Racial Segregation and Disparities Across Nursing Homes: Mechanisms, Interactions, and Policy Tradeoffs

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Abstract

Racial minorities are disproportionately admitted to lower-quality nursing homes, but the forces generating segregation across facilities need not be the same as those generating racial gaps in quality. Using nationwide administrative data on nursing home residents in the U.S. from 2000–2010, I show that neighborhood sorting explains an important share of across-facility segregation, yet substantial disparities remain in the quality of nursing homes that different racial groups are admitted to, even conditional on fixed effects for zip code of prior residence. I then document three additional mechanisms that may drive across-facility segregation and disparities: (i) race-based admissions policies, where nursing homes become less likely to admit minority residents when capacity is strained; (ii) in-group preferences, whereby shocks to the minority share at nursing homes lead to persistent changes in the racial composition, and (iii) heterogeneity in responsiveness to quality, where information shocks lead to larger changes in where White residents are admitted. To quantify the contributions of these explanations, I estimate a two-sided matching model with latent choice set constraints in three large states, using distance and short-run within-facility occupancy shocks for identification. Counterfactual simulations show that neighborhood sorting and race-based admissions policies are complementary drivers of segregation: while the sum of their individual contributions accounts for just over one-half of segregation, eliminating both simultaneously reduces segregation by 85–90 percent. In contrast, the drivers of disparities do not always align with drivers of segregation and vary substantially across states as well as between Black-White and Hispanic-White comparisons within states, implying that policies which reduce segregation need not reduce—and may even worsen—disparities for some minority groups.

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1 Introduction

Racial segregation is a pervasive phenomenon in a number of important settings, such as across schools (Billings, Deming and Rockoff 2014), neighborhoods (Card, Mas, and Rothstein 2008), and healthcare institutions (Baicker et al. 2004). In many of these cases, minorities tend also to be disproportionately concentrated in lower-quality institutions, leading to concerns over racial disparities. This has led to a vast literature documenting these patterns and offering rigorous evidence for various candidate mechanisms. Yet, several unanswered questions remain. First, the literature often studies one mechanism at a time, making it difficult to compare their quantitative importance and leaving open the possibility that these explanations may interact in ways that single-channel analyses struggle to explain. Second, discussions of segregation and disparities do not always make a clear distinction between the two concepts: segregation (the extent to which members of different racial groups sort across providers) and disparities (differences in average quality of providers used by different groups) need not be mechanically linked, and underlying drivers of these patterns may differ. Third, the literature on racial segregation and disparities in economics typically compare two racial groups—most commonly Blacks and Whites. Yet, racial diversity in the U.S. has been growing over the past few decades, and it is unclear whether mechanisms and policy effects generalize across minority groups.

This paper studies these questions in the nursing home setting, a sector that attracts $91 billion of annual federal funding (Kaiser Family Foundation 2025), and that more than half of elderly Americans are expected to use at some point (Hurd, Michaud, and Rohwedder, 2017). Taking advantage of administrative data on the universe of residents in nursing homes between 2000 and 2010, I start by documenting descriptively high levels of racial segregation and disparities for Black and Hispanic nursing home residents relative to Whites. I then provide reduced form evidence for four potential drivers of these patterns: (i) neighborhood sorting, (ii) race-based admissions policies, (iii) in-group preferences, and (iv) heterogeneity in responsiveness to quality. Finally, to quantify the contributions of these channels in a single framework and to study interactions between these explanations, I estimate a structural model that incorporates these mechanisms, and conduct counterfactual simulations.

Descriptively, I find that levels of racial segregation in nursing homes are high and comparable to levels of residential segregation. In addition, substantial racial disparities are present, with Black (and respectively, Hispanic) residents being admitted to nursing homes with 0.12 s.d. (0.14 s.d.) lower quality than White residents on average. At the same time, there is substantial heterogeneity in segregation and disparities across states, and yet there is no clear cross-sectional relationship between

the two objects, providing the first hint that the distinction between segregation and disparities is not merely semantic. Moreover, states in which Black-White disparities are highest are not always the ones in which Hispanic-White disparities are greatest and vice versa, suggesting that underlying drivers of disparities may differ across minority groups.

To assess the importance of neighborhood sorting for racial segregation, I compute segregation at the local level (based on 15-mile radii around each zip code) and compare it to state level segregation. I find that local-market nursing home segregation tends to be far smaller than state-level segregation, indicating that neighborhood sorting may be an important driver of segregation across nursing homes. At the same time, controlling for zip code fixed effects reduces the Black-White and Hispanic-White quality gaps, but sizable gaps remain, suggesting that neighborhood sorting does not fully explain disparities.

I then provide evidence that provider gatekeeping may be another mechanism giving rise to segregation and disparities. When beds are scarce, a nursing home faces a higher option value of keeping capacity available for future residents, creating incentives to become more selective in admissions (Gandhi 2023). Hence, if nursing homes have preferences over residents from different racial groups—whether it is taste-based discrimination (Becker [1957] 1971) or due to pure profit maximization—then racial composition of admissions should vary with capacity strain. Indeed, I find that providers are less likely to admit Black and Hispanic residents when capacity is strained, even conditional on nursing home-by-year-by-month fixed effects. This pattern is difficult to reconcile with a purely demand-driven story and is consistent with a role for race-based admissions policies in explaining segregation and disparities.

Next, I turn to demand-side mechanisms, starting with in-group preferences, i.e., individuals deriving greater utility from living and interacting with members from the same racial group. In addition to high autocorrelation in the share of admissions of a given race in a nursing home over time (conditional on time-invariant facility-level confounders and local demographic trends), I find that a large shock to the minority share at a nursing home leads to long-run changes in the racial composition of admissions, consistent with tipping point predictions from models of in-group preferences (Schelling 1971; Card, Mas, and Rothstein 2008). These patterns do not seem to be driven by a persistent supply-side change either: short-run within-facility fluctuations in the racial composition also predicts the race of new admissions.

The final mechanism I consider is heterogeneity in responsiveness to quality by racial group. In

addition to partial correlations between racial composition of admissions and nursing home quality controlling for the aforementioned mechanisms, event studies exploiting two shocks to information about nursing home quality are especially suggestive. First, the introduction of star ratings—a policy with the explicit aim of improving consumers' nursing home choice—led to greater improvements for White residents relative to Hispanic residents living in the same zip code. Second, following a severe deficiency citation at a nursing home—a rare and salient violation which is deemed to pose immediate jeopardy to residents' safety and health—the share of White admissions fall, whereas shares of Black and Hispanic admissions rise.

Reduced form evidence however, cannot cleanly disentangle demand-side explanations from supply-side ones. For instance, in the presence of race-based admissions policies, even if a severe deficiency citation at a nursing home leads to demand falling uniformly across racial groups, the minority share of admissions may nonetheless rise, given that minority applications that would have been rejected in the pre-violation era (when capacity constraints were more binding) are now being accepted. Hence, to more cleanly disentangle these explanations and to quantify their contributions to segregation and disparities, I estimate a structural model that incorporates all four mechanisms. Specifically, I consider a two-sided matching model of residents' nursing home choice on the demand side and facilities' admissions policies on the supply side, which is identified using distance and short-run fluctuations in occupancy as demand- and supply-side instruments. I estimate the model separately in California, Florida, and Texas, and conduct counterfactual simulations.

The counterfactual simulations deliver two headline results. First, while neighborhood sorting, race-based admissions policies, and in-group preferences each play a substantial role in explaining segregation, their effects are non-additive. In particular, while summing the contributions of neighborhood sorting and race-based admissions policies predicts reductions in segregation (as measured by the Black/non-Black DI) of roughly 55–60 percent, jointly eliminating the two mechanisms yields reductions of about 85–90 percent in all three states. This complementarity implies that neighborhood sorting and provider gatekeeping amplify each other: when neighborhoods are segregated, the effect of equalizing admissions policies across racial groups on segregation (while still large) is limited by residents' choosing proximate nursing homes in highly segregated neighborhoods, and conversely, integrating neighborhoods does not transform fully into integrated provider use in the presence of race-based admissions policies.

Second, the drivers of disparities not only do not always line up with drivers of segregation, but

also vary sharply across states and even across minority groups within the same state. A striking example can be found in Florida, where neighborhood sorting is estimated to be the most important (or at least, second most important, depending on the exact measure) driver of segregation. Yet, this mechanism holds the least explanatory power for Black-White disparities in the state and even has the opposite-signed effect on Hispanic residents, i.e., eliminating residential segregation is estimated to leave Hispanic residents substantially *worse off* (relative to White residents) than the status quo. This heterogeneity cautions against extrapolating policy conclusions from a specific region or population to another, and underscores the need to specify the policy objective: reducing segregation versus closing quality gaps.

This paper is linked to a vast literature on racial segregation and disparities. A number of previous studies have produced credible evidence on various explanations for these patterns in a number of settings. For example, Card, Mas and Rothstein (2008) show support for one of the key implications of Schelling's model of in-group preferences—the existence of tipping points—in the context of neighborhood choice, while Aaronson, Hartley, and Mazumder (2021) and Derenoncourt (2022) highlight the role of discrimination and location in the evolution of segregation and disparities. In addition, Billings, Deming, and Rockoff (2014) establish a direct link between segregation and outcomes disparities using a natural experiment induced by the end of race-based busing in Charlotte-Mecklenburg schools (CMS), and Oosterbeek, Sóvágó, and van der Klaauw (2021) document how heterogeneous "preferences" may interact with school segregation in Amsterdam.

My paper contributes to this literature by studying several of these explanations simultaneously within a single setting, since most previous studies have focused on one explanation in isolation. This allows me to compare their effects on segregation and disparities, as well as potential interaction effects between various counterfactual policies. I show that policies which reduce segregation may be different than those that reduce racial disparities, and may even have effects of opposite signs on segregation and disparities, as well as for different minority groups. Moreover, I find that there are important complementarities in mechanisms driving segregation.

More narrowly, this paper is related to a literature on racial segregation and disparities in healthcare settings (Baicker et al. 2004; Smith et al. 2007; Rahman and Foster 2015; Einav et al. 2025). As I discuss in greater detail later in the paper, reduced form evidence often struggles to disentangle demand and supply side explanations, so in this study I estimate a structural model in order to identify the underlying mechanisms. The closest study to this paper is Rahman and Foster, who also study the

role of in-group preferences, location, and preference heterogeneity in the context of nursing homes, focusing on White and Black residents. However, they acknowledge that their structural estimates may reflect both residents' preferences and nursing homes' admission decisions (since they do not model admissions policies), and this paper I find that race-based admissions rules potentially play an important role in generating both segregation and disparities.

This paper proceeds as follows. In section 2, I provide some background on nursing homes and introduce my main data sources, before laying out some descriptive statistics on racial segregation and disparities. In section 3, I present reduced form evidence for various explanations for segregation and disparities. In section 4, I introduce and estimate an empirical matching model that incorporates all of these elements, and in section 5, I conduct counterfactual simulations to quantify the importance of these factors for explaining racial segregation and disparities. Section 6 concludes.

2 Background

There are roughly 15,000 nursing homes in the US providing care for about 1.3 million Americans (CDC), and an estimated 56 percent of Americans aged 57–61 are expected to spend at least one night in a nursing home during their lifetimes (Hurd, Michaud, and Rohwedder 2017). However, a large literature has documented substantial segregation across nursing homes (see the meta-analysis by Mack et al. 2020), and that minorities tend to disproportionately choose lower-quality nursing homes (Mor et al. 2004; Li et al. 2015). Quality of nursing homes vary widely and can have meaningful impacts on important outcome such as short-term mortality (Cheng 2025), so these patterns of racial segregation and disparities paint a worrying picture when it comes to tackling racial gaps in healthcare. Finally, most residents are covered (at least in part) by insurance (most often Medicare or Medicaid), so differential distance to nursing homes is typically a much more important factor in residents' nursing home choice compared to differences in out-of-pocket prices.

2.1 Data

The primary data source for this paper is the Minimum Data Set 2.0 (MDS). All nursing homes that receive federal funding are required to fill out MDS assessment forms at regular intervals (42 CFR §483.20).[1,2] Data collected from the MDS assessments includes information on residents' demo-

[1]The set of nursing homes receiving federal funding account for roughly 96 percent of all nursing homes (Grabowski, Gruber, and Angelelli 2008).

[2]Assessment forms must completed upon admission, at discharge (or death), quarterly in between, and whenever there is a significant change in status. MDS forms are typically filled out by a registered nurse (RN), or at least certified by one.

graphics, cognitive status, communication and hearing patterns, vision patterns, mood and behavior patterns, psychosocial well-being, physical functioning and structural problems, continence issues, disease diagnoses (including ICD-9 codes), health conditions, oral health, nutrition, dental status, skin conditions, activity pursuit patterns, medications, special treatments and procedures, and discharge potential.

I supplement the MDS with data on nursing homes from other sources. This includes the Online Survey Certification and Reporting (OSCAR) surveys (which contain information such as nursing homes' ownership status and staffing levels), data on deficiency citations, and five-star ratings for nursing homes.[3] For more details on the data used in this paper, see Appendix section A.

For my main analysis, I consider a composite quality index, based on RN (registered nurse) staffing, LPN (licensed practical nurse) staffing, and (the negative of) standard deficiencies (which are deficiency citations given by inspectors either during their annual visits). I standardize each of these components (so they all have mean zero and unit variance), before taking their sum and standardizing the sum to create the final quality index. While there have been concerns that staffing levels and inspection results may not reflect true year-round nursing home quality (Geng, Stevenson, and Grabowski 2019; Gandhi, Olenski, and Shi 2025), these quality measures are nonetheless ones that CMS typically focuses on (e.g., in the construction of the star ratings), are commonly used by researchers as quality measures (Hackmann 2019; Gandhi 2023; Chen and Dillender 2025), and remain predictive of patient outcomes (Friedrich and Hackmann; Chen and Dillender). I also check that my main results are robust to these and some other individual quality measures, leaving most of these results in the appendix.

There are several other potential quality measures that I do not use for various reasons. Probably the most well-known nursing home quality measure is the star rating provided by the CMS, but it is only available from the end of 2008 onwards, whereas my sample ranges from 2000–2010. Similarly, in addition to annual inspections, inspectors may also visit a nursing home in response to a complaint and I term deficiency citations from such visits as "complaint deficiencies", but this measure is only available from 2006 onwards. Finally, one could construct value-added quality measures based on

Any willful misrepresentation in the MDS forms may result in penalties under the False Claims Act. This is not limited to upcoding and variables that affect reimbursements directly but also other variables related to resident well-being. This is because nursing homes "must provide services to attain or maintain the highest practicable physical, mental, and psychosocial well-being of each resident" (42 CFR §1395i–3) to be certified to receive federal funding. Hence, any misrepresentation pertaining to resident wellbeing may be interpreted as being related to misrepresentation connected to a requirement for federal funding, and thus falls under the False Claims Act. Moreover, several studies on the accuracy of MDS data have found it to be fairly reliable (Shin and Scherer, 2009).

[3]The OSCAR data is available from 2000 onwards from LTCFocus.org, which is maintained by Brown University Center of Gerontology and Healthcare Research. LTCFocus is sponsored by the National Institute on Aging (1P01AG027296) through a cooperative agreement with the Brown University School of Public Health. Data on deficiencies, Medicare cost reports, and five-star ratings are available from the CMS website.

resident outcomes (Olenski and Sacher 2024; Einav, Finkelstein, and Mahoney 2025), but this is complicated by the recent finding in Einav et al. (2025) the "value-added" of a nursing home for Black and White residents may be quite different.

2.2 Sample and Summary Statistics

For the reduced form analysis, I consider the entire sample of residents in the US from 2000–2010. However, estimating the structural model on the full sample is computationally infeasible, so for this part of the analysis I consider three large states in my sample with a substantial fraction of both Black and Hispanic residents—California, Florida, and Texas—from 2008 to 2010.

Table 1 shows summary statistics for nursing homes residents in the entire US, overall and separately by race. We observe that residents are typically White, female, advanced in age, and have less than a bachelor's degree. Moreover, most of them are admitted from acute care hospitals (and are thus likely to be short stay), 8 percent die within 90 days of admission, and 22 percent are already diagnosed with dementia at admission. Comparing characteristics of residents from different racial groups, the most notable differences are that White residents are on average older, more educated, and more likely to die within 90 days of admission, compared to Black and Hispanic residents. This last fact may seem somewhat surprising, but is partly explained by minority residents being substantially younger than White residents at admission.[4] Appendix Table A.1 shows these summary statistics by state for the three states used in the structural estimation.

Next, Table 2 shows summary statistics for nursing homes across the US in column 1, weighted by the number of residents admitted between 2000–2010. Nursing homes have over a hundred beds on average, and occupancy rates are often above 80 percent. In addition, more than half of nursing homes are owned by chains, and more than 60 percent are for-profit. I also show summary statistics for various quality measures, including staffing hours for RNs, LPNs and Certified Nursing Assistants (CNAs), and standard deficiencies.[5]

2.3 Broad Patterns of Racial Segregation and Disparities

To measure racial segregation across nursing homes, I use the index of dissimilarity. This index measures segregation across two racial groups and lies between 0 and 1, representing perfect integration

[4] One potential reason for why White residents are older at admission may be that they have better resources which allow them to avoid going to nursing homes unless truly necessary.

[5] Specifically, in Table 2 I show standard deficiency citations. since data on complaint deficiencies are only available from 2006 onwards.

and complete segregation respectively. For two groups A, and B, the dissimilarity index D of some geographical region is defined by:

$$D = \frac{1}{2} \sum_j \left| \frac{a_j}{\sum_{j'} a_{j'}} - \frac{b_j}{\sum_{j'} b_{j'}} \right|,$$

where a_j (respectively b_j) is the number of residents of group A (B) in nursing home j. An interpretation of the index D is that it is the proportion of one of the two groups that would have to move to different nursing homes in order for the distribution of the groups in each nursing home to match the overall distribution of these groups in the geographical region under consideration. Since the index of dissimilarity is only defined for two distinct racial groups, I compute this measure separately based on Black versus non-Black racial groups, and Hispanic versus non-Hispanic racial groups. Focusing on the distribution of state-level nursing home segregation shown in Figure 1, we observe that dissimilarity indices for most states range from 0.3 to 0.7, consistent with other research finding that nursing home segregation are similar to those for residential segregation (Mack et al. 2020; Fisher, Mustaine, Simon, and Bowblis forthcoming).

To measure racial disparities across nursing homes, I regress quality of the nursing home that residents are admitted to on race indicators, taking the coefficient estimates on the race indicators β^q_{black} and $\beta^q_{hispanic}$ as the racial gaps:

$$q_{j(i)} = \beta^q_0 + \beta^q_{black} black_i + \beta^q_{hispanic} hispanic_i + \epsilon^q_i, \tag{1}$$

clustering standard errors at the nursing home level. As my main quality measure, I use a standardized quality index based on registered nurse (RN) staffing, licensed practitioner nurse (LPN) staffing, and fewer standard deficiencies (Kling, Liebman, and Katz 2007). Figure 2 shows that while Blacks and Hispanics tend to be admitted to lower-quality nursing homes than Whites on average, there is substantial heterogeneity in these disparities across states.[6] Moreover, states with high levels of Black-White disparities do not necessarily have high levels of Hispanic-White disparities and vice versa. These patterns suggest that (i) the underlying drivers of racial disparities across states may not be the same, and (ii) even within a state, the mechanisms generating Black-White and Hispanic-White disparities may also differ. Appendix Figures A.2, A.4, A.5, and A.6 show that the same patterns hold qualitatively when we use RN staffing, LPN staffing, fewer standard deficiencies, fewer complaint

[6] Coefficient estimates with large standard errors due to small sample sizes are omitted for legibility purposes.

deficiencies, or star ratings individually as the quality measure.

In addition, while there exists substantial statewide racial segregation and disparities, the cross-sectional relationship between the two are weak. Indeed, the scatterplots in Figure 3 shows the lack of a consistent cross-sectional relationship between the estimated racial disparities and segregation at the state level.[7] This absence of a clear cross-sectional relationship persists when we consider racial disparities based on other quality measures, such as RN staffing, LPN staffing, fewer standard deficiencies, and fewer complaint deficiencies, as Appendix Figures A.7, A.8, A.9, and A.10 show.

3 Reduced Form Evidence

In this section, I present several pieces of reduced form evidence on the potential causes of segregation and disparities across US nursing homes.

3.1 Neighborhood Sorting

If neighborhoods are highly segregated and residents prefer not to travel long distances to nursing homes, then neighborhood segregation feeds into nursing home segregation. As a first piece of evidence that residential segregation feeds into in nursing home segregation, in Figure 5 I show a binscatter of MSA-level Black-White dissimilarity indices for residential segregation against state-level Black/non-Black nursing home dissimilarity indices,[8] and we observe that there is indeed a strong positive correlation between residential and nursing home segregation.

Next, I show that after accounting for residential segregation, measured nursing home segregation becomes much smaller. In particular, given that most residents choose a nursing home relatively close to them, I compute dissimilarity indices based on a 15-mile radius of each 5-digit zip code for any resident's prior residential address and compare this to the state-level dissimilarity indices. To understand what this comparison tells us, consider two extremes as a thought experiment. If distance to nursing homes does not matter for residents choosing their nursing homes and residents are willing

[7] Clearly, under perfect integration, the average quality of nursing homes chosen by majority and minority groups will be the same. However, a reduction in segregation that does not achieve full integration need not necessarily reduce the gap in quality chosen by majority and minority groups. To see how this may be possible, consider a simplified example with 3 nursing homes, A, B, and C, with cardinal quality measures given by 5, 2, and 1 respectively. There are 200 residents from the majority group, and 100 residents from the minority group, and initially all minority group residents reside in nursing home B, whereas majority group residents are split equally between nursing homes A and C. Now, suppose that 50 minority residents move from nursing home B to C, and 50 majority residents move from nursing homes C to B. This achieves a reduction in segregation, but the average gap in the quality of nursing homes chosen by majority and minority groups increases from $(5+1)/2-2=1$ to $(5/2+2/4+1/4)-(2+1)/2=7/4$.

[8] Data on MSA-level Black-White dissimilarity indices was downloaded from https://censusscope.org/us/rank_dissimilarity_White_Black.html on October 15, 2023.

to travel to any nursing home within their own state, then this local measure of segregation will be identical to the statewide measure. By contrast, if distance does matter to residents, and residential segregation is the only source of residential segregation, then the local segregation measure will be close to zero. In fact, Figure 4 shows that the truth lies somewhere in between these two extremes: dissimilarity indices are almost all smaller than 0.4, as compared to 0.3–0.7 at the state level, which suggests that residential segregation is an important explanation for overall nursing home segregation, but dissimilarity indices for many zip codes are also significantly different from zero, rejecting the notion that residential segregation is the sole cause.

To show the extent to which residential segregation can explain disparities, I estimate equation (1) with fixed effects for the zip code where residents used to live before being admitted to a nursing home. The results in Table 3 show that conditioning on zip code of prior residence reduces the racial gaps (relative to the unconditional gaps), but minority residents still tend to be admitted to lower-quality nursing homes, so residential segregation is unlikely to entirely explain racial disparities. Appendix Table A.2 shows that the same qualitative patterns hold when considering individual quality measures, such as staffing, fewer standard and complaint deficiencies, and nursing homes' 2009 star ratings.

3.2 Race-Based Admissions Policies

Geographical proximity is not the only potential barrier to access: nursing homes may also discriminate against minorities in their admissions process. Indeed, Gandhi (2023) shows that when capacity is strained, nursing homes tend to become more selective in the types of residents they admit and are less likely to admit Medicaid residents (who tend to be less profitable), due to the fact that the option value of an empty bed is increasing in capacity strain. Nursing homes may also find minority residents less attractive if certain minority characteristics are negatively correlated with profitability (e.g., Medicaid status) or due to outright taste-based discrimination. If this is the case and higher-quality nursing homes experience greater demand, then these selective admissions practices may give rise to the observed racial disparities.[9]

To probe this possibility, I test two predictions from a model of selective admissions. First, due to capacity constraints, nursing homes should admit fewer new residents when they are close to capacity. Second, and more importantly, the characteristics of residents that nursing homes admit during times

[9]This is related to findings on discrimination in the rental market, where Christensen and Timmons (2023) find that the gap in response rates to minority and White individuals in a correspondence study is greater when demand for the rental property is higher.

of high and low occupancy should differ, given that nursing homes are more selective when they are closer to capacity.

To test the first prediction, I run regressions at the nursing home-day level of the form:

$$admissions_{jd} = \alpha^{cap} + \beta^{cap} occupancy_{jd} + \delta^{cap}_{jm} + \epsilon^{cap}_{jd},$$

where $admissions_{jd}$ and $occupancy_{jd}$ are respectively measures of new admissions, and lagged seven-day average of some occupancy measure for nursing home j on day d, controlling for nursing-home month fixed effects δ^{cap}_{jm} in order to isolate temporary occupancy fluctuations (as opposed to longer term expansions and contractions in capacity). The results in Table 4 indicate that nursing homes indeed admit fewer residents when capacity is strained, and Appendix Table A.4 shows that these patterns remain extremely strong when considering other measures of capacity strain.

I test the second prediction estimating the relationship between race of an admitted resident and capacity strain at the time of admission:

$$\mathbb{I}[race_i = r] = \delta^{select}_{j,r} + \beta^{select}_{r} occupancy_{j(i),d(i)} + \epsilon^{select}_{i,r},$$

where $occupancy_{j(i),d(i)}$ is the lagged seven-day average of an occupancy measure at the nursing home i was admitted to at the time of i's admission $d(i)$, controlling for nursing home fixed effects $\delta^{select}_{j,p}$. The results in Figure 6 show a clear relationship where nursing homes are less likely to admit Black and Hispanic residents when capacity is strained, a pattern that is robust across different measures of capacity strain.

3.3 In-Group Preferences

Another potential explanation for why minorities continue choosing lower-quality nursing homes despite the presence of higher-quality nursing homes nearby is in-group preferences (Schelling 1971). For example, individuals from a given racial group may prefer to interact with other members of the same racial group due to shared experiences, or because they believe they will be treated with more respect. If this is the case, then an initial distribution of minorities concentrated in lower-quality nursing homes may persist moving forward even in the absence of other inequities.

A key prediction of models of in-group preferences is that a shock to the minority share may lead to an equilibrium switch: specifically, a positive shock to the share of a racial group r at a nursing

home may have persistent effects, as future residents of race r find that nursing home more attractive while residents of other races r' find it less attractive (Card, Mas and Rothstein 2008; Billings, Deming and Rockoff 2014; Hailey 2022). While the sample sizes for individual nursing homes are too small to conduct a tipping point analysis of Card, Mas and Rothstein (who do so in the neighborhood context using Census tract data),[10] here I present descriptive and event study evidence.

I start by estimating autoregressive models at the nursing home-year level, based on the share of admitted residents who are of a specific minority group (either Black or Hispanic):

$$s_{jt}^{r} = \alpha^{r,ingroup} + \beta^{r,ingroup} s_{j,t-1} + \delta_{j}^{r,ingroup} + \gamma_{ct}^{r,ingroup} + \epsilon_{jt}^{r,ingroup}, \tag{2}$$

where s_{jt}^{r} is the share of residents admitted to nursing home j that are of race r, and observations are weighted by the number of admissions the nursing home j receives in year t. I control for time-invariant factors affecting share of Black admissions by including nursing home fixed effects $\delta_{j}^{r,ingroup}$, and demographic trends by including county-year fixed effects $\gamma_{ct}^{r,ingroup}$.

Estimates of equation (2) for different races are shown in the three panels of Table 5. We observe that there is a high degree of year-to-year autocorrelation in the share of admissions of a given race in nursing homes, unconditionally but also conditional on nursing home fixed effects to account for time-invariant demand- and supply-side explanations and county-by-year fixed effects to account for demographic trends. While the inclusion nursing home fixed effects in a relatively short panel may raise concerns about the Nickell bias (1981), this would bias us against finding persistence, given that Nickell bias attenuates estimates of the autocorrelation coefficient towards zero.

As a second test of the equilibrium switch behavior predicted by models of in-group preferences, I estimate event studies testing whether a large shock to the share of admissions to a nursing home of a specific race leads to persistent changes in the race of admissions in future years. Specifically, I estimate event studies of the form:

$$s_{jt}^{r} = \alpha^{r,shock} + \sum_{k \neq -1} \beta_{k}^{r,shock} \mathbb{I}[t - E_{j}^{r} = k] + \delta_{j}^{r,shock} + \gamma_{t}^{r,shock} + \epsilon_{jt}^{r,shock},$$

where E_{j}^{r} is the year in which nursing home j receives a much higher than usual number of minority residents of race r, i.e., $s_{j,E_{j}^{r}}^{r} - s_{j,E_{j}^{r}-1}^{r} \geq C$ for some threshold C. Mechanically, $\beta_{0}^{r,shock}$ will be large

[10] Specifically, the model predicts an unstable equilibrium for the minority share in a neighborhood, and a perturbation in the minority share above (respectively, below) this point may lead to a stable equilibrium with the neighborhood being filled mainly with minority (majority) individuals.

given the way the event is defined. However, the real test of in-group preferences is whether this shock leads to persistently higher shares of minority admission in future years, i.e., whether $\beta_k^{r,shock} > 0$ for $k > 0$.[11]

Figure 7 shows results from these event studies using methods from Borusyak, Jaravel, and Spiess (2021), where I consider a year-to-year increase of at least 25pp. in the Black and Hispanic shares of admissions respectively. Consistent with in-group preferences, we observe that a positive shock to the Black (Hispanic) share of admissions of at least 25pp. leads to a more than 10pp. higher share of Black (Hispanic) share of admissions in each of the following 5 years. We observe that there is little evidence of pretrends for Black admissions other than the dip at $t = -1$ (which is mechanical due to how the event is defined), and while some of the pretrend coefficients are statistically significant for Hispanic admissions, the magnitude of these coefficients are far smaller than the effect size. In Appendix Figure A.11, I conduct the same exercise but define the event as either a 10, 15, or 20pp. increase in the Black or Hispanic share of admissions as the "event". We observe qualitatively similar results, with a shock to minority share of admissions having persistent effects, and relatively little pretrends.

Finally, an issue with these tests of whether a shock to the minority share leads to an "equilibrium switch" is that the same pattern can also be explained by an unobserved and persistent change on the supply side. For example, if a new nursing home administrator takes over and decides that the nursing home should admit more (or fewer) minority residents moving forward, the minority share of admissions will also be persistently higher (lower) in the future. Hence, I also conduct a test of in-group preferences, leveraging only within-month variation in occupancy of different races at a nursing home.

Specifically, I run regressions at the nursing home-day level, regressing a measure of new admissions of a particular race on a day on a measure of the racial composition of the nursing home at the end of the previous day, controlling for nursing home-month fixed effects:

$$admissions_{jd}^{r} = \alpha_r^{shortrun} + \sum_{r'} \beta_{r,r'}^{shortrun} occupancy_{jd}^{r'} + \delta_{r,jm}^{shortrun} + \epsilon_{rjd}^{shortrun}.$$

A model of in-group preferences predicts that the coefficient on occupancy of the same race should be positive ($\beta_{r,r}^{shortrun} > 0$), whereas coefficients on occupancy of other races should either be zero or negative if residents dislike other races ($\beta_{r,r'}^{shortrun} \leq 0$ if $r \neq r'$). In the example with the new nursing

[11] Note that I use share of minority admissions in the previous year rather than share of minority residents in the nursing home as the outcome, so that any persistent increase after the shock is not mechanical. In particular, if I instead used share of minority residents in the nursing home as the outcome, then part of the estimated effect in subsequent years will be mechanical if some residents admitted in previous period(s) remain the nursing home for a long duration of time.

home administrator, we will have $\beta_{r,r}^{shortrun} = 0$ since the effect will be absorbed by the nursing home-month fixed effects.

The results in Table 6 show that consistent with in-group preferences, on days when occupancy of a particular race at a nursing home is temporarily elevated, residents of the same race is more likely than usual to be admitted ($\beta_{r,r} > 0$), whereas residents of other races are typically as likely as usual or less likely to be admitted ($\beta_{r,r'} \leq 0$). While a few of the different-race coefficients $\beta_{r,r'}$ are positive and statistically significant given the huge sample size, they are always at least tens of times smaller and typically hundreds of times smaller in magnitude than the same race coefficients ($\beta_{r,r}$). Appendix Table A.5 shows that the same results hold using log occupancy of residents from different racial groups, although the sample size is smaller (given that there is often no resident of a specific racial group in a nursing home on a particular day).

3.4 Heterogeneity in Responsiveness to Quality

While in-group preferences may explain how racial disparities can persist or even worsen over time, this explanation does not shed light on how these racial disparities arose in the first place. One possibility is that minorities may be less responsive to nursing home quality than Whites. So, to test whether this is plausible, I start by running descriptive regressions testing whether changes in nursing home quality predicts the race of admitted residents. Specifically, I estimate the regression equation:

$$race_i = \alpha_{0,r}^{fe} + \beta_{1,r}^{fe} q_{j(i)} + \beta_{2,r}^{fe} s_{j(i),t(i)-1}^{r} + \beta_{3,r}^{fe} occpct_{j(i),t(i)} + \delta_{j(i),r}^{fe} + \gamma_{c(i),t(i),r}^{fe} + zip_{i,r} + \epsilon_{i,r}^{fe}, \quad (3)$$

separately for Whites, Blacks and Hispanics, where $race_i$ is a indicator for whether the admitted resident is of a particular race, and $q_{j(i)}$ is the quality of the nursing home that she goes to. In the richest specification, I include $s_{j(i),t(i)-1}^{r}$ to control for in-group preferences, occupancy percentage as a proxy for capacity strain, fixed effects for nursing homes $\delta_{j(i),r}^{fe}$ to control for time-invariant unobserved race-specific preferences for different nursing homes, county-year fixed effects $\gamma_{c(i),t(i),r}^{fe}$ to control for demographic trends, and zip code fixed effects $zip_{i,r}$ to control for residential segregation.

Table 7 shows estimates of equation (3). In the odd columns, we observe that the unconditional associations between race of admissions and nursing home quality are strong, with the signs of the coefficient estimates consistent with White residents being more responsive to quality than Black and Hispanic residents. The inclusion of controls in the even columns attenuates these associations

substantially although the signs remain consistent (albeit insignificant for predicting Hispanic residents in column 6). The signs on controls are also consistent with the aforementioned mechanisms: previous share of residents of a specific race strongly predicts the race of new admissions (in line with in-group preferences), and increases in capacity strain are associated with higher (lower) probability of admitting White (respectively, Black and Hispanic) residents (consistent with race-based admissions policies).

Next, I move beyond correlational evidence by studying the effect of two different shocks to consumer information about nursing home quality on nursing home choice by residents from different racial groups. The first shock to consumer information I consider is the introduction of star ratings at the end of 2008 by the CMS, the stated aim of which was to increase consumer responsiveness to quality. While this policy was introduced nationwide, I compare the quality of nursing homes chosen by residents of different races within the same zip code, before and after the star ratings where introduced. Specifically, I estimate event study regressions at the resident level of the form:

$$\begin{aligned} q_{j(i)} =& \delta^{star}_{zip(i),t(i)} + \gamma_{Black} Black_i + \gamma_{Hispanic} Hispanic_i \\ &+ \sum_{r \in \{Black, Hispanic\}} \sum_{k \neq -1} \beta^{star}_{Black,k} \mathbb{I}[t(i) - 2009 = k] \cdot \mathbb{I}[race(i) = r] + \epsilon^{star}_i. \end{aligned}$$

where $\delta^{star}_{zip(i),t(i)}$ are zip-code-by-year fixed effects. Given findings from earlier studies that residents tend not to be very responsive to number of deficiency citations received by nursing homes (Zhao 2016; Cheng 2025), I focus on a standardized index for RN and LPN staffing as the quality measure in these regressions. The event study coefficients $\beta^{star}_{r,k}$ for race $r \in \{black, hispanic\}$ reveal whether the quality of nursing homes chosen by residents from race r increased by more (if $\beta^{star}_{r,k} > 0$) or less (if $\beta^{star}_{r,k} < 0$) than White residents living in the same zip code k years after the star ratings were introduced.

Figure 8 plots the event study coefficients $\beta^{star}_{r,k}$ for Black and Hispanic residents. We observe that there are relatively little pretrends for either minority race, supporting the parallel trends assumption. The post-period coefficients for Hispanic residents are negative and statistically different from zero whereas coefficients for Black residents are not statistically different from zero, providing suggestive evidence that nursing home choice improved by more among Whites than Hispanics but not more than Blacks post-star ratings.

A shortcoming of the event studies based on star ratings is that the policy was rolled out nationwide, so it is difficult to disentangle the effect of information from other secular trends. So, in a second set of event studies, I consider the effect of a likely salient shock about particular nursing homes' quality

on differential admission patterns by race in subsequent years.

Each nursing home is subject to annual inspections by state survey agencies, during which inspectors assess compliance with federal health and safety standards through on-site reviews, audits, and resident interviews. Inspectors issue deficiency citations for problems they find, which range from relatively minor problems (e.g., incomplete documentation) to more serious problems. Given previous findings that residents tend not to be very responsive to general deficiency citations (Zhao 2016; Cheng 2025), here I focus the most serious category of deficiency citations—problems deemed to pose immediate jeopardy to residents' safety or health (e.g., severe medication overdoses, or gross infection-control failures, et cetera)—which I henceforth refer to as severe deficiencies. For context, in each year of the sample, while 85 percent of nursing homes are cited for some type of deficiency, less than 3 percent are cited for severe deficiencies, suggesting that these rare events are more likely to be salient shocks to residents about nursing home quality.

To estimate the effect of severe deficiencies on admission patterns for residents of different races, I run event studies comparing admission patterns in a nursing home cited for a severe deficiency with admission patterns located in the same county, to account for potential spatial correlations in deficiency patterns.[12] To account for heterogeneous treatment effects with staggered treatment, I estimate stacked event studies (Cengiz, Lindner, and Zipperer 2019; Deshpande and Li 2019; Wing, Freedman, and Hollingsworth 2024). Specifically, for each year b in the sample, I consider a separate subexperiment comparing nursing homes treated in year b (i.e., receiving a severe deficiency citation) with a control group of nursing homes that were not treated in the same county. I then stack these subexperiments to obtain the estimating equation:

$$s^r_{jctb} = \alpha^{def,r}_{jcb} + \delta^{def,r}_{ctb} + \sum_{k \neq -1} \beta^{def,r}_{k} \mathbb{I}\left[E^{def}_{j} = b, t = b + k\right] + \epsilon^r_{jctb},$$

where s^r_{jtb} are the share of residents admitted to nursing home j located in county c in year t that are of race r, $\alpha^{def,r}_{jb}$ are nursing home-by-stack fixed effects, $\delta^{def,r}_{ctb}$ are county-by-calendar year-by-stack fixed effects, and E^{def}_{j} is the year in which nursing home j received a severe deficiency citation (defined as missing for nursing homes that never experienced such an event). Observations are weighted so that each admitted resident receives equal weight, and standard errors are clustered at the nursing home level.

[12] For example, the introduction of an inspector in the area who conducts more thorough inspections, or a disease outbreak in the region that makes care deficiencies more obvious to inspectors could both induce spatial correlation in deficiency patterns.

The three panels of Figure 9 shows changes in the share of White, Black, and Hispanic admissions in the years before and after a severe deficiency citation at a nursing home relative to other nursing homes in the same county. The pre-period coefficients are not statistically different from zero, supporting the parallel trends assumption. On the other hand, the post-period coefficients for White residents are negative for White residents, and positive for Black and Hispanic residents (although they tend not to be statistically significant for Black residents), suggesting that White residents respond more to severe deficiency citations than minority residents do. As a robustness check, Appendix Figure A.12 shows stacked event studies that replace s^r_{jctb} with the log difference between minority and White admissions. With this specification, the pooled estimate for both Black and Hispanic residents are now positive and statistically significant, although there are some pre-trends for the log difference between Hispanic and White residents.

A fundamental difficulty with the reduced form evidence on potential causes of racial segregation and disparities presented in this section is the difficulty in disentangling demand and supply side explanations. Consider the evidence just presented that share of White admissions rose whereas share of minority admissions fell following a severe deficiency citation. While it is indeed possible that this is due to White residents being more responsive to the information shock about nursing home quality, it could also be explained by race-based admissions if a fall in demand led to the nursing home no longer rejecting minority residents at higher rates. Hence, in the next section, I introduce a structural model to more cleanly disentangle the different mechanisms.

4 Structural Estimation

4.1 Overview of Empirical Matching Model

In order to disentangle residents' preferences from nursing homes' admission decisions, I estimate an empirical matching model similar to Agarwal and Somaini (2022) and Cheng (2025). I assume that resident i's indirect decision utility for each nursing home $j \in \mathcal{J}_i \equiv \{j|dist_{ij} \leq 15\ miles\}$ is given by:

$$v_{ij} = w_j'\kappa^1 + w_j'\kappa^2 x_i + dist_{ij}'\kappa^{dist} + \epsilon_{ij}, \tag{4}$$

where x_i and w_j are resident and nursing home characteristics respectively, $dist_{ij}$ is a measure of distance between resident i and nursing home j, and ϵ_{ij} is an idiosyncratic utility shock. For the

location normalization, I omit the constant term, and to set the scale normalization, I assume that $\epsilon_{ij} \sim N(0,1)$.

Nursing homes' admissions policies are given by:

$$\pi_{ij} = x_i'\psi^1 + w_j'\psi^2 x_i + occ'_{d(i),j}\psi^{occ} + \omega_{ij}, \tag{5}$$

where $occ_{d(i),j}$ is a measure of nursing home j's occupancy in the period leading up to i's admission date $d(i)$, and ω_{ij} is an idiosyncratic shock. I assume that nursing home j is willing to admit resident i if and only if $\pi_{ij} \geq \underline{\pi}$, so resident i's constrained choice set is $\{j \in \mathcal{J}_i | \pi_{ij} \geq \underline{\pi}\}$. Note that these constraints are not observed in the data, an issue I will return to below. The location normalization is set by including a constant term in equation (5) and setting $\underline{\pi} = 0$, and the scale normalization is achieved by assuming $\omega_{ij} \sim N(0,1)$.

To elaborate on how this model incorporates elements such as in-group preferences, racial heterogeneity in responsiveness to quality, and discrimination, equation (4) typically takes the form:

$$\begin{aligned} v_{ij} =& \kappa_0^{Black} s_{d(i)j}^{Black} + \kappa_0^{Hisp} s_{d(i)j}^{Hisp} + \kappa_1^{Black} s_{d(i)j}^{Black} Black_i + \kappa_1^{Hisp} s_{d(i)j}^{Hisp} Hispanic_i \\ &+ q_j'\kappa_0^q + \kappa_{Black}^q Black_i \cdot q_j + \kappa_{Hisp}^q Hispanic_i \cdot q_j' + dist_{ij}'\kappa^{dist} + \epsilon_{ij}, \end{aligned}$$

where $s_{d(i)j}^r$ is the share of nursing home j's admissions that are of race r in the 365 days leading up to i's admission date $d(i)$. We can think of κ_0^r and $\kappa_0^r + \kappa_1^r$ respectively as measuring preferences among those of race $r' \neq r$ and race r for a higher share of recently admitted residents being of race r. In the absence of racial preferences among residents, we will expect $\kappa_0^r = \kappa_1^r = 0$. Similarly, κ_0^q captures White residents' demand for quality, whereas $\kappa_0^q + \kappa_r^q$ captures demand for quality among residents of race r (for non-White residents). If there was no racial heterogeneity in responsiveness to quality, then we should have $\kappa_r^q = 0$. The supply side equation typically takes the form:

$$\begin{aligned} \pi_{ij} =& \psi_0 + w_j'\psi^w + \psi^{black} Black_i + \psi^{hisp} Hispanic_i \\ &+ \psi^{black,q} Black_i \cdot q_j + \psi^{hisp,q} Hispanic_i \cdot q_j + occ'_{d(i)j}\psi^{occ} + \omega_{ij}. \end{aligned}$$

Note that I allow race-specific preferences in admissions policies to vary by nursing home quality, so as to not conflate heterogeneity in race-specific admissions policies by quality with demand-side heterogeneity in responsiveness to quality by race. In the absence of discriminatory admissions practices,

we would expect $\psi^r = 0$ and $\psi^{r,q} = 0$ for both minority races. On the other hand, in the presence of discriminatory admissions practices, we would generally expect $\psi^r \neq 0$, and moreover, ψ^r may be a function of the demand-side parameters for in-group preferences κ_1^r due to dynamic externalities. In particular, admitting a resident of race r today may increase (respectively, decrease) demand from resident's of the same race (different races) in the future, a point I will return to in the counterfactual simulations.

Agarwal and Somaini (2022) provide a sharp set of identification conditions for such a model, and the key substantive requirement is that we need both demand and supply side instruments. Hence, I use distance as the demand side instrument and temporary fluctuations in nursing homes' occupancy (specifically log of lagged seven-day occupancy residualized of nursing home-month fixed effects) as the supply instrument. The relevance condition for both instruments are likely to be satisfied: residents have a strong preference for nursing homes close to where they used to live, and nursing homes are less likely to admit new residents when capacity is strained, as seen in Table 4. The exclusion restriction for the demand instrument is also likely satisfied, since nursing homes are unlikely to care about where their residents originally lived.

The exclusion restriction for the supply instrument deserves closer scrutiny, and for better intuition we start by considering why using occupancy (instead of temporary fluctuations in occupancy) is likely to violate the exclusion restriction, and its implications for structural model's estimates. All else equal, residents may prefer less crowded nursing homes (thus violating the exclusion restriction), and if higher-quality nursing homes are in greater demand, this will lead us to underestimate residents' demand for quality. Moreover, if preferences for "crowdedness" also varies by race, then our estimates of heterogeneity in responsiveness to quality will also be biased.

The use of *temporary fluctuations* in nursing home occupancy (specifically, within nursing home-month fluctuations) addresses this issue in two ways. First, short-term fluctuations in occupancy are less likely to matter for residents. Second, by residualizing the occupancy measure of nursing home-month fixed effects, we eliminate potential correlations between occupancy and nursing home characteristics such as quality, as well as the share minority in the past year. Appendix Figure A.13 illustrates this by showing that the distribution of temporary occupancy fluctuations of nursing homes within 15 miles of each resident is essentially identical across above-median and below-median-quality nursing homes close to White, Black, and Hispanic residents. Similarly, Appendix Figure A.14 shows that the distribution of the supply instrument is identical when we split by above- and below-median

share of Black and Hispanic admissions in the past year. Finally, Appendix Figures A.15–A.19 show that the same pattern holds when splitting the sample based on various individual quality measures, and Appendix Figure A.20 shows that the same results hold when we interact the share of admissions Black or Hispanic with the race of the resident.

Finally, estimation of this model has to deal with the curse of dimensionality. In particular, there are $2^{|\mathcal{J}_i|} - 1$ possible constrained choice sets for resident i. The average number of nursing homes $|\mathcal{J}_i|$ within 15 miles of a resident in California is 50 for example, and can be as large 200 for some residents. Hence, methods such as maximum likelihood that require us to sum over each distinct possibility are computationally infeasible. Therefore, I use Gibbs sampling with data augmentation (for v_{ij} and π_{ij}) for my estimation, since this obviates the need to individually compute the probability of each potential choice set, without needing to make additional substantive assumptions.

At a high level, in each iteration of the Gibbs sampler, I draw utility and profit shocks ϵ_{ij} and ω_{ij} in such a way that the resulting latent variables respect the matching outcomes. I then update the posterior distribution of the parameters before moving onto the next iteration. For example, if resident i is admitted to a nursing home $\mu(i)$, when drawing the utility shock $\epsilon_{i,\mu(i)}$ we must make sure that the resulting indirect utility $v_{i,\mu(i)}$ must be no smaller than v_{ij} for any $j \in \mathcal{J}_i$ where $\pi_{ij} \geq 0$, so we draw $\epsilon_{i,\mu(i)}$ from a distribution that is truncated from below (for details on the algorithm for the Gibbs sampler, see Appendix section B). Under regularity conditions, the draws of the parameters will eventually converge to their stationary distribution. We can then form Bayesian confidence sets based on the distribution of these draws, which are also endowed with a frequentist interpretation as a consequence of the Bernstein von-Mises theorem. Due to computational constraints, I limit the sample to residents and nursing homes in three different states between 2008–2010.

4.2 Structural Estimation Results

Table 8 shows results from the structural estimation, separately for California, Florida, and Texas. We start by observing that the estimates for the demand and supply instruments (distance and occupancy respectively) have the expected sign and are highly statistically significant, which is reassuring for the identification of the model.

On the demand side, we observe that the coefficient estimates on the interactions between the resident's own race and the share of nursing home admissions being of the same race in the past year are positive and highly statistically significant, consistent with in-group preferences. Patterns

of heterogeneity in responsiveness to quality by race is less uniform: while White residents seem to be responsive to quality on average (given the positive and highly statistically significant coefficient estimates on the quality index), minority residents in some states seem less responsive. In particular, Black and Hispanic residents in Florida and Hispanic residents in Texas seem less responsive to quality than White residents in the same states, while minority residents in California and Black residents in Texas do not seem less responsive than White residents.

Turning to nursing homes' admissions policies, we observe that the coefficient estimates on Black and Hispanic residents are negative and highly statistically significant. Note that while the supply-side equation includes interactions between quality and minority race indicators, the quality index has been normalized to have mean zero (and standard deviation one). Hence, the negative estimates on minority indicators are consistent with discrimination against minorities in the average nursing home's admissions policies.

To account for time-invariant preferences for nursing homes that are not captured by the variables included in the utility equation, in Appendix Table A.6 I include nursing home fixed effects in the utility equation as a robustness check. We see that the estimates associated with in-group preferences, heterogeneity in responsiveness to quality, and race-based admissions policies remain qualitatively similar with the inclusion of facility fixed effects in utility. In addition, to check whether the differences in heterogeneity in responsiveness to quality across states is due to low responsiveness to deficiencies diluting the results, Appendix Table A.7 replaces the quality index with a staffing index based on RN and LPN staffing. The results show that both Black and Hispanic residents are less responsive than White residents to staffing in Florida and Texas, while Hispanic residents in California do not seem any less responsive than White residents.

While in-group preferences, race-based admissions policies, and (to a certain extent) heterogeneity in responsiveness to quality seem to be present in all three states, it is difficult to compare the importance of each of these explanations (and residential segregation) in explaining segregation and disparities and to study interactions between these mechanisms based on the coefficients alone. Hence, I address this in the next section using counterfactual simulations.

5 Counterfactual Simulations

In this section, I conduct counterfactual simulations to assess how important different factors are for explaining segregation and choice disparities, and to understand how they interact with each other.

Specifically, I mimic the elimination of various mechanisms by modifying certain parameters from the structural model (except for neighborhood sorting, which I elaborate on next). I then simulate the dynamic evolution of segregation and disparities with the modified parameters, and compare the steady-state segregation and disparities to those obtained from simulations based on the original parameter estimates. In these simulations, I abstract away from endogenous quality adjustments by nursing homes, setting quality for each nursing home to its average over the time period of the structural estimation.

To simulate a successful ban on discriminatory admissions practices nursing homes, I set the race-specific parameters ψ^r in the admissions equation to zero. To mimic the elimination of in-group preferences, I set the parameters for race $(\kappa_0^{r\prime}, \kappa_1^{r\prime})'$ in residents' utility equation to zero. Next, to simulate the homogeneous responsiveness to quality, I set the interactions between nursing home quality and minority race indicators $\kappa_r^q = 0$. Finally, to mimic the elimination of residential segregation, I randomize the zip code of prior residence for each resident, effectively randomizing them to different counterfactual choice sets.

Recall our earlier discussion that the race-specific parameters in admissions policies ψ^r reflect both nursing homes' static preferences for patients of specific races and the dynamic implications of admitting a given resident on future demand from residents of different races. Hence, when eliminating in-group preferences but not discriminatory admissions policies in the counterfactual simulations, we may nonetheless want to adjust ψ^r to account for the fact that the dynamic externality is no longer present. To do so, first note that increasing the share of admissions of race r by 1 p.p. today increases the long-run share of admissions of race r by $\sum_{k\geq 1}\left(\beta^{r,ingroup}\right)^k = \beta^{r,ingroup}/(1-\beta^{r,ingroup})$, where estimates of $\beta^{r,ingroup}$ are given in Table 5. With an annual discount factor of δ, the present value multiplier is $G_r \equiv \delta\beta^{r,ingroup}/(1-\delta\beta^{r,ingroup})$, and the component of ψ^r and $\psi^{r,q}$ that is due to the dynamic externality is:

$$\psi^{r,dynamic} = \frac{G_r}{1+G_r}\cdot\psi^r, \psi^{r,q,dynamic} = \frac{G_r}{1+G_r}\cdot\psi^{r,q}.$$

Adopting a discount factor of $\delta = 0.95$, the dynamic component of race-specific admissions policies $G_r/(1+G_r)$ is roughly 23 percent for Black residents and 17 percent for Hispanic residents.

I run 100 independent simulations each lasting 5000 days, and average over these simulations. I assume that the initial distribution of residents in each nursing home at the start of the simulation reflects the average shares of residents from different racial groups admitted to said nursing home. This

is a natural starting point for most counterfactuals except when I eliminate residential segregation; in this case the appropriate initial distribution is unclear, so I view these results as likely providing a lower bound for the importance of this mechanism. Given that the initial distribution of residents across nursing homes in these simulations are somewhat arbitrary, I focus on the second half of each simulation run after the system has approximately reached a steady state, when computing measures of segregation and disparities. To measure the effect of each explanation on segregation, I compute the average statewide dissimilarity index under the relevant counterfactual, and compare it to the average statewide dissimilarity index in the "status-quo" simulations which use the estimated structural parameters without modification. For more details on the simulations, see Appendix section C.

Table 9 shows the effect of eliminating each explanation separately on segregation and disparities, with the first two columns showing the percent reduction in the Black/non-Black and Hispanic/non-Hispanic dissimilarity indices respectively, and the last two columns showing changes in Black-White and Hispanic-White disparities (with positive values indicating an improvement in the quality of nursing homes minorities are admitted to, relative to Whites). Starting first with segregation, we observe that eliminating discrimination in admissions policies, residential segregation, and in-group preferences each leads to substantial falls in the dissimilarity indices, typically on the order of a 10–40 percent reduction (but as large as a 60 percent reduction in the Hispanic/non-Hispanic dissimilarity index in Florida when removing residential segregation), while heterogeneity in responsiveness to quality does not seem to explain patterns of segregation in these three states. The relative ranking of these three mechanisms for nursing home segregation vary by state and by whether we use the Black/non-Black or Hispanic/non-Hispanic dissimilarity index, although discriminatory admissions policies is often the most important mechanism. This is due in large part to the substantial estimated heterogeneity in race-based admissions policies across nursing homes (i.e., the interactions between quality and race in the supply-side equations), which acts as an additional force directing residents of a specific racial group to each nursing home.

Columns 3 and 4 similarly shows that the relative importance of different explanations for Black-White and Hispanic-White disparities varies across states. Moreover, even within a state, the significance of different mechanisms for explaining Black-White disparities may differ from their value in explaining Hispanic-White disparities: we observe in Florida that eliminating residential segregation would lower Black-White but leave Hispanics worse off. This last finding can be explained by the fact that nursing homes near Hispanic residents in Florida are substantially higher-quality (about 0.2 s.d.

on average) than nursing homes near where Black and White residents live, as shown in Appendix Table A.3.

Next, Table 10 explores complementarities and substitutabilities between these individual explanations, by considering the effect of simultaneously eliminating residential segregation and one other mechanism on segregation and disparities. We would consider the two mechanisms as complements (or conversely, substitutes) if the effect of simultaneously removing both leads to a greater (respectively, smaller) fall in segregation or disparities than adding the individual effects of removing each separately (from Table 9). We observe that the clearest evidence of complementarity comes for the effect of these mechanisms on segregation, and in particular between residential segregation and discriminatory admissions policies. Specifically, while summing the individual contributions of the two mechanisms from Table 9 suggests a reduction in the Black/non-Black dissimilarity index of about 55-60 percent in the absence of interaction effects in each of the three states, we observe that eliminating both mechanisms simultaneously in Table 10 reduces segregation by about 85–90 percent.

6 Conclusion

This paper shows that segregation and disparities across nursing homes in the U.S. are related but distinct concepts, and are driven by different underlying forces. Mechanisms driving these patterns interact and vary across places and groups, such that policies which successfully reduce segregation may fail to close quality gaps, and an interventions that help one minority group may leave other minorities worse off. These findings caution against extrapolating findings from a single region or minority group to settings with different regions or populations.

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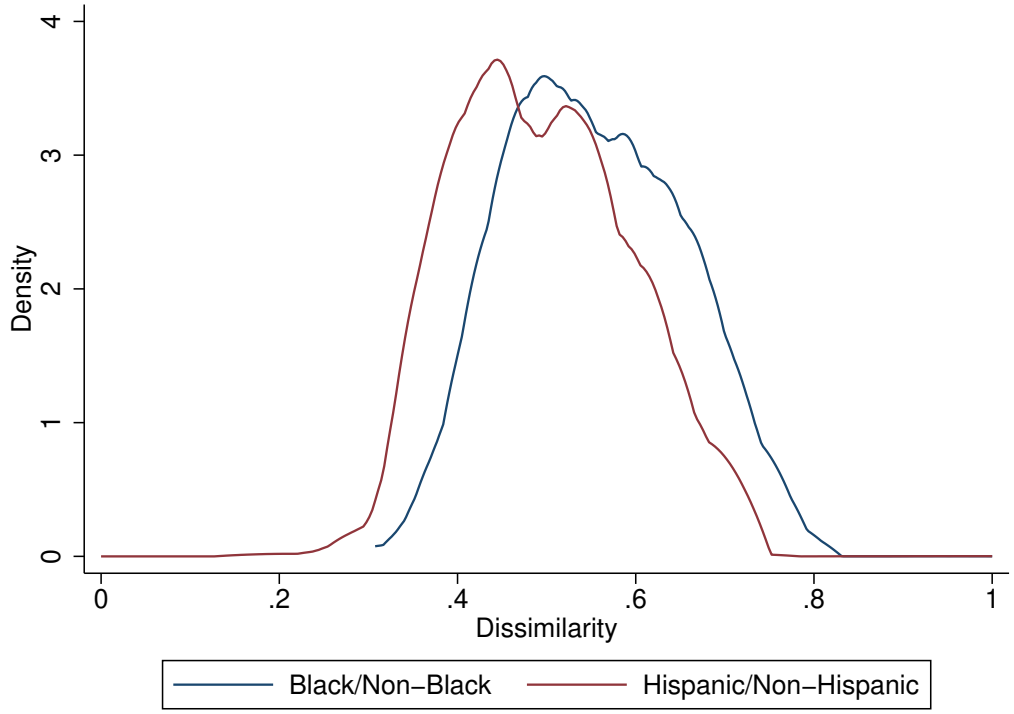
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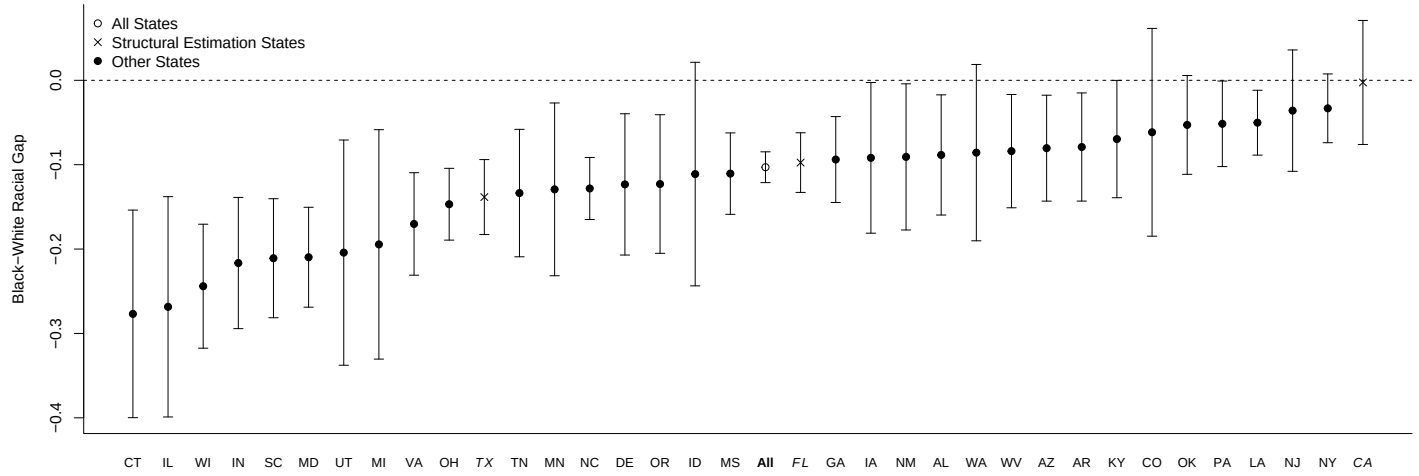
Tables and Figures

Figure 1: Patterns of Racial Segregation (Statewide Index of Dissimilarity)

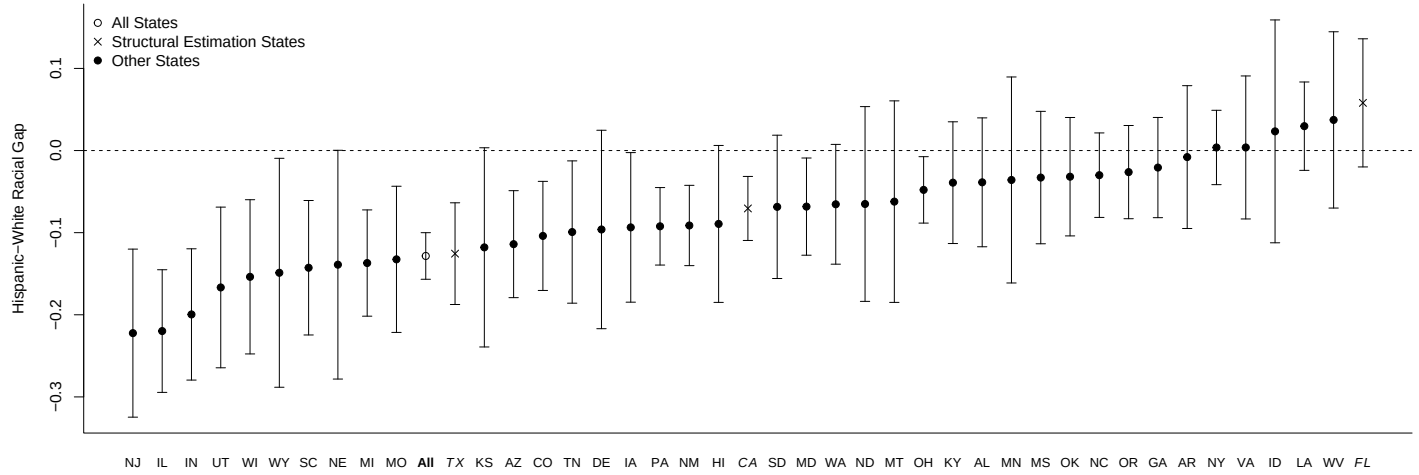


Notes: This figure shows kernel density plots of the dissimilarity index for Black versus non-Black residents and Hispanic versus non-Hispanic residents, measured at the state level.

Figure 2: Racial Gaps in Nursing Home Quality



(a) Black-White Gap

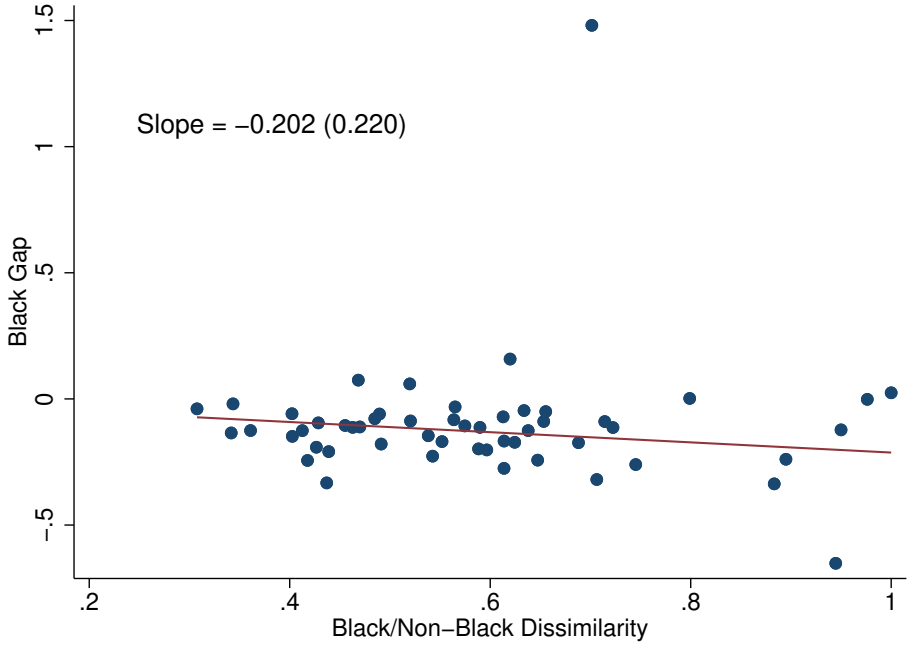


(b) Hispanic-White Gap

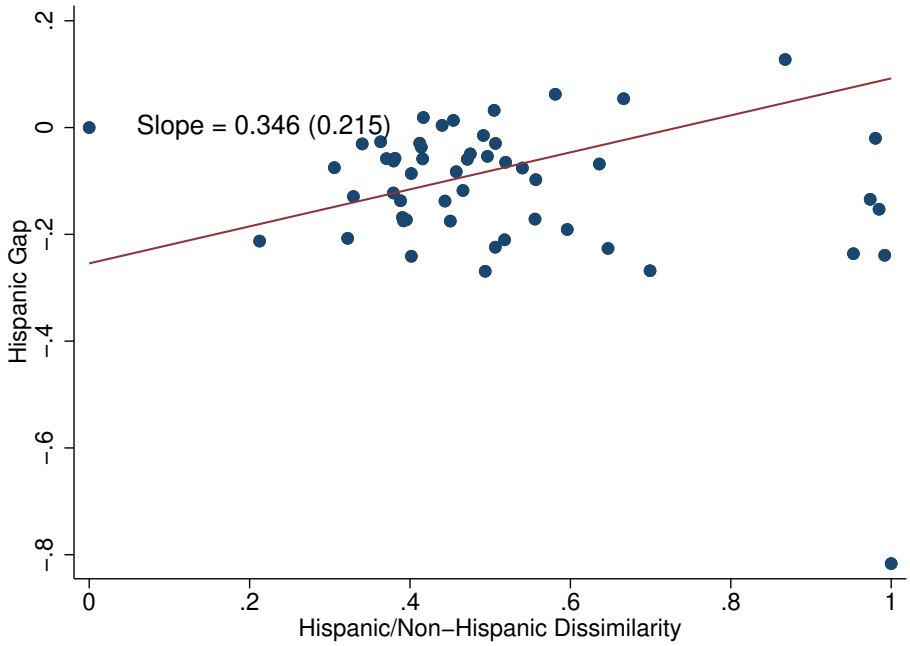
Notes: These figures display the estimated gaps in quality of nursing homes residents of different races are admitted to, using a quality index based on RN staffing, LPN staffing, and negative deficiency citations. Error bars indicate 95 percent confidence intervals for the estimates.

Figure 3: Cross-Sectional Relationship Between State-Level Segregation and Disparities

(a) Black/Non-Black

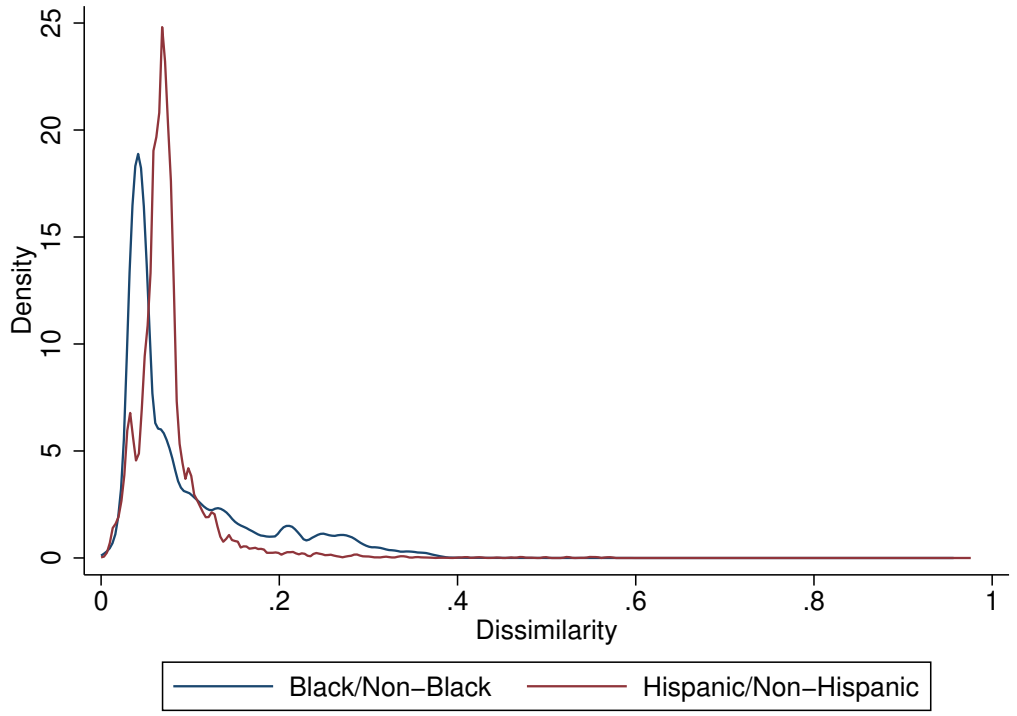


(b) Hispanic/Non-Hispanic



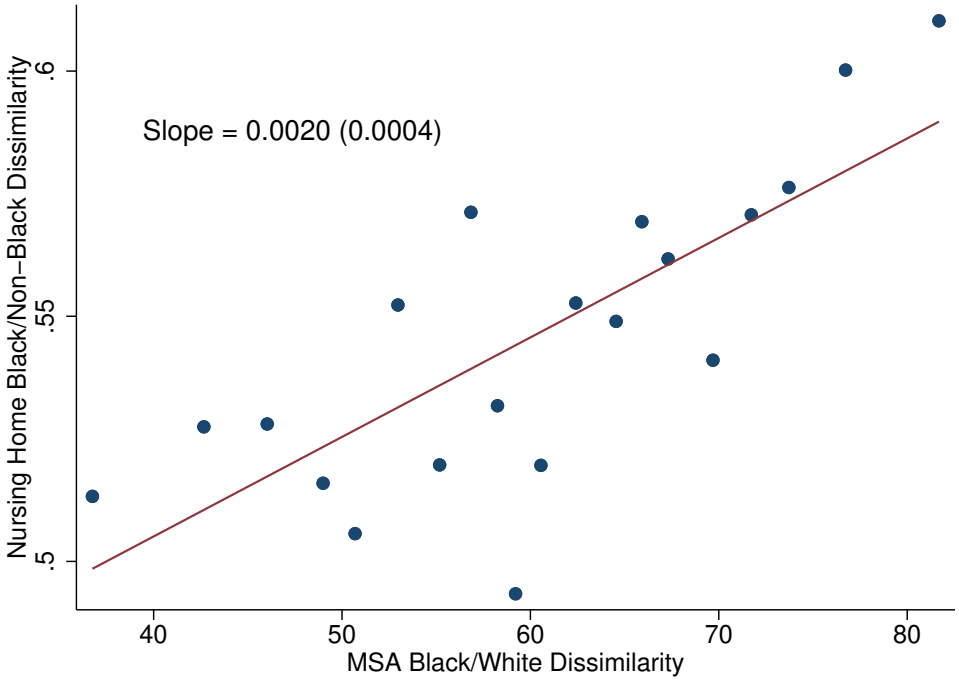
Notes: These figures display scatter plots of the estimated racial gap (based on the quality index) against segregation at the state level. Observations are weighted by the number of residents admitted to the state.

Figure 4: Patterns of Racial Segregation (Index of Dissimilarity Based on 15-Mile Radius)



Notes: This figure shows kernel density plots of the dissimilarity index for Black versus non-Black residents and Hispanic versus non-Hispanic residents, measured based on neighborhoods in a 15-mile radius of each zip code and at the state level.

Figure 5: Association Between Residential and Nursing Home Segregation

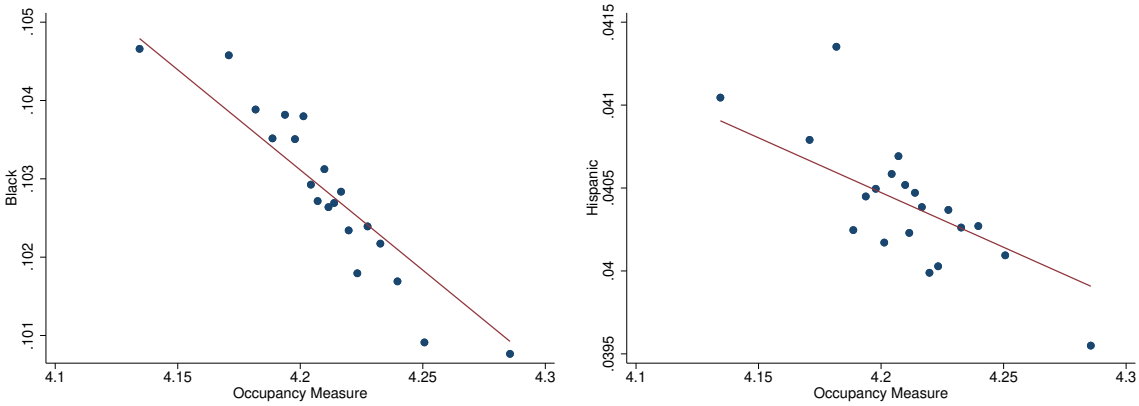


Notes: This figure shows a binscatter of MSA-level Black-White dissimilarity indices for residential segregation against state-level Black/non-Black nursing home dissimilarity indices. For MSAs that straddle multiple states, I create "duplicates" when merging them to state-level nursing home segregation data. Observations are weighted by the number of first stays for nursing home residents in the state during 1999–2010.

Figure 6: Reduced Form Evidence of Selective Admissions by Race

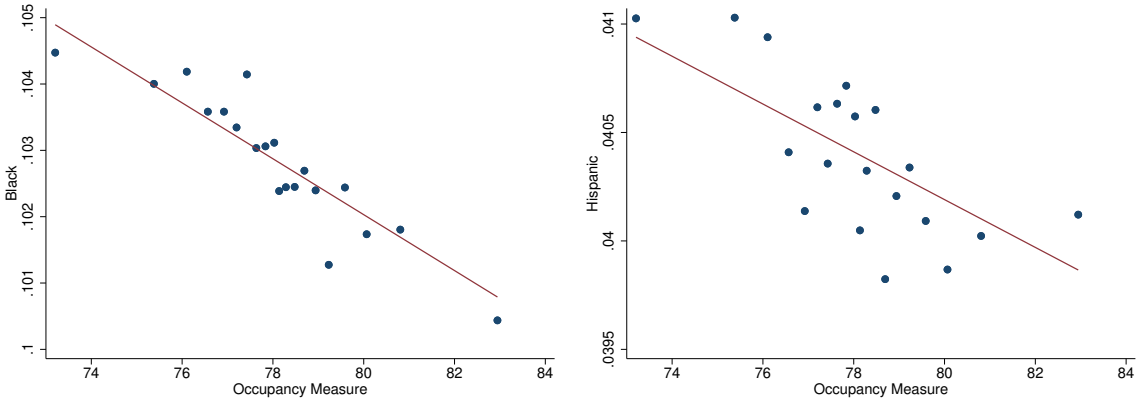
(a) $Pr(Black)$ versus Lagged Log Occ.

(b) $Pr(Hispanic)$ versus Lagged Log Occ.



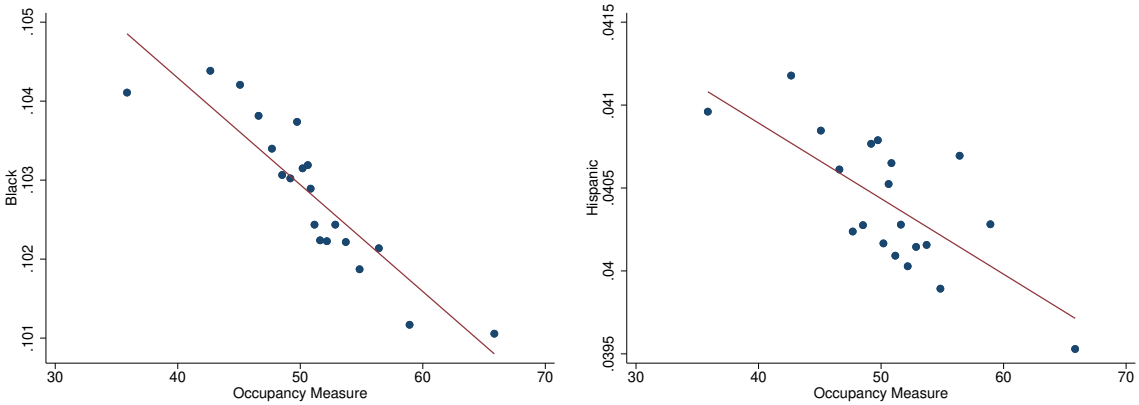
(c) $Pr(Black)$ versus Lagged Occ.

(d) $Pr(Hispanic)$ versus Lagged Occ.



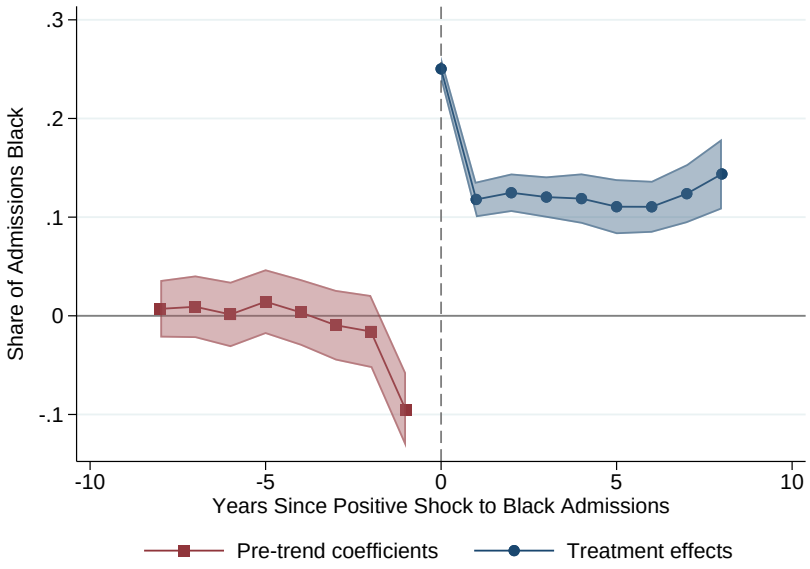
(e) $Pr(Black)$ versus Lagged Occ. Percentile

(f) $Pr(Hispanic)$ versus Lagged Occ. Percentile

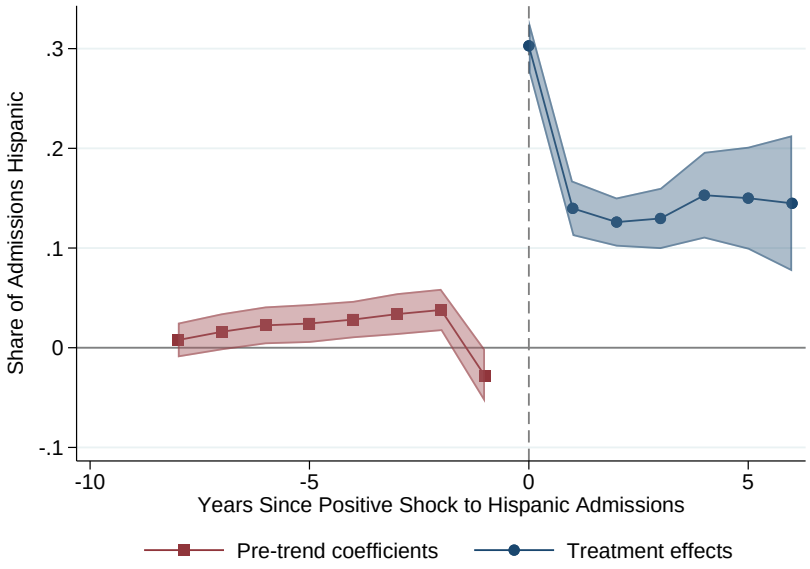


Notes: These figures show binscatters of the probability that an admitted resident is Black (in panels A, C, and E) or Hispanic (in panel B, D, and F) as a function of capacity strain faced by the nursing home at the time of said admission, for different measures of capacity strain (namely, lagged 7-day log occupancy in panels A and B, lagged 7-day occupancy in panels C and D, and lagged 7-day occupancy percentile in panels E and F).

Figure 7: Event Study on the Effect of a Positive Shock to the Share of Minority Admissions



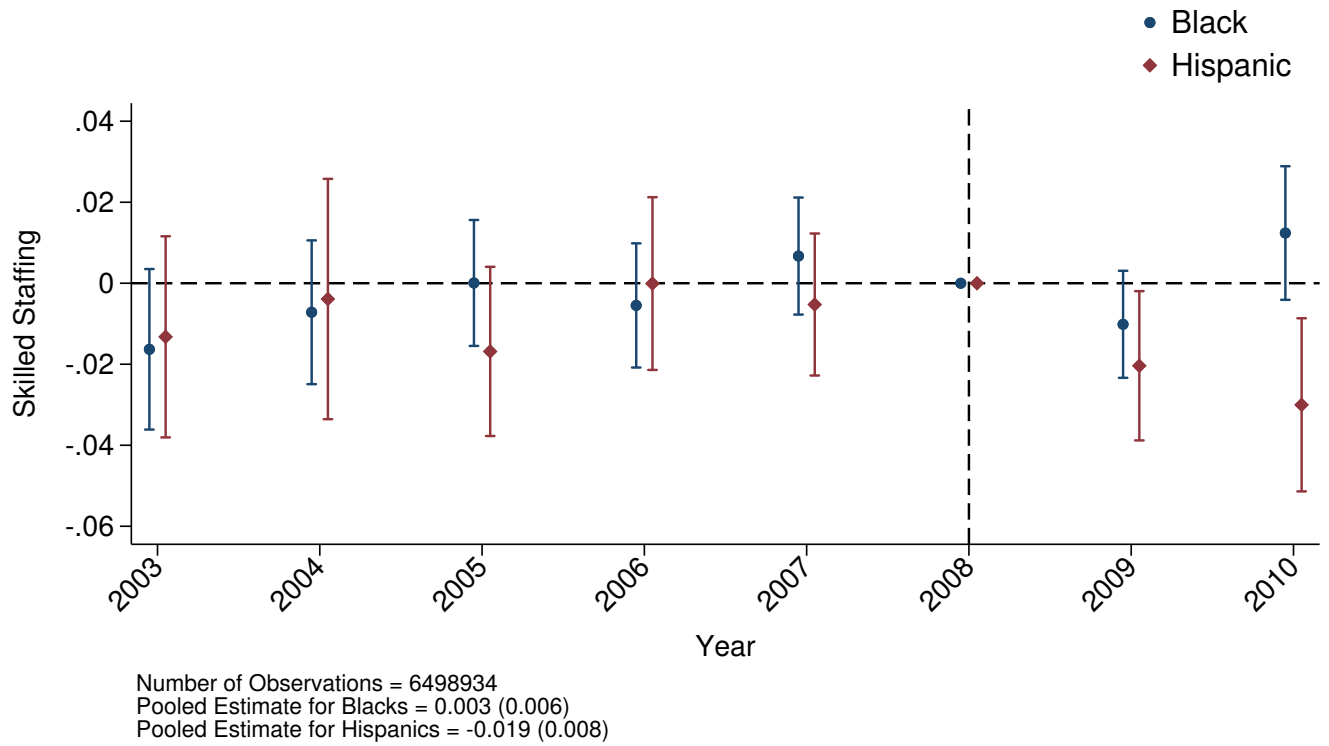
(a) Increase in Share of Black Admissions



(b) Increase in Share of Hispanic Admissions

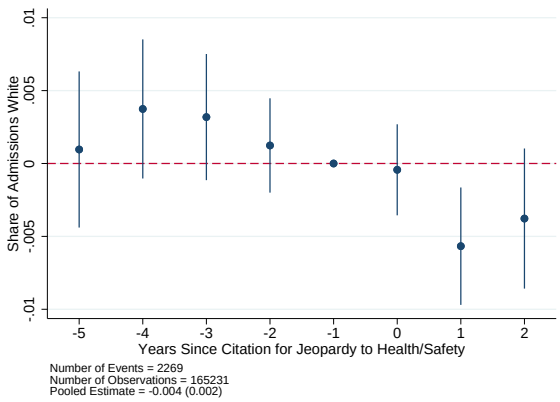
Notes: These figures show event study estimates of the effect of a large shock to the minority share of admissions (defined as a year-to-year increase in the minority share of admissions of at least 25pp.) on future minority share of admissions, based on event study methods of Borusyak, Jaravel, and Spiess (2021).

Figure 8: Event Study Estimates Around the Introduction of Star Ratings

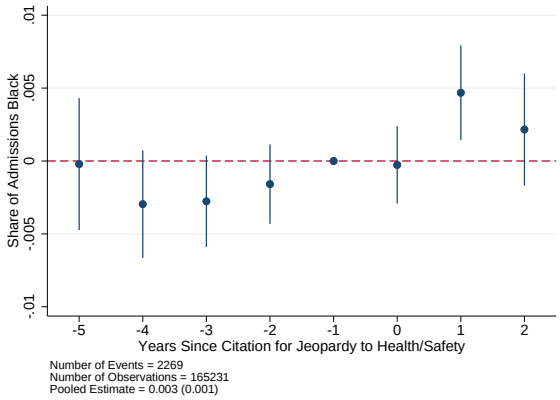


Notes: This figure shows event study estimates on the effect of the introduction of star ratings on the quality of nursing home chosen by residents of different races living in the same zip code, with White residents being the omitted category. Standard errors are clustered at the nursing home level.

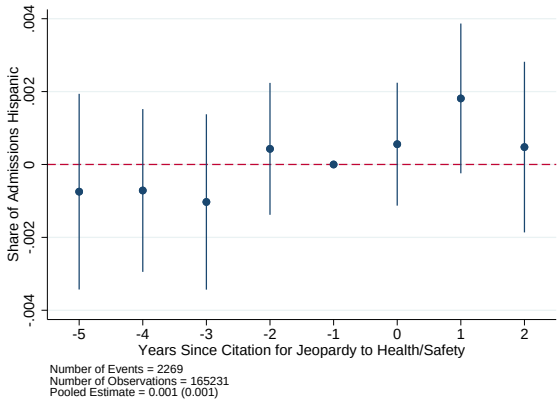
Figure 9: Stacked Event Study Estimates on Admission Patterns Following Severe Deficiency Citation



(a) Share of White Admissions



(b) Share of Black Admissions



(c) Share of Hispanic Admissions

Notes: These figures show stacked event study estimates on the effect of a severe deficiency citation at a nursing home on the share of residents of different races being admitted to the nursing home in subsequent years (compared to other nursing homes in the same county without a severe deficiency citation). Standard errors are clustered at the nursing home level.

Table 1: Summary Statistics for Residents

	All	White	Black	Hispanic
Age	77.57	78.63	71.15	73.29
	(12.76)	(11.98)	(15.27)	(14.76)
Female	0.623	0.633	0.573	0.555
	(0.485)	(0.482)	(0.495)	(0.497)
Married	0.324	0.335	0.224	0.330
	(0.468)	(0.472)	(0.417)	(0.470)
Less than High School	0.271	0.240	0.409	0.542
	(0.445)	(0.427)	(0.492)	(0.498)
High School/Some College	0.594	0.619	0.499	0.376
	(0.491)	(0.486)	(0.500)	(0.484)
At Least Bachelor's Degree	0.108	0.117	0.0586	0.0416
	(0.310)	(0.321)	(0.235)	(0.200)
Medicare	0.714	0.731	0.644	0.580
	(0.452)	(0.443)	(0.479)	(0.494)
Medicaid	0.0991	0.0768	0.208	0.217
	(0.299)	(0.266)	(0.406)	(0.413)
Admitted from Acute Care Hospital	0.843	0.841	0.850	0.856
	(0.363)	(0.365)	(0.357)	(0.351)
Admitted from Home	0.110	0.113	0.0964	0.0989
	(0.313)	(0.317)	(0.295)	(0.299)
Dementia	0.246	0.248	0.245	0.231
	(0.431)	(0.432)	(0.430)	(0.421)
White	0.833			
	(0.373)			
Black	0.102			
	(0.302)			
Hispanic	0.0397			
	(0.195)			
Number of Residents	8,573,357	7,138,106	872,859	340,522

Notes: This table contains summary statistics for residents who had their first stays in a nursing home between 2000 and 2010.

Table 2: Summary Statistics for Nursing Homes

Number of Beds	141.3
	(80.72)
Occupancy Percentage	86.44
	(12.01)
Chain	0.611
	(0.487)
For Profit	0.754
	(0.431)
Cited Deficiencies	6.987
	(6.384)
Registered Nurse Staffing (hours per patient-day)	0.365
	(0.389)
Licensed Practical Nurse Staffing (hours per patient-day)	0.830
	(0.535)
Certified Nursing Assistant Staffing (hours per patient-day)	2.225
	(1.087)
Number of Nursing Homes	17,248

Notes: This table contains summary statistics for nursing homes, weighted by the number of residents admitted between 2000 and 2010.

Table 3: Association Between Quality Index and Minority Status

	Quality Index (s.d.)	
	(1)	(2)
Race: Black	-0.120***	-0.110***
	(0.0110)	(0.00487)
Race: Hispanic	-0.140***	-0.0711***
	(0.0168)	(0.00757)
Constant	0.0178**	0.0140**
	(0.00738)	(0.00588)
Zip Code Fixed Effects		X
Number of Observations	8,567,753	8,566,289
R-squared	0.002	0.094

Notes: The unit of observation is a resident. Standard errors are clustered at the nursing home level.

Table 4: Evidence of Capacity Constraints

	Number of New Residents		
	(1)	(2)	(3)
Lagged 7-Day Avg. Log Occupancy	-0.298***		
	(0.00527)		
Lagged 7-Day Avg. Occupancy		-0.00935***	
		(0.000107)	
Lagged 7-Day Avg. Occ. Percentile			-0.00246***
			(2.45e-05)
Nursing Home-Month Fixed Effects	X	X	X
N	40,033,450	40,033,450	40,033,450
R-squared	0.205	0.205	0.205

Notes: This table shows regression results at the nursing home-day level wherein the dependent variable is number of new patients, and the independent variables are various measures of nursing home occupancy. Standard errors are clustered at the nursing home level.

Table 5: Autocorrelation in the Racial Composition of Admissions

Panel A: Share of Admitted Residents who are White			
	(1)	(2)	(3)
Previous Share White	0.968***	0.306***	0.248***
	(0.00173)	(0.0109)	(0.0110)
Nursing Home Fixed Effects		X	X
County x Year Fixed Effects			X
Number of Nursing Home-Years	121,984	121,469	114,962
R-squared	0.922	0.953	0.962
Panel B: Share of Admitted Residents who are Black			
	(1)	(2)	(3)
Previous Share Black	0.963***	0.276***	0.246***
	(0.00214)	(0.0130)	(0.0133)
Nursing Home Fixed Effects		X	X
County x Year Fixed Effects			X
Number of Nursing Home-Years	121,984	121,469	114,962
R-squared	0.917	0.951	0.960
Panel C: Share of Admitted Residents who are Hispanic			
	(1)	(2)	(3)
Previous Share Hispanic	0.967***	0.244***	0.184***
	(0.00375)	(0.0165)	(0.0183)
Nursing Home Fixed Effects		X	X
County x Year Fixed Effects			X
Number of Nursing Home-Years	121,984	121,469	114,962
R-squared	0.906	0.946	0.955

Notes: This table shows regression results at the nursing home-year level, with weights equal to the number of residents who were admitted to the nursing home during that year. Standard errors are clustered at the nursing home level.

Table 6: Effect of Short-Term Fluctuations in Racial Composition on Admissions of Different Racial Groups

	White Admissions	Black Admissions	Hispanic Admissions
Panel A: Number of Admissions by Racial Group	(1)	(2)	(3)
White Occupancy	0.0675***	-7.59e-05	-0.000107***
	(0.000456)	(4.68e-05)	(2.16e-05)
Black Occupancy	0.00131***	0.0643***	-0.000143*
	(0.000391)	(0.000448)	(7.74e-05)
Hispanic Occupancy	0.000547	-0.000433**	0.0686***
	(0.000503)	(0.000170)	(0.000585)
Nursing Home-Month Fixed Effects	X	X	X
Number of Observations	40,095,480	40,095,480	40,095,480
R-squared	0.310	0.221	0.249
	Any White Admissions	Any Black Admissions	Any Hispanic Admissions
Panel B: Any Admissions by Racial Group	(1)	(2)	(3)
White Occupancy	0.0329***	-0.000162***	-8.69e-05***
	(0.000235)	(2.71e-05)	(1.64e-05)
Black Occupancy	0.000595***	0.0473***	-9.51e-05*
	(0.000158)	(0.000448)	(5.69e-05)
Hispanic Occupancy	0.000617***	-0.000384***	0.0537***
	(0.000223)	(0.000124)	(0.000857)
Nursing Home-Month Fixed Effects	X	X	X
Number of Observations	40,095,480	40,095,480	40,095,480
R-squared	0.225	0.186	0.189

Notes: This table shows regression estimates at the nursing home-day level of admissions of residents of different races on occupancy of different races at the end of the previous day, controlling for nursing home-month fixed effects. Standard errors are clustered at the nursing home level.

Table 7: Association Between Race of Admissions and Nursing Home Quality

	Admitted Resident is White (x100)		Admitted Resident is Black (x100)		Admitted Resident is Hispanic (x100)	
	(1)	(2)	(3)	(4)	(5)	(6)
Quality Index	2.21***	0.0978***	-1.47***	-0.0861***	-0.735***	-0.0139
	(0.196)	(0.0319)	(0.170)	(0.0258)	(0.0992)	(0.0191)
Previous Share White		17.5***				
		(0.801)				
Previous Share Black				16.4***		
				(0.870)		
Previous Share Hispanic						15.2***
						(1.7)
Occupancy Percentage		0.0112***		-0.00616***		-0.00514***
		(0.0025)		(0.00206)		(0.00154)
Nursing Home FEs		X		X		X
County x Year FEs		X		X		X
Zip Code FEs		X		X		X
Number of Observations	8,473,698	7,684,528	8,473,698	7,684,528	8,473,698	7,684,528
R-squared	0.003	0.397	0.002	0.396	0.001	0.311

Notes: This table shows regression results at the resident level. Previous share of a given race is defined as the fraction of admissions in the previous year to the nursing home that the resident is admitted to who belong to the race. Standard errors are clustered at the nursing home level.

Table 8: Main Structural Estimates

	California	*Florida*	*Texas*
Residents' Preferences	(1)	(2)	(3)
Utility (Distance to Facility)	-0.166***	-0.182***	-0.163***
	(0.001)	(0.001)	(0.001)
Utility (Previous Share Black)	-0.997***	-1.405***	-1.396***
	(0.019)	(0.019)	(0.021)
Utility (Black x Previous Share Black)	1.355***	1.598***	1.709***
	(0.040)	(0.033)	(0.037)
Utility (Previous Share Hispanic)	-1.162***	-0.975***	-1.409***
	(0.017)	(0.024)	(0.034)
Utility (Hispanic x Previous Share Hispanic)	1.905***	1.049***	1.326***
	(0.036)	(0.036)	(0.041)
Utility (Quality Index)	0.089***	0.153***	0.157***
	(0.004)	(0.003)	(0.005)
Utility (Quality Index x Black)	-0.024	-0.110***	-0.014
	(0.025)	(0.014)	(0.046)
Utility (Quality Index x Hispanic)	0.001	-0.096***	-0.146***
	(0.007)	(0.016)	(0.011)
Nursing Homes' Admission Policies			
Occupancy	-11.088***	-11.561***	-8.369***
	(0.021)	(0.217)	(0.706)
Race (Black)	-0.955***	-0.341***	-1.102***
	(0.035)	(0.028)	(0.128)
Race (Hispanic)	-0.358***	-0.224***	-0.558***
	(0.014)	(0.038)	(0.062)
Quality Index x Black	0.101**	-0.054	0.068
	(0.046)	(0.051)	(0.193)
Quality Index x Hispanic	-0.131***	-0.068	0.592***
	(0.023)	(0.059)	(0.036)
Nursing Home Characteristics in Supply-Side Equation	X	X	X

Notes: This table shows estimates of the structural model using Gibbs sampling. A burn-in period corresponding to the first half of the chain was used. Nursing home characteristics in the supply side include the quality index, for-profit, and chain ownership. The supply-side equation also includes and intercept and year indicator.

Table 9: Results from Counterfactual Simulations: Importance of Individual Mechanisms

	Percent Reduction in Black/Non-Black DI	Percent Reduction in Hisp./Non-Hisp. DI	Change in Black-White Gap in Quality	Change in Hisp.-White Gap in Quality
Panel A. California	(1)	(2)	(3)	(4)
No Residential Segregation	21.0%	35.0%	0.06 s.d.	0.07 s.d.
Race-Neutral Admissions	34.5%	38.3%	0.11 s.d.	0.08 s.d.
No In-Group Preferences	23.4%	36.3%	0.09 s.d.	0.10 s.d.
Homogeneous Resp. to Quality	0.0%	0.0%	0.01 s.d.	-0.01 s.d.
Baseline Dissimilarity Index/Racial Gap	0.69	0.56	-0.15 s.d.	-0.12 s.d.
	Percent Reduction in Black/Non-Black DI	Percent Reduction in Hisp./Non-Hisp. DI	Change in Black-White Gap in Quality	Change in Hisp.-White Gap in Quality
Panel B. Florida	(1)	(2)	(3)	(4)
No Residential Segregation	29.5%	60.3%	0.03 s.d.	-0.26 s.d.
Race-Neutral Admissions	33.6%	12.1%	0.10 s.d.	0.01 s.d.
No In-Group Preferences	26.9%	10.8%	0.11 s.d.	0.01 s.d.
Homogeneous Resp. to Quality	0.9%	0.2%	0.04 s.d.	0.02 s.d.
Baseline Dissimilarity Index/Racial Gap	0.56	0.69	-0.17 s.d.	0.19 s.d.
	Percent Reduction in Black/Non-Black DI	Percent Reduction in Hisp./Non-Hisp. DI	Change in Black-White Gap in Quality	Change in Hisp.-White Gap in Quality
Panel C. Texas	(1)	(2)	(3)	(4)
No Residential Segregation	15.2%	33.8%	0.06 s.d.	0.05 s.d.
Race-Neutral Admissions	40.7%	22.6%	0.02 s.d.	0.07 s.d.
No In-Group Preferences	15.2%	15.5%	0.03 s.d.	0.06 s.d.
Homogeneous Resp. to Quality	-0.1%	0.1%	0.00 s.d.	0.01 s.d.
Baseline Dissimilarity Index/Racial Gap	0.71	0.73	-0.06 s.d.	-0.07 s.d.

Notes: This table shows counterfactual simulation results.The dissimilarity indices (DIs) as well as racial disparities are computed using the second half of the simulation run after these measures have stabilized. The change in Black-White disparities is computed as the difference in quality of nursing homes that Blacks versus Whites are admitted to in the simulations listed in the row title, compared to the same difference in quality of nursing homes that Blacks versus Whites are admitted to in the simulations under the estimated structural parameters, and similarly for the change in Hispanic-White disparities (so that positive values indicating a greater improvement for minorities relative to Whites). Baseline disparities are computed as the difference in quality of nursing homes that Blacks versus Whites are admitted to in the simulations under the estimated structural parameters (so that negative values indicate minorities being admitted to lower-quality nursing homes). Results are averaged over 100 independent simulation runs.

Table 10: Results from Counterfactual Simulations: Interactions Between Mechanisms

	Percent Reduction in Black/Non-Black DI	Percent Reduction in Hisp./Non-Hisp. DI	Fall in Black-White Disparities	Fall in Hispanic-White Disparities
Panel A. California	(1)	(2)	(3)	(4)
No Residential Segregation	21.0%	35.0%	0.06 s.d.	0.07 s.d.
No Residential Segregation + Race-Neutral Admissions	86.9%	85.1%	0.13 s.d.	0.13 s.d.
No Residential Segregation + No In-Group Preferences	56.5%	76.8%	0.13 s.d.	0.14 s.d.
No Residential Segregation + Homogeneous Resp. to Quali	21.1%	35.0%	0.07 s.d.	0.07 s.d.
Baseline Segregation or Disparities	0.69	0.56	-0.15 s.d.	-0.12 s.d.
	Percent Reduction in Black/Non-Black DI	Percent Reduction in Hisp./Non-Hisp. DI	Fall in Black-White Disparities	Fall in Hispanic-White Disparities
Panel B. Florida	(1)	(2)	(3)	(4)
No Residential Segregation	29.5%	60.3%	0.03 s.d.	-0.26 s.d.
No Residential Segregation + Race-Neutral Admissions	86.8%	90.0%	0.13 s.d.	-0.21 s.d.
No Residential Segregation + No In-Group Preferences	70.9%	86.0%	0.12 s.d.	-0.22 s.d.
No Residential Segregation + Homogeneous Resp. to Quali	30.5%	60.7%	0.07 s.d.	-0.24 s.d.
Baseline Segregation or Disparities	0.56	0.69	-0.17 s.d.	0.19 s.d.
	Percent Reduction in Black/Non-Black DI	Percent Reduction in Hisp./Non-Hisp. DI	Fall in Black-White Disparities	Fall in Hispanic-White Disparities
Panel C. Texas	(1)	(2)	(3)	(4)
No Residential Segregation	15.2%	33.8%	0.06 s.d.	0.05 s.d.
No Residential Segregation + Race-Neutral Admissions	85.8%	87.4%	0.06 s.d.	0.06 s.d.
No Residential Segregation + No In-Group Preferences	35.9%	65.7%	0.07 s.d.	0.05 s.d.
No Residential Segregation + Homogeneous Resp. to Quali	15.2%	33.9%	0.06 s.d.	0.06 s.d.
Baseline Segregation or Disparities	0.71	0.73	-0.06 s.d.	-0.07 s.d.

Notes: This table shows counterfactual simulation results.The dissimilarity indices (DIs) as well as racial disparities are computed using the second half of the simulation run after these measures have stabilized. The change in Black-White disparities is computed as the difference in quality of nursing homes that Blacks versus Whites are admitted to in the simulations listed in the row title, compared to the same difference in quality of nursing homes that Blacks versus Whites are admitted to in the simulations under the estimated structural parameters, and similarly for the change in Hispanic-White disparities (so that positive values indicating a greater improvement for minorities relative to Whites). Baseline disparities are computed as the difference in quality of nursing homes that Blacks versus Whites are admitted to in the simulations under the estimated structural parameters (so that negative values indicate minorities being admitted to lower-quality nursing homes). Results are averaged over 100 independent simulation runs.

Appendix

A Data Appendix

Data on residents was obtained from the Minimum Data Set 2.0 (MDS), which was then superseded by the Minimum Data Set 3.0 after 2010. I focus on the earlier period given inconsistencies in the variables collected across versions, and the fact that the earlier version contains residents' zip code of prior residence. In principle, zip code for some residents in the later period can be obtained by linking the MDS data with Medicare and Medicaid data, but I will still have to drop residents without Medicare or Medicaid. Data on nursing homes was obtained from the Online Survey Certification and Reporting (OSCAR) data, and was downloaded from LTCFocus, a product of the Shaping Long-Term Care in America Project being conducted at the Brown University Center for Gerontology and Healthcare Research and supported, in part, by the National Institute on Aging. This data contains yearly level information on nursing homes such as the street address, and average RN, LPN, and CNA staffing levels. Additional information on deficiency citations and star ratings were obtained from the CMS website.

In constructing my sample of residents, I drop the relatively small number of residents with errors in birth or death dates (e.g., with different birth or death dates recorded across different assessments). In addition, I drop residents admitted to nursing homes with Medicare Provider Numbers that could not be linked to the OSCAR data. Race for Black and Hispanic individuals is coded based on the corresponding variable in the MDS data, and the base category (which I refer to as White in the main text) includes a small number of Asian and individuals of other races. These races were self-reported by the resident (or their family if the resident has trouble communicating), and only one race category can be chosen. For the structural demand estimation sample, I consider only resident-nursing home pairs within 15 miles of each other. In addition, I drop nursing homes that admit fewer than 30 residents over the period of my structural estimation sample (2008–2010) to ensure sufficient power.

Two key variables for the structural estimation are distance between residents and nursing homes (which serves as the demand-side instrument), and temporary occupancy fluctuations (which I use as the supply-side instrument). To construct distances, I combine residents' zip code from the MDS with nursing homes' street address from the OSCAR data, which I convert to latitude and longitude using the Google Maps API. The stata command "geodist" was then used to compute the distance between

residents' zip code of prior residence, and nursing homes' locations.

For each facility, I define temporary occupancy fluctuations as the average log occupancy (or average occupancy or within-nursing home occupancy percentile as robustness checks) in that facility over the prior seven days residualized by facility-by-year-by-month fixed effects. I focus on the week prior to admissions instead of a shorter term measure such as the day of/before admission given that residents (or hospital discharge planners) typically need some time to search for and coordinate with nursing homes. In addition, I residualize lagged 7-day log occupancy of nursing home-month fixed effects, to abstract from expansions or contractions that a nursing home may be undergoing (for example, if a nursing home is expanding, it will be more likely to admit new residents even though its occupancy seems high). The OSCAR contains data on total number of beds at a nursing home which one could in principle use as a measure of capacity, but this variable is measured with substantial error and only updated annually. In fact, measures of occupancy over time based on residents' admission and discharge dates from the MDS frequently exceeds total number of beds reported by nursing homes in the OSCAR data, which calls into question the use of this variable as a measure of capacity. For the structural model, I consider all nursing homes within 15 miles of a resident as her potential choice set (before accounting for unobserved choice set constraints due to rejections by nursing homes).

B Algorithm for Gibbs Sampler

In the following description for the Gibbs sampler, when drawing structural error terms in sequence for $j \in \mathcal{J}_i$, I assume an increasing order (although obviously any other order works as well). In addition, to simplify notation, I denote variables in residents' utility and nursing homes' admissions equations by $\mathbf{X}_{ij}$ and W_{ij} respectively,[13] and refer to the nursing home that resident i ends up in by $\mu(i)$.

Denoting iterations of the Gibbs sampler by k and indicating the values of various parameters in the kth iteration of the Gibbs sampler using a superscript k, the steps for implementing the Gibbs sampler are as follows.

1. Initialization ($k = 0$): I assume that $(\epsilon_{ij}, \omega_{ij}) \sim^{i.i.d.} N(0, I_2)$ and set the following conjugate priors for the parameters: $(\kappa', \psi')' \sim N(0, 100I)$.

   (a) Set the initial values of the parameters $\theta^0 = \left(\kappa^{0\prime}, \psi^{0\prime}\right)$ at their prior mean.

[13] These include resident characteristics x_i, nursing home characteristics w_j, distance between residents and nursing homes $dist_{ij}$, occupancy fluctuations at nursing homes occ_{ij}, and interactions between these variables.

(b) Initial data augmentation: For each resident i, draw the vector ϵ_i^0 such that $v_{i,\mu(i)}^0 \geq v_{ij}^0$ for all $j \in \mathcal{J}_i$.

i. Draw $\omega_{i,\mu(i)}^0$ such that $\omega_{i,\mu(i)}^0 \geq -W_{ij}'\psi^0$ and for $j \neq \mu(i)$ draw ω_{ij}^0 from the unconditional distribution.

ii. Set $\epsilon_{i,\mu(i)}^0$ equal to three times the standard deviation of the prior. For $j \neq \mu(i)$, draw ϵ_{ij}^0 such that $\epsilon_{ij}^0 \leq \left(\mathbf{X}_{i,\mu(i)} - \mathbf{X}_{ij}\right)'\kappa^0 + \epsilon_{i,\mu(i)}^0$ if $\pi_{ij}^0 \geq 0$ or draw ϵ_{ij}^0 unconditionally otherwise.

2. For $k+1 = 1, ..., K$:

(a) Draw the profit shocks $\omega_i^{k+1}|v_i^k; \psi^k$ in sequence for $j \in \mathcal{J}_i$.

i. If $v_{ij}^k < v_{i,\mu(i)}^k$, draw ω_{ij}^{k+1} unconditional on assignment (given that even if i is eligible for j, i would not choose j).

ii. If $v_{ij}^k > v_{i,\mu(i)}^k$, draw ω_{ij}^{k+1} from a truncated normal with mean and variance given by the conditional distribution and truncation point $\omega_{ij}^{k+1} < -W_{ij}\psi^k$ (given that otherwise i would choose j over $\mu(i)$).

iii. Finally, if $j = \mu(i)$, draw from the conditional distribution with truncation point given by $\omega_{ij}^{k+1} \geq -W_{ij}'\psi^k$ (given that i must always be eligible for the facility she was ultimately assigned to).

(b) Update π_i^{k+1} according to $\pi_{ij}^{k+1} = W_{ij}'\psi^k + \omega_{ij}^{k+1}$.

(c) Draw the utility shocks $\epsilon_i^{k+1}|\pi_i^{k+1}; \kappa^k$ in sequence, for $j \in \mathcal{J}_i$.

i. If $\pi_{ij}^{k+1} < 0$, draw ϵ_{ij}^{k+1} unconditionally (given that i would not choose such a facility even if she were eligible for it).

ii. If $\pi_{ij}^{k+1} \geq 0$ and $j \neq \mu(i)$, draw ϵ_{ij}^{k+1} from the conditional distribution with truncation point given by $\upsilon_{ij}^{k+1} < \mathbf{X}_{ij}'\kappa^k$.

iii. For $j = \mu(i)$, draw $\epsilon_{i,\mu(i)}^{k+1}$ such that $v_{i,\mu(i)}^{k+1}$ is larger than the current values of $v_{i,j'}$ for $j' \neq j$ and $\pi_{ij'} \geq 0$.

(d) Update v_i^{k+1} according to $v_{ij}^{k+1} = \mathbf{X}_{ij}'\kappa^k + \epsilon_{ij}^{k+1}$.

(e) Update the parameters θ based on the new indirect utilities v^{k+1} and profits π^{k+1}.

i. First, we update κ. Denote the design matrix in the equation for indirect utilities by

$\mathbb{X}$. In matrix notation, we have:

$$v = \mathbb{X}\kappa + \epsilon,\ \epsilon \sim N(0, I).$$

We have a normal conjugate prior for κ, with mean μ_κ^0 and covariance matrix Σ_κ^0. The posterior distribution of κ conditional on v and W is:

$$\kappa|(v, \mathbb{X}) \sim N(\tilde{\mu}_\kappa, \tilde{\Sigma}_\kappa),$$

where the posterior mean and covariance matrix are given by:

$$\begin{aligned}\tilde{\mu}_\kappa &= \left(\frac{\mathbb{X}'\mathbb{X}}{\sigma_\epsilon^2} + \left(\Sigma_\kappa^0\right)^{-1}\right)^{-1}\left(\left(\Sigma_\kappa^0\right)^{-1}\mu_\kappa^0 + \frac{\mathbb{X}'\kappa}{\sigma_\epsilon^2}\right) \\ &= \left(\mathbb{X}'\mathbb{X} + \left(\Sigma_\kappa^0\right)^{-1}\right)^{-1}\left(\left(\Sigma_\kappa^0\right)^{-1}\mu_\kappa^0 + \mathbb{X}'\kappa\right),\end{aligned}$$

$$\begin{aligned}\tilde{\Sigma}_{\theta_v} &= \left(\frac{\mathbb{X}'\mathbb{X}}{\sigma_\epsilon^2} + \left(\Sigma_\kappa^0\right)^{-1}\right)^{-1} \\ &= \left(\mathbb{X}'\mathbb{X} + \left(\Sigma_\kappa^0\right)^{-1}\right)^{-1}.\end{aligned}$$

We then set κ^{k+1} by drawing from this posterior distribution.

A. Next, we will update ψ. Denote the design matrix in the equation for the admissions rule by W. In matrix notation, we have:

$$\pi = W\psi + \omega,\ \omega \sim N(0, I).$$

We have a normal prior for ψ, with mean μ_ψ^0 and covariance matrix Σ_ψ^0, so the posterior distribution of θ_π conditional on π and W is:

$$\psi|(\pi, W) \sim N(\tilde{\mu}_\psi, \tilde{\Sigma}_\psi),$$

with posterior mean and covariance matrices given by:

$$\begin{aligned}\tilde{\mu}_\psi &= \left(\frac{W'W}{\sigma_\omega^2} + \left(\Sigma_\psi^0\right)^{-1}\right)^{-1}\left(\left(\Sigma_\psi^0\right)^{-1}\mu_\psi^0 + \frac{W'\psi}{\sigma_\omega^2}\right) \\ &= \left(W'W + \left(\Sigma_\psi^0\right)^{-1}\right)^{-1}\left(\left(\Sigma_\psi^0\right)^{-1}\mu_\psi^0 + W'\psi\right),\end{aligned}$$

$$\begin{aligned}\tilde{\Sigma}_\psi &= \left(\frac{W'W}{\sigma_\omega^2} + \left(\Sigma_\psi^0\right)^{-1}\right)^{-1} \\ &= \left(W'W + \left(\Sigma_\psi^0\right)^{-1}\right)^{-1}.\end{aligned}$$

We then set ψ^{k+1} by drawing from this posterior distribution.

C Simulation Details

Recall that our structural model is based on equations for residents' decision utility and nursing homes' admission rules respectively:

$$\begin{aligned}v_{ij} =& \kappa_0^{black} s_{ij}^{black} + \kappa_0^{hisp} s_{ij}^{hisp} + \kappa_1^{black} s_{ij}^{black} black_i + \kappa_1^{hisp} s_{ij}^{hisp} hispanic_i \\ &+ q_j'\kappa_0^q + black_i q_j'\kappa_{black}^q + hispanic_i q_j'\kappa_{hisp}^q + dist_{ij}'\kappa^{dist} + \epsilon_{ij},\end{aligned}$$

$$\pi_{ij} = \psi_0 + \psi^{black} black_i + \psi^{hisp} hispanic_i + \tilde{x}_i'\psi^{\tilde{x}} + occ_{ij}'\psi^{occ} + \omega_{ij}.$$

Nursing home j is willing to admit resident i if and only if $\pi_{ij} \geq 0$, and resident i chooses the nursing home which yields the highest decision utility among the set of nursing homes that are willing to admit her. For computational feasibility, for each resident i, I only consider nursing homes within 15 miles of her $\mathcal{J}_i \equiv \{j | dist_{ij} \leq 15\ miles\}$. I denote estimated using "hats", e.g., $(\hat{\kappa}', \hat{\psi}')'$, but for the counterfactuals I switch to using "stars".

To simulate the elimination of in-group preferences, I set $\kappa_0^{r*} = \kappa_1^{r*} = 0$, and to simulate the elimination of racial heterogeneity in responsiveness to quality, I set $\kappa_r^{q*} = 0$. Similarly, to simulate the elimination of discriminatory admissions practices, I set $\psi^{r*} = 0$. To simulate the elimination of residential segregation, I permute the zip codes of prior address for residents. Hence, counterfactual distances between resident i and different nursing homes $dist_{ij}^*$ will generally differ from the original distances $dist_{ij}$, and i is faced with a different potential choice set $\mathcal{J}_i^* \equiv \{j | dist_{ij}^* \leq 15\ miles\}$, unless

she is randomized to the same zip code. By virtue of the permutation process, the unconditional geographical distribution of residents' prior addresses remains unchanged, but the distribution of races within each zip code will reflect the overall distribution of race (in expectation), hence eliminating residential segregation.

In terms of notation, I will use κ^*, ψ^*, and $dist^*$ throughout the description of simulations, and it should be understood that this is either equal to its estimated or original value if the corresponding component of the simulation is not turned on, or equal to a counterfactual value otherwise. For example, if we are considering a counterfactual with no residential segregation, $dist^*_{ij}$ will generally be different from $dist_{ij}$, whereas in a counterfactual where we take residential segregation as given, I still use the same notation $dist^*_{ij}$, but this will be equal to $dist_{ij}$.

The simulation algorithm is as follows:

1. Setup:
   (a) For each nursing home j, I set the share of j's admissions that are of race r in the last 365 days prior to the start of the simulation to the mean of this value over the estimation period.
   (b) For each nursing home j, I assume that its quality measures are time-invariant over the simulation period, and set this equal to the average over the estimation period.
   (c) For the simulations, I set the number of new arrivals each day N^*_d to the mean in the data.
2. Simulation: for day $d^* = 1, ..., D^* = 5000$ of the simulation:
   (a) If the counterfactual assumes no residential segregation, I permute the zip codes of prior address for residents.
   (b) I randomly discharge $N^*_{d^*}$ residents currently residing in nursing homes.
   (c) I then randomly draw $N^*_{d^*}$ new residents and simulate their choices. For resident $i^* = 1, ..., N^*_d$:
      i. I draw $\epsilon_{ij} \sim N(0,1)$ and compute:

$$\begin{aligned} v_{i^*j} =& \kappa_0^{black*} s_{d^*j}^{black*} + \kappa_0^{hisp*} s_{d^*j}^{hisp} + \kappa_1^{black*} s_{d^*j}^{black} black_i + \kappa_1^{hisp} s_{d^*j}^{hisp} hispanic_i \\ &+ q'_j \kappa_0^{q*} + black_i q'_j \kappa_{black}^{q*} + hispanic_i q'_j \kappa_{hisp}^{q*} + dist'^*_{ij} \kappa^{dist*} + \epsilon_{ij}, \end{aligned}$$

for each nursing home $j \in \mathcal{J}^*_{i^*} \equiv \{j' | dist^*_{ij'} \leq 15\ miles\}$.

ii. Also, for each $j \in \mathcal{J}_{i^*}^*$, I draw $\omega_{i^*j} \sim N(0,1)$ and compute:

$$\pi_{i^*j} = \psi_0^* + \psi^{black*} black_{i^*} + \psi^{hisp*} hispanic_{i^*} + \tilde{x}'_{i^*}\psi^{\tilde{x}*} + occ'^*_{d(i^*)j}\psi^{occ*} + \omega_{i^*j}.$$

iii. I set i^*'s nursing home to be $\mu(i^*) \equiv argmax_j\{v_{i^*j}|\pi_{i^*j} \geq 0, j \in \mathcal{J}_{i^*}^*\}$.[14]

(d) Next, I update the shares of residents admitted to each nursing home that is of each race in the 365 days leading up to the next day:

i. Letting N_{dj}^r be the number of residents of race r that is admitted to nursing home j on day d of the simulation and N_{dj} be the number of residents of any race that is admitted to j on day d, I set:

$$s_{d^*+1,j}^{r*} \equiv \frac{\sum_{d=d^*-364}^{d^*} N_{dj}^r}{\sum_{d=d^*-364}^{d^*} N_{dj}}.$$

(e) Finally, I update the occupancy measures of each nursing home for the next day in the simulation:

$$occ_{d^*+1,j}^* = log\left(\sum_{d=d^*-6}^{d^*} N_{dj}\right) - log(\bar{N}_j),$$

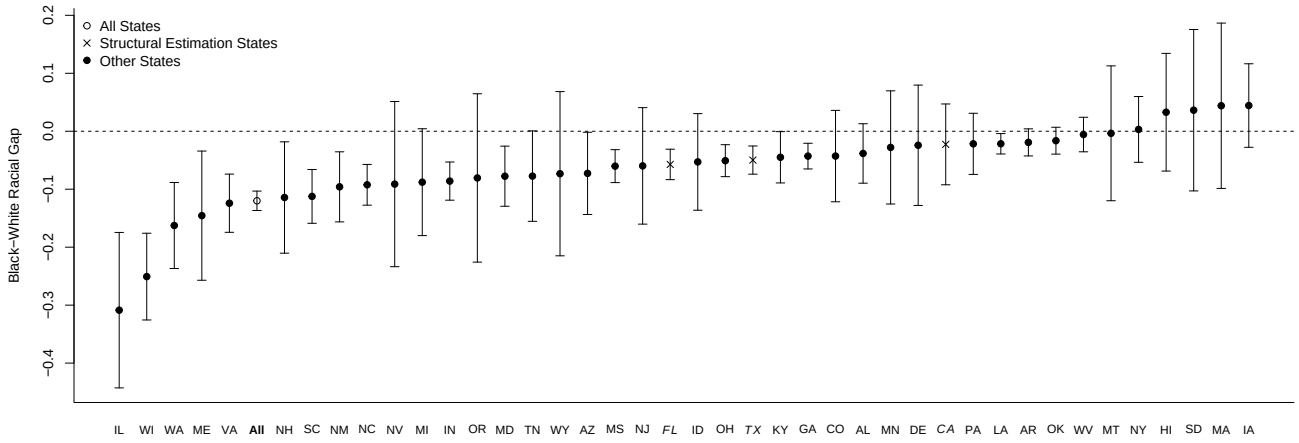
where $\bar{N}_j$ is the mean occupancy measure at nursing home j in the data.

3. Measuring segregation and disparities: to measure segregation and disparities on a day d^* for the simulations, I use data from the past 100 days (i.e., days $d^* - 99$ up to day d^*).

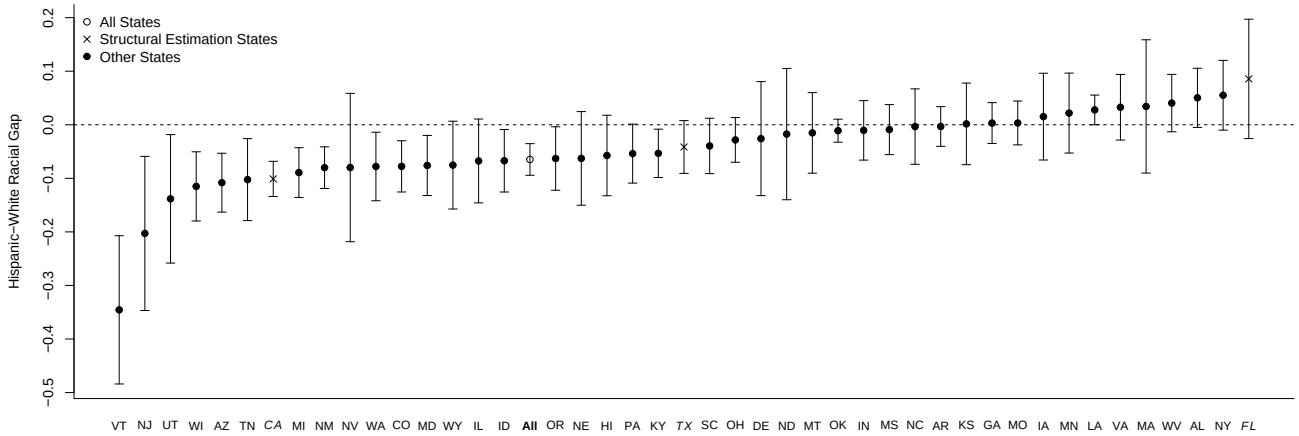
[14] If $\pi_{i^*j} < 0$ for all $j \in \mathcal{J}^*{}_{i^*}$, then I simply drop the resident, but this occurs extremely rarely in any of the simulations.

A Appendix Figures and Tables

Figure A.1: Racial Gaps in Nursing Home Quality as Measured by RN Staffing (Standardized)



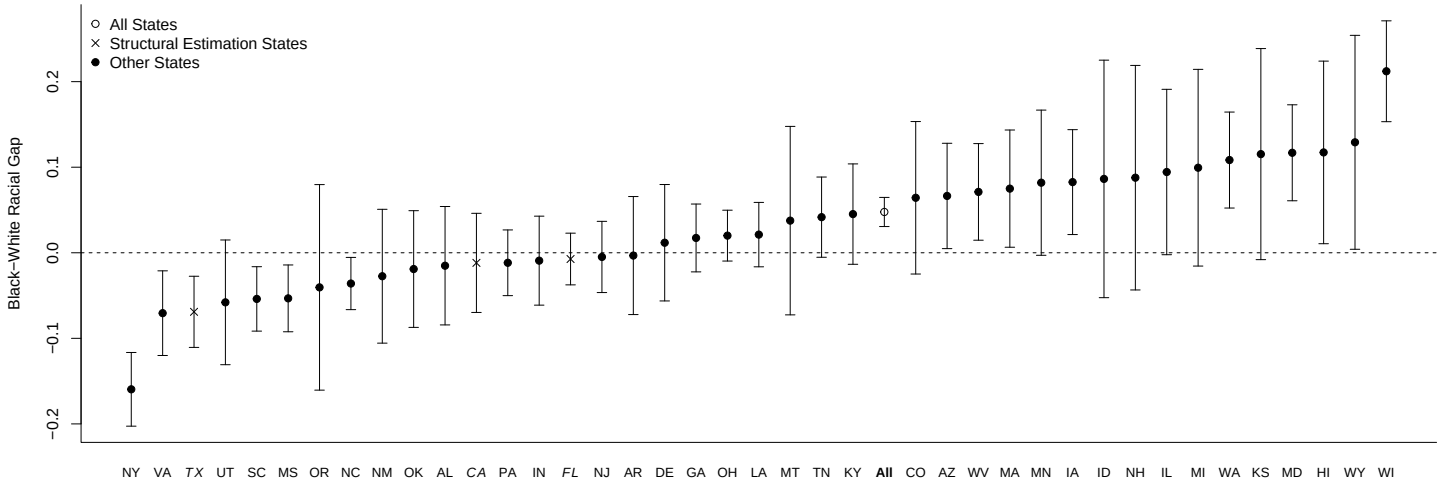
(a) Black-White Gap



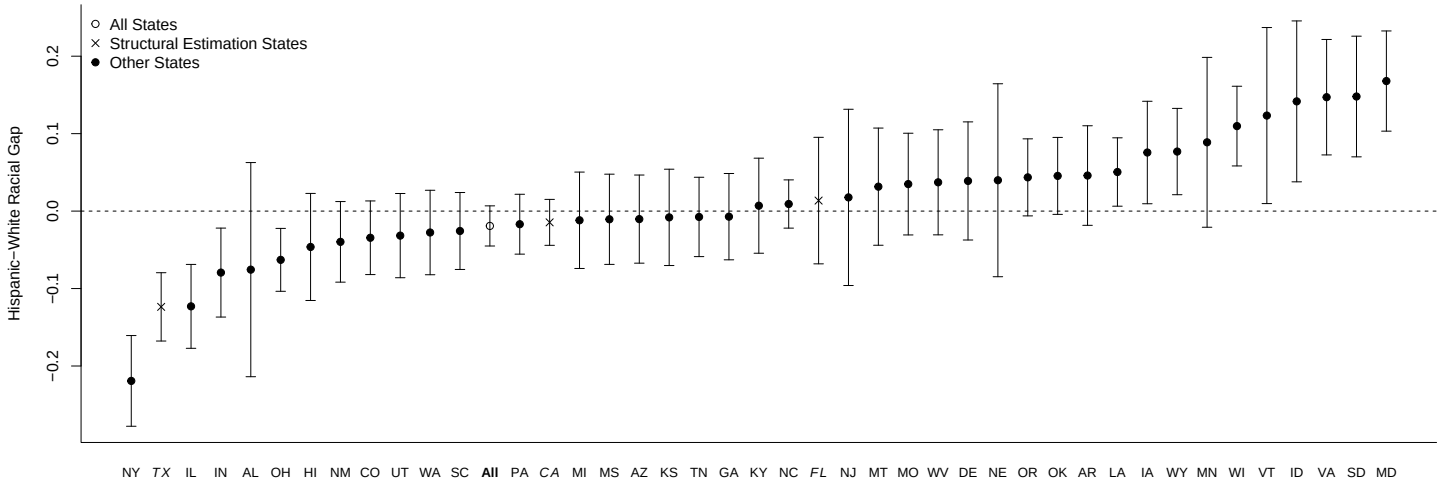
(b) Hispanic-White Gap

Notes: These figures display the estimated racial gaps in nursing home quality by state when RN staffing (standardized to have zero mean and unit variance) is used as the quality measure. Error bars indicate 95 percent confidence intervals for the estimates.

Figure A.2: Racial Gaps in Nursing Home Quality as Measured by LPN Staffing (Standardized)



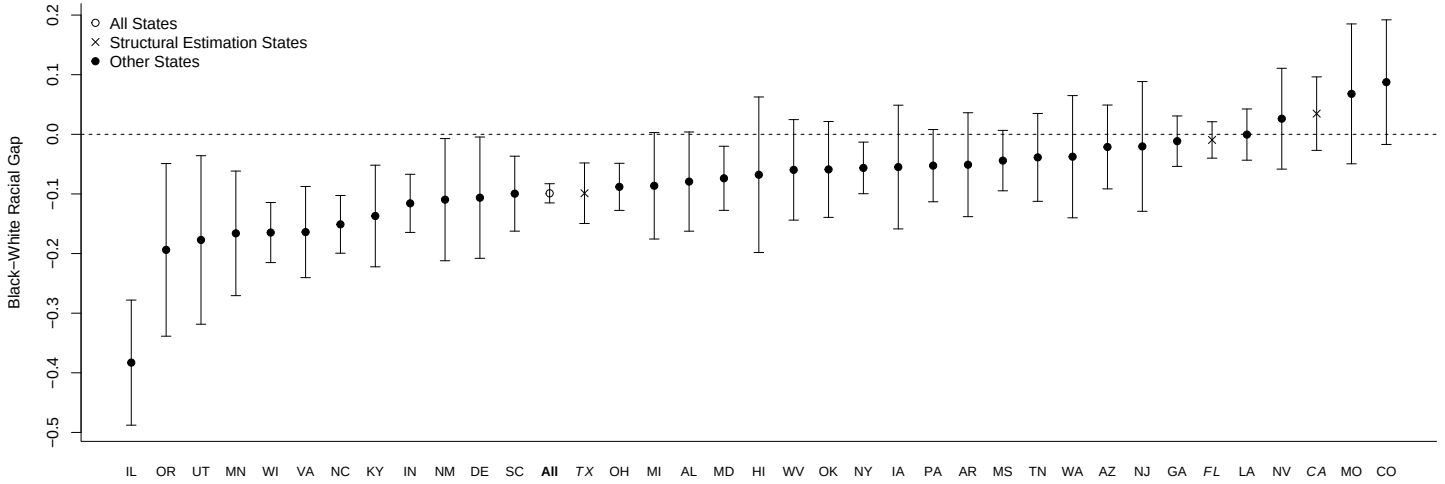
(a) Black-White Gap



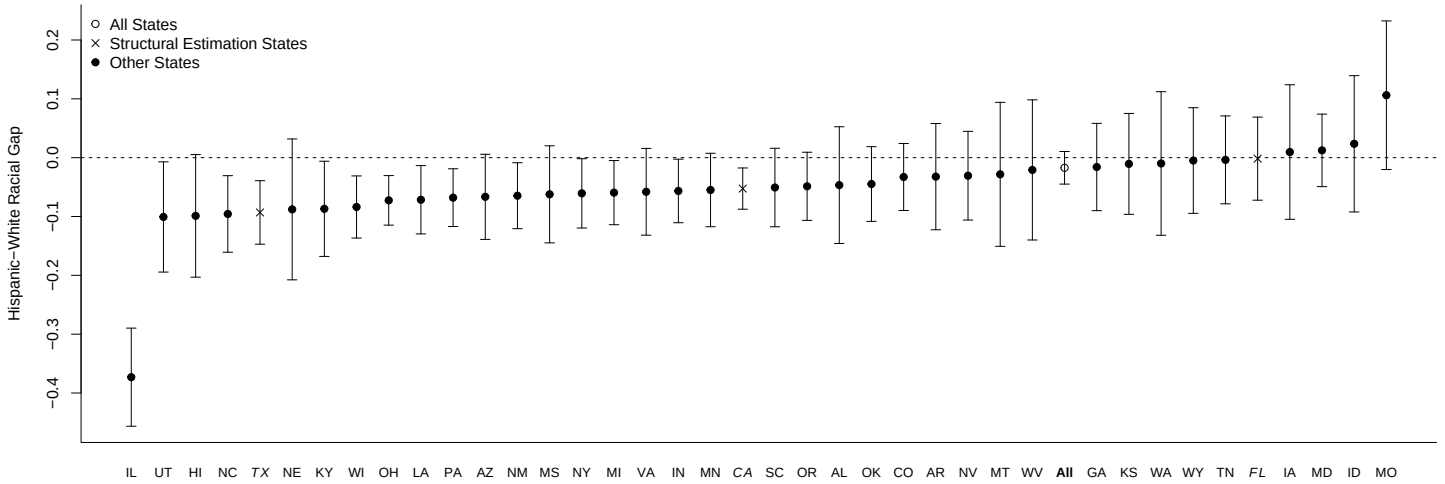
(b) Hispanic-White Gap

Notes: These figures display the estimated racial gaps in nursing home quality by state when LPN staffing (standardized to have zero mean and unit variance) is used as the quality measure. Error bars indicate 95 percent confidence intervals for the estimates.

Figure A.3: Racial Gaps in Nursing Home Quality as Measured by CNA Staffing (Standardized)



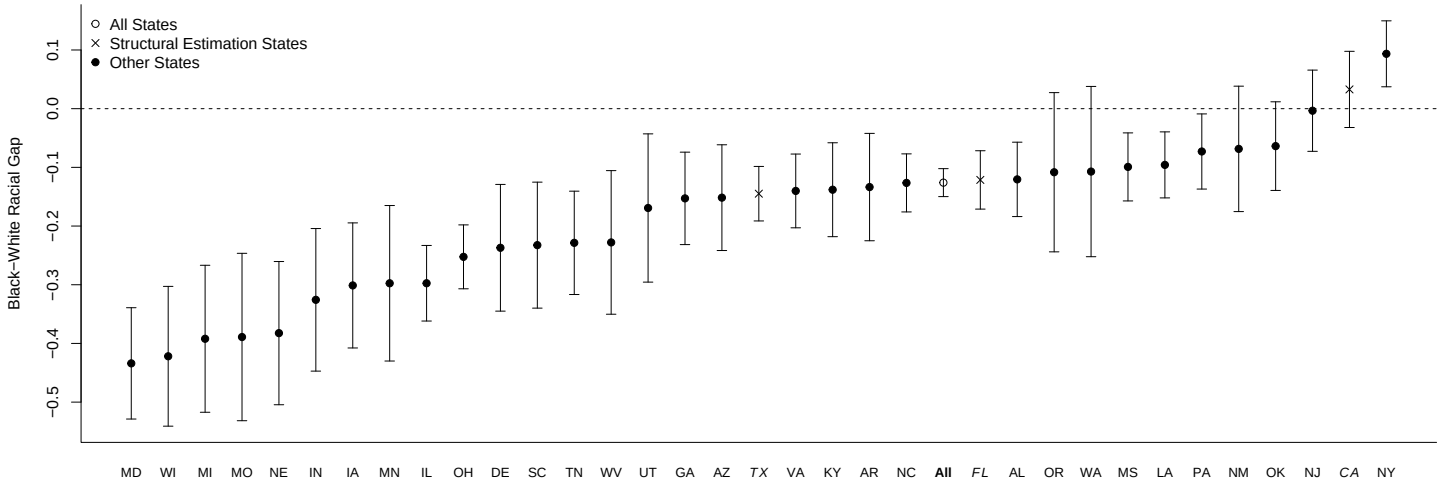
(a) Black-White Gap



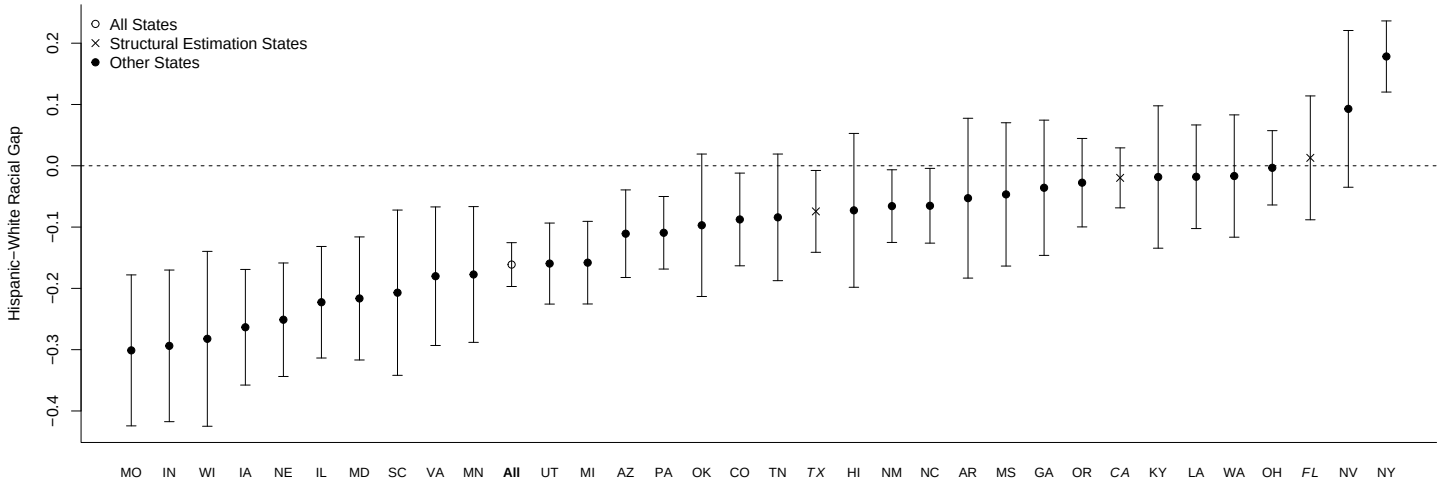
(b) Hispanic-White Gap

Notes: These figures display the estimated racial gaps in nursing home quality by state when CNA staffing (standardized to have zero mean and unit variance) is used as the quality measure. Error bars indicate 95 percent confidence intervals for the estimates.

Figure A.4: Racial Gaps in Nursing Home Quality as Measured by Fewer Standard Deficiencies (Standardized)



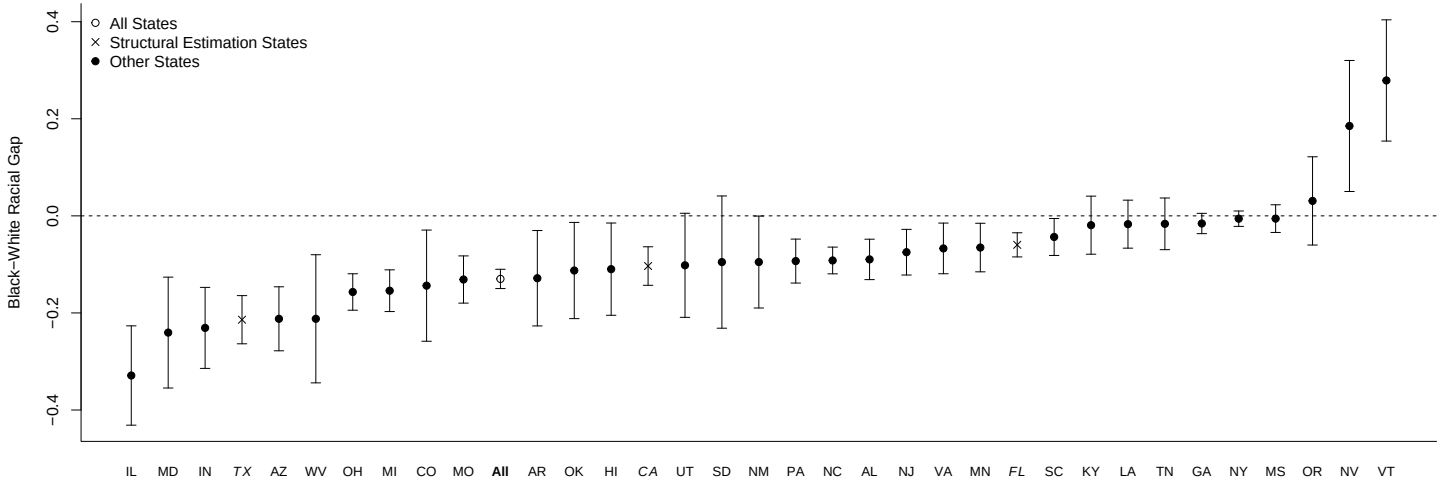
(a) Black-White Gap



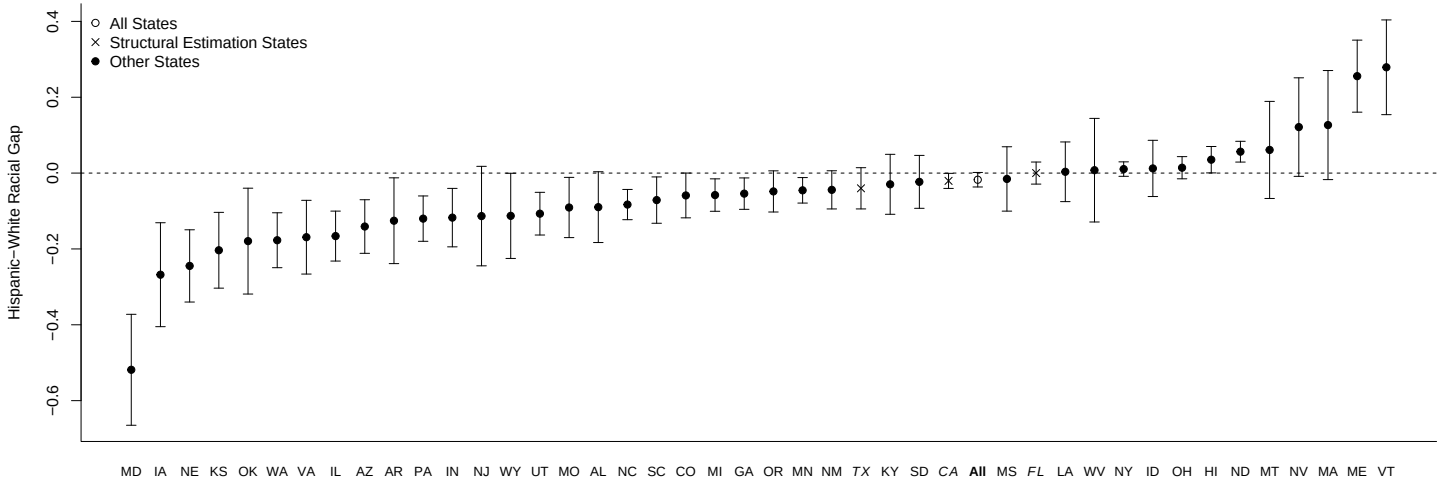
(b) Hispanic-White Gap

Notes: These figures display the estimated racial gaps in nursing home quality by state when the negative of standard deficiencies (standardized to have zero mean and unit variance) is used as the quality measure. Error bars indicate 95 percent confidence intervals for the estimates.

Figure A.5: Racial Gaps in Nursing Home Quality as Measured by Fewer Complaint Deficiencies (Standardized)



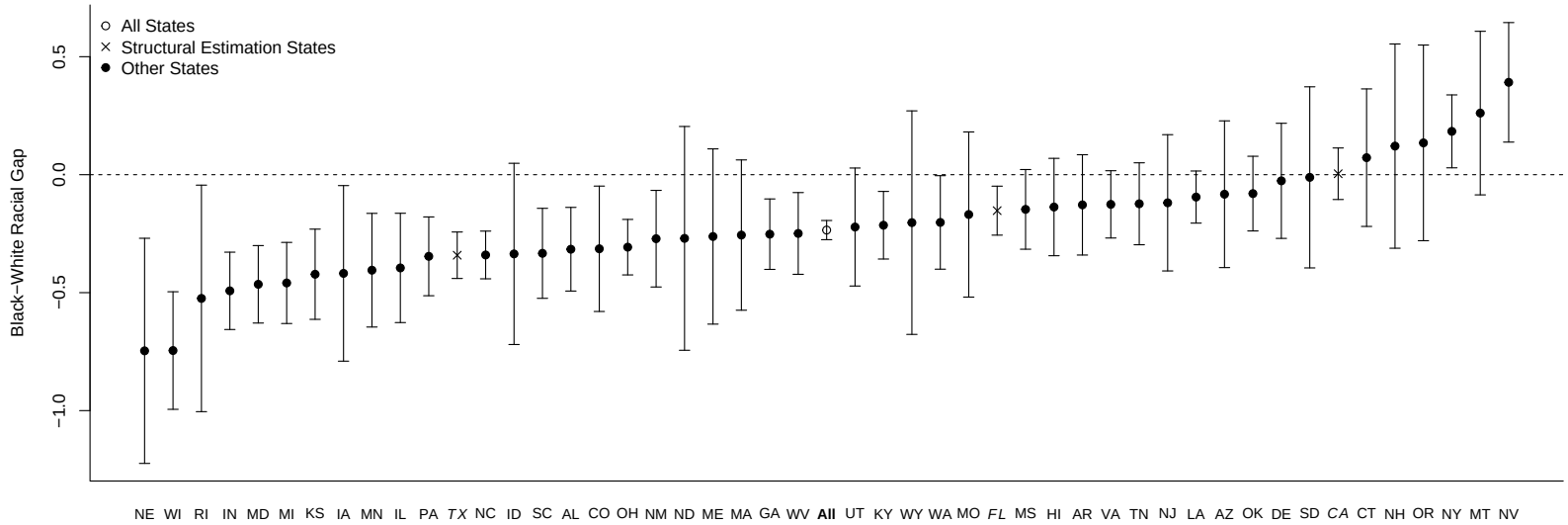
(a) Black-White Gap



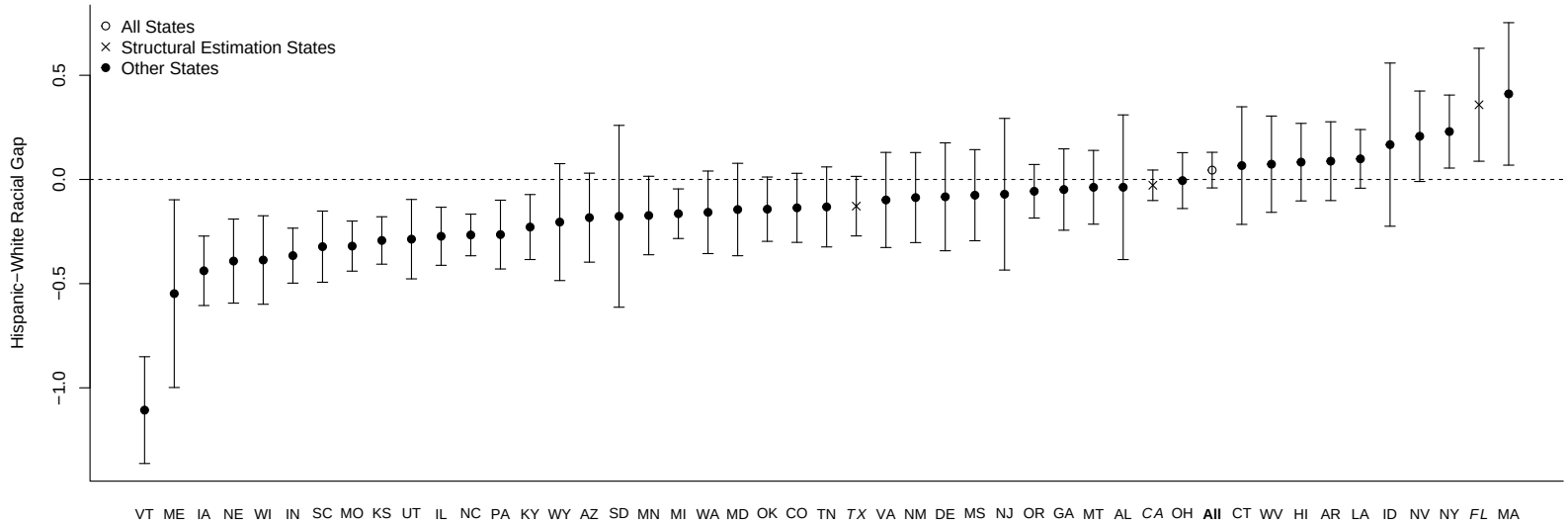
(b) Hispanic-White Gap

Notes: These figures display the estimated racial gaps in nursing home quality by state when the negative of complaint deficiencies (standardized to have zero mean and unit variance) is used as the quality measure. Error bars indicate 95 percent confidence intervals for the estimates.

Figure A.6: Racial Gaps in Nursing Home Quality as Measured by Star Ratings (Standardized)



(a) Black-White Gap

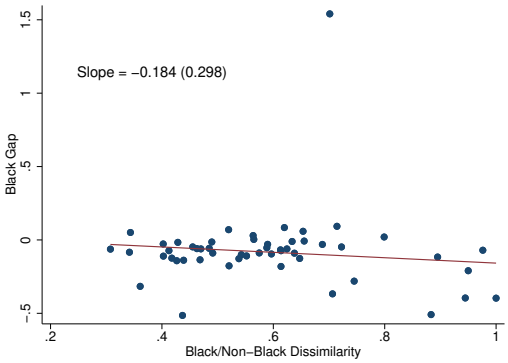


(b) Hispanic-White Gap

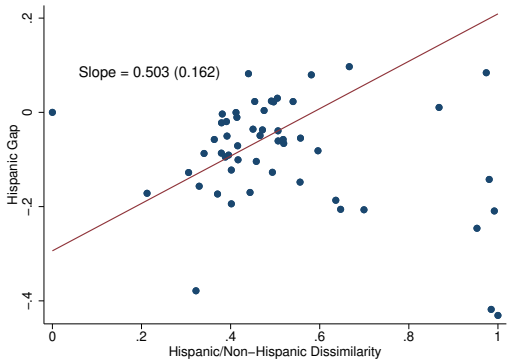
Notes: These figures display the estimated racial gaps in nursing home quality by state when 2009 star ratings (standardized to have zero mean and unit variance) is used as the quality measure. Error bars indicate 95 percent confidence intervals for the estimates.

Figure A.7: Cross-Sectional Relationship Between State-Level Segregation and Disparities (RN Staffing)

(a) Black/Non-Black



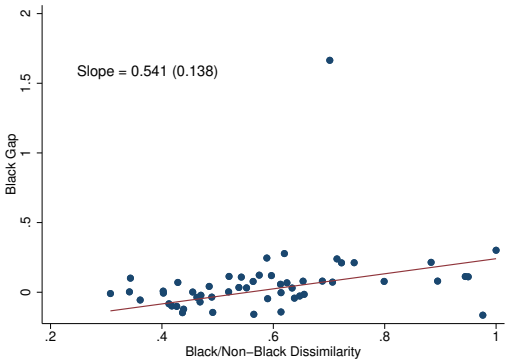
(b) Hispanic/Non-Hispanic



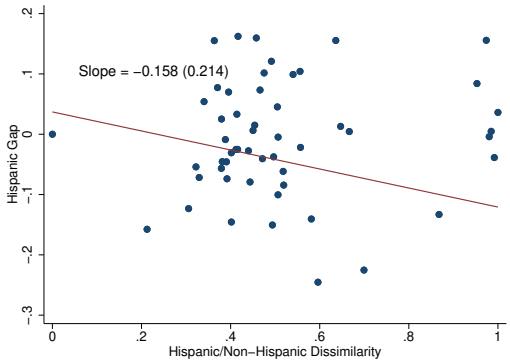
Notes: These figures display scatter plots of the estimated racial gap (based on standardized RN staffing) against segregation at the state level. Observations are weighted by the number of residents admitted to the state.

Figure A.8: Cross-Sectional Relationship Between State-Level Segregation and Disparities (LPN Staffing)

(a) Black/Non-Black



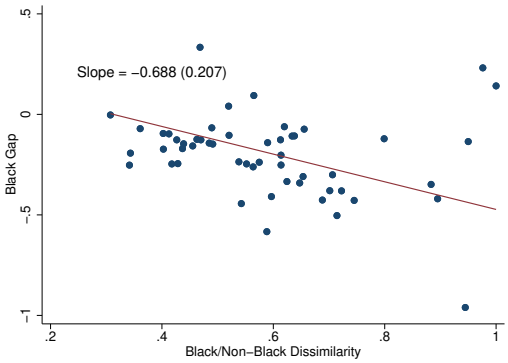
(b) Hispanic/Non-Hispanic



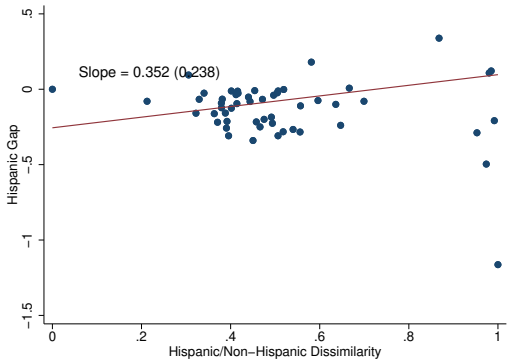
Notes: These figures display scatter plots of the estimated racial gap (based on standardized LPN staffing) against segregation at the state level. Observations are weighted by the number of residents admitted to the state.

Figure A.9: Cross-Sectional Relationship Between State-Level Segregation and Disparities (Fewer Standard Deficiencies)

(a) Black/Non-Black



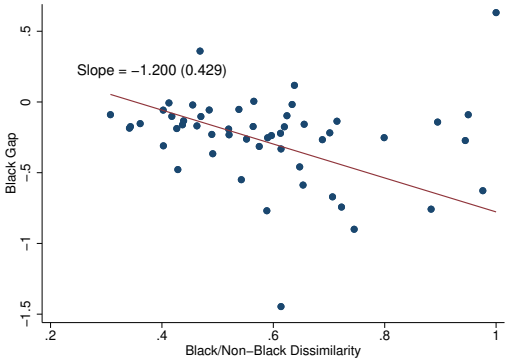
(b) Hispanic/Non-Hispanic



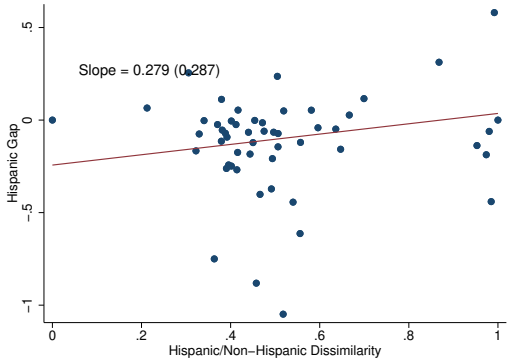
Notes: These figures display scatter plots of the estimated racial gap (based on standardized fewer standard deficiencies) against segregation at the state level. Observations are weighted by the number of residents admitted to the state.

Figure A.10: Cross-Sectional Relationship Between State-Level Segregation and Disparities (Fewer Complaint Deficiencies)

(a) Black/Non-Black

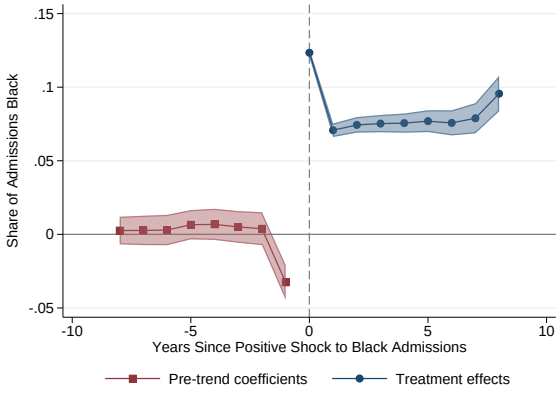


(b) Hispanic/Non-Hispanic

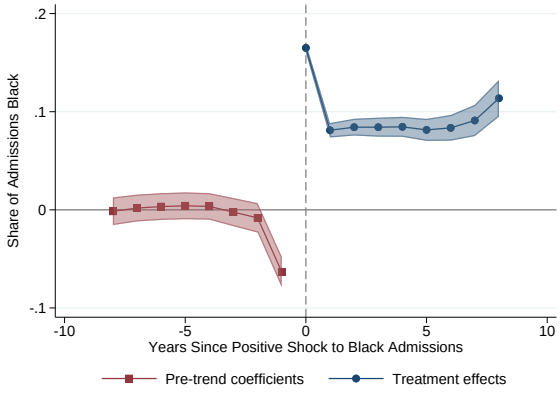


Notes: These figures display scatter plots of the estimated racial gap (based on standardized fewer complaint deficiencies) against segregation at the state level. Observations are weighted by the number of residents admitted to the state.

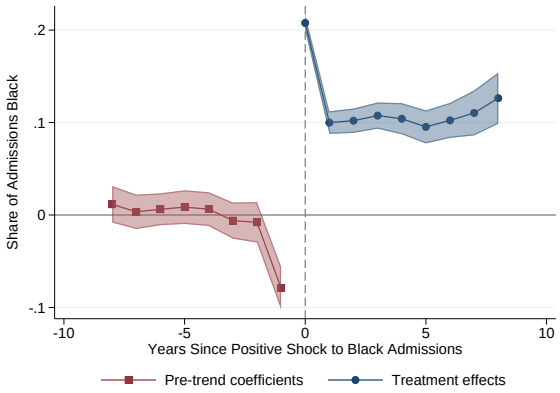
Figure A.11: Event Study on the Effect of a Positive Shock to the Share of Minority Admissions (Other Event Thresholds)



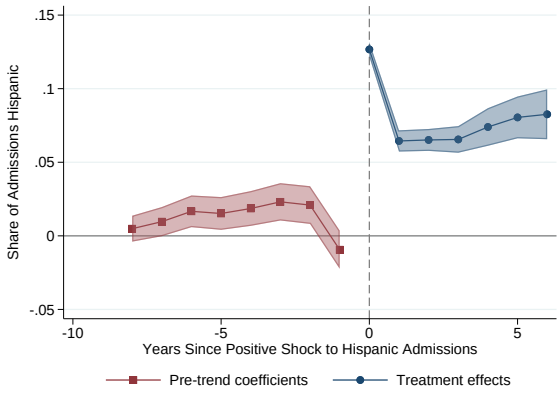
(a) >10pp. Increase in Share of Black Admissions



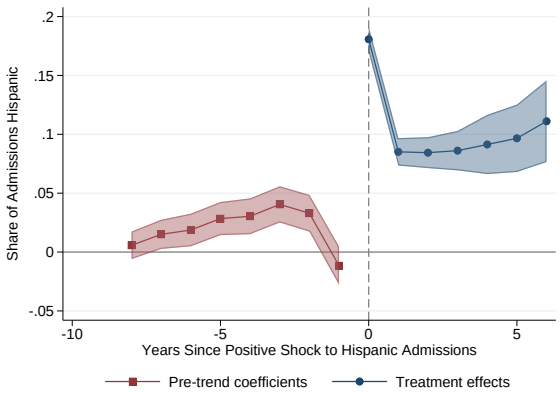
(b) >15pp. Increase in Share of Black Admissions



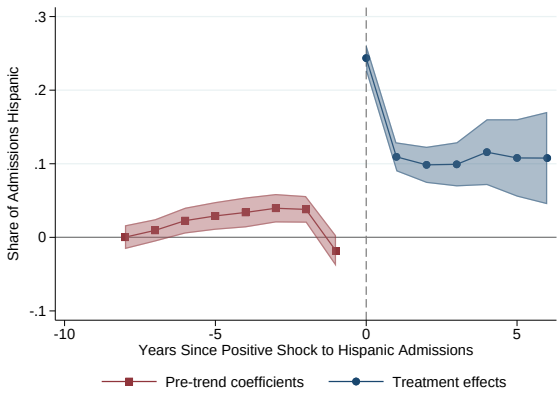
(c) >20pp. Increase in Share of Black Admissions



(d) >10pp. Increase in Share of Hispanic Admissions



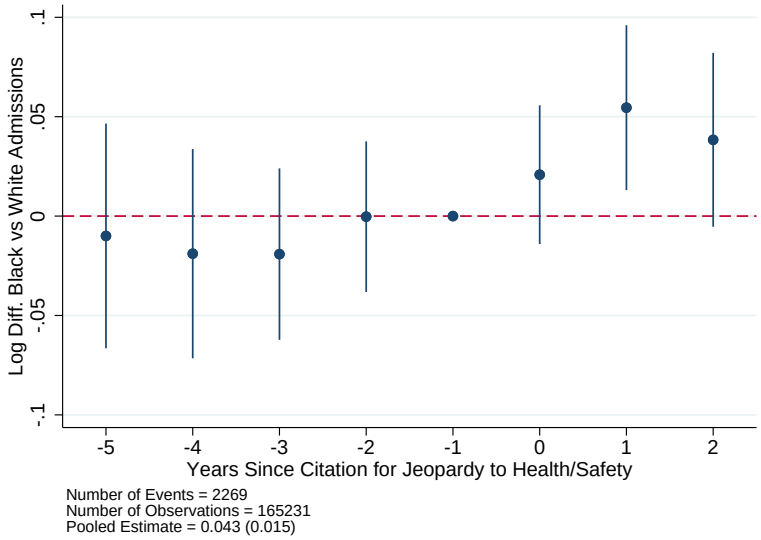
(e) >15pp. Increase in Share of Hispanic Admissions



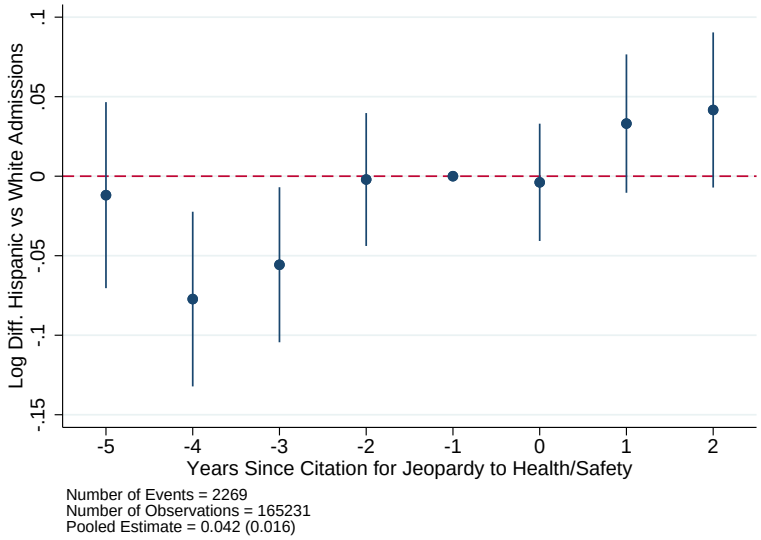
(f) >20pp. Increase in Share of Hispanic Admissions

Notes: These figures show event study estimates of the effect of a large shock to the minority share of admissions (defined as a year-to-year increase in the minority share of admissions of at least 10, 15, or 20pp.) on future minority share of admissions, based on event study methods of Borusyak, Jaravel, and Spiess (2021).

Figure A.12: Stacked Event Study Estimates on Admission Patterns Following Severe Deficiency Citation (Log Difference Between Minority and White Admissions)



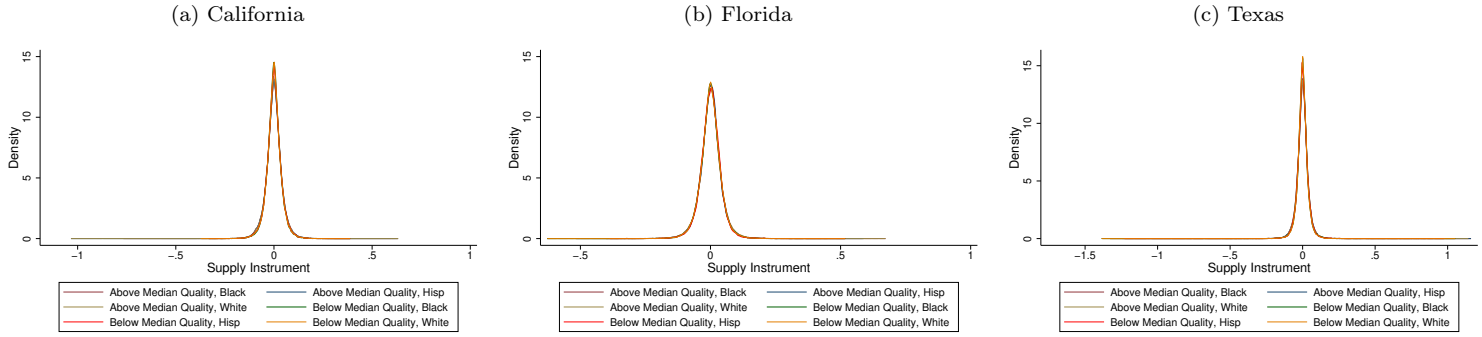
(a) $log\left(\frac{BlackAdmissions+1}{WhiteAdmissions+1}\right)$



(b) $log\left(\frac{HispanicAdmissions+1}{WhiteAdmissions+1}\right)$

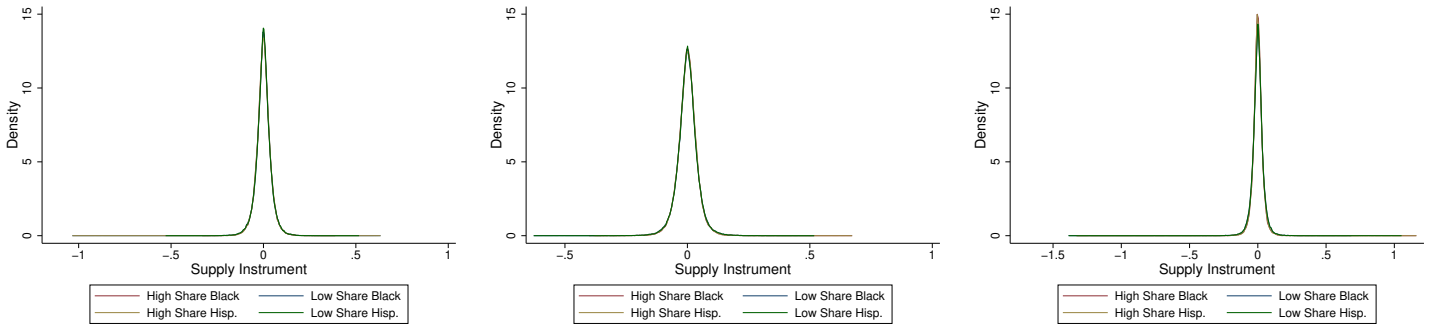
Notes: These figures show stacked event study estimates on the effect of a severe deficiency citation at a nursing home on the log difference between minority admissions (plus one) and white admissions (plus one) in subsequent years (compared to other nursing homes in the same county without a severe deficiency citation). Standard errors are clustered at the nursing home level.

Figure A.13: Exclusion Restriction for Temporary Occupancy Fluctuations (Split by Quality Index and Race of Resident)



Notes: This figure display kernel density plots of temporary occupancy fluctuations in the three states used for the structural estimation (defined as lagged 7-day log occupancy residualized of nursing home-month fixed effects) of nursing homes within 15 miles of each resident at their time of admission. The unit of observation is a nursing home-resident pair, and the sample is split by whether nursing homes are above-median or below-median in quality (based on the quality index), and the race of the resident.

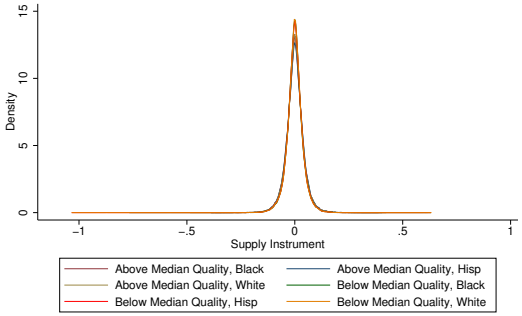
Figure A.14: Exclusion Restriction for Temporary Occupancy Fluctuations (Split by Share of Minority Admissions in the Past Year)



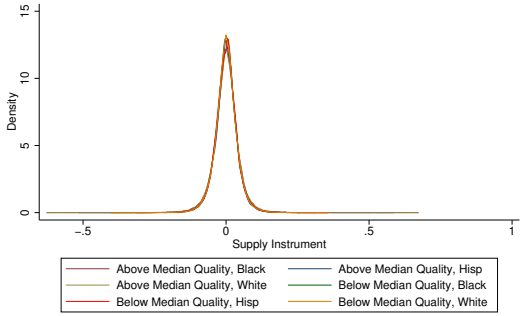
Notes: This figure display kernel density plots of temporary occupancy fluctuations in the three states used for the structural estimation (defined as lagged 7-day log occupancy residualized of nursing home-month fixed effects) of nursing homes within 15 miles of each resident at their time of admission. The unit of observation is a nursing home-resident pair, and the sample is split by whether the share of nursing home admissions Black (or Hispanic) in the last 365 days is above or below the median for this share.

Figure A.15: Exclusion Restriction for Temporary Occupancy Fluctuations (Split by RN Staffing and Race of Resident)

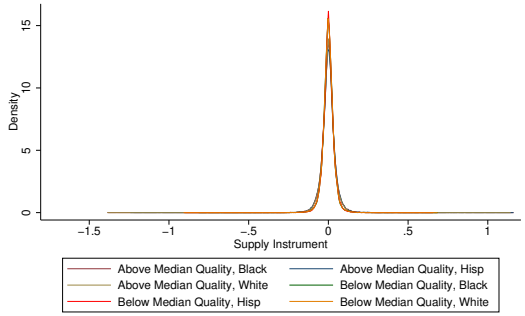
(a) California



(b) Florida



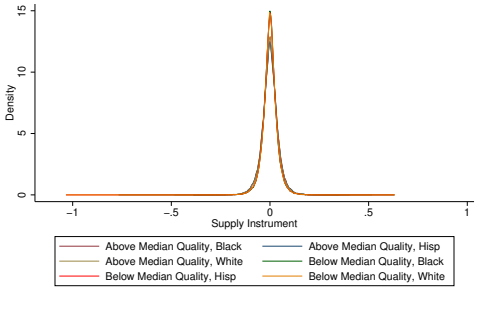
(c) Texas



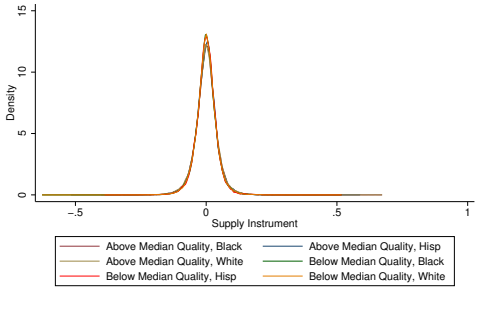
Notes: This figure display kernel density plots of temporary occupancy fluctuations in the three states used for the structural estimation (defined as lagged 7-day log occupancy residualized of nursing home-month fixed effects) of nursing homes within 15 miles of each resident at their time of admission. The unit of observation is a nursing home-resident pair, and the sample is split by whether nursing homes are above-median or below-median in quality (based on RN staffing), and the race of the resident.

Figure A.16: Exclusion Restriction for Temporary Occupancy Fluctuations (Split by LPN Staffing and Race of Resident)

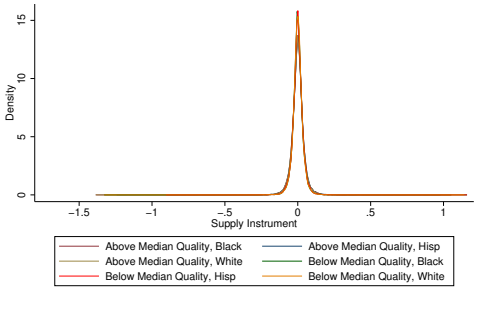
(a) California



(b) Florida



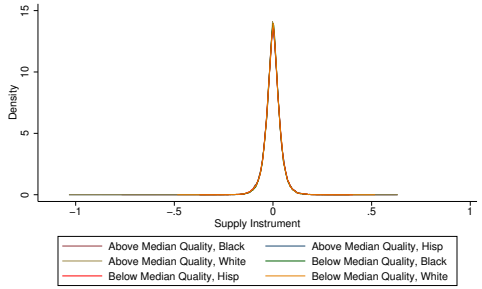
(c) Texas



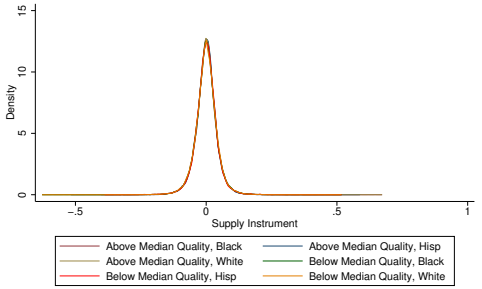
Notes: This figure display kernel density plots of temporary occupancy fluctuations in the three states used for the structural estimation (defined as lagged 7-day log occupancy residualized of nursing home-month fixed effects) of nursing homes within 15 miles of each resident at their time of admission. The unit of observation is a nursing home-resident pair, and the sample is split by whether nursing homes are above-median or below-median in quality (based on LPN staffing), and the race of the resident.

Figure A.17: Exclusion Restriction for Temporary Occupancy Fluctuations (Split by Standard Deficiencies and Race of Resident)

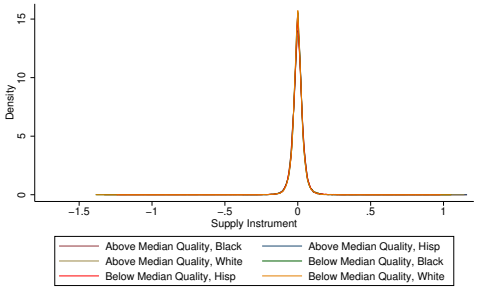
(a) California



(b) Florida



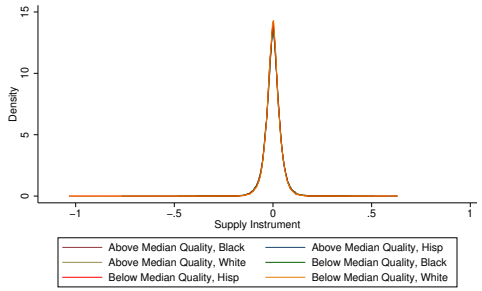
(c) Texas



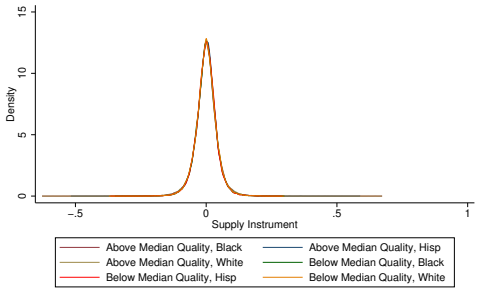
Notes: This figure display kernel density plots of temporary occupancy fluctuations in the three states used for the structural estimation (defined as lagged 7-day log occupancy residualized of nursing home-month fixed effects) of nursing homes within 15 miles of each resident at their time of admission. The unit of observation is a nursing home-resident pair, and the sample is split by whether nursing homes are above-median or below-median in quality (based on fewer standard deficiencies), and the race of the resident.

Figure A.18: Exclusion Restriction for Temporary Occupancy Fluctuations (Split by Complaint Deficiencies and Race of Resident)

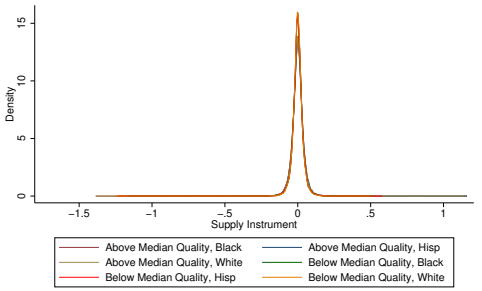
(a) California



(b) Florida

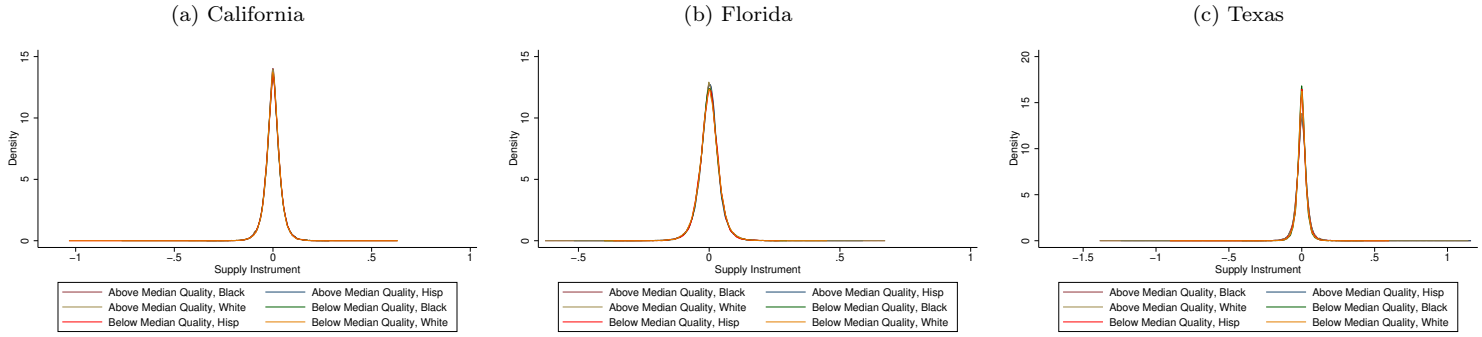


(c) Texas



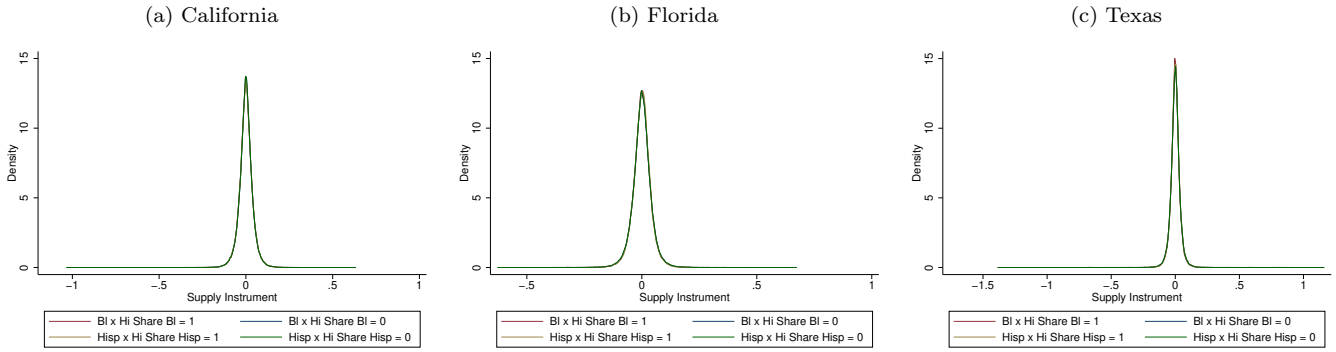
Notes: This figure display kernel density plots of temporary occupancy fluctuations in the three states used for the structural estimation (defined as lagged 7-day log occupancy residualized of nursing home-month fixed effects) of nursing homes within 15 miles of each resident at their time of admission. The unit of observation is a nursing home-resident pair, and the sample is split by whether nursing homes are above-median or below-median in quality (based on fewer complaint deficiencies), and the race of the resident.

Figure A.19: Exclusion Restriction for Temporary Occupancy Fluctuations (Split by 2009 Star Ratings and Race of Resident)



Notes: This figure display kernel density plots of temporary occupancy fluctuations in the three states used for the structural estimation (defined as lagged 7-day log occupancy residualized of nursing home-month fixed effects) of nursing homes within 15 miles of each resident at their time of admission. The unit of observation is a nursing home-resident pair, and the sample is split by whether nursing homes are above-median or below-median in quality (based on 2009 star ratings), and the race of the resident.

Figure A.20: Exclusion Restriction for Temporary Occupancy Fluctuations (Split by Share of Minority Admissions in the Past Year Interacted with Race of Resident)



Notes: This figure display kernel density plots of temporary occupancy fluctuations in the three states used for the structural estimation (defined as lagged 7-day log occupancy residualized of nursing home-month fixed effects) of nursing homes within 15 miles of each resident at their time of admission. The unit of observation is a nursing home-resident pair, and the sample is split by whether the interaction between the share of admissions in the last 365 who are Black (or Hispanic) being above-median and whether the resident is Black (or Hispanic) is equal to one or zero.

Table A.1: Summary Statistics for Residents by State

	All	California	Florida	Texas
Age	77.57	77.42	77.89	77.51
	(12.76)	(13.10)	(12.21)	(12.73)
Female	0.623	0.609	0.601	0.621
	(0.485)	(0.488)	(0.490)	(0.485)
Married	0.324	0.328	0.367	0.327
	(0.468)	(0.469)	(0.482)	(0.469)
Less than High School	0.271	0.206	0.194	0.296
	(0.445)	(0.404)	(0.396)	(0.457)
High School/Some College	0.594	0.631	0.663	0.577
	(0.491)	(0.483)	(0.473)	(0.494)
At Least Bachelor's Degree	0.108	0.135	0.117	0.0953
	(0.310)	(0.341)	(0.322)	(0.294)
Medicare	0.714	0.533	0.706	0.747
	(0.452)	(0.499)	(0.456)	(0.435)
Medicaid	0.0991	0.131	0.0479	0.126
	(0.299)	(0.337)	(0.214)	(0.332)
Admitted from Acute Care Hospital	0.843	0.881	0.896	0.760
	(0.363)	(0.324)	(0.305)	(0.427)
Admitted from Home	0.110	0.0869	0.0680	0.167
	(0.313)	(0.282)	(0.252)	(0.373)
Dementia	0.246	0.231	0.220	0.271
	(0.431)	(0.422)	(0.414)	(0.444)
White	0.833	0.737	0.825	0.742
	(0.373)	(0.440)	(0.380)	(0.437)
Black	0.102	0.0685	0.0855	0.105
	(0.302)	(0.253)	(0.280)	(0.307)
Hispanic	0.0397	0.109	0.0788	0.140
	(0.195)	(0.311)	(0.269)	(0.347)
Number of Residents	8,573,357	773,552	816,024	500,431

Notes: This table contains summary statistics for residents who had their first stays in a nursing home between 2000 and 2010.

Table A.2: Association Between Other Measures of Nursing Home Quality and Minority Status

	RN Staffing (s.d.)		LPN Staffing (s.d.)		Fewer Standard Deficiencies (s.d.)		Fewer Complaint Deficiencies (s.d.)		2009 Star Ratings (s.d.)	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Race: Black	-0.138***	-0.0714***	0.0303***	-0.0325***	-0.129***	-0.114***	-0.252***	-0.134***	-0.235***	-0.154***
	(0.0113)	(0.00492)	(0.0102)	(0.00452)	(0.0125)	(0.00442)	(0.0248)	(0.00766)	(0.0207)	(0.00849)
Race: Hispanic	-0.0726***	-0.0481***	-0.0269*	-0.0311***	-0.167***	-0.0655***	0.00766	-0.0638***	0.0448	-0.0890***
	(0.0171)	(0.00663)	(0.0161)	(0.00915)	(0.0191)	(0.00512)	(0.0186)	(0.00536)	(0.0436)	(0.0101)
Constant	0.0169**	0.00919	-0.00202	0.00456	0.0198***	0.0142***	0.0261***	0.0168***	0.0220*	0.0191*
	(0.00800)	(0.00605)	(0.00724)	(0.00548)	(0.00739)	(0.00434)	(0.00849)	(0.00605)	(0.0129)	(0.0102)
Zip Code FE		X		X		X		X		X
Num. Obs.	8,577,363	8,575,899	8,568,306	8,566,842	8,578,937	8,577,473	4,218,959	4,216,977	8,458,704	8,457,229
R-squared	0.002	0.107	0.000	0.108	0.002	0.174	0.006	0.207	0.005	0.276

Notes: The unit of observation is a resident. Standard errors are clustered at the nursing home level.

Table A.3: Characteristics of Nursing Homes in Residents' Choice Sets (By Race)

	(1)	(2)	(3)	(4)
California	All	White	Black	Hispanic
Quality Index	0.007	0.008	0.031	0.006
	(0.191)	(0.202)	(0.122)	(0.171)
Nursing Homes Within 15 Miles	48.804	39.709	78.949	68.063
	(46.789)	(39.694)	(56.849)	(57.114)
Distance to Nursing Homes	8.367	8.244	8.701	8.576
	(1.990)	(2.086)	(1.530)	(1.905)
Florida	All	White	Black	Hispanic
Quality Index	-0.014	-0.035	-0.010	0.178
	(0.271)	(0.262)	(0.266)	(0.280)
Nursing Homes Within 15 Miles	21.336	20.571	23.400	26.162
	(13.538)	(13.894)	(12.096)	(9.955)
Distance to Nursing Homes	7.975	7.931	7.748	8.578
	(1.968)	(2.014)	(1.973)	(1.329)
Texas	All	White	Black	Hispanic
Quality Index	-0.087	-0.083	-0.140	-0.061
	(0.240)	(0.242)	(0.203)	(0.255)
Nursing Homes Within 15 Miles	15.112	14.314	20.097	14.170
	(11.696)	(11.622)	(12.239)	(10.622)
Distance to Nursing Homes	7.427	7.426	8.011	6.917
	(2.874)	(2.948)	(2.586)	(2.727)

Notes: This table contains summary statistics for nursing homes within 15 miles of each resident who had their first stays in a nursing home in the indicated state between 2008 and 2010. The unit of observation is a resident-nursing home pair.

Table A.4: Robustness Checks for Evidence on Capacity Constraints

(a) Indicator for Any New Admission as the Dependent Variable

	Any New Residents		
	(1)	(2)	(3)
Lagged 7-Day Avg. Log Occupancy	-0.206***		
	(0.00347)		
Lagged 7-Day Avg. Occupancy		-0.00588***	
		(6.71e-05)	
Lagged 7-Day Avg. Occ. Percentile			-0.00165***
			(1.47e-05)
Nursing Home-Month Fixed Effects	X	X	X
N	40,033,450	40,033,450	40,033,450
R-squared	0.205	0.169	0.169

Notes: This table shows regression results at the nursing home-day level wherein the dependent variable is a dummy for any new residents, and the independent variables are various measures of nursing home occupancy. Standard errors are clustered at the nursing home level.

(b) Flow of Residents as the Dependent Variable

	Flow of Residents		
	(1)	(2)	(3)
Lagged 7-Day Avg. Log Occupancy	-2.831***		
	(0.0374)		
Lagged 7-Day Avg. Occupancy		-0.0852***	
		(0.000430)	
Lagged 7-Day Avg. Occ. Percentile			-0.0213***
			(0.000111)
Nursing Home-Month Fixed Effects	X	X	X
N	40,033,450	40,033,450	40,033,450
R-squared	0.035	0.045	0.040

Notes: This table shows regression results at the nursing home-day level wherein the dependent variable is the flow of residents (difference between number of residents today and yesterday), and the independent variables are various measures of nursing home occupancy. Standard errors are clustered at the nursing home level.

Table A.5: Effect of Short-Term Fluctuations in Racial Composition on Admissions of Different Racial Groups (Log Occupancy of Different Racial Groups)

	White Admissions	Black Admissions	Hispanic Admissions
Panel A: Number of Admissions by Racial Group	(1)	(2)	(3)
Log of White Occupancy	2.215***	-0.00180	-0.00774***
	(0.0486)	(0.00360)	(0.00276)
Log of Black Occupancy	0.00238	0.266***	-0.00118*
	(0.00279)	(0.00351)	(0.000666)
Log of Hispanic Occupancy	0.00446*	0.000580	0.211***
	(0.00230)	(0.000911)	(0.00257)
Nursing Home-Month Fixed Effects	X	X	X
Number of Observations	11,554,850	11,554,850	11,554,850
R-squared	0.325	0.201	0.220
	Any White Admissions	Any Black Admissions	Any Hispanic Admissions
Panel B: Any Admissions by Racial Group	(1)	(2)	(3)
Log of White Occupancy	1.169***	-0.00618***	-0.00584***
	(0.0213)	(0.00201)	(0.00172)
Log of Black Occupancy	0.00235*	0.232***	-0.00119**
	(0.00123)	(0.00250)	(0.000523)
Log of Hispanic Occupancy	0.00284***	0.000231	0.191***
	(0.00109)	(0.000626)	(0.00196)
Nursing Home-Month Fixed Effects	X	X	X
Number of Observations	11,554,850	11,554,850	11,554,850
R-squared	0.242	0.162	0.164

Notes: This table shows regression estimates at the nursing home-day level of admissions of residents of different races on log occupancy of different races, controlling for nursing home-month fixed effects. Standard errors are clustered at the nursing home level.

Table A.6: Structural Estimates with Nursing Home Fixed Effects in Utility

	California	*Florida*	*Texas*
Residents' Preferences	(1)	(2)	(3)
Utility (Distance to Facility)	-0.179***	-0.195***	-0.179***
	(0.001)	(0.001)	(0.001)
Utility (Previous Share Black)	-0.145	-0.318***	-0.588***
	(0.081)	(0.074)	(0.108)
Utility (Black x Previous Share Black)	1.575***	1.965***	2.004***
	(0.045)	(0.040)	(0.055)
Utility (Previous Share Hispanic)	-0.354***	-0.393***	-0.579***
	(0.064)	(0.092)	(0.125)
Utility (Hispanic x Previous Share Hispanic)	2.081***	1.952***	1.779***
	(0.051)	(0.042)	(0.066)
Utility (Quality Index)	0.007**	-0.024***	0.041***
	(0.003)	(0.005)	(0.007)
Utility (Quality Index x Black)	-0.043***	-0.108***	-0.086***
	(0.011)	(0.026)	(0.017)
Utility (Quality Index x Hispanic)	0.007	-0.053***	-0.143***
	(0.010)	(0.018)	(0.014)
Nursing Homes' Admission Policies			
Occupancy	-12.595***	-12.782***	-8.706***
	(0.382)	(0.275)	(0.029)
Race (Black)	-0.762***	-0.623***	-0.787***
	(0.018)	(0.020)	(0.075)
Race (Hispanic)	-0.443***	-0.722***	-0.199***
	(0.024)	(0.051)	(0.048)
Quality Index x Black	0.074**	-0.088***	0.052
	(0.030)	(0.077)	(0.069)
Quality Index x Hispanic	-0.165***	-0.172***	0.214***
	(0.036)	(0.044)	(0.091)
Nursing Home Characteristics in Supply-Side Equation	X	X	X
Nursing Home Fixed Effects in Utility Equation	X	X	X

Notes: This table shows estimates of the structural model using Gibbs sampling. A burn-in period corresponding to the first half of the chain was used. Nursing home characteristics in the supply side include the quality index, for-profit, and chain ownership. The supply-side equation also includes and intercept and year indicator.

Table A.7: Structural Estimates Using Staffing Index

	California	*Florida*	*Texas*
Residents' Preferences	(1)	(2)	(3)
Utility (Distance to Facility)	-0.169***	-0.182***	-0.163***
	(0.001)	(0.001)	(0.001)
Utility (Previous Share Black)	-0.949***	-1.429***	-1.373***
	(0.020)	(0.019)	(0.023)
Utility (Black x Previous Share Black)	1.394***	1.646***	1.746***
	(0.042)	(0.034)	(0.039)
Utility (Previous Share Hispanic)	-1.038***	-0.938***	-1.345***
	(0.019)	(0.025)	(0.037)
Utility (Hispanic x Previous Share Hispanic)	1.925***	1.013***	1.289***
	(0.037)	(0.037)	(0.042)
Utility (Staffing Index)	0.273***	0.267***	0.224***
	(0.003)	(0.004)	(0.017)
Utility (Staffing Index x Black)	-0.327***	-0.136***	-0.151***
	(0.011)	(0.019)	(0.016)
Utility (Staffing Index x Hispanic)	0.024***	-0.165***	-0.222***
	(0.008)	(0.020)	(0.020)
Nursing Homes' Admission Policies			
Occupancy	-9.066***	-10.799***	-8.765***
	(0.198)	(0.219)	(0.681)
Race (Black)	-1.220***	-0.389***	-0.559***
	(0.050)	(0.033)	(0.117)
Race (Hispanic)	-0.446***	-0.338***	-0.111***
	(0.029)	(0.042)	(0.038)
Staffing Index x Black	1.075***	0.028	1.039***
	(0.027)	(0.064)	(0.093)
Staffing Index x Hispanic	-0.024	0.189**	1.177***
	(0.016)	(0.074)	(0.155)
Nursing Home Characteristics in Supply-Side Equation	X	X	X

Notes: This table shows estimates of the structural model using Gibbs sampling. A burn-in period corresponding to the first half of the chain was used. Nursing home characteristics in the supply side include the staffing index, for-profit, and chain ownership. The supply-side equation also includes and intercept and year indicator.