances such additional hires will increase expenditures. However, in reality, they could also achieve the goal of improving staffing scores without increased expenditures through changes to documentation or by temporarily hiring staff before an inspection (when the data are collected). Alternative routes to a better score on staffing might include the substitution of more expensive staff with cheaper staff. There is some evidence that nursing homes substitute from non-clinical staff to clinical staff in response to the state requirements on minimum clinical staffing in nursing homes [57]. While the 5-star system did not mandate minimum clinical staffing, it is possible that nursing homes may prioritize the type of staffing that would boost their staffing ratings.

The decision to hire more staff to improve scores vs. less costly mechanisms to improve scores may depend on baseline quality, Medicaid share, and profit status. On one hand, there is evidence for diminishing returns to additional staffing on mortality [59] and adverse events [60] and for diminishing returns in quality improvement more generally [61]. Thus, nursing homes that start with low staffing scores may have the most to gain from hiring new staff. On the other hand, nursing homes that start with low quality or those with a higher share of Medicaid patients are also the most likely to face resource constraints that may impede the desire to hire more staff, and may also have the most to gain from increasing reported quality scores even in the absence of real improvement. Similarly, for-profit facilities have a strong incentive to maximize profits and thus, may pursue less costly paths to improve staffing scores. Consequently, for-profit facilities, low-quality facilities or those facilities with higher Medicaid-share may look for multiple mechanisms to improve their star ratings for staffing in the post-5-star period including reallocation of staff, misreporting the staffing numbers, and hiring more staff temporarily prior to inspection.

Finally, if a nursing home decides to hire more clinical staff in order to improve quality and/or reported quality ratings, there remains the decision of which types of staff to hire. A large body of literature supports the importance of RN staffing as a key driver of nursing home quality, over and above the role of other types of staff [62-64]; thus, nursing homes may choose to prioritize RN staffing. This is reinforced through the star rating system, as the overall staffing rating formula gives equal weight to RN staffing and total staffing, effectively double-counting RN hours. However, because RNs are paid more than other nurses, facilities that are facing severe financial constraints or facilities with strong profit incentives might be motivated to game the RN hours. A secondary strategy to improve overall staffing while fulfilling some RN functions (at lesser cost) would be to increase LPN hours.

EMPIRICAL FRAMEWORK AND STATISTICAL METHODOLOGY

Data

We use three main data sources: Medicare Cost reports (2007-2010), Online Survey, Certification and Reporting (OSCAR,2007-2010), and raw Nursing Home Compare rating scores (2007-2010).

We primarily use Medicare Cost reports to obtain nursing-home-level information on several expenditure measures. Medicare-certified nursing homes are required to file annual Medicare Cost Report (also known as Health Care Cost Report Information System or HCRIS - CMS form 2540-96) containing information on facility characteristics and expenditures. A small fraction of nursing homes report costs for less than 365 days and when that happens, we combine multiple reports to ensure that the facilities included in our analysis have costs reported for a full 12 months. It is a common practice to require a 12-month cost report in analysis [65]. We also follow the literature to exclude outliers for expenditures and staffing ratios that fall outside of 1st and 99th percentiles [66] and this ensures that we have reasonable, positive costs.

Total expenditures in Medicare cost reports can be divided into several components including clinical expenditures, capital expenditures, and administrative expenditures. These expenditures can be further divided into staffing and non-staffing components. For our analysis, we focus on clinical staffing expenditures (CMS form 2540-96, Worksheet A, lines 9, 16-20). While we do not have salary information specific to RNs, LPNs, and CNAs, we believe that clinical staffing expenditures are the best available proxy for staffing expenditures related to RNs, LPNs, and CNAs in a nursing home setting. In our robustness checks, we also use a broader measure of clinical expenditures identified in prior research [67] and include staffing expenditures for skilled nursing, nursing administration, lab services, therapy services etc. to account for potential misclassification of expenditures.

We obtain nursing home characteristics from OSCAR. OSCAR is a dataset compiled by CMS based on inspections of Medicare-certified nursing homes that occur at least once every 12-15 months. It has nursing-home level information on facility characteristics including resident census, ownership type, chain membership, size, urban/rural location, staffing, and data used to calculate several case-mix indicators.

Finally, we use the raw rating scores used by CMS to assign star ratings to nursing homes (the underlying continuous scores, not simply the star categories). These raw scores were not available publicly for the time period in our data but were obtained through a special request to CMS. Specifically, we use the adjusted RN, adjusted LPN, and adjusted nurse aide scores. CMS did not release the new 5-star rating for nursing homes until December of 2008 but the data has monthly raw scores from the beginning of 2008. For the years 2008-10, we use the staffing scores at the end of each year. We use the raw scores from January of 2008 to proxy for the staffing scores for the year 2007; since most of the staffing scores in January of 2008 reflect staffing data from health inspections that occurred sometime in 2007, it is a reasonable proxy. We also conduct a sensitivity analysis using data from 2008 onwards.

Since we are using different data sources for staffing scores and expenditures, it is important to align the data between the different sources as closely as possible. After requiring all facilities to have 12 months of expenditure data, we classify facility expenditure reports into different years based on when the fiscal year ends. A majority of facilities report expenditures for the calendar year (70%) but some facilities have fiscal years different from calendar years. A further 9% have a fiscal year that ends in September, and another 14% have a fiscal year that ends in July. Since staffing inspections occur throughout the year, there is not a single optimal approach to combining the two data sources. To best match the timing of expenditures to the timing of the staffing rating, we use the most recent staffing score collected by the end of each calendar year for our main analysis and conduct a sensitivity analysis that requires a new inspection within each fiscal year.

Study Sample

This study is limited to Medicare-certified, freestanding nursing homes. We exclude hospital-based nursing homes because their cost structures are different from freestanding nursing homes. In addition, because our data sets were not collected for research and include erroneous values, we take several steps to avoid potential data errors and outliers influencing our regression estimates. First, we adopt the CMS guidelines and follow the literature [68] to exclude facilities that a) report more residents than beds, b) have zero RN hours but have 60 or more beds, c) have total staffing hours per resident day that are less than 0.5 or more than 12, and d) report zero residents. These criteria exclude about 5% of our sample.

Furthermore, we limit our analytical data to those observations between the 1st and 99th percentiles on the key dependent variable (clinical staffing expenditures per resident day), and on independent variables (adjusted staffing quality scores for RNs, LPNs, and nurse aide). We exclude the entire facility if any observation for a given facility falls into the outlier category for either the expenditures or the staffing measures. In each regression, we exclude approximately 15% of the observations based on these exclusion criteria. We conduct sensitivity analysis using a different definition for outliers as described in the robustness section below.

Dependent Variables

Our key dependent variable of interest is clinical staffing expenditures per resident day. Clinical staffing expenditures per resident day are obtained by dividing the total clinical staffing expenditures in a year by the number of inpatient days during that year. Factor substitutions in a nursing home can lead to an increase in staffing scores without increasing overall staffing expenditures. In order to address this issue, we should either limit our expenditures to include spending related to only the clinical staff or we should incorporate other staffing measures in the regression model as additional controls. As described earlier in the data section, clinical staffing expenditures comprise staffing expenditures that are more likely to be related to RNs, LPNs, and nurse aides; this clinical staffing expenditure measure excludes staffing expenditures on certain clinical activities like therapists and lab technicians as well as non-clinical activities like housekeeping, dietary, laundry, and other general services. When we restrict our expenditure measures to include only clinical staff, staffing substitutions should have limited impact on the relationship between expenditures and clinical staffing ratios. Since expenditures could be misclassified at times, as a robustness check, we use a broader measure of clinical expenditures on staffing, as described in the robustness section. Expenditures are normalized to 2011 US dollars using the medical care component of the consumer price index.

Key Independent Variables

We have three continuous staffing variables of interest based on self-reported data –RN staffing, LPN staffing, and nurse aide staffing. These staffing measures are taken directly from CMS calculations for Nursing Home Compare. RN staffing represents registered nurses per resident per day and is based on self-reported data in the two-week period prior to state inspection. Similarly, LPN staffing includes hours for licensed practical nurses and licensed vocational nurses per resident per day. Finally, staffing scores for nurse aides include hours for nurse aides in training and medication aides per resident per day. Adjustments for resident case-mix are made for all three staffing variables as per the CMS measure definitions; case-mix differences based on Resource Utilization Groups (RUG-III) are used to adjust the staffing ratios for RN, LPN, and nurse aides to account for resident differences in health status and care need [10]. Substitutions that occur between clinical staffing types can make it difficult to interpret the findings on the relationship between expenditures and clinical staffing. Since we explicitly include the three separate staffing variables in one regression model, it allows us to examine the contribution of each while controlling for the others.

Covariates

In all regressions, we control for several variables that might confound the relationship between expenditures and staffing ratios. Most importantly, we include additional adjustments for case-mix to control for the possibility that the CMS measures do not adequately capture this confounder. Specifically, we control for resident resource needs using the Activities of Daily Living (ADL) index and Special Care Index (SCI) [69]. The ADL index is derived from the proportion of residents needing assistance for bathing, dressing, toileting, transferring, and eating while the SCI accounts for proportions of residents with need for respiratory care, suctioning, IV therapy, tracheostomy, and parenteral feeding [69]. In addition, we control for payer mix (the percent of residents whose stay is paid by Medicare and Medicaid). To control for market-level influences, we include an indicator for nursing home market concentration, as the additional gains from improving quality may not be substantial for nursing homes in markets without competition. We estimate nursing home market concentration at the county level using the Herfindahl–Hirschman Index (HHI) defined as the sum of the squares of market shares of all nursing homes in terms of inpatient days.[70] A recent study explored alternative definitions of HHI and found that a more robust definition of HHI that accounts for chains is 0.2 points higher than a traditional definition of HHI used in our study [71]. Since HHI is not our primary variable of interest, our definition of HHI should be adequate as a control measure. We do include chain ownership as an additional control variable as well. Finally, we control for facility characteristics that may change over time including total bed size, profit status.

Statistical Analyses

First, we summarize key facility characteristics across all facilities. We also summarize the reported staffing quality scores and clinical staffing expenditures pre- (2007-08) and post-5-star era (2009-2010).

Next, we use a series of facility and year fixed-effects regressions to estimate the relationship between changes in spending and changes in staffing scores within facilities over time. Facility fixed-effects regressions allow us to control for unobserved but plausibly time-invariant confounding variables at the facility level. Similarly, year fixed effects will capture common time trends across all facilities. Subgroup analyses include facilities stratified by profit status, baseline Medicaid share, and baseline quality levels. A facility is classified as having a high Medicaid share if the share of Medicaid residents as a percentage of total beds (Medicaid residents x 100/ total beds) in the given facility is above the median (54.2) for all facilities at baseline, low Medicaid share otherwise. We classify a facility as a low-quality facility if the facility received an overall quality rating of 1-2 stars at baseline; we defined a facility as a high-quality facility if the overall quality rating was 4-5 stars at baseline. For all regressions, standard errors are clustered at the facility level to account for dependence among observations from the same facility.

We use the following model to analyze the relationship between nursing home expenditures and staffing scores:

$$\mathrm{Y_{it}} = \beta_0 + \beta_{1j}\mathrm{Staffing_{jit}} + \beta_2\mathrm{Post}_t + \beta_{3j}\mathrm{Staffing_{jit}} \times \mathrm{Post}_t + \beta_4\mathrm{X_{it}} + \beta_5\mathrm{Year_t} + \beta_6\mathrm{Facility_i} + \varepsilon_{it}$$

In this model, Y_{it} represents clinical staffing expenditures for facility *i* at time *t*; $Staffing_{jit}$ represents the three adjusted staffing variables (RN, LPN, and nurse aides) for facility *i* at time *t*; *Post* equals 1 if the year is following the 5-star release (i.e., Year=2009 or 2010), 0 otherwise; *X* represents a vector of exogenous controls described earlier, *Year* represents time fixed effects, and *Facility* represents facility fixed effects. ε is a random error term. The coefficients of interest in this regression are β_{1j} and β_{3j}. If β_{1j} is positive and significant, it implies that better staffing scores are associated with higher clinical staffing expenditures in the pre-5-star era. Similarly, if β_{3j} is negative and significant, it suggests that the relationship between expenditures and staffing scores is weaker in the post-5-star era.

Robustness Checks

We conduct a number of robustness checks to see if our findings are sensitive to our definition of clinical staffing expenditures as well as other data cleaning decisions made in our analyses. First, state inspections are generally carried out within every 12 months on average but sometimes these inspections can be up to 15 months apart. This implies that we may not have a new state inspection every year for some facilities. In cases where there is no new state inspection, the staffing scores largely reflect the staffing levels reported in the last inspection, although adjustment for patient case-mix can change the actual staffing scores. We exclude observations without a new state inspection within the fiscal year and re-estimate the main models. Second, to allow for nursing homes to respond to the release of 5-star ratings, we only use the first and last year of observations and re-estimate our main model. Third, our decision to exclude outliers that fall outside of 1st and 99th percentile for each measure is somewhat arbitrary even though based on common practice [66]. To address this issue, we consider two other approaches to excluding outliers. First, we exclude observations with clinical staffing expenditures in top or bottom 2.5% instead of 1%. Second, we exclude outliers only for the clinical staffing expenditures (while the outliers for staffing are partly addressed by our initial exclusion criteria that excludes facilities that report total staffing hours per resident day below 0.5 and above 12; it does not exclude outliers by specific staffing type) and re-estimate our main models.

Fourth, in our main analysis, we proxy the 2007 staffing scores using the staffing scores in January of 2008. While a small fraction of facilities have inspections each month, and most of the staffing scores in January of 2008 represent inspections that occurred in 2007, these scores in January of 2008 are still a proxy for 2007 scores and are subject to error. Thus, we use data only from 2008 onwards and re-estimate our main models.

Fifth, staffing expenditures are potentially subject to misclassification and thus, our approach to identify clinical staffing expenditures may not be ideal. As a sensitivity analysis, we use a broader measure of clinical expenditures for staffing as the dependent variable of interest. These expenditures not only include clinical staffing expenditures related to nurses and nurse aides but also include staffing expenditures on therapy, laboratory, nursing administration and others identified as clinical in nature in a recent study [67].

RESULTS

Descriptive characteristics of our sample are shown in Table 8. We have a total of 37,095 observations for 11,091 facilities; mostly for-profit (74.0%); with total occupancy averaging 84.4% (±13.7) while Medicaid occupancy averaging 52.4 (±17.9). The average case-mix in terms of the ADL index is 10.3, and the SCI index is 0.22. Average clinical salary expenditures per person per day are similar in the pre-5-star period and post-5-star period ($68.29 vs. $68.24). Average staffing quality scores are lower in the pre-5-star period than post-5-star period: RN staffing scores (0.32 vs. 0.34), LPN staffing scores (0.95 vs. 0.97), and nurse aide staffing scores (2.34 vs. 2.37).

Table 8: Summary Statistics for the Sample of Nursing Homes (2007-2010)

Characteristics	Mean (SD)
Herfindahl-Hirchman Index	0.237 (0.265)
Special care index	0.223 (0.157)
ADL index	10.34 (1.137)
Facility total beds	116.9 (63.37)
Total occupancy %	84.39 (13.70)
Medicaid occupancy %	52.35 (17.87)
Medicare occupancy %	12.12 (8.971)
RN staffing score : pre-5-star	0.320 (0.130)
RN staffing score : post-5-star	0.342 (0.131)
LPN staffing score : pre-5-star	0.951 (0.312)
LPN staffing score : post-5-star	0.971 (0.314)
Nurse aide staffing score : pre-5-star	2.339 (0.481)

Table 8, continued: Summary Statistics for the Sample of Nursing Homes (2007-2010)

Characteristics	Mean (SD)
Nurse aide staffing score : post-5-star	2.367 (0.477)
Clinical staffing expenditures : pre-5-star ($)	68.29 (18.93)
Clinical staffing expenditures : post-5-star ($)	68.24 (18.06)
	N (%)
For-profit	27,443 (74.0)
Not-for-profit	8,353 (22.5)
Government-owned	1,299 (3.50)
Multi-facility organization	21,713 (58.5)
Number of facilities	11,091
Observations	37,095

Notes: Facilities that have staffing scores and expenditures below 1st and above 99th percentiles are excluded from the sample. Expenditures are measured per person per day. Staffing quality measures are adjusted for case-mix.

Table 9a shows the results from the facility fixed effects regressions for the overall group as well as groups stratified by profit status, Medicaid share, and baseline quality. Regression results show that improved staffing scores are significantly associated with higher expenditures for all staffing types ($p<0.01$) in the baseline period, as expected. In the overall sample, a one-hour increase in RN staffing per resident day is associated with a $6.56 increase in clinical staffing expenditures per resident day in the pre-5-star period. The effect was lower during the post-5-star period, indicating a weakening of the relationship between staffing and expenditures. Similarly, an hour increase in LPN staffing is associated with a $1.6 increase in clinical staffing expenditures in the pre-5-star era and this relationship is again weaker in the post-5-star period. There is no difference in the relationship between nurse aide staffing scores and expenditures in the pre- vs. post-5-star period. These results are broadly consistent across the different subgroups except that the differential relationship between RN staffing and expenditures appears to be largely driven by facilities that are for-profit and/or those with a high share of Medicaid residents.

Table 9a: Association between Changes in Clinical Staffing Expenditures and Changes in Staffing Scores - Fixed Effects Regressions

	All	Not-for-profit	For-profit	Low Medicaid	High Medicaid	High Quality	Low Quality
Post	0.56***	0.96***	0.41**	1.31***	-0.12	0.47*	0.35
	(0.15)	(0.36)	(0.17)	(0.22)	(0.21)	(0.27)	(0.24)
Adjusted RN	6.56***	5.78***	7.16***	6.46***	6.81***	6.85***	6.66***
	(0.56)	(1.35)	(0.64)	(0.84)	(0.74)	(0.99)	(0.90)
Adjusted LPN	1.60***	1.90***	1.53***	1.53***	1.63***	1.86***	1.67***
	(0.23)	(0.56)	(0.25)	(0.33)	(0.30)	(0.43)	(0.33)
Adjusted nurse aide	1.32***	2.00***	1.17***	1.43***	1.15***	1.20***	1.17***
	(0.16)	(0.41)	(0.17)	(0.23)	(0.23)	(0.29)	(0.24)
Post X Adjusted RN	-1.23**	0.0018	-2.31***	-1.30	-1.81**	-1.34	-1.48
	(0.55)	(1.20)	(0.66)	(0.80)	(0.74)	(0.91)	(0.96)
Post X Adjusted LPN	-0.99***	-0.94*	-1.04***	-1.48***	-0.49	-0.95**	-0.82**
	(0.22)	(0.53)	(0.25)	(0.32)	(0.31)	(0.38)	(0.36)
Post X Adjusted nurse aide	0.22	-0.041	0.015	0.31	0.070	0.42*	0.16
	(0.14)	(0.32)	(0.15)	(0.20)	(0.18)	(0.23)	(0.21)
Observations	37095	7620	26828	17907	19188	11381	17629

Notes:
a. Facilities that have staffing scores and expenditures below 1st and above 99th percentiles are excluded from the sample.
b. Results are obtained using facility and time fixed effects controlling for other covariates. Standard errors in parentheses are clustered at the facility level.*p<0.1, ** p<0.05, *** p<0.01.

Table 9b shows results for groups cross-stratified by profit status and Medicaid share. The results are largely similar to our main results except that the for-profit facilities have a weaker relationship between RN and LPN staffing and expenditures in the post-5-star period irrespective of whether they have high or low share of Medicaid residents. However, the magnitude of the coefficient on the interaction term for RN staffing in the post-5-star period is much higher and highly significant only for for-profit, high-Medicaid facilities. Among not-for-profit facilities, there is a significantly weaker relationship between staffing and expenditures in the post-5-star period only for LPN staffing and only among those with low Medicaid share. The sample sizes for not-for-profit facilities stratified by Medicaid share are much smaller.

Table 9b: Association between Changes in Clinical Staffing Expenditures and Changes in Staffing Scores - Fixed Effects Regressions

	Not-for-profit & Low Medicaid	Not-for-profit & High Medicaid	For-profit & Low Medicaid	For-profit & High Medicaid
Post	1.76***	-0.18	1.12***	-0.20
	(0.48)	(0.56)	(0.26)	(0.23)
Adjusted RN	6.70***	4.12**	6.56***	7.86***
	(1.89)	(1.88)	(0.96)	(0.85)
Adjusted LPN	2.09***	1.53**	1.33***	1.74***
	(0.77)	(0.75)	(0.38)	(0.34)
Adjusted nurse aide	2.17***	1.49***	1.20***	1.10***
	(0.59)	(0.51)	(0.24)	(0.26)
Post X Adjusted RN	-0.36	0.17	-1.66*	-3.60***
	(1.73)	(1.48)	(0.92)	(0.94)
Post X Adjusted LPN	-1.51**	-0.022	-1.52***	-0.63*
	(0.69)	(0.84)	(0.36)	(0.34)
Post X Adjusted nurse aide	-0.062	-0.075	0.26	-0.26
	(0.44)	(0.46)	(0.24)	(0.20)
Observations	4444	3176	12349	14479

Notes:
a. Facilities that have staffing scores and expenditures below 1st and above 99th percentiles are excluded from the sample.
b. Results are obtained using facility and time fixed effects controlling for other covariates. Standard errors in parentheses are clustered at the facility level.*p<0.1, ** p<0.05, *** p<0.01.

Results from our robustness checks are presented in a series of tables (Tables 10-14) and are largely consistent with our main findings. When we excluded observations without a new state inspection during the fiscal year to ensure that the expenditures represent staffing during that year, increased staffing continues to be associated with higher expenditures but the association is weaker between LPN staffing and expenditures in the post-5-star era; a weaker relationship between RN staffing and expenditures in the post-5-star period is observed only among for-profit facilities and for-profit facilities with high Medicaid share (Tables 10a-10b).

Table 10a: Association between Changes in Clinical Staffing Expenditures and Changes in Staffing Scores - Fixed Effects Regressions (Sensitivity Analysis - New Survey within the Fiscal Year)

	All	Not-for-profit	For-profit	Low Medicaid	High Medicaid	High Quality	Low Quality
Post	0.53***	1.21***	0.37*	1.32***	-0.24	0.38	0.31
	(0.18)	(0.41)	(0.20)	(0.26)	(0.23)	(0.32)	(0.26)
Adjusted RN	6.43***	5.11***	7.27***	6.61***	6.35***	7.01***	6.16***
	(0.64)	(1.50)	(0.74)	(0.95)	(0.82)	(1.14)	(0.99)
Adjusted LPN	1.68***	1.61**	1.68***	1.78***	1.47***	1.92***	1.70***
	(0.26)	(0.65)	(0.29)	(0.38)	(0.35)	(0.49)	(0.38)
Adjusted nurse aide	1.53***	2.51***	1.30***	1.71***	1.28***	1.49***	1.35***
	(0.18)	(0.48)	(0.20)	(0.25)	(0.27)	(0.33)	(0.27)
Post X Adjusted RN	-0.59	-0.042	-1.84**	-0.68	-1.06	-1.01	-0.49
	(0.64)	(1.41)	(0.77)	(0.94)	(0.84)	(1.08)	(1.08)
Post X Adjusted LPN	-1.04***	-1.20**	-1.06***	-1.66***	-0.36	-0.93**	-0.82**
	(0.26)	(0.58)	(0.30)	(0.38)	(0.33)	(0.45)	(0.40)
Post X Adjusted nurse aide	0.18	-0.083	-0.0059	0.26	0.025	0.39	0.15
	(0.16)	(0.38)	(0.17)	(0.23)	(0.21)	(0.27)	(0.25)
Observations	29185	5959	21147	14072	15113	8929	13824

Notes:
a. Facilities that have staffing scores and expenditures below 1st and above 99th percentiles are excluded from the sample.
b. Results are obtained using facility and time fixed effects controlling for other covariates. Standard errors in parentheses are clustered at the facility level.*p<0.1, ** p<0.05, *** p<0.01.

Table 10b: Association between Changes in Clinical Staffing Expenditures and Changes in Staffing Scores - Fixed Effects Regressions (Sensitivity Analysis - New Survey within the Fiscal Year)

	Not-for-profit & Low Medicaid	Not-for-profit & High Medicaid	For-profit & Low Medicaid	For-profit & High Medicaid
Post	1.76***	0.30	1.23***	-0.43*
	(0.55)	(0.60)	(0.31)	(0.26)
Adjusted RN	6.25***	2.71	7.07***	7.65***
	(2.19)	(1.97)	(1.12)	(0.95)
Adjusted LPN	1.58*	1.52*	1.80***	1.55***
	(0.88)	(0.89)	(0.44)	(0.39)
Adjusted nurse aide	3.09***	1.42**	1.32***	1.26***
	(0.70)	(0.56)	(0.26)	(0.31)
Post X Adjusted RN	-0.65	0.89	-1.06	-3.27***
	(2.12)	(1.57)	(1.10)	(1.05)
Post X Adjusted LPN	-1.60**	-0.39	-1.74***	-0.42
	(0.80)	(0.73)	(0.46)	(0.38)
Post X Adjusted nurse aide	-0.25	0.085	0.27	-0.34
	(0.53)	(0.50)	(0.25)	(0.24)
Observations	3476	2483	9726	11421

Notes:
a. Facilities that have staffing scores and expenditures below 1st and above 99th percentiles are excluded from the sample.
b. Results are obtained using facility and time fixed effects controlling for other covariates. Standard errors in parentheses are clustered at the facility level.*p<0.1, ** p<0.05, *** p<0.01.

When we used only the first and last year of observations to allow sufficient time for nursing homes to respond to the release of 5-star ratings, the results are essentially similar to our main findings (Tables 11a-11b). More specifically, we observe a consistently negative relationship between staffing and expenditures for LPN staffing across different groups, and with RN staffing among for-profit and facilities with a higher share of Medicaid in the post-5-star period. Like in previous analyses, we do not observe a significant relationship between adjusted nurse aide staffing and expenditures in the post-5-star period overall and across all groups of nursing homes.

Table 11a: Association between Changes in Clinical Staffing Expenditures and Changes in Staffing Scores - Fixed Effects Regressions (Sensitivity Analysis - First & Last Year of Observation)

	All	Not-for-profit	For-profit	Low Medicaid	High Medicaid	High Quality	Low Quality
Post	0.73***	0.78	0.74***	1.66***	-0.063	0.89**	0.30
	(0.22)	(0.49)	(0.26)	(0.32)	(0.30)	(0.40)	(0.34)
Adjusted RN	9.00***	9.14***	9.48***	8.36***	10.0***	9.81***	9.14***
	(0.89)	(2.29)	(1.00)	(1.32)	(1.17)	(1.57)	(1.45)
Adjusted LPN	2.28***	3.46***	2.06***	2.23***	2.32***	2.95***	2.30***
	(0.37)	(0.99)	(0.41)	(0.55)	(0.49)	(0.70)	(0.54)
Adjusted nurse aide	1.59***	1.85***	1.61***	1.73***	1.40***	1.32***	1.56***
	(0.24)	(0.66)	(0.27)	(0.34)	(0.35)	(0.46)	(0.36)
Post X Adjusted RN	-1.49*	0.25	-3.23***	-1.16	-2.53**	-2.34*	-1.55
	(0.80)	(1.87)	(0.96)	(1.20)	(1.04)	(1.40)	(1.35)
Post X Adjusted LPN	-1.46***	-0.95	-1.78***	-2.01***	-0.90*	-1.62***	-1.11**
	(0.34)	(0.75)	(0.40)	(0.49)	(0.46)	(0.59)	(0.54)
Post X Adjusted nurse aide	0.25	0.18	-0.031	0.25	0.16	0.52	0.063
	(0.19)	(0.44)	(0.21)	(0.27)	(0.26)	(0.32)	(0.30)
Observations	21502	4380	15610	10445	11057	6600	10205

Notes:
a. Facilities that have staffing scores and expenditures below 1st and above 99th percentiles are excluded from the sample.
b. Results are obtained using facility and time fixed effects controlling for other covariates. Standard errors in parentheses are clustered at the facility level.*p<0.1, ** p<0.05, *** p<0.01.

Table 11b: Association between Changes in Clinical Staffing Expenditures and Changes in Staffing Scores - Fixed Effects Regressions (Sensitivity Analysis - First & Last Year of Observation)

	Not-for-profit & Low Medicaid	Not-for-profit & High Medicaid	For-profit & Low Medicaid	For-profit & High Medicaid
Post	1.62**	-0.37	1.75***	-0.077
	(0.67)	(0.73)	(0.39)	(0.34)
Adjusted RN	9.89***	8.03***	7.98***	11.2***
	(3.22)	(2.99)	(1.48)	(1.35)
Adjusted LPN	3.94***	2.40*	1.81***	2.40***
	(1.37)	(1.36)	(0.63)	(0.53)
Adjusted nurse aide	2.29***	0.94	1.66***	1.52***
	(0.86)	(1.00)	(0.39)	(0.37)
Post X Adjusted RN	-0.44	0.42	-2.08	-4.93***
	(2.79)	(1.99)	(1.38)	(1.33)
Post X Adjusted LPN	-1.39	0.054	-2.49***	-1.18**
	(0.98)	(1.15)	(0.59)	(0.52)
Post X Adjusted nurse aide	0.0043	0.22	0.095	-0.19
	(0.58)	(0.67)	(0.32)	(0.28)
Observations	2554	1826	7240	8370

Notes:
a. Facilities that have staffing scores and expenditures below 1st and above 99th percentiles are excluded from the sample.
b. Results are obtained using facility and time fixed effects controlling for other covariates. Standard errors in parentheses are clustered at the facility level.*p<0.1, ** p<0.05, *** p<0.01.

Tables 12a-12b present the findings from our analysis that included data only from 2008-10 and the results again largely confirm our main findings. In particular, the association between LPN staffing and clinical staffing expenditures in the post-5-star period is weaker overall and across subgroups. Furthermore, we observe a consistently negative relationship between RN staffing and expenditures among for-profit facilities and facilities with a higher share of

Medicaid in the post-5-star period. Like in previous analyses, we do not observe a significant relationship between adjusted nurse aide staffing and expenditures in the post-5-star period for most of the subgroups of nursing homes.

Table 12a: Association between Changes in Clinical Staffing Expenditures and Changes in Staffing Scores - Fixed Effects Regressions (Sensitivity Analysis - Using only 2008-2010 Data)

	All	Not-for-profit	For-profit	Low Medicaid	High Medicaid	High Quality	Low Quality
Post	-0.12	0.24	-0.30^{*}	0.36^{*}	-0.57^{***}	-0.24	-0.24
	(0.15)	(0.37)	(0.17)	(0.22)	(0.22)	(0.28)	(0.23)
Adjusted RN	5.76^{***}	5.23^{***}	6.58^{***}	5.80^{***}	5.85^{***}	5.12^{***}	6.36^{***}
	(0.65)	(1.53)	(0.76)	(0.98)	(0.85)	(1.16)	(1.05)
Adjusted LPN	1.41^{***}	1.38^{**}	1.43^{***}	1.25^{***}	1.51^{***}	1.52^{***}	1.58^{***}
	(0.26)	(0.61)	(0.29)	(0.38)	(0.34)	(0.45)	(0.37)
Adjusted nurse aide	0.98^{***}	1.71^{***}	0.86^{***}	0.93^{***}	0.99^{***}	0.77^{**}	0.82^{***}
	(0.18)	(0.46)	(0.19)	(0.26)	(0.25)	(0.32)	(0.26)
Post X Adjusted RN	-1.73^{***}	-1.24	-2.63^{***}	-2.16^{***}	-1.78^{**}	-1.37	-2.31^{**}
	(0.56)	(1.19)	(0.69)	(0.81)	(0.79)	(0.91)	(1.00)
Post X Adjusted LPN	-0.98^{***}	-1.08^{**}	-0.95^{***}	-1.35^{***}	-0.62^{*}	-0.90^{**}	-0.85^{**}
	(0.23)	(0.54)	(0.25)	(0.31)	(0.33)	(0.38)	(0.36)
Post X Adjusted nurse aide	0.32^{**}	0.030	0.12	0.52^{**}	0.067	0.33	0.42^{*}
	(0.14)	(0.36)	(0.15)	(0.21)	(0.19)	(0.24)	(0.22)
Observations	28475	5841	20592	13808	14667	8754	13524

Notes:
a. Facilities that have staffing scores and expenditures below 1st and above 99th percentiles are excluded from the sample.
b. Results are obtained using facility and time fixed effects controlling for other covariates. Standard errors in parentheses are clustered at the facility level.*p<0.1, ** p<0.05, *** p<0.01.

Table 12b: Association between Changes in Clinical Staffing Expenditures and Changes in Staffing Scores - Fixed Effects Regressions (Sensitivity Analysis - Using only 2008-2010 Data)

	Not-for-profit & Low Medicaid	Not-for-profit & High Medicaid	For-profit & Low Medicaid	For-profit & High Medicaid
Post	0.70	-0.50	0.16	-0.71***
	(0.49)	(0.61)	(0.24)	(0.24)
Adjusted RN	6.97***	2.30	6.08***	7.24***
	(2.15)	(2.14)	(1.15)	(0.99)
Adjusted LPN	1.41*	1.28	1.24***	1.58***
	(0.83)	(0.86)	(0.43)	(0.37)
Adjusted nurse aide	1.76***	1.40***	0.62**	1.04***
	(0.68)	(0.53)	(0.26)	(0.28)
Post X Adjusted RN	-2.05	-0.24	-2.19**	-3.62***
	(1.69)	(1.61)	(0.96)	(0.99)
Post X Adjusted LPN	-1.65**	-0.11	-1.17***	-0.76**
	(0.67)	(0.92)	(0.35)	(0.36)
Post X Adjusted nurse aide	0.13	-0.13	0.50**	-0.29
	(0.50)	(0.46)	(0.24)	(0.20)
Observations	3430	2411	9505	11087

Notes:
a. Facilities that have staffing scores and expenditures below 1st and above 99th percentiles are excluded from the sample.
b. Results are obtained using facility and time fixed effects controlling for other covariates. Standard errors in parentheses are clustered at the facility level.*p<0.1, ** p<0.05, *** p<0.01.

The results for the main analysis are similar when we excluded observations using alternative exclusion criteria that excluded only the facilities with clinical expenditures outside the 1st and 99th percentile (Tables 13a-13b). More specifically, we observe a consistently negative relationship between staffing and expenditures for LPN staffing across different groups, and with RN staffing among for-profit and for-profit facilities with a higher share of Medicaid in the post-5-star period. Like in previous analyses, we do not observe a significant relationship between adjusted nurse aide staffing and expenditures in the post-5-star period overall and across all groups of nursing homes. When we excluded observations with clinical expenditures in the top or bottom 2.5% instead of 1%, the results are largely similar (results available upon request).

Table 13a: Association between Changes in Clinical Staffing Expenditures and Changes in Staffing Scores - Fixed Effects Regressions (Sensitivity Analysis - Alternative Exclusion Criteria for Outliers)

	All	Not-for-profit	For-profit	Low Medicaid	High Medicaid	High Quality	Low Quality
Post	0.54***	1.10***	0.32**	1.28***	-0.13	0.51*	0.34
	(0.14)	(0.35)	(0.15)	(0.21)	(0.19)	(0.26)	(0.21)
Adjusted RN	6.55***	6.75***	6.77***	6.44***	6.80***	7.19***	6.55***
	(0.54)	(1.33)	(0.61)	(0.80)	(0.71)	(0.96)	(0.85)
Adjusted LPN	1.51***	2.31***	1.33***	1.51***	1.46***	1.83***	1.55***
	(0.19)	(0.53)	(0.20)	(0.28)	(0.25)	(0.40)	(0.26)
Adjusted nurse aide	1.25***	1.82***	1.12***	1.29***	1.16***	1.12***	1.16***
	(0.15)	(0.39)	(0.16)	(0.21)	(0.21)	(0.28)	(0.22)
Post X Adjusted RN	-1.29**	-0.33	-2.11***	-1.32*	-1.91***	-1.58*	-1.51*
	(0.53)	(1.20)	(0.62)	(0.77)	(0.72)	(0.90)	(0.91)
Post X Adjusted LPN	-0.98***	-1.27**	-0.89***	-1.47***	-0.49*	-1.01***	-0.82***
	(0.20)	(0.51)	(0.22)	(0.30)	(0.28)	(0.37)	(0.31)
Post X Adjusted nurse aide	0.20	0.024	-0.025	0.34*	0.016	0.43*	0.13
	(0.13)	(0.32)	(0.15)	(0.19)	(0.18)	(0.22)	(0.20)
Observations	38563	7857	27973	18718	19845	11877	18201

Notes:
a. Facilities that have staffing scores and expenditures below 1st and above 99th percentiles are excluded from the sample.
b. Results are obtained using facility and time fixed effects controlling for other covariates. Standard errors in parentheses are clustered at the facility level.*p<0.1, ** p<0.05, *** p<0.01.

Table 13b: Association between Changes in Clinical Staffing Expenditures and Changes in Staffing Scores - Fixed Effects Regressions (Sensitivity Analysis - Alternative Exclusion Criteria for Outliers)

	Not-for-profit & Low Medicaid	Not-for-profit & High Medicaid	For-profit & Low Medicaid	For-profit & High Medicaid
Post	1.89***	-0.051	1.00***	-0.26
	(0.47)	(0.51)	(0.23)	(0.21)
Adjusted RN	7.65***	5.00**	6.10***	7.54***
	(1.78)	(1.97)	(0.92)	(0.80)
Adjusted LPN	2.49***	1.89**	1.26***	1.42***
	(0.69)	(0.81)	(0.30)	(0.26)
Adjusted nurse aide	2.00***	1.29**	1.01***	1.20***
	(0.55)	(0.52)	(0.22)	(0.24)
Post X Adjusted RN	-0.92	0.24	-1.22	-3.60***
	(1.69)	(1.49)	(0.87)	(0.89)
Post X Adjusted LPN	-1.85***	-0.29	-1.32***	-0.53*
	(0.67)	(0.77)	(0.32)	(0.30)
Post X Adjusted nurse aide	-0.0089	0.015	0.27	-0.33*
	(0.42)	(0.46)	(0.22)	(0.19)
Observations	4633	3224	12924	15049

Notes:
a. Facilities that have staffing scores and expenditures below 1st and above 99th percentiles are excluded from the sample.
b. Results are obtained using facility and time fixed effects controlling for other covariates. Standard errors in parentheses are clustered at the facility level.*p<0.1, ** p<0.05, *** p<0.01.

Finally, when we repeated the analyses with a broader measure of clinical staffing expenditures as the dependent variable, the results largely corroborate our main findings (Tables 14a-14b). In particular, the association between LPN staffing and clinical staffing expenditures in the post-5-star period is weaker overall and across subgroups. Furthermore, we observe a consistently negative relationship between RN staffing and expenditures among facilities with a higher share of Medicaid in the post-5-star period. Like in previous analyses, we do not observe a significant relationship between adjusted nurse aide staffing and expenditures in the post-5-star period for most of the subgroups of nursing homes.

Table 14a: Association between Changes in Clinical Staffing Expenditures and Changes in Staffing Scores - Fixed Effects Regressions (Sensitivity Analysis - Broader Measure of Clinical Staffing Expenditure)

	All	Not-for-profit	For-profit	Low Medicaid	High Medicaid	High Quality	Low Quality
Post	1.36***	1.28***	1.35***	2.49***	0.34	1.20***	1.26***
	(0.18)	(0.43)	(0.21)	(0.28)	(0.24)	(0.33)	(0.29)
Adjusted RN	6.80***	5.98***	7.03***	6.73***	7.06***	7.20***	5.94***
	(0.67)	(1.60)	(0.76)	(1.02)	(0.83)	(1.17)	(1.02)
Adjusted LPN	1.58***	2.17***	1.45***	1.41***	1.70***	2.29***	1.60***
	(0.27)	(0.65)	(0.31)	(0.40)	(0.34)	(0.50)	(0.39)
Adjusted nurse aide	1.38***	1.99***	1.23***	1.53***	1.16***	1.17***	1.26***
	(0.19)	(0.48)	(0.20)	(0.27)	(0.26)	(0.34)	(0.28)
Post X Adjusted RN	-0.32	1.02	-0.83	0.15	-1.80**	-0.45	0.86
	(0.66)	(1.53)	(0.78)	(1.02)	(0.80)	(1.11)	(1.10)
Post X Adjusted LPN	-0.91***	-0.96	-0.90***	-1.56***	-0.26	-1.15**	-0.57
	(0.27)	(0.62)	(0.31)	(0.40)	(0.34)	(0.46)	(0.42)
Post X Adjusted nurse aide	0.16	0.40	-0.14	0.21	0.048	0.52*	0.099
	(0.16)	(0.38)	(0.18)	(0.24)	(0.22)	(0.27)	(0.26)
Observations	37053	7586	26816	17846	19207	11367	17618

Notes:

a. Facilities that have staffing scores and expenditures below 1st and above 99th percentiles are excluded from the sample.

b. Results are obtained using facility and time fixed effects controlling for other covariates. Standard errors in parentheses are clustered at the facility level.*p<0.1, ** p<0.05, *** p<0.01

Table 14b: Association between Changes in Clinical Staffing Expenditures and Changes in Staffing Scores - Fixed Effects Regressions (Sensitivity Analysis - Broader Measure of Clinical Staffing Expenditure)

	Not-for-profit & Low Medicaid	Not-for-profit & High Medicaid	For-profit & Low Medicaid	For-profit & High Medicaid
Post	2.17***	-0.21	2.54***	0.38
	(0.59)	(0.61)	(0.33)	(0.27)
Adjusted RN	6.81***	4.30**	6.18***	8.05***
	(2.24)	(2.16)	(1.21)	(0.92)
Adjusted LPN	2.64***	1.42*	1.13**	1.81***
	(0.90)	(0.85)	(0.48)	(0.39)
Adjusted nurse aide	1.98***	1.67***	1.32***	1.12***
	(0.68)	(0.60)	(0.30)	(0.29)
Post X Adjusted RN	1.38	0.59	0.67	-3.39***
	(2.24)	(1.77)	(1.20)	(0.97)
Post X Adjusted LPN	-1.89**	0.60	-1.40***	-0.49
	(0.83)	(0.91)	(0.47)	(0.39)
Post X Adjusted nurse aide	0.59	0.050	-0.078	-0.28
	(0.51)	(0.56)	(0.28)	(0.24)
Observations	4426	3160	12302	14514

Notes:
a. Facilities that have staffing scores and expenditures below 1st and above 99th percentiles are excluded from the sample.
b. Results are obtained using facility and time fixed effects controlling for other covariates. Standard errors in parentheses are clustered at the facility level.*p<0.1, ** p<0.05, *** p<0.01

DISCUSSION

In this study, we analyze the relationship between nursing home expenditures and reported staffing ratios in the pre- vs. post-5-star period. We find that higher reported staffing scores are significantly associated with higher expenditures but the relationship between expenditures and LPN (and RN for for-profit and high-Medicaid facilities) staffing quality scores is weaker following the release of the 5-star system. In terms of magnitudes, an additional hour of RN and LPN staffing cost a facility $6.6 and $1.6, respectively in the pre-5-star period. However, in the post-5-star period, an additional hour of RN and LPN cost a facility only $5.33 (a decrease of $1.23), and $0.61 (a decrease of $0.99), respectively. The baseline magnitudes of the estimates appear small relative to typical wages but there could be several reasons for this. First, the staffing measures are case-mix adjusted and it is difficult to interpret such estimates. Second, while we hypothesized that gaming of reported staffing was exacerbated substantially after the 5-star system was implemented, this does not mean that no gaming existed before. In fact, the idea of nursing homes "staffing up" before a survey has been a well-known concern for decades. Thus, we would not expect incremental costs of an hour of staffing to be equal to an hourly wage rate even in the pre-5-star period. In order to verify if the baseline magnitudes of our estimates are lower because of our control variables, we estimated fixed-effects regressions where our expenditures were a function of only staffing ratios, the post variable, and an interaction between staffing ratios and the post variable. The results from these fixed-effects regressions without other controls yield similar magnitudes and significance for the coefficients. Accordingly, our focus in this analysis is not so much in the magnitudes but rather on the relationship between these staffing scores and expenditures pre- vs. post-5-star period. Our findings suggest potential gaming by nursing homes with respect to reported LPN and RN staffing.

The results from this study are subject to several limitations. In particular, our study is based on pre-post differences in expenditures and staffing scores rather than a more robust difference-in-difference study design. Since all nursing homes were subject to 5-star rating system, we lack a control group for a difference-in-difference design. However, we have minimized the bias to the extent possible using nursing home and year fixed effects. While the nursing home fixed effects model accounts for time-invariant unobserved covariates and year fixed effects adjust for common trends across all nursing homes, and we include a number of potential time-varying confounding variables in the regression, other time-varying confounding may remain.

In addition, there are some limitations to the quality and expenditure measures used in our study. CMS does not routinely audit the accuracy of data reported in Medicare cost reports[72]. Many studies have used Medicare cost reports [65,67] but we are not aware of any studies that have evaluated the validity of the data. Since facilities are not directly reimbursed based on their cost reports, there may be less incentive to misreport cost data; however, nursing homes do not have an incentive to spend substantial resources to accurately report cost data either. We are generally less concerned about the reliability of total expenditures reported by facilities since these expenditures are reported based on facilities' accounting systems, but the allocation mechanism of expenditures into different categories (clinical/staffing etc.) may not be uniform across different facilities. However, as long as these differences are constant over time, they should not create bias in our fixed-effects approach. We attempted to address this issue of misclassification by using different measures for staffing expenditures and the results were similar. We draw further confidence from the fact that the estimated clinical expenditures per resident per day using staffing ratios from our data and the 2010 wage data from the Bureau of Labor Statistics for RNs ($28.84), LPNs ($20.5) and nurse aides ($11.7) employed in nursing care facilities is approximately $57 – a measure close to the $68 we observe in our data. [73]

Although there are anecdotal reports and speculation about the reliability of nursing home staffing quality information, our study is the first to add new evidence on whether nursing homes increased expenditures to improve staffing scores in Nursing Home Compare. Our finding that higher staffing ratios are associated with higher clinical staffing expenditures on average is not surprising, given that hiring new staff will generally require additional expenditures. The lack of pre- vs. post-5-star difference in the relationship between expenditures and staffing scores for nurse aides is also unsurprising since nurse aides are cheaper than LPNs and RNs. However, the weaker association between expenditures and LPN and RN staffing scores in the post-5-star era is revealing. The staffing measures are calculated as ratios per resident-day, so a nursing home might improve scores by hiring cheaper staff with less experience, but at some level higher staffing ratios should incur higher expenditures. The increase in staffing scores without a corresponding increase in spending supports the current skepticism about the validity of these improvements and the underlying data.

The weakening of the relationship between reported staffing and expenditures after the 5-star was more pronounced and more consistent overall for LPN staffing than for RN staffing, which is somewhat surprising given the underlying incentives. RN staffing is a better target for gaming if a facility wants to improve its staffing ratings since RN staffing counts twice in the overall staffing rating. At the same time, increasing reported LPN hours contributes to higher overall staffing ratings and the increases may be harder to verify; given that RN hours are tightly constrained, a substantial increase in reported hours may attract attention by surveyors. "Staffing up" LPN hours before a survey is also cheaper than staffing up on RNs.

Importantly, for-profit facilities with a high Medicaid census exhibit a weakening relationship between staffing and expenditures for both LPN and RN hours, consistent with incentives. The returns to achieving a higher quality rating may be attractive enough for these facilities to attempt different ways to improve their scores in the post-5-star period. As we hypothesized in the conceptual framework, for-profit facilities with a higher share of Medicaid residents may not have the financial means to hire new RN staff and thus may have resorted to inflating their RN staffing prior to inspections or may have simply misreported their RN staffing to improve their staffing ratings.

The weakening relationship between expenditures and staffing scores in the post-5-star period raises several possible alternative explanations for what could have happened following the release of 5-star rating system. First, the OSCAR-based measure used by CMS is based on the two-week period prior to an inspection, and this period may not be representative of staffing levels throughout the year. Nursing homes may anticipate the timing of their inspection and may "staff up" during this period. Second, the self-reported staffing levels during the two-week period may be subject to manipulation. For example, nursing homes may count staffs that are not actually providing resident care in the staffing ratios. While our analysis cannot distinguish among these explanations and cannot completely rule out alternative pathways such as shifting to less experienced, lower-cost staff, our findings suggest that the self-reported staffing data from OSCAR surveys may not be reliable and that CMS's ongoing development of a system to collect staffing information from payroll data is well advised. When these data become available and are incorporated into Nursing Home Compare, our findings suggest that scores in the staffing domain can become more meaningful. At the same time, those new data will require ongoing monitoring for other ways in which the data might be manipulated.

CHAPTER 4

MALNUTRITION INEQUALITY BETWEEN DALITS AND NON-DALITS IN NEPAL- A DECOMPOSITION ANALYSIS

ABSTRACT

Although Nepal has made substantial progress in childhood health over the years, malnutrition inequalities continue to exist between marginalized (Dalits) and non-marginalized (non-Dalits) groups. In order to design appropriate policies to lower malnutrition inequality, it is necessary to understand the determinants of malnutrition and their relative contributions to inequalities. Child's age and gender, mother's age, family education (mother's and father's), family wealth as well as the availability of health facilities are determinants of malnutrition but the extent to which differences in the distribution of these variables lead to inequalities in malnutrition between Dalits and non-Dalits is not well understood in the Nepal context. Height-for-age z-scores (HAZ) are often used to assess malnutrition among children. In this study, we use Blinder-Oaxaca decomposition techniques to decompose the average difference in HAZ scores between Dalit and non-Dalit groups into the portions explained by differences in the distribution of determinants (characteristics effect) and by differences in the effects of the determinants (coefficient effect) using data on children below the age of 5 from the Demographic and Health Survey for Nepal for 2006, 2011, and 2016. To make the interpretations easier, we use the negative of HAZ scores (NHAZ) such that larger NHAZ scores imply worse malnutrition. For descriptive purposes, we also estimate the prevalence of stunting, a severe form of malnutrition defined as HAZ<-2, for the Dalit and non-Dalit groups over time.

In 2006, the average difference in NHAZ scores between the Dalits and non-Dalits was 0.26 with about 69% of this difference attributable to the characteristics effect; differences in family education and wealth contributed about 24% and 21% of the total difference, respectively ($p<0.01$ for both). In 2011, the average difference in NHAZ score decreased slightly to 0.24 but about 81% of this gap was attributable to the characteristics effect; differences in family education and wealth contributed about 32% ($p<0.05$) and 31% ($p<0.05$) of the total difference, respectively. The average difference in NHAZ score was 0.09 and not significantly different from zero in 2016 ($p>0.1$). In 2016, the characteristics effect accounted for more than 100% of the difference (160%) with family education and wealth contributing about 71% and 55% of the difference in NHAZ score, respectively. Results from a detailed analysis of components of wealth score show that differences in good sanitation, access to electricity, transportation (bike or car), and traditional house floor contribute substantially to the remaining disparity in malnutrition in 2016. Stunting prevalence decreased from about 57% in 2006 to 40% in 2016 for the Dalit group while it decreased from 48% to 36% for the non-Dalit group during the same period.

Our findings show that malnutrition inequality between the Dalit group and non-Dalit group has declined substantially from 2006 to 2016. Across all years, differences in family education and wealth account for most of the difference in malnutrition inequality. A large contribution of family education and wealth to malnutrition inequality suggests that policies should be designed to narrow the gaps in education and wealth if we are to address malnutrition inequalities between Dalit and non-Dalit groups in Nepal. More specifically, focusing on reducing the gaps in modifiable factors like sanitation, electricity, and transportation services can narrow the remaining disparity in malnutrition.

INTRODUCTION

While the caste system in Nepal was officially abolished in 1963,[74] paving the way for legal equality among people from different caste groups, members of marginalized population groups continue to face cultural and social discrimination. People from lower castes are poorer and have lower levels of education and lower access to, and utilization of, health care resources. Poorer child health outcomes are another consequence of this marginalization. Although Nepal has seen a decline in the prevalence of child malnutrition, about 41% of the children under the age of 5 still suffered from stunting in 2011.[11] The prevalence of stunting is about 31% for hill Brahmins, a more privileged class in Nepali society, compared with 51% for hill Dalits, a traditionally marginalized group [11]. Furthermore, there is a concern that the gap between marginalized communities and others may be growing over time.

Malnutrition is a complex phenomenon that may involve under-nutrition, lack of micro-nutrients, and obesity. In this study, we focus on the failure to grow properly, or protein-energy malnutrition[75]. Malnutrition can negatively affect the ability of individuals to move up the socio-economic ladder. First, many children who suffer from malnutrition are likely to die, especially in developing countries[76]. Second, children who survive malnutrition are more likely to have poor cognitive skills [77], to delay school enrolment, to have lower educational attainment [78], and subsequently to have lower earnings [79]. As a result, malnutrition is likely to persist in poor and marginalized households over time. Several reports on Nepal have highlighted inequalities in health care services utilization and outcomes across caste/ethnicity lines and the need to address the concerns of traditionally marginalized communities [11,80,81].

Inequalities are a growing concern in many developing countries, including Nepal. The government of Nepal affirmed its commitment to improve the health status of "…vulnerable groups, particularly those whose health needs often are not met-women and children, the rural population, the poor, the underprivileged, and the marginalized population" in its Second Long Term Health Plan, 1997-2017 [82]. Despite prioritizing the reduction of health inequality between different population groups[11], we are not aware of any published data on the determinants of health inequality which could inform policymakers in Nepal on policies that could decrease malnutrition inequality.

In this study, we sought to quantify the importance of determinants of malnutrition inequality between traditionally marginalized communities and other groups. In particular, we analyze the factors contributing to the malnutrition inequalities between marginalized groups and others using Blinder-Oaxaca [83,84] decomposition techniques. We estimate whether household education and wealth are associated with malnutrition inequality, and how much of the malnutrition inequality can be attributed to these and other observable factors. These two findings can be combined to inform policies aimed at narrowing the disparity in malnutrition between marginalized and non-marginalized groups.

CONCEPTUAL FRAMEWORK

Our theoretical framework for the analysis of malnutrition inequalities between groups rests on two key ideas: a) there are known determinants of malnutrition, and b) these determinants differ in levels, or have differential impacts on health across groups. For example, even with improved education, people from lower caste groups may not be able to afford good sanitation, perhaps due to lack of enough wealth. United Nations Children's Fund (UNICEF) created a framework for understanding child malnutrition using both individual, household and societal factors [75]. In particular, it discusses the role of the availability of resources as well as the ability of families to use these resources in determining malnutrition.

UNICEF (1998) regards malnutrition as an outcome directly related to three factors: poor diet, disease, and poor maternal and child health care practices. Diarrhea and other environment-related illnesses can negatively impact a child's growth. Adequate hydration during diarrhea may help the children recover quickly. Similarly, proper vaccination may help the children fight diseases. However, several socioeconomic elements may contribute to these factors as well. Social position is considered a key determinant of subsequent health whether through education, income, or other underpinnings of social structure [85]. Families from different cultural, political, religious, and economic backgrounds are faced with differential availability of resources and their ability to use these resources is affected by their own education, culture, and the prevalence of discrimination towards them. Marginalized groups tend to be poorer and may not be able to afford nutritious diets or health care services. In addition, marginalized groups also have poor education that may lead to substandard child-care practices– for instance, poorly educated mothers may not know the dietary needs of children even when they are able to afford a good diet for the children and do not lack food security. Similarly, discriminatory practices against traditionally marginalized communities at the societal level can lead to poor access to health care services among these groups. These features can all work together to increase inequality in malnutrition rates between marginalized vs. other groups.

EMPIRICAL FRAMEWORK AND STATISTICAL METHODOLOGY

Data

We use the most recent three rounds of Demographic and Health Survey (DHS 2006, DHS 2011, DHS 2016) data from Nepal [86-88]. These surveys are financed by the United States Agency for International Development (USAID) and conducted in over 90 low and middle income countries around the world. The DHS program worked with the Population Division of the Ministry of Health and Population, Nepal to design the survey and prepare questionnaires. New Era, a local organization, implemented the surveys in Nepal.

Conducted every 5 years, the DHS is a nationally representative, comprehensive survey. It is designed to be representative for subgroups including urban/rural areas, ecological areas (hill, mountain, and terai), and development regions (Eastern, Central, Western, Mid-western, and Far-western), and is stratified by ecological region[87]. The surveys combined the Western, Mid-western and Far-western mountain regions into one domain due to small population sizes. Response rates are very high, exceeding 98% for household surveys for each of the three waves we study.

The DHS is designed to provide estimates of a variety of population characteristics and outcomes. In particular, the survey is widely used to study child health indicators, with information on child age, sex, height, weight, and utilization of health care services including vaccination. Similarly, there is information on mothers: caste/ethnicity, education, body mass index, use of media, number of children, region of residence, and use of healthcare services. We also have information on other characteristics of the household, including asset-based wealth scores, husband's education, sanitation, and access to water and health facilities.

Sample

We include all children below the age of 5 as of the survey date that provide measurements for height and age; only a subsample of households are selected for the male/household questionnaire and have this anthropometric information for children. For the purposes of our analysis, marginalized groups include people from certain caste groups, collectively known as "Dalits": Kami, Damai/Dholi, Sarki, Badi, Gaine, Unidentified Dalits, Chamar/Harijan, Musahar, Dushad/Paswan, Tatma, Khatwe, Dhobi, Baantar, Chidimar, Dom, and Halkhor [80]. Dalits have traditionally been kept out of higher skilled jobs and mostly focused on metal works (Kami), tailoring (Damai), and leather work (Sarki). All other caste groups were classified as Non-Dalits.

Key Variables

Dependent variables

Height-for-age is a common measure of chronic malnutrition [89,90]. In the data, height measurement is available for children below the age of 5 in the male/household subsample. Height-for-age z-score (HAZ) is calculated as:

$$HAZ = \frac{Height_{age,sex} - Height_{referencemedian_{age,sex}}}{Std(Height_{reference_{age,sex}})}$$

The reference population uses the new growth standards from the WHO [91], which are representative of the growth and development of children from different global cultures, ethnicities, and living conditions. We consider the negative of the HAZ score to make the interpretation easier – the larger the value, the worse the malnutrition. Finally, we define stunting as HAZ<-2 i.e., height-for-age is 2 standards deviation below the reference median.

Independent variables

Family wealth: We used an asset-based measure of income to rank households for the purposes of our analysis. This index has been widely used in studies using DHS data to study income inequality and is similar to a measure of wealth based on expenditures [92]. It uses various household level assets (e.g., whether the family owns a car or bike, source of drinking water, availability of a toilet facility etc.) and generates the wealth score via principal component analysis.

In order to evaluate the role of key variables that determine the wealth index, instead of the aggregate measure of wealth, we use separate measures related to sources of drinking water, type of sanitation, access to electricity, ownership of bike or car, use of clean fuel (liquified petroleum gas, natural gas, biogas, or electricity), house floor type (we consider traditional house floors to include floors using sand, mud, and dung), and ownership of agricultural land and livestock. We selected these variables as they represent either potentially modifiable factors or factors that are likely to account for variations in wealth; together, these variables account for about 75% of the variation in wealth score. Selection of potentially modifiable factors may allow us to identify specific policy suggestions.

Education: We model mother's education and father's education separately in the regressions. However, we summarize the disparity explained by these two variables into one category: parental education. In sensitivity analyses, we separate out the disparity attributable to father's and mother's education.

Other independent variables: Although education and wealth are described as the key determinants of health, there are other variables that can also impact inequality in malnutrition. In Nepal, people have strong preferences for male children and gender could play a role in health inequalities. Similarly, age, sanitation, water access, and urban/rural status are also known to be related to malnutrition. As with education, we also combine the effect of water access and sanitation into one category. More details on the variables included in our analysis are provided in Table 15.

Table 15. Description of Variables

Variable	Description
Child's characteristics	
Female	Whether the child is a female (1/0)
Child's age	Age of child in months
Mother's characteristics	
Education	Mother's education in years
Age	Mother's age in years
Mother's body mass index (BMI)	Mother's BMI
Number of children	Number of children in the household
Uses media	Whether the mother read newspapers, listened to a radio, or watched television at least once a week (1/0)
Health facility visits	Whether the mother visited a health facility in the past 12 months (1/0)
Father's education	Father's education in years
Number of household members	Number of people living in the household
Family wealth	5 categories of asset-based wealth index: Poorest, poorer, middle income, richer, richest
Health facility distance	Whether the mother thinks the closest health facility is far from home (1/0)

Table 15, continued: Description of Variables	
Variable	Description
Good sanitation	Whether the household has a toilet facility (1/0)
Good water	Whether the household has a proper water supply including piped water, public tap, tube well or borehole, protected well/spring, rain water, and bottled water (1/0)
Access to electricity	Whether the household has access to electricity (1/0)
Has bike or car	Whether the household has bike or a car (1/0)
Clean fuel	Whether the household uses liquified petroleum gas, natural gas, biogas, or electricity to cook (1/0)
Traditional house floor	Whether the house floor is made using sand, mud, or dung (1/0)
Owns agricultural land	Whether the household owns agricultural land (1/0)
Owns livestock	Whether the household owns any livestock (1/0)
Provinces	Nepal created a federal system with 7 provinces in 2015 (we retain these designations for 2011 and 2006 data as well)
Rural	Whether the household lives in a rural area (1/0); Many villages were combined to create municipalities in 2014 and 2016 data will reflect the changes in such administrative designations

Statistical Analyses

First, we summarize the variables used in the study. Results are presented as proportions for binary variables and means for continuous variables.

Next, we use Blinder-Oaxaca decomposition techniques to assess the extent to which the differences in malnutrition between the Dalits and non-Dalits are explained by the measured differences in the determinants of health [83,84]. Even though the Blinder-Oaxaca technique has been traditionally used to study wage differentials, more recently, it has been used to study differences in health inequalities as well [93,94].

We use multiple linear regressions of the outcome variable on all observed potential determinants of the outcome to conduct the decomposition [95]. In our study, the outcome variable is the negative of the height-for-age z-score (NHAZ), measuring the level of malnutrition. Let us suppose that X represents a vector of independent variables including family wealth and education. We have two groups of people – Dalits and non-Dalits; with the indicator variable Dalits equaling 1 if a person is from the marginalized community. β_{pooled} represents coefficients from a pooled regression that includes both Dalits and non-Dalits in the regression. Using a linear probability model, we can write the equation as follows:

$$NHAZ_i = \delta\, Dalit_i + \beta_{\text{pooled}}\, X_i' + \varepsilon_i \qquad (1)$$

The difference in malnutrition as measured by NHAZ scores between Dalits and non-Dalits can be represented by the difference in the expected values obtained using the estimated common coefficients from a pooled regression model as the reference coefficients [96]. For variables with multiple categories, the decomposition estimates depend on the choice of reference category. In our estimates, we follow the literature to obtain normalized coefficients[97].

$$Malnutrition\ Difference = E(NHAZ_{Dalits}) - E(NHAZ_{non-Dalits})$$

$$= [\mathrm{E}(\mathrm{X}_{\mathrm{Dalits}}) - \mathrm{E}(\mathrm{X}_{\mathrm{non-Dalits}})]'\beta_{\mathrm{pooled}}$$

$$+\big[E(X_{non-Dalits})'(\beta_{non-Dalits} - \beta_{pooled}\big)$$

$$+E(X_{Dalits})'(\beta_{pooled} - \beta_{Dalits})] \qquad (2)$$

Using equation 2, we disaggregate the difference in malnutrition between Dalits and non-Dalits into the part that is attributable to the differences in prevalence of characteristics ("characteristics effect") and the part attributable to the differences in the coefficients on those characteristics ("coefficients effect"). In equation 2, $[E(X_{Dalits}) - E(X_{non-Dalits})]'\beta_{pooled}$ represents the "characteristics effect" and depends only on the differences in average characteristics (Table 16) and coefficients from the pooled regression model (Table 17). In our study, we follow prior literature [98] and focus on the part attributable to the differences in characteristics because it is the amount of malnutrition inequality that could be eliminated if both Dalits and non-Dalits had the same (average) characteristics. On the other hand, it is difficult to interpret the coefficient effects because they may capture the potential impact of unobserved variables.

All the regressions are estimated adjusting for the survey design. In Blinder-Oaxaca decomposition techniques, it is possible that the "coefficient effects" narrow the disparity while "characteristic effects" worsen the disparity. In instances when the two components are in the opposite direction, "characteristic effects" may account for more than the raw difference in malnutrition. For example, in a study comparing malnutrition inequality using HAZ scores between urban and rural residents in Yemen, the disparity attributable to "characteristics effects" is 61.47 when the raw difference was only 57.30 [99].

Sensitivity Analyses

We conduct a number of analyses to explore the robustness of our findings as well as to delve deeper into policy implications. First, we explore different functional forms for education and mother's BMI to see if our findings are sensitive to the use of education and BMI as continuous variables. Second, we separate out the malnutrition inequality attributable to mother's education from father's education to see which educational differences are driving the malnutrition inequality. Finally, we use some potentially modifiable components of the wealth index in order to understand which specific factors are responsible for malnutrition inequality. More specifically, we use good sanitation, good water, access to electricity, ownership or bike or a car, use of clean fuel for cooking, house floor (whether the floor is made of sang, mud, or dung), and finally, ownership of agricultural land and livestock. These variables will give us insight into potential policy suggestions by identifying variables that drive malnutrition inequality between Dalits and Non-Dalits.

RESULTS

We describe sample characteristics over time in Table 16, stratified by Dalit status. Our analysis includes 5,216 children in 2006, 2,324 children in 2011, and 2,344 children in 2016. The proportion of the sample in the Dalit group ranges from 15% to 19% in different years. Over time, both Dalit and non-Dalit groups have improved in parental education, health care utilization, and access to good water and sanitation. However, across all years, Dalits have lower levels of education, are less likely to use media, and are more likely to be in the poorest and poorer categories than non-Dalits. Dalits in our sample reside in all 7 provinces but a larger share (23% in 2006 to as high as 34% in 2016) tend to live in province 2 which comprises flat lands near the Indian border. These flat lands have a much lower altitude than the hills and mountains that make up most of the other provinces.

Table 16: Summary Statistics

	2006		2011		2016	
	Non-dalits	Dalits	Non-dalits	Dalits	Non-dalits	Dalits
Number of observations	4,408	808	1,879	445	1,999	345
Child's characteristics						
Female	48.8%	49.2%	48.6%	51.9%	47.6%	47.2%
Child's age (months)	30.1	29.9	29.6	29.1	30.0	28.8
Mother's characteristics						
Education (years)	2.7	1.4	3.9	1.8	5.2	3.1
Age (years)	26.9	26.5	27.1	25.9	26.4	26.0
Body mass index	20.5	19.7	21.3	20.6	21.6	21.3
Number of children	3.0	3.4	2.8	3.0	2.4	2.8
Uses media	57.1%	48.9%	57.6%	40.9%	54.6%	45.0%
Health facility visits (past 12 months)	70.4%	67.3%	76.9%	74.7%	82.2%	79.0%
Father's education (years)	5.5	3.3	6.0	3.8	6.9	4.7
Household characteristics						
Number of household members	6.9	6.5	6.2	5.9	6.2	5.9
Family wealth[1]						
Poorest	23.5%	35.9%	22.6%	38.0%	19.3%	26.7%
Poorer	20.9%	25.3%	19.6%	22.6%	20.5%	29.4%
Middle income	20.5%	18.3%	23.2%	24.7%	23.5%	18.2%
Richer	19.0%	13.5%	18.1%	12.5%	21.7%	20.9%
Richest	16.0%	7.1%	16.4%	2.1%	15.0%	5.0%
Health facility far	43.1%	50.8%	55.7%	56.5%	57.6%	64.6%
Good sanitation	30.7%	13.4%	43.8%	24.1%	71.8%	65.6%
Good water	52.9%	57.2%	63.1%	55.4%	71.2%	64.1%
Access to electricity	45.2%	28.3%	69.4%	57.7%	89.8%	82.8%
Has bike or car	3.4%	0.8%	10.1%	2.5%	20.6%	7.0%
Clean fuel	8.2%	2.6%	15.8%	2.5%	22.9%	16.5%
Traditional house floor	78.9%	88.4%	70.7%	84.3%	62.6%	74.6%
Owns agricultural land	71.5%	54.0%	70.0%	48.0%	81.3%	59.0%
Owns livestock	84.0%	81.2%	79.2%	67.9%	78.8%	74.2%

Table 16, continued: Summary Statistics

	2006		2011		2016	
	Non-dalits	Dalits	Non-dalits	Dalits	Non-dalits	Dalits
Number of observations	4,408	808	1,879	445	1,999	345
Provinces						
Province 1	16.7%	19.3%	23.0%	13.8%	17.4%	7.7%
Province 2	20.3%	23.5%	19.0%	29.1%	26.3%	34.4%
Province 3	18.3%	6.4%	14.6%	6.8%	15.7%	12.3%
Province 4	8.2%	10.1%	9.2%	7.9%	6.1%	8.1%
Province 5	17.3%	20.6%	18.3%	15.4%	20.6%	22.0%
Province 6	4.8%	5.9%	5.3%	12.3%	5.5%	6.4%
Province 7	14.4%	14.2%	10.6%	14.7%	8.5%	9.1%
Rural location	87.7%	89.6%	90.5%	94.1%	46.8%	48.3%

Notes: Although the households are categorized into 5 equal groups, the percentages here are different in each category because our sample includes only a subset of households selected for male surveys that had anthropometric measurements. Clean fuel includes the use of liquified petroleum gas, natural gas, biogas, or electricity. Traditional house floor includes floors using sand, mud, or dung.

Figure 2 summarizes the prevalence of stunting in Nepal over time for Dalits and non-Dalits. Both groups have improved over time but Dalits have a consistently higher rate of stunting prevalence. However, the difference in the prevalence of stunting between Dalits and non-Dalits is much lower in 2016 (39.8% vs 35.5%) than in 2011 (47.2% vs. 39.2%) or 2006 (56.6% vs. 48.4%).

Figure 2: Stunting prevalence in Nepal (DHS Data, 2006-2016)

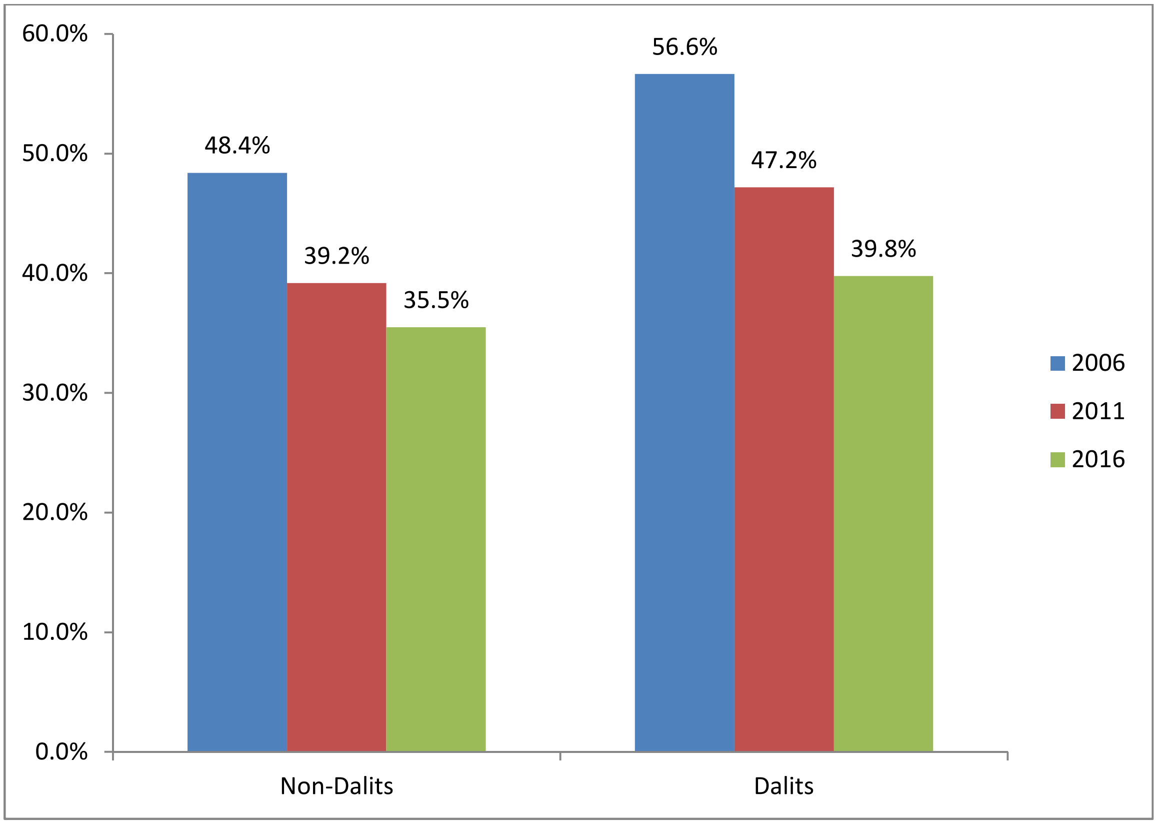


Table 17 shows the pooled regression coefficients from the regression of NHAZ score on all characteristics for each of the years. The directions of coefficients for each of the years are largely consistent and as expected. As the age of the child increases, the NHAZ score increases, implying a higher level of malnutrition. Higher parental education levels are associated with lower NHAZ scores, implying a positive impact of education on malnutrition, though only the education level of the mother in 2006 is significant. The coefficient on father's and mother's education appears similar in 2011 and 2016. Similarly, use of media is associated with lower NHAZ score. Finally, the richer/richest households are associated with significantly lower NHAZ scores compared with the poorest households across all years.

Table 17: Pooled Regression Results - the Association between Observable Characteristics and NHAZ score

	2006	2011	2016
Number of observations	5,216	2,324	2,344
Child's characteristics			
Born to Dalit family	0.081 (0.065)	0.047 (0.096)	-0.054 (0.110)
Female	-0.0018 (0.037)	-0.019 (0.058)	-0.068 (0.057)
Child's age (months)	0.093*** (0.004)	0.081*** (0.008)	0.073*** (0.007)
Child's age squared (months)	-0.0012*** (0.000)	-0.0010*** (0.000)	-0.00088*** (0.000)
Mother's characteristics			
Education (years)	-0.042*** (0.009)	-0.019 (0.013)	-0.014 (0.011)
Age (years)	-0.011* (0.006)	-0.015 (0.009)	-0.0034 (0.008)
Body mass index	-0.00048*** (0.000)	-0.000064 (0.000)	-0.00039*** (0.000)
Number of children	0.089*** (0.018)	0.076** (0.031)	0.042 (0.032)
Uses media	-0.10** (0.046)	-0.065 (0.098)	-0.15** (0.066)
Health facility visits (past 12 months)	0.0074 (0.050)	0.13 (0.080)	-0.059 (0.076)
Father's education (years)	-0.0044 (0.007)	-0.017 (0.014)	-0.016 (0.011)
Number of household members	-0.011* (0.007)	-0.0084 (0.014)	0.027* (0.014)
Family wealth (Ref: Poorest)			
Poorer	-0.16** (0.066)	-0.096 (0.117)	-0.20* (0.111)
Middle income	-0.17** (0.079)	-0.36*** (0.122)	-0.20* (0.121)
Richer	-0.34*** (0.074)	-0.39*** (0.134)	-0.26** (0.127)
Richest	-0.44*** (0.100)	-0.43*** (0.142)	-0.54*** (0.147)
Health facility far	0.015 (0.056)	0.13 (0.093)	0.017 (0.064)

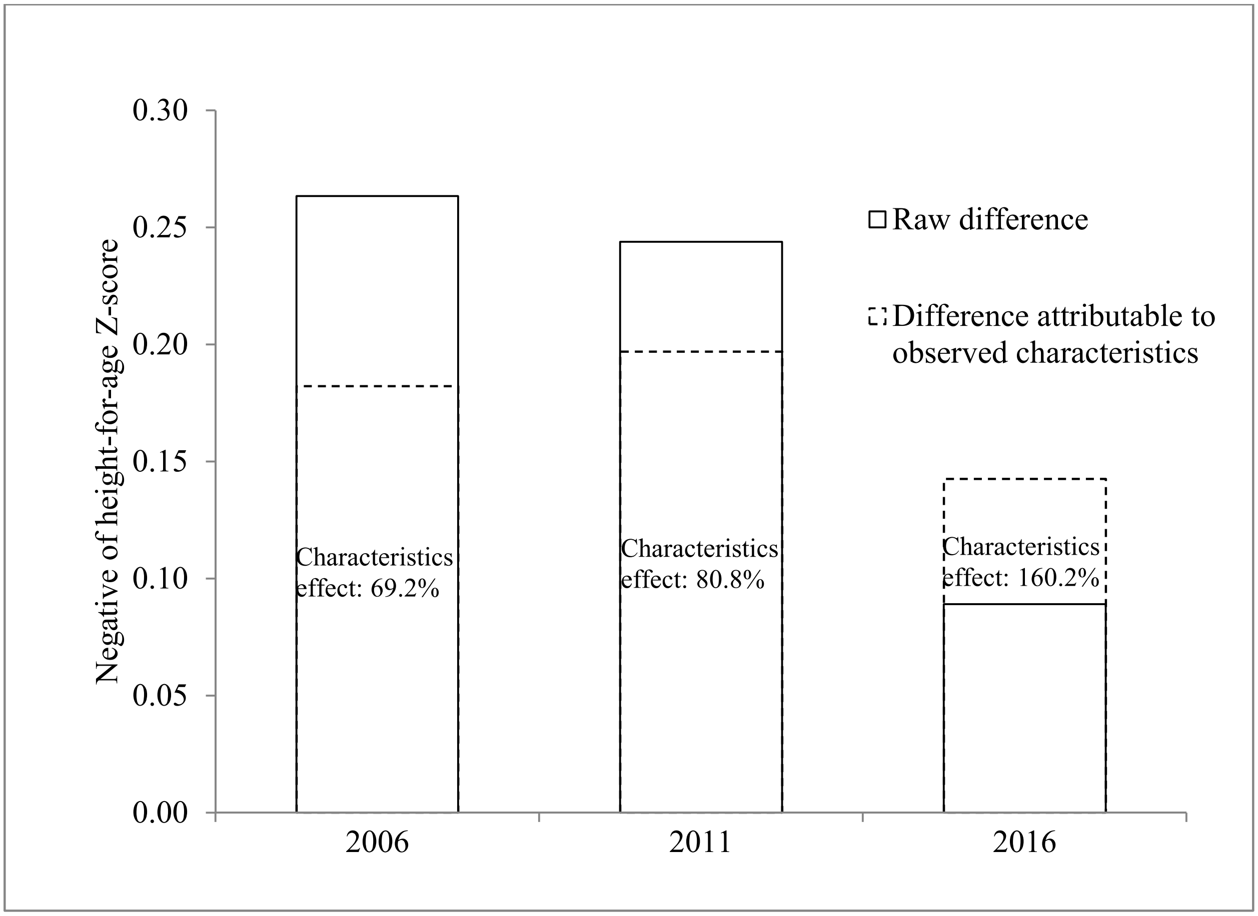
Table 17, continued: Pooled Regression Results - the Association between Observable Characteristics and NHAZ score

	2006	2011	2016
Number of observations	5,216	2,324	2,344
Provinces (Ref: Province 1)			
Province 2	0.20** (0.094)	-0.067 (0.154)	-0.045 (0.093)
Province 3	0.29*** (0.107)	-0.26* (0.141)	0.16 (0.141)
Province 4	0.44*** (0.092)	-0.13 (0.173)	0.032 (0.127)
Province 5	0.40*** (0.098)	0.053 (0.120)	0.18* (0.106)
Province 6	0.38*** (0.090)	0.21 (0.132)	0.53*** (0.125)
Province 7	0.090 (0.102)	-0.048 (0.118)	-0.013 (0.106)
Rural location	0.049 (0.070)	0.16 (0.106)	0.015 (0.068)

Notes: Statistical significance is denoted by: * for p<0.1, ** for p<0.05, and *** for p<0.01.

Malnutrition inequality as measured by the difference in NHAZ score between Dalits and non-Dalits over time is shown in Figure 3; a positive NHAZ score difference implies worse malnutrition for Dalits. While Dalits have a consistently higher level of malnutrition, the raw difference in NHAZ score decreases over time. In 2006, the raw difference in NHAZ score is 0.26 of which 59% was attributable to the observable characteristics. Similarly, the raw difference in NHAZ score is 0.24 in 2011 with about 81% of this difference attributable to the observable characteristics. In 2016, the raw difference in NHAZ score is only 0.09 and it is not significantly different from zero. Since the coefficient effect is narrowing the disparity in malnutrition in 2016, differences in observable characteristics account for more than 100% (147%) of the raw difference suggesting that if both groups had the same average characteristics, other things being the same, the disparity would favor the Dalits.

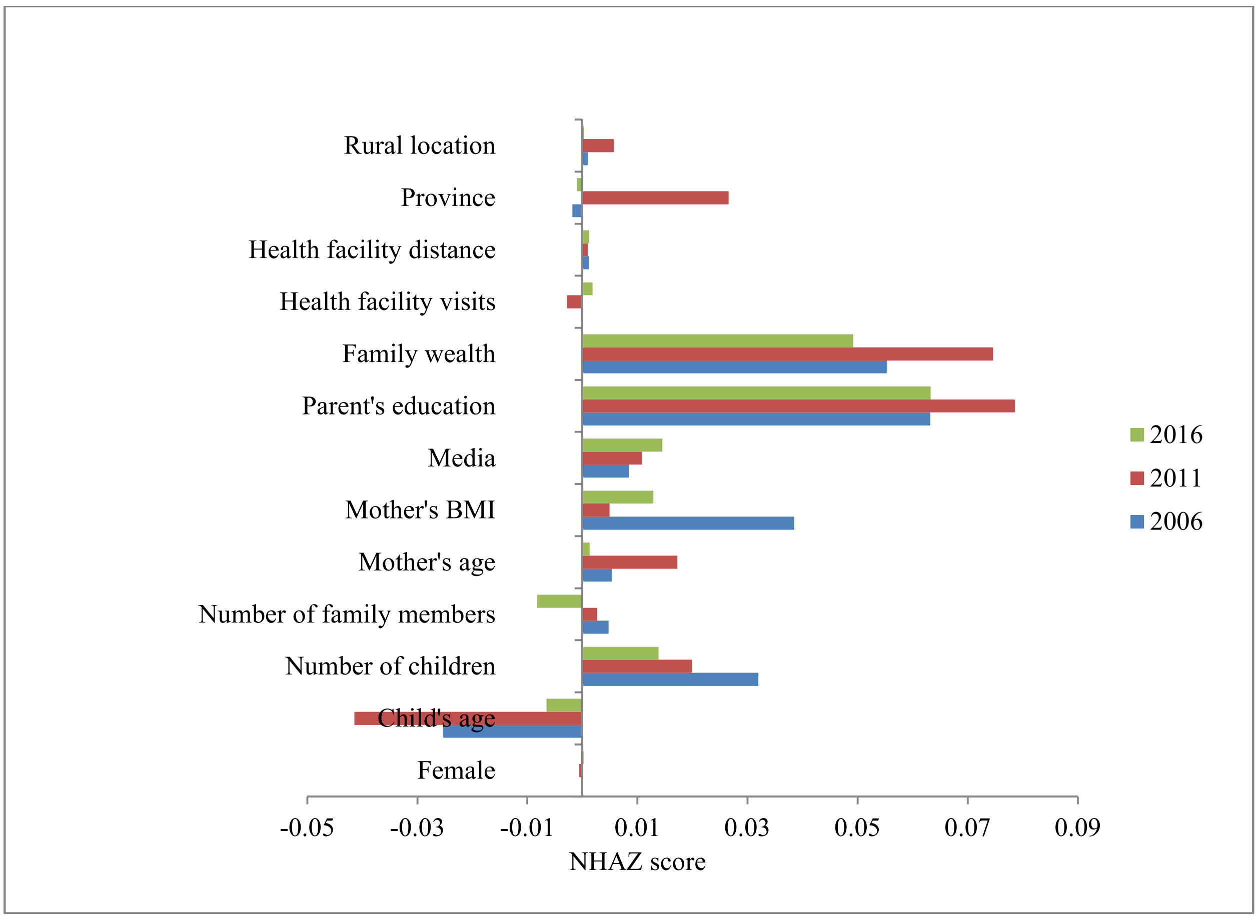
Figure 3: Malnutrition Inequality in Nepal – Dalits vs. Non-Dalits (DHS Data, 2006-2016)



Note: Of the 0.26 difference in NHAZ score in 2006, 69% or 0.18 is attributable to differences in observed characteristics. Similarly, 0.20 of the 0.24 (80.8%) and 0.14 of the 0.09 (160.2%) difference in NHAZ score in 2011 and 2016, respectively is attributable to the differences in observed characteristics.

Figure 4 shows the detailed decomposition results. As shown in Equation 2, the inequality in malnutrition, as measured by differences in NHAZ scores, between Dalits and non-Dalits explained by the differences in characteristics is obtained using two components: a) the differences in the prevalence of characteristics (Table 16), and b) the effect of characteristics on NHAZ scores (Table 17). For example, in Figure 4, differences in parental education explain 0.06 of the difference in NHAZ score between Dalits and non-Dalits in 2016: Dalits have lower levels of education and higher education is associated with lower NHAZ scores. Similarly, differences in family wealth also contribute to the disparity in malnutrition, accounting for 0.049 of the difference in NHAZ score between Dalits and non-Dalits in 2016: a higher proportion of Dalits are in the low-wealth categories and higher wealth categories are associated with lower NHAZ scores. Finally, differences in child's age work in the opposite direction and narrow the disparity in NHAZ scores (-0.007) between Dalits and non-Dalits: higher age is associated with higher NHAZ scores and children from Dalit families are slightly younger.

Figure 4: Malnutrition Inequality Attributable to Observed Characteristics – Dalits vs. Non-Dalits (DHS Data, 2006-2016)



Note: Positive NHAZ score implies worse malnutrition. In the above figure, the contribution to malnutrition inequality is obtained using a) regression coefficients (Table 17) and b) differences in means of characteristics (Table 16). For example, lower education is associated with higher malnutrition and Dalits have lower education.

Thus, the differences in education contribute to malnutrition inequality. Only the inequality explained by parent's education and family wealth are significantly different from zero in all years. Additionally, in 2006, the differences attributable to number of children, mother's BMI, and media were significant.

Results from our sensitivity analyses are largely consistent with our main findings. First, the effect of education and mother's BMI appear similar whether we use them as categorical variables or continuous variables. Second, malnutrition inequality attributable to mother's education appears similar to that of father's education in 2011 and 2016. For example, difference in mother's education explains about 0.026 of the difference in NHAZ score compared with 0.022 for father's education in 2016. In 2006, however, 0.052 of the difference in NHAZ score is attributable to differences in mother's education compared with only 0.017 for father's education.

In Table 18, we show the relationship between observable characteristics including several components of wealth score and NHAZ score. The relationship between observable characteristics and NHAZ score is similar to that shown in Table 17 for non-wealth related variables. The relationship between wealth-related variables and NHAZ score is as expected. Several variables including access to good water and sanitation, ownership of transportation services like a bike or a car, and use of clean fuel for cooking are associated with lower levels of malnutrition whereas having a traditional house floor and ownership of agricultural land are associated with higher levels of malnutrition.

Table 18: Pooled Regression Results - the Association between Observable Characteristics and NHAZ score (Selected Components of Wealth Score)

	2006	2011	2016
Number of observations	5,216	2,324	2,344
Child's characteristics			
Born to Dalit family	0.11* (0.065)	0.046 (0.092)	-0.034 (0.107)
Female	-0.0068 (0.037)	-0.034 (0.060)	-0.061 (0.056)
Child's age (months)	0.093*** (0.004)	0.083*** (0.008)	0.074*** (0.007)
Child's age squared (months)	-0.0012*** (0.000)	-0.0010*** (0.000)	-0.00089*** (0.000)
Mother's characteristics			
Education (years)	-0.041*** (0.009)	-0.018 (0.013)	-0.013 (0.010)
Age (years)	-0.010* (0.006)	-0.013 (0.009)	-0.0019 (0.008)
Body mass index	-0.00045*** (0.000)	-0.000069 (0.000)	-0.00037*** (0.000)
Number of children	0.087*** (0.018)	0.075** (0.030)	0.045 (0.032)
Uses media	-0.13*** (0.047)	-0.073 (0.097)	-0.14** (0.063)
Health facility visits (past 12 months)	0.011 (0.048)	0.13* (0.078)	-0.036 (0.074)
Father's education (years)	-0.0079 (0.007)	-0.017 (0.013)	-0.010 (0.011)
Household characteristics			
Number of household members	-0.015** (0.006)	-0.0053 (0.014)	0.030** (0.015)
Health facility far	0.023 (0.057)	0.12 (0.094)	0.0070 (0.066)
Good sanitation	-0.085 (0.073)	-0.029 (0.092)	-0.29*** (0.091)
Good water	-0.22*** (0.050)	-0.17** (0.082)	-0.020 (0.090)
Access to electricity	-0.024 (0.060)	-0.21*** (0.079)	-0.19* (0.097)
Has bike or car	0.097 (0.108)	-0.065 (0.107)	-0.16* (0.087)
Clean fuel	-0.17 (0.121)	-0.037 (0.145)	-0.11 (0.099)

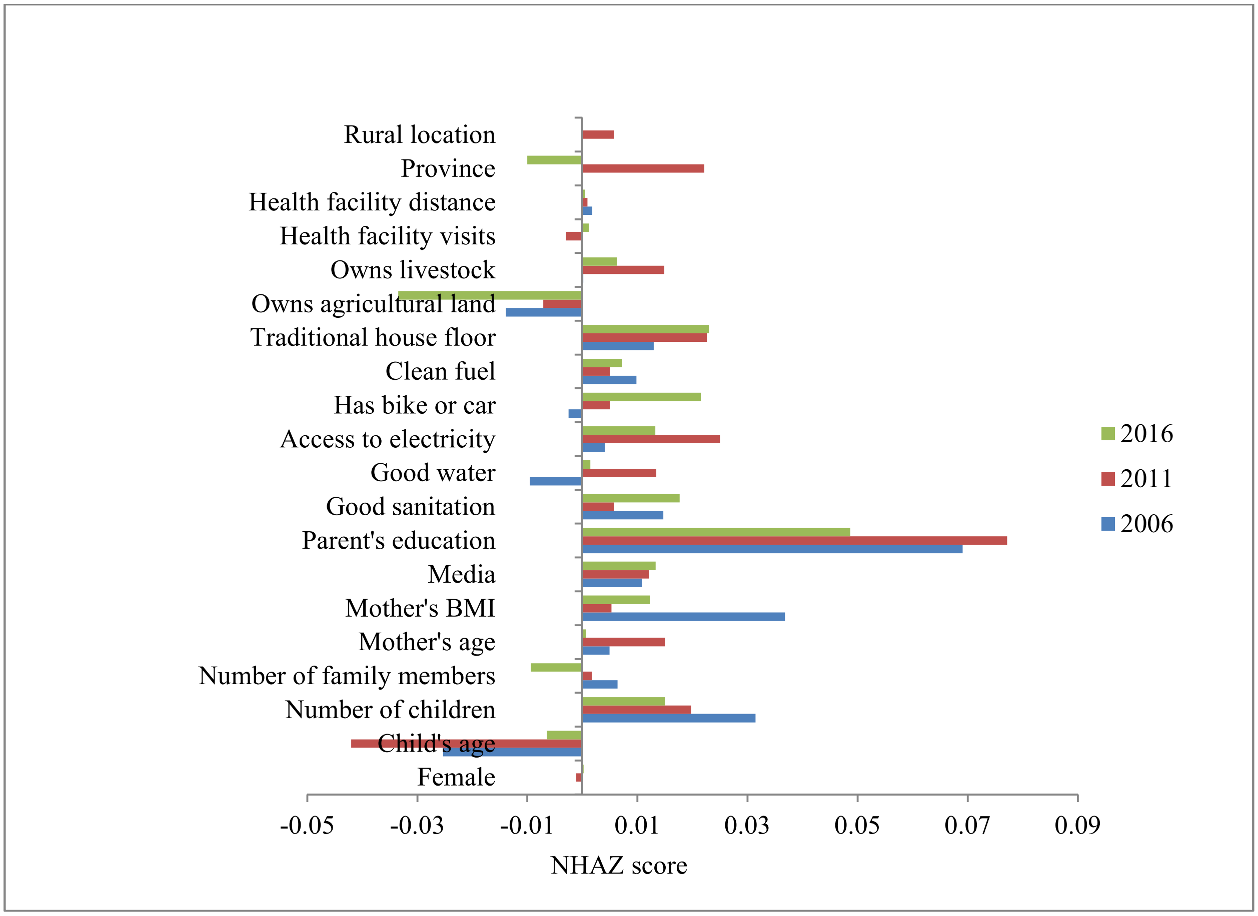
Table 18, continued: Pooled Regression Results - the Association between Observable Characteristics and NHAZ score (Selected Components of Wealth Score)

	2006	2011	2016
Number of observations	5,216	2,324	2,344
Owns agricultural land	0.080*	0.033	0.15*
	(0.047)	(0.078)	(0.081)
Owns livestock	-0.0044	-0.13	-0.14
	(0.065)	(0.102)	(0.095)
Provinces (Ref: Province 1)			
Province 2	0.26***	-0.11	-0.17*
	(0.096)	(0.151)	(0.098)
Province 3	0.29***	-0.25*	0.14
	(0.109)	(0.142)	(0.137)
Province 4	0.44***	-0.14	0.059
	(0.100)	(0.171)	(0.122)
Province 5	0.41***	0.045	0.13
	(0.091)	(0.119)	(0.101)
Province 6	0.39***	0.19	0.56***
	(0.082)	(0.150)	(0.129)
Province 7	0.15	-0.011	0.015
	(0.093)	(0.123)	(0.104)
Rural location	0.00027	0.16	-0.0048
	(0.067)	(0.108)	(0.066)

Notes: Statistical significance is denoted by: * for p<0.1, ** for p<0.05, and *** for p<0.01.

In Figure 5, we show malnutrition inequality attributable to differences in selected components of the wealth index as well as other variables. Results are broadly consistent for most of the non-wealth related variables and parental education continues to be important in driving the disparity in malnutrition. Different components of the wealth index have different contributions to malnutrition inequality. Ownership of agricultural land appears to narrow the disparity in malnutrition between Dalits and Non-Dalits. More specifically, ownership of agricultural land is associated with higher levels of malnutrition and Dalits have lower rates of ownership of agricultural land. In contrast, other components of wealth index including ownership of bike or car, and having traditional house floor increase the disparity in malnutrition. In particular, fewer Dalits have bike or a car and having bike or a car is associated with lower levels of malnutrition. Similarly, more Dalits have traditional house floors and having traditional house floors is associated with higher levels of malnutrition.

Figure 5: Malnutrition Inequality Attributable to Observed Characteristics – Dalits vs. Non-Dalits (Selected Components of Wealth Score; DHS Data, 2006-2016)



Note: Positive NHAZ score implies worse malnutrition. In the above figure, the contribution to malnutrition inequality is obtained using a) regression coefficients (Table 18) and b) differences in means of characteristics (Table 16). For example, lower education is associated with higher malnutrition and Dalits have lower education. Thus, the differences in education contribute to malnutrition inequality. Only the inequality explained by parent's education is significantly different from zero in all years. Additionally, in 2006, the differences attributable to number of children, mother's BMI, and media were significant whereas in 2016, access to transportation (bike or car), traditional house floor and ownership of agricultural land were significant.

DISCUSSION

In this study, we find that malnutrition inequality between the Dalits and non- Dalits has declined substantially from 2006 to 2016. Across all years, differences in family education and wealth account for most of the difference in malnutrition inequality. A large contribution of parental education and family wealth to malnutrition inequality suggests that policies should be designed to continue narrowing the gaps in these two characteristics in order to further reduce malnutrition inequalities between Dalits and non-Dalits in Nepal. More specifically, focusing on reducing the gaps in modifiable factors like sanitation, electricity, and transportation services can narrow the remaining disparity in malnutrition.

Our findings are largely consistent with the existing literature on malnutrition inequalities from other countries. In a study evaluating malnutrition inequalities between caste groups in India, a country with a caste system that has excluded certain groups from the mainstream society for hundreds of years, researchers found that people from Scheduled Castes and Scheduled Tribes had worse malnutrition with differences education, wealth, and utilization of health care services being the key determinants for the differences in malnutrition [94]. Similarly, another study found poorer outcomes for indigenous populations compared with non-indigenous populations for a majority of health outcomes, including child malnutrition[100].

There has been a large decrease in malnutrition disparity attributable to differences in the number of children and mother's BMI over the years. In the case of mother's BMI, these declines are primarily driven by smaller differences in the means of body mass index between the two groups over time. On the other hand, while the number of children in the household has been declining, the differences in the number of children between these two groups have been fairly constant. Thus, the lower malnutrition disparity attributable to differences in the number of children in 2016 appears to be driven by lower coefficients.

Although education continues to play a substantial role in explaining the disparity between Dalits and non-Dalits in Nepal, its impact has declined over the years; the role of the media in explaining the disparity in malnutrition has grown slightly during the same time. Education and use of media may be substitutable in terms of sources of information on nutrition, and given challenges in improving the formal education system in Nepal, especially among the Dalits[101], nutritional education through the media may be more tractable. While the importance of media has grown, there has not been a substantial rise in the percentage of women who read newspapers, listen to radio or watch TV. Perhaps, the lack of growth in the number of women using these traditional sources of media is explained by the growth in use of social media. We were unable to identify women using social media sites like Facebook in our data, but given the growing use of Facebook all over the world including Nepal, it may be one of the more cost-effective approaches to imparting information on child health.

The importance of family wealth in continuing to explain a substantial amount of disparity in malnutrition between Dalits and non-Dalits over time poses significant challenges to reducing disparities. In our detailed analysis using several components of wealth score rather than the wealth score itself, we found that differences in sanitation, access to electricity, ownership of transportation services like a bike or a car, and traditional house floor contribute substantially to gaps in malnutrition. Even though we may not be able to give everyone a bike or a car, or provide subsidies to build modern houses, policies designed to improve sanitation, and providing access to electricity can narrow gaps in malnutrition inequality. In contrast, ownership of agricultural land is associated with higher levels of malnutrition. Given that fewer Dalits own agricultural land, they may have been forced to seek employment outside of agriculture that pays more. Employment programs that encourage hiring of people from the Dalits may be one promising approach, although a recent study highlighted a challenge in increasing the proportion of Dalits enrolled in training and employment programs[102].

There are several limitations to the inequality analysis conducted in this study. First, we should be careful in interpreting the findings from this study as causal effects. Although we made every effort to include variables that may be determinants of malnutrition inequality, it is possible that there are other unobserved or omitted variables that could affect the estimated effects. Ideally, we would want to include episodes of diarrhea, rehydration techniques, and appropriate vaccinations in the analysis to get deeper into the mechanisms of malnutrition. Similarly, information on micro-nutrients including vitamins and iodine would have added to some of the underlying causes of malnutrition. However, we have limited data on those variables to include in the analysis. There may also be genetic variations that drive malnutrition but we do not have information on such variables. Our study describes the relationship between differences in the determinants of malnutrition and malnutrition inequalities and policy prescriptions based on our findings are valid to the extent the associations are causal. Similarly, studies involving health and income often suffer from reverse causality. However, our focus on malnutrition of the child rather than the parents, and our use of a wealth measure based on family assets rather than a more variable wage/income measure, should mitigate potential reverse causality.

Although malnutrition inequality between Dalits and non-Dalits in Nepal has been recognized for some time, our study fills an important gap by quantifying the amount of disparity along with the relative importance of different observable variables in explaining the disparity. Our finding that education and family wealth are meaningful drivers of malnutrition inequality points to several policy implications. Since the role of education, while still important, is decreasing while that of media is increasing, future efforts should focus more on using media, including social media, to impart information on nutritional needs of children. It is difficult to narrow gaps in family wealth without concrete policies aimed at not only increasing employment of Dalits but also including them in the political and social processes of the society. Government programs should explore other avenues to narrow gaps in wealth between Dalits and non-Dalits. More specifically, focusing on reducing the gaps in modifiable factors like sanitation, electricity, and transportation services can narrow the remaining disparity in malnutrition.

SUMMARY

Objectives

This dissertation had three primary aims: 1) to evaluate the health outcomes and expenditures of Medicare residents with post-acute care needs admitted to high-spending vs. low-spending skilled nursing facilities (SNFs), 2) to examine whether improvements in reported staffing quality in nursing homes are corroborated by increases in nursing home expenditures in the pre vs. post the 5-star rating system, and 3) to understand malnutrition inequalities between marginalized communities (Dalits) and non-marginalized communities (non-Dalits) in Nepal.

Summary

In chapter 2, we utilized instrumental variable methods to evaluate the causal effects of admission to high-spending SNFs on patient outcomes and expenditures. We found that patients admitted to high-spending SNFs were significantly less likely to be rehospitalized but there was no difference in mortality. Despite a reduction in rehospitalization, combined SNF and hospital expenditures were higher for those admitted to high-spending SNFs vs. low-spending SNFs; the increased spending for the post-acute care stay more than offset the reduction in spending from fewer hospitalizations. These findings have important policy implications. Increasing health care expenditures are a growing concern for CMS and at least from CMS's perspective, our findings show that the returns to additional expenditures on post-acute care in SNFs are low in terms of rehospitalization and mortality; patients may care about gains in other outcomes including changes in functional status that have not been analyzed in this study. Future studies should explore patient heterogeneity in detail to identify certain subgroups of patients that may benefit from longer length of stay. Policies designed to decrease the length of stay for Medicare residents for whom the additional length of stay has little value may lead to lower expenditures without affecting patient mortality.

In Chapter 3, we found that the relationship between expenditures and licensed practical nurses (LPN) staffing was weaker in the overall sample following the publication of a 5-star composite measure of nursing home quality, as well as across multiple subgroups. In addition, we observed a weaker relationship between expenditures and registered nurses (RN) staffing among for-profit facilities with a high share of Medicaid residents in the post-5-star period. The finding that the relationship between expenditures and staffing is weaker in the post-5-star era is concerning as it suggests a potential for gaming of self-reported staffing scores. While the Centers for Medicare and Medicaid Services (CMS) has instituted a more robust reporting system for staffing through the payroll system in recent years to address potential gaming, our findings suggest a need to continue monitoring staffing data in nursing homes.

Finally, in Chapter 4 we found that malnutrition inequality between Dalits and non-Dalits has declined substantially from 2006 to 2016. Furthermore, using Blinder-Oaxaca decomposition techniques, we found that the differences in family education and wealth account for most of the difference in malnutrition inequality across all years. Although it is encouraging that malnutrition inequality between these two groups has declined in recent years, differences in the levels of education and wealth remain. Policies designed to narrow the gaps in education and wealth are important if we are to further address malnutrition inequalities between Dalit and non-Dalit groups in Nepal. It may be possible to address the gaps in education with alternative methods of imparting information on nutritional needs of children including the use of informal education through social media. However, concrete policies to increase employment may be needed to narrow the gaps in wealth. In the meantime, focusing on reducing the gaps in modifiable factors like sanitation, electricity, and transportation services can narrow the remaining disparity in malnutrition.

Taken together, these results address important questions on the relationship between costs and quality in US nursing homes while exploring malnutrition inequality in Nepal. Although we did not explore potential changes in other outcomes including changes in functional status, a lack of substantial reduction in rehospitalization along with no difference in mortality suggests that we may be able to decrease post-acute care spending without impacting patient mortality. Since CMS is constantly looking for ways to reduce spending, our findings suggest that post-acute care in nursing homes may be a reasonable target to pursue. Similarly, we found evidence of potential gaming in US nursing homes with respect to the staffing quality following the release of 5-star rating system for nursing homes. Even though CMS has made an effort to continuously improve nursing home ratings over the years, our findings underscore a need to continue monitoring staffing changes and improving the staffing reporting system for reliable data. Finally, our study on the malnutrition inequality between the Dalits and non-Dalits in Nepal identifies gaps in education and wealth as the key drivers of malnutrition inequality. While we find that malnutrition inequality has declined substantially over the years, further reduction in malnutrition inequality may require policies to narrow gaps in education and wealth. Overall, this dissertation has investigated important policy-relevant questions and has the potential to inform the policies aimed at decreasing health care expenditures, improving nursing home quality, and reducing malnutrition inequality.

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APPENDIX

Appendix Table 19: Sample Selection Criteria

- At least 66 years of age at the time of admission to SNFs
- Admitted to SNFs within 3 days of discharge from the hospitalization
- Admitted to SNFs within 100 miles from their home ZIP codes; we exclude individuals admitted to SNFs far from their homes because these patients are likely traveling and/or might have particular unobservable reasons for selecting those SNFs
- Patients within 100 miles of both high-spending and low-spending SNFs; we need this requirement to ensure that we can measure the differential distance from the closest high-spending facility to the closest low-spending facility for the given patient
- Admitted between 2012 and 2nd quarter of 2015; we exclude patients who have had prior SNF stays as far back as 2011
- Admitted to facilities that are not hospital-based; hospital-based facilities have a different payment structure. About 95% of approximately 15,000 SNFs in 2015 are not hospital-based [27]
- Enrolled in Medicare fee-for-service throughout the study period; we exclude patients who were enrolled in managed care at any point since they have a different payment structure and we do not have complete data on these individuals
- Admitted to facilities in contiguous United States; we exclude patients from Virgin Islands, Puerto Rico, Hawaii, and Alaska
- Not discharged to hospice or left the SNF against advice
- Positive payments from Medicare

Appendix Table 19, continued: Sample Selection Criteria

- Had continuous eligibility for at least one year prior to the admission and 3 months following the admission
- Patients without missing data
- Admitted to facilities with at least 20 observations
- Patients with 90-day Medicare expenditures within the 1^{st} and 99^{th} percentiles ; we exclude a small fraction of patients with outlier payments because the expenditure models do not perform well with outliers

Appendix Table 20: MS-DRG codes used to identify patient subgroups

Subgroups	MS-DRGs
AMI	280, 281, 282
Heart failure	291, 292, 293
COPD	190, 191, 192
GI hemorrhage	377, 378, 379
Hip and femur procedures	480, 481, 482
Joint replacement	469, 470
Kidney/urinary tract infection	689, 690
Pneumonia	193, 194, 195
Septicemia	871, 872
Stroke	64, 65, 66

Source: Huckfeldt et al. 2016.

Appendix Table 21: Diagnosis codes used to identify of potentially avoidable hospitalizations

Condition	ACSCs	ANHACs
Urinary tract infection	590.0, 590.1, 590.2, 590.3, 590.8, 590.9, 595.0, 595.1, 595.2, 595.4, 595.89, 595.9, 597.0, 598.00, 598.01, 599.0, 601	
Pneumonia	481, 482.2, 482.3, 482.4, 482.9, 483,485, 486	480, 482.0, 482.1, 507.0
Sepsis		038
Clostridium difficile infection, Diarrhea, gastroenteritis		003.0, 004, 005, 006.0, 007, 008 (except 008.45), 009, 558.9, 787.91
Constipation/fecal impaction,obstipation		560.39, 564.00, 564.01, 564.09
Injuries		800–897, 900–995
Cellulitis		681–683, 686
Skin ulcers		707.0, 707.1, 707.8, 707.9
Asthma, COPD	490, 491, 492, 493, 494, 496, 466.0, 466.1	
Angina	411.1, 411.8, 413	
Congestive heart failure	398.91, 402.01, 402.11, 402.91, 404.01, 404.03, 404.11, 404.13, 404.91, 404.93, 428, 518.4	
Poor glycemic control	250.02–250.03, 250.1–250.9, 251.0, 251.2, 790.29	
Hypertension	401.0, 401.9, 402.00, 402.10, 402.90, 403.00, 403.10, 403.90, 404.00, 404.10,404.90	
Hypotension		458.0, 458.1, 458.21, 458.29, 458.8, 458.9
Dehydration	276.5	276.8, 584.5–584.9, 588.8, 588.9
Perforated appendicitis	540.0, 540.1	
Anemia		280, 281, 285.2, 285.9
Weight loss—failure to thrive		783.2, 783.3, 783.7
Nutritional deficiencies		260–263, 268.0, 268.1
Seizures		345, 346, 436, 780.31, 780.39
Delirium, acute confusion		290.3, 290.41, 290.81, 293.0, 293.1
Psychosis, severe agitation		290.42, 290.43, 290.8, 290.9, 293.8,293.9, 297, 298
Chest pain		786.5
Fever		780.6

Note: All 3 and 4 digit diagnosis codes include all diagnoses beginning with those codes. We combine ambulatory-care sensitive conditions (ACSC) and nursing home-specific avoidable conditions (ANHAC) to identify potentially avoidable hospitalizations using principal diagnosis codes. Source: Spector et al. 2013.

Appendix Table 22: Patient and Hospital Characteristics by SNF Spending Status & Differential Distance (DD) (N=1,961,927)

	High Spending	Low Spending	Standardized Difference	Differential Distance ≤Median	Differential Distance >Median	Standardized Difference
hosp_chf	0.16	0.17	-0.02	0.16	0.16	0.01
hosp_valve	0.09	0.08	0.02	0.08	0.09	-0.01
hosp_htn_c	0.74	0.74	0.00	0.74	0.73	0.01
hosp_dmcx	0.05	0.05	-0.01	0.05	0.05	0.00
hosp_aids	0.00	0.00	-0.01	0.00	0.00	0.00
hosp_coag	0.07	0.07	-0.00	0.07	0.07	-0.00
hosp_anemdef	0.24	0.26	-0.03	0.25	0.24	0.02
hosp_pulmcirc	0.04	0.04	0.00	0.04	0.04	-0.01
hosp_para	0.04	0.04	-0.02	0.04	0.04	0.02
hosp_hypothy	0.22	0.21	0.01	0.21	0.21	-0.00
hosp_lymph	0.01	0.01	0.00	0.01	0.01	-0.00
hosp_obese	0.10	0.10	-0.00	0.10	0.10	-0.00
hosp_alcohol	0.02	0.02	-0.00	0.02	0.03	-0.01
hosp_perivasc	0.09	0.09	-0.00	0.09	0.09	0.00
hosp_neuro	0.14	0.16	-0.03	0.15	0.15	0.02
hosp_renlfail	0.19	0.19	-0.00	0.19	0.19	-0.00
hosp_mets	0.02	0.02	-0.01	0.02	0.02	0.00
hosp_wghtloss	0.09	0.10	-0.04	0.10	0.09	0.03
hosp_drug	0.01	0.01	-0.01	0.01	0.01	0.00
hosp_chrnlung	0.22	0.23	-0.01	0.22	0.22	0.00
hosp_liver	0.01	0.02	-0.01	0.02	0.01	0.00
hosp_tumor	0.03	0.03	-0.01	0.03	0.03	0.00
hosp_lytes	0.38	0.39	-0.02	0.39	0.39	0.00
hosp_psych	0.04	0.05	-0.04	0.05	0.04	0.02
hosp_dm	0.22	0.24	-0.04	0.24	0.23	0.02
hosp_ulcer	0.00	0.00	0.00	0.00	0.00	-0.00
hosp_arth	0.04	0.04	0.02	0.04	0.04	-0.01
hosp_bldloss	0.01	0.01	-0.00	0.02	0.01	0.00
hosp_depress	0.14	0.14	0.01	0.14	0.15	-0.01
pri1yr_chf	0.07	0.08	-0.03	0.08	0.07	0.02
pri1yr_valve	0.04	0.04	-0.00	0.04	0.04	0.00
pri1yr_htn_c	0.28	0.29	-0.04	0.29	0.28	0.02
pri1yr_dmcx	0.03	0.03	-0.02	0.03	0.03	0.01
pri1yr_aids	0.00	0.00	-0.00	0.00	0.00	0.00
pri1yr_coag	0.03	0.03	-0.01	0.03	0.03	0.01

Appendix Table 22, continued: Patient and Hospital Characteristics by SNF Spending Status & Differential Distance (DD) (N=1,961,927)

	High Spending	Low Spending	Standardized Difference	Differential Distance ≤Median	Differential Distance >Median	Standardized Difference
pri1yr_anemdef	0.10	0.11	-0.04	0.11	0.10	0.02
pri1yr_pulmcirc	0.02	0.02	-0.01	0.02	0.02	0.00
pri1yr_para	0.02	0.02	-0.02	0.02	0.02	0.01
pri1yr_hypothy	0.08	0.08	-0.02	0.08	0.08	0.01
pri1yr_lymph	0.01	0.01	-0.00	0.01	0.01	0.00
pri1yr_obese	0.04	0.05	-0.02	0.05	0.04	0.01
pri1yr_alcohol	0.01	0.01	-0.01	0.01	0.01	-0.00
pri1yr_perivasc	0.05	0.05	-0.02	0.05	0.05	0.01
pri1yr_neuro	0.05	0.06	-0.03	0.06	0.05	0.01
pri1yr_renlfail	0.08	0.09	-0.02	0.09	0.08	0.01
pri1yr_mets	0.01	0.01	-0.01	0.01	0.01	0.00
pri1yr_wghtloss	0.03	0.04	-0.03	0.04	0.03	0.02
pri1yr_drug	0.00	0.00	-0.01	0.00	0.00	0.01
pri1yr_chrnlung	0.10	0.11	-0.03	0.11	0.10	0.01
pri1yr_liver	0.01	0.01	-0.01	0.01	0.01	0.01
pri1yr_tumor	0.02	0.02	-0.01	0.02	0.02	0.01
pri1yr_lytes	0.15	0.16	-0.03	0.15	0.15	0.02
pri1yr_psych	0.02	0.02	-0.03	0.02	0.02	0.02
pri1yr_dm	0.10	0.11	-0.04	0.11	0.10	0.02
pri1yr_ulcer	0.00	0.00	-0.00	0.00	0.00	0.00
pri1yr_arth	0.02	0.02	0.00	0.02	0.02	-0.00
pri1yr_bldloss	0.01	0.01	-0.01	0.01	0.01	0.01
pri1yr_depress	0.06	0.06	-0.02	0.06	0.06	0.01
hosp_operation_nervous	0.02	0.02	0.02	0.02	0.02	-0.01
hosp_operation_respiratory	0.01	0.01	-0.01	0.01	0.01	0.01
hosp_operation_cardio	0.03	0.03	0.01	0.03	0.03	-0.01
hosp_operation_othercardio	0.14	0.14	-0.02	0.14	0.14	0.01
hosp_trt_hip_frac	0.13	0.11	0.05	0.12	0.13	-0.03
hosp_trt_oth_frac	0.10	0.08	0.07	0.08	0.09	-0.03

Appendix Table 22, continued: Patient and Hospital Characteristics by SNF Spending Status & Differential Distance (DD) (N=1,961,927)

	High Spending	Low Spending	Standardized Difference	Differential Distance ≤Median	Differential Distance >Median	Standardized Difference
hosp_amputation_lowext	0.01	0.01	-0.01	0.01	0.01	-0.00
pri1yr_operation_nervous	0.01	0.01	-0.00	0.01	0.01	0.00
pri1yr_operation_respiratory	0.01	0.01	-0.01	0.01	0.01	0.01
pri1yr_operation_cardio	0.01	0.01	-0.01	0.01	0.01	0.01
pri1yr_operation_othercardio	0.06	0.07	-0.02	0.06	0.06	0.01
pri1yr_trt_hip_frac	0.01	0.02	-0.01	0.02	0.01	0.01
pri1yr_trt_oth_frac	0.01	0.01	-0.00	0.01	0.01	0.00
pri1yr_amputation_lowext	0.00	0.00	-0.01	0.00	0.00	0.00
dual_partial	0.05	0.05	-0.02	0.05	0.05	-0.00
dual_elgbl_mons	2.07	2.61	-0.12	2.44	2.17	0.06
hosp_length	7.43	7.93	-0.07	7.77	7.53	0.03
hosp_lengthsq	103.05	119.05	-0.03	113.51	106.77	0.01
oneyr_hospstay	3.25	3.68	-0.05	3.56	3.31	0.03
oneyr_hospstaysq	78.66	92.73	-0.03	88.87	80.44	0.02
hosp_teaching	0.51	0.49	0.05	0.50	0.50	-0.00
hosp_dsh	0.79	0.81	-0.04	0.80	0.79	0.02
hosp_urban	0.71	0.70	0.01	0.71	0.70	0.02
hosp_chain	0.64	0.65	-0.02	0.65	0.64	0.01
hosp_num_beds	332.04	339.58	-0.02	343.88	323.49	0.06
hosp_mcare_ipdays	30220.68	30603.97	-0.01	31125.87	29333.56	0.07
hosp_ip_totaldays	82367.31	84010.42	-0.02	85196.82	80131.90	0.06
hosp_mcare_discharges	5687.51	5683.47	0.00	5793.27	5524.88	0.06
hosp_tot_discharges	17041.42	17207.42	-0.01	17472.03	16599.66	0.06

Notes: Elixhauser comorbidities are measured during the prior hospital as well as during the one year period prior to the hospitalization.