

Selective Admissions in Nursing Homes: Evidence from a Randomized Audit Study*

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Abstract

It has been widely documented that patients in the US who are associated with disadvantaged demographics receive care at lower quality nursing homes. To understand the role that selective admissions may play in contributing to this pattern, we conducted a nationwide audit study of the impact of patient race, payer, and medical condition on responses to about 5,500 availability inquiries sent to about 3,000 nursing homes. We find 10-15% lower availability for Medicaid patients compared to private-pay patients and for patients with Alzheimer’s disease compared to those without; these availability gaps generally increase with nursing home quality. We find no statistically significant evidence of differential availability by race. To quantify the implications of these selective admissions practices, we embed the audit study results in a model of constrained nursing home choice. We estimate that if, counterfactually, Medicaid patients had the same choice sets as their private-pay counterparts, they would attend higher quality nursing homes on average, but the private-Medicaid gap in quality would be reduced by only 5-10%. Our results suggest that supply-side availability differences by payer are widespread, but that they are unlikely to be the primary factor behind the observed gap in quality of nursing homes attended.

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1 Introduction

Over one third of Americans who reach age 65 will spend some portion of their remaining lives in a nursing home (Kemper and Murtaugh 1991; Brown and Finkelstein 2009; Hurd et al. 2014). There are longstanding, widespread concerns about the quality of these nursing homes (Rau 2018; Rau and Lucas 2018; Goldstein and Gebeloff 2019; Jacobs and Richtel 2019) and about the systematic differences in the quality of nursing homes attended by different types of patients. A large existing literature has documented that patients are more likely to be in a lower quality nursing home if they are Black or Hispanic (Mor et al. 2004; Smith et al. 2007; Estrada et al. 2021; Einav et al. 2025b; Cheng 2026), on Medicaid (Rahman et al. 2014a,b; Gandhi 2026), or suffering from Alzheimer’s disease or related dementia (ADRD) (Yan et al. 2020; Kosar et al. 2023).

Why do more disadvantaged patients tend to go to lower quality nursing homes? A key distinction is whether, and to what extent, the answer lies in supply-side differences in nursing home availability (that is, selective admissions) as opposed to demand-side differences in choices made by different prospective nursing home residents. On the supply side, selective admissions would arise if nursing homes are, on average, systematically less willing to admit a patient of a given race, with particular health conditions, or with a particular source of payment. On the demand side, different patient choices might reflect differences in preferences, locations, information, or anticipated admission decisions. These two types of explanations have potentially very different implications for welfare and policy.

We therefore conducted a large-scale, nationwide audit study of about 5,500 inquiries at about 3,000 nursing homes in the United States between March and August 2025.¹ We independently randomized the payer status, medical condition, and perceived race of a fictitious elderly woman whose fictitious daughter was writing to inquire about the availability of a nursing home for her mother. All inquiries were on behalf of patients coming from the community, rather than the hospital, so that the relevant payers were either private payment or Medicaid coverage. The average response rate (either by phone or email) to our web-based inquiries was 35%. Our primary outcome was a response that did not rule out availability (hereafter “availability”), which was the case for approximately 30% of the inquiries.

The experimental findings show no statistically significant evidence that availability differs by patient race. Compared to inquiries involving distinctively white names for both mother and daughter, inquiries involving distinctively Black names for both mother and daughter have a statistically insignificant lower availability rate of 1.4 percentage points (standard error = 1.0), or about 5%. This null result may reflect either a lack of selective admissions on race or that our inquiries did not effectively signal race. However, our procedures for signaling race followed standard practices in this literature that have detected differences by race in employment and other contexts (e.g., Bertrand and Mullainathan 2004; Gaddis 2017; Kline et al. 2022).

In contrast, availability is significantly higher for inquiries made on behalf of private-pay patients compared to Medicaid patients, and for patients not described as having Alzheimer’s. Compared to private-pay patients, availability for Medicaid patients is lower by 4.8 percentage points (standard error = 1.3), or about 15%. Compared to patients whose health problems are not described as including

¹This type of audit study is also known as a “correspondence study” or a “secret-shopper study.”

Alzheimer’s, availability for patients with Alzheimer’s is lower by 3.2 percentage points (standard error = 1.4), or about 11%. Availability gaps by payer or by Alzheimer’s disease are generally increasing in nursing home quality.

The findings from the audit study indicate the presence of selective admissions by payer and by Alzheimer’s condition. By themselves, however, they are not sufficient for quantitative statements about the contribution of selective admissions practices to the observed differences in the quality of nursing homes attended by patients with different payers or different health conditions. Indeed, as we discuss below, even the sign of the impact of availability gaps in contributing to quality gaps is a-priori ambiguous.

In the final part of the paper, therefore, we embed the audit-study results in a model of nursing home choice. This allows us to assess the quantitative importance of differential availability across patient types in contributing to the observed differences in the quality of nursing homes attended by different patients. We use nationwide administrative data on the universe of patients entering nursing homes in 2022 (the latest currently available year of data) and the characteristics of the nursing homes they attend. To align with the audit study, we limit our analysis to patients coming from the community.

We focus on estimating the quantitative role played by selective admissions in contributing to the gap in quality of nursing homes between private-pay and Medicaid patients.² We first document that, nationwide, private-pay patients on average attend substantially higher quality nursing homes than Medicaid patients, even when comparing patients who live in the same zip code. We then use the audit-study results to generate an empirical probability that each nursing home in the national data would be available to a Medicaid patient, as well as the probability it would be available to a private-pay patient. We use these experimentally-estimated probabilities to generate constrained choice sets of nursing homes; crucially, these choice sets vary between Medicaid and private-pay patients. We combine our empirically estimated constrained choice sets from the audit study with the observed nursing home attendance of private-pay and Medicaid patients in the observational data to estimate a model of nursing home (constrained) choice. This allows us to account for selective admissions and to recover the undistorted choice parameters of patients. We use these estimates to assess how the nursing homes that Medicaid patients go to would change if, counterfactually, they experienced the same availability rates as private-pay patients. Despite the quality-availability gradient revealed by the audit study, we estimate that selective admissions account for only 5-10% of the observed quality gap in nursing homes across payers. Indeed, most of this quality gap can be explained by demand-side parameters: if we retain the availability gap by payer, but assign Medicaid patients the estimated choice parameters of private-pay patients, most (75-85%) of the overall quality gap disappears.

Conceptually, our use of audit-study results to identify latent choice sets that can then be used to recover undistorted choice parameters is most closely related to [Christensen and Timmins \(2023\)](#), who conduct a related set of analyses for racial discrimination in the rental housing market. Substantively, our focus on selective admissions in US nursing homes is most closely related to [Gandhi \(2026\)](#), whose

²In principle, we could conduct a similar analysis for Alzheimer’s patients. In practice, the number of Alzheimer’s patients is too small for estimation purposes using the 2022 data, and we are loathe to use earlier years of data to increase sample size because of likely contamination from the Covid pandemic.

estimates from a model of nursing home admissions in California indicate that when occupancy rates are higher, nursing homes are less likely to admit Medicaid patients.³

More broadly, our paper also relates to studies of supply-side constraints on the availability of health care for Medicaid patients outside of the nursing home setting. There is a long-standing concern that the relatively low provider reimbursement rates offered by Medicaid reduce health-care providers' willingness to treat Medicaid patients. Several studies have documented these constraints using quasi-experimental variation in Medicaid. For example, [Alexander and Schnell \(2024\)](#) show that higher Medicaid reimbursement rates for physicians increase access to physician care for Medicaid patients, and [Li \(2022\)](#) finds that when Medicare enrollees gain Medicaid coverage their use of primary and preventive care declines despite the decrease in patient cost-sharing. In addition, numerous audit studies have documented that primary care and specialty care outpatient providers have lower willingness to accept Medicaid patients compared to privately-insured patients.⁴ Other audit studies have shown differential access to mental health care on the basis of race and other forms of identity.⁵ Audit studies of nursing home admissions, however, are rare.⁶

Looking beyond the health-care sector, there is a rich tradition in the social sciences of using audit studies to investigate differential treatment on the basis of researcher-manipulated features of the fictional applicant. In contexts ranging from voting to education to car purchases, audit studies have been used to examine differential treatment on the basis of race, gender, sexual orientation, age, ethnicity, language, socioeconomic status, immigration status, criminal records, and religion (e.g., [Ayres and Siegelman 1995](#); [Pager 2003](#); [Baldini and Federici 2011](#); [White et al. 2015](#); [Mishel 2016](#); [Burn et al. 2019](#); [Carlsson and Eriksson 2019](#); [Olsen et al. 2022](#); [Francis et al. 2024](#)). A prominent focus of these audit studies has been the examination of racial discrimination in labor markets (e.g., [Bertrand and Mullainathan 2004](#); [Pager 2007](#); [Neumark 2018](#); [Kline et al. 2022](#)) and in housing markets (e.g., [Ahmed and Hammarstedt 2008](#); [Hanson and Hawley 2011](#); [Hanson et al. 2011, 2016](#); [Christensen and Timmins 2023](#)).

The rest of the paper proceeds as follows. Section 2 provides background on the nursing home setting. Sections 3 and 4 present, respectively, the design and results of the audit study. Section 5 embeds these results in a model of nursing home choice in order to assess their quantitative implications. The final section concludes.

³In a similar spirit, [Cheng \(2026\)](#) estimates that nursing homes are less likely to admit Black and Hispanic patients when occupancy rates are high.

⁴[Hsiang et al. \(2019\)](#) provides a meta-analysis of 34 audit studies on differential access to physicians for Medicaid patients relative to privately-insured patients. For some specific examples, see [Cama et al. \(2017\)](#), [Lee et al. \(2018\)](#), and [Nguyen et al. \(2019\)](#) who study, respectively, access to pediatric mental health care, ophthalmology, and pediatric orthopedic care.

⁵See, for example, [Kugelmass \(2016\)](#), [Shin et al. \(2016\)](#), [Button et al. \(2020\)](#), and [Gates et al. \(2022\)](#).

⁶An important source of inspiration – and proof of concept – for our study was the *Boston Globe's* 2020 investigation of nursing home discrimination. Reporters emailed vignettes with different payer information from a fictitious daughter seeking a nursing home for her community-based mother to 200 nursing homes in Massachusetts; they found that nursing homes were twice as likely to say that they had no room when the email indicated that the patient had Medicaid ([Kowalczyk and Arsenault 2020](#)). In concurrent, independent work, [Estenson et al. \(2025\)](#) conducted an audit study in the summer of 2025 of almost 1,000 California nursing homes on behalf of a fictitious grandparent being discharged from the hospital after hip surgery; they found substantially higher availability for those who were covered by Medicare and Medicaid than those who were only covered by Medicaid.

2 Nursing Homes in the United States

In 2024 there were about 15,000 federally certified nursing homes in the United States, providing care to over 1.2 million patients (Chidambaram and Burns 2025) at an annual cost of \$220 billion, or roughly 4% of national health expenditures (CMS 2024b). Essentially all nursing homes (96% of beds) are federally certified to treat Medicare- and Medicaid-covered patients (Harrington et al. 2018). Nursing homes provide two types of care: short-term care to patients recovering from hospitalization or illness, and long-term care to patients in need of ongoing assistance with daily living. Most short-term patients are covered by Medicare, which pays for up to 100 days of short-term nursing and rehabilitation services. Medicare coverage requires that the patient be sent to the nursing home following discharge from a qualifying hospital stay; such patients may be recovering from a surgical procedure (e.g., hip replacement) or a health event (e.g., stroke). Some patients are initially covered by Medicare as short-term patients but do not recover within 100 days and transition to either private payment or (more commonly) Medicaid coverage.

Our focus is on nursing home patients who arrive from the community, rather than those discharged from a hospital. Admissions from the community are typically for patients who need longer-term care, rather than those recovering from an acute event. As a result, although they constitute only about 20% of admissions, admissions from the community account for a much larger share of nursing home days. For example, data from the universe of nursing home admissions in 2018 and 2019 indicate that a quarter of admissions from the community last 332 days or longer, compared to only 52 days for admissions from the hospital (Appendix Table A1). Nursing home patients admitted from the community are covered either by Medicaid or by private payment; they are not covered by Medicare because Medicare coverage requires that the patient be discharged to the nursing home from an acute hospital stay. About one-third of admissions from the community are covered by Medicaid at admission.⁷

We limit our analysis to patients from the community for two main, logistical reasons. First, essentially all elderly patients entering a nursing home from the hospital are covered by Medicare initially; although nursing homes may be reluctant to take Medicare patients if they are likely to be long-term patients and transition to Medicaid (Gandhi 2026), it is more natural to make the patient’s payer status salient in an inquiry on behalf of a patient coming from the community. Second, it is common for family members (rather than hospital discharge staff) to make inquiries to nursing homes about availability on behalf of patients coming from the community; this made implementation of the audit study easier.

Nursing homes may have incentives to practice selective admissions based on patient characteristics. They have a financial incentive to avoid accepting Medicaid payments, as Medicaid’s nursing home reimbursement rates are substantially lower than those of other payers (Ettner 1993; Uli 1995; Ching et al. 2015; Hackmann 2019; Gandhi et al. 2021; MedPAC 2021). Although regulations prohibit treating residents differently based on how they pay or soliciting or receiving additional payments

⁷Because many patients – both from the community and from the hospital – transition to Medicaid coverage after exhausting their other resources, at any point in time, about three-fifths of nursing home residents have Medicaid as their primary payer (Chidambaram and Burns 2025).

from patients on top of what their Medicaid coverage would provide, significant scope remains to consider payer in admissions.⁸ Nursing homes also have incentives to avoid Alzheimer’s patients who tend to have higher staffing needs and higher risks of adverse outcomes that could reduce the nursing home’s quality rating. Although nursing homes are legally prohibited from discriminating in patient admissions on the basis of a patient’s disability (such as Alzheimer’s), they may decline admissions if they cannot meet a patient’s medical needs – for example because they lack staff, equipment, or relevant licensure (Higgins 2026). As a result, there is significant discretion for selective admissions based on medical conditions.

3 Audit Study Design

3.1 Experimental Design

Using online contact forms on nursing home websites, we submitted two inquiries about availability to almost 3,000 nursing homes in the summer of 2025, experimentally varying the patient’s payer, medical condition, and perceived race. For each inquiry, we measured the number of responses received (via email or voicemail), as well as whether any response indicated possible availability, the sentiment or tone of the response, and the duration between the inquiry and the response. The audit study was preregistered with the Open Science Framework (OSF), where an analysis plan was archived, and registered on the AEA RCT Registry (AEARCTR-0018639) (Einav et al. 2024).⁹ In the rest of this section, we provide an overview of our approach. Appendix A.1 provides more detail on key design elements; as we describe there, several aspects of the design were chosen to minimize risk of detection or due to ethical considerations.

Each inquiry to a nursing home involves a daughter seeking admission from the community on behalf of her elderly mother. The inquiry asks if a bed is available, and includes a vignette describing the mother’s (randomly varied) condition and payer status; it also includes mother’s and daughter’s (randomly varied) racially-concordant names. To preserve power and limit the treatment space, we included only inquiries from and on behalf of women, removing the possibility of gender effects in the study. We focus on women because the majority of nursing home residents are women (authors’

⁸Common practices include limiting the number of beds available to Medicaid patients, either explicitly or as a result of Medicaid paying for only shared rooms, and requiring a period of private pay before transitioning to Medicaid (ElderLawAnswers 2016). The legality of these practices is unclear and may vary from state to state (Alliance America 2025). The 1987 Nursing Home Reform Act prohibits nursing homes from requiring applicants to waive their Medicaid rights, demanding assurances that applicants will not apply for or are ineligible for Medicaid, or requiring third parties (such as a family member) to guarantee payment on an applicant’s behalf (United States Congress 1987, CMS 2016). However, the law lacks mechanisms for enforcement and leaves open significant gray areas (Gandhi 2026). Several states have codified stronger rules. California, for example, explicitly prohibits requiring periods of private pay before converting to Medicaid (Gandhi 2026). Connecticut and New Jersey require nursing homes to admit applicants on a first-come-first-served basis without regard to payer (State of Connecticut 1988; State of New Jersey 2006).

⁹All direct experimental analyses were preregistered, unless denoted with a caret (^). The preregistration and analysis plan envisioned an email-based study, which was attempted and rejected after a pilot in Fall 2024 found evidence not only of large-scale problems with emails being undelivered or sent to spam, but also of potentially differential rates of such blockages based on the email address, which was being used as part of the way to signal race. The study was redesigned to use online contact forms. An explanation of where the current paper deviates from the analysis plan can be found in Appendix A.4. All preregistered results that are not presented in the main text are presented in Appendix A.5.

calculations based on data described in Section 5) and because adult daughters tend to take on a greater proportion of elder care responsibilities (Grigoryeva 2017). Following a two-day, small-scale pilot in March 2025, inquiries were submitted manually in two, three-week rounds (June 2025 and August 2025) using online contact forms.

We have 24 main treatment arms, randomized in a $2 \times 3 \times 4$ design based on race (Black or white), payer status (Medicaid, private pay, or unspecified), and four vignettes for different medical conditions. We signal race for elderly mothers and their daughters with racially congruent names (i.e., names that have been found to be associated primarily with either white or Black individuals). We signal payer status within the body of the free-form message sent via the online contact form, which also presented one of four key vignettes. Figure 1 shows a sample message inserted into a web-based contact form.

Payer information. Payer information was relayed using a separate line at the end of the free-form inquiry to increase salience. The private-pay treatment included the line “Our family has the financial means to pay privately for her care long-term,” while the Medicaid treatment ended with “She is on Medicaid;” in the unspecified payer arm, the line was left blank. The Medicaid wording follows language used in prior investigative reporting on nursing home admissions practices from the *Boston Globe* (Kowalczyk and Arsenault 2020). The private-pay language was developed through pilot testing to clearly communicate financial capacity and expected duration of payment, while including the key term “private” which is how self-paying families are referred to in the industry. The unspecified payer condition serves as a neutral baseline against which explicit Medicaid or private-pay signals can be compared.

Patient medical conditions. We constructed four core vignettes designed to capture common nursing home conditions for which a patient in the community might seek nursing home placement as well as typical demographic characteristics of such patients. Specifically, the four core vignettes centered around (i) chronic conditions requiring monitoring; (ii) falls and safety concerns; (iii) mobility limitations; and (iv) Alzheimer’s disease. To minimize risk of detection of the audit study, we created four distinctive versions of each vignette – by varying the age range of the patients from 77 to 86 and including minor other variations == for a total of sixteen vignettes. Appendix A.1.1 provides more detail on the vignettes and how they were selected.

Signaling race. We signaled race for elderly mothers and their daughters with racially congruent names – meaning that they have high race-specific share and are perceived by respondents as being the intended race – that were pre-tested in prior work (Gaddis 2017). This approach follows standard naming practices in the audit study literature (e.g., Bertrand and Mullainathan 2004; Kline et al. 2022). To increase the salience of the racially-congruent names, we used both first and last names and both mother and daughter names multiple times in the online inquiry. This included using the full name of the sender (daughter) in a distinct field; the full name of the patient (mother) in a distinct field if such a field existed; embedding the racially-congruent name in the sender’s (daughter’s) email

address; and the use of first names of mother and daughter in the free-form message field. We included eight sets of unique name pairs per racial condition, with each pair including a racially congruent first name for the mother and the daughter, and a racially-congruent shared last name. Appendix Table A2 provides the names used in the study, and Appendix A.1.2 provides more detail on how they were selected.

Randomization. We assigned each facility in our sample to receive two inquiries, to be delivered over two study implementation rounds (as well as a small pilot). Round one inquiries were constructed using independent, simple random assignment of race (Black or white assigned with equal probability), payer (Medicaid, private, unspecified assigned with equal probability), and medical vignette (one of 16 possibilities, with four each corresponding to the four core vignettes, again with equal probability). Within race, we randomly assigned one of eight possible name pairs with equal probability. Round two inquiries were constructed using random assignments conditional on not repeating the same payer, race, or vignette used for that facility in round one. 167 inquiries were sent as part of a pilot in March 2025; 2,773 inquiries were sent as part of round one (over three weeks in June 2025); and 2,654 inquiries were sent in round two (over three weeks in August 2025).

3.2 Estimation and Measurement of Key Variables

Estimating equation. Due to the random assignment of payer, vignette, and race treatments, analysis is simple. Our primary estimating equation is

$$y_{ij} = \alpha + \tau' T_i + \gamma' x_i + \epsilon_{ij}, \quad (1)$$

where y_{ij} denotes an outcome associated with the response to inquiry i at facility j , T_i is a vector of treatment indicators, and x_i is a vector of other characteristics associated with the inquiry. Standard errors are clustered at the facility level to allow for an arbitrary correlation in outcomes across rounds within facilities.

The treatment indicators consist of an indicator for whether the inquiry was for a Black patient (as opposed to an inquiry for a white patient), indicators for whether the inquiry was made for a Medicaid patient or whether the inquiry was made with no payer specified (with the omitted category an inquiry for a private-pay patient), and an indicator for whether the inquiry was made using an Alzheimer’s vignette (as opposed to one of the other three core vignettes based on chronic conditions requiring monitoring, falls and safety concerns, or mobility limitations). The vector of controls x_i consists of indicators for the study round (round one, round two, and the pilot) since the randomization was conducted within round; to potentially improve power, in our baseline analysis it also includes indicators for the day of the week on which the inquiry was sent although, as we show below, this has no impact on the results.

Outcomes. For each inquiry, we observe the number of responses received and the information contained in the response. We pre-specified our primary outcome to be an indicator for receiving

a response within 30 days that did not indicate a lack of availability; the outcome is coded one if the inquiry receives a response that either affirmatively indicates availability or does not explicitly indicate a lack of availability (e.g., offered to follow up or asked for more information but did not state availability outright); a zero indicates that the inquiry either did not receive a response or received a response indicating no availability. Hereafter, we refer to this primary outcome as “availability.”¹⁰

We also analyzed whether the inquiry received any response within 30 days, the number of responses received within 30 days (as a proxy for the nursing home’s eagerness to reach the patient), the duration (in hours) between the inquiry and the response (if any), and an indicator for whether the sentiment (or tone) of the response was positive.¹¹ Both availability and sentiment were coded based on large language models that we prompt-engineered and then manually checked for a random sample of 200 replies.

Appendix A.2.1 provides more details on how each outcome is measured.

Nursing home quality. Measuring nursing home quality is notoriously difficult. Since 2008, CMS has constructed and publicly posted several quality ratings for nursing homes on a five-star scale (with five being the best). CMS posts an overall five-star rating as well as the five-star rating for its three sub-components: the “inspection rating” relies on deficiencies found in annual inspections, the “quality rating” relies on the health of patients residing in the nursing home at a point in time, and the “staffing rating” relies on levels of staffing and staff turnover. Patients and their families are encouraged to use these five-star ratings in choosing a facility, and many do (CMS 2008, United States Government Accountability Office 2016). However there are widespread concerns about the reliability of the CMS ratings (e.g., Thomas 2014). In particular, the “quality rating” may be strongly affected by sorting of heterogeneous patients to different facilities, and both the “inspection rating” and “quality rating” are easy to game (Gandhi et al. 2025).

Given the challenges with measuring nursing home quality, we report results for three different measures, all measured on a 1-5 scale. One is the overall five-star quality rating published by CMS. Despite its limitations and potential gamability, it is by far the most visible and most widely used rating.

Our second quality measure is the five-star staffing rating, which is the sub-component of the overall rating that is most difficult to game. Historically, the staffing rating was based on staffing information derived from annual inspections and was subject to concerns that nursing homes strategically up-staffed during inspections (Chen and Dillender 2025; Gandhi et al. 2025). Starting in 2018, however, the staffing rating has been based on quarterly payroll data and is therefore considered to be quite reliable (Geng et al. 2019; Gandhi et al. 2021).

The third quality measure comes from our past work (Einav et al. 2025a, henceforth “EFM Value-

¹⁰For an inquiry that receives multiple responses, we code the response as indicating availability if any response affirmatively indicates availability or if none received a response indicating lack of availability.

¹¹Following prior work (White et al. 2015; Bergman and McFarlin 2018; Giulietti et al. 2019), sentiment analysis was designed to detect differences in tone or content of a message, as this may affect the recipient’s perceptions of availability and desire to continue seeking a bed. Inquiries that did not receive a response were coded as not having positive sentiment. If an inquiry received multiple responses we coded the sentiment as positive if any of the responses were coded as positive.

Added”). It uses changes in patient health assessments over their time in the nursing home to create a value-added measure for each nursing home; the measure accounts for patient selection both into and out of the nursing home. This measure has the advantage that it should not be affected by heterogeneous sorting of patients into different facilities and facilities do not have incentives to game it. However, it is based on data from earlier years (2011-2016) and is based on the experience of patients admitted from the hospital, rather than from the community. To make interpretation easier across the three quality measures, we convert the EFM Value-Added to a 1-5 scale by assigning each continuous value-added measure to its percentile in the distribution, and partitioning the percentiles into five bins based on national quintiles. There is substantial variation in nursing home value-added both across and within geographic areas (Einav et al. 2025a).

Given the various limitations associated with each measure, we report results using each one of these throughout. It is reassuring that for most of the analyses, the qualitative conclusions are not sensitive to the choice of the quality measure. Appendix A.2.2 provides more detail on the quality measures and their sources.

Other nursing home characteristics. In addition to quality, we examine availability gaps by several other key nursing home characteristics: number of beds, ownership status (for-profit or not), geographic region, occupancy rates (measured on the day of the inquiry), and whether the nursing home was part of a chain. For availability gaps by payer we also look at Medicaid and private-pay reimbursement rates, and for availability gaps for Alzheimer’s patients we also look at whether the nursing home has an Alzheimer’s unit.

Appendix A.2.3 provides more detail on the underlying data sources and variable definitions. In general the measurement of these variables is straightforward. However, due to data limitations, our measure of the gap in reimbursement rate between private payers and Medicaid likely contains substantial measurement error.¹² This measurement error may bias against finding any difference in private-Medicaid availability by the reimbursement gap.

3.3 Audit Study Sample

We formed our target sample of nursing homes to send inquiries to using the June 2024 *Provider Information* nursing home dataset (CMS 2024c), a publicly available list of all active, certified nursing facilities in the United States. We excluded about 7% of facilities because they did not accept patients from the community, and we excluded about 60% of facilities because we could not locate an online contact form (our mode of sending inquiries). In order to reduce the risk of detection of the audit study, when groups of nursing homes were commonly owned we randomly sampled 16 of the facilities (equal to the number of unique vignettes and also unique names). As a result, of the approximately 15,000 nursing homes in the United States, we attempted to send inquiries to 4,023. During implementation of the study, we further excluded approximately 1,100 nursing homes that we could not contact for feasibility reasons, such as an invalid website address, no opportunity to provide a free-form message,

¹²We are only able to measure reimbursement rates at the state-level rather than the facility-level, and the reimbursement data are from 2019, considerably before our 2025 audit study.

or a request for information such as patient address that we were not prepared to provide. Appendix Figure A1 provides a diagram describing the construction of the sample and flow through the study, and Appendix A.3 describes the sample construction in more detail.

Ultimately, we submitted 5,594 inquiries to 2,940 unique nursing homes. Given our restrictions to nursing homes that use online contact forms with our required features, these 2,940 nursing homes may not be representative of the full population of active nursing homes. Nonetheless, Appendix Table A3 shows that our sample of nursing homes in the audit study appears broadly representative of nursing homes in the United States on a number of dimensions, including Medicaid share, share with an Alzheimer’s special care unit, for-profit status, staffing, quality, and occupancy rate. The average nursing home in our sample is slightly larger (mean number of beds of 115 compared to 107 in the entire population), and is slightly more likely to be in the Northeast and less likely to be in the Midwest, but our analysis sample still has a large number of facilities in every region.

4 Experimental Results

4.1 Average Treatment Effects

We received responses to 35% of our inquiries. Although we allowed responses to come in for up to 30 days after the inquiry, the median response came within a day, and 96% came within a week. Conditional on receiving a response, the 75th percentile inquiry received 1 response; the mean number was 1.3.

Most of the responses (85%) indicated availability. Our primary outcome variable (an indicator for “availability”) is therefore 1 for 30% of the inquiries. Of responses indicating availability, only about one-third gave an affirmative indication of availability; the other two-thirds were ambiguous, but not negative. Only 13% of all inquiries (about 40% of those that received a response) received a response with positive sentiment.

Table 1 shows the main differences in outcomes across treatment arms.¹³ All outcomes are lower for inquiries with distinctively Black names relative to those with distinctively white names, but none of these differences are statistically significant. For our primary outcome, the results indicate a 1.4 (standard error = 1.0) percentage point (5%) lower availability. By way of comparison, in their audit study of hiring, Kline et al. (2022) estimate that applications from distinctively Black names have a 2.1 percentage point (9%) lower likelihood of an employer contact relative to a distinctively white name, a magnitude that we cannot rule out with our confidence intervals.

Inquiries sent on behalf of patients with Alzheimer’s disease are 3.2 (standard error = 1.4) percentage points less likely to receive a response indicating possible availability, or about 11% lower than the 30% availability rate for inquiries sent on behalf of patients with other health problems (falls, limited mobility, or other chronic conditions). Other outcomes are also uniformly lower for patients with Alzheimer’s, although these differences are not always statistically significant: inquiries on their

¹³To account for multiple testing, we controlled for the false discovery rate (FDR) within each treatment domain (race, payer, or vignette) using the sharpened q-value procedure of Benjamini et al. (2006); in practice, these made little difference to the results (see Appendix Tables A4 through A7).

behalf are 2.5 (standard error = 1.5) percentage points less likely to receive any response and 2.7 (standard error = 1.0) percentage points less likely to receive a response conveying positive sentiment; they receive on average 0.03 (standard error = 0.03) fewer responses.

Inquiries sent on behalf of Medicaid patients are 4.8 (standard error = 1.3) percentage points less likely to receive a response indicating possible availability than inquiries sent on behalf of private-pay patients; this represents a 15% lower availability rate for Medicaid patients compared to private-pay patients. As private-pay patients from the community have some risk of exhausting their resources and transitioning to Medicaid coverage, the availability gap for those who can credibly commit to privately financing their whole stay and those who cannot may be higher than what we measure. The probability of any response is also lower (1.7 percentage points, standard error = 1.4) for Medicaid patients than private-pay patients, but this difference is not statistically significant. Thus, most of the difference between private-pay and Medicaid patients is in whether the response indicates availability, not in whether they get a response. Some messages indicating lack of availability for Medicaid patients explicitly called out lower availability for Medicaid. For example, one response to an inquiry from a Medicaid patient read, “If someone has private pay, we have occasional openings. If someone needs Medicaid, the wait time could be more than two years.”

Additional outcomes are also suggestive of a greater eagerness to attract private-pay patients relative to Medicaid patients. Medicaid patients receive on average 0.08 (standard error = 0.02) fewer responses, and are 2.3 (standard error = 1.0) percentage points less likely to receive a response with positive sentiment. Medicaid patients also tend to receive their responses later (by 3.4 hours on average), although this difference is not statistically significant.

When no payer is specified in the inquiry, responses tend to be broadly similar to those for Medicaid patients. Availability is 0.7 percentage points higher than for Medicaid patients, but this difference is not statistically distinguishable. Other outcomes – such as the probability of any response, the number of responses, or the probability of a response with positive sentiment – are also statistically indistinguishable between Medicaid and no payer specified. Given that about one-third of patients coming from the community are covered by Medicaid, we would expect the results when no payer is specified to lie in between those for private payer and Medicaid; if however individuals who can pay privately are more likely to indicate that when making inquiries, nursing homes may assume that a large share of the payer-unspecified inquiries are in fact associated with Medicaid coverage.

Using the same basic estimating equation as in Table 1, we also report availability separately for each vignette (Appendix Figure A2), each name (Appendix Figure A3), and each day of the week (Appendix Figure A4); this does not reveal additional, systematic availability gaps. Likewise, excluding controls for day of the week has no noticeable effect on our estimates (Appendix Table A8). Finally, in the analysis plan we included speculation that availability might differ within race by payer status; yet, the results do not reveal any such pattern (Appendix Table A7).

4.2 Heterogeneity in Availability Gaps by Facility Characteristics

We explore whether availability gaps by payer or by Alzheimer’s condition vary by facility characteristics. As discussed in Appendix A.5.1, not only do we find no statistically-significant evidence of an

overall white-Black availability gap, we also find no evidence of white-Black availability gaps when we subset the analysis by facility characteristics.

Nursing home quality. Availability gaps between Medicaid and private-pay patients are generally increasing in nursing home quality. Figure 2 shows the results for the three different quality measures; Appendix Table A9 reports the underlying estimates. For the CMS overall five-star quality rating (top row), the difference in availability between Medicaid and private-pay patients is mostly uniform across ratings. However, for the two other measures of quality (middle and bottom rows of Figure 2), the availability gap is larger for higher quality nursing homes, specifically for nursing homes in the top one or two quality ratings compared to lower quality ratings. Consider for example the staffing rating (middle row). For private-pay patients, availability is similar (at about 40%) at 1-star, 4-star, and 5-star nursing homes, and slightly lower (about 35%) at 2-star or 3-star nursing homes. By contrast, for Medicaid patients, availability is roughly similar (at about 35%) for 1-star, 2-star, and 3-star nursing homes, and markedly lower (about 30%) for 4-star and 5-star nursing homes. The availability gap for private-pay vs. Medicaid patients is thus much larger at 4-star and 5-star nursing homes (about 10 percentage points) than at lower quality ones (about 1-2 percentage points). There is a similar qualitative pattern when using EFM value-added (bottom row); specifically, there is a noticeable widening of the availability gap for 4-star and particularly 5-star nursing homes.

Across all three quality measures, availability gaps between patients with and without Alzheimer’s are increasing in quality. Figure 3 shows the results, and Appendix Table A10 reports the underlying estimates. Again the results are more pronounced for the staffing rating and the EFM value-added measure than for overall quality. For both these measures, the availability gap is substantially (and statistically) wider for the highest quality rating compared to the lower quality ratings.

Other nursing home characteristics. We also examine heterogeneity in availability gaps by other facility characteristics. These include occupancy rate, number of beds, for-profit status, chain status, and region. Appendix A.5.1 presents the results. For both patients with Alzheimer’s and Medicaid patients, the availability gap is concentrated in not-for-profit and non-chain nursing homes. Larger availability gaps for non-chains are reminiscent of Kline et al. (2022)’s finding of larger racial callback gaps for firms without centralized hiring practices. For Medicaid patients (but not Alzheimer’s patients), availability gaps are higher at higher-occupancy facilities; a 10 percentage point increase in occupancy rate is associated with an additional 2.2 percentage point (standard error = 0.9) widening of the private-Medicaid availability gap. A higher availability gap when occupancy rates are higher is consistent with Gandhi (2026), who estimates that selective admissions for Medicaid relative to private-pay patients are more pronounced when occupancy rates are higher.

The availability gap for private-pay vs. Medicaid patients appears to increase with the percentage gap in reimbursement rates for nursing homes by private payers relative to Medicaid, although the difference is not statistically significant. As noted in Section 3, we suspect that our current measure of reimbursement rates has substantial measurement error, which may be biasing downward our estimates of the relationship between the availability gap and reimbursement rate difference. This is unfortunate

since it would be valuable to know more precisely how changes in Medicaid reimbursement rates might potentially affect availability gaps.¹⁴

The availability gap for Alzheimer’s patients is not smaller at nursing homes that have a dedicated Alzheimer’s unit. This suggests that the existence of a dedicated Alzheimer’s unit is not a key driver of availability gaps. Consistent with this interpretation, only 14% of nursing home patients with Alzheimer’s are in nursing homes with a dedicated Alzheimer’s unit (authors’ calculation using the data described in the next section).

5 Quantitative Impact on Nursing-Home Attendance

The audit-study results indicate systematically lower nursing home availability for Medicaid patients than for private-pay patients, with these availability gaps increasing with nursing home quality. A natural question therefore is whether the experimentally-estimated availability gaps map to economic objects of interest, and whether the statistically significant availability gaps we documented are quantitatively important.

To investigate this question, we focus on one specific object of interest, which we highlighted in the beginning of this paper: the lower quality of nursing homes attended by Medicaid patients (Rahman et al. 2014a,b; Gandhi 2026). It is intuitive to speculate that if nursing homes are less available for Medicaid patients, and in particular if this lower availability is concentrated at higher quality nursing homes, then Medicaid patients are more likely to end up in lower quality nursing homes. Yet, other demand-side factors may confound this intuition, as nursing home choices also depend on the size of the choice set (i.e., the number of nursing homes in the market), the location of patients relative to different nursing homes, patients’ preferences for quality and for proximity, and their information set.

The ambiguity extends not only to the quantitative impact of the estimated availability gaps in contributing to the observed lower quality of nursing homes attended by Medicaid patients, but even to the sign of that impact. For instance, if distance to the nursing home is the key driver of nursing home choice, and Medicaid patients are located near low-quality nursing homes, then *lower* availability for Medicaid patients relative to private-pay patients would make Medicaid patients *more likely* to go to a higher quality, more distant option.

In this section, therefore, we investigate the quantitative implications of the audit-study results for the role of differential availability of nursing homes for Medicaid and private-pay patients in contributing to observed quality differences in the nursing homes that these patients attend. To do so, we follow the approach that Christensen and Timmins (2023) use in the context of discrimination in rental housing and embed the audit-study results in a model of nursing home choice. We then use the model estimates to quantify how the quality of nursing homes attended by Medicaid patients would change if they were to face the availability patterns experienced by private-pay patients, and how much of the observed quality gap this exercise would close.

¹⁴In related work, Hackmann (2019)’s estimates from a model of the nursing home industry in Pennsylvania suggest that increases in Medicaid reimbursement rates would increase the quality of nursing home care, which in turn would increase demand for and hence use of nursing homes by elderly Medicaid patients.

5.1 Data

The backbone of our empirical analysis in this section is the 2022 Long-Term Care “Minimum Data Set” for Resident Assessment and Care Screening (CMS 2024a), hereafter referred to as the MDS. The MDS contains information on all nursing home patients, regardless of payer, at all federally certified nursing homes.¹⁵

To construct our analysis sample, we restrict attention to admissions from the community of Traditional Medicare (TM) enrollees who are 65 years old and older. Appendix Table A11 provides more detail on these sample restrictions. The focus on TM enrollees allows us to link the MDS patient to data (in their Medicare enrollment and claims files) that provide additional, essential patient-level information on 5-digit zip code of residence, an indicator for dual eligibility for Medicaid coverage, and their Medicare-covered hospital and nursing home stays. The focus on nursing home admissions from the community aligns the sample with the context of the audit study.¹⁶ We use the MDS nursing home identifier to merge in publicly available nursing-home-level data; see Appendix A.2.3 for more details on these variable sources and definitions.

Our analysis sample consists of 458,665 patient stays in 14,350 nursing homes. We identify admissions as covered by Medicaid if the patient is dually eligible for Medicaid.¹⁷ Because none of these admissions is covered by Medicare, which requires a prior hospital stay, we consider all other admissions in the sample to be private-pay at the time of admission. About 35% of the patients are covered by Medicaid at the time of admission. Medicaid patients are younger, more likely to be female, and more likely to be Black than private-pay patients (Appendix Table A12).

Table 2 shows that, across all three quality measures, Medicaid patients on average go to lower quality nursing homes. Moreover, even within market and within zip code, Medicaid patients go to lower quality nursing homes. For example, relative to a mean overall quality rating of 2.98 stars for private-pay patients, Medicaid patients go to nursing homes that have an average overall quality rating that is 0.35 stars lower (about 12%); conditional on zip code, Medicaid patients go to nursing homes that are 0.31 stars lower (about 10%). The gaps are similar for the other two quality measures. By embedding the audit-study results in a choice model, we can ask how much of these quality differences reflect differences in nursing home availability rather than patient choices conditional on availability.

¹⁵This data set has been widely used by researchers studying the economics of nursing homes (e.g., Grabowski et al. 2008; Hackmann 2019; Gupta et al. 2024; Hackmann et al. 2024; Einav et al. 2025a,b; Cheng 2026; Gandhi 2026).

¹⁶We consider a nursing home admission to be from the community if (i) we do not have a Medicare claim record for a hospital stay within the 30 days prior to the admission date, (ii) we do not have a Medicare claim record for a nursing home stay in the 30 days before or after the admission date, and (iii) the MDS does not indicate the admission was covered by Medicare.

¹⁷In principle, Medicaid claims data could be used to identify Medicaid-covered stays directly. In practice, these data are incomplete and do not provide a reliable way to classify stays as Medicaid-covered, so we rely on dual eligibility instead.

5.2 Choice Model

Baseline model. Let the choice utility of patient i , who is covered by payer $g(i) \in \{\text{Private}, \text{Medicaid}\}$, from attending nursing home j be

$$u_{ij} = \delta_{j,g(i)} - \tau_{g(i)} m_{ij} + \varepsilon_{ij}, \quad (2)$$

where $\delta_{j,g(i)}$ is the average choice utility a patient of type $g(i)$ gets at nursing home j , m_{ij} is distance in log-miles between the centroid of the five-digit zip code of patient i 's residence and each nursing home j ,¹⁸ and ε_{ij} is an iid type-1 extreme value residual.

The set of nursing homes in patient i 's market is denoted by J_i . We assume that each patient makes a discrete choice of nursing home, choosing the nursing home j that maximizes their choice utility out of all the options available to them. As in Einav et al. (2025a), markets are defined by 680 geographic areas, and patient i 's market is based on their residential five-digit zip code.¹⁹ On average, each market consists of 29 nursing homes (median of 28). The outside option ($j = 0$) is going to a nursing home outside of the market, and the mean choice utility of each patient from choosing the outside option is normalized to zero (that is, $u_{i0} = \varepsilon_{i0}$). About 11% of the patients in the sample choose nursing homes outside of their market.

We allow all the parameters of the model, and in particular $\tau_{g(i)}$, to vary flexibly across markets. In other words, we use the individual-level choice data to estimate a standard conditional logit model separately for each market and payer type using maximum likelihood.

Limited availability. We use the audit-study results to adjust the baseline choice model to accommodate constrained choice sets.

To do so, we first use the audit-study results on availability to estimate two random forests to predict availability across a range of nursing home characteristics. One model predicts availability for inquiries made on behalf of Medicaid patients and the other for inquiries made on behalf of private-pay patients. The result of this exercise is a predicted availability for each nursing home and payer type, $\hat{p}_{jg}$, where $g \in \{\text{Medicaid}, \text{Private}\}$. Appendix Table A13 lists the predictors used in the random forest models and Appendix Figure A5 shows the distribution of the resulting $\hat{p}_{jg}$'s by payer.

We then assume that each patient draws their actual choice set randomly, assuming independent (across patients and nursing homes) availability conditional on the estimated $\hat{p}_{jg}$.²⁰ Heuristically, one can think of this random choice set model as representing patients making choices using their full, unconstrained choice set J_i , inquiring about availability sequentially in the order of their utility u_{ij} , and choosing the first nursing home that is available to them.

To estimate this constrained choice model, we simulate choice sets for each patient using the estimated $\hat{p}_{jg}$'s. That is, for each patient i , we simulate $L = 20$ choice sets by independently including

¹⁸Each nursing home's location is defined using the precise longitude and latitude of its address.

¹⁹We begin with the standard market definition for hospital choice, namely the 306 Hospital Referral Regions (HRRs). Each HRR is composed of one or more Hospital Service Areas (HSAs). We partition the 118 largest HRRs into smaller choice sets, which are geographically connected HSAs within each HRR. These, along with the 188 smallest HRRs, yield a total of 680 choice sets, which we refer to as "markets."

²⁰We assume that the outside option is always available, so that $\hat{p}_{0g} = 1$.

each $j \in J_i$ with probability $\hat{p}_{jg}$, and always including the nursing home chosen for patient i (as well as the outside option). Estimation then proceeds by creating L duplicates of the original sample, each associated with a different simulated choice set for patient i (but the same choice), and a maximum likelihood estimation as in a model which does not account for limited availability. Appendix B provides more details on the estimator.

5.3 Results

Model estimates. Figure 4 presents choice parameters from estimating equation (2) under the assumption that each patient faces the nursing-home-by-payer availability probabilities $\hat{p}_{jg}$ predicted from the audit study. Under the assumption that our predicted availabilities reflect the experienced choice sets, the choice parameter model estimates under these constrained choice sets reflect the “true” demand of patients, uncontaminated by supply-side restrictions on availability.

The panels of Figure 4 use the $\hat{\delta}_{jg(i)}$ ’s estimated under constrained choice sets to summarize the within-market mean utility from going to a nursing home in each rating bin relative to the lowest 1-star bin, which is the omitted category; it shows results for each payer type and for each of the three quality measures. For comparison, Appendix Figure A6 shows the same summary of the choice parameters from estimating equation (2) under the alternative assumption that each patient is making their choice from the unconstrained choice set of all nursing homes in their market. Under both assumptions about the choice set each type of patient faces, private-pay patients exhibit higher demand for nursing homes in every quality bin relative to the lowest bin. By contrast, using either the overall rating or the staffing rating, Medicaid patients exhibit lower demand for nursing homes in most quality bins relative to the lowest quality bin, and this aversion becomes somewhat steeper once we account for choice set constraints. We suspect that this finding does not imply that Medicaid patients dislike quality per se. Rather, it likely reflects a lack of information about quality or may be driven by other aspects of lower quality nursing homes that Medicaid patients value (e.g., the patient population at these nursing homes).

The choice parameters indicate that, all else equal, both private-pay and Medicaid patients are less likely to choose nursing homes that are further away from where they live. To see this, the notes to Figure 4 and Appendix Figure A6 summarize the estimated coefficients on log distance across markets. As expected, they are consistently negative. Moreover, the coefficients on distance are very similar for Medicaid and private-pay patients. In the constrained choice model (Figure 4), the median market estimate for private-pay patients ($\hat{\tau}_{\text{Priv}} = -1.724$) indicates that, all else equal, a one-unit increase in log distance to a given nursing home (m_{ij}) decreases the relative odds that nursing home is chosen by 82% ($e^{-1.724} \approx 0.18$); for Medicaid patients, the median market estimate ($\hat{\tau}_{\text{Med}} = -1.763$) indicates that a one-unit increase in log distance to a nursing home decreases the relative odds of its being chosen by 83% ($e^{-1.763} \approx 0.17$). The coefficients on log distance decrease substantially in absolute value when we estimate the model assuming unconstrained choice sets (Appendix Figure A6) rather than constrained choice sets. This is intuitive. If we assume that patients face no constraints, then when we observe them choosing a nursing home that is far away we infer that they are not as sensitive to distance. When availability constraints are introduced, the choice of a far-away nursing home can

now be rationalized with greater distance disutility combined with some the possibility that closer nursing homes are unavailable.

Counterfactuals. We use the estimates from the constrained choice model to generate choices under counterfactual assumptions about Medicaid patients’ availability and choice parameters. Table 3 shows the results. To make the numbers comparable, all market-specific private-pay estimates are re-weighted to reflect the distribution of Medicaid patients across markets; therefore, the comparisons between private-pay and Medicaid patients are not confounded by the differential distribution of patients with different payers across markets.

Each panel shows results for a different quality measure. Comparing the model rows to the observed rows within each panel indicates that model fit is quite good. The estimates indicate that, as observed, within a market Medicaid patients are more likely to go to lower quality nursing homes than private-pay patients. For example, using the overall five-star rating (panel A), Medicaid patients are about 37% more likely to go to 1-star nursing homes (27.3% compared to 19.9%) and about 35% less likely to go to 5-star nursing homes (12.4% compared to 19.1%); on average, Medicaid patients attend nursing homes that have 0.34 fewer stars than private-pay patients. These within-market payer gaps in average quality are similar for the other quality measures in panels B and C. Medicaid patients also go to nursing homes that are about 0.2 miles closer to their homes (average distance of 7.86 miles from home to nursing home for Medicaid patients, compared to 8.03 miles for private-pay patients).

The first counterfactual row of each panel shows what would happen if, counterfactually, we were to give Medicaid patients the availability that private-pay patients face.²¹ The second-to-last column shows that this raises the average quality of the nursing homes that Medicaid patients would attend, closing between 5% and 10% of the within-market quality gap of nursing homes attended by Medicaid patients relative to private-pay patients. For example, using the overall five-star rating (panel A), we find that giving Medicaid patients the private-pay choice sets raises the average quality of the nursing home they attend from 2.625 stars to 2.643 stars; the 0.018 increase in stars closes 5% of the average quality gap between private-pay and Medicaid patients. The increase in quality reflects small shifts from the bottom of the rating distribution to the top; giving Medicaid patients the private-pay choice sets reduces the probability that they go to a one-star nursing home by 0.4 percentage points (about 1.4%) and raises the probability that they go to a five-star nursing home by 0.4 percentage points (about 3%).

The estimates of the choice parameters help explain why the effect of changing Medicaid patients’ choice set is modest. Medicaid patients’ availability disadvantage is concentrated at higher-quality nursing homes (Figure 2), but the choice parameter estimates (Figure 4) indicate that Medicaid patients do not value these nursing homes more than lower-quality ones. As a result, making higher quality nursing homes more available to Medicaid patients moves relatively few Medicaid patients into them.

Indeed, the second counterfactual row of each panel in Table 3 confirms this observation. Instead

²¹Given average occupancy rates of about three-quarters (see Appendix Table A12) we conduct the counterfactuals without considering capacity constraints.

of assigning Medicaid patients the choice sets of private-pay patients, we assign Medicaid patients the choice parameters (the δ s and τ s) associated with private-pay patients while maintaining the differential choice sets. Recall from Figure 4 that private-pay patients’ choice utility rises with nursing home quality while Medicaid patients’ choice utility either falls with quality (overall and staffing ratings) or is flat (EFM value-added). As a result, this counterfactual closes most of the within-market quality gap: 83% for the overall rating, 77% for the staffing rating, and 74% for EFM value-added. Within the model, differences in choice parameters, rather than in availability, account for most of the payer gap in the quality of nursing homes attended.

The average counterfactual impacts in Table 3 mask meaningful heterogeneity in impacts across markets. This is not surprising. As noted at the outset, the sign as well as the magnitude of the impact on quality of nursing home attended of the audit-study availability findings depend on market-specific characteristics, including the number of nursing homes in the market, where different patients are located relative to nursing homes of different quality levels, and patients’ choice parameters. Appendix Table A14 shows this heterogeneity across markets in the impact of the private-Medicaid availability differences on the quality gap of nursing homes attended by private-pay and Medicaid patients.²² Consider, for example, what happens to the overall rating (panel A), if we counterfactually give Medicaid patients the availability faced by their private-pay counterparts. In the 95th-percentile market, Medicaid patients experience an increase of 0.11 stars (closing over 50% of the private-Medicaid quality gap in that market). However, in roughly one-quarter of markets the average quality of nursing home attended by Medicaid patients actually *declines* slightly in the counterfactual. Similar cross-market heterogeneity is evident for the other two quality measures.

Finally, we note that all of our findings are derived under the assumption that our “availability” measure reflects experienced availability. In practice, our measure may have both false negatives and false positives. For example, some nursing homes that did not respond to online inquiries may in fact have availability if a patient or their family member follows up by phone, while some nursing homes that replied with an answer that did not preclude availability might subsequently determine that they did not have availability. To explore the sensitivity of our results to the assumption about the overall level of availability, we therefore re-estimate the constrained choice model and the resulting availability counterfactuals with all availability rates scaled by a constant proportional factor a , giving a new availability rate $\tilde{p}_{jg} = a \cdot \hat{p}_{jg}$ for both payer groups. The factor $a = 1$ reproduces our baseline estimates; we consider other values of a from close to zero up to about 1.6, the largest factor for which no scaled availability exceeds one. Reassuringly, Appendix Figure A7 shows that the quantitative results remain quite stable across a wide range of values of a : the counterfactual increase in the quality of nursing homes attended by Medicaid patients is essentially unchanged whether we assume availability is a fraction of what we measured or well above it.

²²The average increase across markets in quality of nursing home attended by Medicaid patients in Appendix Table A14 matches the results in Table 3; the percentage reductions in the within-market payer gap are slightly different because in Appendix Table A14 we are reporting the average of this ratio across markets.

6 Conclusion

We conducted a nationwide audit study of nursing homes to test for selective admissions by race, payer status, and health conditions. We found no statistically significant evidence of lower availability for inquiries sent on behalf of patients with distinctively Black names than inquiries sent on behalf of patients with distinctively white names, either overall or for specific types of nursing homes. However, we found statistically significant lower availability for patients with Alzheimer’s disease and for Medicaid patients, with larger availability gaps for higher quality nursing homes.

In the final part of the paper we consider the quantitative implications of these experimentally-estimated availability gaps. Specifically, we quantify the contribution of availability gaps in explaining the observed lower quality of nursing homes attended by Medicaid patients compared to private-pay patients. To do so, we embed the results from the audit study in a model of (constrained) nursing home choice. Our estimates suggest that if Medicaid patients faced the choice sets of private-pay patients, only 5-10% of the average quality gap (of nursing homes attended by these two groups of patients) would be eliminated. By contrast, giving Medicaid patients the estimated demand-side, choice parameters of private-pay patients would eliminate most (75-85%) of the gap.

Our analysis focused only on patients who are admitted to the nursing home from the community; these tend to be long-stay patients. It does not speak directly to potential selective admissions for patients discharged from the hospital; these patients almost all have Medicare coverage initially but face differential probabilities – based on their expected length of stay and their resources – of ending up as Medicaid patients.

Nonetheless, our findings indicate a widespread practice of lower nursing home availability for Medicaid patients compared to private-pay patients, but that these selective admissions practices do not explain a meaningful share of the lower quality of nursing homes attended by Medicaid patients compared to private-pay patients.

More broadly, our analyses illustrate the value of going beyond the experimental evidence itself and the complementarities that can exist between experimental estimates and additional modeling with observational data. The audit study documents the existence of selective admissions, but assessing their consequences for where patients ultimately receive care requires embedding the experimental estimates in a model of constrained nursing home choice.

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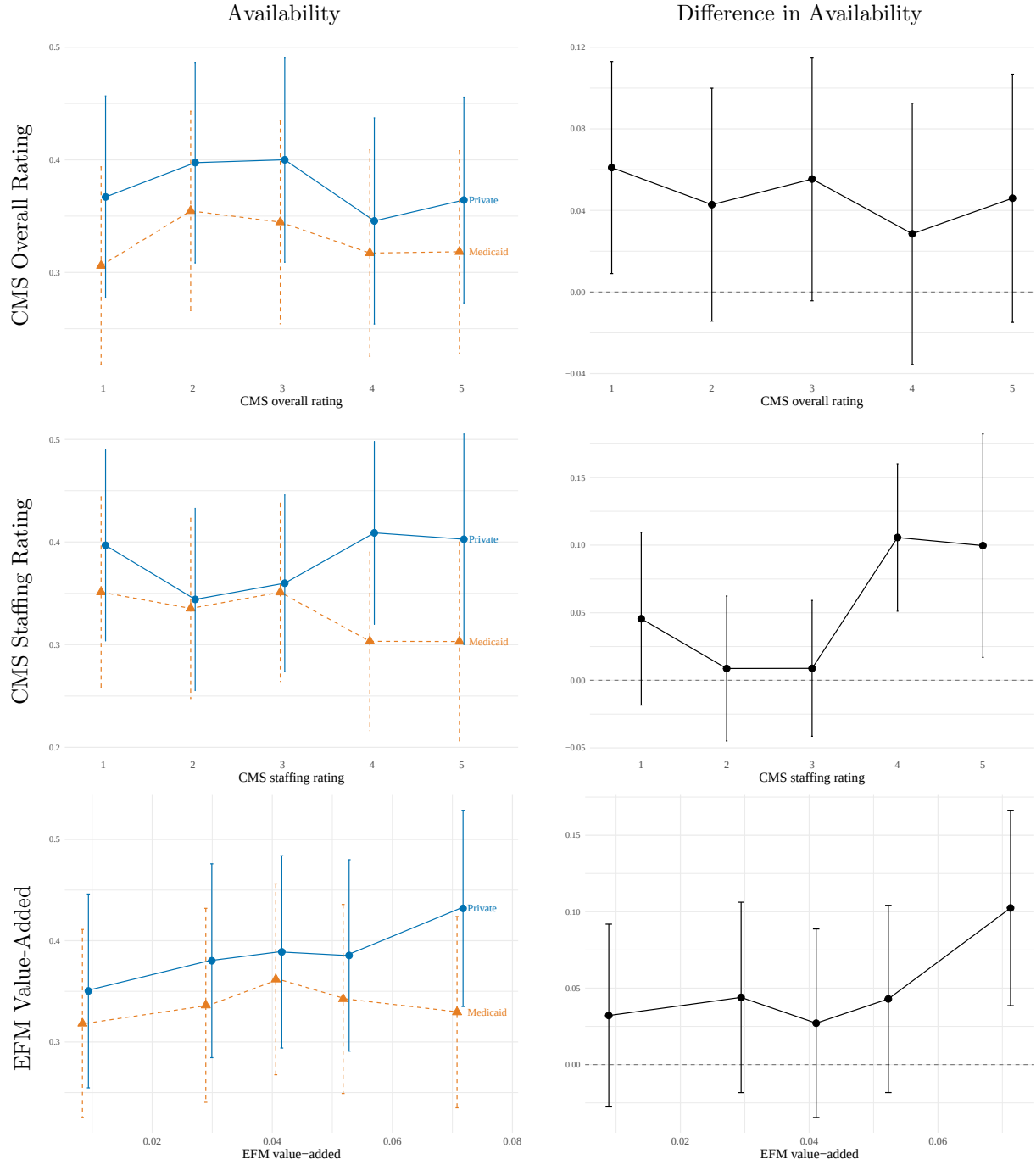
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Figure 1: Example Vignette in an Online Contact Form

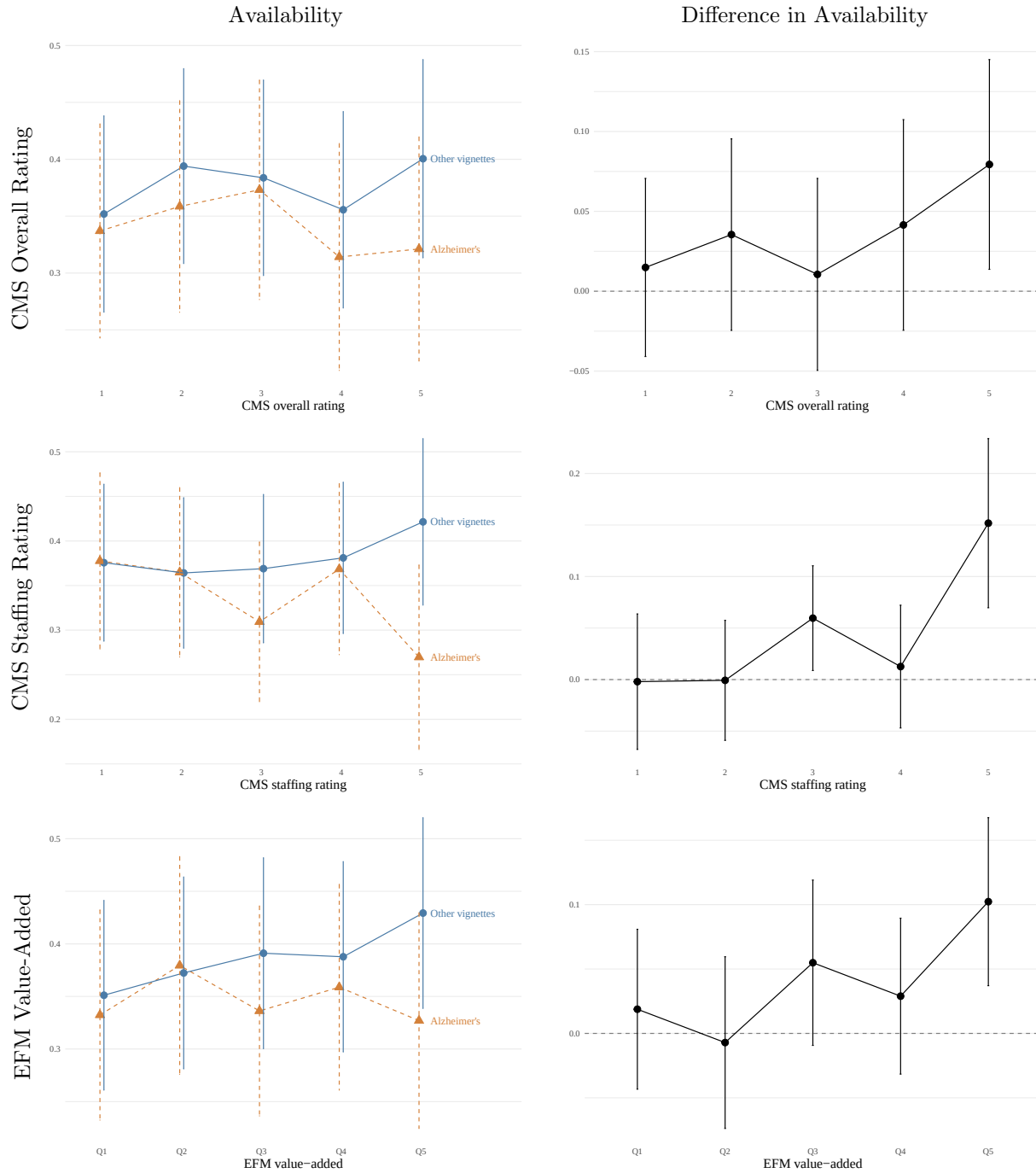
Name
Ashanti Washington
Email
ashantirwashington@gmail.com
Phone
405-613-4952
Message
Hello,
 My name is Ashanti, and I'm reaching out about my 81-year old mother Keisha, who recently got diagnosed with Alzheimer's. She is still in pretty good shape (can hold a conversation, etc), but in the long term we think it would make sense for her to stay in a nursing home like yours. She also has heart disease, though she's been eating healthy and exercising to help combat it.
 Do you have any openings for her?
 She is on Medicaid.
 Thanks!!

Figure 2: Availability for Private Pay vs Medicaid, by Nursing Home Quality



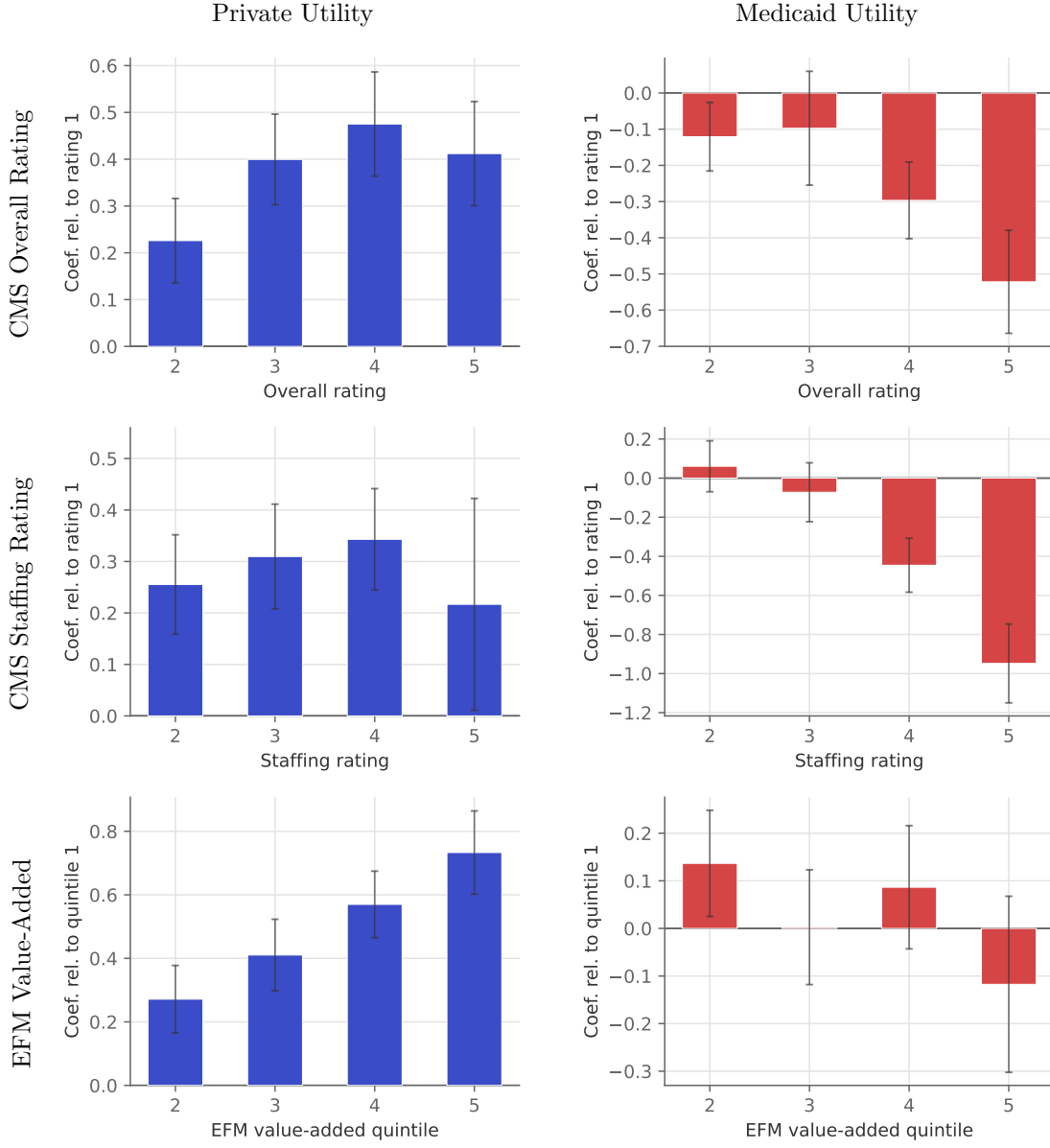
Notes: Figure reports the results of estimating equation 1, allowing for an interaction term for the payer indicators (Medicaid or no payer specified) and the quality rating; controls are included for indicators for inquiry round and for day of the week and the error term is clustered on nursing home. The left column shows the estimated mean availability (and 95 percent confidence interval) for private payers and for Medicaid, while the right column shows the estimated difference in availability (private minus Medicaid). We exclude some inquiries due to data availability. $N = 5,552$ (Overall), 5,547 (Staffing), and 5,002 (EFM value-added).

Figure 3: Availability for Alzheimer's vs. Other Patients, by Nursing Home Quality



Notes: Figure reports the results of estimating equation 1, allowing for an interaction term for vignette (1–3 or 4) and the quality rating; controls are included for indicators for inquiry round and for day of the week and the error term is clustered on nursing home. The left column shows the estimated mean availability (and 95 percent confidence interval) for the Alzheimer's and other vignettes, while the right column shows the estimated difference in availability (other vignettes minus the Alzheimer's vignette). N = 5,552 (Overall), 5,547 (Staffing), and 5,002 (EFM value-added) inquiries.

Figure 4: Preferences for Quality by Payer



Notes. This figure reports the difference in average $\hat{\delta}_{j,g}$ between each rating bin and the lowest bin, controlling for market fixed effects. Coefficients (with 95 percent confidence intervals based on standard errors clustered by market) come from a regression of the market-by-payer specific $\hat{\delta}_{j,g}$ from estimating equation 2 on indicators for rating bins 2–5 (with bin 1 as the omitted category) as well as market fixed effects; the regression is weighted by the number of (total) patient-stays in each nursing home. The left column shows estimates for private-pay patients and the right column for Medicaid patients. The top row uses bins of the overall CMS rating, the middle row bins of the CMS staffing rating, and the bottom row national quintiles of EFM value-added (nursing homes without an EFM value-added score are excluded from that row). The $\hat{\delta}_{j,g}$ come from the constrained-choice model with simulated choice sets drawn using the audit-study-based acceptance probabilities $\hat{p}_{jg}$ that vary by payer and nursing home. The log distance coefficients $\hat{\tau}_g$ are estimated separately for each market; across the 680 markets, weighted by (total) patient-stays, $\hat{\tau}_{Priv}$ has a mean of -1.850 (standard deviation 0.650) and 10th, 50th, and 90th percentiles of -2.658 , -1.724 , and -1.228 , and $\hat{\tau}_{Med}$ has a mean of -1.989 (standard deviation 0.882) and percentiles of -3.211 , -1.763 , and -1.154 . Appendix Figure A6 shows the same estimates from the model that does not account for choice set constraints.

Table 1: Average Treatment Effects from Audit Study

	Availability	Any response	Outcomes Number of responses	Positive sentiment	Hours to first response
	(1)	(2)	(3)	(4)	(5)
<i>Panel A: Treatment effects</i>					
Black	-0.014 (0.010)	-0.015 (0.010)	-0.028 (0.017)	-0.015 (0.008)	-0.897 (2.580)
Alzheimer's vignette	-0.032 (0.014)	-0.025 (0.015)	-0.031 (0.026)	-0.027 (0.010)	-4.803 (2.521)
Payer					
Medicaid	-0.048 (0.013)	-0.017 (0.014)	-0.075 (0.024)	-0.023 (0.010)	3.375 (3.247)
No payer specified	-0.041 (0.014)	-0.031 (0.014)	-0.061 (0.024)	-0.042 (0.010)	-0.619 (3.055)
<i>Panel B: Reference group means</i>					
White	0.304	0.360	0.490	0.136	26.959
Non-Alzheimer's vignettes	0.304	0.359	0.484	0.135	27.382
Private pay	0.326	0.369	0.522	0.149	25.337

Notes: Panel A reports the results from estimating equation 1, with each column showing results for a different outcome. All the estimates control for indicators for inquiry round and for day of the week; robust standard errors clustered on nursing home are in parentheses. Columns 1–4 use the full estimation sample of 5,594 inquiries sent to 2,940 nursing homes; column 5 is estimated among the 1,791 inquiries (sent to 1,268 nursing homes) with valid data on the timing of response; 132 responses are excluded from column 5 because response timing is missing or invalid. Panel B shows the means of the omitted category for payer (private payer), race (white) and medical condition (non-Alzheimer's vignettes).

Table 2: Quality Ratings of Nursing Home Stays by Payer

	Mean rating		Medicaid – private-pay gap		
	Private-pay (1)	Medicaid (2)	No FE (3)	Market FE (4)	Zip code FE (5)
Overall rating	2.98	2.63	−0.35 (0.02)	−0.35 (0.01)	−0.31 (0.01)
Staffing rating	2.68	2.38	−0.30 (0.02)	−0.30 (0.01)	−0.26 (0.01)
EFM value-added (quintile)	3.24	2.81	−0.43 (0.02)	−0.31 (0.01)	−0.26 (0.01)

Notes: Table reports the quality rating of the nursing home attended separately for private-pay and Medicaid patients. Each row uses a different quality measure: the CMS overall rating, the CMS staffing rating, and the national quintile of the EFM value-added score (nursing homes without a score are excluded). Columns 1–2 report group means. Columns 3–5 report the Medicaid minus private-pay difference from a regression of the rating on a Medicaid indicator with no fixed effects, with market fixed effects, and with patient zip code fixed effects; standard errors, clustered by market, are in parentheses. The sample includes 455,691 stays in 14,203 nursing homes for the overall rating, 454,246 stays in 14,135 nursing homes for the staffing rating, and 437,862 stays in 12,965 nursing homes for EFM value-added.

Table 3: Counterfactual Nursing Home Attendance

	Rating bin / quintile shares					Mean	Miles
	1	2	3	4	5		
<i>Panel A: Overall rating</i>							
Observed, private (reweighted)	0.197	0.207	0.216	0.186	0.194	2.973	8.35
Observed, Medicaid	0.271	0.234	0.211	0.160	0.124	2.632	8.07
Model, private (reweighted)	0.199	0.207	0.218	0.185	0.191	2.964	8.03
Model, Medicaid	0.273	0.235	0.211	0.157	0.124	2.625	7.86
Counterfactual: Medicaid patients with private ...							
availability	0.269	0.233	0.211	0.159	0.128	2.643	7.62
choice parameters	0.209	0.213	0.218	0.183	0.177	2.906	8.57
<i>Panel B: Staffing rating</i>							
Observed, private (reweighted)	0.263	0.206	0.222	0.220	0.088	2.663	
Observed, Medicaid	0.329	0.230	0.224	0.171	0.046	2.375	
Model, private (reweighted)	0.265	0.207	0.222	0.218	0.087	2.655	
Model, Medicaid	0.332	0.229	0.223	0.170	0.046	2.368	
Counterfactual: Medicaid patients with private ...							
availability	0.327	0.224	0.223	0.176	0.049	2.395	
choice parameters	0.278	0.216	0.222	0.205	0.078	2.588	
<i>Panel C: EFM value-added (quintiles)</i>							
Observed, private (reweighted)	0.183	0.185	0.199	0.203	0.230	3.111	
Observed, Medicaid	0.239	0.215	0.204	0.184	0.158	2.806	
Model, private (reweighted)	0.181	0.188	0.199	0.203	0.230	3.114	
Model, Medicaid	0.238	0.215	0.206	0.184	0.157	2.808	
Counterfactual: Medicaid patients with private ...							
availability	0.233	0.212	0.204	0.185	0.165	2.835	
choice parameters	0.194	0.197	0.199	0.201	0.210	3.036	

Notes: This table uses the results from estimating the constrained choice model to report results under alternative assumptions about choice sets. Specifically it reports the share of patient-stays going to nursing homes in each bin of the given quality rating (columns 1–5), the mean rating (column 6), and the mean distance in miles from patient to chosen nursing home (column 7). Bins are the 1–5 star ratings in Panels A and B and national quintiles of the EFM value-added score in Panel C; shares are over rated nursing homes. The Private rows are reweighted to reflect the distribution of Medicaid patients across markets, so that all private–Medicaid contrasts are within-market. Within each panel, the first two Observed rows show the raw data; the next two Model rows show the predicted allocation under the estimated constrained-choice model with audit-study-based availability probabilities $\hat{p}_{jg}$ that vary by payer and nursing home; and the last two Counterfactual rows show counterfactuals for Medicaid patients facing either the private availability probabilities while choosing with their own estimated choice parameters $\hat{\delta}_{j,\text{Medicaid}}$ and $\hat{\tau}_{\text{Medicaid}}$ (*availability*) or facing their own availability probabilities but choosing with the estimated choice parameters for private-pay patients $\hat{\delta}_{j,\text{Priv}}$ and $\hat{\tau}_{\text{Priv}}$ (*choice parameters*). The Model and Counterfactual rows are computed on common simulated choice sets, so that differences between them do not reflect simulation noise. Stays at nursing homes outside the patient’s market (the outside option) are assigned the rating distribution of the observed out-of-market stays in that market for the payer group whose choice parameters the row uses: Medicaid for the Medicaid Model row and the *availability* counterfactual, and private-pay for the private Model row and the *choice parameters* counterfactual. Mean distance traveled is invariant to the quality measure used and is therefore shown only in Panel A.

Online Appendix

A Audit Study Appendix

A.1 Audit Study Design

A.1.1 Choice of Medical Vignettes

We created sixteen vignettes capturing a range of conditions for which an individual might seek nursing home placement. Conditions were data-driven — using assessments from the Minimum Data Set at nursing home entry and conditions drawn from the Medicare Master Beneficiary Summary File — to determine common conditions present at nursing home entry that were not highly correlated with particular racial groups. They were also influenced by websites providing advice to those considering nursing homes (e.g., “A Place for Mom” and chat forums such as Reddit’s “r/AskOldPeopleAdvice”); these additional websites were consulted in response to pilot testing where respondents questioned the need for a nursing home based on the severity of several initial vignettes.

We constructed four core vignette types, with additional variations to create 16 messages:

1. Heart failure/respiratory disease and vision problems,
2. Falls and chronic condition,
3. Wheelchair use and chronic condition,
4. Alzheimer’s disease and chronic condition

Each inquiry includes health conditions motivating placement and an age ranging from 77 to 86. The complete set of vignettes is listed in Appendix C.

A.1.2 Choice of Names to Signal Race

For both Black and white inquiries, we constructed eight unique pairs of mother-daughter first names and (shared) last names; these are shown in Appendix Table A2.

First names. We generated racially distinctive mother-daughter first name pairs from a set of names evaluated for racial “congruence” in Gaddis (2017). To be racially congruent and successfully signal race, names must have a high race-specific share and be perceived by respondents as being the intended race. Gaddis used a survey to measure racial perceptions of first names with a high race-specific share drawn from New York State birth records from 1994 to 2012 in order to measure racial congruence. Gaddis’ list has two advantages over other sources for names such as previous audit studies or birth records. First, he tests racial congruence of names when paired with a distinctively Black or white last name, which mimics how names appeared in our study. Second, New York State birth records include the mother’s education, which we can use as a proxy for socioeconomic status.

We excluded first names associated with the lowest and highest quartile of mother’s education within race.²³ We also excluded the name “Heaven” from the list, to avoid names with additional connotations. We then selected the 16 highest scoring Black and white women’s names; for each name, at least 80% of respondents in Gaddis (2017) associated the name with the intended race. We used a

²³We do not attempt to equalize perceived socioeconomic status across names and races. Prior research shows racial distinctiveness and socioeconomic perceptions are tightly linked (Fryer and Levitt 2004). After excluding names in the highest and lowest within-race education quartiles where possible, remaining socioeconomic signals are treated as intrinsic to the racial cue.

large number of names for generalizability, as effects averaged over several names are more likely to reflect the impact of race than the particulars of a given name.

To assign first names to mothers or daughters, we sorted names within race using the year of peak popularity gathered from [Social Security Administration \(n.d.\)](#) name popularity data. These data report popularity for the entire population, not separated by race. Within race, we designated the half with earlier peak popularity for mothers and the half with later peak popularity for daughters. We then randomly paired mother and daughter names.

Black women of the age of our prospective patients are less likely to have racially distinctive names, because the practice of giving Black children racially distinctive names is relatively recent. As shown in Appendix Table [A2](#), the names chosen for Black mothers entered the top 1000 most popular baby names beginning in 1955, whereas any baby born after 1949 would be younger than 75 in 2024. Presenting an age and medical conditions alongside name in the inquiry text should mitigate concerns about age perception, as respondents do not need to infer age from the mother’s name alone.

Last names: Following [Gaddis \(2017\)](#), we selected last names with the highest race-specific share from the top 1,000 names recorded in the 2000 US Census. This yielded ten last names that were at least 95% white but only six last names that were at least 50% Black. Because we have eight pairs of Black first names, we repeated the two most common Black last names (Washington and Jefferson). We randomly matched last names with first name pairs by race (without replacement, with the exception of Washington and Jefferson).

We assigned each sender (daughter) an email address containing their first and last name using either Gmail or Outlook. When addresses were unavailable, we added middle initials (chosen arbitrarily based on availability, avoiding letters that were likely to appear unusual) or 1-3 numbers at the end. By including full names in email addresses we make use of a common email format and gain an additional racial cue opportunity ([Bergman and McFarlin 2018](#)). The complete list of email addresses is in Appendix Table [A15](#).

Each sender was also assigned a phone number with the area code 405 (Oklahoma City metropolitan area) provisioned from [Twilio](#). The area code was chosen to be consistent across senders, intended to be relatively anonymous, with a neutral racial and socioeconomic signal. Because phone numbers were in greater supply than appropriate emails, each combination of sender name, condition, and payer had a unique phone number, allowing for easier data matching.

A.1.3 Implementation Protocol

Seven research assistants (RAs) manually submitted inquiries using online contact forms.²⁴ This process was not automated, in order to account for differences between forms and features like Captchas that prevent automatic or high volume submissions. For consistency, RAs were instructed to follow the structured protocol below for submitting inquiries, and to record specific details of each submission. They used a custom application that we built to achieve fidelity of implementation and recording.

Initial assessment. Each RA was assigned a set of facilities indicated by name and URL on a spreadsheet. For each facility, RAs were instructed to first verify that the website contained an appropriate contact form. Submissions were attempted only when the form corresponded to a single facility²⁵, contained a free-text message field (so that the vignette could be entered), did not require a

²⁴We are grateful to Sophia Fend, Max Goldstein, Maura Hogaboom, Ro Huang, Ken Lin, Neha Narayan, and Cliona Poje for their help.

²⁵This could not be determined definitively as we do not observe how inquiries are routed on the backend; however, forms were not submitted if they included a dropdown menu or checkboxes for multiple facilities or if the user was taken from a specific nursing home website to a higher-level company website when accessing a contact form.

mandatory address or ZIP-code for the patient, and did not require scheduling a particular tour time. Forms failing these criteria were not submitted, and the RA entered the reason why submission could not occur.

Message formatting. In order to ensure delivery of the correct message content, RAs used a custom application that we built that displayed content for one facility at a time. RAs entered the URL from the assignment spreadsheet into a browser to access the contact form. The same URL was also pasted into the app, revealing the full text of the inquiry for that facility. RAs copied the previously randomly assigned message content directly from the application and pasted it into the facility’s contact form. This procedure was designed to minimize transcription errors and to try to ensure that the randomized treatment content was delivered exactly as assigned.

RAs were instructed to format the message similarly to an email, if allowed by the interface, including line breaks between the greeting, body text, payer message, and sign-off. Subject lines were included if forms allowed.

Because websites sometimes imposed formatting constraints or character limits, minor adjustments were permitted when necessary. In such cases, priority was given to preserving the placement and visibility of the payer message and RAs were instructed to preserve the core treatment elements: the mother–daughter names, the clinical scenario described in the vignette, and the payment message when present. Any truncated or modified messages were recorded in the submission log.

Additional fields. To minimize discretion, we specified rules for the RAs to follow when completing additional form fields that were commonly encountered.

- **Type of care.** When asked, research assistants selected “Skilled Nursing” or “Long-Term Care.” Categories such as assisted living, residential living, or memory care were avoided unless no alternative option existed.
- **Referral type.** When forms asked how the facility had been discovered, RAs were instructed to select “online” or the least-specific available option.
- **Tour.** If a form asked whether the sender was interested in scheduling a tour, RAs were instructed to indicate yes if the form was asking for a general expression of interest, but did not schedule tours or make reservations.
- **Contact information.** RAs included both the email address and phone number as contact options when possible. When a preferred contact method was required, RAs selected phone, because voicemail data was easier to link to the particular inquiry (see Section [A.1.5](#)).
- **Optional fields.** Fields other than those above were left blank.

Tracking. RAs tracked submissions using our custom-built application. They recorded the submission status, which generated a timestamp, and were able to indicate why an inquiry was not submitted (e.g., invalid link, missing message field, multi-location portal, or mandatory address fields). Decisions made, such as truncating a message, selecting a particular type of care, or expressing interest in a tour, were recorded at this time. These logs served as the primary record of treatment delivery. Each submission was also recorded in a centralized tracking spreadsheet.

These records were frequently reconciled with each other throughout the implementation period to ensure that no data was lost and that each attempted submission was recorded. In three cases, facilities where it was ambiguous whether a message had been submitted were reclassified as submitted after a response or automated confirmation was observed.

Monitoring. Incoming emails and voicemails were monitored daily, with a particular focus on evidence of detection of the study or unusual response patterns. No suspicion of the study was observed. Real time monitoring also allowed us to sort out unrelated messages, spam, or auto-replies, which was an efficient means of removing this content from the response data.

Treatment fidelity. Treatment fidelity was high. We encountered only 10 instances where the incorrect treatment was delivered to a facility. In 6 other cases, an additional message was sent, one with the correct information and one with an incorrect treatment. Results were analyzed using an intent-to-treat approach with treatment classified using the intended content, even if other content was delivered. In cases where multiple messages were sent, the correspondence from the correct inquiry was retained.

Deliverability. There is no evidence that we encountered deliverability issues. Appendix Figure A8 displays the number of inquiries sent by calendar date along with the response rate for messages sent on those dates. Response rates were stable over time with no indication of worsening response rates that could indicate delivery issues over the course of the study. As shown in Appendix Figure A4, response rates, and therefore availability, varied by the day of the week an inquiry was sent, with messages sent earlier in the week more likely to receive a response, but this feature is balanced across randomized conditions. Availability was also broadly similar among submitting RAs.

A.1.4 Ethical Considerations

Participants were not informed that they were involved in a research study or told the purpose of the study. The research could not have been conducted if the purpose was known to the subjects, because the goal of the project was to make inferences from natural behavior that would otherwise be unobservable. A respondent would likely behave differently if they knew they were participating in a research study or if they knew that the purpose of the study was to estimate the degree of racial or anti-Medicaid bias. Our results would not be able to speak to whether such bias existed outside of the confines of the study.

Ethical forethought is critical in studies that do not provide informed consent. We considered the possibility of reputational harm to nursing homes, the burden of responding to our messages, and the risk of spoiling the pool for future researchers when conducting this audit study.

There was a potential reputational risk if responses from a nursing home indicated bias. We minimize this risk of harm by only reporting average effects and by not identifying individual nursing homes. We did not (and cannot) estimate nursing home-specific levels of selective admissions.

The burden on respondents was minimal. We limited the number of inquiries per nursing home to two (separated by several weeks) and did not continue conversations beyond the initial inquiry. We did not contact nursing homes that required scheduling a specific tour as part of their contact form. An email or phone response from a nursing home likely only took a few minutes to craft, if one chose to do so, evidenced by the fact that we received many messages immediately following our inquiries and many messages that were quite short and basic. Limiting the burden on nursing homes also reduced the risk to actual applicants who may also need email responses from the nursing homes in our study.

We chose not to debrief participants as this might have raised concerns about their participation as well as raise suspicions about future correspondence, which could harm actual applicants to the nursing home or future research studies.

This study was approved by the Committee on the Use of Humans as Experimental Subjects (COUHES) at MIT (Protocol 2311001166). Stanford University determined it was not engaged in human subjects research.

A.1.5 Audit Data Collection

Outcome data was drawn from the content of responses to our inquiries. We linked inquiries to the replies received using a mix of automated and manual methods, with different procedures used for phone and email data. We included responses received within 30 days of each inquiry. Automated replies, marketing messages (occasionally, submitting an inquiry signed us up for a newsletter), and unrelated communications were removed from the dataset using manual sorting and keyword filters. For voicemails, we dropped transcriptions shorter than 50 characters to exclude incomplete or non-informative messages.

Voicemail matching. Because phone numbers were unique to each name, payer, and vignette combination, the set of facilities that could plausibly generate a voicemail was small and well-defined by design. We first attempted exact matching on phone number. If this was not successful, we used metadata where possible to narrow the set of candidate facilities and then tasked an LLM (OpenAI’s GPT-4.1, accessed via API) to use the transcript, metadata, and candidate set to select exactly one match from the list of candidate facilities, which we then manually reviewed. Remaining unmatched messages were manually matched by two research assistants working independently (with disagreements resolved by adjudication from a third research assistant) using the voicemail, transcription, metadata, and list of candidate facilities. Automated matching (where phone number and LLM match agreed) was successful for 80% of messages.²⁶ 16% were provisionally matched automatically and manually verified. 4% of matches were purely manual.

Email matching. From incoming email messages from nursing homes, we extracted identifying features such as name, email address, physical address, phone number, and sender from message headers, subject lines, and message bodies using rule-based text extraction in R. We first attempted to match facilities to their email messages using a deterministic, tiered approach: exact matching on phone number, then exact matching based on address (often narrowing to one possible candidate in the data), followed by attempting to match on a combination of name and zip code or name and email domain. (Domains were often not an exact match with a facility’s website domain, so exact matching on email address alone was not productive). Automated matches were manually reviewed by one research assistant. Unmatched emails were manually matched by two RAs, with a third review as a tiebreaker. 58% were automatically matched and 42% were manually matched, with no messages left unmatched.

Match verification. The following consistency checks were implemented as part of the data build, primarily as a check on implementation and matching to ensure that treatments were correctly assigned and that there were no false positive matches.

- Sample coverage:
 - Every nursing home attributed to a response appeared in the randomized study sample, ensuring no false positive matches or hallucinated facilities.
 - All responses came from nursing homes that were recorded as “submitted” rather than a nursing home we excluded or failed to treat.

²⁶The matching process was run multiple times during the study, with previously verified matches stored and incorporated into the pipeline before running it again, which improved our ability to match as we proceeded. A phone number or email address that was initially fully or partially manually matched could then be automatically matched for future messages. 18% were automatically matched because they were carried over from matches in a prior round.

- Each nursing home appeared at most once per round in the matched data.²⁷
- Correct treatment assignment: For each matched response, we verified the treatment assignment implied by the match corresponded to the assigned treatment. This was generally verified using the sender’s contact information. A response addressed to Tionna from a facility that had been assigned to receive an inquiry from Amy would indicate either an incorrect match or a treatment submission error.²⁸
- Timing of responses: All responses occurred on or after the corresponding inquiry send date; there were no responses dated before the inquiry was sent.

A.2 Measurement of Key Variables

A.2.1 Outcome Definitions

We coded “any response” as 1 if the inquiry received any response by voicemail or by email (not counting auto-replies) within 30 days and 0 otherwise and “number of responses” as the total number of responses across voicemails and emails (not counting auto-replies) received within 30 days.

Availability. Our primary outcome (“availability”) is coded 1 if the inquiry received a non-negative response regarding availability within 30 days. We used GPT-4o mini to code nursing home responses to inquiries about availability as yes, no, offering a waitlist, or unclear.²⁹ Availability is coded as a 1 if the response was a yes or unclear. It is coded as 0 otherwise. Unclear responses generally offered to follow up or asked for more information, rather than stating availability outright. Offers of a waitlist or a statement of availability for a different type of patient (i.e., having availability for private pay but not Medicaid) were treated as no availability. Outcomes were measured for each response message. If an inquiry received multiple responses, we coded the inquiry as receiving a response of “availability” as follows. First, if any response indicated a positive (yes) on availability it was coded as available (and within available as ‘yes’); second, if none of the responses indicated a yes, but none received a no, they were coded as available (and within available as ‘unclear’). Appendix Table A16 shows high agreement between the LLM and human coders on a random sample of 200 messages.

Examples of messages coded yes:

- “Hello Aaliyah, We received your inquiry message from the website and just wanted to follow up with you on this, as we do currently have space available. First step would be to have her primary doctor’s office send us some medical records on her to ensure we can meet her clinical needs.”
- “Hi, Stephanie, this is Heather, i’m calling from xxx health and Rehab in xx, xx. I received a inquiry from you regarding your mom. If you could give me a call when you get this xxx-xxx-xxxx. And again, my name is Heather in admission. I. I’ll be in the office for a little bit little bit today, but if I don’t get back to you today, I will touch base with you Monday morning. Um we do have availability and I would love to go over that process with you. Again, my name is Heather xxx-xxx-xxxx. Thank you.”

²⁷Six nursing homes were sent multiple inquiries in error. We include in the analysis data the inquiry and responses corresponding to the correct treatment.

²⁸10 inquiries were sent with the incorrect treatment. We analyzed the data using the original treatment assignments, using an intent-to-treat framework, rather than adjusting the assignment to match the delivered treatment. This would tend to slightly attenuate resulting treatment effects, although the number of affected observations was small.

²⁹A small number of responses (19) said that they did not have availability now but would at some point in the next 30 days (some said in a week, 2 weeks, etc). We coded these as indicating availability.

Examples of messages coded no:

- “Good morning, We currently have a pretty significant waiting list. We do not have any availability at this time. If you would like us to put her on the waiting list we sure can. When she gets to the top of the list we would reach out to you to ensure that we can meet her needs. I can’t really give a timeline to when it will be.”
- “Hi, this is Holly with xx nursing center. I just got an email from you asking if we had any long term for your mom right now. We do not have any long term beds open. I am sorry if you have any other questions you can call me back at xxx-xxx-xxxx. Thanks”

Examples of messages coded unclear:

- “Good afternoon, Please see attached community admission form and financial disclosure. Please fill out at your earliest convenience and email back to me. We will also need clinical notes/insurance information sent by her Primary care physician faxed to xxx-xxx-xxxx for review. If you have any questions please contact me at xxx-xxx-xxxx.”
- “Good morning, my name is Tiffany and I’m calling from xxxx rehabilitation center. I was trying to reach to mia. I received your email in regards to your mother needing rehab placement. You can give me a call back at xxx-xxx-xxxx. Thank you.”

Some responses indicated that there was availability for private-pay patients but none for Medicaid. If flagged by the LLM, these were coded as no if the payment message was Medicaid and yes otherwise. Examples:

- “good morning, this message is for aliyah. Booker. My name is xxx. I am calling you from xxx. You had inquired through our website, looking for skilled nursing care for your mom and shared with us a little bit about her situation. Unfortunately, we’re not going to be able to accommodate her. We. We do not take direct admissions for medic when somebody is on Medicaid. We’re a life planned community, so we leave those skilled nursing rooms for our independent living residents. So unfortunately not gonna be an option for your mom, but I, I appreciate you reaching out just the same. If you have any other questions, feel free to call me at xxx-xxx-xxxx. Thank you so much bye.”
- “Hello Tamia, Unfortunately, we do not have any Medicaid beds available at our facility. We require at least 2 years of funds private pay before spending down into Medicaid due to our bed availability being so limited. I apologize for the inconvenience. Thank you.”
- “XXX is a private pay long term care facility. We only have a few Medicaid beds which we reserve for residents that have paid privately for at least two years.”

Sentiment. Sentiment was coded using GPT-o4 mini with the following prompt: “You are coding nursing-home replies to a family asking about a mother’s care. Return a sentiment score and label using the following rubric. Avoid using length or availability alone; focus on tone and content.

- Positive (0.7-1.0) – Warm or sympathetic tone (e.g., expresses care about the mother), welcoming, supportive, friendly.
- Neutral (0.4-0.6) – Informational or logistical response without strong warmth or rejection; polite but matter-of-fact.

- Negative (0.0-0.3) – Dismissive or strongly constrained in a way that feels unhelpful (e.g., ‘we cannot help’, ‘we will not accept’).”

If an inquiry received multiple responses, the inquiry-level outcome took the maximum sentiment from the set of response messages.³⁰ Examples of messages with positive sentiment:

- With availability: “Hello Erica, Thank you for your interest in XX. It sounds like your mother would be a perfect fit for our facility. At the moment we have one private room available. Another family is interested in the room and we will be making our decision soon as to whether we will admit the person or not. Please feel free to call me with specific questions, xxx-xxx-xxxx. Best regards, xxxx”
- With no availability: “Hello Tionna, xx here from xxx Care Center. Would you be interested in placing your loved one on our waiting list. Currently, we have five on our waiting list. Do you mind if I call you to get more information if your interested? I look forward to connecting with you soon if you are okay with it. Thank you, xxx”

Examples of messages with negative sentiment:

- With no availability: “Hi is xxx. This is xx in admissions, at xx nursing rehab. Returning your call concerning your mom. Uh we it’s, I, we, we do not have services here at our facility to be able to help you out so I can’t help you. I’m sorry. Thank you so much bye.”
- With waitlist: “We received an inquiry in regards to looking for long term care for your mother. We would need a financial application completed. I’ve attached that for you to complete and return. We do not currently have any Medicaid beds available and do not anticipate any for the foreseeable future. Once we receive the financial application, we would need to have clinical information in order to review for appropriateness to care for her. Thank you, xxx”

A.2.2 Measurement of Nursing Home Quality

We use three different quality measures. The first two are CMS’ overall quality rating and CMS’ staffing quality ratings (a subset of the overall ratings). These quality ratings run from 1 to 5, with 5 being the highest. CMS bases its overall quality rating on performance in three domains: health inspections (based on the number, scope, and severity of deficiencies identified through inspections and surveys), quality measures (based on MDS and claims-based quality measures), and staffing. CMS bases its staffing rating on six underlying measures, including three nurse staffing level measures (hours per resident per day) and three measures of staff turnover. The staffing measures are derived from data submitted each quarter through the Payroll-Based Journal (PBJ) System, along with daily resident census derived from Minimum Data Set, Version 3.0 (MDS 3.0) assessments. The nurse staffing level measures are case-mix adjusted based on the distribution of MDS 3.0 assessments by nursing case-mix Groups (CMGs) from the Patient-Driven Payment Model (PDPM) and cover a single quarter. The turnover measures use six consecutive quarters of PBJ data to define annual turnover for nursing staff and administrators. Overall quality is available for 2,919 of the 2,940 facilities in our sample. Staffing quality is available for 2,916 of the 2,940 facilities in our sample.

For the audit study analysis in Section 4, we use the CMS ratings from the July 2025 CMS (2025b) Provider Information dataset. For the choice model analysis in Section 5 which currently uses the 2022

³⁰Our investigation of LLM performance on this task suggested high-quality, stable results. Human coders proved far less consistent, therefore we do not present an agreement table as we do for availability.

MDS, we use information from the CMS Nursing Homes Provider Information dataset from December 2022 (CMS 2022b).

The third quality measure, EFM value-added, is from Einav et al. (2025). As described in Section 4, it uses changes in patient health assessments over the course of the nursing home stay to construct a value-added measure for each nursing home that accounts for patient selection both into and out of the facility, based on 2011–2016 data on patients admitted from the hospital. We convert the continuous value-added measure to a 1–5 scale by assigning each facility to the national quintile of its value-added score. Inquiries to facilities with a non-missing EFM value-added score account for 5,002 of our 5,594 inquiries.

A.2.3 Data Sources and Measurement of Other Nursing Home Characteristics

Occupancy rate. Occupancy rate is defined as the daily resident census divided by the number of federally certified beds. Daily resident counts are provided by the Payroll Based Journal Daily Nurse Staffing (PBJ) dataset. Federally certified bed counts are sourced from the CMS Provider Information dataset.

For the analysis of the audit study we use the resident count for the date that the inquiry was sent from the 2025 PBJ dataset (CMS 2025a) and the bed count from CMS (2025b). From our baseline analysis sample of 2,940 nursing homes, we exclude 11 nursing homes with missing PBJ or CMS bed data; for 40 nursing homes with calculated occupancy rates exceeding 1, we set their occupancy rate to 1.

For the choice model analysis in Section 5 which uses 2022 MDS data, we use 2022 data on the average daily resident census (CMS 2022a), and the number of certified beds is based on the 2022 CMS Nursing Home Provider Information dataset (CMS 2022b).

Private and Medicaid reimbursement rates. We use two different data sets to approximate private and Medicaid reimbursement rates at the state level. For private reimbursement rates, we use an online resource put together by the American Council on Aging (2019) which shares the average self-pay daily cost for a shared room (the only room type that would be Medicaid-eligible) for each state in 2019.

For Medicaid reimbursement rates, we use a Medicaid and CHIP Payment and Access Commission (2023) analysis that estimates mean Medicaid daily base payments within each state in 2019. These MACPAC estimates include resident contributions to costs, but do not include lump sum supplemental payments that states make to nursing homes, which may be significant in some states. Note that MACPAC does not share data for Alaska, Idaho, or New Hampshire. As a result, we have private and Medicaid reimbursement rates for 2,904 of the 2,940 facilities in our analysis sample.

Importantly, our measures of both private and Medicaid reimbursement rates have significant limitations. First, both are at the state (rather than facility) level. Second, MACPAC’s estimates do not include lump sum Medicaid payments to states; they therefore are likely to underestimate Medicaid payments, and the degree of this underestimation may vary by state. The American Council on Aging does not publish a detailed recounting of their methodology.

We define the reimbursement rate difference as the percentage difference in private and Medicaid rates, or $(private - Medicaid)/private$.

Using these data we estimate that the average state has a private reimbursement rate that is about 16% above the Medicaid rate. Six states (Oregon, Delaware, Arkansas, Kansas, Utah, and Oklahoma) in our data have higher Medicaid than private reimbursement rates, possibly indicating low quality data. At the high end, the top two states, Massachusetts and Connecticut, have reimbursement rate differences of 47% and 45%, respectively.

Number of certified beds. Federally certified bed counts are sourced from the CMS Provider Information dataset CMS (2025b). Bed counts are non-missing for all nursing homes in our audit sample.

Profit status. Profit status is sourced from the Ownership Status variable in the CMS Provider Information dataset CMS (2025b). It is coded as 1 if the nursing home is for-profit and 0 if it is government-owned or nonprofit. Profit status is non-missing for all nursing homes in our sample.

Chain status. Chain status is sourced from the CMS Provider Information dataset CMS (2025b). It is coded as 1 if CMS records a non-missing chain name for the facility, and 0 otherwise. There are no missing entries.

Alzheimer’s unit status. Alzheimer’s unit status is sourced from LTC focus LTCFocus (2022). It is coded as 1 if a facility reported having any Alzheimer’s Disease beds and 0 otherwise.

A.3 Construction of Audit Study Analysis Sample

Appendix Figure A1 shows our sample exclusions from the initial sample of 14,845 nursing homes in the United States to the 4,023 nursing homes that formed our main *target sample* of nursing homes to which we attempted to send inquiries, to the construction of our final *analysis sample* of 2,940 nursing homes to whom we submitted at least one inquiry. Randomization of treatments was done based on our target sample. We randomly assigned each facility in our target sample to receive two inquiries, to be delivered over two study implementation rounds. In practice, in about 30 percent of cases we were unable to submit an inquiry to a facility in the target sample. In all, our analysis sample consists of the 2,940 nursing homes to which we submit a total of 5,594 inquiries. 2,654 received two inquiries; of the nursing homes that received only one inquiry, 167 were in the pilot, and the other 119 were in round 1.

A.3.1 Target Sample for Inquiries

Our initial target sample for submitting inquiries was the 4,023 nursing homes that we determined accepted patients from the community and that have online contact forms that met our criteria. To form this sample, we began with the June 2024 CMS (CMS 2024), a publicly available list of skilled nursing facilities in the United States that contains facility-level identifiers such as name, address, and CMS Certification Number (CCN) (provider number), as well as ownership information. The June 2024 dataset contained 14,845 skilled nursing facilities. We first excluded approximately 1,000 facilities that reported accepting only Medicare or were hospital-based (i.e. listed as “Provider Resides in Hospital”); this was done in order to focus on facilities that were likely to take patients from the community or on Medicaid. We then used a webscraper to locate online contact forms for the remaining facilities, as no list of nursing homes provided a list of websites or contact forms. We excluded 8,504 facilities where we could not find a website (about 65 percent of exclusions), could not find a contact form (about 25 percent), or where the contact form was shared among multiple facilities (about 10 percent). This resulted in 5,338 nursing homes potentially eligible for the study.

Based on the results of the small-scale pilot of inquiries sent to a random sample of 200 nursing homes from the list of 5,338 in March 2025, we made one additional category of exclusion intended to reduce the risk of detection of the audit study: for groups of nursing homes with shared ownership, we randomly sampled 16 facilities (equal to the number of names and vignettes constructed, though treatment randomization was not stratified within ownership group). This exclusion was made because in the pilot we observed that some nursing home chains appeared to route contact form inquiries

through centralized admissions or marketing staff responsible for multiple facilities. In several cases, inquiries submitted to different facilities within the same ownership group generated responses from the same email address. This raised the possibility that sending multiple audit inquiries to facilities within a large chain could increase the risk that staff detect similarities across messages. We used the “Affiliated Entity” recorded in the CMS Provider Information dataset, which identifies ownership groups and chains, to make these exclusions. In the end, our target sample of nursing homes to which we would attempt to send inquiries included 4,023 distinct nursing homes.

A.3.2 Randomization

Pilot. We randomly selected 200 nursing homes from the 5,338 we initially deemed eligible for study for a pilot in March 2025. In the pilot, each facility was only contacted once, and only four vignettes were used (the A version for each of the key vignette categories). Race, payer, and vignette were each assigned by simple random assignment in a 2 x 3 x 4 factorial design. Of these 200, we were able to submit inquiries for 167.

Round one. Round one of the full study was implemented over a three-week period in June 2025. The 4,023 nursing homes in our target sample were randomly assigned to a 2 x 3 x 16 treatment using simple random assignment of race (Black or white), payer (Medicaid, private, unspecified), and medical vignette (one of 16 possibilities). Within the race treatment we further randomly assigned one of the eight possible name treatments, again using simple random assignment.

Round two. Our round two target sample was the 2,822 nursing homes that we had successfully submitted a round one inquiry to; as detailed in the next sub-section, round one implementation revealed that we could not submit inquiries to about 30 percent of the facilities in the target sample. Round two inquiries were constructed using random assignments conditional on not repeating the same payer, race, or vignette treatment used for that facility in round one.

A.3.3 Analysis Sample of Delivered Inquiries

We define our analysis sample as the 5,594 inquiries that we ultimately sent to 2,940 nursing homes. This consists of 167 inquiries submitted during the pilot, 2,773 inquiries submitted during round one, and 2,654 inquiries submitted during round two. At most one inquiry was sent to each nursing home in each of these three stages, and at most two inquiries in total were sent to any given nursing home over the course of the study.

As detailed in Appendix Figure A1, we discovered during implementation (or in a few cases, shortly thereafter) that about thirty percent of the 4,023 facilities in our target sample were in fact not suitable to our study. In particular, many of the facilities did not have a working website for submitting a contact form (either the website form was non-functioning or we arrived at the incorrect website and could not find the correct one, collectively noted as “invalid” in Appendix Figure A1); in addition, some had a form that served multiple facilities, or did not provide a free-text field for us to submit our message vignette, or required information (like patient zip code) that we chose not to provide. In addition, it turned out that a small number of forms were intended for other purposes, such as to contact current residents or for job inquiries. This information could not be gleaned until we visited the website. Most exclusions were determined during study fielding; a small number (78) were made after implementation was complete.³¹

³¹We noticed during implementation that some websites in our target sample were not in fact nursing homes; they were instead, for example, Chambers of Commerce, local law firms, or nursing home placement services where the webscraper found contact forms. In addition, a small number of facilities did not meet our sampling frame because rather than

In round two, we attempted to contact only those we successfully contacted in round one. Because some round one statuses were subsequently updated based on additional information, and because issues were not always stable between rounds (for example, a form that allowed submission during Round 1 occasionally removed its message field or introduced new required fields by Round 2, preventing submission of the second inquiry) round one submissions and round two attempts do not match exactly.

A.4 Preregistration and Changes from the Prespecified Analysis Plan

This trial was preregistered with the Open Science Framework (OSF) and registered on the AEA RCT Registry (AEARCTR-0018639). An analysis plan was archived after analyzing pilot data from our initial attempt to implement the study using email rather than online contact forms (Einav et al. 2024). The preregistration and analysis plan were embargoed during the implementation of the study to prevent detection. A replication package of code and data will be posted to Dataverse upon publication, so that other researchers can reproduce, extend, and adapt our analyses.

The preregistration and analysis plan envisioned an email-based study, which was attempted and rejected after a pilot in Fall 2024 found evidence not only of large-scale problems with emails being undelivered or sent to spam, but of potentially differential rates of such blockages based on the email address, which was being used as part of the way to signal race. The study was redesigned to use online contact forms.

Design modifications. In switching to contact forms, we made other adaptations to the study based on the results of our email pilot.

1. We expanded from 4 to 8 name pairs per race to allow for greater generalizability and to reduce the risk that results are driven by any particular name.
2. We similarly expanded from 4 vignettes to 16 (based on the same 4 core types) to allow for greater variety in messages.
3. We added phone number as a contact method, both because forms often required phone numbers and because the responses in our email pilot confirmed that phone was most facilities’ preferred method of communication.
4. Because of the manual nature of submitting contact forms, we did not impose the same timing and send volume limits that we established for the email study (which were sent from 12pm to 2pm at a rate designed to stay below mass email thresholds that would trigger blockages). Online contact forms were submitted during Eastern business hours, with no limit on the number of submissions per day.
5. We planned to use blinded human coders to augment sentiment and availability coding by LLMs. This turned out to not always be feasible or desirable, because coding often required knowledge of the treatment, for example if a response indicated that a facility only had private beds available. In practice, we have largely relied on LLM coding. Appendix Table A16 shows that LLMs were quite accurate at determining availability relative to human coders.

serving elderly long-term care patients from hospitals or the community, they provided skilled nursing care to a different population — such as pediatric nursing care, psychiatric nursing care, or care for a particular condition such as cerebral palsy. As a result of these discoveries, after implementation we conducted a full audit of every URL contacted to confirm that URLs corresponded to the intended recipient facility, the form was not for multiple facilities, and the target population was correct. All candidate facilities for exclusion were reviewed independently by two reviewers. Decisions were based solely on pre-treatment public information, in order to avoid risk of bias in constructing the sample. When in doubt, we deferred to the original submission decision.

6. We specified a number of data sources for covariates. In practice, we use the CMS (2024) Provider Information data whenever possible, because it has the best coverage of our sample.

Analysis modifications.

1. We prespecified models with and without controls; however, while our analysis plan emphasized models without controls, our primary outcome results (e.g. Tables 1-4) all include controls for round (because randomization took round into account) and day of week sent (because this was less balanced in the contact form version of the study and because we observe differences in response rate depending on the day sent). Appendix Table A8 shows results without controls for day-of-week.
2. Examining heterogeneity by occupancy was not pre-specified. This was instead hypothesized as something to investigate when looking at the null results for race, with the argument that preferences for certain patients over others may not bind when beds are widely available but may come into play as availability becomes tighter.
3. Examining heterogeneity by chain status was also not prespecified, though for-profit status was. The importance of chains became clear during the audit study, as many nursing homes appeared to have centralized admissions processes that covered multiple facilities.

A.5 Additional Prespecified Audit Study Results

A.5.1 Heterogeneity in Availability Gaps by Facility Characteristics

White-Black Availability gap. We examine heterogeneous effects on the white-Black availability gap along the same dimensions. Appendix Figures A9 through A11 present results by occupancy, quality, and number of beds, respectively, and Appendix Table A18 presents results by profit status, chain status, and region. We find no evidence of differential effects along any of these dimensions, consistent with our main finding of null effects on the White-Black availability gap overall.

Private Pay vs. Medicaid Patient Availability Gap. Appendix Figure A12 shows availability for private-pay patients and Medicaid patients by decile of the occupancy rate distribution among the nursing homes in our analysis sample; column (1) of Appendix Table A19 summarizes the findings.

Appendix Table A20 and Appendix Figure A13 report additional heterogeneity in the private-Medicaid availability gap by for-profit status, chain status, region, and number of beds.

Appendix Figure A14 shows availability for private-pay patients and Medicaid patients by quintile of the average percent gap in reimbursement rates for private payers relative to Medicaid for nursing homes in that state; column (2) of Appendix Table A19 summarizes the findings. At the mean reimbursement rate difference among the nursing homes in our analysis sample (13.6%), availability for Medicaid patients is 4.8 (standard error = 1.3) percentage points lower than for private-pay patients. A 10 percentage point increase in the reimbursement rate difference is associated with a 1.5 (standard error = 0.7) percentage point decline in availability for private-pay patients, and an additional 1.4 (standard error = 0.8) percentage point widening of the private-Medicaid availability gap, though this interaction is not statistically significant. As noted above, we suspect that our current measure of reimbursement rates has substantial measurement error, which may be biasing downward our estimates of the relationship between the availability gaps and reimbursement rate differences.

Availability Gap for patients with and without Alzheimer’s Appendix Figures A15 and A16 present heterogeneity in the availability gap by occupancy rate and number of beds, respectively, and Appendix Table A21 presents results by profit status, chain status, and region.

A.5.2 Availability by Disaggregated Treatment

Appendix Figure A2 shows the availability rate for the four major vignettes and sixteen vignette subcategories. Statistical tests show that within each major vignette, none of the four sub-vignettes are statistically distinguishable, indicating that the specific clinical details do not affect availability. Among the six possible pairwise comparisons of the four major vignettes, only one comparison is statistically significant after correcting for multiple comparisons (Tukey 1953): vignette 2 (falls and chronic conditions) exhibits 4.52 percentage points higher availability than vignette 4 (Alzheimer’s) (standard error = 1.7).

Appendix Figure A3 shows availability for the sixteen possible daughter names, which ranges from 32% to 40%. None of the 120 pairwise comparisons are significant and no names differ significantly from the mean of the others after correcting for multiple comparisons (Tukey 1953).

Finally, to examine whether availability differs across all 24 vignette-payer-race combinations, we conducted pairwise comparisons with Tukey (1953) adjustment for multiple testing. Of the 276 possible pairs, 23 are statistically significant at $p < 0.05$ (Appendix Table A17). The significant pairwise combinations align with the main analysis findings, where payer and vignette are the primary drivers of availability. Of the 23 significant pairs, 20 involve a difference in payer type. Eight of these 20 pairs hold both vignette and race constant – meaning that all private–Medicaid comparisons with race and vignette fixed are statistically significant. No significant pair differs only in race. 10/23 of the significant pairs include Vignette 4 (Alzheimer’s), which aligns with the main results on vignette. However, none of these 10 pairs hold payer constant.

B Estimation Appendix

This appendix provides estimation details for the constrained-choice-set model introduced in Section 5. The model is estimated separately by market and payer group $g \in \{\text{Priv}, \text{Mcd}\}$. For expositional ease, we discuss estimation for one such market and payer group and suppress the market index. Within this cell, the deterministic component of patient i ’s choice utility in equation (2) is $V_{ij} = \delta_{j,g} - \tau_g m_{ij}$, where m_{ij} is distance in log-miles and the outside option $j = 0$ is normalized to $V_{i0} = 0$.

Availability is unobserved, so the probability that patient i chooses inside home j marginalizes over the availability of the *other* homes in her market J_i . Letting y_i denote i ’s chosen home and $S \subseteq J_i \setminus \{j\}$ denote the set of other available homes,

$$\Pr(y_i = j) = \hat{p}_{j,g} \cdot \mathbb{E}_S \left[\frac{e^{V_{ij}}}{1 + e^{V_{ij}} + \sum_{k \in S} e^{V_{ik}}} \right], \quad \Pr(y_i = 0) = \mathbb{E}_S \left[\frac{1}{1 + \sum_{k \in S} e^{V_{ik}}} \right], \quad (3)$$

where each home k enters S independently with its predicted availability rate $\hat{p}_{k,g}$ (the random-forest predictions described in Section 5), and the 1 in the denominator is the always-available outside option ($e^{V_{i0}} = e^0$).

Simulated maximum likelihood. The simulated maximum likelihood (SML) estimator replaces the expectation in (3) with an average over L simulated availability draws. For each patient, we draw L independent sets $S_{i1}, \dots, S_{iL}$ (with home k included with probability $\hat{p}_{k,g}$), including the chosen nursing home, and maximize

$$\hat{\ell}_L(\theta) = \sum_i \ln \left[\frac{1}{L} \sum_{r=1}^L p_i(\theta; S_{ir}) \right], \quad p_i(\theta; S) = \frac{e^{V_{iy_i}}}{1 + \sum_{k \in S} e^{V_{ik}}}. \quad (4)$$

C Vignettes

Vignette 1: Heart failure/respiratory + vision problems

Vignette 1(A). Subject line: Nursing home availability for my mother

Hello,

I'm sending this message on behalf of my 82-year-old mother, {MOTHER NAME}. She has been having some trouble living independently recently. Unfortunately, she has been going through heart failure for about two years now, and she has some issues with cataracts, which limits her being able to get around safely at times. Given these challenges, she is looking for a more stable living situation at a nursing facility, but otherwise, she is in good spirits.

{PAYMENT MESSAGE}

Do you have any openings?

Thank you!

{DAUGHTER NAME}

Vignette 1(B). Subject line: Searching for nursing home care for my mother

Hi there –

I'm reaching out on behalf of my mother, {MOTHER NAME}, who is 80 years old. She has glaucoma, which frequently affects her mobility, and was diagnosed with heart failure a little over a year ago. She is still sharp but has recently faced challenges with living independently, and we both think a nursing facility would be a safer environment.

Do you currently have any space?

{PAYMENT MESSAGE}

Thank you!

{DAUGHTER NAME}

Vignette 1(C). Subject line: Inquiry about availability for my mother

Hi,

My mother, {MOTHER NAME}, is 81 and has been facing more challenges living on her own lately. She has been living with COPD for a couple of years and has increasingly suffered from worsening vision and hearing, which often limits her ability to get around safely. She's still doing well mentally and emotionally, but she and I both believe that being in a nursing facility would help her thrive.

{PAYMENT MESSAGE}

Do you have any space available?

Thank you!

{DAUGHTER NAME}

Vignette 1(D). Subject line: Nursing facility placement for my mother

Hello,

My name is {DAUGHTER NAME}, and I'm reaching out about my 79-year-old mother, {MOTHER NAME}. After a couple years dealing with heart failure and mobility challenges due to poor vision, she is no longer able to live independently. She is otherwise positive and is hoping to transition to a more stable care setting!

{PAYMENT MESSAGE}

Do you currently have openings at your facility?

Thank you!

Vignette 2: Falls + chronic condition

Vignette 2(A). Subject line: Seeking a good nursing home for my mother

Hi there –

My mother {MOTHER NAME} is 86 years old, and the family is looking to transfer her to nursing home care. In the last year, she has had several falls and often complains about struggling with her balance. She is also anemic and has high cholesterol. Otherwise, she is in pretty good health for someone of her age, but I worry about her safety at home, and she and I both agree that it is time to move to a facility.

{PAYMENT MESSAGE}

Is there any space at your nursing home?

Thanks,

{DAUGHTER NAME}

Vignette 2(B). Subject line: Looking for nursing home placement for my mother

Hi,

We are seeking to move my 83-year-old mother, {MOTHER NAME}, into a nursing home. Lately, she has experienced several falls and has ongoing balance issues. She also has high blood pressure and cholesterol. While she's in fairly good shape otherwise, for her safety and well-being, we both feel it's time for her to have professional care.

Is there any availability at your facility?

{PAYMENT MESSAGE}

Thank you!

{DAUGHTER NAME}

Vignette 2(C). Subject line: Availability for my mother at your nursing home

Hello,

I'm reaching out about my 82-year-old mother. {MOTHER NAME} has had multiple falls recently

and struggles with balance, in addition to living with diabetes. She's still relatively healthy, but her safety at home has become a concern. She and the family both feel that moving to a nursing home would be the right next step.

Do you have any openings?

{PAYMENT MESSAGE}

Thanks,

{DAUGHTER NAME}

Vignette 2(D). Subject line: Nursing home inquiry for my mother

Hi there,

My name is {DAUGHTER NAME}, and I'm writing on behalf of my 81-year-old mother, {MOTHER NAME}. Although she's doing fairly well, she's had a few bad falls in the past year and has ongoing balance problems. She also has arthritis and high cholesterol. Given these challenges, she thinks that a nursing home would be a better environment for her at this point.

Is there any space available?

{PAYMENT MESSAGE}

Thanks!

{DAUGHTER NAME}

Vignette 3: Wheelchair use + chronic condition

Vignette 3(A). Subject line: Opening for my mother

Hello –

I am searching for a nursing home for my 77-year-old mother, {MOTHER NAME}. She has been having some health challenges recently, particularly around mobility, and is currently in a wheelchair, which is making it difficult for her to care for herself. She also has diabetes, which she had previously been managing well, but she recently has been having issues regulating her blood sugar and medication. The family has been taking care of her, but we do think that she might receive better care in the hands of professionals.

{PAYMENT MESSAGE}

Is there any availability at your facility?

Thank you,

{DAUGHTER NAME}

Vignette 3(B). Subject line: Looking for a nursing home for my mother

Hi,

My name is {DAUGHTER NAME}, and I'm writing about my mother, {MOTHER NAME}, who is 80 years old. Recently, her health has declined — she's now using a wheelchair, making it hard for

her to live independently. She also has high cholesterol and blood pressure, which have been hard to control lately. She and I both believe professional care would help support her needs better than we can at home.

Would your facility be able to accommodate her?

{PAYMENT MESSAGE}

Thank you!

{DAUGHTER NAME}

Vignette 3(C). Subject line: Nursing home placement inquiry

Hello there,

I'm searching for a nursing home for my mother, who is 79. In the past year, {MOTHER NAME}, transitioned to a wheelchair and has had increasing difficulty with mobility. She also struggles with handling her COPD properly now. She is hoping to find a facility where she can receive better day-to-day care.

Would you have any openings?

{PAYMENT MESSAGE}

Thanks,

{DAUGHTER NAME}

Vignette 3(D). Subject line: Availability for my 78-year-old mother

Hello,

I'm reaching out regarding my mother, {MOTHER NAME}. She's 78 years old, currently wheelchair-bound, and has been having trouble caring for herself. Additionally, her cholesterol, which had been under control, has recently been harder for her to regulate. We think she would benefit greatly from professional nursing home care.

{PAYMENT MESSAGE}

Do you have any open spots?

Thank you,

{DAUGHTER NAME}

Vignette 4: Alzheimer's + chronic condition

Vignette 4(A). Subject line: Openings for an upcoming move

Hello,

My name is {DAUGHTER NAME}, and I'm reaching out about my 81-year-old mother, {MOTHER NAME} who recently got diagnosed with Alzheimer's. She is still in pretty good shape (can hold a conversation, etc.), but in the long term we think it would make sense for her to stay in a nursing home like yours. She also has heart disease, though she's been eating healthy and exercising to help

combat it.

{PAYMENT MESSAGE}

Do you happen to have any openings for her?

Thanks!!

Vignette 4(B). Subject line: Nursing home availability for my mother

Hi,

I'm writing about my 83-year-old mother, {MOTHER NAME}. She was diagnosed with Alzheimer's a few months ago. Though she's still able to hold conversations and is fairly independent for now, the family believes that long-term, a nursing home would be best. She also has COPD but has been managing it well so far.

{PAYMENT MESSAGE}

Do you have any availability?

Thanks!!

{DAUGHTER NAME}

Vignette 4(C). Subject line: Inquiring about openings for my mother

Hi there –

I'm reaching out about my mother, who is 84 years old. {MOTHER NAME} was recently diagnosed with Alzheimer's, though she remains attentive and conversational at the moment. She also has high cholesterol, but with medication, diet, and exercise, she has been handling it well.

{PAYMENT MESSAGE}

Would you happen to have any spots for her?

Thank you,

{DAUGHTER NAME}

Vignette 4(D). Subject line: Seeking a nursing home spot for my mother

Hello,

I am looking into nursing home options for my 81-year-old mother, {MOTHER NAME}. She was diagnosed with Alzheimer's not too long ago, and although she is still functioning well day-to-day, she and I both would like to plan ahead for a supportive environment. She also has diabetes, which she works hard to regulate.

Would your facility be able to accommodate her?

{PAYMENT MESSAGE}

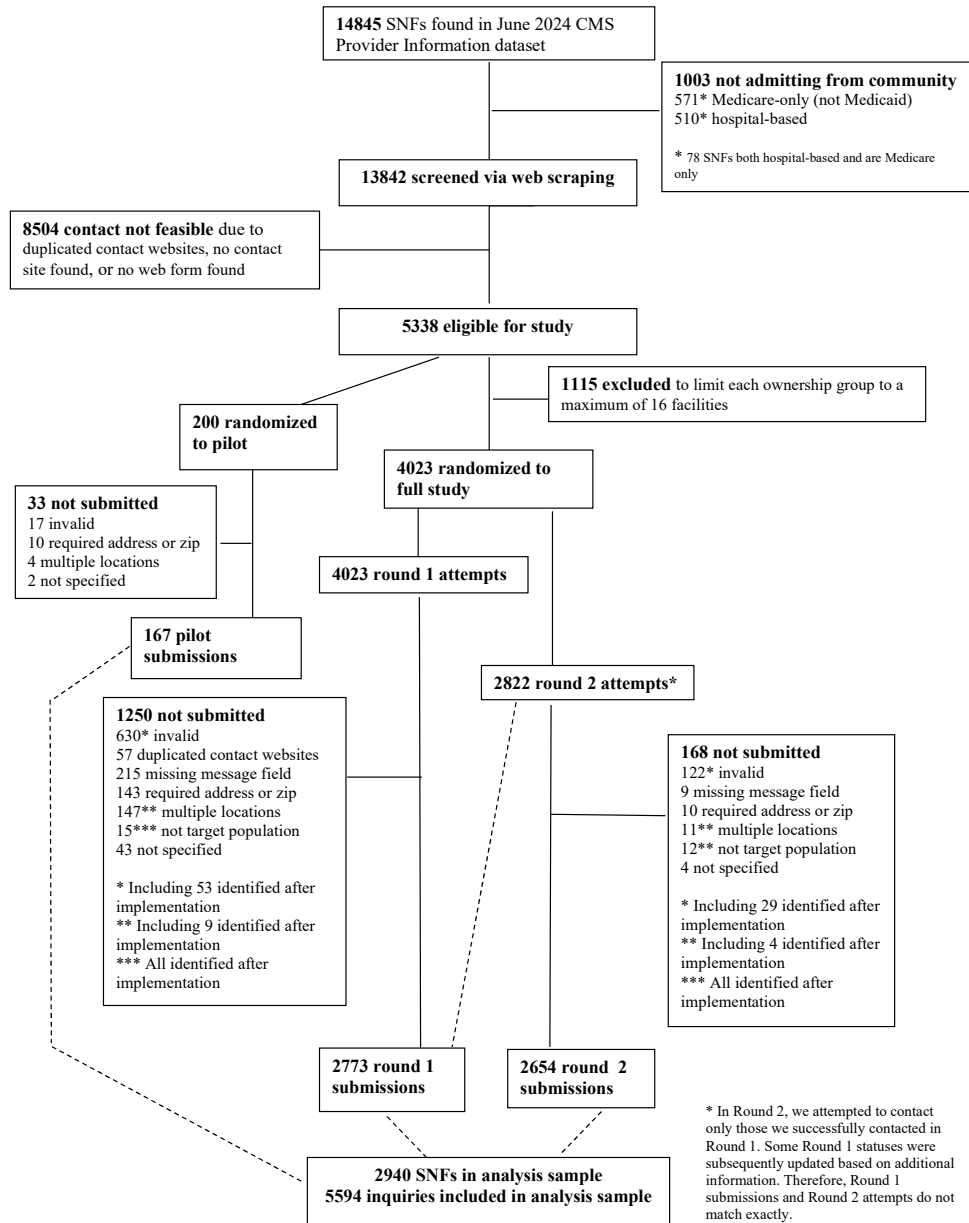
Thanks!!

{DAUGHTER NAME}

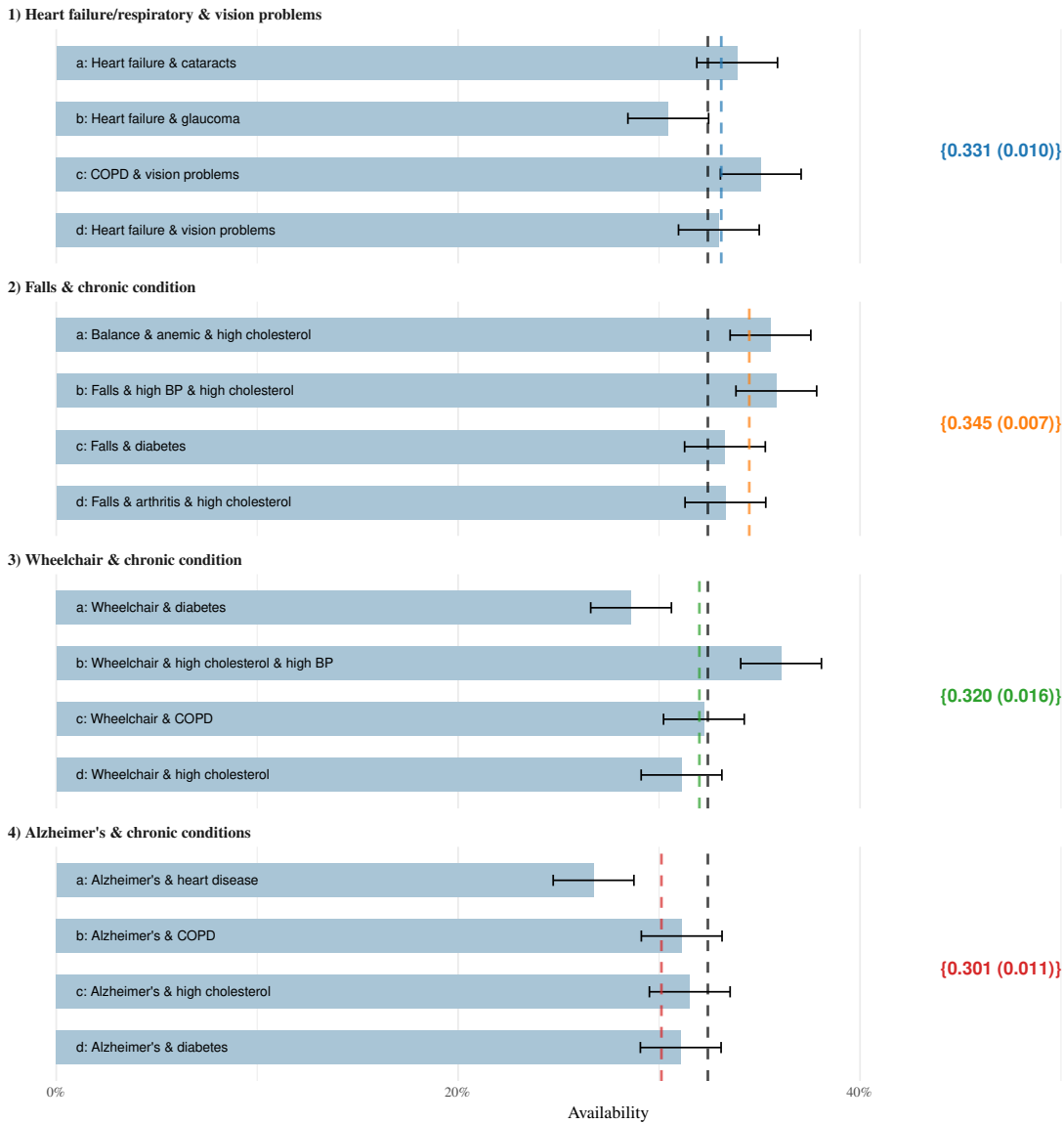
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Appendix Figure A1: CONSORT Diagram

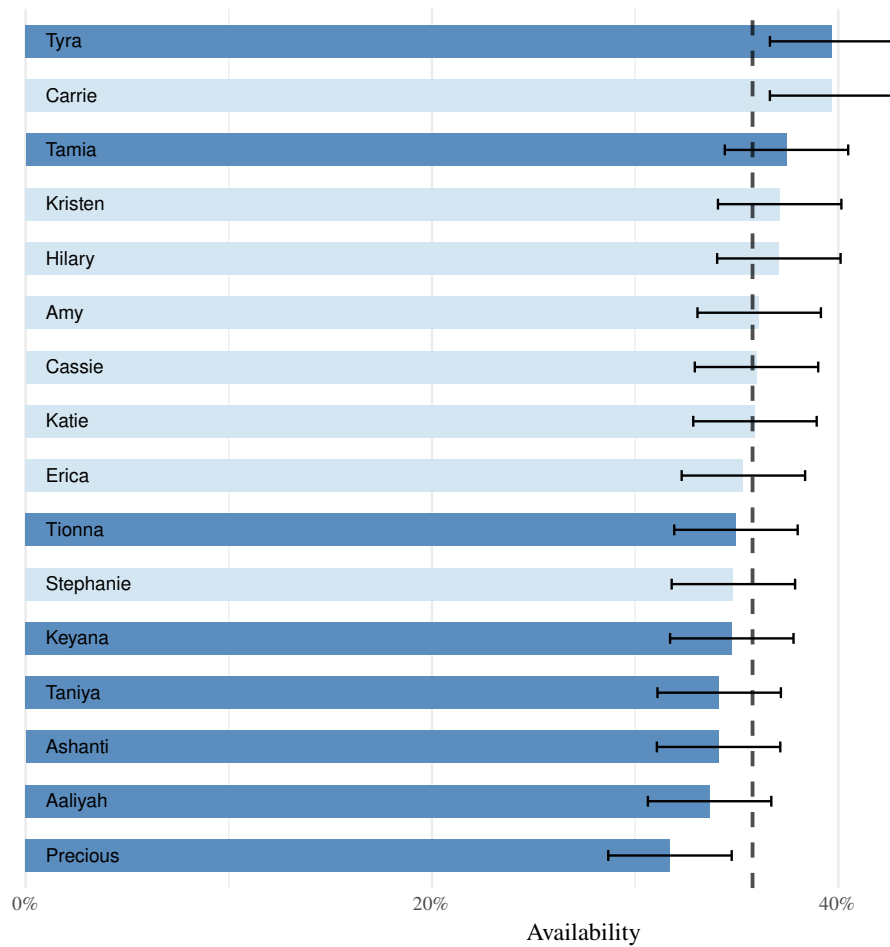


Appendix Figure A2: Availability by Vignette



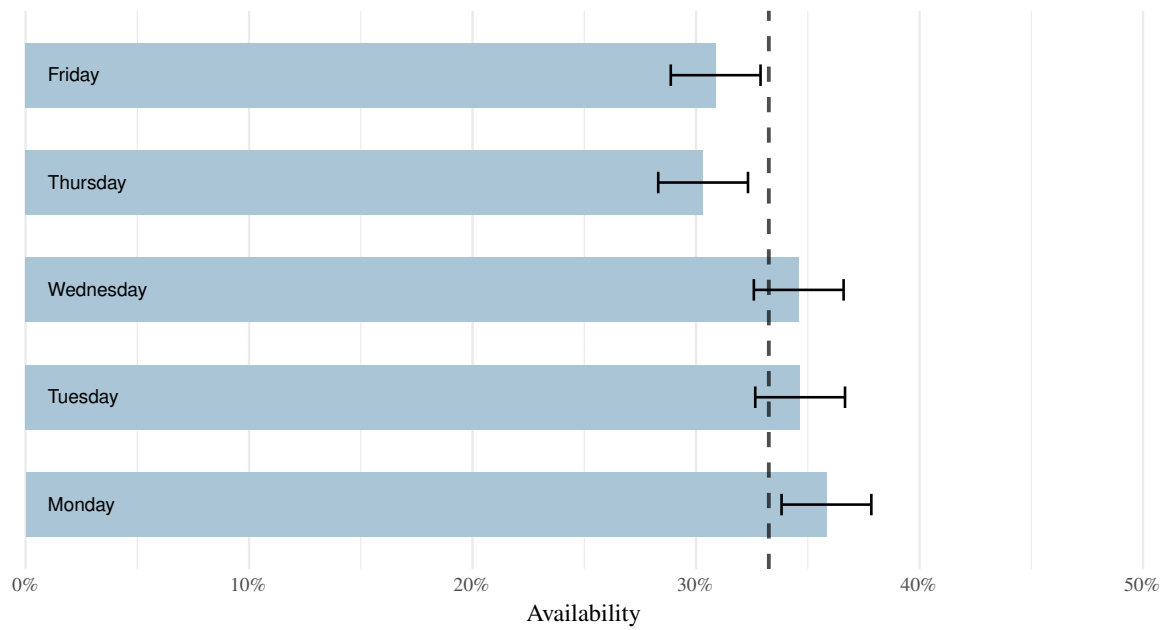
Note: Figure shows results from estimating equation 1 with a full set of indicator variables for each of the 16 vignettes. As with the baseline analysis (e.g., Table 1), regressions also include indicators for race and payer status, as well as controls for day of week, and round. Error bars show unadjusted 95% confidence intervals. Black dashed line indicates mean availability.

Appendix Figure A3: Availability by Sender Name



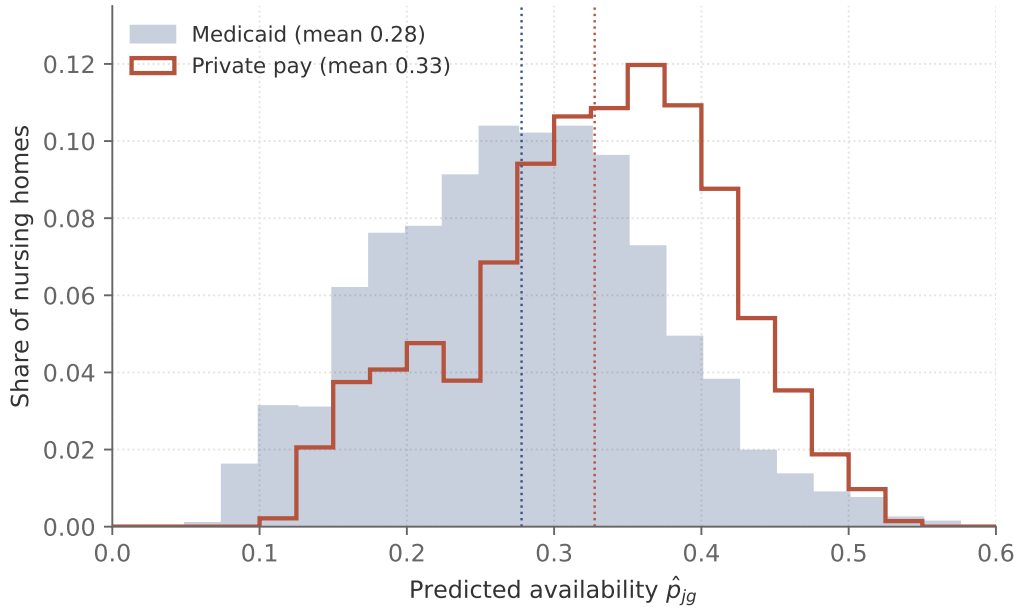
Note: Figure shows results from estimating equation 1 with a full set of indicator variables for each of the 16 names. As with the baseline analysis (e.g., Table 1), regressions also include an indicator for payer status, as well as controls for day of week, vignette, and round. Error bars show unadjusted 95% confidence intervals. Black dashed line indicates mean availability.

Appendix Figure A4: Availability by Day of Week of Inquiry



Note: Figure shows results from estimating equation 1 with a full set of indicator variables for each day of the week. As with the baseline analysis (e.g., Table 1), regressions also include indicators for race and payer status, as well as controls for vignette, and round. Error bars show unadjusted 95% confidence intervals. Black dashed line indicates mean availability.

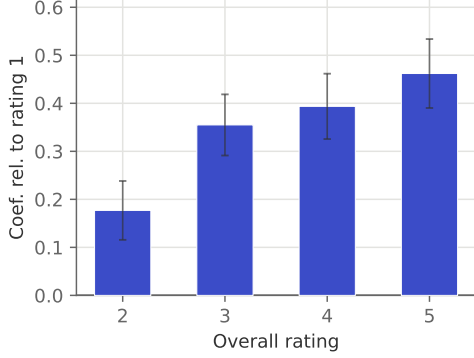
Appendix Figure A5: Distribution of Predicted Availability by Payer



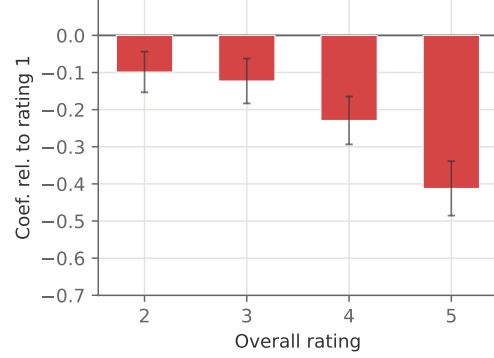
Notes: Figure shows the distribution across nursing homes of predicted availability, $\hat{p}_{jg}$, from the two random forest availability models described in Section 5: one fit to audit inquiries made on behalf of Medicaid patients and one fit to inquiries made on behalf of private-pay patients (Appendix Table A13 lists the covariates included in each random forest). Each nursing home's prediction is formed from its own characteristics, averaging over the randomization distribution of the audit-design variables (inquiry race, vignette, and study round). Bins are 0.025 wide; dotted vertical lines indicate the mean availabilities (0.28 for Medicaid and 0.33 for private pay). The standard deviation across nursing homes is 0.09 for both payers, and the 5th–95th percentile range is 0.13–0.43 for Medicaid and 0.17–0.46 for private pay. $N = 2,773$ nursing homes that received at least one non-pilot inquiry.

Appendix Figure A6: Preferences for Quality by Payer, Unconstrained Choice Sets

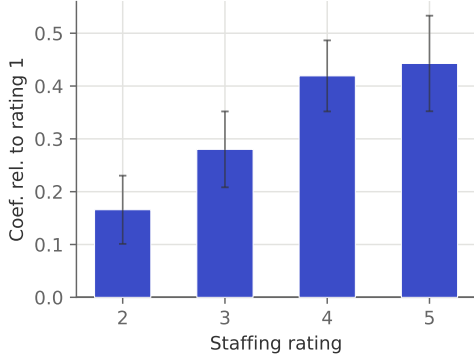
(a) Private Utility by Overall Rating



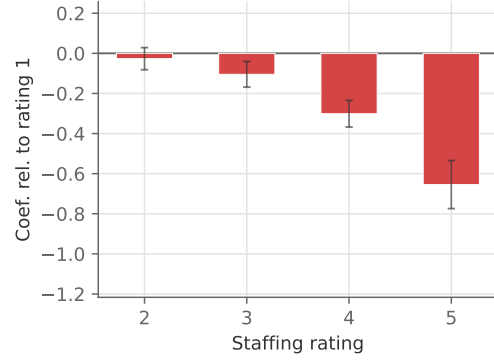
(b) Medicaid Utility by Overall Rating



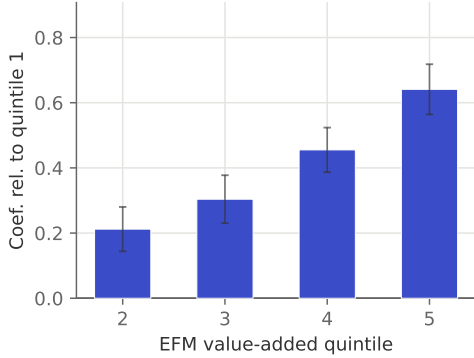
(c) Private Utility by Staffing Rating



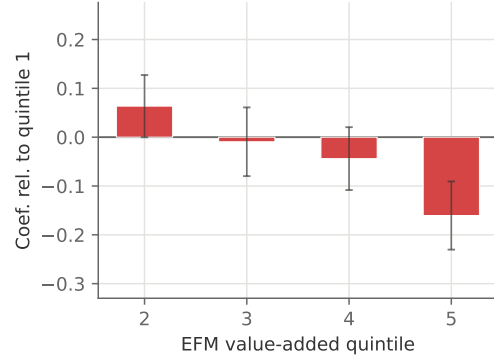
(d) Medicaid Utility by Staffing Rating



(e) Private Utility by EFM Value-Added



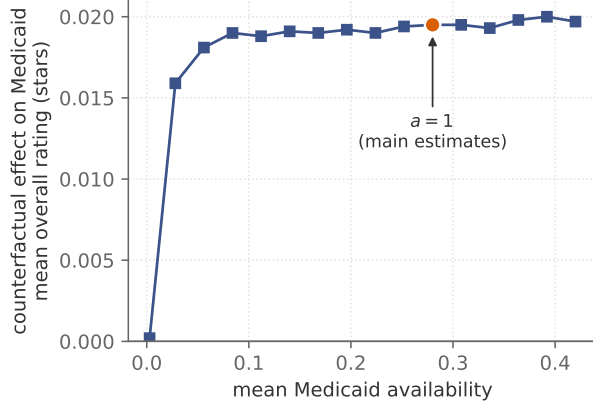
(f) Medicaid Utility by EFM Value-Added



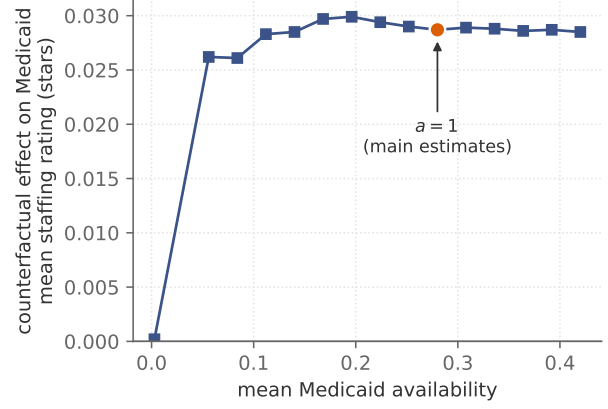
Notes. This figure reports the difference in average $\hat{\delta}_{j,g}$ between each rating bin and the lowest bin, controlling for market fixed effects. Coefficients (with 95 percent confidence intervals based on standard errors clustered by market) come from a regression of the market-by-payer specific $\hat{\delta}_{j,g}$ from estimating equation 2 on indicators for rating bins 2–5 (with bin 1 as the omitted category) as well as market fixed effects; the regression is weighted by the number of (total) patient-stays in each nursing home. Panels (a) and (b) use bins of the overall CMS rating, panels (c) and (d) the staffing rating, and panels (e) and (f) national quintiles of EFM value-added (nursing homes without an EFM value-added score are excluded from those panels). The $\hat{\delta}_{j,g}$ come from demand estimates that do not account for choice set constraints, so that each patient chooses from all nursing homes in their market. The log distance coefficients $\hat{\tau}_g$ are estimated separately for each market; across the 680 markets, weighted by (total) patient-stays, $\hat{\tau}_{Priv}$ has a mean of -1.171 (standard deviation 0.223) and 10th, 50th, and 90th percentiles of -1.429 , -1.181 , and -0.883 , and $\hat{\tau}_{Mcd}$ has a mean of -1.220 (standard deviation 0.266) and percentiles of -1.551 , -1.231 , and -0.859 . Figure 4 shows the same estimates from the constrained-choice model; each panel uses the same vertical scale in both figures.

Appendix Figure A7: Availability Counterfactual under Proportionally Scaled Availability

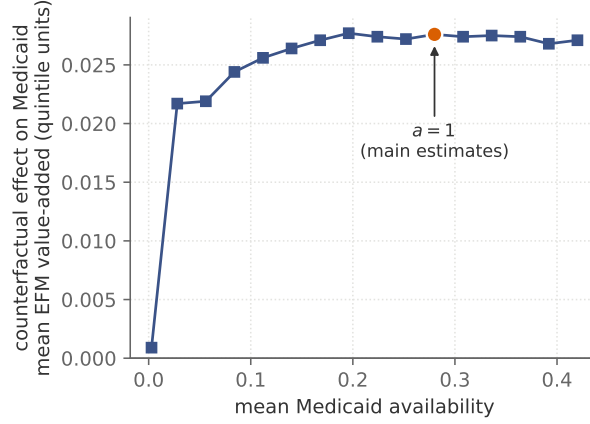
(a) Overall Rating



(b) Staffing Rating

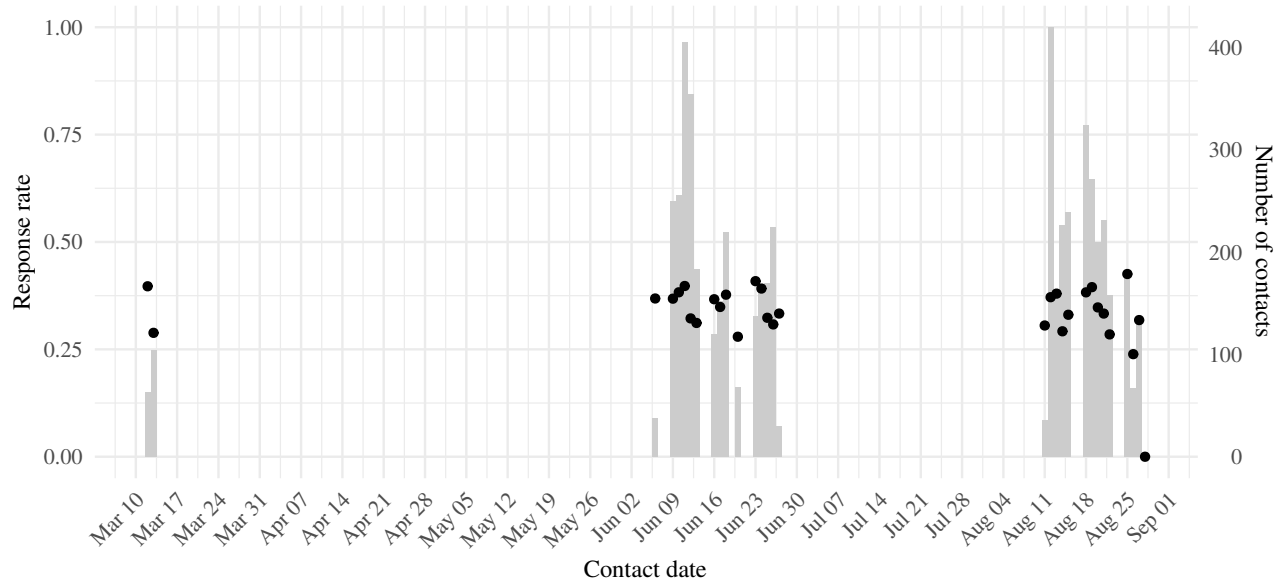


(c) EFM Value-Added



Notes: Figure shows the increase in the average quality of nursing homes attended by Medicaid patients if they faced the availability that private-pay patients face (the private-availability counterfactual in Table 3, relative to the model's Medicaid baseline), under a range of assumed availability levels. We scale the predicted availability of every nursing home for both payer groups by a common factor a , $\tilde{p}_{jg} = a \cdot \hat{p}_{jg}$, and re-estimate the constrained choice model and the counterfactual at each value of a . The x-axis reports the resulting mean assumed Medicaid availability, i.e., a times the mean predicted Medicaid availability of 0.28; $a = 1$ (the orange circle marked with an arrow) reproduces our main estimates, and the largest value, $a = 1.66$, is chosen so that no scaled availability exceeds one. Panels (a), (b), and (c) use the overall CMS rating, the staffing rating, and EFM value-added, respectively.

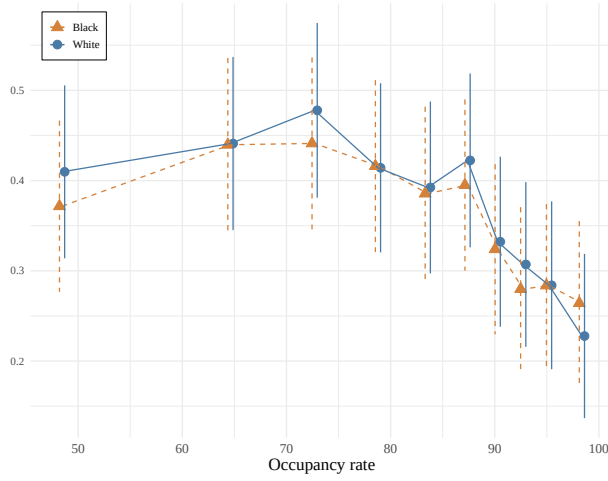
Appendix Figure A8: Daily Response Rates over Time



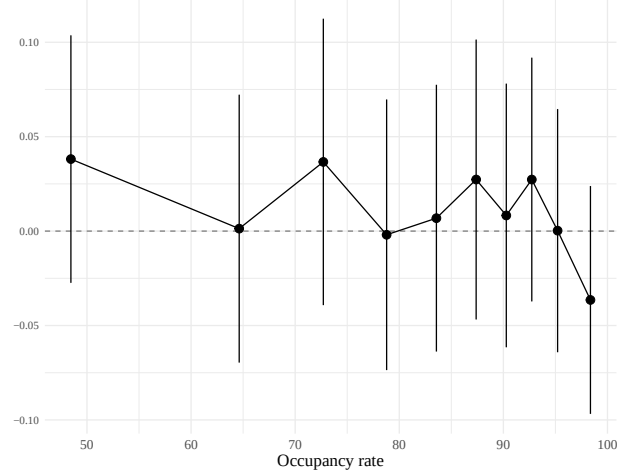
Note: Dates in which only a single facility was contacted are omitted. N = 5,594 contacts.

Appendix Figure A9: White vs Black Availability by Occupancy[^]

(a) Availability by Occupancy Rate



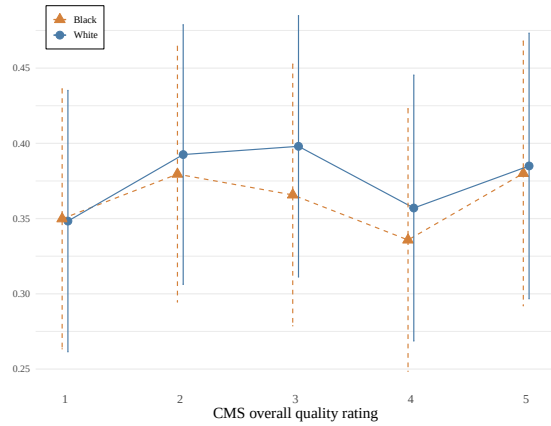
(b) White-Black Difference in Availability by Occupancy Rate



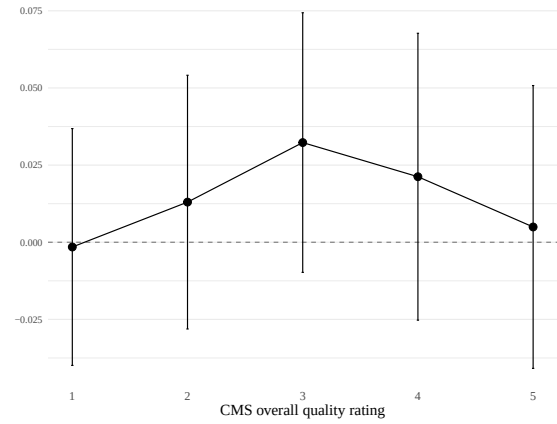
Notes: Figure reports the results of estimating equation 1, allowing for an interaction term for race and the decile of the nursing home's occupancy rate; controls are included for indicators for inquiry round and for day of the week, and the error term is clustered on nursing home. Panel (a) shows the estimated mean availability (and 95 percent confidence interval) for each race, while panel (b) shows the estimated difference in availability. $N = 5,548$ inquiries. We exclude 46 of the 5,594 inquiries due to data availability. [^] indicates analysis of availability by occupancy was not prespecified.

Appendix Figure A10: White vs Black Availability by Nursing Home Quality

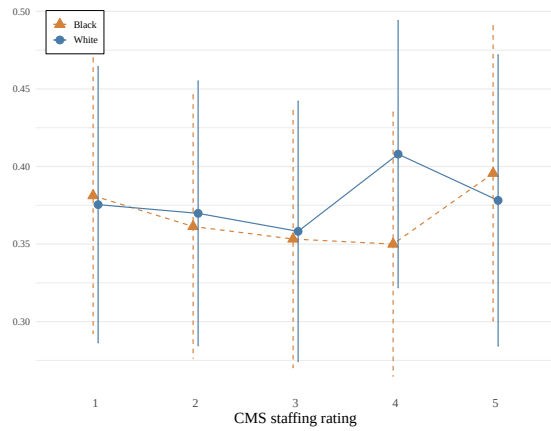
(a) Availability by Overall Rating



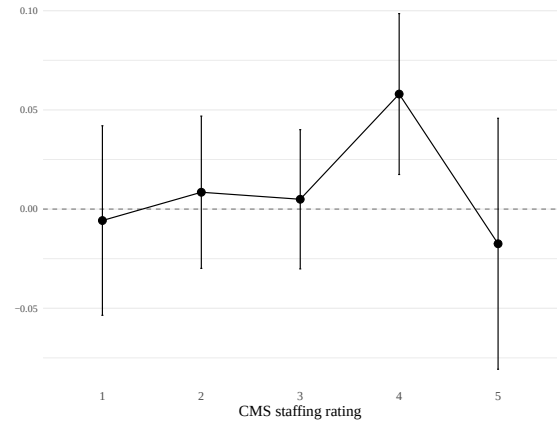
(b) White-Black Difference in Availability by Overall Rating



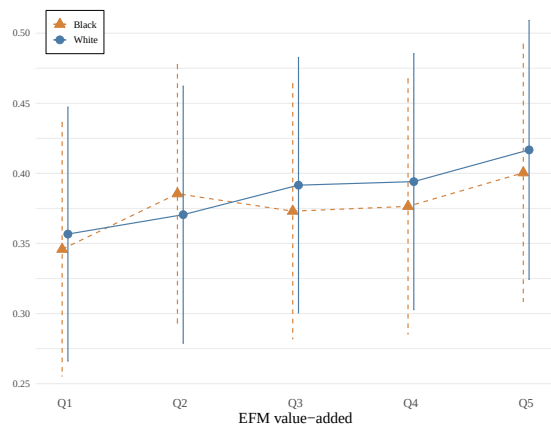
(c) Availability by Staffing Rating



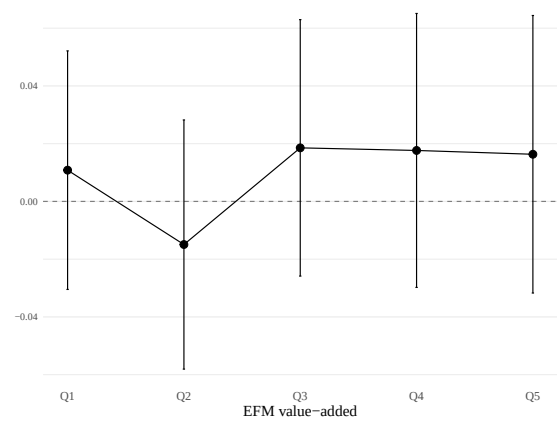
(d) White-Black Difference in Availability by Staffing Rating



(e) Availability by EFM Value-Added



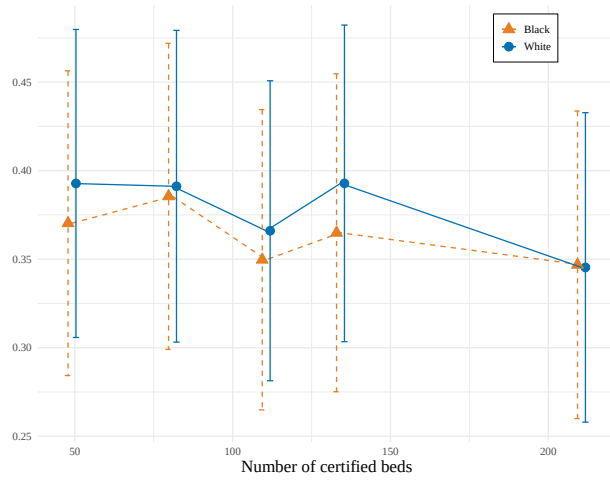
(f) White-Black Difference in Availability by EFM Value-Added



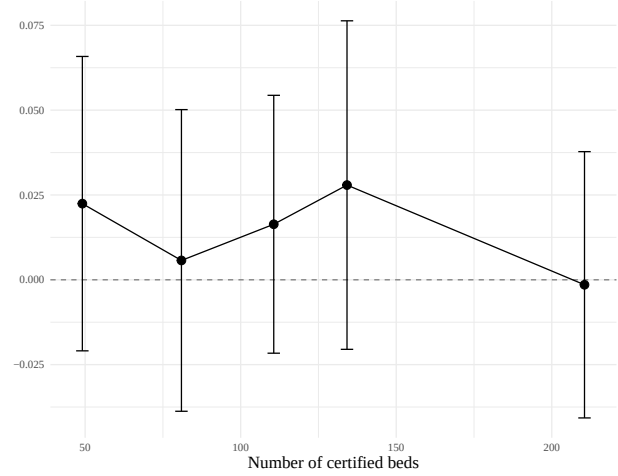
Notes: Figure reports the results of estimating equation 1, allowing for an interaction term for race and the quality rating; controls are included for indicators for inquiry round and for day of the week and the error term is clustered on nursing home. Panel (a) shows the estimated mean availability (and 95 percent confidence interval) for each race, while panel (b) shows the estimated difference in availability. N = 5,552 (Overall), 5,547 (Staffing), and 5,002 (EFM value-added) inquiries.

Appendix Figure A11: White vs Black Availability by the Number of Beds

(a) Availability by Certified Beds



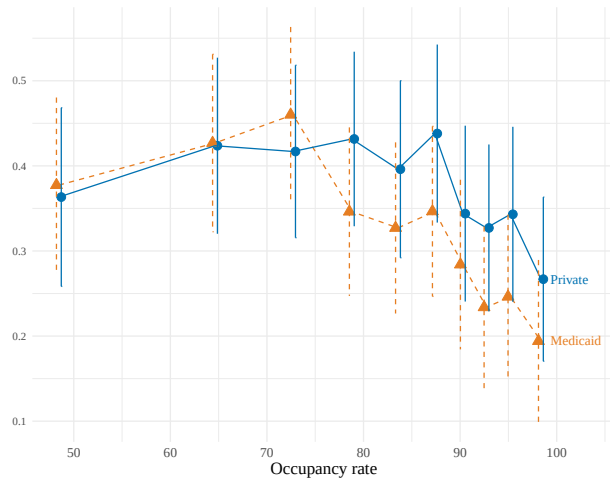
(b) White-Black Difference in Availability by Certified Beds



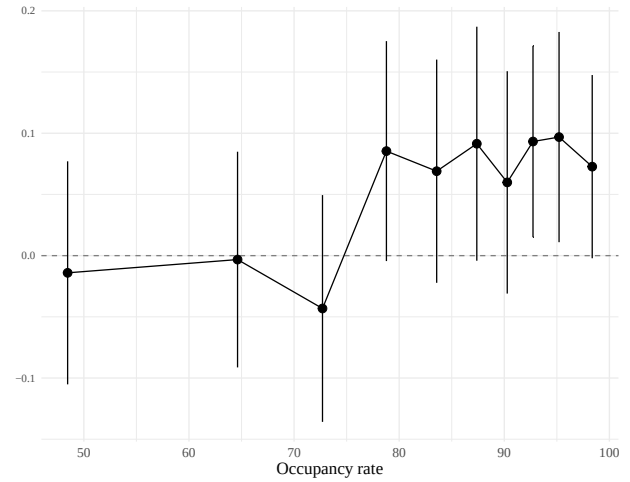
Notes: Figure reports the results of estimating equation 1, allowing for an interaction term for race and the quintile of the number of certified beds; controls are included for indicators for inquiry round and for day of the week and the error term is clustered on nursing home. Panel (a) shows the estimated mean availability (and 95 percent confidence interval) for each race, while panel (b) shows the estimated difference in availability. $N = 5,594$ inquiries.

Appendix Figure A12: Private vs Medicaid Availability by Occupancy[^]

(a) Availability by Occupancy Rate



(b) Difference in Availability for Private vs. Medicaid by Occupancy Rate

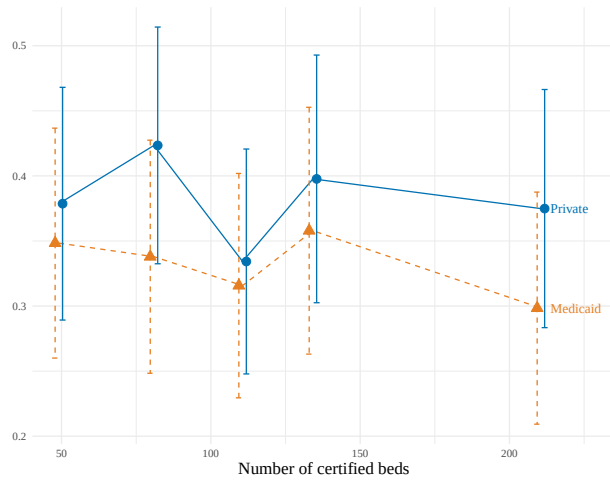


Notes: Figure reports the results of estimating equation 1, allowing for an interaction term for the payer indicators (Medicaid or no payer specified) and the decile of the nursing home's occupancy rate; controls are included for indicators for inquiry round and for day of the week, and the error term is clustered on nursing home. Panel (a) shows the estimated mean availability (and 95 percent confidence interval) for private payers and for Medicaid, while panel (b) shows the estimated difference in availability. $N = 5,548$ inquiries. We exclude 46 of the 5,594 inquiries due to data availability.

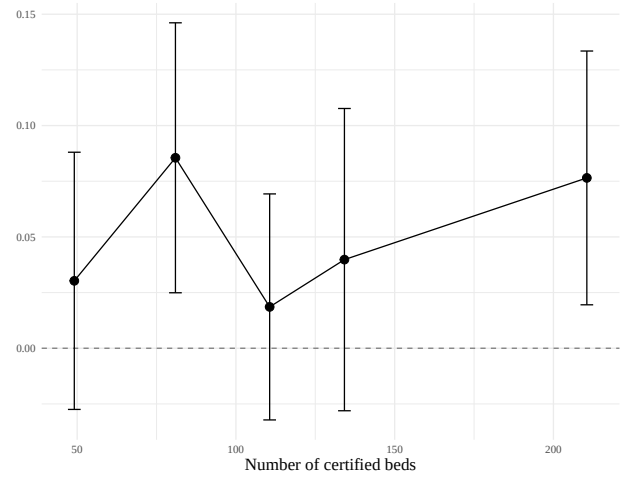
[^] indicates analysis was not prespecified.

Appendix Figure A13: Private vs Medicaid Availability by the Number of Beds

(a) Availability by Certified Beds



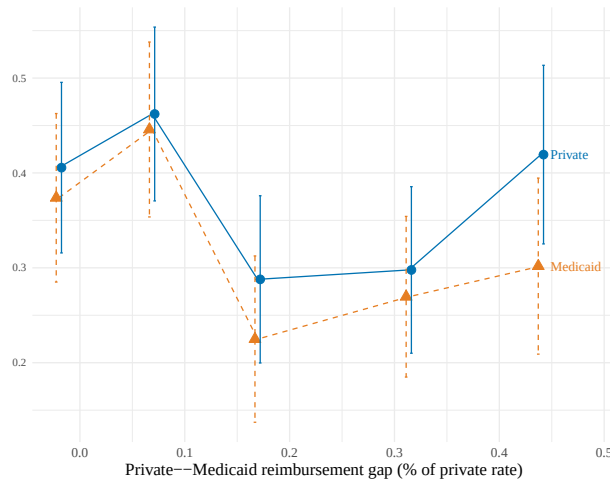
(b) Difference in Availability for Private vs. Medicaid by Certified Beds



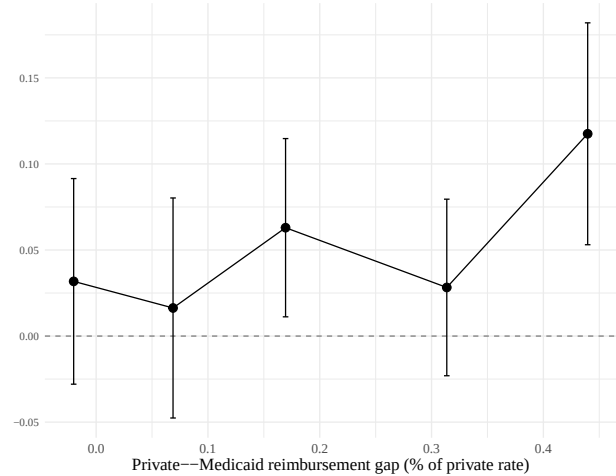
Notes: Figure reports the results of estimating equation 1, allowing for an interaction term for payer and the quintile of the number of certified beds; controls are included for indicators for inquiry round and for day of the week and the error term is clustered on nursing home. Panel (a) shows the estimated mean availability (and 95 percent confidence interval) for private payers and for Medicaid, while panel (b) shows the estimated difference in availability. $N = 5,594$ inquiries.

Appendix Figure A14: Private vs Medicaid Availability by the Private-Medicaid Reimbursement Rate Gap

(a) Availability by Reimbursement Gap



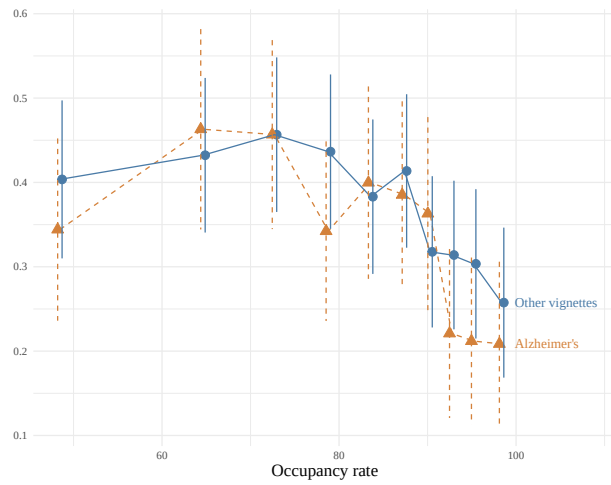
(b) Difference in Availability for Private vs. Medicaid by Reimbursement Gap



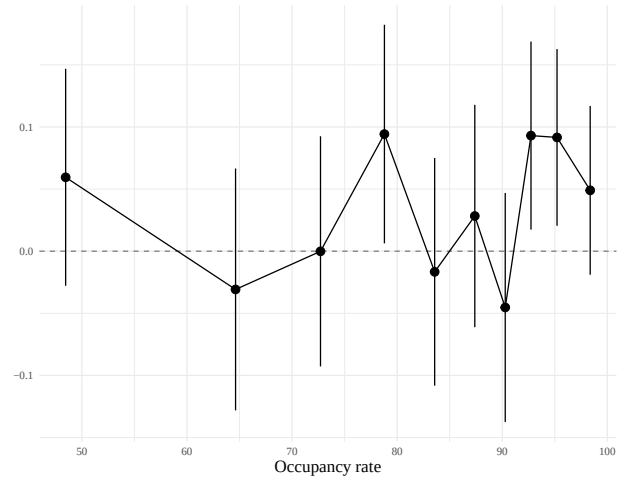
Notes: Figure reports the results of estimating equation 1, allowing for an interaction term for the payer indicators (Medicaid or no payer specified) and the quintile of the percentage gap in average state reimbursement rates for private payers compared to Medicaid (i.e., private rate - Medicaid rate as a share of the private rate); controls are included for indicators for inquiry round and for day of the week and the error term is clustered on nursing home. Panel (a) shows the estimated mean availability (and 95 percent confidence interval) for private payers and for Medicaid, while panel (b) shows the estimated difference in availability. $N = 5,524$ inquiries. We exclude 70 of the 5,594 inquiries due to data availability.

Appendix Figure A15: Other Vignettes vs Alzheimer's Vignette Availability by Occupancy[^]

(a) Availability by Occupancy Rate



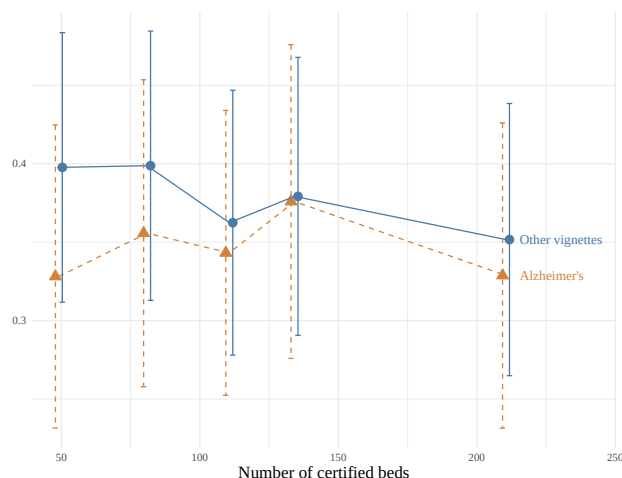
(b) Difference in Availability for Other Vignettes vs. Alzheimer's Vignette by Occupancy Rate



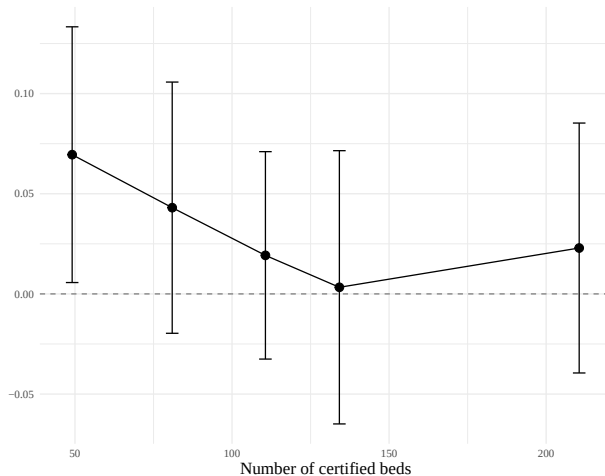
Notes: Figure reports the results of estimating equation 1, allowing for an interaction term for vignette (1-3 or 4) and the decile of the nursing home's occupancy rate; controls are included for indicators for inquiry round and for day of the week, and the error term is clustered on nursing home. Panel (a) shows the estimated mean availability (and 95 percent confidence interval) for the Alzheimer's and other vignettes, while panel (b) shows the estimated difference in availability. $N = 5,548$ inquiries. We exclude 46 of the 5,594 inquiries due to data availability. [^] indicates analysis of availability by occupancy was not prespecified.

Appendix Figure A16: Other Vignettes vs Alzheimer's Vignette Availability by Number of Beds

(a) Availability by Certified Beds



(b) Difference in Availability for Other Vignettes vs. Alzheimer's Vignette by Certified Beds



Notes: Figure reports the results of estimating equation 1, allowing for an interaction term for vignette (1-3 or 4) and the quintile of the number of certified beds; controls are included for indicators for inquiry round and for day of the week and the error term is clustered on nursing home. Panel (a) shows the estimated mean availability (and 95 percent confidence interval) for the Alzheimer's and other vignettes, while panel (b) shows the estimated difference in availability. $N = 5,594$ inquiries.

Appendix Table A1: Length of Episodes by Admission source, Payer Status, and Alzheimer's Status

	Percentiles					
	p10	p25	p50	p75	p90	N
<i>Panel A: By admission source</i>						
Overall	8	14	25	64	394	1,684,860
From community	6	13	34	332	> 549	304,031
From hospital	8	14	24	52	228	1,326,857
<i>Panel B: Within admissions from community</i>						
Medicaid	7	19	118	> 549	> 549	83,789
Private	6	12	27	209	> 549	220,242
Alzheimer's	6	17	122	> 549	> 549	119,478
No Alzheimer's	6	12	23	99	> 549	171,167
Medicaid $\times$ Alzheimer's	8	39	253	> 549	> 549	41,685
Medicaid $\times$ No Alzheimer's	7	15	42	404	> 549	42,104

Note: Table reports the summary statistics of length of episodes in days using data from the 2018 and 2019 MDS on admission in the first half of 2018. We follow them through the end of 2019 so that episode length is right-censored at 549 days, which is the maximum observable length for an episode starting at the end of the first half of 2018. Censored values in the table are reported as > 549. Section 5.1 provides more detail on variable definitions.

Appendix Table A2: Name Pairs by Racial Group

<i>Panel A: Black Name Pairs</i>									
Mother				Daughter				Last name	
First name	Years in top 1000	Peak popularity	Racial congruence	First name	Years in top 1000	Peak popularity	Racial congruence	Name	Percent Black
Monique	1955–2008	1980	$\geq 80\%$	Taniya	2001–2009	2006	$\geq 90\%$	Mosley	53
Keisha	1967–1997	1976	≥ 80	Ashanti	1979–2008	2002	≥ 90	Washington	90
Aisha	1973–2022	1977	≥ 80	Tionna	–	2000	≥ 90	Jefferson	75
Ebony	1971–2005	1982	≥ 90	Precious	1978–2010	1996	≥ 80	Jackson	53
Kenya	1968–2017	1973	≥ 80	Aaliyah	1994–2002	2012	≥ 80	Booker	66
Tanisha	1970–1998	1982	≥ 90	Keyana	–	1995	≥ 90	Washington	90
Denisha	1987–1995	1994	≥ 90	Tamia	1996–2014	2001	≥ 80	Banks	54
Shanice	1988–1999	1992	≥ 90	Tyra	1964–2007	1998	≥ 90	Jefferson	75
<i>Panel B: White Name Pairs</i>									
Mother				Daughter				Last name	
First name	Years in top 1000	Peak popularity	Racial congruence	First name	Years in top 1000	Peak popularity	Racial congruence	Name	Percent white
Laurie	1908–1994	1960	$\geq 90\%$	Kristen	1946–2015	1982	$\geq 90\%$	Meyer	96
Joan	1900–1993	1933	≥ 90	Amy	1900–2022	1976	≥ 90	Larsen	96
Heidi	1939–2022	1974	≥ 90	Erica	1945–2018	1988	≥ 90	Walsh	96
Susan	1900–2020	1960	≥ 90	Katie	1900–2022	1987	≥ 90	Becker	96
Lisa	1937–2022	1969	≥ 90	Stephanie	1900–2022	1987	≥ 90	Decker	95
Barbara	1900–2022	1944	≥ 90	Hilary	1949–1993	1990	≥ 90	Andersen	95
Deborah	1900–2022	1955	≥ 80	Carrie	1900–2007	1977	≥ 90	McGrath	96
Marlene	1920–2012	1936	≥ 90	Cassie	1900–2009	1982	≥ 90	Stein	96

Notes: Table reports mother–daughter name pairs separately by racial group. Panel A reports Black name pairs, and Panel B reports White name pairs. Information on “years in top 1000” names and year of peak popularity of first names comes from [Social Security Administration \(n.d.\)](#) name popularity data. Information on racial congruence of first names comes from [Gaddis \(2017\)](#) and is approximated by the authors since [Gaddis \(2017\)](#) provides only a figure of results, not a table or raw data. “Percent Black” and “Percent white” report the racial composition associated with the listed last name, based on the 2000 Census.

Appendix Table A3: Audit Summary Statistics: Population vs. In-Sample vs. Out-of-Sample Nursing Facilities

Measure	Population (1)	In sample (2)	Out of sample (3)
SNFs (n)	14,752	2,940	11,812
<i>A. General facility characteristics</i>			
Certified beds per facility: mean	106.8	115.3	104.6
Certified beds per facility: median	100.0	106.0	99.0
Occupancy rate	79.7	81.2	79.3
Multi-facility indicator	0.68	0.62	0.70
For-profit indicator	0.73	0.77	0.72
Alzheimer's special care unit	0.14	0.14	0.14
Percent Medicaid	59.1	60.2	58.9
Percent Medicare	13.6	13.2	13.7
Admissions per bed	2.14	1.97	2.19
<i>B. Resident demographics</i>			
Share from hospital	83.7	84.0	83.6
Share female	63.2	62.8	63.3
Share Black	13.6	13.7	13.6
Share Hispanic	5.3	5.6	5.2
Share White	76.2	74.7	76.6
Share under 65	17.4	17.2	17.4
Average age	77.7	78.1	77.7
<i>C. Staffing</i>			
Hours per resident day (total)	3.92	3.90	3.92
Share of hours that are RN	0.17	0.16	0.17
Share of hours that are LPN	0.23	0.23	0.23
Share of hours that are CNA	0.60	0.61	0.60
<i>D. Quality ratings</i>			
CMS overall rating ^a	2.92	2.86	2.93
CMS health inspection rating ^a	2.81	2.76	2.82
CMS quality measure rating ^a	3.43	3.41	3.44
CMS staffing rating ^a	2.84	2.85	2.84
EFM value-added	0.04	0.04	0.04
<i>E. Region</i>			
Northeast	16.3%	23.3%	14.6%
Midwest	32.1%	27.3%	33.3%
South	35.9%	33.2%	36.6%
West	15.6%	16.2%	15.5%

Note: Population is all nursing facilities in CMS (2025b). ‘In sample’ includes all facilities that received contact inquiries. ‘Out of Sample’ consists of all of the facilities in the CMS Provider Information dataset that were not contacted. All facility characteristics are from the CMS Provider Information dataset except for share female, share Black, share Hispanic, share white and share with Alzheimer’s special care unit which are from LTCFocus (2022). Racial percentages exclude Asian and other groups and use midpoint imputation for small cells; 1 to 3% of facilities are missing data for various quality or staffing measures.

^a Ratings are from 1 to 5 with 5 as the highest.

Appendix Table A4: Race Differences in Outcomes

	Response (1)	Avail. (2)	Avail: yes (3)	Unclear avail. (4)	Avail: no (5)	Avail: waitlist (6)	Pos. sentiment (7)	No. of responses (8)
White	0.3807 (0.0421)	0.3359 (0.0408)	0.0943 (0.0247)	0.2417 (0.0366)	0.0199 (0.0107)	0.0249 (0.0138)	0.0927 (0.0265)	1.454 (0.1064)
Black	0.3662 (0.0419)	0.3221 (0.0405)	0.0746 (0.0243)	0.2476 (0.0365)	0.0232 (0.0106)	0.0208 (0.0141)	0.0777 (0.0261)	1.431 (0.1044)
White-Black gap	0.015 (0.010) {0.137} [0.298]	0.014 (0.010) {0.153} [0.298]	0.020 (0.007) {0.004} [0.030]	-0.006 (0.009) {0.520} [0.440]	-0.003 (0.004) {0.383} [0.440]	0.004 (0.004) {0.265} [0.440]	0.015 (0.008) {0.047} [0.196]	0.023 (0.032) {0.460} [0.440]

Table reports the results from estimating equation 1, with each column showing results for a different outcome. Availability in column (2) includes responses that indicate availability (column 3) or are unclear (column 4). All the estimates control for indicators for inquiry round and for day of the week (as well as for the other treatment indicators for payer and for vignette, whose estimates are shown in Appendix Tables A5 and A6), respectively. Robust standard errors clustered on nursing home are in (parentheses), p-values are shown in curly brackets and sharpened q-values (following Benjamini et al. (2006) adjusted for multiple testing across outcomes within the race domain are in [square brackets]. N = 5,594 inquiries (sent to 2,940 nursing homes).

Appendix Table A5: Payer Differences in Outcomes

	Response (1)	Avail. (2)	Avail: yes (3)	Unclear avail. (4)	Avail: no (5)	Avail: waitlist (6)	Pos. sentiment (7)	No. of responses (8)
Private pay	0.3973 (0.0418)	0.3631 (0.0405)	0.1013 (0.0244)	0.2618 (0.0364)	0.0145 (0.0107)	0.0196 (0.0141)	0.1197 (0.0267)	1.482 (0.1048)
Medicaid	0.3800 (0.0420)	0.3146 (0.0404)	0.0755 (0.0244)	0.2391 (0.0363)	0.0382 (0.0119)	0.0272 (0.0145)	0.0971 (0.0268)	1.337 (0.0986)
No payer	0.3662 (0.0419)	0.3221 (0.0405)	0.0746 (0.0243)	0.2476 (0.0365)	0.0232 (0.0106)	0.0208 (0.0141)	0.0777 (0.0261)	1.431 (0.1044)
Private–Medicaid	0.017 (0.014) {0.210} [0.136]	0.048 (0.013) {0.000} [0.002]	0.026 (0.009) {0.005} [0.013]	0.023 (0.012) {0.059} [0.069]	-0.024 (0.005) {0.000} [0.001]	-0.008 (0.005) {0.140} [0.113]	0.023 (0.010) {0.029} [0.045]	0.145 (0.041) {0.000} [0.002]
Private–none	0.031 (0.014) {0.026} [0.045]	0.041 (0.014) {0.003} [0.011]	0.027 (0.009) {0.004} [0.012]	0.014 (0.012) {0.254} [0.155]	-0.009 (0.004) {0.052} [0.069]	-0.001 (0.005) {0.806} [0.401]	0.042 (0.010) {0.000} [0.001]	0.052 (0.042) {0.215} [0.136]
Medicaid–none	0.014 (0.014) {0.325} [0.195]	-0.008 (0.014) {0.577} [0.310]	0.001 (0.009) {0.916} [0.401]	-0.008 (0.012) {0.483} [0.290]	0.015 (0.005) {0.004} [0.012]	0.006 (0.005) {0.213} [0.136]	0.019 (0.010) {0.050} [0.069]	-0.093 (0.042) {0.028} [0.045]

Table reports the results from estimating equation 1, with each column showing results for a different outcome. Availability in column (2) includes responses that indicate availability (column 3) or are unclear (column 4). All the estimates control for indicators for inquiry round and for day of the week (as well as for the other treatment indicators for race and for vignette, whose estimates are shown in Appendix Tables A4 and A6), respectively. Robust standard errors clustered on nursing home are in (parentheses), p-values are shown in curly brackets and sharpened q-values (following Benjamini et al. (2006) adjusted for multiple testing across outcomes within the payer domain are in [square brackets]. N = 5,594 inquiries (sent to 2,940 nursing homes).

Appendix Table A6: Vignette Differences in Outcomes

	Response (1)	Avail. (2)	Avail: yes (3)	Unclear avail. (4)	Avail: no (5)	Avail: waitlist (6)	Pos. sentiment (7)	No. of responses (8)
Other vignettes	0.3662 (0.0419)	0.3221 (0.0405)	0.0746 (0.0243)	0.2476 (0.0365)	0.0232 (0.0106)	0.0208 (0.0141)	0.0777 (0.0261)	1.431 (0.1044)
Other – Alzheimer’s	0.025 (0.015) {0.082} [0.115]	0.032 (0.014) {0.022} [0.047]	-0.001 (0.009) {0.892} [0.880]	0.033 (0.012) {0.005} [0.029]	-0.005 (0.005) {0.326} [0.354]	-0.001 (0.005) {0.785} [0.880]	0.027 (0.010) {0.007} [0.029]	-0.004 (0.047) {0.936} [0.880]

Table reports the results from estimating equation 1, with each column showing results for a different outcome. Availability in column (2) includes responses that indicate availability (column 3) or are unclear (column 4). All the estimates control for indicators for inquiry round and for day of the week (as well as for the other treatment indicators for race and for payer, whose estimates are shown in Appendix Tables A4 and A5), respectively. Robust standard errors clustered on nursing home are in (parentheses), p-values are shown in curly brackets and sharpened q-values (following Benjamini et al. (2006) adjusted for multiple testing across outcomes within the vignette domain are in [square brackets]. N = 5,594 inquiries (sent to 2,940 nursing homes).

Appendix Table A7: Race $\times$ Payer Interactions in Outcomes

	Response (1)	Avail. (2)	Avail: yes (3)	Unclear avail. (4)	Avail: no (5)	Avail: waitlist (6)	Pos. sentiment (7)	No. of responses (8)
White $\times$ Medicaid	0.3953 (0.0433)	0.3284 (0.0417)	0.0908 (0.0254)	0.2376 (0.0372)	0.0320 (0.0122)	0.0348 (0.0152)	0.1050 (0.0279)	1.371 (0.1045)
White $\times$ private	0.4108 (0.0434)	0.3800 (0.0420)	0.1222 (0.0255)	0.2578 (0.0376)	0.0115 (0.0109)	0.0193 (0.0139)	0.1317 (0.0278)	1.471 (0.1100)
White $\times$ none	0.3808 (0.0432)	0.3335 (0.0418)	0.0978 (0.0256)	0.2357 (0.0372)	0.0226 (0.0112)	0.0247 (0.0140)	0.1022 (0.0273)	1.468 (0.1133)
Black $\times$ Medicaid	0.3792 (0.0431)	0.3151 (0.0414)	0.0800 (0.0250)	0.2351 (0.0371)	0.0411 (0.0129)	0.0229 (0.0145)	0.1034 (0.0276)	1.317 (0.1014)
Black $\times$ private	0.3982 (0.0429)	0.3605 (0.0415)	0.1002 (0.0252)	0.2603 (0.0371)	0.0142 (0.0109)	0.0234 (0.0146)	0.1221 (0.0277)	1.510 (0.1074)
Black $\times$ none	0.3660 (0.0432)	0.3250 (0.0417)	0.0712 (0.0247)	0.2538 (0.0377)	0.0206 (0.0109)	0.0204 (0.0146)	0.0678 (0.0266)	1.407 (0.1051)
None-Medicaid (W-B)	-0.001 (0.034) {0.970} [1.000]	-0.005 (0.032) {0.880} [1.000]	0.016 (0.020) {0.426} [1.000]	-0.021 (0.027) {0.451} [1.000]	0.011 (0.013) {0.379} [1.000]	-0.008 (0.013) {0.546} [1.000]	0.033 (0.022) {0.143} [1.000]	0.008 (0.090) {0.932} [1.000]
Private-none (B-W)	0.002 (0.034) {0.949} [1.000]	-0.011 (0.033) {0.739} [1.000]	0.005 (0.021) {0.828} [1.000]	-0.016 (0.028) {0.573} [1.000]	0.005 (0.010) {0.619} [1.000]	0.008 (0.012) {0.469} [1.000]	0.025 (0.024) {0.292} [1.000]	0.100 (0.098) {0.307} [1.000]

Table reports the results from estimating equation 1, with each column showing results for a different outcome. Availability in column (2) includes responses that indicate availability (column 3) or are unclear (column 4). All the estimates control for indicators for inquiry round and for day of the week (as well as for the other treatment indicator for vignette, whose estimates are shown in Appendix Table A6). Robust standard errors clustered on nursing home are in (parentheses), p-values are shown in curly brackets and sharpened q-values (following Benjamini et al. (2006) adjusted for multiple testing across outcomes within the race $\times$ payer domain are in [square brackets]. N = 5,594 inquiries (sent to 2,940 nursing homes).

Appendix Table A8: Treatment Effects With and Without Day-of-Week Controls

	Availability		Any response		# responses		Positive sentiment	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Black	-0.014 (0.010)	-0.013 (0.010)	-0.015 (0.010)	-0.014 (0.010)	-0.028 (0.017)	-0.027 (0.017)	-0.015 (0.008)	-0.015 (0.008)
Alzheimer's vignette	-0.032 (0.014)	-0.031 (0.014)	-0.025 (0.015)	-0.025 (0.015)	-0.031 (0.026)	-0.031 (0.026)	-0.027 (0.010)	-0.027 (0.010)
Medicaid	-0.048 (0.013)	-0.047 (0.013)	-0.017 (0.014)	-0.016 (0.014)	-0.075 (0.024)	-0.074 (0.023)	-0.023 (0.010)	-0.022 (0.010)
No payer specified	-0.041 (0.014)	-0.041 (0.014)	-0.031 (0.014)	-0.032 (0.014)	-0.061 (0.024)	-0.062 (0.024)	-0.042 (0.010)	-0.042 (0.010)
Day of week fixed effects	Y	N	Y	N	Y	N	Y	N

Note: Odd-numbered columns include controls for day of the week and inquiry round. Even-numbered columns exclude day-of-week controls but retain round controls. All models include SNF-level clustering for standard errors. N = 5,594 inquiries.

Appendix Table A9: Nursing Home Quality and the Payer Availability Gap

	Rating					Grouped rating	
	1	2	3	4	5	1–3	4–5
<i>Panel A: CMS Overall Rating</i>							
Private mean	0.367 (0.046)	0.397 (0.045)	0.400 (0.046)	0.346 (0.047)	0.364 (0.047)	0.388 (0.041)	0.356 (0.043)
Medicaid mean	0.306 (0.045)	0.355 (0.045)	0.345 (0.046)	0.317 (0.047)	0.318 (0.046)	0.336 (0.041)	0.319 (0.043)
No payer mean	0.308 (0.046)	0.340 (0.045)	0.337 (0.045)	0.312 (0.046)	0.404 (0.048)	0.330 (0.041)	0.356 (0.044)
Private – Medicaid	0.061 (0.027)	0.043 (0.029)	0.055 (0.030)	0.029 (0.033)	0.046 (0.031)	0.053 (0.017)	0.037 (0.022)
Difference in gaps	-0.016 (0.028)						
Observations	1237	1209	1165	980	961	3611	1941
Number of nursing homes	650	637	614	514	504	1901	1018
	Rating					Grouped rating	
	1	2	3	4	5	1–3	4–5
<i>Panel B: CMS Staffing Rating</i>							
Private mean	0.397 (0.047)	0.344 (0.045)	0.360 (0.044)	0.409 (0.045)	0.403 (0.052)	0.364 (0.041)	0.407 (0.044)
Medicaid mean	0.351 (0.047)	0.335 (0.045)	0.351 (0.044)	0.303 (0.044)	0.303 (0.049)	0.345 (0.042)	0.303 (0.043)
No payer mean	0.325 (0.048)	0.356 (0.045)	0.297 (0.043)	0.364 (0.046)	0.399 (0.054)	0.325 (0.041)	0.375 (0.044)
Private – Medicaid	0.046 (0.033)	0.009 (0.027)	0.009 (0.026)	0.106 (0.028)	0.100 (0.042)	0.019 (0.016)	0.104 (0.023)
Difference in gaps	0.085 (0.028)						
Observations	962	1273	1485	1281	546	3720	1827
Number of nursing homes	501	673	777	681	284	1951	965
	Quintile					Grouped quintiles	
	Q1	Q2	Q3	Q4	Q5	Bottom 3	Top 2
<i>Panel C: EFM Value-Added</i>							
EFM value-added mean	0.009	0.029	0.041	0.052	0.071	0.026	0.062
Private mean	0.350 (0.049)	0.380 (0.049)	0.389 (0.048)	0.385 (0.048)	0.432 (0.049)	0.373 (0.044)	0.408 (0.045)
Medicaid mean	0.318 (0.047)	0.336 (0.049)	0.362 (0.048)	0.342 (0.048)	0.329 (0.048)	0.338 (0.044)	0.336 (0.045)
No payer mean	0.319 (0.048)	0.352 (0.049)	0.329 (0.048)	0.363 (0.049)	0.398 (0.049)	0.333 (0.044)	0.381 (0.045)
Private – Medicaid	0.032 (0.030)	0.044 (0.032)	0.027 (0.031)	0.043 (0.031)	0.102 (0.033)	0.035 (0.018)	0.072 (0.023)
Difference in gaps	0.037 (0.029)						
Observations	1001	1001	1000	999	1001	3002	2000
Number of nursing homes	527	525	526	524	527	1578	1051

Notes: Table reports the results of estimating equation 1, allowing for an interaction term for the payer indicators (Medicaid or no payer specified) and quality measures. All regressions include controls for indicators for inquiry round, day of the week, race, and vignette; standard errors (clustered on nursing home) are in parentheses. In Panels A and B, columns 1–5 report mean availability by rating; the two rightmost columns show grouped ratings (1–3 and 4–5). In Panel C, columns Q1–Q5 report mean availability by EFM value-added quintile; the two rightmost columns report the grouped bottom three and top two quintiles. Samples differ slightly across panels because of missing quality data: overall rating $N = 5,552$; staffing rating $N = 5,547$; EFM value-added $N = 5,002$.

Appendix Table A10: Nursing Home Quality and the Vignette Availability Gap

	Rating					Grouped rating	
	1	2	3	4	5	1–4	5
<i>Panel A: CMS Overall Rating</i>							
Other vignettes mean	0.352 (0.044)	0.394 (0.044)	0.384 (0.044)	0.356 (0.044)	0.400 (0.044)	0.372 (0.041)	0.401 (0.044)
Alzheimer's mean	0.337 (0.048)	0.359 (0.047)	0.373 (0.049)	0.314 (0.051)	0.321 (0.050)	0.349 (0.042)	0.322 (0.050)
Other vignettes – Alzheimer's	0.015 (0.028)	0.035 (0.031)	0.011 (0.031)	0.041 (0.034)	0.079 (0.034)	0.024 (0.015)	0.079 (0.033)
Difference in gaps						0.056 (0.037)	
Observations	1237	1209	1165	980	961	4591	961
Number of nursing homes	650	637	614	514	504	2415	504
	Rating					Grouped rating	
	1	2	3	4	5	1–4	5
<i>Panel B: CMS Staffing Rating</i>							
Other vignettes mean	0.376 (0.045)	0.364 (0.043)	0.369 (0.042)	0.381 (0.043)	0.421 (0.048)	0.372 (0.041)	0.421 (0.048)
Alzheimer's mean	0.378 (0.050)	0.365 (0.048)	0.309 (0.046)	0.368 (0.049)	0.270 (0.053)	0.351 (0.042)	0.270 (0.053)
Other vignettes – Alzheimer's	-0.002 (0.034)	-0.001 (0.030)	0.060 (0.026)	0.013 (0.030)	0.152 (0.042)	0.021 (0.015)	0.152 (0.042)
Difference in gaps						0.131 (0.044)	
Observations	962	1273	1485	1281	546	5001	546
Number of nursing homes	501	673	777	681	284	2632	284
	Quintile					Grouped quintiles	
	Q1	Q2	Q3	Q4	Q5	Bottom 4	Top 1
<i>Panel C: EFM Value-Added</i>							
EFM value-added mean	0.009	0.029	0.041	0.052	0.071	0.033	0.071
Other vignettes mean	0.351 (0.046)	0.372 (0.047)	0.391 (0.046)	0.388 (0.046)	0.429 (0.046)	0.376 (0.043)	0.430 (0.046)
Alzheimer's mean	0.332 (0.051)	0.379 (0.053)	0.336 (0.051)	0.359 (0.050)	0.327 (0.052)	0.352 (0.045)	0.328 (0.052)
Other vignettes – Alzheimer's	0.019 (0.032)	-0.007 (0.034)	0.055 (0.033)	0.029 (0.031)	0.102 (0.033)	0.024 (0.016)	0.102 (0.033)
Difference in gaps						0.078 (0.037)	
Observations	1001	1001	1000	999	1001	4001	1001
Number of nursing homes	527	525	526	524	527	2102	527

Notes: Table reports the results of estimating equation 1, allowing for an interaction term for the Alzheimer's indicator (vignette 4) and quality measures. All regressions include controls for payer type, race, inquiry round, and day of the week; standard errors (clustered on nursing home) are in parentheses. In Panels A and B, columns 1–5 report mean availability by rating; the two rightmost columns show grouped ratings (1–4 and 5). In Panel C, columns Q1–Q5 report mean availability by EFM value-added quintile; the two rightmost columns report the grouped bottom four and top quintile. The *Other vignettes – Alzheimer's* row reports the difference in availability between the other vignettes and Alzheimer's inquiries. Samples differ slightly across panels because of missing quality data: overall rating $N = 5,552$; staffing rating $N = 5,547$; EFM value-added $N = 5,002$.

Appendix Table A11: Nursing Home Stay Sample Restrictions

	Stays	SNFs
Full sample	3,990,362	14,902
Traditional Medicare and age 65+	1,472,280	14,686
First stays and admission from the community	544,324	14,797
Non-missing zip code	458,665	14,350

Note: Table shows the sample restrictions applied to go from the full sample of nursing home admissions in the 2022 Minimum Data Set (MDS) (top row) to our analysis sample of 458,665 patient-stays and 14,350 SNFs (bottom row); at each step, it shows the remaining number of patient-stays and SNFs. The “full sample” includes all nursing home stays in 2022. The second row (“Traditional Medicare and age 65+”) restricts the sample to patient-stays in which the patient is enrolled in Traditional Medicare and is at least 65 years old. The third row (“First stays and admission from the community”) further restricts the sample to the first stay of each episode and patient-stays that enter from the community, where community admissions are defined in Footnote 16. The last row (“Non-missing zip code”) restricts to patient-stays with non-missing beneficiary zip code.

Appendix Table A12: Summary Statistics of Nursing Home Stays

	All (1)	Private-pay (2)	Medicaid (3)
<i>Patient characteristics</i>			
Age at admission	80.25	81.46	78.03
Age 65–74 (%)	29.7	23.9	40.4
Age 75–84 (%)	36.4	37.5	34.3
Age 85+ (%)	33.9	38.6	25.3
Female (%)	58.8	55.3	65.4
White (%)	75.6	82.7	62.5
Black (%)	13.6	9.4	21.2
Other or unknown race (%)	10.8	7.9	16.2
Medicaid at admission (%)	35.1	0.0	100.0
Alzheimer’s at admission (%)	9.0	8.3	10.3
<i>Nursing home characteristics</i>			
Overall rating (% of stays)			
1	22.4	19.8	27.1
2	21.4	20.3	23.4
3	21.2	21.2	21.1
4	17.9	18.9	16.0
5	17.2	19.8	12.4
Overall rating (mean)	2.86	2.98	2.63
Staffing rating (% of stays)			
1	28.8	26.5	32.9
2	21.5	20.6	23.0
3	21.6	21.2	22.4
4	20.3	21.9	17.1
5	7.9	9.7	4.6
Staffing rating (mean)	2.57	2.68	2.38
EFM value-added quintile (% of stays)			
1	18.2	15.2	23.9
2	19.2	17.9	21.5
3	20.2	20.0	20.4
4	20.5	21.6	18.4
5	22.0	25.3	15.8
EFM value-added quintile (mean)	3.09	3.24	2.81
Occupancy rate (%)	76.4	76.4	76.6
Number of stays	458,665	297,583	160,828
Number of nursing homes	14,350	14,033	13,542

Notes: Table reports summary statistics on patient and nursing home characteristics for our baseline analysis sample of 2022 nursing home admissions from the community, for all admissions (column 1) and separately for private-pay and Medicaid-covered admissions (columns 2 and 3). Medicaid coverage is defined by dual eligibility for Medicaid at admission. Alzheimer’s status is the Alzheimer’s disease indicator in the Medicare chronic conditions data. Race is from the MDS; “other or unknown” includes all patients not recorded as White or Black. Overall and staffing ratings are from the CMS Nursing Homes Provider Information dataset (CMS 2022b); EFM value-added quintiles are national quintiles of the EFM value-added score (Einav et al. 2025). Shares by rating are computed among stays at nursing homes with the rating observed; nursing homes without an EFM value-added score are excluded from that block. Occupancy rate is the daily resident census divided by the number of certified beds on the day of admission. The daily resident census is reported in the CMS Payroll Based Journal Daily Nurse Staffing dataset (CMS 2022a), and the number of certified beds is based on the CMS Nursing Home Provider Information dataset; for admission days without a census report we use the nursing home’s 2022 average.

Appendix Table A13: Covariates in the Random Forest Availability Models

Group	Variables
Quality ratings	CMS overall, health inspection, quality measure (QM), long-stay QM, and staffing ratings (1–5); EFM value-added score
Capacity / utilization	certified beds, average daily residents, occupancy rate, admissions per bed, share admitted from hospital
Ownership / structure	for-profit, chain, multi-facility
Nurse staffing	LPN, RN, CNA, and total nurse hours per resident-day; LPN, RN, and CNA shares of nurse hours
Resident mix	% Medicaid, % Medicare, % female, % Black, % Hispanic, % white, average age, % under 65
State reimbursement rates	Medicaid rate, private rate, and the private–Medicaid difference in dollars and in percent
Geography	state and census-region indicators
Audit design	inquiry race, vignette (sixteen sub-categories), and study round

Notes: Table lists the covariates in the random forests that predict nursing home availability by payer (one forest for inquiries made on behalf of Medicaid patients and one for inquiries made on behalf of private-pay patients, both fit on the audit-study inquiries). The forests include every facility characteristic used in the heterogeneity analysis of Section 4.2 except the Alzheimer’s-unit indicator; these variables are defined in Appendix A.2.3, with EFM value-added entering as the continuous score rather than its quintile. The remaining facility covariates are from the July 2025 CMS Provider Information dataset (CMS (2025b)), except for share female, share Black, share Hispanic, and share white, which are from LTCFocus (2022). The audit design variables are included in the forests and averaged over their randomization distribution when making per-facility predictions.

Appendix Table A14: Heterogeneity Across Markets in Counterfactual Change in Average Quality for Medicaid Patients

	Δ Quality		Share of gap	
	Unweighted	Weighted	Unweighted	Weighted
<i>Panel A: Overall rating</i>				
Mean	0.017	0.018	0.068	0.079
SD	0.062	0.048	0.288	0.275
p5	−0.057	−0.049	−0.257	−0.186
p10	−0.040	−0.035	−0.150	−0.109
p25	−0.015	−0.012	−0.038	−0.031
p50	0.009	0.012	0.031	0.037
p75	0.040	0.043	0.127	0.132
p90	0.077	0.082	0.303	0.318
p95	0.114	0.112	0.497	0.540
<i>Panel B: Staffing rating</i>				
Mean	0.027	0.027	0.100	0.112
SD	0.059	0.044	0.351	0.357
p5	−0.032	−0.033	−0.220	−0.232
p10	−0.020	−0.022	−0.117	−0.121
p25	−0.001	0.000	−0.005	0.000
p50	0.018	0.023	0.058	0.076
p75	0.048	0.050	0.162	0.164
p90	0.082	0.082	0.357	0.346
p95	0.107	0.108	0.528	0.621
<i>Panel C: EFM value-added (quintiles)</i>				
Mean	0.024	0.027	0.067	0.084
SD	0.051	0.050	0.315	0.308
p5	−0.046	−0.040	−0.303	−0.271
p10	−0.028	−0.024	−0.158	−0.116
p25	−0.004	−0.005	−0.030	−0.027
p50	0.018	0.023	0.042	0.066
p75	0.052	0.054	0.168	0.176
p90	0.086	0.090	0.342	0.351
p95	0.108	0.115	0.473	0.471

Notes. This table reports, for each quality measure, the distribution across markets of the change in the average rating of nursing homes chosen by Medicaid patients when they face the private availability probabilities (Δ Quality), and of that change as a share of the market's own model private–Medicaid gap. Panel A uses the overall CMS rating, Panel B the staffing rating, and Panel C national quintiles of the EFM value-added score. Unweighted columns show the distribution across markets without weighting; weighted columns weight markets by patient-stays in each market.

Appendix Table A15: Email Addresses

Gmail	Outlook
ashantiwashington@gmail.com	aaliyahbooker@outlook.com
preciousjackson158@gmail.com	keyanajwashington@outlook.com
tamiabanks375@gmail.com	tyrajefferson@outlook.com
taniyamosley4@gmail.com	carriemcgrath1@outlook.com
tionnarjefferson@gmail.com	ericawwalsh@outlook.com
amytlarsen@gmail.com	kristenrmeyer@outlook.com
cassiehstein@gmail.com	stephaniebdecker@outlook.com
katietbecker@gmail.com	
hilarylandersen@gmail.com	

Appendix Table A16: Categories of Agreement — Availability

Category	Count	Percent
Humans agree and GPT agrees	185	92.5%
Humans agree but GPT doesn't	9	4.5%
Humans need tiebreak and GPT agrees with it	5	2.5%
Humans need tiebreak and GPT disagrees with it	1	0.5%

Note: Sample: 200 messages randomly selected and double-coded by two human reviewers; ties adjudicated by a third reviewer.

Appendix Table A17: Pairwise Comparisons: Vignette $\times$ Payer $\times$ Race Combinations

Comparison	Estimate	Std. Error	p-value (Tukey)
Vignette 2 Private White vs Vignette 4 Medicaid Black	0.108	0.023	0.001
Vignette 2 Private White vs Vignette 4 Medicaid White	0.094	0.021	0.003
Vignette 2 Private Black vs Vignette 4 Medicaid Black	0.094	0.021	0.003
Vignette 2 Private White vs Vignette 4 None Black	0.100	0.024	0.006
Vignette 1 Private White vs Vignette 4 Medicaid Black	0.093	0.023	0.016
Vignette 2 Private White vs Vignette 4 None White	0.086	0.022	0.018
Vignette 2 Private Black vs Vignette 4 None Black	0.086	0.022	0.018
Vignette 1 Private White vs Vignette 1 Medicaid Black	0.063	0.016	0.023
Vignette 2 Private White vs Vignette 2 Medicaid Black	0.063	0.016	0.023
Vignette 3 Private White vs Vignette 3 Medicaid Black	0.063	0.016	0.023
Vignette 4 Private White vs Vignette 4 Medicaid Black	0.063	0.016	0.023
Vignette 2 Private White vs Vignette 3 Medicaid Black	0.087	0.023	0.038
Vignette 1 Private White vs Vignette 4 Medicaid White	0.079	0.021	0.039
Vignette 1 Private Black vs Vignette 4 Medicaid Black	0.079	0.021	0.039
Vignette 1 Private White vs Vignette 1 Medicaid White	0.049	0.013	0.042
Vignette 2 Private White vs Vignette 2 Medicaid White	0.049	0.013	0.042
Vignette 3 Private White vs Vignette 3 Medicaid White	0.049	0.013	0.042
Vignette 4 Private White vs Vignette 4 Medicaid White	0.049	0.013	0.042
Vignette 1 Private Black vs Vignette 1 Medicaid Black	0.049	0.013	0.042
Vignette 2 Private Black vs Vignette 2 Medicaid Black	0.049	0.013	0.042
Vignette 3 Private Black vs Vignette 3 Medicaid Black	0.049	0.013	0.042
Vignette 4 Private Black vs Vignette 4 Medicaid Black	0.049	0.013	0.042
Vignette 3 Private White vs Vignette 4 Medicaid Black	0.083	0.023	0.050

Notes: N = 5,594 inquiries. 276 total pairwise comparisons of 24 vignette-payer-race combinations ($4 \times 3 \times 2$). P-values are adjusted using Tukey's HSD test to control for family-wise error rate. Only comparisons with p-value < 0.05 are shown. Estimate is predicted probability difference (percentage points) in availability, controlling for day of week and round; positive values favor the first comparison group.

Appendix Table A18: Effects of Facility Characteristics on the White–Black Availability Gap

	Profit status		Chain status [^]		Region			
	Not-for-profit	For-profit	Non-chain	Chain	Midwest	Northeast	South	West
White mean	0.446 (0.044)	0.353 (0.041)	0.411 (0.043)	0.363 (0.041)	0.447 (0.043)	0.339 (0.043)	0.373 (0.042)	0.261 (0.045)
Black mean	0.435 (0.044)	0.339 (0.040)	0.397 (0.043)	0.349 (0.041)	0.420 (0.043)	0.325 (0.043)	0.373 (0.042)	0.244 (0.043)
White – Black	0.012 (0.022)	0.014 (0.011)	0.014 (0.016)	0.014 (0.012)	0.027 (0.020)	0.014 (0.019)	-0.000 (0.017)	0.017 (0.022)
Difference in gaps	0.003 (0.024)		-0.001 (0.020)		P-value = 0.768			
Observations	1299	4295	2136	3458	1513	1310	1855	916
Nursing homes	686	2254	1117	1823	802	686	977	475

Notes: Table reports the results of estimating equation 1, allowing for an interaction term for the race indicator (Black inquirer) and facility characteristics. Columns present heterogeneous effects by (1) profit status (not-for-profit vs. for-profit), (2) chain status (non-chain vs. multi-facility operators), and (3) region (Census Bureau regions). All regressions include controls for payer type, inquiry round, and day of the week (as well as for the vignette); standard errors (clustered on nursing home) are in parentheses. The *White – Black* row reports the difference in availability for inquiries with a White name vs. those with a Black name. [^] indicates the outcome was not prespecified.

Appendix Table A19: Effects of Occupancy and Reimbursement Rate Differences on Availability by Payer

	Occupancy rate [^] (1)	Reimbursement rate difference (2)
Medicaid	-0.050 (0.013)	-0.048 (0.013)
Characteristic	-0.019 (0.007)	-0.015 (0.007)
Medicaid × characteristic	-0.022 (0.009)	-0.014 (0.008)
No payer	-0.042 (0.014)	-0.040 (0.014)
No payer × characteristic	-0.015 (0.009)	-0.005 (0.008)
Observations	5,548	5,524
Number of nursing homes	2,929	2,904

Notes: Columns report separate regressions of availability on payer treatments, a facility characteristic (occupancy rate or reimbursement rate difference), and their interaction. Occupancy rate (col. 1) and reimbursement rate difference (col. 2) are centered at their sample means and scaled so coefficients correspond to a 10-percentage-point increase. The reimbursement rate difference is defined as (private rate–Medicaid rate)/private rate at the state level. All specifications control for race, vignette, study round, and day of week; standard errors clustered on nursing home are in parentheses. [^] indicates the outcome was not prespecified.

Appendix Table A20: Effects of Facility Characteristics on the Private-Medicaid Availability Gap

	Profit status		Chain status [^]		Region			
	Not-for-profit	For-profit	Non-chain	Chain	Midwest	Northeast	South	West
Private mean	0.470 (0.045)	0.347 (0.041)	0.428 (0.044)	0.354 (0.041)	0.436 (0.044)	0.370 (0.045)	0.377 (0.043)	0.237 (0.045)
Medicaid mean	0.369 (0.045)	0.315 (0.041)	0.341 (0.043)	0.329 (0.042)	0.385 (0.044)	0.264 (0.044)	0.350 (0.043)	0.225 (0.045)
No payer mean	0.417 (0.046)	0.311 (0.041)	0.379 (0.044)	0.319 (0.041)	0.417 (0.045)	0.296 (0.045)	0.328 (0.043)	0.231 (0.045)
Private – Medicaid	0.101 (0.029)	0.033 (0.015)	0.087 (0.022)	0.025 (0.017)	0.051 (0.026)	0.106 (0.026)	0.027 (0.024)	0.012 (0.029)
Difference in gaps	-0.068 (0.032)		-0.062 (0.027)		P-value = 0.063			
Observations	1299	4295	2136	3458	1513	1310	1855	916
Nursing homes	686	2254	1117	1823	802	686	977	475

Notes: Table reports the results of estimating equation 1, allowing for an interaction term for the payer indicators (Medicaid or no payer specified) and facility characteristics. Columns present heterogeneous effects by (1) profit status (not-for-profit vs. for-profit), (2) chain status (non-chain vs. multi-facility operators), and (3) region (Census Bureau regions). All regressions include controls for indicators for inquiry round and day of the week (as well as for the other treatment indicators for patient race and vignette); standard errors (clustered on nursing home) are in parentheses. The *Private – Medicaid* row reports the difference in availability for inquiries indicating a private payer vs. Medicaid. [^] indicates the outcome was not prespecified.

Appendix Table A21: Effects of Facility Characteristics on the Alzheimer's vs Other Vignettes Availability Gap

	Profit status		Chain status [^]		Alzheimer's unit status [^]		Region			
	Not-for-profit	For-profit	Non-chain	Chain	No	Has	Midwest	Northeast	South	West
Other vignettes mean	0.462 (0.043)	0.350 (0.041)	0.420 (0.042)	0.358 (0.041)	0.371 (0.041)	0.404 (0.045)	0.453 (0.043)	0.337 (0.043)	0.370 (0.042)	0.260 (0.043)
Alzheimer's vignette mean	0.374 (0.048)	0.335 (0.042)	0.354 (0.045)	0.347 (0.043)	0.340 (0.042)	0.343 (0.052)	0.369 (0.047)	0.310 (0.048)	0.377 (0.045)	0.225 (0.047)
Other vignettes – Alzheimer's	0.089 (0.030)	0.015 (0.016)	0.066 (0.023)	0.011 (0.017)	0.030 (0.015)	0.061 (0.037)	0.084 (0.028)	0.027 (0.028)	-0.007 (0.025)	0.035 (0.029)
Difference in gaps	-0.074 (0.034)		-0.055 (0.029)		0.030 (0.040)		P-value = 0.110			
Observations	1299	4295	2136	3458	4763	759	1513	1310	1855	916
Nursing homes	686	2254	1117	1823	2501	402	802	686	977	475

Notes: Table reports the results of estimating equation 1, allowing for an interaction term for the Alzheimer's vignette indicator (vignette 4) and facility characteristics. Columns present heterogeneous effects by (1) profit status (not-for-profit vs. for-profit), (2) chain status (non-chain vs. multi-facility operators), (3) Alzheimer's special care unit status, and (4) region (Census Bureau regions). All regressions include controls for payer type, race, inquiry round, and day of the week; standard errors (clustered on nursing home) are in parentheses. The *Other vignettes – Alzheimer's vignette* row reports the difference in availability for other vignettes vs. Alzheimer's vignette inquiries. [^] indicates the outcome was not prespecified.