Racial Differences in Nursing Home Value Added*

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Abstract

We use detailed data on the evolution of health for about 0.8 million Black and 5.4 million white nursing home patients covered by Medicare between 2011 and 2019 to estimate race-specific value-added measures for more than 8,000 nursing homes in the United States. We estimate that the average nursing home value-added experienced by Black patients is about 30% lower than that received by white patients. Most of this gap reflects differences in value-added experienced by similar Black and white patients within the *same* nursing home, rather than differences in value-added across the nursing homes they go to.

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1 Introduction

There are large and persistent differences in the health of Black versus white Americans. For example, all-cause mortality was 20% higher for Black than white Americans in 2015 (Cunningham et al. 2017). A large literature has investigated the causes of these differences and identified a multifaceted and interrelated set of factors. These include social determinants, such as differences in income and education; institutional factors that give rise to historical and current inequities; medical determinants, such as differences in underlying co-morbidities; and differences in the quality of medical care received.[1]

Racial differences in the quality of medical care received may, in turn, reflect differences across and within providers. Across-provider differences may be driven by differences in insurance coverage or by the spatial distribution of providers.[2] Within-provider differences may reflect communication frictions, issues of trust, or biases.[3] Naturally, these two sources of disparities have starkly different implications.

In this paper, we document racial gaps in the quality of health care received and decompose it into across- and within-provider differences. We do so in the specific context of nursing home care, a large sector that in 2016 provided care to over 1.3 million patients at an annual cost of $160 billion, or roughly 5% of that year's national health expenditures (Harrington et al. 2018; CMS 2019a).

Academic researchers and government agencies have expressed longstanding concerns about the overall quality of nursing home care,[4] as well as about racial disparities in the quality of that care. However, as we describe below, most of the research on racial disparities in the quality of nursing home care – like the research on racial disparities in health care more broadly – has focused on differences in the quality of facilities attended by Black versus white patients. There is considerably less evidence on *within-facility differences* in the quality of care received by race, let alone the relative magnitude of between versus within facility differences in contributing to the overall differences in the quality of care received.

To address this evidentiary gap, in this paper we develop and estimate a model of nursing-

[1] See, among others, Chandra and Skinner (2004), Institute of Medicine (2003), Williams and Jackson (2005), Case and Deaton (2015), Chetty et al. (2016), Hardeman, Medina, and Kozhimannil (2016), Case and Deaton (2017), Lavizzo-Mourey, Besser, and Williams (2021), and Chandra, Kakani, and Sacarny (2024).

[2] See Bach et al. (2004), Barnato et al. (2005), Skinner et al. (2005), Hasnain-Wynia et al. (2007), Jha et al. (2007), and Asch et al. (2021)

[3] See Institute of Medicine (2003), Chandra and Staiger (2010), Alsan and Wanamaker (2018), Alsan, Garrick, and Graziani (2019), Obermeyer et al. (2019), Greenwood et al. (2020), and Frakes and Gruber (2022).

[4] See, for example, Wunderlich, Sloan, and Davis (1996), USGAO (2016, 2019), Harrington et al. (2018), Rau (2018), Rau and Lucas (2018), CMS (2019b), Goldstein and Gebeloff (2019), and Jacobs and Richtel (2019).

home value-added in improving patient health outcomes that may vary by race. Specifically, we extend the Einav, Finkelstein, and Mahoney (2025) (hereafter, EFM) framework for estimating average nursing-home specific value added to allow for differences in nursing-home specific value-added by race. The estimates allow us to document differences in value-added experienced by Black and white patients, and to decompose these differences into those arising from differences in the nursing homes they go to and differences in value-added experienced within the same nursing home.

We focus on Medicare patients, for whom nursing homes are intended to provide short-term care that aids in the recovery from a hospitalization or other medical event. Our primary data source is the Long-Term Care Minimum Data Set (MDS), which records patient-level data on approximately 100 health measures at admission and at subsequent intervals, including measures of physical health, mental health, daily functioning and cognitive capacity. We analyze data from 2011 to 2019 on 5.4 million white Medicare patients and 0.8 million Black Medicare patients at about 8,000 different nursing homes. While the model can be applied to any of the approximately 100 measured health outcomes, our preferred specification follows EFM and combines these measures into a one-dimensional "health index" that measures how fit the patient is to return to the community.

The estimates imply large differences in nursing-home value added by race. The average white patient attends a nursing home that increases their average health index – i.e. the weekly probability of being discharged back to the community – by 6.1 percentage points between admission and 30 days. By contrast, the average Black patient attends a nursing home that increases her average health index by only 4.1 percentage points, or about 30% lower than the value for white patients. Essentially all of this difference in experienced value-added reflects within-market differences, rather than a differential distribution of Black and white patients across geographic markets with different average nursing home quality. This is encouraging since there are likely more policy levers for achieving reallocation of patients within markets than across them.

That said, most of the within-market difference reflects differences in the quality of care received by Black and white patients within the same nursing home, rather than differences in the nursing homes they attend. Specifically, we find that if Black patients used the same facilities but counterfactually received the average value-added of white patients in these facilities, over three-quarters of the within-market white-Black gap in value added would be eliminated. In contrast, if Black patients were allocated across nursing homes within their markets in the same proportions as white patients, the within-market gap would shrink by only about 5%.

2 Empirical Context

2.1 Nursing homes in the US

Nursing homes provide both short-term care to patients recovering from a hospitalization or illness, and long-term care to patients in need of ongoing assistance with their daily living. Most short-term patients are covered by Medicare, which pays for short-term nursing and rehabilitation services for patients recovering from a surgical procedure (e.g., hip replacement) or a health event (e.g., stroke); 70% of nursing home patients have Medicare as the primary payer at the time of admission. Crucially, Medicare coverage is predicated on the expectation that the patient is on a path to recovery and return to the community, which is why we will focus on a health index that captures the probability of discharge to the community as a key marker of the quality of nursing home care, or "success."

Essentially all nursing homes (96% of beds) are certified to treat Medicare patients (Harrington et al. 2018); Medicare refers to these as Skilled Nursing Facilities (SNFs), a terminology we will adopt for the remainder of the paper. During our study period, Traditional Medicare reimbursed SNFs at a prospective daily rate, which depends on both the SNF's geographic location and a measure of the patient's health at admission derived from health assessments.[5] Starting at the 21st day in the SNF, patients must pay daily co-pays (either directly or via supplemental coverage), and after 100 days Medicare coverage ends.

2.2 Racial differences in nursing-home care: existing evidence

A large literature has documented differences in the average quality of nursing homes attended by patients of different races. Relative to white patients, Black patients tend to go to nursing homes with lower quality as measured by staffing ratios, nursing skill-mix, deficiency rates from state inspections, star ratings, and finances (e.g., Grabowski 2004; Mor et al. 2004; Smith et al. 2007; Konetzka and Werner 2009; Fennell et al. 2010; Li et al. 2015; Mack et al. 2018; Travers et al. 2018; Rivera-Hernandez, Kumar, et al. 2019; Rivera-Hernandez, Rahman, et al. 2019; Estrada, Agarwal, and Stone 2021).

A smaller set of papers has documented racial differences within a nursing home in the quality of care received. Most of these papers have focused on differences in inputs, such as the use of anticoagulant therapy, feeding tubes, end-of-life care, and vaccinations (Christian, Lapane, and Toppa 2003; Grabowski and McGuire 2009; Travers et al. 2018; Estrada, Agarwal, and Stone 2021). A few papers, like ours, have examined outcome-based

[5] In our data and analysis below, we focus on the approximately 70% of Medicare nursing home patients with coverage from Traditional Medicare (henceforth "Medicare"), as opposed to coverage from a private Medicare Advantage plan.

measures such as re-hospitalization rates or the presence of pressure ulcers (Li, Glance, et al. 2011; Li, Yin, et al. 2011; Rivera-Hernandez, Kumar, et al. 2019).

This existing literature examining within-nursing home differences in race-specific measures faces two econometric challenges that we will address in the approach we develop in Section 4 below. The first challenge is distinguishing between differences in the quality of care patients receive and differences in the underlying health of the patient at admission ("selection in"). Differences in patient health within a nursing home by race seem likely given racial differences in health, as well as evidence of racial differences in the probability of nursing home access and admission (e.g., Akamigbo and Wolinsky 2007; Feng et al. 2011; Thomeer, Mudrazija, and Angel 2015). The second challenge is distinguishing between differences in the quality of care provided on a "per day" basis and differences in patients' length of stay at the nursing home ("selection out"). If Black and white patients tend to stay for different amounts of time, that could naturally produce differences in rates of vaccination, for example, or the probability of developing pressure ulcers during the stay.

3 Data and initial evidence

Data sources Our primary data source is the Long-Term Care Minimum Data Set (MDS) for Resident Assessment and Care Screening. These data are drawn from federally mandated, standardized assessments of the health status of all patients in SNFs and have been widely used to study the economics of nursing homes (e.g., Grabowski, Gruber, and Angelelli 2008; Cornell et al. 2019; Hackmann 2019; Gandhi 2020; Gupta et al. 2023; Hackmann, Pohl, and Ziebarth 2024; Einav, Finkelstein, and Mahoney 2025). During our 2011-2019 study period, assessments for Medicare-covered patients were required at various points, including at admission, at discharge, and after 30 days in the nursing home. The assessments provide detailed information on patient health, along with basic demographics (age, race, gender, and marital status), length of stay, and discharge destination.

We merge the patient-stay-level MDS with patient-level Medicare data which allows us to, among other things, identify the patient's 5-digit zip code of residence and whether the patient is dually eligible for Medicaid (a proxy for low income). We also merge in facility-level data from the OSCAR/CASPER system, which is created during the annual re-certification process.

Sample construction We start with the full sample of all patient-stays at SNFs during the eight fiscal years from October 1, 2011 through September 30, 2019. This full sample contains 38.5 million patient-stays, admitted to 16,805 distinct SNFs. As detailed in Appendix Table A1, we make a number of sample restrictions. The first six restrictions follow EFM and bring the sample to 10.5 million patient-stays at 14,962 distinct SNFs.[6] Given our focus on Black-white racial disparities, we then further restrict our sample to only white non-Hispanic and Black non-Hispanic patients (93% out of the 10.5 million patient-stays). Finally, we restrict to health-care markets with a meaningful number of Black patients by restricting to markets that account for at least 0.05% of all Black patient-stays in the country; throughout the paper we follow EFM and define markets based on sub-HRRs.[7] This final restriction excludes 5% of the remaining Black patients and 39% of the remaining white patients. The final sample consists of 8,043 SNFs in 317 distinct markets, with 6.2 million patients (5.4 million white patients and 0.8 million Black patients). Appendix Figure A1 shows the markets that are in our analysis sample.

Descriptive patterns Table 1 shows summary statistics, separately by race. The average white patient is 81 years old; 63% are female, 36% are married, and 14% are dually eligible for Medicaid at admission. Black patients are on average 3 years younger, slightly more likely to be male, much less likely to be married (26%), and much more likely to be dually eligible for Medicaid (39%). Black patients also have worse outcomes. They have a substantially longer SNF stays (average length of 50 days compared to 40 days for white patients) and are less likely to be in the community 30 days after admission (30% compared to 39% for white patients) or 90 days after admission (50% relative to 62%).

Table 2 presents some initial evidence of racial differences in SNF value-added by measuring the white-Black difference in the probability of being in the community 30 and 90 days after nursing home admission; recall that for Medicare patients, the goal of the SNF stay is to provide short-term care until the patient is well enough to return to the community. Black patients are approximately 10 percentage points less likely than white patients to be back in the community 30 and 90 days after admission (column 2), and this difference increases slightly after controlling for patient age and sex (column 3). Approximately two-thirds of this difference can be attributed to Black patients being sicker at the time of admission to the SNF; when we add controls for a rich set of indicators for health at admission, the dif-

[6]The most important of these restrictions for patient sample size is to patients who, at the time of admission, are at least 65 years old and who are covered by Medicare; the most important in terms of SNF sample size is the restriction to SNFs that have at least 50 patients at admission, which is done to ensure adequate sample size for estimating value-added.

[7]The US is partitioned into 306 Hospital Referral Regions (HRRs) that are designed to approximate health-care markets for tertiary medical care, each containing at least one hospital that performs operations on the heart and brain (Wennberg and Cooper 1998). In EFM, in order to reduce the computational burden associated with very large choice sets of SNFs, we construct sub-HRRs, which partition the 118 largest HRRs into several smaller choice sets which are geographically connected Health Services Areas (HSAs) within each HRR. These, along with the 188 smallest HRRs, yield a total of 680 sub-HRRs.

ferences drop to less than 4.0 percentage points (column 4). Adding market fixed effects to control for the market in which the SNF is located has little effect (column 5). However, the remaining differences are substantially reduced by the inclusion of SNF fixed effects (column 6). We view this evidence as descriptive, and perhaps suggestive. As discussed earlier, these estimates do not control for selection in or selection out of the SNF, which is what we turn to next.

4 Econometric Model

To estimate SNF-specific value added, we first define the patient's health production function, which depends on their health at admission, the nursing home they attend, and their race. We use this model to define race-specific value added and discuss estimation. The model extends the one developed in EFM to allow SNF-specific value added to vary by patient race. We summarize the key elements of the model and estimation here; Appendix A provides more details.

4.1 Defining race-specific nursing home value added

To fix ideas, consider a population of patients, each denoted by i, who are randomly assigned to a set of SNFs, each denoted by j. Patients arrive at SNFs with baseline health h_{i1} at the start of period 1 (initial health assessment). We then observe health h_{i2} at period 2 (30-day assessment) for all patients.

Given this setup, we define the race-specific value added of SNF j as α_j^r in the equation

$$h_{i2} = \alpha_j^{r(i)} + \theta_h h_{i1} + x_i'\theta_x + \varepsilon_i, \tag{1}$$

where $r(i) \in \{B, W\}$ represents patient race, h_{i1} controls for the effect of baseline health, and x_i controls for (non-race) patient demographics, and ε_i is a mean-zero i.i.d error term. The value added term, α_j^r, can be interpreted as the average 30-day improvement in the health of patients of race r at SNF j, conditional on baseline health.[8]

In our baseline model, we assume that the serial correlation in health (captured by θ_h) and effects of non-race patient demographics (captured by θ_x) do not vary by race or across SNFs. These assumptions are needed for the cross- and within-SNF differences in α_j^r to be comparable. They are also standard when estimating differences in value-added across sub-

[8]In practice, we will estimate θ_h to be close to 1 (0.90). As a result, our measure of SNF value added roughly measures the average improvement in patient health between admission and 30 days, and we will use the terms "health improvement" and "value added" interchangeably in what follows.

groups in other contexts such as the school value-added literature (e.g. Angrist et al. 2017). Nevertheless, in sensitivity analysis below, we show that relaxing the assumption of race-invariant serial correlation in health has little effect on our results.

4.2 Addressing selection

Estimating equation (1) for a given health measure would be straightforward if patients were randomly assigned to SNFs and if we observed health for all patients in periods 1 and 2. In practice, as discussed earlier, neither condition holds.

First, patients are not randomly assigned to SNFs ("selection in"). If patient health improvements are correlated with SNF quality, then estimates of α_j^r may be biased, although the direction of this bias is unclear. For example, if savvy patients are more likely to choose higher-quality SNFs and more likely to improve, this would bias upward the estimates of α_j^r for these high-quality SNFs. Alternatively, if SNF quality is particularly important for those who would not improve otherwise, and such patients select high-quality SNFs, estimates of α_j^r for high-quality SNFs would be biased downwards. As in EFM, we address selection in by using the distance between a patient's residence and the nursing homes in their market as an exogenous shifter of SNF choice; here, we also allow SNF choice and the impact of distance to vary by race.

Specifically, in each market, we estimate a model of SNF choice in which the utility of patient i from SNF j is given by

$$u_{ij} = \delta_j^{r(i)}(h_{i1}, x_i) - \tau^{r(i)} m_{ij} + \eta_{ij}, \tag{2}$$

where $\delta_j^{r(i)}(h_{i1}, x_i)$ is the average utility from SNF j for patients of race $r(i)$ with characteristics (h_{i1}, x_i), m_{ij} is the log distance between patient i's residence and SNF j, and η_{ij} is an i.i.d error term drawn from a Type 1 Extreme Value distribution. This model generates the predicted probability of each patient i choosing each SNF j (within their market), and we use these predicted probabilities to construct a control function. As mentioned above, we use the distance between the patient's residence and the SNF (m_{ij}) as an excluded (from the health production function in equation (1)) shifter of these predicted probabilities.

Second, not all patients are still in the SNF at the time of the period 2 health assessment ("selection out"). On average, about 61% of white patients and 57% of Black patients have left the SNF prior to the 30-day assessment. Of those who have been discharged, Appendix Table 1 indicates that the majority (63% of white patients and 53% of Black patients) are discharged "downstream" to the community, while the rest are discharged "upstream" (to a hospital or hospice or they die at the SNF). If patient health improvements are correlated with SNF discharge propensities, estimates of α_j^r using only those patients who remain in the SNF until the 30-day assessment may be biased.[9] As in EFM, we address this issue with an explicit model of the nursing home's discharge decision that is similar in spirit to Heckman (1979). The model allows for a SNF-specific discharge threshold that is a function of patient health and non-race patient demographics, and allows this SNF-specific health discharge threshold to vary by patient race.

4.3 Implementation

Health index The model is organized around the health measures, h_{i1} and h_{i2}, captured at admission and at 30 days, respectively. The MDS provides us with 109 health measures covering a wide range of outcomes, including physical health (e.g., vomiting, shortness of breath, and falls), physical limitations to activities of daily living (e.g., walking, dressing, or toileting measured on a 5-point scale), mental health (e.g. depression), cognitive ability (e.g. delirium), and measures that relate pain, use of equipment, and interactions with others.

We can estimate equation (1) for any individual health measure, or any combination of measures. Our preferred approach follows EFM and constructs a univariate health index that combines the 109 measures in a way that is guided by SNFs' purpose with regard to Medicare patients: shepherding them to the point where they can safely be discharged back to the community. Specifically, we use a regression-tree predictive model to estimate the probability that a patient is discharged to the community within 7 days of their 30-day assessment, and use these predicted values as our health index. From this perspective, a higher quality SNF is one that can nurture a patient more quickly to the level of health that is conducive to community discharge. Loosely, our health index can be thought of as a weighted average of the underlying 109 health measures, with the weights reflecting the importance of these measures in increasing the likelihood that the patient can be discharged back to the community. See EFM for more details on the construction of the health index.

In our baseline index, we estimate a single regression-tree predictive model based on all patients in our data, and use the resultant weights for all patients, regardless of race. In sensitivity analyses below, however, we show that constructing race-specific weights – and hence race-specific health indices – does not meaningfully affect our findings.

[9] More specifically, if discharge decisions across SNFs are not strongly correlated with SNF value added, this bias will generate a compression of estimates of α_j^r around the mean. SNFs with higher value added will have a sicker pool of patients at day 30 than they would without discharge, since they are likely to discharge to the community the patients that improve the most, understating the health improvements. SNFs with lower value added will also have a sicker pool of patients at day 30, but because the sickest are more likely to die or be transferred to a hospital before the 30-day assessment, the observed pool of patients may be healthier, overstating health improvements.

For our baseline health index, we estimate an average health index for white patients at admission of 0.14, indicating that they have a 14% chance of being discharged to the community within 7 days of admission. We estimate a slightly lower (0.12) average health index for Black patients at admission, indicating that Black patients are in slightly worse observable health at admission. In the cross-section, a one percentage point better (higher) health index at admission is associated with approximately one day shorter stay at the SNF for both white patients and Black patients (see Appendix Figure A2). Thus one can alternatively think about a SNF with a 1 percentage point higher value added as one that is able to get a patient to the same level of health one day faster.

Estimation The model is estimated in two steps; Appendix B provides more details. We first estimate the SNF demand model, market-by-market, separately for white patients and Black patients using equation (2). This allows us to construct the choice probabilities that are inputs into the control function that is used to account for potential endogenous sorting of patients into SNFs.[10] With the control function estimates in hand, we then jointly estimate the remaining components of the model – the (race-specific) value added, the (race-specific) discharge model, and the (non-race specific) serial correlation and demographic coefficients – by maximum likelihood.

In our sample there are some SNFs with very few patients of a given race; in such cases, it is difficult to obtain a credible estimate of race-specific value added. To address this issue, we pool (market-by-market) all SNFs that have fewer than 25 Black patients at admission, and estimate a single average (rather than SNF-specific) Black value added for these SNFs. Similarly (but this is less common), we also estimate a pooled white value added within a given market for all SNFs that have fewer than 25 white patients.[11] Finally, to address the fact that estimation noise causes the distribution of value-added estimates to exhibit excess dispersion, we shrink all of our race-specific value-added estimates towards a race-specific mean using an empirical Bayes methodology.

[10] For computational tractability, we follow EFM and limit the shifters of δ_j in the choice model to the baseline health index h_{i1} and to indicators for three age bins and for Medicaid dual-eligibility as the demographics x_i. As in EFM, these same components of x_i are also used for estimating the health production function in equation (1).

[11] In practice, this means that we estimate a pooled white-Black gap in value added within market for 0.17% of white patients and for 11% of Black patients.

5 Results

5.1 Differences in race-specific value added within nursing homes

Table 3 summarizes our estimates of α_j^W and α_j^B for each SNF in the sample, weighting each SNF by its total number of patients. The average white value added is 0.06. Combined with our estimate of $\theta_h = 0.90$ for the coefficient on health at admission in equation (1), this implies that the average SNF increases the weekly probability of discharge to the community for a white patient by nearly 6 percentage points between the initial and 30-day health assessments.

We estimate a substantial difference in the average white and Black value added. The average Black value added is 0.042. To put the average white-Black gap in value added of 0.018 in perspective, recall that in the cross-section of admitted patients, a one percentage point improvement in the health index at admission is associated with approximately one day less in the nursing home (Appendix Figure A2). The average white-Black gap in value added thus implies that if Black patients and white patients were randomly assigned to a SNF, the Black patient would have to stay in the SNF about 2 days longer, relative to a 23 day median length of stay, in order to be discharged with the same health improvement as the white patient.

There is heterogeneity across SNFs in both white and Black value added. The standard deviation of white value added is 0.029 and the standard deviation of Black value added is 0.021, both roughly half of their respective means.[12] Figure 1 explores the within-SNF relationship between the white and Black value added. The top panel shows a moderate correlation (of 0.36) between Black and white value added, suggesting that SNFs that provide high value added to one group are somewhat more likely to provide high value added to the other. The bottom panel shows the corollary of this result, namely a strong correlation (of 0.75) between the white-Black gap in value added and white value added.[13]

Our results naturally raise the question of what nursing home characteristics predict larger within-facility racial differences in value added. Table 4 explores how value added correlates with SNF characteristics within a market. The white-Black gap is smaller at nursing homes with a larger share of Black patients, and a larger share of patients dually

[12] As noted, all estimates have been shrunk towards the mean using an empirical Bayes methodology to remove excess variation due to estimation noise.

[13] A natural concern is that these correlations may be biased by the fact that, as described above, we group small SNFs (within a market) and estimate a common white-Black gap for these SNFs. Yet, the qualitative results remain similar when we restrict this exercises to SNFs for which we can estimate both Black and white SNF-specific value added: the correlation between Black and white value added is then 0.39 and the correlation between the white-Black gap and white value added is 0.73.

eligible for Medicaid, larger nursing homes, nursing homes with higher occupancy rates, and for-profit nursing homes; however, this reflects a "leveling down" effect, with lower value-added for white patients rather than higher value added for Black patients in these facilities. SNFs with higher CMS star ratings, and SNFs whose patients on average have a better experience (e.g., higher rates of flu shots, lower rates of pressure ulcers, lower rates of use of anti-psychotics, and lower use of restraints) tend to have higher value-added and higher white-Black gaps in value added. Appendix Figure A3 shows how the average white-Black gap varies across the continental U.S.

One potential explanation for the within-SNF value added gap is the presence of a living spouse, which (see Appendix Table 1) is much larger for white patients (36%) than Black patients (26%). To the extent that a surviving spouse can serve as an advocate for better nursing home care or motivate the patient to improve their health, the difference in marriage rates could contribute to our findings. However, Appendix Figure A4 shows no correlation between the within SNF white-Black value added gap and the respective within-SNF difference in marriage rates, suggesting that differential marriage rates are unlikely to be an important mechanism.

5.2 The white-Black gap in experienced value added

The estimates in Table 3 reported *within* nursing-home differences in race-specific value added, weighting each nursing home by the total number of patients it received. We now explore the white-Black gap in the average value added *experienced* by white patients compared to Black patients. The gap in experienced value added reflects not only within nursing-home differences but also differences in which nursing homes Black and white patients tend to go to. Specifically, the gap in experienced value added is defined as:

$$Gap^{Exp} = \frac{1}{N_W} \sum_{i \in W} \alpha^W_{j(i)} - \frac{1}{N_B} \sum_{i \in B} \alpha^B_{j(i)}, \tag{3}$$

where N_W and N_B are the total number of white and Black patients, respectively, in the entire sample. To compute experienced value added, we assign each white patient the white value-added estimate at the SNF they went to (α^W_j), and we assign to each Black patient the Black value-added estimate at the SNF they went to (α^B_j).

Table 5 shows the results. Row A shows that the resultant average experienced value added for white patients and Black patients (0.061 and 0.041) are virtually identical to the (total-patient weighted) average value added for white and Black patients across SNFs in Table 3 (0.060 and 0.042), and therefore yields a very similar experienced value added gap of 0.020 (compared to 0.018). To adjust for differences in the distribution of white patients and Black patients across markets with potentially different average value added, in row B we re-weight the experienced value added for white patients by the number of Black patients in each market. This reduces the average experienced white value added very slightly (from 0.061 to 0.059) and as a result slightly reduces the "within-market" average experienced white-Black gap (from 0.020 to 0.018). In other words, the white-Black gap in value added is predominantly a within-market pattern.

The remainder of Table 5 examines the sources of the within-market gap in average experienced value added between white and Black patients (shown in row B). Row (i) indicates that most of the gap in experienced value added stems from within-nursing home differences in Black versus white value added. When we fix Blacks' SNF allocations but, counterfactually, assign them the estimate of the white value added (rather than the Black value added) in the SNF they go to, Black value added increases substantially (from 0.041 to 0.055), eliminating 78% of the white-Black (within-market) gap, which declines from 0.018 to 0.004.

By contrast, row (ii) shows that very little of the gap can be explained by within-market differences in which SNFs Black and white patients go to, indicating that reallocation is not a sufficient mechanism to close racial gaps. We estimate that counterfactually distributing Black patients to SNFs within their market according to the SNF market shares of white patients only slightly increases Black patient value added (from 0.041 to 0.042), reducing the gap by only about 5%, from 0.018 to 0.017. Interestingly, this modest reduction reflects partially offsetting effects. If we hold fixed Black patients in their residential locations but assign them the white patients' preferences based on the estimates from the choice model in equation (2), we reduce the difference in experienced value from 0.018 to 0.015 (row (iii)). However, if we shift Black patients' residential locations to match the distribution of white patients within markets, but then have Black patients choose based on their race-specific estimated preferences for SNFs, the gap increases from 0.018 to 0.026 percentage points (row (iv)). Taken together, the results from Table 5 indicate that differences in value added experienced by Black and white patients within the same SNF are the most relevant force behind our estimate of the racial differences in experienced value added, with small additional contributions from Black patients' choice of SNFs.

A key contribution to our analysis is to control for selection into and out of the SNF in estimating value added. Appendix Table A4 explores the importance of these controls. With no selection controls, the gap in experienced value added is 0.012, slightly more than half of 0.020 in our baseline specification. The controls for selection out are the primary driver of the difference, with the gap growing to 0.018 when we add them. The controls for selection in matter slightly less, increasing the gap to 0.017. The importance of the selection out controls is consistent with large differences in length of stay by race (see Appendix Table 1) biasing the no-controls results.

5.3 Sensitivity

As mentioned above, we explored the sensitivity of our main findings to two key modeling decisions in our baseline results. First, we assumed that the weights which define the health index h_i did not vary by race. Second, we assumed that the serial correlation in health (as captured by θ_h) was the same for Black and white patients. We made these assumptions to facilitate a straightforward interpretation of the results. In this section, we now show that our core results are robust to relaxing each of these.

We start by exploring a race-specific health index. Specifically, we re-estimate the regression-tree predictive model of the relationship between the probability that a patient is discharged to the community within 7 days of their 30-day assessment and the 109 observed health measures separately for Black and white patients. We then use the results of the race-specific regression trees to create race-specific weights for each of the 109 health measures to form race-specific health indices h_{i1} and h_{i2}. Appendix Table A5 shows summary statistics for average health improvements (i.e. h_{i2} - h_{i1}) based on these race-specific health indexes, along with statistics based on the non-race specific index for comparison. Appendix Table A6 shows the correlation between the race-specific indexes and the pooled index separately at 5 and 30 days after admission. Naturally, the health index estimated on the sample of white patients is very similar to that for the pooled sample, as the pooled sample is 84% white. Relative to the baseline (pooled) health index, the health index estimated on the sample of Black patients shows a slightly lower mean improvement among all patients (0.029 versus 0.034). However, the race-specific and pooled health indices are strongly correlated. For example, among Black patients the correlations are 0.88 and 0.89 at 5 and 30 days, respectively; naturally they are even higher for white patients (0.95 and 0.96, respectively). Not surprisingly therefore, Appendix Table A6 also shows that the value-added estimates based on race-specific health indices are also highly correlated with the baseline value-added estimates based on the pooled health index. Most importantly, Appendix Tables A7 replicates our decomposition of experienced value added using value-added estimates based on race-specific health indices. It shows that the experienced value-added gap is slightly higher than the baseline estimate (0.023 compared to 0.020 in the baseline Table 5). However, as before, the gap in experienced value-added is largely explained by within-nursing home differences.

We perform a similar set of sensitivity analyses in which we relax the assumption of race-invariant serial correlation in health (θ_h) and instead re-estimate value-added allowing for race-specific serial correlation in estimating equation (1). Appendix Table A6 shows that the value added estimates that allow for race-specific θ_h are highly correlated with the baseline value added estimated (correlation of 0.92 and 0.97 for Black and white patients, respectively), as is the within-SNF gap in value added (correlation of 0.95). Most importantly, Appendix Table A8 shows our decomposition of experienced value added when estimated using race-specific θ_h. The overall gap in experienced valued-added is now somewhat smaller (0.015 compared to 0.020 in the baseline Table 5). However, as before, most of the gap is explained by value-added differences within SNFs. Specifically, when we assign Black patients the value added of white patients in their chosen facilities, two-thirds of the gap is closed.

6 Conclusion

We estimated race-specific value added for more than 8,000 nursing homes and found that the average Black patient experiences a value-added that is 30% lower than that experienced by the average white patient. Most of this gap is driven by differences in value added experienced by Black and white patients within the same nursing home.

Nursing homes provide care to over 1 million elderly individuals annually. Most of the existing literature on racial disparities in nursing home care has focused on racial disparities in the quality of facilities attended by Black patients and white patients. This may in part reflect the considerable challenges to estimating value added differences across races within the same facilities, as such analyses must account for both potentially differential selection of patients into nursing homes on unobserved health, as well differential discharge propensities. Our findings of substantial gaps in the quality of care received by Black and white patients within the same nursing home suggest the importance of further work to shed light on the factors that affect the quality of care received by patients of different race from the same health-care provider.

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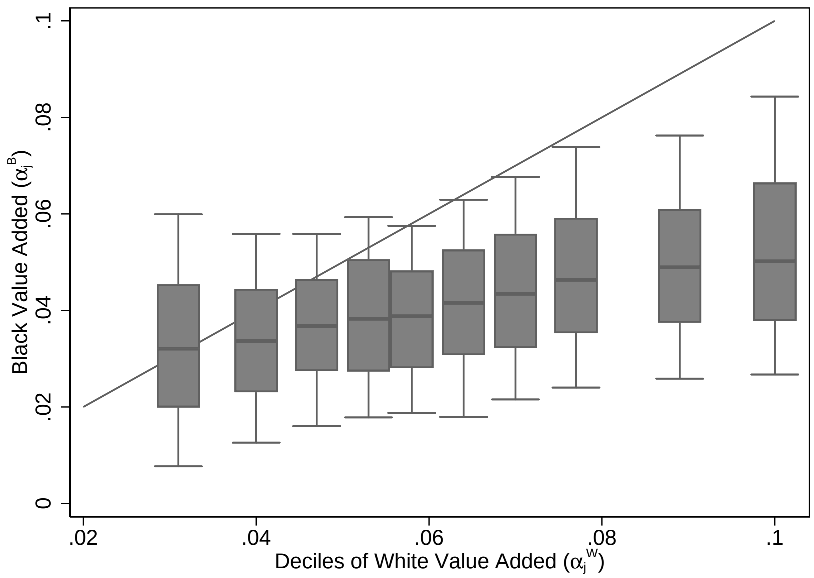
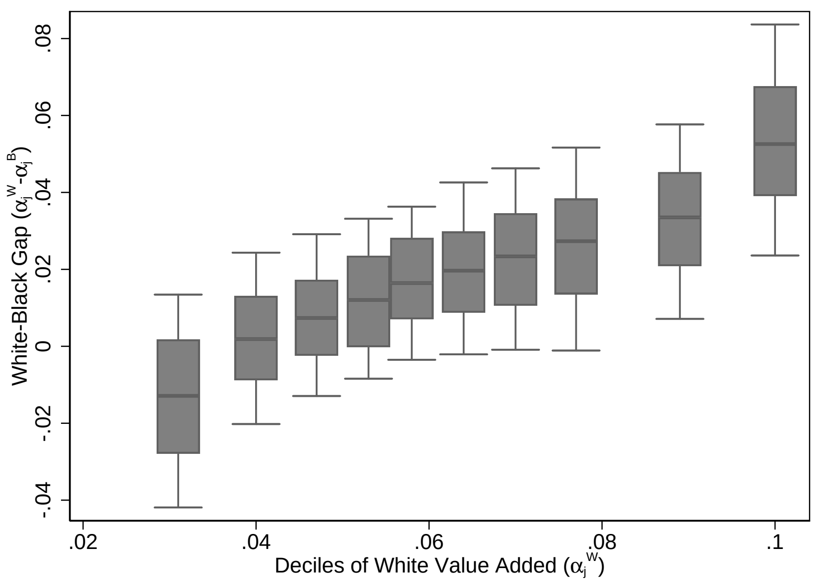
Figure 1: The Relationship Between Black and White Value Added

(A) Black vs. White Value Added



(B) White-Black Gap vs. White Value Added



Notes: Panel (A) shows the distribution of Black value added α_j^B for each decile of white value added across nursing homes α_j^W; each SNF j is weighted by its total number of patients and estimates are empirical-Bayes adjusted. The line in panel (A) is a 45-degree line, and the correlation between Black value added and white value added is 0.36. Panel (B) shows the distribution of the white-Black gap $(\alpha_j^W - \alpha_j^B)$ for each decile of white value added; in both cases, the deciles are computed by weighting each nursing home by its number of patients; each SNF j is weighted by its total number of patients and estimates are empirical-Bayes adjusted. The box-and-whiskers plot show the median in the middle of the box, and the 25th and 75th percentiles, respectively, by the bottom and top of each box. The whiskers (or error bars) shows the 10th and 90th percentiles. The correlation between the white-Black gap and white value added in panel (B) is 0.75. Estimates are based on 8,043 SNFs.

Table 1: Summary Statistics

	White	Black
No. of patients	5,420,251	782,536
Average age	81.3	78.2
Share female	0.63	0.61
Share married	0.36	0.26
Share dual eligible	0.14	0.39
Average length of stay (days)	40.6	50.6
Median length of stay (days)	21.0	22.0
Status at 30 days		
Still in the SNF	0.39	0.43
In the community	0.39	0.30
In an acute-care hospital	0.17	0.22
Died or at a hospice	0.02	0.02
Other	0.03	0.03
Status at 90 days		
Still in the SNF	0.06	0.10
In the community	0.62	0.50
In an acute-care hospital	0.22	0.30
Died or at a hospice	0.04	0.03
Other	0.06	0.06

Notes: Table shows summary statistics for patients in our sample. There are 6,202,787 patient-stays in total, 782,536 of which are Black patients and 5,420,251 of which are white patients. These stays occur at 8,043 SNFs. Means are shown separately for Black and white patients.

Table 2: Descriptive Differences in Rates of Discharge to the Community

	Average for white patients	White-Black difference				
	(1)	(2)	(3)	(4)	(5)	(6)
Community at 30 days	0.388	0.089	0.107	0.038	0.034	0.011
		(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Community at 90 days	0.618	0.114	0.123	0.040	0.039	0.013
		(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Controls:						
Age and sex		No	Yes	Yes	Yes	Yes
Health at admission		No	No	Yes	Yes	Yes
Market fixed effects		No	No	No	Yes	Yes
SNF fixed effects		No	No	No	No	Yes

Notes: Table shows the white-Black gap in the probability of being in the community at 30 days and 90 days from a patient-level regression of this outcome on an indicator for whether the patient is white, and the controls described in the table. Health at admission consists of indicator variables for the 109 health measures at admission in the MDS. These estimates are based on 6,202,787 patient-stays, 782,536 of which are for Black patients and 5,420,251 of which are white patients. These stays occur at 8,043 SNFs in 317 markets. Heteroskedasticity robust standard errors are shown in parentheses.

Table 3: Model Estimates

	Mean	Std. Dev.	Percentiles		
			10th	50th	90th
α^W	0.060	0.029	0.031	0.058	0.089
α^B	0.042	0.021	0.018	0.041	0.067
Gap (α^W - α^B)	0.018	0.029	-0.013	0.017	0.049

Notes: Table shows summary statistics of Black value added (α_j^B), white value added (α_j^W), and the white-Black gap ($\alpha_j^W - \alpha_j^B$); each SNF j is weighted by its total number of patients and estimates are empirical-Bayes adjusted. Estimates are based on 8,043 SNFs.

Table 4: Correlates

Right-hand side variable	Dependent variable α^W	α^B	Gap (α^W - α^B)
SNF Demographics			
Share Black	-0.004	-0.001	-0.003
	(<0.001)	(<0.001)	(<0.001)
Share Dual	-0.008	-0.004	-0.004
	(<0.001)	(<0.001)	(<0.001)
SNF Characteristics			
Number of beds (100s)	-0.003	-0.001	-0.002
	(<0.001)	(<0.001)	(<0.001)
Occupancy rate	-0.002	-0.001	-0.002
	(<0.001)	(<0.001)	(<0.001)
For Profit	-0.003	-0.002	-0.002
	(<0.001)	(<0.001)	(<0.001)
CMS Star Ratings			
Overall Rating	0.005	0.003	0.003
	(<0.001)	(<0.001)	(<0.001)
Quality Rating	0.002	0.001	0.0003
	(<0.001)	(<0.001)	(0.0003)
Inspection Rating	0.005	0.002	0.003
	(<0.001)	(<0.001)	(<0.001)
Staffing Rating	0.006	0.003	0.003
	(<0.001)	(<0.001)	(<0.001)
Patient Experience			
Flu Shot During Stay	0.003	0.001	0.002
	(<0.001)	(<0.001)	(<0.001)
No Pressure Ulcer at 30 Days	0.001	-0.0003	0.001
	(0.001)	(0.0004)	(0.001)
No Antipsychotics at 30 Days	0.007	0.004	0.003
	(<0.001)	(<0.001)	(<0.001)
Physician Exams at 30 Days	0.004	0.002	0.002
	(0.001)	(<0.001)	(0.001)
No Restraints at 30 Days	0.002	0.001	0.001
	(<0.001)	(<0.001)	(<0.001)
Speech Therapy Hours at 30 Days	-0.005	-0.003	-0.002
	(<0.001)	(<0.001)	(0.001)
Occupational Therapy Hours at 30 Days	0.001	0.001	-0.001
	(<0.001)	(<0.001)	(0.001)
Physical Therapy Hours at 30 Days	0.003	0.003	0.001
	(0.001)	(<0.001)	(0.001)

Notes: Table examines the within-market correlation of various SNF-level characteristics shown in the left hand column with SNF-level value added estimates. The columns show results from regressing α_j^W, α_j^B, and $\alpha_j^W - \alpha_j^B$, respectively, on the SNF characteristic as well as market fixed effects; these regressions are weighted by the number of patients in each SNF and value-added estimates are empirical-Bayes adjusted. Each right-hand side variable is standardized to have mean 0 and variance 1. Heteroskedasticity robust standard errors are shown in parentheses. Estimates are based on 8,043 SNFs.

Table 5: Decomposition of Differences in Experienced Value Added

		White	Black	Gap
A.	Experienced value added	0.061	0.041	0.020
B.	**Aligning distribution of patients across markets**: white patients are reweighted by Black shares across markets	0.059	(unchanged)	0.018
(i)	**Within SNF effect:** Black patients' SNF choices stay the same, but they are assigned the white value added instead of the Black value added in their chosen SNF	(unchanged)	0.055	0.004
(ii)	**Sorting across SNFs:** Black patients are assigned the distribution of SNF choices that white patients make (but experience the Black value added)	(unchanged)	0.042	0.017
(iii)	**Demand effect:** Black patients experience Black value added, use their own location and characteristics, but are assigned the demand parameters of white patients	(unchanged)	0.045	0.015
(iv)	**Location effect:** Black patients experience Black value added, use their own characteristics and demand preferences, but are assigned the location (zipcode) distribution of white patients	(unchanged)	0.033	0.026

Notes: Table explores the components of the white-Black gap in experienced value added by conducting various counterfactuals that affect Black experienced value added within markets. Row A shows our baseline estimates of experienced value added. It shows estimates of experienced white value added, experienced Black value added, and the white-Black gap in experienced value added (as defined in equation (3)); in each case, the SNF's race-specific value added is weighted by the number of patients of that race in that SNF. Row B re-weights the average market-level experienced white value added by the number of Blacks patients in each market; by construction, this affects the reported white experienced value added but not the Black experienced value added. In all subsequent rows, our counterfactuals use this re-weighting. Row (i) assigns each patient the white value added of the SNF they go to. In rows (ii) through (iv), the counterfactuals adjust which SNFs Black patients go to, but always allocate them the race-specific value added of that SNF. Row (ii) allocates Black patients to SNFs within markets according to each SNFs market share of white patients. Row (iii) allocates Black patients to SNFs within markets given their observed locations but the white patient demand function (i.e. δ_j^W and τ_j^W in equation (2)). Row (iv) allocates Black patients across zip codes within a market according to zip code shares of white patients, and allocates them to SNFs based on this counterfactual location and the Black patient demand function (i.e. δ_j^B and τ_j^B in equation (2)). Estimates are based on 8,043 SNFs.

Online Appendix

Racial Differences in Nursing Home Value Added

by Einav, Finkelstein, Mahoney, and Okun

A Modeling Selection In and Out

To control for selection into the SNF, we model race-specific SNF choice. Let the utility of patient i from SNF j be given by

$$u_{ij} = \delta_j^{r(i)}(h_{i1}, x_i) - \tau^{r(i)} m_{ij} + \eta_{ij} \tag{4}$$

where $\delta_j^{r(i)}$ is the average utility from SNF j for patients of race $r(i)$ with characteristics (h_{i1}, x_i), m_{ij} is the log distance between patient i's residence and SNF j, and η_{ij} is an i.i.d error term drawn from a Type 1 Extreme Value distribution.

Conditional on the patient's choice of SNF, c_{ij}, h_{i1}, and the demand shocks, η_{ij}, expected health in period 2 is given by

$$\mathbb{E}[h_{i2}|c_{ij}, h_{i1}, \eta_{i1}, ..., \eta_{i|J_i|}] = \alpha_j^{r(i)} + \theta h_{i1} + \sum_{k \in J_i} \phi_k^{r(i)}(\eta_{ik} - \mu_\eta) + \varphi^{r(i)}(\eta_{ij} - \mu_\eta) \tag{5}$$

where J_i is patient i's choice set and μ_η is the mean of the error terms. Integrating over the η's yields

$$\mathbb{E}[h_{i2}|c_{ij}, h_{i1}, m_{i1}, ..., m_{i|J_i|}] = \alpha_j^{r(i)} + \theta h_{i1} + \sum_{k \in J_i} \phi_k^{r(i)} \beta_{ik} + \varphi^{r(i)} \beta_{ij} \tag{6}$$

where

$$\beta_{ik}(j) = \begin{cases} -\log \hat{p}_{ik} & k = j \\ \frac{\hat{p}_{ik}}{1-\hat{p}_{ik}} \log(\hat{p}_{ik}) & \text{otherwise} \end{cases}, \tag{7}$$

and the logit choice probabilities are the predicted values from the choice model described in equation (4):

$$\hat{p}_{ij} = \frac{\exp\left(\delta_j^{r(i)}(h_{i1}, x_i) - \tau^{r(i)} m_{ij}\right)}{\sum_{k \in J_i} \exp\left(\delta_k^{r(i)}(h_{i1}, x_i) - \tau^{r(i)} m_{ik}\right)}. \tag{8}$$

We now discuss how we model selection out. Define discharge to the community as discharge "downstream" and discharge to a hospital or hospice or death in the SNF as discharge "upstream." Following EFM, SNFs first make a downstream discharge decision for each patient $d_i^D \in \{0, 1\}$. Then, SNFs make an upstream discharge decision, $d_i^U \in \{0, 1\}$, for the set of patients for which $d_i^D = 0$.

We assume a stylized probit discharge rule for downstream discharge as in EFM. Specifically SNFs discharge patients downstream according to the following rule:

$$d_i^D = 1 \iff h_{i2} \geq \lambda_j^{r(i)} + v_i^{r(i)} \tag{9}$$

where $\lambda_j^{r(i)}$ is SNF j's downstream discharge threshold for a patient of race $r(i)$ and $\nu_i^{r(i)}$ is an i.i.d race-specific error term, drawn from $N(0, \sigma_\nu^{r(i)})$.

We model upstream discharge as a function of h_{i2} as

$$\Pr(d_i^U = 1 | d_i^D = 0) = \Phi(\gamma_0 + \gamma_1 h_{i2}) \tag{10}$$

where $\Phi(\cdot)$ is the standard normal cumulative density function.

B Estimation

To estimate the model described above, we first estimate SNF demand by race according to the specification in equation (2) market-by-market to construct the control functions, β_{ik}, which are used in equation (6). Given the control functions, we estimate the model by maximum likelihood. A computational challenge is that seven parameters (the "national" parameters) enter the likelihood for all SNFs $(\theta_h, \theta_x, \sigma_\epsilon^W, \sigma_\nu^W, \varphi^W, \sigma_\epsilon^B, \sigma_\nu^B, \varphi^B)$. To address this, we construct a grid of national parameters, and for a given grid point we estimate the model market-by-market. Then, we search over the grid to find the set of seven national parameters that maximize the likelihood and use the corresponding market-level estimates for the other parameters.

Another challenge is that there are some SNFs with very few patients of a given race, meaning we cannot easily estimate race-specific value added for these SNFs. However, it is problematic to simply omit these SNFs from our sample since they may be relevant for counterfactual exercises that reallocate patients to SNFs. Therefore, as described in the text, we pool small SNFs together within markets and estimate a common white-Black gap in value added for these SNFs.

Table 3 showed summary statistics of the estimates of Black value added (α_j^B), white value added (α_j^W), and the white-Black gap ($\alpha_j^W - \alpha_j^B$). Appendix Table A2 shows estimates of the other parameters of the model. The estimated λ_j^B's have a mean of 0.28 and a standard deviation of 0.57. The estimated λ_j^W's have a slightly lower mean of 0.27, and a standard deviation of 0.26. In other words, on average SNFs keep Black patients slightly longer (i.e. require them to get to a higher level of health) before discharge to the community than white patients. The estimated ϕ_j^B's have a mean of 0.02 and a SD of 0.04. The estimated ϕ_j^W's have a mean of 0.01 and a SD of 0.02. The estimated "national" parameters are $\theta_h = 0.90, \sigma_\varepsilon^B = 0.07, \sigma_\varepsilon^W = 0.07, \sigma_\nu^B = 0.20, \sigma_\nu^W = 0.25, \varphi^B = -0.02, \varphi^W = -0.01, \theta_{x_1} = -0.01, \theta_{x_2} = -0.01, \theta_{x_3} = -0.02$.

Empirical Bayes Shrinkage Suppose true value added for white patients in SNF j is α_j^W and true value added for Black patients in SNF j is α_j^B. Our estimates of value added for a patient of race $R \in \{B, W\}$ is given by

$$\hat{\alpha}_j^R = \alpha_j^R + \eta_j^R \tag{11}$$

$$\tag{12}$$

where α_j^R is the true underlying race-specific value added of SNF j and η_j^R reflects measurement noise. The goal of empirical Bayes (EB) shrinkage is to adjust our value added estimates to reduce sampling variance at the cost of increased bias, yielding a minimum mean squared error (MSE) prediction of α_j^R (Morris 1983). Aside from reducing MSE, EB shrinkage also eliminates attenuation bias that would arise in models using α_j^R as a regressor (e.g., Jacob and Lefgren 2007).

Assume first that the parameters of the underlying distribution are known. Specifically, we assume the following distribution of estimated value added $\hat{\alpha}_j^R$:

$$\hat{\alpha}_j^R \mid \alpha_j^R, \pi_j^R \sim N(\alpha_j^R, (\pi_j^R)^2), \quad \alpha_j^R \sim N(\mu^R, (\sigma^R)^2),$$

where π_j^R, μ^R, and σ^R are known. Note that μ^R and σ^R are common across SNFs. The posterior distribution of α_j^R is then

$$\alpha_j^R \mid \hat{\alpha}_j^R, \pi_j^R, \mu^R, \sigma^R \sim N(\alpha_j^{R,EB}, (\pi_j^R)^2(1 - b_j^R)),$$

where

$$\alpha_j^{R,EB} = (1 - b_j^R)\hat{\alpha}_j^R + b_j^R \mu^R$$
$$b_j^R = \frac{(\pi_j^R)^2}{(\pi_j^R)^2 + (\sigma^R)^2}.$$

Written in this form, we see that the EB estimator $\alpha_j^{R,EB}$ "shrinks" the original estimates $\hat{\alpha}_j^R$ towards the prior mean μ^R.

The primary issue that arises from this framework is that π_j^R, μ^R, and σ^R are unknown and must instead be estimated. First, we can estimate σ^R from the standard errors of estimated value-added. Next, we estimate μ^R and σ^R along the lines of Morris (1983). Quantities $\hat{\mu}^R$ and $\hat{\sigma}^R$ are simultaneously determined, so we initialize uniform weights $w_j = 1$ for all j and then estimate via iteration:

1. Compute $\hat{\mu}^R$ then $\hat{\sigma}^R$ using the expressions

$$\hat{\mu}^R := \frac{\sum_j w_j \hat{\alpha}_j^R}{\sum_j w_j}$$
$$(\hat{\sigma}^R)^2 = \max\left\{0, \frac{\sum_j w_j \left\{ \left(\frac{J}{J-1}\right) \left(\hat{\alpha}_j^R - \hat{\mu}^R\right)^2 - (\hat{\pi}_j^R)^2 \right\}}{\sum_j w_j}\right\}.$$

2. If on the second or greater iteration and $\hat{\sigma}^R$ has converged, exit. Otherwise, fix new

w_j using the expression

$$w_j = \frac{1}{(\hat{\pi}_j^R)^2 + (\hat{\sigma}^R)^2}$$

and return to step 1.

This algorithm yields the feasible posterior mean

$$\begin{aligned} \alpha_j^{R,EB} &= (1 - \hat{b}_j^R)\hat{\alpha}_j^R + \hat{b}_j^R \hat{\mu}^R \\ \hat{b}_j^R &= \left(\frac{J-2}{J}\right)\left(\frac{(\hat{\pi}_j^R)^2}{(\hat{\pi}_j^R)^2 + (\hat{\sigma}^R)^2}\right). \end{aligned} \tag{13}$$

The same procedure can be used to shrink SNF-specific parameters other than value added.

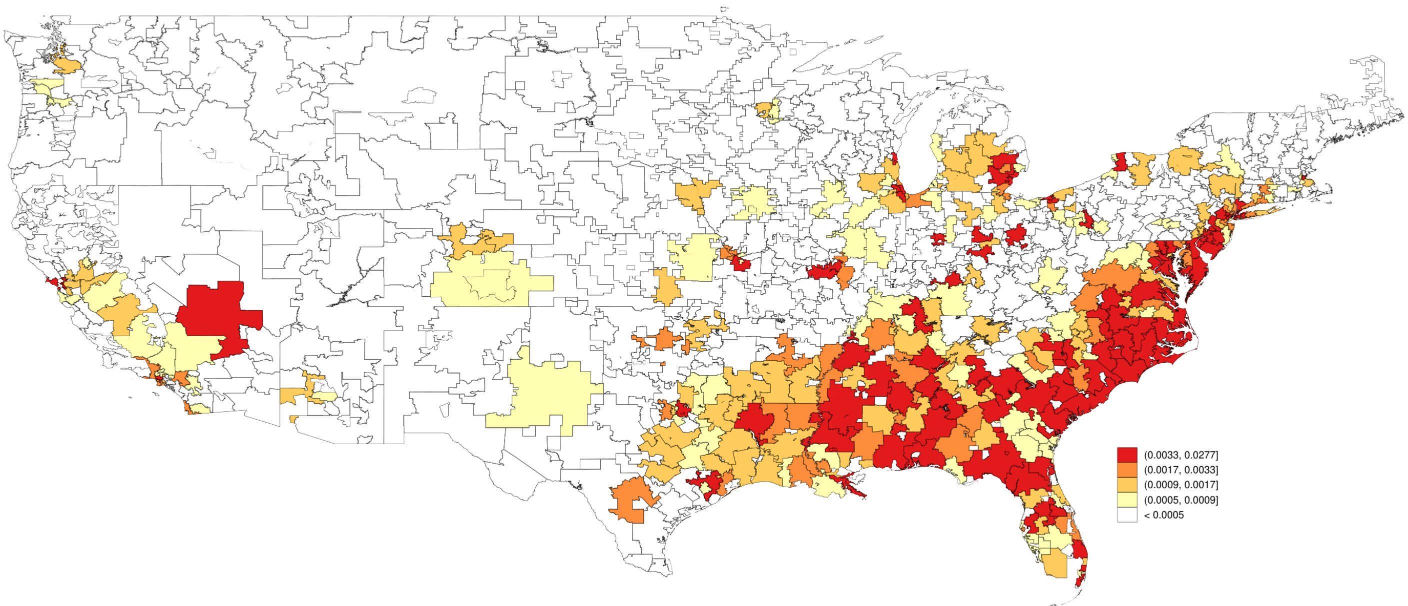
Table A3 shows summary statistics for the unshrunk estimates of α^W, α^B, and their difference. The top panel shows the distributions following the same approach as Table 3; each SNF is weighted by its total number of patients. Naturally, the estimates are more widely dispersed than the shrunken estimates in Table 3. The average gap in value added is also considerably lower (0.007 compared to 0.018 in Table 3). However, this appears to reflect the existence of a few SNFs with relatively large estimates of Black value added but very few Black patients, so that the estimates are shrunk considerably by the empirical-Bayes adjustment. Indeed, in the bottom panel of Table A3 reports experienced value added – which accounts for which nursing homes Black and white patients go to – the unshrunk white-Black gap in experienced value added becomes much larger (0.013) and is closer to our baseline gap in experienced value added (0.020).

References

Jacob, Brian A, and Lars Lefgren. 2007. "What do parents value in education? An empirical investigation of parents' revealed preferences for teachers." *The Quarterly Journal of Economics* 122 (4): 1603–1637.

Morris, Carl N. 1983. "Parametric Empirical Bayes Inference: Theory and Applications." *Journal of the American Statistical Association* 78 (381): 47–55.

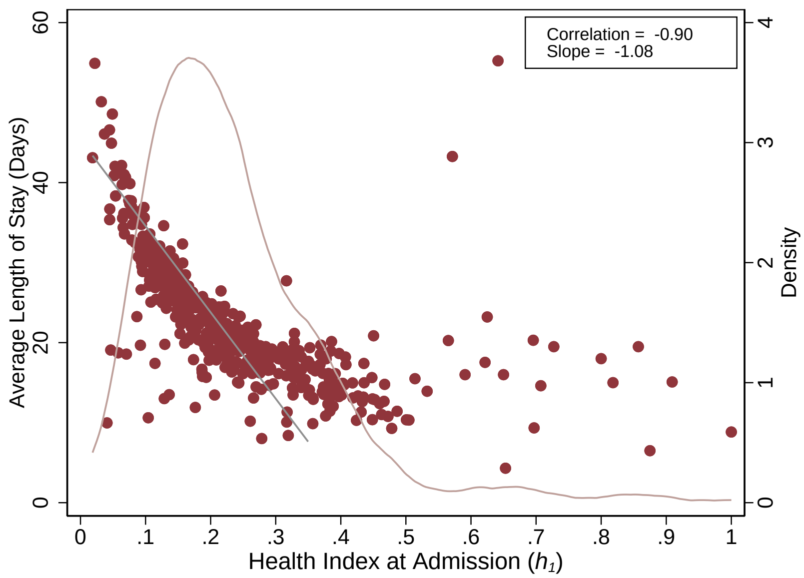
Figure A1: Share of Black admissions in each market



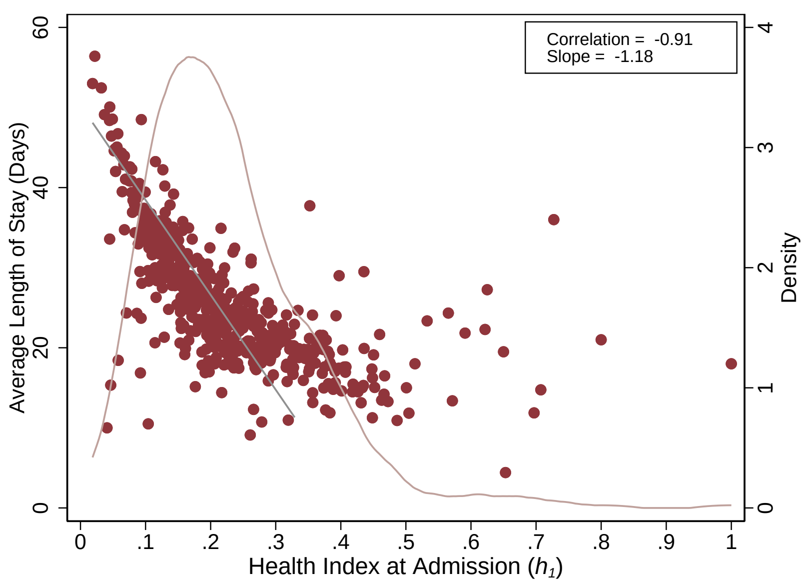
Notes: The figure shows a map of the 680 markets in the US. The map shows each market's share of Black patient-stays out of all Black patient-stays nationwide (before we make the market restriction in the last row of Appendix Table A1). Markets shown in white are fully excluded from our sample due to the market sample restriction. The 317 markets are shown in color are the markets in our final sample.

Figure A2: The Relationship Between Length of Stay and the Health Index

(A) White Patients

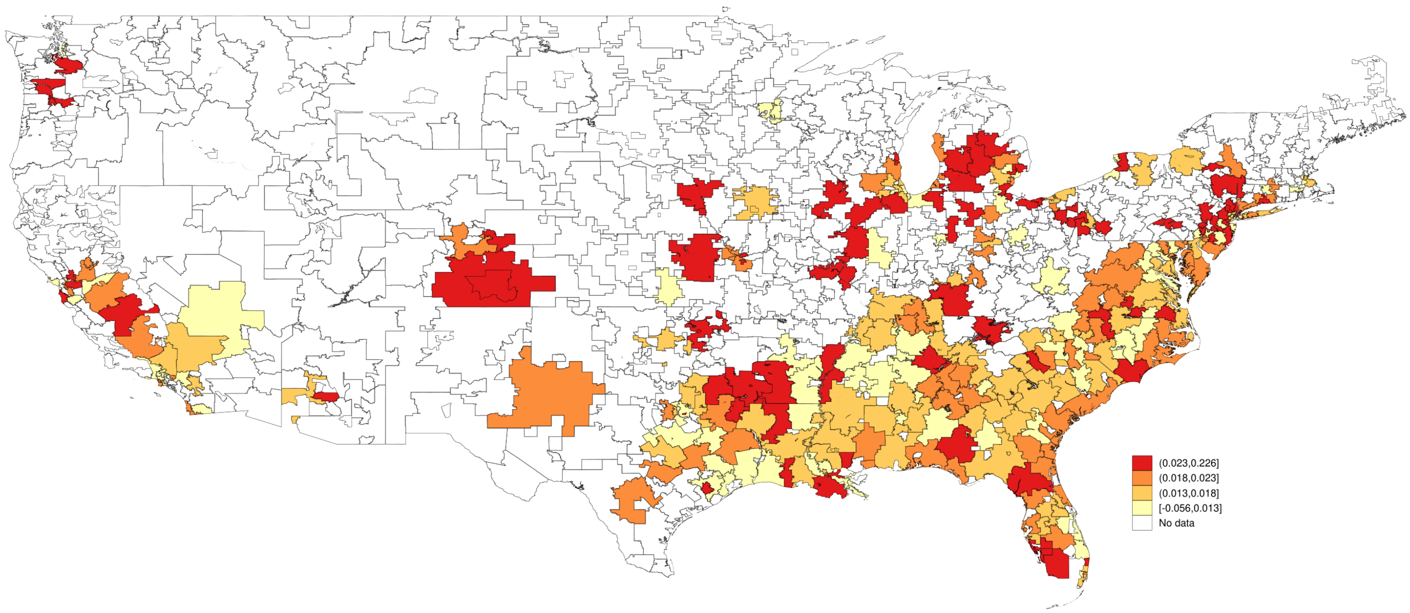


(B) Black Patients



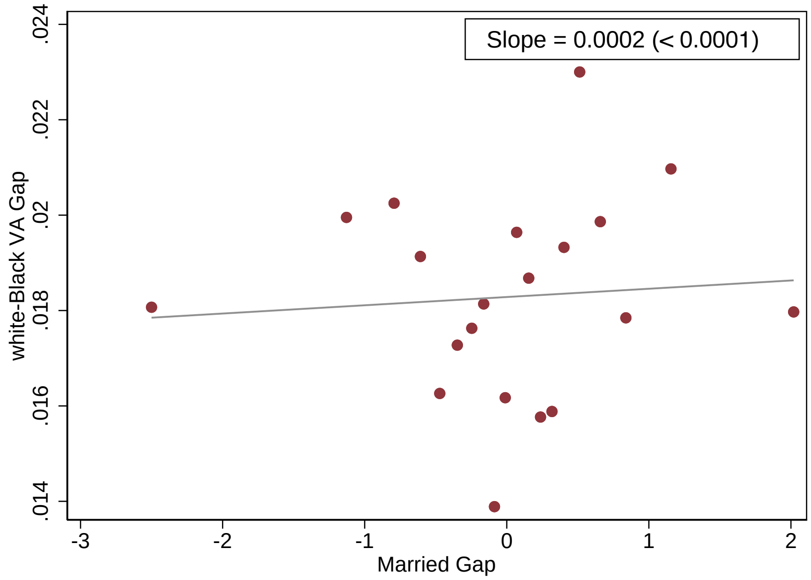
Notes: The figure shows the relationship between length of stay in the SNF and the health index at admission, h_{i1}, by race for all patients discharged to the community. Panel (A) shows this relationship for all 3,444,494 white patients discharged to the community. Panel (B) shows this relationship for all 416,201 Black patients discharged to the community. Each point in the scatter plot represents the average length of stay at one of the 635 unique values of h_{i1} from the regression tree. The line is the linear fit between average length of stay and and h_{i1} for patients with h_{i1} below the 95th percentile. The density is the density of the health index at admission for patients who are discharged to the community.

Figure A3: Average White-Black Gap in Value-Added Across Markets



Notes: The figure shows a map of the average white-Black gap ($\alpha_j^W - \alpha_j^B$) for the 317 markets in our sample. The market averages are computed by weighting each nursing home by its number of patients. Estimates are based on 8,043 SNFs.

Figure A4: Correlation Between White-Black Marriage Rates and Value Added



Notes: Figures examines the within-market correlation of white-Black gaps in marriage rates and value added. We standardize the gap in marriage so that it has mean zero and unit variance. The value-added estimates are empirical-Bayes adjusted. The line is from a SNF-level regression weighted by the total number of patients in each SNF conditional on market fixed effects, and the slope reported in the legend is the slope from that regression, with the heteroskedasticity robust standard errors are shown in parentheses. This figure is based on value-added estimates and marriage rates by race for the 8,043 SNFs in our sample.

Table A1: Sample Restrictions

	Stays	SNFs
1. Full sample	38,505,728	16,805
2. Medicare and >= 65	18,128,312	16,776
3. First stays	12,309,644	16,217
4. CCS codes	11,381,462	16,148
5. Has 5-day health assessment	10,569,681	16,078
6. SNF has at least 50 episodes	10,467,130	14,962
7. Black and white patients only	9,811,758	14,959
8. Market restriction	6,202,787	8,043

Notes: Table shows the various sample restrictions we make to arrive at our final sample of 6,202,787 patient-stays and 8,043 SNFs. The "full sample" consists of all Medicare and Medicaid patient-stays between October 1, 2011 and September 30, 2019; the start of of our study period corresponds to the introduction of version 3.0 of the Minimum Data Set (MDS) and the end corresponds to the end of the fiscal year prior to the Covid 19 pandemic. The next row ("Medicare and ≥ 65") restricts the sample to patient-stays whose admission is covered by Traditional Medicare and are at least 65 years old. The next row ("First stays") restricts to the first stay of each patient episode, as well as patients who enter the SNF directly from an acute-care hospital. The "CCS codes" row restricts to patient-stays with non-missing Clinical Classification Software (CCS) codes from acute hospital stay prior to SNF admission. The "Has 5-day health assessment" row restricts to patient-stays with a 5-day assessment. The "SNF has at least 50 episodes row" restricts to SNFs with at least 50 patient episodes. All of these preceding rows follow the sample restrictions in EFM, while the last two rows add additional restrictions. Specifically, the "Black and white patients only" row restricts to Black non-Hispanic and white non-Hispanic patients. The final row excludes markets that account for less than 0.05% of all Black admissions in the country during our sample period.

Table A2: Parameter Estimates

Parameter	Estimate
A. "National" parameters:	
θ_h	0.90
φ^W	-0.01
φ^B	-0.02
σ_ϵ^W	0.07
σ_ν^W	0.25
σ_ϵ^B	0.07
σ_ν^B	0.20
θ_{x1}	-0.01
θ_{x2}	-0.01
θ_{x3}	-0.02
B. Selection-In parameters:	
Average ϕ_j^W	0.01
Std. Dev. of ϕ_j^W	0.02
Average ϕ_j^B	0.02
Std. Dev. of ϕ_j^B	0.04
C. Selection-Out parameters:	
Average λ_j^W	0.27
Std. Dev. of λ_j^W	0.26
Average λ_j^B	0.28
Std. Dev. of λ_j^B	0.57

Notes: The table shows parameter estimates for the national parameters, the downstream discharge thresholds, and the selection-in coefficients for 8,043 SNFs.

Table A3: Model Estimates Without Shrinkage

	Mean	Std. Dev.	Percentiles 10th	50th	90th
SNF Value Added					
α^W	0.060	0.038	0.026	0.059	0.093
α^B	0.053	0.066	-0.003	0.046	0.117
Gap (α^W - α^B)	0.007	0.068	-0.054	0.011	0.065
Experienced Value Added					
white	0.061	0.038	0.027	0.060	0.093
Black	0.048	0.056	-0.004	0.042	0.107
Gap	0.013				

Notes: The top panel shows summary statistics of SNF value added for for white patients (α_j^W), Black patients (α_j^B), and the white-Black gap ($\alpha_j^W - \alpha_j^B$), weighting each SNF j by its total number of patients as in Table 3. The bottom panel shows estimates of experienced value as in Table 5; experienced value added accounts for which nursing homes Black and white patients go to (see equation 3). Estimates are based on 8,043 SNFs.

Table A4: Alternative Estimates of Gap in Experienced Value Added

	No Selection Controls	Selection In (Only)	Selection Out (Only)	Full Model (Selection In and Out)
A. Experienced value added	0.012	0.017	0.018	0.020

Notes: Table shows white-Black gaps in experienced value added under various models. "No selection controls" estimates the health production function in equation (1), which produces estimates of race-specific SNF fixed effects. "Selection in" estimates the health production function using the "selection in" control function. "Selection out" estimates the health production function via maximum likelihood estimation with the selection out controls. "Full model" refers to our baseline model discussed in the body of the paper which includes both selection in and selection out controls; it therefore replicates the result in row A of Table 5. Estimates are based on 8,043 SNFs.

Table A5: Summary Statistics of Health Improvements Under Various Health Indices

	Mean	Std. Dev.	Percentiles		
			25th	50th	75th
Black Patients					
White Index	0.025	0.060	0.000	0.000	0.044
Black Index	0.021	0.055	0.000	0.000	0.035
Pooled	0.025	0.060	0.000	0.000	0.043
White Patients					
White Index	0.036	0.067	0.000	0.016	0.064
Black Index	0.030	0.063	0.000	0.002	0.057
Pooled	0.035	0.067	0.000	0.016	0.062
All Patients					
White Index	0.034	0.067	0.000	0.013	0.061
Black Index	0.029	0.062	0.000	0.000	0.055
Pooled	0.034	0.067	0.000	0.013	0.060

Notes: Table shows summary statistics of health improvements from 5 to 30 days under race-specific health indices and our pooled health index which is used for our main results. Statistic are shown separately by race. The white index is trained on White patients who are discharged to the community within 7 days of their 30 day assessment. Once trained, we predict a white health index for all patients. The Black index is trained and predicted analogously. Statistics in the table are shown separately for Black and white patients and for all patients. Statistics are based on 2,430,038 patients who are still in the SNF at 30 days.

Table A6: Correlating Alternative Health Indices and Alternative Value Added Estimates

	Constant	Slope	Correlation Coefficient
Race-specific health indices			
Black health index at 5 days	0.010	0.960	0.880
	(0.000)	(0.000)	
Black health index at 30 days	0.007	0.980	0.890
	(0.000)	(0.001)	
White health index at 5 days	0.005	0.960	0.950
	(0.000)	(0.000)	
White health index at 30 days	0.005	0.960	0.960
	(0.000)	(0.000)	
Value added with race-specific health index			
Black value added	0.016	0.650	0.880
	(0.000)	(0.001)	
White value added	0.022	0.620	0.910
	(0.000)	(0.001)	
White-Black gap	0.004	0.670	0.900
	(0.000)	(0.001)	
Value added with race-specific θ_h			
Black value added	0.007	0.780	0.920
	(0.000)	(0.000)	
White value added	-0.003	0.920	0.970
	(0.000)	(0.000)	
White-Black gap	-0.003	0.880	0.950
	(0.000)	(0.000)	

Notes: Table shows results of regressing the value of a variable from our baseline specification (either the health index h_i, our value added estimates α_j, or the within SNF white-Black gap in value added $(\alpha_j^W - \alpha_j^B)$ used in the body of the paper on an alternative, race-specific version of that same variable as described by the row label. Specifically we consider race-specific health indices at 5 and 30 days (the Black health index for Black patients and the white health index for white patients) and alternative value added estimates (using either race-specific health indices or race-specific θ_h). Regressions and correlations are run at the patient level for the health index and at the SNF level for value added estimates, weighted by the number of patient-stays in each SNF. Statistics are based an all 6,202,787 patient-stays and 8,043 SNFs in our main sample.

Table A7: Decomposition of gap in experienced value added (race-specific health indices)

		White	Black	Gap
A.	Experienced value added	0.062	0.038	0.023
B.	**Aligning distribution of patients across markets**: white patients are reweighted by Black shares across markets	0.060	(unchanged)	0.021
(i)	**Within SNF effect:** Black patients' SNF choices stay the same, but they are assigned the white value added instead of the Black value added in their chosen SNF	(unchanged)	0.055	0.005
(ii)	**Sorting across SNFs:** Black patients are assigned the distribution of SNF choices that white patients make (but experience the Black value added)	(unchanged)	0.040	0.020
(iii)	**Demand effect:** Black patients experience Black value added, use their own location and characteristics, but are assigned the demand parameters of white patients	(unchanged)	0.042	0.018
(iv)	**Location effect:** Black patients experience Black value added, use their own characteristics and demand preferences, but are assigned the location (zipcode) distribution of white patients	(unchanged)	0.036	0.023

Notes: Table explores the components of the white-Black gap in experienced value added by conducting various counterfactuals that affect Black experienced value added within markets. In this table we use value added estimates from a model that allows for a race-specific health index. Row A shows our estimates of experienced value added. It shows estimates of experienced white value added, experienced Black value added, and the white-Black gap in experienced value added; in each case, the SNF's race-specific value added is weighted by the number of patients of that race in that SNF. Row B re-weights the average market-level experienced white value added by the number of Blacks patients in each market; by construction, this affects the reported white experienced value added but not the Black experienced value added. In all subsequent rows, our counterfactuals use this re-weighting. Row (i) assigns each patient the white value added of the SNF they go to. In rows (ii) through (iv), the counterfactuals adjust which SNFs Black patients go to, but always allocate them the race-specific value added of that SNF. Row (ii) allocates Black patients to SNFs within markets according to each SNFs market share of white patients. Row (iii) allocates Black patients to SNFs within markets given their observed locations but the white patient demand function (i.e. δ_j^W and τ_j^W). Row (iv) allocates Black patients across zip codes within a market according to zip code shares of white patients, and allocates them to SNFs based on this counterfactual location and the Black patient demand function (i.e. δ_j^B and τ_j^B). Estimates are based on 8,043 SNFs.

Table A8: Decomposition of gap in experienced value added (race-specific θ_h)

		White	Black	Gap
A.	Experienced value added	0.054	0.039	0.015
B.	**Aligning distribution of patients across markets**: white patients are reweighted by Black shares across markets	0.052	(unchanged)	0.014
(i)	**Within SNF effect:** Black patients' SNF choices stay the same, but they are assigned the white value added instead of the Black value added in their chosen SNF	(unchanged)	0.048	0.005
(ii)	**Sorting across SNFs:** Black patients are assigned the distribution of SNF choices that white patients make (but experience the Black value added)	(unchanged)	0.039	0.013
(iii)	**Demand effect:** Black patients experience Black value added, use their own location and characteristics, but are assigned the demand parameters of white patients	(unchanged)	0.041	0.011
(iv)	**Location effect:** Black patients experience Black value added, use their own characteristics and demand preferences, but are assigned the location (zipcode) distribution of white patients	(unchanged)	0.037	0.015

Notes: Table explores the components of the white-Black gap in experienced value added by conducting various counterfactuals that affect Black experienced value added within markets. In this table we use value added estimates from a model that allows for a race specific θ_h. Row A shows our estimates of experienced value added. It shows estimates of experienced white value added, experienced Black value added, and the white-Black gap in experienced value added; in each case, the SNF's race-specific value added is weighted by the number of patients of that race in that SNF. Row B re-weights the average market-level experienced white value added by the number of Blacks patients in each market; by construction, this affects the reported white experienced value added but not the Black experienced value added. In all subsequent rows, our counterfactuals use this re-weighting. Row (i) assigns each patient the white value added of the SNF they go to. In rows (ii) through (iv), the counterfactuals adjust which SNFs Black patients go to, but always allocate them the race-specific value added of that SNF. Row (ii) allocates Black patients to SNFs within markets according to each SNFs market share of white patients. Row (iii) allocates Black patients to SNFs within markets given their observed locations but the white patient demand function (i.e. δ_j^W and τ_j^W). Row (iv) allocates Black patients across zip codes within a market according to zip code shares of white patients, and allocates them to SNFs based on this counterfactual location and the Black patient demand function (i.e. δ_j^B and τ_j^B). Estimates are based on 8,043 SNFs.