PATIENT PEER EFFECTS: EVIDENCE FROM NURSING HOME ROOM ASSIGNMENTS*

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Abstract

We provide causal evidence that patient peer effects generate mortality impacts comparable to provider quality differences. Drawing on administrative records covering over 2.5 million stays across 7,200 U.S. nursing homes from 2000–2010, we isolate plausibly exogenous variation in room assignments driven by room availability at the time of admission. We estimate that assignment to a roommate diagnosed with Alzheimer's disease (AD) or Alzheimer's disease related dementias (ADRD), relative to being assigned no roommate, increases 90-day mortality by 1.1 percentage points on average (7% of baseline)—equivalent to receiving care at a nursing home half a standard deviation worse in quality. Effects differ sharply by patient type: patients with AD/ADRD benefit substantially from cognitively healthy roommates but not from private rooms, suggesting important peer monitoring and support roles. By contrast, mortality of patients without AD/ADRD does not depend on roommate cognitive health but is reduced in private rooms. Exploiting this heterogeneity, we derive a set of efficient room assignment policies that characterize the health production possibility frontier for outcomes of different patient types. We find that better room assignment can reduce overall mortality by 0.6 percentage points—saving roughly 1,400 life-years per year in our sample.

JEL Codes: D62, I11, I12, I18, J14.

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I Introduction

High and rising healthcare expenditures have renewed longstanding policy and academic debates about improving healthcare productivity (OECD, 2024). A large literature on practice variation documents substantial differences in spending and treatment decisions with little correlation to patient outcomes (Fisher et al., 2003a,b), suggesting that additional spending often yields limited health benefits (Garber and Skinner, 2008). Yet this work focuses almost exclusively on *formal* inputs—such as physicians, nurses, and capital—largely overlooking patients and their interactions as *informal* inputs into health production.[1] In settings from hospital wards to nursing homes, patients share space and interact repeatedly, creating scope for peer effects. If a patient's recovery or mortality depends on the health and behavior of nearby patients, the social composition of care settings may shape productivity alongside traditional inputs. Despite its potential importance for clinical efficiency, facility design, and policy (The White House, 2022), the causal impact of patient peer effects remains largely unexplored.

We show that patients themselves are productive inputs in the health production function. In the context of U.S. nursing homes, we provide the first causal evidence that roommate assignments affect mortality, with effects comparable in magnitude to differences in overall facility quality. We show that these peer effects are large, asymmetric, and policy-relevant. Optimizing roommate assignments can meaningfully reduce mortality at minimal cost, particularly in under-resourced providers.

We focus on a large and growing sector. With declining fertility, rising childlessness, and increasing prevalence of Alzheimer's disease and related dementias (AD/ADRD), formal long-term care services play an increasingly central role in the management of chronic diseases for a rapidly aging population. Nursing homes are central to this system: more than half of individuals currently aged 57–61 are projected to spend time in a nursing home (Hurd, Michaud, and Rohwedder, 2017), and about 30% of current residents have an active

[1] More recent work has highlighted important differences in productivity between health care providers, discussed below, and the role of input misallocation, e.g. the overuse of ineffective medical treatments and underuse of effective ones (Hollingsworth, 2008; Chandra and Skinner, 2012; Chandra, Colla, and Skinner, 2023).

diagnosis of AD/ADRD. Yet, despite annual nursing home expenditures of approximately $219.9 billion (Centers for Medicare & Medicaid Services, 2024), much of which is publicly financed, low quality of care is still an ongoing policy concern. While a growing literature studies how provider incentives and resources shape care quality (Hackmann, 2019; Gandhi et al., 2024; Einav, Finkelstein, and Mahoney, 2025), most traditional levers to increase quality—such as increasing reimbursements or offering financial incentives for nursing homes to increase staffing—tend to be expensive, potentially adding to already-high costs. Given that nearly 80% of nursing home patients share rooms, understanding how patients affect each other's health may offer a cost-effective way of improving patient outcomes. Yet, beyond infection transmission, we know little about whether—and how—peer effects operate in this setting.

The limited existing evidence on patient peer effects is not surprising, given that roommate assignment is rarely observed in the data. Even when it is, identification of peer effects is complicated by the potential for selection and common shocks: facilities may match patients by acuity, diagnosis, demographics, or behavior, and room-level shocks may induce correlations in roommates' health. We overcome these challenges using administrative data covering 2.5 million patient stays across more than 7,200 U.S. nursing facilities from 2000–2010. We construct a novel daily panel dataset at the room level—tracking occupancy and characteristics of occupants in each room over time—which we use to isolate quasi-random differences in predetermined roommate characteristics driven by bed availability. Specifically, conditional on facility-by-time fixed effects, patient composition, and operational strain, high-frequency variation in the type of rooms available at admission generates plausibly exogenous differences in whether one is assigned a roommate, and if so, the characteristics of one's roommate(s). The instruments strongly predict room assignment—with first-stage F-statistics exceeding 20,000—and we provide extensive evidence—including balance tests and robustness checks—supporting the other IV assumptions.

Our empirical analysis yields three main findings. First, patient peer effects are quantitatively large and generate substantial within-facility variation in outcomes. Assignment to a roommate with AD/ADRD increases 90-day mortality by 1.1 percentage points on average

(7% of baseline) relative to being assigned no roommate. This effect is driven primarily by the intensive margin—cognitive health of the roommate one is assigned—rather than the extensive margin—whether one is assigned any roommate—suggesting that infection transmission is unlikely to be the main mechanism driving these results.

Second, we document striking heterogeneity, revealing important substitutabilities in health production. Patients with AD/ADRD benefit substantially from cognitively healthy roommates, experiencing a 3.4 percentage point mortality reduction relative to being assigned a roommate who also has AD/ADRD, and a 1.4 percentage point reduction relative to being assigned no roommate. Conversely, patients without AD/ADRD are unharmed by cognitively impaired roommates but do benefit from placement in a private room. Our preferred interpretation is that cognitively healthy patients can provide important monitoring and behavioral support for patients with AD/ADRD, generating a unidirectional positive externality. This asymmetry is difficult to reconcile by infection control, privacy preferences, or symmetric social interaction—it points to peer production of health through caregiving spillovers. Indeed, peer effects are concentrated in facilities with below-median staffing and in facilities without Alzheimer's units (which provide specialized dementia-focused care), consistent with peer monitoring playing a more valuable role when formal care is inadequate.

Third, our findings identify patient assignment as a previously overlooked lever for improving healthcare delivery. Because patients with AD/ADRD benefit substantially from cognitively intact roommates—while cognitively intact patients are unharmed by roommates with AD/ADRD—mixing patients by cognitive status in shared rooms can reduce average mortality. We formalize this insight through simulated assignment rules, showing that mortality-minimizing assignment policies differ markedly from current practice and can yield large reductions in average mortality. While current assignments tend to match patients by cognitive status, the mortality-minimizing policy groups patients with and without AD/ADRD as roommates, leading to reductions in 90-day mortality of at least 0.6 percentage points. Crucially, these gains do not necessarily require additional staffing or capital. These average gains mask important heterogeneity across patients and providers. We find that assignment policies that minimize average mortality predominantly benefit patients with AD/ADRD and can harm cognitively healthy patients in about 2.4% of providers. We therefore consider alternative assignment rules along a health production possibility frontier that imply different tradeoffs between the two groups of patients, including an assignment policy that maximizes quality-adjusted life years (QALYs). We find that the QALY-optimal assignment rule reduces the share of providers in which cognitively healthy patients can be harmed to 0.8%, while achieving 93% of the survival gains under the mortality-minimizing assignment policy.

Taken together, our findings speak to a broader literature on the sources of disparities in healthcare outcomes. A large literature documents substantial geographic and provider-level variation in health outcomes (Murray et al., 2006; Chetty et al., 2016; Currie and Schwandt, 2016; Chandra et al., 2016a; Einav, Finkelstein, and Mahoney, 2025). These differences are typically attributed to variation in individuals' health investments and capital (Grossman, 1972), variation in provider quality in hospitals (Geweke, Gowrisankaran, and Town, 2003; Chandra et al., 2016a; Doyle, Graves, and Gruber, 2019; Hull, 2018) and nursing homes (Olenski and Sacher, 2024; Einav, Finkelstein, and Mahoney, 2025; Cheng, 2025), diminishing returns to medical inputs (Fisher et al., 2003a,b; Fuchs, 2004; Finkelstein and Gentzkow, 2026), and place-based factors such as medical care, environment, and local risk exposures (Finkelstein, Gentzkow, and Williams, 2016; Deryugina and Molitor, 2021; Finkelstein, Gentzkow, and Williams, 2021). We contribute to this literature by highlighting a complementary and largely unexplored mechanism: interactions between patients themselves. This mechanism implies that health production depends not only on formal inputs and providers, but also on the composition of patients within care settings.

Second, we contribute to the empirical literature on peer effects, where a large body of work documents the important roles that peers play in education, labor markets, and development (Sacerdote, 2001; Duflo, Dupas, and Kremer, 2011; Card et al., 2012). In health settings, while there is a literature that studies peer effects in health behaviors such as smoking and drinking among younger populations (Nakajima, 2007; Kremer and Levy, 2008; Card and Giuliano, 2013), whether peer interactions generate meaningful differences in health outcomes at older ages—and within institutional care settings—remains largely an open question (Deryugina and Molitor, 2021). We provide some of the first causal evidence on peer effects in formal care and how they interact with inputs such as capital and labor. Moreover, we provide rare evidence that peers can have large effects on mortality, a particularly stark outcome.

Third, our evidence points to important within-provider quality differences. Recent evidence suggests that many disparities arise within rather than between providers (Alsan, Garrick, and Graziani, 2019; Einav et al., 2025), yet the mechanisms driving this within-provider variation—despite their importance for effective policy design—remain poorly understood. Our results indicate that peer effects drive part of within-nursing-home variation in quality. Our analysis also relates closely to concurrent work by McWilliam (2025), which studies outcomes under private versus shared rooms among post-acute nursing home patients and finds limited effects on mortality and related outcomes. We complement this work by showing that outcomes depend not only on whether a room is private or shared, but also on roommate characteristics—a margin absent from private-versus-shared comparisons. Moreover, we document substantial heterogeneity: private rooms benefit cognitively healthy patients but may be neutral or even harmful for patients with AD/ADRD, who benefit from cognitively healthy roommates.

This paper proceeds as follows. Section II describes the nursing home setting and our data. Section III outlines our IV strategy, discussing the identifying assumptions and providing evidence that they are satisfied. Section IV presents our peer effect estimates, and explores implications for room assignment policies as well as mechanisms. Section V concludes.

II Background and Data

II.A Background

Nursing homes represent a substantial component of the U.S. long-term care system, with approximately 1.2 million Americans residing in certified nursing homes at any given time (Kaiser Family Foundation, 2025). Total revenues for U.S. nursing care facilities exceed $200 billion annually (Martin et al., 2025), reflecting the sector's significant economic footprint. Medicare and Medicaid together finance about two-thirds of nursing home spending, underscoring the sector's central importance for both public health and fiscal sustainability.

The importance of this sector is growing with demographic change. The prevalence of Alzheimer's disease and related dementias (AD/ADRD) is projected to rise from over 6 million Americans today to 13.8 million by 2050 (Matthews et al., 2019). Individuals with AD/ADRD are significantly more likely to require nursing home care than those without cognitive impairments; between 2017 and 2019, more than three million nursing home patients have been diagnosed with AD/ADRD (Mukamel et al., 2023), and Alzheimer's disease has become the costliest disease in the U.S., accounting for more than $350 billion in costs in 2021 (Chandra, Coile, and Mommaerts, 2023). Because such a large proportion of nursing home patients have AD/ADRD, understanding how facility practices shape outcomes for this population has become an urgent policy priority.

II.A.1 Room Sharing: Benefits, Costs, and Policy Debates

A distinctive feature of nursing home care is that most patients share rooms. In our sample, detailed below, almost 80% of patients are assigned to a shared room upon admission. Unlike hospitals, where room sharing is typically brief, nursing home stays often last months or years, creating extended peer exposure.

Room sharing involves important tradeoffs. Shared rooms may provide social interaction, companionship, and cognitive stimulation—potentially valuable given high rates of loneliness and social isolation among nursing home patients (Trybusińska and Saracen, 2019; Zhang et al., 2023). However, roommates may also impose costs: sleep disruption, noise, exposure to behavioral disturbances (particularly common among patients with AD/ADRD), loss of privacy, and elevated risk of infectious-disease transmission (Brown et al., 2021; Konetzka, Grabowski, and Mor, 2024).

These tradeoffs have motivated ongoing policy debates about room configuration standards. The Biden Administration's 2022 nursing home reform agenda explicitly proposed accelerating the phase-out of rooms with three or more patients and promoting single-occupancy rooms (The White House, 2022). States such as Massachusetts, Michigan, and Ohio have introduced incentives to encourage the adoption of private rooms. Germany has taken an even more ambitious approach: several German federal states have implemented regulatory mandates requiring nursing homes to convert multi-patient rooms into predominantly single-occupancy rooms over a defined transition period (Herr, Lückemann, and Reichert, 2025). However, these policies remain controversial. Single rooms substantially increase construction costs and may reduce social interaction, with uncertain net effects on patient well-being.

Resolving this debate requires understanding not just whether room sharing affects outcomes on average, but also whether effects depend on roommate characteristics. This heterogeneity is particularly relevant for patients with AD/ADRD. Dementia-related symptoms such as confusion, agitation, wandering, and repetitive vocalizations can be distressing to cognitively intact roommates. At the same time, social interaction and peer monitoring may benefit individuals with AD/ADRD themselves (Nichols, 2014). Specialized dementia care units—which often feature single rooms or modified environments—are designed to address these needs but remain uncommon: only 4.5% of nursing home beds are in special care units (Joyce et al., 2018). Most patients with AD/ADRD thus reside in general care units, where room assignments determine their daily social environment.

II.A.2 Room Assignment as a Policy Lever

Room assignment policies represent a potentially important but understudied margin for improving nursing home outcomes. Unlike many proposed interventions, optimizing room assignments requires primarily better information and revised protocols rather than additional staffing or costly facility modifications. If peer effects vary systematically with roommate characteristics, facilities can improve outcomes by better matching patients—for instance, avoiding particularly poor matches, or prioritizing single rooms for patients most likely to be harmed by room sharing.

Despite the potential policy relevance, empirical evidence on peer effects in nursing homes is extremely limited. Prior research has examined facility-level quality measures (Grabowski, Gruber, and Angelelli, 2008), the effectiveness of specialized dementia units (Joyce et al., 2018), and infection transmission in shared rooms (Brown et al., 2021; Konetzka, Grabowski, and Mor, 2024). However, we are not aware of prior work that credibly identifies causal effects of roommate characteristics on patient outcomes.

II.B Data

To quantify the causal effect of nursing home room assignments on patient mortality, we combine three primary data sources. First, we use the Minimum Data Set (MDS) to measure room assignment as well as patient and peer health characteristics at admission. We focus on the effects of three mutually exclusive types of assignments: being assigned no roommate, a roommate with AD/ADRD, and roommates without AD/ADRD. Second, we link the data to Medicare claims data to measure patient mortality, our primary outcome of interest. Third, we incorporate facility-level data from the On-Line Survey, Certification, and Reporting (OSCAR) system to validate our room measures and explore potential mechanisms.

II.B.1 Minimum Data Set (MDS)

The MDS provides standardized patient assessments for all patients in Medicare or Medicaid-certified nursing homes, regardless of payer source. Mandated by federal law, these assessments are conducted at admission, discharge, quarterly intervals in between, and whenever there is a significant change in status during nursing home stays.[2] The data have been widely

[2]In addition, during our study period, assessments were also required for Medicare-covered patients at days 14, 30, and 60.

used in prior research and offer detailed information on patient demographics, health status, and functional limitations. We use version 2.0, which was in effect during our 2000-2010 study period.

Room Assignment Measures

The key innovation in our empirical strategy is the use of a room identifier variable contained in MDS assessments. By combining room identifiers with admission and discharge dates, we can reconstruct the daily composition of patients in each nursing home room throughout our sample period.

Constructing room-level variables. We combine the room identifier with admission and discharge dates to build a nursing-home-by-room-by-day database, which tracks the daily room composition at all nursing home rooms. This allows us to identify the type of room each patient is assigned at admission, as well as the types of rooms available at the nursing home she is assigned to on the day of admission. In particular, to identify which rooms are available on each calendar day, we construct room capacity as the maximum number of patients co-residing in the room at any point during the corresponding calendar year, which allows us to measure available beds as the difference between room capacity and current utilization.

Validation of room measures. We conduct two validation exercises to ensure our room identifier captures meaningful variation in actual room assignments.

First, Appendix Figure A.1 compares the number of distinct room identifiers in the MDS to bed counts from OSCAR facility data. Consistent with expectations, the number of rooms is smaller than the number of beds and increases approximately linearly with facility size, with a slope consistent with most rooms containing one or two beds.

Second, Appendix Table A.1 documents substantial homophily in roommate pairings. Patients are far more likely to share rooms with others of the same gender, similar demographics, and similar health status—patterns consistent with room assignments reflecting deliberate matching decisions rather than random measurement error.

Taken together, this evidence suggests that our room measures capture meaningful information on actual room assignments. While measurement error cannot be entirely ruled out, we note that such error would likely attenuate our estimates toward zero, making our findings conservative lower bounds on the true peer effects.

Defining Treatment: Room Types. Our identification strategy exploits quasi-random variation in assignment to three room types, defined by the presence and health status of roommates at the time of admission (more precisely, we characterize the room type at the end of the day before the focal resident's admission).[3] We classify each admission into one of three mutually exclusive categories:

1. **Empty room**: The patient is assigned to a room without roommates. This includes private and empty multi-bed rooms.
2. **Shared room with AD/ADRD roommate**: The patient is assigned to share a room with at least one roommate who has a documented AD/ADRD diagnosis.
3. **Shared room without AD/ADRD roommate**: The patient is assigned to share a room with at least one roommate, none of whom have documented AD/ADRD.

These room types represent the ”treatment” in our empirical analysis. By construction, our measure of room composition is pre-determined and thus not affected by the health of the newly admitted patient.

Health and Demographic Measures

We construct measures of both focal patients' own health characteristics and their roommates' characteristics at the time of admission.

[3] Throughout the paper, we use time of admission as a shorthand for the day before the focal resident's admission. The most granular time unit available in our data is the day level.

AD/ADRD diagnosis. Our primary measure of peer cognitive impairment is an indicator for whether a roommate has a diagnosis of Alzheimer's disease or related dementias (AD/ADRD). The MDS dementia diagnosis fields capture physician-documented conditions that are clinically active and relevant to the patient's current care plan. These fields reflect facility-recognized diagnoses rather than staff observations or cognitive test scores alone. Prior validation studies show that they provide highly specific markers of dementia but may miss milder or undocumented cases (Niznik et al., 2025). We construct an analogous measure to characterize focal patients' own dementia status.

Cognitive, functional status, and patient demographics. As an additional measure of cognitive impairment, we use the Cognitive Performance Scale (CPS), a validated summary measure ranging from 0 (intact) to 6 (very severe impairment) and Activities of Daily Living (ADL)—ranging from 0 to 28—where higher values indicate greater difficulty with tasks like eating, dressing, and toileting. These measures have been used as proxies of cognitive and physical impairment in numerous studies (Grabowski, Gruber, and Angelelli, 2008; Rahman, Norton, and Grabowski, 2016; Cornell et al., 2019). The MDS also provides information on patient demographics (age, sex, race), and prior living situation (community, hospital, another nursing home). Together with the measures of cognitive and functional status, we use these variables primarily for balance tests for our identification strategy and as controls in robustness checks, but we also examine peer effects based on roommates' CPS and ADL scores in supplementary analysis.

II.B.2 Medicare Claims Data

We link MDS records to Medicare beneficiary files and claims data using unique beneficiary identifiers. This linkage allows us to track health outcomes even after patients are discharged from nursing homes, avoiding potential selection bias from conditioning on continued nursing home residence.

Our primary outcome is mortality within 90 days of nursing home admission, measured using the death date recorded in the Medicare Beneficiary Summary File. We focus on

90-day mortality because it is a well-measured, policy-relevant outcome that has been used extensively in health economics research (Chandra et al., 2016b; Finkelstein, Gentzkow, and Williams, 2021). In robustness checks, we examine alternative time horizons (30-day, 180-day, and 360-day mortality).

We also extract 27 chronic condition indicators from the Medicare Chronic Conditions Warehouse, including conditions such as diabetes, heart failure, and chronic obstructive pulmonary disease. We use these measures in balance tests for our IV strategy and as controls for baseline health in robustness exercises.

II.B.3 OSCAR Facility Data

We merge OSCAR data to obtain annual facility-level characteristics for each nursing home in our sample. OSCAR collects these data through periodic surveys and certification inspections conducted by state agencies. We use OSCAR data for two purposes. First, as described above, we use bed counts to validate our room identifier measures (Appendix Figure A.1). Second, we use facility characteristics—including staffing ratios and the presence of specialized Alzheimer's or dementia care units—to explore potential mechanisms underlying our main results.

II.B.4 Sample Construction

We construct our analysis sample using MDS 2.0 data from 2000–2010 for twelve large states: California, New York, Florida, Texas, Pennsylvania, Ohio, Illinois, New Jersey, Massachusetts, Indiana, Michigan, and North Carolina. These states were selected based on data availability and quality, and collectively account for approximately 60% of U.S. nursing home patients.[4]

By linking the MDS to Medicare claims data, we restrict the sample to newly admitted patients aged 65 and older enrolled in traditional (fee-for-service) Medicare at some point during our study period. This restriction ensures complete ascertainment of mortality

[4]Calculations are based on patient counts in 2024 from Nursing Home Compare available at `https://www.kff.org/state-category/providers-service-use/`, last accessed November 18th, 2025.

outcomes while covering the majority of nursing home admissions. During our sample period, about 80% of the elderly were enrolled in traditional Medicare plans (Gold et al., 2011). Importantly, while we restrict focal patients to Medicare beneficiaries, we observe the full set of roommates regardless of payer source.

We further limit the data to each patient's first observed nursing home stay. Room assignment in subsequent stays may follow different rules (e.g., due to bed-hold policies)[5], and later stays are observed only for patients who survive the initial admission, potentially biasing the sample. Our final dataset contains 2.5 million nursing home stays across more than 7,200 facilities and 480,000 unique rooms. Further details on the sample construction are provided in Appendix Section A.

II.C Summary Statistics

Columns 1–4 of Table I provide summary statistics on baseline characteristics and 90-day mortality for the full sample, patients assigned to rooms without a roommate, patients assigned roommate(s) with AD/ADRD, and patients assigned roommate(s) none of whom have AD/ADRD respectively. Columns 5 and 6 show differences in means for these variables across different subsamples along with standard errors for these differences clustered at the nursing home level.

In the full sample (column 1), more than half of patients are female, the average age is 78, and most are white, have less than a bachelor's degree, and are admitted for post-acute care. Residents face substantial cognitive and physical impairments and multiple chronic conditions; roughly 30% have an AD/ADRD diagnosis at admission, and 15% die within 90 days.

Turning to differences across room assignments, patients who are older, female, and have greater cognitive impairment (with higher CPS scores and higher AD/ADRD prevalence) are disproportionately assigned roommates with AD/ADRD. More educated patients with fewer chronic conditions and physical impairments are more likely to be assigned an empty

[5] If a patient is discharged to a hospital and expected to return, the nursing home may hold her bed during the interim.

room. Patients assigned a roommate with AD/ADRD have the highest 90-day mortality rate, followed by patients assigned to empty rooms, and finally, patients assigned roommates without AD/ADRD. However, room composition differs across nursing homes, and even within a nursing home room assignment is not random, so these patterns should not be interpreted causally.

III Empirical Strategy

Our primary goal is to quantify the causal effects of nursing home room assignments on patients' health outcomes. Our main specification is:

$$Y_{i,r,j,t} = \beta_0 + \beta_1 \text{ Empty}_{r,j,t} + \beta_2 \text{ AD}_{r,j,t} + \Gamma'_{j,t}\beta_\gamma + \varepsilon_{i,r,j,t}, \tag{1}$$

where $Y_{i,r,j,t}$ is a future health outcome (90-day mortality in our main specifications) for patient i. $r(i,t)$, or simply r, denotes the room in nursing home j to which patient i is assigned on day t. $\text{Empty}_{r,j,t}$ indicates whether the assigned room r is empty at time t, and $\text{AD}_{r,j,t}$ indicates whether room r has at least one roommate with AD/ADRD at time t. The excluded group comprises patients assigned to a shared room, in which none of the roommates has a diagnosis of AD/ADRD. The coefficients of interest are β_1 and β_2, which capture the causal effects of being assigned to an empty room or a roommate with AD/ADRD respectively, relative to being assigned roommates who do not have AD/ADRD.

We include a vector of time-varying controls in $\Gamma_{j,t}$, with nursing-home–by–year fixed effects and flexible controls for daily occupancy rates and patient composition (measured at the end of the day before i's admission).[6] These controls serve two purposes. First, the nursing-home–by–year fixed effects absorb persistent differences in quality, staffing, and patient populations across facilities—differences that directly affect health outcomes and may also be correlated with room availability and assignment practices. Second, the

[6]Specifically, controls for capacity strain and patient composition include fixed effects for deciles of within-nursing-home-by-year-by-month variation in occupancy rates, share of patients at the nursing home who have AD/ADRD, CPS scores of at least 1, 2, 3, 4, 5, and 6, and ADL scores of at least 7, 14, and 21, at the end of the day before the focal patient's admission.

daily controls capture short-run fluctuations in crowding and resident mix within a facility, proxying for the operational pressure ("strain") faced by the nursing home at the time of admission, as well as the potential for time-varying admission and discharge practices as a function of capacity or occupational strain (Gandhi, 2023; Hackmann, Pohl, and Ziebarth, 2024), which again may correlate with patients' future health outcomes as well as room availability and assignments.

Together, these variables ensure that identification comes from comparisons between patients admitted to the same nursing home in the same year, under similar operational conditions, but assigned to different room types due to short-run variation in the types of rooms available. By flexibly controlling for the overall resident mix in the facility, Γ_{jt} also nets out peer interactions that occur outside the room (e.g., in hallways, dining areas, or during common activities),[7] so that β_1 and β_2 isolate the incremental effects of the assigned roommate environment.

We note that some residents transition between rooms over the course of their nursing home stay. Because such transitions are likely endogenous, we abstract from them and focus on the effects of the initial room assignment.[8]

Identification Challenges: There are at least three empirical challenges that may bias OLS estimates of peer effects. First, in peer effects models with contemporaneous outcomes, it is difficult to separate whether patient A affects patient B or vice versa, an issue Manski (1993) refers to as the reflection problem. We address this concern by measuring roommate characteristics (AD/ADRD status) at the time of patient i's admission, ensuring these measures are predetermined and cannot be influenced by i's subsequent health trajectory.

The second issue is endogenous selection out of nursing homes, i.e., differential attrition and competing risks. In principle, the length of nursing home stay is endogenous to patient

[7]In particular, while Król-Zielińska et al. (2011) shows that nursing home patients spend the majority of their time in their rooms, they may still interact with patients who are not their roommates during mealtimes (if they have their meals in a common area rather than their rooms), or during group activities.

[8]It is also possible that patients' initial roommate at admission leaves, or another roommate joins midway through their stays. Nonetheless, changes in the roommate environment after initial admission imply that our estimates of the effect of room assignment on 90-day mortality should be interpreted as a lower bound on the effect of being in a particular type of room for the entirety of one's stay (or up to 90 days, whichever comes first).

and provider incentives and to changes in health (Hackmann, Pohl, and Ziebarth, 2024; Einav, Finkelstein, and Mahoney, 2025). Given that almost 15 percent of patients die within 90 days and more than a third (respectively, 60 percent) exit their nursing home within 30 days (90 days), this introduces serious econometric challenges when the measurement of outcomes is contingent on residing in a nursing home and/or staying alive, e.g. outcomes collected in quarterly MDS assessments. To avoid this, we focus on 90-day mortality as recorded in Medicare claims data, which we can measure regardless of whether the patient is still residing in the nursing home at the time of death.

The third challenge is endogenous room assignment within facilities. While we flexibly control for time-varying quality differences between nursing homes and patient composition within nursing homes, a valid concern is that assignment to rooms within nursing homes is not random. For instance, the evidence presented in Table I suggests that patients with cognitive impairments are more likely to be assigned a room shared with a patient who has a diagnosis of AD/ADRD. To address this concern, we use an instrumental variable strategy which leverages high-frequency (daily) variation in room composition.

III.A IV Strategy

We instrument room assignment – $\text{Empty}_{r,j,t}$ and $\text{AD}_{r,j,t}$ – with the share of rooms with a vacant bed at the nursing home that are empty – $s^{\text{Empty}}_{j,t}$ – and the share of rooms with a vacant bed that have an existing patient with AD/ADRD – $s^{\text{AD}}_{j,t}$ – at the time of i's admission. Intuitively, if all available rooms are empty (or already have an existing patient with AD/ADRD) on the day of admission, then any newly admitted patient will be assigned to an empty room (respectively, a roommate with AD/ADRD). Precisely, we measure $s^{\text{Empty}}_{j,t}$ and $s^{\text{AD}}_{j,t}$ on the day prior to i's admission to ensure that our instruments are not mechanically affected by i's admission. Hence, the first stage equations are:

$$\text{Empty}_{r,j,t} = \tau_0 + \tau_1\, s^{\text{Empty}}_{j,t} + \tau_2\, s^{\text{AD}}_{j,t} + \Gamma'_{j,t}\tau_\gamma + \eta_{irjt}, \tag{2}$$

$$\text{AD}_{r,j,t} = \alpha_0 + \alpha_1\, s^{\text{Empty}}_{j,t} + \alpha_2\, s^{\text{AD}}_{j,t} + \Gamma'_{j,t}\alpha_\gamma + \nu_{irjt}. \tag{3}$$

To provide context, Appendix Figure A.2 presents histograms of our instruments. We observe wide variation in the overall distribution of these instruments in panels (a) and (b) of the figure, although the share of available rooms that are empty is typically smaller than the share of available rooms with a patient that has AD/ADRD. However, this variation may also be due to differences between nursing-home-years (e.g., the share of rooms with a patient who has AD/ADRD may be higher in nursing homes that have Alzheimer's units) or short-run variation in general capacity strain and patient composition at the facility level (e.g., the share of rooms that are empty may be higher when occupancy rates are lower), and our IV strategy leverages variation conditional on nursing-home-by-year fixed effects as well as short-run variation in occupancy rates and patient composition. Indeed, panels (c) and (d) show that the residualized distributions of the instruments are tighter.[9] Nonetheless, we observe that substantial variation in the instruments remains, due to volatility in admissions and discharges (both in volume and composition).

III.A.1 Identification

To interpret the 2SLS estimates of β_1 and β_2 as the causal effects of being assigned an empty room or a room shared with a patient with an AD/ADRD diagnosis, our instrumental variables need to satisfy the relevance and exclusion restriction/conditional independence assumptions. Furthermore, in the presence of heterogeneous treatment effects, in order to interpret β_1 and β_2 as properly weighted averages of treatment effects for different types

[9] Specifically, we plot the distributions of the variables residualized of nursing-home-by-year fixed effects and flexible controls for occupancy rates and patient composition, with the overall mean added back. Note that it is possible for these residualized variables to have support outside of $[0, 1]$: for example, if the average share of available rooms with a patient with AD/ADRD is 0.5 in the full sample and 0.75 in a nursing home in a given year, then if this share drops to zero for that nursing home in a given day during that year, the value of the residualized variable (with the grand mean added back) would be $0 - 0.75 + 0.5 = -0.25$. We drop the very small number of cases where the residualized variables lie outside of $[0, 1]$ from the histograms for easier visualization.

of patients, the relationship between treatments and instruments needs to exhibit average conditional monotonicity and no cross-effects (Bhuller and Sigstad, 2024). In this section, we summarize empirical evidence supporting the validity of these identifying assumptions.

Relevance: Our approach requires that our instruments have strong predictive power for the endogenous variables.[10] We assess this by examining the relationships between $\text{Empty}_{r,j,t}$ and $s^{\text{Empty}}_{j,t}$ as well as between $\text{AD}_{r,j,t}$ and $s^{\text{AD}}_{j,t}$, conditional on the other instrument as well as the controls (i.e., nursing-home-by-year fixed effects, and short-run variation in facility-level occupancy rates and patient composition).

The blue dots in Figure I present the first stage results. Figure Ia presents results in a binscatter plot for one of our instruments: the share of available rooms occupied by at least one patient with AD/ADRD at the time of admission, $s^{AD}_{j,t}$ (holding the other instrument fixed). The blue line (circle markers) shows a positive relationship between the probability of being assigned to a roommate with AD/ADRD (vertical axis) and the instrument $s^{AD}_{j,t}$ (horizontal axis), $\alpha_2 > 0$. Moreover, the relationship is remarkably linear, which supports the linear specification in equation (3). We find that a 1 percentage point increase in the share of available rooms with a patient diagnosed with AD/ADRD increases the probability of being assigned a patient diagnosed with AD/ADRD by 1.17 percentage points, with a t-statistic of about 200, providing strong support for the relevance of this instrument.

The blue dots in Figure Ib present corresponding evidence for the second instrument: the share of available empty rooms, $s^{Empty}_{j,t}$ (holding $s^{AD}_{j,t}$ fixed). The blue line (circle markers) shows a clear positive relationship between the probability of being assigned to an empty room (vertical axis) and $s^{Empty}_{j,t}$ (horizontal axis), $\tau_1 > 0$. Again, the relationship is also remarkably linear (supporting the linear specification), and we find that a 1 percentage point increase in the share of available empty rooms increases the probability of being assigned an empty room by 0.95 percentage point (with a t-statistic of about 160), indicating that we have a strong first stage.

[10] Specifically, in the case with two endogenous variables and two excluded instruments, the 2×2 matrix of first stage coefficients must have rank 2.

Conditional Independence and Exclusion Restriction: For our instruments to be valid, we need the instruments to be uncorrelated with unobserved health shocks $\epsilon_{i,r,j,t}$. This in turn requires two assumptions: conditional independence—that the instruments are uncorrelated with potential outcomes—and the exclusion restriction—that the instruments can only affect patient outcomes through room assignment.

The exclusion restriction may fail if the instruments proxy for broader facility-level conditions—such as overall resident composition or operational strain—that directly affect mortality (e.g., through peer effects operating beyond the room level or staffing constraints). Our baseline controls directly address this concern. The vector $\Gamma_{j,t}$ includes nursing-home–by–year fixed effects as well as daily measures of occupancy and resident composition measured the day before admission. These fixed effects absorb persistent differences in quality, staffing, and patient populations across facilities. The daily controls capture short-run fluctuations in crowding and resident mix, proxying for operational strain at the time of admission. Identification therefore comes from comparisons between patients admitted to the same nursing home in the same year under similar operational conditions but facing different room availability. By flexibly controlling for overall resident composition, the specification also nets out peer interactions operating outside the assigned room, so that β_1 and β_2 isolate the incremental effect of the roommate environment itself. In robustness exercises, we show that the results are qualitatively unchanged when adding further controls, including room fixed effects and resident characteristics.

Conditional independence may also fail if certain patients delay admission until a preferred room type becomes available or select nursing homes based on availability of different room types, conditional on the rich set of aforementioned control variables.[11] If the types of patients that select nursing homes based on availability of room types differ on observables, these imbalances will show up in balance tests that we conduct below. Moreover, institutional details suggest that this type of selection is unlikely.

[11]To clarify, our aforementioned controls address systematic differences at the nursing-home-year level as well as daily variation in patient composition and operational strain, meaning that any remaining selection biases must stem from high-frequency variation in bed availability conditional on these controls.

Post-acute care patients—who make up almost two-thirds of our sample—often report having only one or two days to choose a nursing home before being discharged from the hospital (Shugarman and Brown, 2006). Information on nursing homes given to these patients by discharge planners typically only contains generic publicly available information about facilities (Tyler et al., 2017),[12] so these binding time constraints make it difficult for short-stay patients to delay admission or select between nursing homes based on room availability. At the same time, while long-stay residents and their families typically spend more time choosing between nursing homes (often touring facilities weeks before admission), high turnover and clinical volatility make the eventual roommate's health and behavior a moving target that is difficult to anticipate.[13] Furthermore, in robustness checks, we find that our main results remain qualitatively unchanged in both the short-stay and long-stay subsamples, and are particularly strong for post-acute care patients.

We provide direct empirical evidence supporting conditional independence and the exclusion restriction in a series of balance tests. First, we examine whether observed patient characteristics are balanced across the instruments, conditional on the aforementioned controls. For ease of visualization, we combine baseline health and demographic variables into a single measure of baseline mortality risk. We construct this measure using a ridge regression with 5-fold cross-validation of 90-day mortality on 23 baseline demographics and health variables derived from the MDS, 25 baseline chronic conditions derived from Medicare data,[14] and over 500 pairwise interactions between these variables, after residualizing out nursing-home-by–year fixed effects, room assignment, capacity strain, and patient composition.

The red triangles in Figure I plot the relationship between baseline mortality risk and the instruments—the shares of empty rooms and available rooms with an AD/ADRD patient at the time of admission ($s_{j,t}^{Empty}$ and $s_{j,t}^{AD}$). Baseline mortality risk is remarkably stable across

[12]In fact, only 4% of patients interviewed in Tyler et al. (2017) received any information about nursing home quality.

[13]Moreover, federal privacy laws (e.g., Health Insurance Portability and Accountability Act) prevent facilities from disclosing detailed roommate information, so residents often commit to a nursing home without knowing whether a roommate's needs may disrupt their care.

[14]We omit two variables from the Medicare chronic conditions—specifically, Alzheimer's disease, and Alzheimer's disease and related disorders or senile dementia—due to their high degree of overlap with dementia diagnosis from the MDS (which is included in the ridge regression).

variation in both instruments. In particular, the regression of baseline mortality risk on each instrument is statistically insignificant despite the large sample size.[15]

To probe the conditional independence assumption for our instruments further, Appendix Figure A.5 examines balance across 40 baseline characteristics with respect to our instrument, comparing the magnitude of potential imbalances with the reduced form estimates for the instruments. Specifically, we regress 90-day mortality as well as each of the baseline characteristics on each instrument and nursing-home-by-year fixed effects (without controlling for the other instrument so that the reduced form coefficients are easier to interpret).[16] To ensure comparability of the coefficients' scale and sign across regressions for different variables, we multiply the coefficient estimates (and standard errors) by the dependent variables' associations with 90-day mortality.

The results in Appendix Figure A.5 show that for both instruments, the magnitudes of the reduced form estimates (shown at the top of the two panels) are far larger than the coefficient estimates for baseline characteristics. The coefficient estimates for a number of baseline characteristics are statistically different from zero at the five percent significance level, but have inconsistent signs. When we aggregate baseline characteristics into a single measure of baseline mortality risk, this measure is not significantly correlated with $s_{j,t}^{\text{AD}}$ in panel (a) or with $s_{j,t}^{\text{Empty}}$ in panel (b).

Together, these results indicate that the instruments are orthogonal to baseline health risk and do not operate through broader facility-level composition or operational strain. Instead, variation in the instruments reflects quasi-random room availability within nursing-home–year, supporting both conditional independence and the exclusion restriction.

Average Conditional Monotonicity and No Cross-Effects: In the presence of heterogeneous treatment effects, we need additional assumptions to interpret the IV estimates

[15] To quantify the contribution of uncertainty in the construction of baseline mortality risk to the regression standard errors, we bootstrap the entire prediction-and-regression procedure. Uncertainty in the ridge estimate contributes only about one-tenth of the total standard error, so the relationships between the instruments and baseline mortality risk remain statistically insignificant even without this standard error correction.

[16] In particular, the IV estimate with a single endogenous variable and a single instrument is given by the ratio of the reduced form coefficient to the first stage coefficient, whereas in the case with two endogenous variables and two instruments, the IV estimates are given by the inverse of the 2×2 matrix of first stage coefficients multiplied by the reduced form coefficients, which is harder to show graphically.

as properly weighted averages of treatment effects across different patients (i.e., with non-negative weights and zero weights on the ”wrong” treatment effect).[17] Bhuller and Sigstad (2024) show that in contrast to IV with a single endogenous variable where only monotonicity is required, in IVs with multiple endogenous variables two assumptions are required: average conditional monotonicity and no cross-effects.

To describe these two assumptions, note that we can generate rotation-invariant instruments such that each instrument is associated with a single treatment using the predicted values from regressions of each treatment variable on both instruments (and the controls). We denote these instruments by $P^{\text{Empty}}_{j,t}$ and $P^{\text{AD}}_{j,t}$. Average conditional monotonicity requires that $P^{\text{Empty}}_{j,t}$ (respectively, $P^{\text{AD}}_{j,t}$) only affects $\text{Empty}_{r,j,t}$ ($\text{AD}_{r,j,t}$) weakly positively, while no cross-effects requires that $P^{\text{Empty}}_{j,t}$ does not affect $\text{AD}_{r,j,t}$ (conditional on $P^{\text{AD}}_{j,t}$) and vice versa.

These assumptions have a testable implication similar to that for monotonicity in IV with one treatment variable: if we divide the data into different subsamples based on baseline characteristics, the regressions of $\text{Empty}_{r,j,t}$ ($\text{AD}_{r,j,t}$) on both $P^{\text{Empty}}_{j,t}$ and $P^{\text{AD}}_{j,t}$ (and controls) should result in a positive coefficient estimate on $P^{\text{Empty}}_{j,t}$ ($P^{\text{AD}}_{j,t}$) and a zero estimate (up to statistical uncertainty) on $P^{\text{AD}}_{j,t}$ ($P^{\text{Empty}}_{j,t}$). Appendix Figure A.8 shows histograms of coefficient estimates with $\text{Empty}_{r,j,t}$ and $\text{AD}_{r,j,t}$ as the dependent variables in panels (a) and (b) respectively, for over 3,800 subsamples defined using more than 40 baseline characteristics and their pairwise interactions. The gray bars (respectively, white bars) correspond to estimates for the transformed instrument that matches (does not match) the dependent variable. We observe that all the gray bars are large and positive, supporting average conditional monotonicity, whereas all of the white bars are small and close to zero, supporting the no cross-effects assumption.

[17] Specifically, one can show that the IV estimate for β_1 can be expressed as:

$$\beta_1 = \mathbb{E}[\omega_1^L \beta_1^L + \omega_2^L \beta_2^L],$$

where L indexes response types and $\beta_k^l \equiv \mathbb{E}[\beta_k | L = l]$. Bhuller and Sigstad (2024) show that under the conditional independence and first stage assumptions, the weights on β_1^l sum to one while the weights on β_2^l sum to zero. However, additional assumptions are required so that weights are proper, i.e., that the weights on β_1^l are non-negative, and the weights on β_2^l are zero. A similar expression applies for β_2.

IV Results

IV.A IV Estimates of Room Effects

Table II shows IV estimates of peer effects for the full sample in columns 1 and 2, and split by baseline AD/ADRD status in columns 3 and 4. Column 1 shows that being assigned no roommate at admission reduces 90-day mortality by 0.6 percentage points relative to being assigned a roommate, a 4 percent reduction relative to the mean. Column 2 shows that this effect is mainly driven by the effect of being assigned a roommate with AD/ADRD (relative to the reference group of being assigned roommates that do not have AD/ADRD). Being assigned no roommate at admission reduces 90-day mortality by a statistically insignificant 0.2 percentage points while being assigned a roommate that has AD/ADRD increases mortality by 0.9 percentage points. In both IV specifications, the first-stage F-statistics are in the tens of thousands, so weak instruments are unlikely to be an issue. Combined, this implies that moving from a room shared with a patient with AD/ADRD to an empty room reduces 90-day mortality by 1.1 percentage points. As a point of comparison, OLS estimates of the same equation shown in column 2 of Panel A in Appendix Table A.3 suggest that relative to being assigned roommates who do not have AD/ADRD, being assigned to no roommate increases mortality while being assigned a roommate with AD/ADRD has no statistically significant effect on mortality. This contrast between OLS and IV estimates suggests that room assignment is correlated with unobserved determinants of health and underscores the need for our IV strategy to identify causal effects. Moreover, the small OLS estimates for sharing a room with a patient with AD/ADRD may reflect attenuation from measurement error in room assignment—another concern mitigated by the IV approach.

To put our IV estimates into perspective, we note that Cheng (2025) estimates nursing home value-added based on 90-day survival and finds a standard deviation of 2 percentage points. This means that moving from a room shared with a patient with AD/ADRD to an empty room reduces 90-day mortality by roughly the same amount as moving to a nursing home with 0.5 standard deviation higher value-added. Put differently, this suggests that there are not only large quality differences between nursing homes (Olenski and Sacher, 2024;

Einav, Finkelstein, and Mahoney, 2025; Hackmann, Rojas, and Ziebarth, 2025; Cheng, 2025), but also within nursing homes.

To explore peer-patient health interactions, columns 3 and 4 of Table II estimate peer effects separately for patients with and without AD/ADRD at admission. The results reveal asymmetric effects. Relative to being assigned a roommate without AD/ADRD, being assigned no roommate reduces mortality for patients without AD/ADRD but increases mortality for those with AD/ADRD. Similarly, assignment to a roommate with AD/ADRD increases mortality for patients who also have AD/ADRD, but has no effect on cognitively intact patients. These patterns imply that cognitively intact roommates are particularly beneficial for patients with AD/ADRD—reducing their 90-day mortality by 3.4 percentage points (relative to cognitively impaired roommates)—while patients without AD/ADRD show no survival benefit from cognitively intact roommates relative to no roommate. These findings suggest potential gains from pairing patients with and without AD/ADRD as roommates, as we discuss below.

Importantly, our empirical evidence also supports the identifying assumptions within these subsamples. Appendix Figures A.3-A.4 show that the instruments remain strongly predictive of room assignment separately for patients with and without AD/ADRD, and Appendix Figures A.6-A.7 show that baseline mortality risk and other pre-determined characteristics are well-balanced across instrument values within each group. Thus, the heterogeneous effects are unlikely to reflect differential selection into room types by cognitive status.

One explanation is that cognitively healthy roommates provide informal monitoring—for example, alerting staff when help is needed—which is especially valuable for patients with AD/ADRD who often lack situational awareness. Without a cognitively intact roommate present, this protective monitoring is lost. Conversely, roommates who themselves have AD/ADRD cannot reliably provide this monitoring function, explaining why patients with AD/ADRD benefit specifically from cognitively healthy roommates rather than from any roommate. This monitoring mechanism aligns with findings in Nichols (2014), who argues that patients with significant cognitive impairment often cannot recognize when they need assistance or reliably summon help. Private-room designs eliminate the roommate who might alert staff when a patient is in distress—a loss that is particularly consequential for individuals with AD/ADRD who may depend on others to recognize their needs.

An alternative explanation could be that patients with AD/ADRD demand particular attention, crowding out staff support for their roommates. While this can explain the negative effect of assignment to a roommate with AD/ADRD for cognitively impaired patients, it is difficult to reconcile with the absence of a negative effect for patients without AD/ADRD.

IV.B Robustness Checks

Different Sets of Controls We test whether our IV estimates remain stable as we consider different sets of controls. First, we consider a more parsimonious specification that controls only for nursing-home-by-year fixed effects. Second, we allow for potential market level trends in patient arrivals or exits, as well as differences in admissions and discharges on weekdays or weekends by including county-by-year-by-month fixed effects and day-of-the-week fixed effects in addition to the controls in our main specification. Third, we address the concern that general room amenities (e.g., distance to nursing station, noise level, and temperature) may be correlated with room composition, by including room fixed effects.[18] Finally, we control for a rich set of baseline demographic and health characteristics from the MDS and Medicare data. Appendix Table A.2 shows that the main results remain qualitatively unchanged: relative to assignment to roommates without AD/ADRD, being assigned a roommate with AD/ADRD increases mortality on average and among patients with AD/ADRD but not for patients without AD/ADRD, who benefit from being assigned to private rooms.

To better understand sources of bias in the OLS estimates, in Appendix Table A.3 we conduct the same exercise using the OLS specification. Interestingly, while the OLS estimates differ from the IV estimates in the baseline specification, in the most saturated specifications (in particular, once room fixed effects are included), the signs of the OLS estimates align

[18] Specifically, the concern is that if private rooms tend to have better amenities, or if patients with AD/ADRD are more likely to be assigned to rooms with worse amenities, then it would be difficult to distinguish between the effect of room amenities and the effect of a roommate.

with the IV estimates, suggesting that some of the differences can be explained by selection on observables.

Alternative Time Horizons Next, we test whether the estimated effects of room assignment merely reflect a shifting in the timing of death by a few weeks or months. Appendix Table A.4 shows our main IV estimates with 30-day, 90-day, 180-day and 360-day mortality as the outcome. We observe that treatment effects for 30-day mortality tend to be much smaller in magnitude, consistent with peer effects among roommates requiring some time to manifest. In addition, beyond 90 days, estimated effects on mortality remain stable (or even grow) until at least 360 days. This suggests that our peer effects estimates are not driven by short-run displacement or harvesting, whereby roommate exposure merely shifts the timing of deaths by a few weeks or months. Rather, the effects seem to reflect persistent changes in patients' health trajectories.

Room Composition Affecting Nursing Home Choice: A concern is that room composition may affect patients' nursing home choice—for example, if patients prefer private rooms, they may select a different facility when their otherwise preferred option has no empty rooms. Consistent with the identification discussion, such sorting is likely limited: short-stay patients face binding time constraints when choosing nursing homes, room availability is highly volatile, and short-run fluctuations in roommate composition are difficult to anticipate at the time of nursing home choice. Furthermore, our extensive balance tests provide no evidence for systematic sorting based on availability of different room types.

We nevertheless assess this concern directly by focusing on patients admitted from acute care hospitals, who face tight discharge timelines and are typically guided by discharge planners, leaving little scope to delay admission or sort across facilities based on availability of room types. Columns 1–3 of Appendix Table A.5 show that IV estimates for post-acute patients closely mirror the main results in Table II: assignment to a roommate with AD/ADRD increases 90-day mortality by 1.1 percentage points, patients with AD/ADRD benefit from cognitively intact roommates, and patients without AD/ADRD benefit from being assigned to an empty room. Estimates for patients not admitted from acute care hospitals (columns 4–6) are less precise due to smaller sample sizes but are qualitatively similar.

Bounds Under Potential Violations of Conditional Independence/Exclusion Restriction To account for potential violations of conditional independence, we derive bounds for our IV estimates under various assumptions about the unobservables, similar in spirit to the methods proposed in Altonji, Elder, and Taber (2005), Conley, Hansen, and Rossi (2012), and Oster (2019). At a high level, given assumptions on the maximum amount of variation in the outcome that the instruments, controls and unobservables can explain (R^2_{max}) and the relative degree of selection on observables and unobservables (δ) in the reduced form regression, we can apply the methods in Oster (2019) to obtain bounds for the reduced form coefficients. We then translate this into bounds for the treatment effects by inverting the matrix of first stage coefficients. The sign of our main estimates are robust to bounds obtained under Oster's recommended choices of R^2_{max} and δ (which are based on the R^2 from the reduced form estimates and the movement in reduced form coefficients as we include additional controls): the bounds for the average effect of being assigned a roommate with AD/ADRD (relative to roommates without AD/ADRD) on 90-day mortality is [0.003, 0.011] in the full sample and [0.021, 0.037] in the subsample of patients with AD/ADRD, and the bounds for the effect of being assigned to a room with no roommate is [-0.026, -0.003] for patients without AD/ADRD. Appendix Section C explains these bounds in greater detail, with additional bounds under alternative assumptions shown in Appendix Table A.8, as well as values of (R^2_{max}, δ) required for violations of IV assumptions to completely explain our non-zero treatment effect estimates presented in Appendix Figure A.20.

"Power Asymmetry" in IV Finally, we address the issue of "power asymmetry" in 2SLS estimation when t-tests are used for inference, as pointed out by Keane and Neale (2023).[19] In particular, Keane and Neale (2023) point out that when the direction of the OLS bias has

[19]While Keane and Neale (2023) study 2SLS with a single treatment variable, we assume that a similar intuition holds for the case with two treatment variables.

the same sign as the true parameter, standard errors tend to be too small, whereas standard errors tend to be inflated when the bias and the true parameter have opposite signs. The IV estimates in Table II indicate that on average, being assigned to an empty room reduces 90-day mortality while being assigned a roommate with AD/ADRD increases mortality, yet the OLS estimates shown in Appendix Table A.3 bias us against finding either of these effects (i.e., the biases and the IV estimates have the opposite signs). Hence, if anything, the power asymmetry in t-tests for inference in 2SLS is likely to bias us *against* finding significant IV estimates. Moreover, simulations in Keane and Neale show that the power asymmetry is ameliorated as the strength of the first stage increases, with power being roughly symmetric when the first stage F-statistic is around 105. In our setting, the first stage F-statistic is orders of magnitude larger, so we expect power asymmetry to be a relatively minor issue quantitatively.

IV.C Alternative Room Assignments and Mortality

These findings raise a natural policy question: can better room assignments reduce mortality? In this subsection, we start by considering a simple model that minimizes overall mortality, deriving intuitive optimality conditions and using them to quantify the potential mortality reductions. We then consider a more general set of efficient assignment rules by varying the weights on different patient types, and characterize the health production possibility frontier. Finally, we assess potential survival gains at the nursing home level under several efficient assignment rules.

Conceptual Framework: Formally, we consider a room-specific health production function

$$U_i = f(h(i), h(i')) \tag{4}$$

where U_i is a positive outcome for resident i measured 90 days after admission, here 90-day survival, $h(i)$ is patient i's health at admission, and $h(i')$ is the health of i's roommates at admission. Assignment to an empty room is captured by $f(h(i), \varnothing)$.

We define $\mathcal{A}$ to be the set of all feasible resident-to-room allocations, where each allocation $A \in \mathcal{A}$ consists of a set of such tuples satisfying capacity and feasibility constraints.[20] We treat nursing home capacity, floor and room plans, as well as the patient census, as exogenous, and consider allocating patients across existing rooms. We view this as a short-run planning exercise and leave the optimization of floor plans and capacity to future work.

Let $\mu_r(A)$ be the set of residents assigned to room r under allocation A. We thus solve the following problem:

$$A^* \in \arg\max_{A \in \mathcal{A}} \sum_r \sum_{i \in \mu_r(A)} w_i \cdot f(h(i), h(i')), \tag{5}$$

where $w_i > 0$ are patient-specific weights (for instance, to account for variation in quality-adjusted life-years). Motivated by our empirical setting, we consider a simpler version of this model with two types of patients (with AD/ADRD: $h(i) = AD$ or without $h(i) = noAD$), and two types of rooms (private room with one bed or shared room with two beds).

IV.C.1 Characterization of Survival-Maximizing Room Assignments

To gain intuition for the link between our empirical estimates and the optimal assignment policies, we start by analyzing average mortality ($w_i = 1$) and consider a setting with binding capacity, e.g. when the number of patients is equal to the nursing home's bed capacity. These assumptions simplify the theoretical derivations but we relax them in the quantitative exercises below.

As we detail in the Appendix Section B, the survival-maximizing allocation is then determined by the solution to the following linear programming problem:

$$x_{priv}^{AD,*}, x_{share}^{AD,noAD,*} = \arg\max_{x_{priv}^{AD}, x_{share}^{AD,noAD} \in \mathcal{A}} \psi x_{priv}^{AD} + \theta x_{share}^{AD,noAD}, \tag{6}$$

where x_{priv}^{AD} and $x_{share}^{AD,noAD}$ denote the number of patients with AD/ADRD in private rooms and the number of shared rooms that are mixed (one patient with AD/ADRD, and one

[20] For instance, each patient is assigned to exactly one room, and the number of patients assigned to each room does not exceed the room's capacity.

without), respectively. The solution is governed by two parameters, ψ and θ, which we discuss next.

Privacy premium: The first is the privacy premium, ψ, which denotes the differential benefit from a private room, relative to sharing a room with a resident of the same cognitive health, for residents with AD/ADRD compared to residents without AD/ADRD. Using the estimates from columns 3 and 4 of Table II (after flipping signs to capture effects on survival), we estimate a positive effect of 1.1 percentage points:

$$\begin{aligned} \psi &= (f(AD,\varnothing) - f(AD,AD)) - (f(noAD,\varnothing) - f(noAD,noAD)) \\ &= (-1.4 + 3.4) - (0.9 - 0) = 1.1. \end{aligned} \tag{7}$$

While cognitively intact residents benefit from a private room, relative to sharing a room with another cognitively intact resident, residents with AD/ADRD benefit even more from being in a private room, relative to sharing a room with another resident with AD/ADRD. This provides an argument for allocating residents with AD/ADRD to a private room.

Complementarity parameter: The second parameter θ measures the net health gains from mixed relative to segregated shared rooms:

$$\begin{aligned} \theta &= (f(AD,noAD) + f(noAD,AD)) - (f(AD,AD) + f(noAD,noAD)) \\ &= (0 + 0.3) - (-3.4 + 0) = 3.7. \end{aligned} \tag{8}$$

Our estimates from Table II imply a gain of 3.7 percentage points, suggesting that the production function in shared rooms is submodular, and that mixed rooms can increase average survival relative to segregated rooms.[21]

[21] When θ is positive, the production function in shared rooms is submodular and roommates' health are substitutes (Milgrom and Roberts, 1990), so that mixed rooms increase average survival. On the other hand, when θ is negative, the production function is supermodular and roommates' health are complements, in which case segregated rooms raise average survival.

Implications for room allocations and resident mortality: Positive estimates for ψ and θ suggest that reducing the number of rooms occupied by two AD/ADRD patients increases average survival. Whether this implies maximizing mixed shared rooms depends on the relative magnitudes of the parameters. When $\psi \geq \theta$, the difference in privacy premium outweighs the gains from mixing, so average survival is higher when allocating patients with AD/ADRD to private rooms, even at the cost of fewer mixed rooms. However, we find $\psi < \theta$: the benefit of mixing dominates, so maximizing the number of mixed shared rooms increases average survival.

IV.C.2 Alternative Room Assignment and Average Mortality

To quantify the effect of different assignment policies on average mortality and how it varies by the availability of private rooms, we start by considering a nursing home that has a representative share of residents with AD/ADRD (30%, the sample average). Following the previous characterization, we first assume that the nursing home operates at full capacity. Panel (a) of Figure II compares the simulated average 90-day mortality under the mortality-minimizing rule described in equation (6) to random assignment and segregation by cognitive health. The observed mortality rate is shown using an open circle at a private room share of 35% (which is the sample average) and equals 14.9%. By contrast, the simulated mortality rate is only 14.3% under the optimal assignment rule, suggesting that better room assignments may reduce average 90-day mortality rates by 0.6 percentage point (a 4% reduction relative to baseline). This amounts to roughly 1,400 life-years saved per year in our sample (and potentially even more if we consider patients not included in our sample).[22]

[22] To obtain a back-of-the-envelope calculation of life-years saved per year, we convert 90-day mortality into life-years by assuming that each death within 90 days of admission averted due to the assignment policy results in an additional life year on average. We view this conversion as conservative, and supported by the results on 360-day mortality in Appendix Table A.4. Under this assumption, the implied number of life-years saved per cohort is:

$$\frac{0.006 \times 2,568,901}{11} = 1,401.$$

This is obtained by multiplying the 0.6 percentage point effect by the sample size (of over 2.5 million individuals) and dividing by the 11-year sample period.

We next relax the assumption of binding capacities, and instead simulate mortality under the average occupancy rate in our sample (of 85%). As shown in panel (a) of Appendix Figure A.11, we now find even larger reductions in mortality.

IV.C.3 Alternative Room Assignment and Mortality by Cognitive Health

While alternative room assignments can improve average survival, the gains may be uneven across patients with and without AD/ADRD. Panel (b) of Figure II illustrates this using a survival frontier for a representative nursing home (85% occupancy, 35% private rooms, 30% AD/ADRD). The vertical axis plots 90-day survival for patients with AD/ADRD, and the horizontal axis for patients without. The frontier features a flatter segment and a steeper segment, joined at a kink.

At the leftmost point (red), corresponding to the AD-optimal assignment, moving right along the flatter segment improves outcomes for patients without AD/ADRD but harms patients with AD/ADRD. This is achieved by reallocating patients without AD/ADRD from mixed to empty rooms. The implied tradeoff is between a 0.014 increase in the 90-day mortality rate for a patient with AD/ADRD and a $0.009 - 0.003 = 0.006$ decrease for a patient without AD/ADRD, or a "ratio of lives saved" equal to $\frac{0.014}{0.006} \approx 2.33$.[23] Beyond this point, once empty rooms are exhausted, the frontier becomes steeper, since further gains for patients without AD/ADRD require pairing additional patients with AD/ADRD together as roommates. This generates substantially larger mortality increases for AD/ADRD patients: the corresponding ratio of lives saved rises to 9.[24]

The AD-optimal assignment lies at the leftmost point, while the assignment most favorable to patients without AD/ADRD lies at the rightmost point. Because the ratio of

[23]Note that the slope of the (relevant segment of the) survival frontier is not equal to the ratio of lives saved in general, due to group sizes for the two patient types being unequal. In particular, a life saved in the larger group will increase the average survival rate for the group by a smaller amount than it would in the smaller group. In other words, multiplying the slope of the frontier by the relative group sizes—$\frac{\pi}{1-\pi}$—will yield the ratio of lives saved.

[24]Specifically, survival gains along this segment requires swapping a patient without AD/ADRD in a mixed room with a patient with AD/ADRD who initially had no roommate. The survival gain for the patient without AD/ADRD is again 0.006, but this comes at the cost of increased mortality rates for the two patients with AD/ADRD now living together: 0.034 for the patient who was initially in a mixed room, and $0.034 - 0.014 = 0.020$ for the patient who was initially living alone. As a consequence, the ratio of lives saved along this segment is $\frac{0.034+0.020}{0.006} = 9$.

lives saved exceeds one along the entire frontier, the AD-optimal assignment also minimizes overall mortality. Weighting outcomes by QALYs shifts the optimum. Estimates of QALY ratios between patients without and with AD/ADRD range from 2.65 to 6.33 (e.g., van de Rijt et al., 2020; León-Salas et al., 2015), implying that the QALY-optimal assignment lies at the kink of the frontier.

In general, the shape of the survival frontier varies across facilities and may exhibit a kink, a single segment, or be degenerate, depending on room configuration, patient composition, and occupancy.[25] Typically though, and as discussed in the next subsection, the survival range along the frontier is relatively small, compared to the overall gains when moving from current assignments to the frontier. This points to potentially large survival gains for both patient groups.

IV.C.4 Heterogeneity in Potential Survival Gains Across Nursing Homes

The previous estimates highlight large average potential survival gains, which may mask important heterogeneity across nursing homes. To assess this, we next compute three efficient room assignment rules—the AD-optimal, QALY-optimal, and NoAD-optimal rules—based on each nursing homes' share of private rooms, share of patients with AD/ADRD, and occupancy rate, and simulate the corresponding 90-day survival rate. Potential gains are defined as simulated minus observed survival.

Panels (c) and (d) of Figure II show kernel densities of these gains for patients with and without AD/ADRD. Gains are heterogeneous but positive on average for both groups under all policies. Gains for patients with AD/ADRD are largest under the AD-optimal rule, followed by the QALY-optimal and NoAD-optimal rules, with the reverse ordering for patients without AD/ADRD. Quantitatively, the survival gains are larger for patients with AD/ADRD (0.95–1.8 pp) than for those without (0.21–0.31 pp), indicating greater sensitivity to room assignment.

[25] Panel (c) of Appendix Figure A.17 shows the distribution of these four distinct frontier shapes across nursing homes using different colors and symbols in a scatterplot of patient composition (π) against room configuration (p). We observe that there is substantial heterogeneity across nursing homes, with the survival frontier being degenerate in almost half, having a kink in 44%, only exhibiting the flatter segment in 7%, and only exhibiting the steeper segment in less than 1%.

The QALY-optimal rule closely approximates the AD-optimal rule and substantially outperforms the NoAD-optimal rule for patients with AD/ADRD. Average survival gains for patients with AD/ADRD under the AD-optimal, QALY-optimal, and NoAD-optimal rules are 1.8, 1.5, and 0.95 percentage points respectively. Moreover, survival gains for cognitively impaired patients are negative in only 3% of nursing homes under the QALY-optimal assignment rule, compared to 22% of nursing homes under the NoAD-optimal rule.

For patients without AD/ADRD, the QALY-optimal rule achieves average survival gains of 0.27 percentage points, compared to 0.31 percentage points under the NoAD-optimal policy, and 0.21 percentage points under the AD-optimal policy. Furthermore, survival gains among cognitively healthy patients are negative in only 0.8% of nursing homes under the QALY-optimal rule, relative to 2.4% under the AD-optimal rule.

Combining the two patient types, panel (a) of Appendix Figure A.19 shows the distribution of overall survival gains at the nursing home level. Average survival gains under the AD-optimal, QALY-optimal, and NoAD-optimal assignment rules are 0.72, 0.66, and 0.54 percentage points respectively. So, the QALY-optimal and NoAD-optimal assignment rules respectively achieve average survival gains that are about 93% and 76% of the average gains under AD-optimal rule (which we recall coincides with the overall mortality-minimizing policy).

IV.D Mechanisms for Peer Effects

In this section, we consider heterogeneity in peer effects by patient vaccination status and facility characteristics to better understand the mechanisms underlying our estimated peer effects.

IV.D.1 Heterogeneity within Facilities

Vaccination: While the results in Table II suggest that roommates without AD/ADRD may play a support role which can be especially valuable for patients with AD/ADRD, they do not explain why being assigned to an empty room leads to lower mortality rates for patients without AD/ADRD. In Appendix Table A.6, we explore one possible explanation: lower risk of disease contagion.

To explore this possibility, we estimate the effect of being assigned to a room without a roommate for patients who did or did not receive flu vaccinations in columns 1 and 2, and pneumococcal (PPV) vaccinations in columns 3 and 4. While the effects of being assigned to an empty room are similar for patients who did or did not receive flu vaccines, the effect is smaller for patients who received a PPV vaccine compared to patients who did not receive a PPV vaccine. This provides suggestive evidence that disease contagion may partially explain the reduction in 90-day mortality for patients assigned to empty rooms.

IV.D.2 Heterogeneity Between Facilities and the Scope for Patient Monitoring

As discussed above, one potential explanation for the large peer effects arises from patient monitoring by cognitively intact roommates. Peer monitoring is likely to be especially valuable in nursing homes with inadequate staffing, or that are ill-equipped to care for patients with AD/ADRD. Hence, we explore heterogeneity in peer effects across nursing homes by staffing levels and availability of Alzheimer's special care units.

Staff Shortages: We start by exploring whether peer effects vary with nurse staffing levels, an important determinant of patient health (Lin, 2014; Harrington et al., 2020). Nurse shortages can compromise monitoring capacity, resulting in patient neglect and higher mortality (Friedrich and Hackmann, 2021). If so, patients without AD/ADRD may provide crucial support in understaffed facilities.

Columns 1 and 2 of Table III compare residents in facilities with above- and below-median staffing levels, where staffing is defined as the sum of z-scores for Registered Nurse (RN), Licensed Practical Nurse (LPN), and Certified Nursing Assistant (CNA) levels. Panel A considers all patients, whereas panels B and C split the sample into residents with and without AD/ADRD respectively. We find that positive externalities of cognitively intact residents on roommates with AD/ADRD are larger in facilities with below-median staffing levels. In lower-staffed facilities, 90-day mortality among residents with AD/ADRD is reduced by 4.6 percentage points (Panel B) when sharing a room with a cognitively intact resident relative to sharing a room with another resident with AD/ADRD. By contrast, this reduction amounts to only 2.2 percentage points in facilities with above-median staffing. We also find that assigning a resident with AD/ADRD to an empty room is particularly detrimental to survival in lower-staffed facilities. These results are consistent with a peer monitoring mechanism, and suggest that peer monitoring may serve as a substitute for staffing.

Alzheimer's units: In columns 3 and 4 of Table III, we test whether peer effects vary by the presence of an Alzheimer's unit. Nursing homes with specialized Alzheimer's units are better equipped to support patients with AD/ADRD through enhanced staff training, specialized floor plans designed for monitoring and safety, and tailored environmental features (Joyce et al., 2018), which may dampen positive spillovers from cognitively intact roommates.

Consistent with this, we find that the positive externalities of cognitively intact residents on roommates with AD/ADRD load entirely onto facilities without an Alzheimer's unit. In these facilities, 90-day mortality among residents with AD/ADRD is reduced by 4.4 percentage points (Panel B) when sharing a room with a cognitively intact resident relative to sharing a room with another resident with AD/ADRD. By contrast, the effect flips sign and becomes statistically insignificant in facilities with an Alzheimer's unit. We also find that assigning a resident with AD/ADRD to an empty room is detrimental to survival in facilities without Alzheimer's units (relative to assignment to a cognitively intact roommate). These results are again consistent with a peer monitoring mechanism, and suggest that peer monitoring may also serve as a substitute for specialized Alzheimer's care.

Turning to cognitively intact residents (Panel C), we find no systematic differences in outcomes based on whether they are assigned to a room with a resident with or without AD/ADRD, but we find that they benefit from a private room in facilities without Alzheimer's units.

IV.D.3 Alternative Definitions of Peers

Other Roommate Characteristics In reality, health conditions other than AD/ADRD may generate peer effects among nursing home roommates. We study this possibility by estimating versions of equation (1) where we replace assignment to a roommate with AD/ADRD with measures of cognitive and physical health, as proxied by CPS and ADL scores respectively (with similar adjustments for the instruments).[26] Appendix Table A.7 shows that both cognitive and physical health conditions seem to matter for peer effects, in very similar ways to AD/ADRD: being assigned to a cognitively or physically impaired roommate increases 90-day mortality on average (relative to being assigned a healthy roommate); cognitively or physically impaired patients benefit less from being assigned no roommate than healthy patients do; and being assigned a cognitively or physically impaired roommate increases mortality for sick residents but not for healthy residents. This suggests that our peer effects results may generalize to health conditions other than AD/ADRD, and that room assignment policies which consider additional health conditions other than AD/ADRD can potentially yield even larger reductions in mortality.

Peer Effects Beyond Shared Rooms Residents—especially those in poorer health—spend substantial time in their rooms, but they also interact in common areas (e.g., during meals and group activities). Peer effects may therefore extend beyond the roommate. While not the primary focus of our design, we probe this possibility by varying controls for facility-level occupancy rates and patient composition. In our baseline specification, conditioning on nursing-home-by-year fixed effects, capacity strain, and patient mix ensures the IV strategy isolates variation in room assignment that is driven by within–facility-year, across-room variation in peer composition under similar facility-level patient mix, which we interpret as roommate (shared-room) effects.

When we drop occupancy and patient mix controls, the IV estimand may additionally capture broader exposure—spillovers through common spaces and facility-wide re-

[26] For instance, if the treatments are assignment to an empty room and assignment to a roommate with a CPS score of at least 3, the instruments are the share of available rooms at the time of admission that are empty, and the share of available rooms at the time of admission with a resident who has a CPS score of at least 3.

sponses—because our instruments may correlate with the overall prevalence of AD/ADRD residents and with occupancy. We therefore interpret this specification as potentially encompassing beyond-room spillovers in addition to roommate effects.

Column 1 in Appendix Table A.2 shows that excluding controls for occupancy and peer composition increases the magnitude of the estimated effects (compared to the main specification in column 2). While suggestive, this pattern is consistent with peer effects extending beyond the room and suggests that our baseline estimates may understate the overall role of peers in the health production function in nursing homes.

V Conclusion

This paper provides causal evidence that peer effects among nursing home roommates generate mortality impacts comparable in magnitude to quality differences across facilities. Assignment to a roommate with AD/ADRD, relative to no roommate, increases 90-day mortality by 1.1 percentage points (7% of baseline)—equivalent to receiving care at a nursing home half a standard deviation worse in quality.

We document substantial heterogeneity in these peer effects. Patients with AD/ADRD benefit from cognitively healthy roommates (even more so than being in a private room), suggesting that peers provide important monitoring and support. By contrast, patients without AD/ADRD are unaffected by roommate cognitive health but benefit from privacy. These patterns are most pronounced in facilities with below-median staffing and without specialized dementia units, pointing to substitutability between peer health and institutional resources.

These findings suggest a novel, low-cost channel for improving patient outcomes: strategic room assignment. A simple assignment rule that places AD/ADRD patients with cognitively healthy roommates while prioritizing private rooms for cognitively healthy patients could reduce overall mortality by 0.6 percentage points—without additional staff or facility modifications. This represents a 4% reduction in 90-day mortality rates. While strategic peer assignment has been explored in education settings (Carrell, Sacerdote, and West, 2013), it has received little attention in healthcare, where research has focused primarily on patient-provider matching.

Several caveats merit attention. First, we focus on mortality; effects on other outcomes (e.g., cognitive and physical health, quality of life, family satisfaction, and staff burden) warrant investigation, although rigorous statistical analysis of room effects for other patient outcomes needs to contend with competing risks and differential attrition (given the effects we find for mortality, and the high rates of exit from nursing homes within the first few months of admission). Second, we focus on the effects of being assigned roommates with or without AD/ADRD given the increasing prevalence and costs of these diseases. In reality, peer effects along other dimensions may exist; indeed, we document similar effects and patterns of heterogeneity based on CPS and ADL scores. This suggests that more sophisticated room assignment policies that leverage peer effects and heterogeneity along additional characteristics may yield even greater improvements in patient outcomes. Third, the simple assignment policy considered in this paper is static (assigning all patients simultaneously), whereas in practice patients arrive and exit stochastically.

Taken together, our results suggest that patients themselves are productive inputs in healthcare. In a system where increasing formal inputs is costly and can yield limited gains, reallocating patients across existing capacity—by improving the peer environment—offers a complementary path to improving outcomes. More broadly, the social composition of care settings may be an important but underutilized lever for healthcare productivity.

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A Details on Sample Construction

Cleaning the room identifier. The room identifier requires substantial cleaning because its format varies across nursing homes and within nursing homes over time. In cleaning the room identifier, we address the following main issues.

First, the variable sometimes records bed assignments rather than room assignments. For example, entries like ”15-1” or ”15/A” likely indicate bed 1 or bed A within room 15. In such cases, we strip the bed suffix to obtain the room number.

Second, some entries are too coarse or invalid to be useful. For instance, entries like ”SOUTH” (referring to an entire wing) or ”ROOM” (a placeholder) do not identify specific rooms. We drop patients with such room identifiers from the analysis.

Third, the way a nursing home refers to the same physical room may change over time due to facility expansions, reorganizations, or inconsistencies in data entry. A room initially labeled ”15” might later be recorded as ”A15.” To avoid treating these as distinct rooms—which would create ”phantom” rooms that appear available but do not actually exist—we define the set of available rooms separately for each nursing home and year.[27]

Finally, we drop rooms with maximum recorded occupants exceeding four patients, as these likely reflect coding errors or institutional settings (e.g., hospital wards) that differ meaningfully from typical nursing home rooms. Our main results are robust to alternative occupancy thresholds.[28]

Note that the sample sizes for the IV estimates in columns 1 and 2 of Table II are slightly smaller than shown in column 1 of the summary statistics in Table I, due to Stata dropping these approximately 700 observations due to collinearity with the large number of fixed effects. In addition, the sample sizes in the first two columns of Appendix Tables A.2 and A.3 are about 70 observations less than columns 1 and 2 of Table II due to these observations being dropped when merging in additional facility information used for controls in subsequent specifications. This small difference in number of observations is inconsequential for the analysis: point estimates and standard errors in the three panels of column 2 of Appendix Table A.2—which are based on the same specification as the main results—are identical to their analogous specifications in columns 2–4 of Table II.

Missing Discharge Dates. Some patient stays are missing discharge assessments (which nursing homes are required to fill in when patients leave the facility, whether due to discharge to hospital/community or due to death). In particular, we define a stay as missing a discharge date if no further assessments are recorded for a patient for the stay, with the last (non-discharge) assessment being at least 150 days before the end of the sample. This threshold is chosen in accordance with the definition adopted by the CMS for ”active” patients.[29] In such cases, we assume that the patient was discharged one quarter after the last available assessment (given that nursing homes are required to fill in assessments at least quarterly), or the day before the beginning of the patient’s next stay (at the same nursing home or another

[27] Specifically, we first construct daily room occupancies for the entire sample period. Then, we define a room as available at a point in time t if the room’s maximum occupancy in that year ($y(t)$) is at least one, and the occupancy at time t is less than the maximum occupancy observed in $y(t)$.

[28] Results available from authors upon request.

[29] https://data.cms.gov/resources/facility-level-minimum-data-set-frequency-methodology. Accessed November 22, 2025.

nursing home) if this occurs less than one quarter after the last assessment for the previous stay.

Our final analysis sample contains 2.5 million nursing home admissions across 7,200 facilities and 480,000 unique rooms, with 557,018 (21.7%) assigned to empty rooms, 990,670 (38.6%) to shared rooms with AD/ADRD roommates, and 1,021,931 (39.8%) to shared rooms without AD/ADRD roommates.

B Optimal Room Assignment

B.1 Basic Model for Optimal Assignment Rule

In this subsection, we present a simple model of an assignment rule that minimizes mortality—which we call an optimal assignment rule for simplicity (keeping in mind that in practice one may care about outcomes other than survival)—assuming full capacity for now, and relaxing this in a subsequent subsection.

Consider a static setting, where the social planner decides how to allocate patients with and without AD/ADRD to rooms in a given nursing home. Denote the fraction of patients with AD/ADRD by π and types by $k \in \{AD, noAD\}$. Letting N be the total number of patients and N_k be the number of patients of each type, we thus have:

$$N_{AD} = \pi N, \qquad N_{noAD} = (1 - \pi)N.$$

Suppose the nursing home has R rooms, a fraction p of which are private, and that shared rooms each have a capacity of two. We assume full capacity, so N is both the number of patients and the number of beds. Assuming that N is large so we can ignore integer constraints, this implies that:

$$N = pR + 2(1 - p)R.$$

For notational convenience, we replace the health production function for a patient with health $h(i)$ when sharing with a roommate of health $h(i')$, $f(h(i), h(i'))$, by $u_{share}^{h(i),h(i')}$. Similarly, we replace $f(h(i), \emptyset)$ in the main text by $u_{priv}^{h(i)}$. More concretely, we denote 90-day survival of patients with health $h(i)$ when assigned to a private room by $u_{priv}^{h(i)}$, and 90-day survival of patients with health $h(i)$ when assigned a roommate with health $h(i')$ by $u_{share}^{h(i),h(i')}$, where $h(i), h(i') \in \{AD, noAD\}$.

The decision variables for the optimal assignment problem are:

- The number of patients with AD/ADRD in private rooms, x_{priv}^{AD},
- The number of patients without AD/ADRD in private rooms, x_{priv}^{noAD},
- The number of shared rooms with two patients with AD/ADRD, $x_{share}^{AD,AD}$,
- The number of shared rooms with two patients without AD/ADRD, $x_{share}^{noAD,noAD}$, and,
- The number of shared rooms with one patient who has AD/ADRD and another who does not, $x_{share}^{AD,noAD}$.

The optimal assignment problem can thus be written as the following linear program:

$$\max_{\substack{x_{priv}^{AD}, x_{priv}^{noAD}, x_{share}^{AD,AD},\\ x_{share}^{noAD,noAD}, x_{share}^{AD,noAD}}} \quad V = \underbrace{x_{priv}^{AD} u_{priv}^{AD}}_{\text{AD in Private Rooms}} + \overbrace{x_{priv}^{noAD} u_{priv}^{noAD}}^{\text{No AD in Private Rooms}}$$

$$+ \underbrace{2x_{share}^{AD,AD} u_{share}^{AD,AD}}_{\text{Shared: (AD,AD)}} + \overbrace{2x_{share}^{noAD,noAD} u_{share}^{noAD,noAD}}^{\text{Shared: (noAD, noAD)}} + \underbrace{x_{share}^{AD,noAD}\left(u_{share}^{AD,noAD} + u_{share}^{noAD,AD}\right)}_{\text{Shared: (AD,noAD)}},$$

$$\begin{aligned}
\text{s.t.} \quad & x_{priv}^{AD} \geq 0, x_{priv}^{noAD} \geq 0, x_{share}^{AD,AD}, x_{share}^{noAD,noAD} \geq 0, x_{share}^{AD,noAD} \geq 0, \text{ (Non-Negativity)} \\
& x_{priv}^{AD} + x_{priv}^{noAD} = pR, \text{ (Balance for private rooms)} \\
& x_{share}^{AD,AD} + x_{share}^{noAD,noAD} + x_{share}^{AD,noAD} = (1-p)R, \text{ (Balance for shared rooms)} \\
& x_{priv}^{AD} + 2x_{share}^{AD,AD} + x_{share}^{AD,noAD} = \pi N, \text{ (Balance for Patients with AD)} \\
& x_{priv}^{noAD} + 2x_{share}^{noAD,noAD} + x_{share}^{AD,noAD} = (1-\pi)N, \text{ (Balance for Patients without AD)}
\end{aligned}$$

where the second and third lines of the constraints ensure that room assignments match the different types of rooms, and the last two lines of the constraints ensures room assignments are consistent with the number of different types of patients. Note that one of the last four constraints is redundant, but we retain it for completeness.

Using the constraints and the fact that $x_{priv}^{noAD} = pR - x_{priv}^{AD}$, we can express $x_{share}^{AD,AD}$ and $x_{share}^{noAD,noAD}$ as:

$$x_{share}^{AD,AD} = \tfrac{1}{2}\left(\pi N - x_{priv}^{AD} - x_{share}^{AD,noAD}\right), \qquad x_{share}^{noAD,noAD} = \tfrac{1}{2}\left((1-\pi)N - (pR - x_{priv}^{AD}) - x_{share}^{AD,noAD}\right).$$

This simplifies the linear program to one with two choice variables, which (after some algebraic manipulation) we can write as:

$$\begin{aligned}
\max_{x_{priv}^{AD}, x_{share}^{AD,noAD}} \quad & V = C + \psi x_{priv}^{AD} + \theta x_{share}^{AD,noAD} \\
\text{s.t.} \quad & x_{priv}^{AD} \in [L, U], \\
& x_{share}^{AD,noAD} \in \left[0, \min\{\pi N - x_{priv}^{AD}, (1-\pi)N - (pR - x_{priv}^{AD})\}\right],
\end{aligned}$$

where:

$$\begin{aligned}
\psi &\equiv (u_{priv}^{AD} - u_{share}^{AD,AD}) - (u_{priv}^{noAD} - u_{share}^{noAD,noAD}), \\
\theta &\equiv (u_{share}^{AD,noAD} + u_{share}^{noAD,AD}) - (u_{share}^{AD,AD} + u_{share}^{noAD,noAD}), \\
C &\equiv \pi N u_{share}^{AD,AD} + (1-\pi) N u_{share}^{noAD,noAD} + pR(u_{priv}^{noAD} - u_{share}^{noAD,noAD}), \\
L &\equiv \max\{0, pR - (1-\pi)N\}, \quad U \equiv \min\{\pi N, pR\}.
\end{aligned}$$

The parameter ψ can be interpreted as the difference in privacy premium between patients with and without AD. On the other hand, θ can be interpreted as the surplus from having a mixed room rather than homogeneous shared rooms. Moreover, we observe that θ informs whether health production is supermodular or submodular between patients with and without AD/ADRD in shared rooms. Negative values of θ correspond to supermodularity, and positive values correspond to submodularity (Milgrom and Roberts, 1990).

Given that the feasible set is a polytope, by the fundamental theorem of linear programming, an optimum lies at an extreme point. We consider different cases based on the sign of θ.

Supermodular production: In the supermodular case ($\theta \leq 0$), homogeneous rooms are more efficient than mixed rooms, it is then optimal to set $x_{share}^{AD,noAD} = 0$. In addition, it is optimal to allocate as many private rooms to the type with the greater privacy premium as possible: if $\psi > 0$, set $x_{priv}^{AD,*} = U$, whereas if $\psi \leq 0$, set $x_{priv}^{AD,*} = L$.

Submodular production: In the submodular case ($\theta > 0$), mixed rooms are more efficient than homogeneous rooms. Hence, it is optimal to maximize the number of shared rooms, except when the difference in privacy premium outweighs the gains from mixing ($|\psi| > \theta$), in which case one may sacrifice some mixed rooms in order to assign the type that benefits disproportionately from the privacy premium to private rooms.

Start by considering the simple case where $\theta \geq |\psi|$. For a given choice of x_{priv}^{AD}, the maximum feasible number of mixed rooms is:

$$s_{max}(x_{priv}^{AD}) = \min\{\overbrace{\pi N - x_{priv}^{AD}}^{\text{Remaining Patients with AD}}, \underbrace{(1-\pi)N - (pR - x_{priv}^{AD})}_{\text{Remaining Patients without AD}}\}.$$

This quantity is maximized when the two constraints bind simultaneously, which occurs when $x_{priv}^{AD} = x_{bal}$:

$$x_{bal} \equiv \frac{(2\pi - 1)N + pR}{2}.$$

Hence, if $x_{bal} \in [L, U]$, we set $x_{priv}^{AD,*} = x_{bal}$ and $x_{share}^{AD,noAD,*} = s_{max}(x_{bal})$. On the other hand, if $x_{bal} \notin [L, U]$, we set $x_{priv}^{AD,*} = \text{clip}(x_{\text{bal}}; [L, U])$ and $x_{share}^{AD,noAD,*} = s_{max}(x_{priv}^{AD,*})$, depending on which choice of $x_{priv}^{AD,*}$ results in a larger V. If $|\psi| > \theta$, then we assign as many patients from the type that benefits more from the privacy premium to private rooms as possible: $x_{priv}^{AD,*} = \mathbb{I}[\psi < 0] \cdot L + \mathbb{I}[\psi \geq 0] \cdot U$ and $x_{share}^{AD,noAD,*} = s_{max}(x_{priv}^{AD,*})$.

B.2 Tradeoffs Between Outcomes for Patients with and without AD/ADRD

The optimal assignment problem in the previous subsection maximizes the overall survival rate. A concern with this solution is that it *may* improve one group's outcomes at the expense of the other group's outcomes (depending on two groups' shares in the population and how sensitive each group's outcomes are to room assignments). Hence, a natural extension is to impose a fairness constraint—i.e., lower bound on survival for one group—while maximizing survival for the other group. This allows us to trace out a frontier for the maximum achievable survival rates for the two groups, with any point strictly below the frontier being Pareto dominated. Note that maximizing one group's outcomes subject to the other group's outcomes is simply a different way of tracing out the survival frontier compared to varying welfare weights across the two patient types in the linear program's objective.

Formally, letting $\bar{u}_{AD}$ and $\bar{u}_{noAD}$ denote average survival among patients with and without AD/ADRD respectively:

$$\bar{u}_{AD} = \frac{1}{\pi N}\left(x^{AD}_{priv}u^{AD}_{priv} + 2x^{AD,AD}_{share}u^{AD,AD}_{share} + x^{AD,noAD}_{share}u^{AD,noAD}_{share}\right),$$

$$\bar{u}_{noAD} = \frac{1}{(1-\pi)N}\left(x^{noAD}_{priv}u^{noAD}_{priv} + 2x^{noAD,noAD}_{share}u^{noAD,noAD}_{share} + x^{AD,noAD}_{share}u^{noAD,AD}_{share}\right).$$

We can write the constrained assignment problem as:

$$\begin{aligned}
\max_{\substack{x^{AD}_{priv}, x^{noAD}_{priv}, x^{AD,AD}_{share},\\ x^{noAD,noAD}_{share}, x^{AD,noAD}_{share}}} \quad & \bar{u}_{AD} \\
\text{s.t.} \quad & x^{AD}_{priv} \geq 0,\ x^{noAD}_{priv} \geq 0,\ x^{AD,AD}_{share} \geq 0,\ x^{noAD,noAD}_{share} \geq 0,\ x^{AD,noAD}_{share} \geq 0, \\
& x^{AD}_{priv} + x^{noAD}_{priv} = pR, \\
& x^{AD,AD}_{share} + x^{noAD,noAD}_{share} + x^{AD,noAD}_{share} = (1-p)R, \\
& x^{AD}_{priv} + 2x^{AD,AD}_{share} + x^{AD,noAD}_{share} = \pi N, \\
& x^{noAD}_{priv} + 2x^{noAD,noAD}_{share} + x^{AD,noAD}_{share} = (1-\pi)N, \\
& \bar{u}_{noAD} \geq K.
\end{aligned}$$

Since the number of patients with AD/ADRD is fixed, this is equivalent to maximizing total survival among patients with AD/ADRD:

$$V^{AD} \equiv x^{AD}_{priv}u^{AD}_{priv} + 2x^{AD,AD}_{share}u^{AD,AD}_{share} + x^{AD,noAD}_{share}u^{AD,noAD}_{share}.$$

The feasibility constraints in the unconstrained problem allow us to eliminate x^{noAD}_{priv}, $x^{AD,AD}_{share}$, and $x^{noAD,noAD}_{share}$, so the constrained problem can again be written in terms of two choice variables: x^{AD}_{priv} and $x^{AD,noAD}_{share}$.

However, unlike the unconstrained problem, the parameters ψ and θ are no longer sufficient to characterize the solution. This is because of the asymmetry in the constrained problem: the objective depends only on outcomes for patients with AD/ADRD, whereas the fairness constraint depends only on outcomes for patients without AD/ADRD. It is therefore useful to define these terms separately for the two groups:

$$\psi^{AD} \equiv u^{AD}_{priv} - u^{AD,AD}_{share}, \qquad \theta^{AD} \equiv u^{AD,noAD}_{share} - u^{AD,AD}_{share},$$

$$\psi^{noAD} \equiv u^{noAD}_{priv} - u^{noAD,noAD}_{share}, \qquad \theta^{noAD} \equiv u^{noAD,AD}_{share} - u^{noAD,noAD}_{share},$$

where ψ^h and θ^h are the privacy premium and gains from mixing respectively for a patient of health type h.

Substituting this into the objective, we obtain:

$$V^{AD} = \pi N u^{AD,AD}_{share} + \psi^{AD}x^{AD}_{priv} + \theta^{AD}x^{AD,noAD}_{share}.$$

Similarly, average survival among patients without AD/ADRD can be written as:

$$\bar{u}_{noAD} = u^{noAD,noAD}_{share} + \frac{\psi^{noAD}(pR - x^{AD}_{priv}) + \theta^{noAD} x^{AD,noAD}_{share}}{(1-\pi)N}.$$

Hence, the constrained assignment problem can be written as:

$$\begin{aligned}
\max_{x^{AD}_{priv}, x^{AD,noAD}_{share}} \quad V^{AD} =& \pi N u^{AD,AD}_{share} + \psi^{AD} x^{AD}_{priv} + \theta^{AD} x^{AD,noAD}_{share} \\
\text{s.t.} \quad & x^{AD}_{priv} \in [L, U], \\
& x^{AD,noAD}_{share} \in \left[0, \min\{\pi N - x^{AD}_{priv}, (1-\pi)N - (pR - x^{AD}_{priv})\}\right], \\
& \psi^{noAD}(pR - x^{AD}_{priv}) + \theta^{noAD} x^{AD,noAD}_{share} \geq (1-\pi)N\big(K - u^{noAD,noAD}_{share}\big).
\end{aligned}$$

Because both the objective and the new survival-floor constraint are linear, the feasible set remains a polytope. It follows from the fundamental theorem of linear programming that an optimum lies at an extreme point of the constrained feasible set (whenever the constrained problem is feasible). Geometrically, the constrained problem can be interpreted in terms of the set of attainable survival pairs

$$\Big\{\big(\bar{u}_{noAD}, \bar{u}_{AD}\big) : (x^{AD}_{priv}, x^{AD,noAD}_{share}) \text{ is feasible}\Big\}.$$

This set is a polygon in $(\bar{u}_{noAD}, \bar{u}_{AD})$-space, and the frontier for the maximum achievable survival rates for patients with and without AD is its upper boundary.

The solution can be characterized in a simple way. Let

$$(x^{AD}_{priv,AD-opt}, x^{AD,noAD}_{share,AD-opt})$$

denote a solution to the *unconstrained* problem that maximizes survival among patients with AD/ADRD without fairness constraints (i.e., without the constraint that $\bar{u}_{noAD} \geq K$).

If this AD-optimal assignment already satisfies $\bar{u}_{noAD} \geq K$, then the additional constraint is slack and the constrained optimum is unchanged. On the other hand, if the AD-optimal assignment violates the constraint, then the fairness constraint binds, and the constrained optimum must lie at the intersection of the original feasible set and the boundary of the fairness constraint:

$$\psi^{noAD}(pR - x^{AD}_{priv}) + \theta^{noAD} x^{AD,noAD}_{share} = (1-\pi)N\big(K - u^{noAD,noAD}_{share}\big).$$

In the empirically relevant case:

$$\theta^{AD} > \psi^{AD} > 0 \qquad \text{and} \qquad \psi^{noAD} > \theta^{noAD} > 0,$$

patients with AD/ADRD do best in mixed rooms, followed by private rooms, and finally segregated rooms with another roommate with AD/ADRD. By contrast, patients without AD/ADRD have the best outcomes in private rooms, followed by mixed rooms and finally segregated rooms with roommates without ADRD (although the difference between the last two is not statistically significant). In this case, the unconstrained solution maximizing survival among patients with AD/ADRD occurs where there is maximum mixing:

$$x^{AD}_{priv,AD-opt} = \text{clip}(x_{bal}; [L, U]), \qquad x^{AD,noAD}_{share,AD-opt} = s_{max}(x^{AD}_{priv,AD-opt}),$$

where

$$x_{bal} \equiv \frac{(2\pi - 1)N + pR}{2}, \qquad s_{max}(x^{AD}_{priv}) = \min\{\pi N - x^{AD}_{priv}, (1-\pi)N - (pR - x^{AD}_{priv})\}.$$

As the floor K rises, the constrained optimum initially remains at this AD-optimal assignment. There are then two possibilities. First, it may be the case that the same assignment also maximizes survival among patients without AD/ADRD. In this case, the frontier degenerates to a single point: every feasible value of K selects the same allocation, and there is no trade-off between the two groups. Second, if the AD-optimal assignment does not maximize survival among patients without AD/ADRD, then once K becomes large enough that the fairness constraint binds, the optimum moves along the relevant edge of the feasible set.

Again, consider the empirically relevant sign patterns:

$$\theta^{AD} > \psi^{AD} > 0 \qquad \text{and} \qquad \psi^{noAD} > \theta^{noAD} > 0.$$

The AD-optimal assignment maximizes assignment of patients with AD/ADRD to mixed rooms. Depending on the fraction of the population with AD/ADRD (π) and the fraction of rooms that are private (p), this AD-optimal assignment may or may not include patients with AD/ADRD in private rooms. If private rooms are filled entirely with patients without AD/ADRD, then the frontier is degenerate: average outcomes for patients without AD/ADRD cannot be improved any further. On the other hand, if some private rooms are occupied by patients with AD/ADRD *and* not all patients without AD/ADRD are in private rooms in the AD-optimal assignment, then there is scope to improve outcomes for patients without AD/ADRD. In particular, outcomes for patients without AD/ADRD can be improved by moving them from shared rooms to private rooms at the expense of patients with AD/ADRD, so the frontier is no longer degenerate.

More formally, the upper boundary of the feasible set is

$$x^{AD,noAD}_{share} = \min\{\pi N - x^{AD}_{priv}, (1-\pi)N - pR + x^{AD}_{priv}\},$$

with a kink at

$$x_{bal} = \frac{(2\pi - 1)N + pR}{2},$$

which divides the upper boundary into two segments, as long as $x_{bal} \in [L, U]$.[30]

On the first segment, we have:

$$x^{AD,noAD}_{share} = \pi N - x^{AD}_{priv},$$

which implies

$$x^{AD,AD}_{share} = 0, \qquad x^{noAD,noAD}_{share} = x^{AD}_{priv} - x_{bal}.$$

[30] If $x_{bal} \notin [L, U]$, then this upper boundary consists of only one segment.

If x_{priv}^{AD} is reduced by a small amount while $\delta^{AD} > 0$ while remaining on this segment, then:

$$\Delta x_{priv}^{AD} = -\delta^{AD}, \qquad \Delta x_{share}^{AD,noAD} = \delta^{AD}, \qquad \Delta x_{share}^{noAD,noAD} = -\delta^{AD}, \qquad \Delta x_{priv}^{noAD} = \delta^{AD}.$$

The small number of patients with AD/ADRD who are moved from private to mixed rooms benefit from the move, and so do patients without AD/ADRD who are moved from shared rooms to private rooms as well as patients without AD/ADRD who have a roommate with AD/ADRD instead of a roommate without AD/ADRD. Hence, reducing x_{priv}^{AD} on this segment is a Pareto improvement, so this segment cannot be a part of the non-degenerate frontier (except possibly at an endpoint).

On the second segment, we have:

$$x_{share}^{AD,noAD} = (1-\pi)N - pR + x_{priv}^{AD},$$

which implies that:

$$x_{share}^{noAD,noAD} = 0, \qquad x_{share}^{AD,AD} = x_{bal} - x_{priv}^{AD}.$$

If x_{priv}^{AD} is reduced by $\delta AD > 0$ while remaining on this segment, then:

$$\Delta x_{priv}^{AD} = -\delta AD, \qquad \Delta x_{share}^{AD,noAD} = -\delta AD, \qquad \Delta x_{share}^{AD,AD} = \delta AD, \qquad \Delta x_{priv}^{noAD} = \delta AD.$$

Thus, lowering x_{priv}^{AD} reallocates private rooms toward patients without AD/ADRD, but at the cost of replacing mixed rooms with segregated rooms with two patients both with AD/ADRD. This raises survival for patients without AD/ADRD and lowers survival for patients with AD/ADRD. Therefore, in the non-degenerate case, the binding part of the frontier lies on this segment of the feasibility constraints.

Substituting the expression for this segment into the binding fairness constraint yields:

$$\psi^{noAD}(pR - x_{priv}^{AD}) + \theta^{noAD}\big((1-\pi)N - pR + x_{priv}^{AD}\big) = (1-\pi)N\big(K - u_{share}^{noAD,noAD}\big).$$

Solving for x_{priv}^{AD} yields:

$$x_{priv}^{AD,fair}(K) = \frac{\psi^{noAD}pR + \theta^{noAD}\big((1-\pi)N - pR\big) - (1-\pi)N\big(K - u_{share}^{noAD,noAD}\big)}{\psi^{noAD} - \theta^{noAD}},$$

which we then substitute into $x_{share}^{AD,noAD}$ to obtain:

$$x_{share}^{AD,noAD,fair}(K) = (1-\pi)N - pR + x_{priv}^{AD,fair}(K).$$

Substituting these values into $\bar{u}_{AD}$ and $\bar{u}_{noAD}$ for different values of K yields the survival frontier for the two groups.

Finally, we discuss quantitatively the tradeoff between outcomes of patients with AD/ADRD and those without as we move along the survival frontier (when it is not degenerate). Moving from the AD-optimal frontier to non-dominated assignment rules that are more favorable to patients without AD/ADRD, we are switching a patient without AD/ADRD who was formerly in a mixed room to a private room that was previously occupied by a patient with AD/ADRD. The change in the 90-day mortality rate of the patient without AD/ADRD who got switched to a private room is $(-0.009 - (-0.003)) = -0.006$, while the change in 90-day mortality of the patient with AD/ADRD who got switched from a private room to a shared room with another AD/ADRD patient is $0.034 - 0.014 = 0.020$. In addition, the patient with AD/ADRD who was formerly the roommate of the patient without AD/ADRD who was switched experiences a change in 90-day mortality of $0.034 - 0 = 0.034$. Therefore, the tradeoff along the survival frontier as we move away from the AD-optimal assignment is 9 additional deaths (within 90 days) among patients with AD/ADRD in exchange for 1 fewer death among patients without AD/ADRD (since $-(0.034 + 0.020)/0.006 = -9$).

B.3 Extension: Allowing for Spare Capacity

The previous analysis assumes that the number of patients is equal to nursing home capacity. In reality, the average occupancy rate in nursing homes is roughly 85% in our sample, so in this subsection, we explore implications when we allow for spare capacity. For simplicity, we focus on the empirically relevant case with positive gains from mixing ($\theta > 0$) and a greater privacy premium for patients with AD/ADRD ($\psi > 0$), but where the difference in privacy premium is smaller than the gains from mixing ($\theta > |\psi|$).

Using $S \in (0, 1]$ to represent the occupancy rate, we have:

$$N = S\big(pR + 2(1 - p)R\big).$$

Note that with spare capacity, a private room can be occupied by 0 or 1 patients, whereas a shared room can be occupied by 0, 1, or 2 patients. In line with our main empirical analysis, we assume that the same room effect applies to patients without roommates whether the maximum occupancy of the room they reside in is 1 or 2.

B.3.1 Optimal Room Assignment with Spare Capacity

First, we note that for minimizing overall mortality, the optimal assignment rule still prioritizes maximizing mixed shared rooms. The difference compared to the capacity-constrained case is that after maximizing mixed shared rooms, there may still be a choice of whether to assign patients as roommates, or to give each patient their own room to the extent possible. For our values of θ and ψ, after maximizing mixed rooms, maximizing the patients with their own rooms next is optimal.

More concretely, the maximum number of mixed rooms is given by:

$$\bar{M} = \min\{\pi N, (1 - \pi)N, (1 - p)R\}.$$

If the binding constraint for increasing mixed shared rooms beyond $\bar{M}$ is the number of shared rooms $(1 - p)R$, then the remaining rooms are private and there is no choice but to assign remaining patients to private rooms. If the binding constraint is one of the patient types, then the remaining choice is how to assign the remaining patients (of the other type) across the remaining shared and private rooms. Given that both types have a positive privacy premium, it is optimal to maximize the number of patients of the remaining type having their own room.

B.3.2 Tradeoffs with Spare Capacity

Allowing for spare capacity ($S < 1$) changes the geometry of the survival frontier, assuming that it is not degenerate. The key difference is that at the AD-optimal assignment, there may be empty rooms. If this is the case, then moving from the AD-optimal assignment, the most efficient way to improve outcomes for patients without AD/ADRD is to move a patient without AD/ADRD out of a mixed room and into an empty room. The tradeoff in this case is $\frac{7}{3}$ additional deaths among patients with AD/ADRD for 1 fewer death among patients without AD/ADRD (within 90 days). However, as we move away further away from the AD-optimal assignment, we will reach a point where all the empty rooms are used up (provided that there are not so many rooms that we can give every patient their own room), at which point the only way to improve outcomes for patients without AD/ADRD any further is switch a patient without AD/ADRD from a mixed room to a private room that was formerly occupied by a patient with AD/ADRD, so that the tradeoff is 9 additional deaths among patients with AD/ADRD for 1 fewer death among patients without AD/ADRD (within 90 days). In other words, there may be a kink in the survival frontier, where the ratio of lives saved changes from $\frac{7}{3}$ to 9.

The two possible slopes along the survival frontier have different implications for the QALY-adjusted optimal assignment rule. The ratio of QALYs for patients without AD/ADRD to QALYs for patients with AD/ADRD is estimated to be between 2.65 and 6.33 in van de Rijt et al. (2020) and León-Salas et al. (2015) respectively. These values fall in between the tradeoffs of $\frac{7}{3}$ and 9 implied by the flatter and steeper portions of kinked survival frontiers in our setting, implying that the QALY-adjusted optimal lies at the kink. In cases where only the flatter (respectively, steeper) segment of the survival frontier exists, the QALY-adjusted optimal assignment rule is the part of the segment most favorable to patients without AD/ADRD (with AD/ADRD).

Next, we derive the general condition under which a tradeoff emerges, and conduct comparative statics on how changes in the occupancy rate S, patient population π, and room composition p affect the existence of a tradeoff.

Formally, a tradeoff emerges if and only if the maximum number of mixed rooms $\bar{M}$ is strictly greater than the minimum number of patients without AD/ADRD who "have to" share a room with a roommate by virtue of the room configuration and number of patients of each type, $\underline{x}^{noAD}_{roommate}$. If this condition holds, then we have more patients without AD/ADRD in shared rooms under the AD-optimal assignment than strictly necessary, and outcomes for these patients can be improved by moving some of them out of shared rooms and giving them their own room.

To derive $\underline{x}^{noAD}_{roommate}$, we first introduce some notation. For any room assignment, let r_{single} and r_{double} be the number of rooms with a single occupant and two occupants respectively. Feasibility and accounting constraints give us:

$$r_{single} + r_{double} \leq R, \qquad r_{single} + 2r_{double} = N,$$

which implies that:

$$r_{single} \leq \min\{2R - N, N\} \equiv \bar{r}_{single},$$

where $\bar{r}_{single}$ is the maximum number of patients who can be alone in any assignment.[31] Now, if we assigned as many of these $\bar{r}_{single}$ slots to patients without AD/ADRD as possible, there will still be $(1-\pi)N - \bar{r}_{single}$ patients without AD/ADRD who have to live with a roommate (assuming the number of patients without AD/ADRD exceeds $\bar{r}_{single}$). Therefore, there is a tradeoff between outcomes of patients with and without AD/ADRD if and only if:

$$\bar{M} = \min\{\pi N, (1-\pi)N, (1-p)R\} > \max\{0, (1-\pi)N - \min(2R-N, N)\} = \underline{x}^{noAD}_{roommate}, \tag{A.1}$$

We observe that increasing capacity (i.e., decreasing S and thus increasing R for fixed N) tends to make it more likely that a tradeoff emerges, given that in condition A.1, the left-hand-side is unaffected by increases in capacity unless the number of shared rooms $(1-p)R$ is the only binding constraint preventing further increases in $\bar{M}$ in which case there is already a tradeoff under the AD-optimal assignment (since there are patients with AD/ADRD living alone in a room, who can be swapped with patients without AD/ADRD in mixed rooms to improve outcomes for patients without AD/ADRD). If the number of patients of either type is the constraint to increasing $\bar{M}$ even further, then increasing capacity only decreases the right-hand-side through R (unless there is already as many rooms as patients), which makes it more likely that the inequality will hold.

Similarly, increasing π makes tradeoffs more likely: increasing π by $\Delta\pi$ leads to a change in left-hand-side of condition A.1 of $-(\Delta\pi)N$ and does not change the right-hand-side unless the number of patients without AD/ADRD $(1-\pi)N$ is the binding constraint for increasing mixed rooms beyond $\bar{M}$, in which case the right-hand-side would also change by $-(\Delta\pi)N$. Hence, increasing π makes it weakly more likely that a tradeoff will emerge.

Comparative statics for changes in p are slightly more ambiguous. Assume that the minimum number of patients without AD/ADRD who are required to have a roommate by virtue of patient and room composition $\underline{x}^{noAD}_{roommate}$ is strictly positive, otherwise there will always be a tradeoff (except in degenerate cases such as there being only patients of one type or only private rooms). Then, increasing p by Δp changes the right-hand-side of condition A.1 by $-(\Delta p)SR$ (after expressing N in terms of p and R). The left-hand-side of condition A.1 remains unchanged unless the number of rooms with two beds $(1-p)R$ is the binding constraint for increasing mixed rooms beyond $\bar{M}$, in which case the left-hand-side changes by $-(\Delta p)R$. From this, we observe that when there is no spare capacity ($S = 1$), increasing p will make it weakly more likely that there is a tradeoff. On the other hand, if $S < 1$, then increasing p will make it less likely that a tradeoff will emerge if $(1-p)R \leq \min\{\pi N, (1-\pi)N\}$ (which tends to happen when patient types are relatively balanced and share of private rooms is high), and more likely to emerge otherwise.

To summarize tradeoffs, generally there are four cases:

1. The survival frontier is degenerate, i.e., consists of only a single point, which occurs if and only if $\bar{M} \leq \underline{x}^{noAD}_{roommate}$.

2. The survival frontier has a kink. This occurs if and only if:

$$\bar{M} > \underline{r}_{double} \equiv \max\{0, N-R\} > 0.$$

[31] Note that unlike the case with no spare capacity, r_{single} is not bounded above by the number of private rooms pR because some patients can potentially live alone in a double room when there is spare capacity. As a sanity check, observe that $2R - N = pR$ when there is no spare capacity (i.e., $S = 1$).

In particular, $\underline{r}_{double}$ is the minimum number of rooms with two occupants in any assignment given the constraints imposed by room configuration and patient count. So, if the maximum number of mixed rooms exceeds this value, then there are empty rooms in the AD-optimal assignment, so the ratio of lives saved on the frontier is initially $\frac{7}{3}$ at the AD-optimal point. In this case, the QALY-adjusted optimum lies at the kink.

3. The survival frontier only has a flatter segment, which occurs when $\underline{r}_{double} = 0$ (i.e., $N \leq R$). This is because there are so many rooms that it is feasible to give each patient their own room, as will be the case in the optimum for patients without AD/ADRD. Hence, the steep part of the tradeoff does not exist. The QALY-adjusted optimum lies at the endpoint of the survival frontier that is most favorable to patients without AD/ADRD.

4. The survival frontier only has a steeper segment, which occurs when $\bar{M} > \underline{x}^{noAD}_{roommate}$ (so a tradeoff exists) but $\bar{M} = \underline{r}_{double}$ (so that even at the AD-optimal assignment there are no empty rooms). In this case the only way to improve outcomes of patients without AD/ADRD along the survival frontier is to swap a patient without AD/ADRD in a mixed room with a patient with AD/ADRD living alone, which results in a steep tradeoff. The QALY-adjusted optimum lies at the endpoint of the frontier most favorable to patients with AD/ADRD.

B.4 Comparisons Under Different Assignment Rules

In this subsection, we compare the efficient assignment rules we derived in the earlier subsections to two other counterfactual assignment rules—random assignment and segregation—as well as observed outcomes in the data.[32]

We start by comparing the simulated 90-day mortality rate—overall and by patient type—under different assignment rules for nursing homes facing different patient populations (i.e., for different values of π) and with different room configurations (varying p), with and without spare capacity. In addition, we show the survival frontier for patients with and without AD/ADRD, comparing it to outcomes under random and segregated assignment. We then take our mortality-minimizing assignment rule to the data, quantifying heterogeneity in the potential gains for and tradeoffs faced by nursing homes in our sample, which vary widely in terms of their patient populations (π), room configurations (p) and occupancy rates (S).

B.4.1 Simulating 90-Day Mortality Under Counterfactual Assignment Rules

In order to simulate 90-day mortality under any given assignment rule for each patient type (i.e., with or without AD/ADRD), we simply need to know their average potential outcomes if assigned to different types of rooms: $\mathbb{E}[Y(\text{No Roommate})]$, $\mathbb{E}[Y(\text{Roommate with AD})]$, and $\mathbb{E}[Y(\text{Roommate without AD})]$. The IV estimates give us the effects of being assigned no roommate β_1 and being assigned a roommate with AD/ADRD β_2, relative to the omitted category of being assigned roommate(s) none of whom have AD/ADRD for each type

[32] Under random assignment, we assume that patients are randomly assigned to rooms, whereas under the segregated assignment rule we first randomly assign patients to available single-occupancy slots and among patients who must share we set the share of mixed rooms to zero.

of patient. This gives us two equations for three potential outcomes, so we still need to figure out the ”level”, i.e., the average potential outcomes for the omitted category (for each patient type). While the level is less important for comparing simulated mortality across counterfactual assignment rules, it is important to get the correct level for the omitted category ($\mathbb{E}[Y(\text{Roommate without AD})]$) when comparing simulated 90-day mortality to the observed 90-day mortality rate.

Simply using the observed mortality rate among patients of each type assigned roommates none of whom have AD/ADRD in the data to infer the level for the omitted category is subject to selection bias. Hence, for each type of patient, assuming a constant linear effects model within patient type, we infer the level for the omitted category using the equation:

$$\begin{aligned}\mathbb{E}[Y] =& Pr(\text{No Roommate}) \cdot \mathbb{E}[Y(\text{No Roommate})] \\ &+ Pr(\text{Roommate with AD}) \cdot \mathbb{E}[Y(\text{Roommate with AD})] \\ &+ Pr(\text{Roommate without AD}) \cdot \mathbb{E}[Y(\text{Roommate without AD})]\end{aligned}$$

Average outcomes $\mathbb{E}[Y]$ for patients of each type is observed, and so is the fraction assigned to each room type. In addition, we have:

$$\mathbb{E}[Y(\text{No Roommate})] = \mathbb{E}[Y(\text{Roommate without AD})] + \beta_1,$$

$$\mathbb{E}[Y(\text{Roommate with AD})] = \mathbb{E}[Y(\text{Roommate without AD})] + \beta_2,$$

which allows us to solve for $\mathbb{E}[Y(\text{Roommate without AD})]$ for each patient type.

B.4.2 Comparisons of Mortality Under Different Patient Populations and Room Configurations

Full Capacity: Figure A.9 shows counterfactual 90-day mortality under different assignment rules, varying the proportion of the patient population having AD/ADRD (π) across different panels, and varying the proportion of rooms that are private in each panel, assuming that there is no spare capacity (e.g. nursing homes operate at full capacity). Figure A.10 shows simulated 90-day mortality under the same assignment rules and parameters as Figure A.9, but separately for patients with AD/ADRD and patients without AD/ADRD.

We observe that different assignment rules can lead to quantitatively meaningful differences in mortality: in particular, Figure A.9 shows that even assuming full capacity, under the observed values of π and p in the population ($\pi = 0.3, p = 0.35$), simulated 90-day mortality under the assignment policy that minimizes average mortality is about 0.4 percentage points lower than random allocation, and 1.1 percentage points lower than segregated room assignments. In addition, observed mortality is about 0.6 percentage points higher than under optimal room assignment, a difference equivalent to 4 percent of the baseline 90-day mortality rate. The observed mortality rate is also higher than simulated mortality under random allocation, due to nursing homes' tendency to assign patients with AD/ADRD together as roommates. Figure A.10 shows that these large mortality reductions are driven almost entirely by better outcomes for patients with AD/ADRD: observed mortality for patients without AD/ADRD is higher than simulated mortality for this group under the optimal assignment rule, but quantitatively the difference is small.

In addition, we observe several qualitative patterns. First, the differences in simulated mortality under the different assignment rules tend to be larger when the fraction of private rooms is small, as well as when the two groups are similar in size. For instance, Figure A.9 shows that when all rooms are shared and patients with AD/ADRD account for half of the patient population, the difference in simulated 90-day mortality under segregated and optimal room assignment is 1.85 percentage points.

Second, Figure A.10 shows that reductions in mortality from the optimal room assignment policy are driven primarily by better outcomes for patients with AD/ADRD, consistent with the assignment rule's prioritization of mixing patients with and without AD/ADRD in shared rooms leading to better outcomes for patients with AD/ADRD.

Third, an interesting pattern is that while simulated mortality (for the full population, as well as for patients with AD/ADRD) under the optimal assignment rule tends to be decreasing in the fraction of rooms that are private initially (except when $\pi = 0.5$), at some point there is a kink and it begins to rise with the private room share. This is because the optimal assignment rule's prioritization of mixing patients with and without AD/ADRD in shared rooms. When there are "too many" private rooms (i.e., too few shared rooms), some patients with AD/ADRD who could have had a roommate without AD/ADRD when the share of private rooms is lower are now instead being allocated to private rooms which increases their mortality rate. Also, note that when $\pi = 0.5$, the number of patients with AD/ADRD who have a roommate without AD/ADRD is maximized when all rooms are shared, which explains why simulated mortality under the optimal assignment rule is monotonically increasing in the fraction of rooms that are private.

Fourth, mortality for patients without AD/ADRD under assignment rule minimizing overall mortality is lower than under random allocation or segregated rooms when a low to moderate fraction of patients have AD/ADRD (e.g., $\pi = 0.3, 0.5$), but not when a majority of patients have AD/ADRD (e.g., $\pi = 0.7, 0.9$). The higher mortality rates for patients without AD/ADRD under the optimal assignment rule for high values of π are because the best room type for patients without AD/ADRD is a private room, yet they are disproportionately assigned to shared rooms with a roommate who has AD/ADRD, with this burden becoming increasingly heavy when there are more individuals with AD/ADRD.

Spare Capacity (85% Occupancy): Similarly, Figures A.11 and A.12 show simulated 90-day mortality under different assignment rules for all patients and separately by AD/ADRD status respectively, but now assuming an occupancy rate of 85%, which is the average among nursing homes in our sample. The patterns tend to be similar to the case without spare capacity, but there are nonetheless a few differences.

First, Figure A.11 shows that potential overall survival gains from optimal assignment tend to be larger. For instance, compared to observed mortality using the average share of patients with AD/ADRD and share of rooms private, observed mortality is about 0.8 percentage points higher than simulated mortality under the optimal assignment rule (compared to 0.6 percentage points when assuming full capacity).

Second, we observe in Figure A.11 that for several values of π, the optimal assignment rule is initially decreasing in the fraction of rooms private, before having a flat region, and eventually starts increasing with the fraction of rooms private (the difference with the full capacity case being the flat region). This flat region corresponds to the case where all minority-type patients are in shared rooms (i.e., patients with AD/ADRD if $\pi < 0.5$, or patients without AD/ADRD if $\pi > 0.5$), and all majority-type patients have a room to themselves. In other words, the binding constraint to having more mixed rooms is that there are not enough minority-type patients, and there are enough rooms so that everyone else can have their own room. Increasing the share of private rooms further does not change the optimal assignment, until there are too few rooms with two beds for all minority-type patients to be in mixed rooms (i.e., number of rooms with two beds becomes the binding constraint for increasing mixed rooms even further), which leads to mortality increasing with the fraction of rooms private.

Third, for certain values of π and p, patients without AD/ADRD have worse outcomes under the optimal assignment rule when there is spare capacity compared to when there is none. This is because some patients without AD/ADRD that would have been assigned to private rooms in the full capacity case are now being assigned as roommates with patients who have AD/ADRD (due to the extra rooms available).

B.4.3 Tradeoffs Under Different Patient Populations

Full Capacity: Next, we further explore potential tradeoffs between outcomes of patients with and without AD/ADRD in room assignment policies. Figure A.13 plots the survival frontier for these two types of patients and compares it to various other room assignment policies, assuming full capacity. Each subfigure corresponds to a different fraction of patients having AD/ADRD, assuming that the share of rooms that are private is 35% (the share observed in the data). The frontier is shown by the line, and the point along the frontier where the assignment rule minimizing overall mortality is shown using a green circle. The blue triangle and red squares indicate random and segregated room allocations, whereas the open circle shows the observed survival rates for the two groups when the fraction of patients having AD/ADRD matches the fraction in the data ($\pi = 0.3$).

Note also that the slope of the survival frontier in this figure (when it is not degenerate) is not -9 (which is the negative of the ratio of lives saved). This is because while these figures plot group-specific average survival which is less sensitive for the larger group. If we multiply the y-axis (for patients with AD/ADRD) by π and the x-axis (for patients without AD/ADRD) by $1 - \pi$, the slope will then be -9.

Figures A.13 and A.14 show the survival frontiers assuming full capacity, for various shares of the patient population having AD/ADRD, and where 35% (the observed average) and 70% of rooms are private respectively.

Panel (a) of Figure A.13 shows that for the average share of patients with AD/ADRD (π) and share of rooms private (p) observed in the data, there is essentially no tradeoff between the survival of patients with and without AD/ADRD if we assume full capacity, with the survival frontier collapsing down onto the green point. This is because when π and p are small, one can assign all patients with AD/ADRD to shared rooms with a roommate without AD/ADRD, and still completely fill private rooms with patients without AD/ADRD, so survival rates for the two groups are simultaneously maximized.

Panels (b), (c), and (d) of Figure A.13 show the frontiers for higher shares of patients with AD/ADRD. In these cases, we observe that the frontier is no longer degenerate, so there is a genuine tradeoff between maximizing the survival rates of patients with or without AD/ADRD. In particular, when the share of patients with AD/ADRD is moderate to large and the share of private rooms small, under the (overall-optimal) assignment rule that minimizes overall mortality after maximizing the number of shared rooms that are mixed, some (or all) of the private rooms are occupied by patients with AD/ADRD. So, outcomes for patients without AD/ADRD can be improved by swapping some of the patients with patients with AD/ADRD residing in private rooms. However, this comes at a steep cost for both patients with AD/ADRD whose roommate is changed from a patient without AD/ADRD to a patient with AD/ADRD as well as for patients with AD/ADRD who could have lived in a private room but are now roommates with another patient with AD/ADRD. As explained earlier, the implicit tradeoff moving away from the AD-optimal assignment is 9 more deaths among patients with AD/ADRD for 1 fewer death among patients without AD/ADRD (within 90 days). This steep tradeoff explains why the assignment rule minimizing overall mortality is always on the upper-left endpoint of the frontier (which prioritizes survival of patients with AD/ADRD).

In addition, we observe in all panels of Figure A.13 that simulated mortality under random and segregated room assignments are to the southwest of the survival frontier, indicating that they are Pareto dominated by alternative room assignments. Although survival for patients without AD/ADRD is higher under random assignment compared to the overall-optimal assignment rule when $\pi = 0.7$ or 0.9 when $p = 0.35$ (a result seen earlier in Figure A.10), there are alternative points along the frontier representing room assignments that improve survival for both patients with and without AD/ADRD relative to random assignment.

When 70% of rooms are private, Figure A.14 shows that even with full capacity, there is a tradeoff between outcomes of patients with and without AD/ADRD for all four values of π considered ($\pi = 0.3, 0.5, 0.7, 0.9$). This is in line with the model's prediction that with full capacity, increasing p can only make it (weakly) more likely for a tradeoff to emerge. We also observe that random and segregated room assignments tend to be closer to the survival frontier than when only 35% of rooms are private, reflecting the fact that most of the gains from better room assignments come from more efficient use of shared rooms.

Spare Capacity (85% Occupancy): Next, Figures A.15 and A.16 plot the survival frontier assuming an occupancy rate of 85% (the average in our sample of nursing homes), when 35% and 70% of rooms are private respectively. There are two obvious differences relative to the full capacity case. First, in all values of π and p considered ($\pi = 0.3, 0.5, 0.7, 0.9$, $p = 0.35, 0.7$), there is now a tradeoff, consistent with our model's earlier prediction that tradeoffs are more likely with spare capacity.

Second, in line with the model, there is a kink in the frontier for certain values of the parameters. This is because there may be empty rooms in the AD-optimal assignment, in which case outcomes for patients without AD/ADRD can be improved by moving them from mixed rooms into these empty rooms. Once these empty rooms are exhausted, the only way to improve outcomes for them any further is to switch them with a patient who has AD/ADRD who is residing alone, creating a shared room with two AD/ADRD patients. This leads to a much steeper tradeoff, and the point at which empty rooms are exhausted is illustrated by the kink. Note also that in panel (d) where $\pi = 0.9$, there is no kink because even at the AD-optimal assignment there are no empty rooms. This is because there are too few patients without AD/ADRD to create many mixed rooms, and the remaining AD/ADRD patients are assigned to have their own rooms to the maximum extent possible (since having two patients with AD/ADRD as roommates is the worst outcome for them), thus exhausting all the empty rooms.[33] Finally, we observe that even though the tradeoff is less steep on the margin when there are empty rooms available at the AD-optimal assignment, even in this case the optimal assignment for minimizing overall mortality is still the AD-optimal assignment, since the tradeoff for reducing deaths within 90 days by 1 among patients without AD/ADRD remains at more than 1 additional death (specifically $\frac{7}{3}$) among patients with AD/ADRD.

B.4.4 Potential Gains and Tradeoffs at the Nursing Home Level in the Data

While 35% of rooms are private and 30% of patients have AD/ADRD in our data, individual nursing homes vary widely in their room configuration (p) and patient composition (π). Next, we assess potential reductions in mortality and tradeoffs between outcomes of patients with and without AD/ADRD at the nursing home level.

[33] This corresponds to the failure of the first inequality in the if and only if condition for there to be a kink derived earlier: $\bar{M} > \underline{r}_{double} > 0$.

Specifically, we compute the share of rooms that are private, the share of patients with AD/ADRD, and the (average and group-specific) 90-day mortality rate for each nursing home with at least 100 patients in our sample.[34] This allows us to compare the observed 90-day mortality rate with the simulated 90-day mortality rate under efficient assignment rules for each nursing home assuming no spare capacity. In addition, using nursing homes' reported occupancy rates from the OSCAR data, we can also simulate 90-day mortality under efficient assignment rules using the observed spare capacity.

Figure A.17 shows a scatterplot π_j against p_j for nursing homes in our sample. In panels (a) and (b), nursing homes that face a tradeoff between outcomes of patients with and without AD/ADRD in the optimal assignment rule are shown as red triangles, and nursing homes that do not face this tradeoff shown as blue circles, assuming full capacity or using reported occupancy rates respectively in the two panels. First, in panel (a) we observe that there is wide variation in π_j and p_j across nursing homes, and that nursing homes with higher values of π_j and p_j are more likely to face a tradeoff, consistent with the model. In addition, the (p, π) space is neatly partitioned into upper-right and lower-left regions based on whether there is a tradeoff, and less than 10% of nursing homes face a tradeoff.

On the other hand, panel (b) shows that using reported occupancy rates increases the share of nursing homes that face a tradeoff substantially (to more than 50%), as predicted by the model. We still see that tradeoffs tend to be more likely when π_j and p_j are high, but the regions in the (p, π) space where tradeoffs do or do not occur now overlap, due to heterogeneity in nursing homes' occupancy rates.

Panel (c) further partitions nursing homes that face a tradeoff into three distinct types. Nursing homes facing no tradeoffs remain as blue circles, whereas among nursing homes that do face a tradeoff, those with a kinked survival frontier are shown in red triangles, those with only the relatively flatter segment of the frontier displayed as green squares, and nursing homes with only the steeper segment of the frontier displayed as orange diamonds. We observe that about 44% of nursing homes have a kinked survival frontier (so that the QALY-adjusted optimal assignment rule is at the kink), about 7% of nursing homes have only the flatter segment of the frontier (so that the QALY-adjusted optimum is the optimal assignment rule for patients without AD/ADRD), and 1% have only the steeper segment (so the QALY-adjusted optimum is the same as optimal assignment rule for patients with AD/ADRD, which is also equal to the assignment rule that minimizes overall mortality).

Next, we describe intuitively how the four different types of survival frontiers relate to higher or lower values of π and p in panel (c). First, it is possible that the AD-optimal and the NoAD-optimal assignment rules coincide, in which case the survival frontier collapses onto a single point. This applies to about 48% of nursing homes, illustrated using blue circles. This occurs when there are no empty rooms at the AD-optimal assignment, and all patients assigned their own rooms do not have AD/ADRD. This tends to be the case when occupancy rates are high (so that empty rooms are less common), the share of patients with AD/ADRD is low (so they are less likely to end up living alone), and when the share of rooms private is small (otherwise some patients with AD/ADRD are more likely to end up living alone).

Second, the survival frontier may only have a relatively flat segment (with a slope of -2.33), which is the case in about 7% of nursing homes, illustrated using green squares. This occurs when it is feasible to assign each patient their own room, so that it is possible to assign each patient without AD/ADRD their own room without forcing patients with AD/ADRD

[34] In addition, we drop two nursing homes in our sample with $\pi_j \in \{0, 1\}$ or $p_j \in \{0, 1\}$.

to share rooms. This tends to happen when occupancy rates are low, and the share of private rooms is high, both of which increase the number of rooms relative to patients.[35]

Third, the survival frontier may only have a steep segment (with slope = -9), which happens in less than 1% of nursing homes, shown in orange diamonds. This occurs if at the AD-optimal assignment, there are no empty rooms but some patients with AD/ADRD live alone. This is more common when capacity is scarce (so empty rooms are less likely), the share of patients with AD/ADRD is high (so they are more likely to live alone), and the share of private rooms is small (so that there are relatively fewer rooms, making empty rooms less likely).

Finally, the survival frontier has a kink in about 44% of nursing homes. This occurs when there are empty rooms at the AD-optimal assignment, and there is room scarcity in the sense that it is impossible to assign all patients without AD/ADRD to live alone without forcing some patients with AD/ADRD to share rooms. This tends to occur for intermediate values of the parameters (between the no-tradeoff case, and the cases where the survival frontier has only a single slope), and is illustrated by the cloud of red triangles between these extremes.

Figure A.18 plots kernel densities of potential reductions in mortality by comparing simulated 90-day mortality under the optimal assignment rule (that minimizes overall mortality) with the observed mortality rate for each nursing home (with the blue solid line assuming full capacity, and the red dashed line based on reported occupancy rates). In panel (a), we observe that the average reduction in overall mortality assuming full capacity is roughly 0.6 percentage points, and slightly larger using observed occupancy rates. In addition, given the wide variation in π_j and p_j observed in Figure A.17, there is also substantial variation in the potential survival gain across nursing homes, ranging from roughly 0 to 1.5 percentage points.

Panels (b) and (c) show potential reductions in mortality for patients with and without AD/ADRD respectively. Focusing on the optimal assignment rule based on reported occupancy rates, panel (b) shows that potential reductions in mortality for patients with AD/ADRD are even larger, ranging from about zero to close to 3 percentage points. On the other hand, we observe in panel (c) that gains for patients without AD/ADRD tend to be much smaller under the assignment rule that minimizes overall mortality, with a much smaller range for the heterogeneity as well. The smaller magnitude of gains and heterogeneity for patients without AD/ADRD is expected given that their outcomes are less sensitive to room assignments, but in about 2.4% of nursing homes, average gains for patients without AD/ADRD are negative, highlighting tradeoffs between the two patient types.

To explore tradeoffs under different efficient assignment rules (along the survival frontier), Figure A.19 plots kernel densities of potential reductions in mortality (based on reported occupancy rates) under the assignment rule that minimizes mortality among patients with AD/ADRD (which is also the assignment rule that minimizes overall mortality) using a red solid line, under the assignment rule that minimizes QALY-adjusted mortality using a dashed green line, and under the assignment rule that minimizes mortality among patients without AD/ADRD using a dotted blue line. In panel (a), we observe that the overall survival gains are largest under the assignment rule minimizing overall mortality, followed by the assignment rule that minimizes QALY-adjusted mortality, and finally the

[35] In particular, we can express $R = \dfrac{N}{S(2-p)}$, so we observe that decreasing S and increasing p both increase the room-to-patient ratio.

assignment rule that minimizes mortality among patients without AD/ADRD, as we would expect based on their definitions and the fact that outcomes of patients with AD/ADRD are more sensitive to room assignments. On the other hand, while the average survival gain under the QALY-adjusted optimal assignment rule is only about 0.05 percentage points smaller than assignment rule minimizing overall mortality, survival gains are almost 0.2 percentage points smaller under the assignment rule that minimizes mortality among patients without AD/ADRD, with increases in mortality in about 7% of nursing homes.

Panels (b) and (c) compare potential gains for patients with and without AD/ADRD respectively, under the three efficient assignment rules. As expected, for patients with AD/ADRD the assignment rule minimizing overall mortality tends to produce the largest survival gains (since this is also the AD-optimal assignment rule), followed by the QALY-adjusted optimal assignment rule, and finally the assignment rule most favorable towards patients without AD/ADRD, whereas for patients without AD/ADRD the ordering is reversed. However, in terms of magnitude, we see that the QALY-adjusted optimal rule achieves gains for patients with AD/ADRD that are close to the AD-optimal rule (1.5 percentage points, compared to 1.8 percentage points) with negative gains for AD patients in only about 3 percent of nursing homes, whereas gains for patients with AD/ADRD under the optimal assignment rule for patients without AD/ADRD are significantly worse (about 0.95 percentage points on average, with negative gains in 22% of nursing homes). At the same time, the QALY-adjusted optimal rule achieves gains for patients without AD/ADRD closer to the optimal rule for patients without AD/ADRD (0.27 percentage points on average relative to 0.31 percentage points), than the AD-optimal rule (0.21 percentage points on average).

C Bounds Under Potential Violations of Conditional Independence

Let ρ denote the reduced form coefficients, and let Π denote the square 2×2 matrix of first stage coefficients. Then, the treatment effects β are given by:

$$\beta = \Pi^{-1}\rho.$$

Following Conley, Hansen, and Rossi (2012), we can write violations to conditional independence of the instruments as:

$$\hat{\rho} = \Pi\beta + \Delta,$$

so that the bias in the 2SLS estimate of β is given by:

$$\hat{\beta} - \beta = \Pi^{-1}\Delta.$$

The special case where $\Delta = 0$ corresponds to no violation of the conditional independence assumption, and thus no bias in the 2SLS estimate. In what follows, we will use methods from Oster (2019) to obtain bounds for Δ under different assumptions, and translate these bounds for the reduced form coefficients to bounds for the treatment effects.

Following Oster (2019), let R^2_{max} denote the R-squared from a hypothetical regression of the outcome on the instruments, as well as all observable and unobservable controls, and let δ denote the degree of selection on unobservables relative to selection on observables. In addition, denote the main reduced form estimates and the reduced form estimates with all controls by $\hat{\rho}_{main}$ and $\hat{\rho}_{rich}$ respectively, and similarly the R-squareds from these regressions by R^2_{main} and R^2_{rich} respectively. Then, the bias in the lth component of the reduced form estimate is bounded by:

$$|\hat{\rho} - \rho|_l \leq |\delta_l| \cdot |\hat{\rho}_{main} - \hat{\rho}_{rich}|_l \cdot \frac{R^2_{max} - R^2_{rich}}{R^2_{rich} - R^2_{main}},$$

where $\hat{\rho}$ is the reduced form estimate of our preferred specification. Denoting this bound by $|\Gamma|$, and if we are agnostic about whether $\hat{\beta}_{main}$ or $\hat{\beta}_{rich}$ is our preferred specification, we can form conservative bounds for β_l using:

$$\begin{aligned}\beta_l \in\ & \left[\hat{\beta}_{main,l} - (|\hat{\Pi}^{-1}_{main}|_\circ|\Gamma|)_l, \hat{\beta}_{main,l} + (|\hat{\Pi}^{-1}_{main}|_\circ|\Gamma|)_l\right] \\ & \cup \left[\hat{\beta}_{rich,l} - (|\hat{\Pi}^{-1}_{rich}|_\circ|\Gamma|)_l, \hat{\beta}_{rich,l} + (|\hat{\Pi}^{-1}_{rich}|_\circ|\Gamma|)_l\right],\end{aligned}$$

where $|A|_\circ$ denotes the matrix A with absolute values applied entry-wise: $|A|_{\circ,ij} \equiv |A|_{ij}$.

Appendix Table A.8 shows these bounds for our IV estimates of treatment effects for the full sample, as well as for patients with AD/ADRD, and patients without AD/ADRD. The first two columns reproduce our treatment effect estimates with the main controls (nursing home-by-year, patient composition, and capacity strain fixed effects), or with an even richer set of fixed effects and controls for reference (following the specification in the last column of Appendix Table A.2) respectively. Column 3 shows that under the values of δ and R^2_{max} recommended by Oster (2019)—equal selection ($\delta = 1$) and $R^2_{max} = 1.3R^2_{rich}$—the bounds for the treatment effects that form our main results (the effects of being assigned a roommate with AD/ADRD in the full sample and in the subsample of patients with AD/ADRD, and the effect of being assigned no roommate among patients without AD/ADRD, relative to the omitted category) do not include zero, suggesting that our IV estimates are robust to modest violations of conditional independence. Column 4 shows that under the extreme assumption that $R^2_{max} = 1$—i.e., that the instruments, observed controls, and unobserved controls can explain all the variation in 90-day mortality—most of the bounds include zero, although our results for the effect of being assigned a roommate with AD/ADRD for patients with AD/ADRD remain very robust. Our IV estimates may also be even more robust to violations of conditional independence than these bounds suggest for another reason: for some specifications adding controls strengthens our results, and in these cases violations of the conditional independence assumption are more likely to bias us against finding an effect.

Alternatively, rather than assume values for R^2_{max} and δ and then obtain bounds for β, for a given value of R^2_{max} we can back out the minimum δ in order for violations of conditional independence to explain our non-zero treatment effect estimate (i.e., such that the bounds contain zero). Hence, we can trace out an "indifference curve" in (R^2_{max}, δ) space, such that our treatment effect estimates are robust (respectively, not robust) to violations of conditional independence for values of (R^2_{max}, δ) to the southwest (northeast) of this curve.

Appendix Figure A.20 plots these curves, with each panel corresponding to a treatment effect for a particular sample, focusing on our main results: the effect of being assigned a roommate with AD/ADRD for the full sample in panel (a), the effect of being assigned a roommate with AD/ADRD for patients with AD/ADRD in panel (b), and the effect of being assigned an empty room for patients without AD/ADRD in panel (c). Similar to bounds in Appendix Table A.8, we observe that our results on the effect of being assigned a roommate with AD/ADRD for individuals with AD/ADRD are the most robust: if we assume $R^2_{max} = 0.5$, selection on unobservables has to be about 20 times more important than selection on observables in order to explain the positive IV estimate.

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Tables and Figures

Table I: Summary Statistics

	Full Sample (1)	Assigned No Roommate (2)	Assigned Roommate with AD/ADRD (3)	Assigned Roommate Without AD/ADRD (4)	Diff: (2)-(4) (5)	Diff: (3)-(4) (6)
Female	0.625	0.610	0.648	0.612	-0.001	0.036***
	(0.484)	(0.488)	(0.478)	(0.487)	(0.001)	(0.001)
Education: Bachelor's Degree	0.082	0.097	0.073	0.082	0.015***	-0.008***
	(0.274)	(0.295)	(0.261)	(0.274)	(0.001)	(0.001)
Age	78.224	78.143	79.080	77.439	0.704***	1.640***
	(12.930)	(13.082)	(12.350)	(13.339)	(0.051)	(0.051)
Race: White	0.812	0.832	0.805	0.808	0.024***	-0.003
	(0.390)	(0.374)	(0.396)	(0.394)	(0.002)	(0.002)
Post-Acute Care	0.650	0.644	0.623	0.679	-0.035***	-0.055***
	(0.477)	(0.479)	(0.485)	(0.467)	(0.002)	(0.002)
AD/ADRD	0.298	0.284	0.371	0.235	0.049***	0.136***
	(0.457)	(0.451)	(0.483)	(0.424)	(0.001)	(0.002)
Cognitive Performance Scale	1.801	1.746	2.016	1.623	0.123***	0.393***
	(1.647)	(1.642)	(1.660)	(1.614)	(0.005)	(0.006)
Physical Impairment (ADLs)	14.712	14.470	14.809	14.751	-0.281***	0.058**
	(7.099)	(7.132)	(7.154)	(7.028)	(0.025)	(0.023)
Number of Chronic Conditions	6.540	6.602	6.588	6.461	0.142***	0.127***
	(4.336)	(4.332)	(4.294)	(4.378)	(0.016)	(0.016)
Death Within 90 Days	0.149	0.149	0.152	0.146	0.003***	0.006***
	(0.356)	(0.356)	(0.359)	(0.343)	(0.001)	(0.001)
Number of Observations	2,569,619	557,018	990,670	1,021,931	–	–

Notes: Columns 1–4 report means (with standard deviations in parentheses) for: (1) all patients; (2) patients assigned to empty rooms; (3) patients assigned to a room with at least one roommate with AD/ADRD; and (4) patients assigned to a non-empty room where no roommate has AD/ADRD. Columns 5 and 6 report differences in means relative to column 4, with standard errors clustered at the nursing home level. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table II: Effects of Room Assignment on 90-Day Mortality

	Full Sample		**ADRD**	**No ADRD**
	(1)	(2)	(3)	(4)
Assigned No Roommate	-0.006**	-0.002	0.014**	-0.009**
	(0.003)	(0.003)	(0.007)	(0.004)
Assigned Roommate with ADRD		0.009***	0.034***	-0.003
		(0.003)	(0.006)	(0.004)
F-statistic	29,938	25,473	9,942	17,708
Dependent Variable Mean	0.149	0.149	0.161	0.144
Number of Observations	2,568,901	2,568,901	762,350	1,803,183

Notes: This table shows IV estimates of equation (1). Controls include nursing home-by-year fixed effects and controls for capacity strain and overall patient composition. Standard errors are clustered at the nursing home level. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table III: Heterogeneity by Facility Characteristics

Panel A: All Patients

	Above-Median Staffing (1)	Below-Median Staffing (2)	Alzheimer's Unit (3)	No Alzheimer's Unit (4)
Assigned to Room with No Roommate	0.001	-0.006	0.005	-0.004
	(0.004)	(0.005)	(0.007)	(0.004)
Assigned to Roommate with AD/ADRD	0.009*	0.009*	-0.002	0.012***
	(0.004)	(0.005)	(0.007)	(0.004)
First Stage F-statistic	14,347	13,164	5,253	20,639
Dependent Variable Mean	0.147	0.151	0.146	0.150
Number of Observations	1,313,015	1,255,809	557,071	2,011,753

Panel B: Patients with AD/ADRD

	Above-Median Staffing (1)	Below-Median Staffing (2)	Alzheimer's Unit (3)	No Alzheimer's Unit (4)
Assigned to Room with No Roommate	0.009	0.019*	0.007	0.013*
	(0.009)	(0.010)	(0.015)	(0.007)
Assigned to Roommate with AD/ADRD	0.022**	0.046***	-0.011	0.044***
	(0.009)	(0.008)	(0.014)	(0.007)
First Stage F-statistic	5,369	4,874	2,045	7,848
Dependent Variable Mean	0.165	0.157	0.146	0.166
Number of Observations	373,696	388,626	193,731	568,591

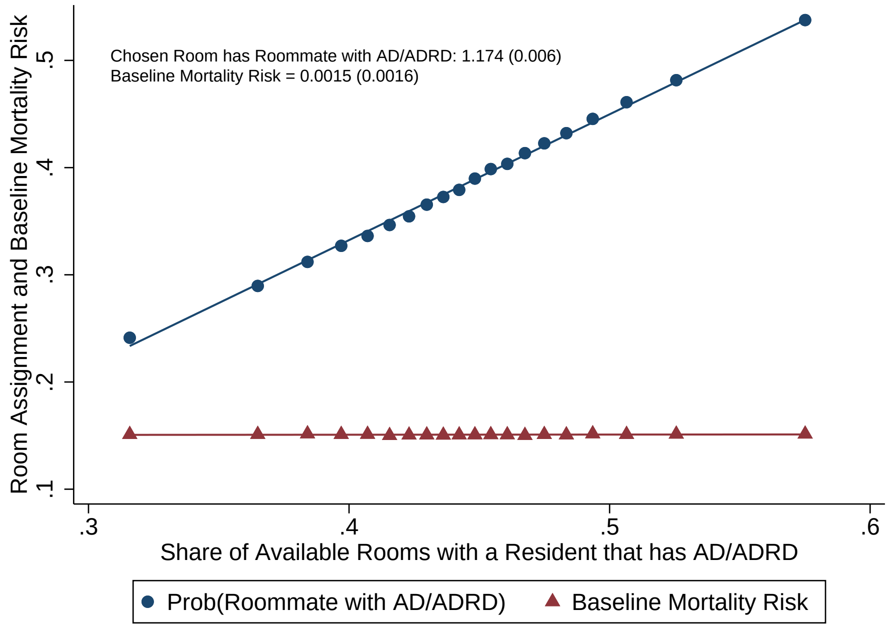
Panel C: Patients without AD/ADRD

	Above-Median Staffing (1)	Below-Median Staffing (2)	Alzheimer's Unit (3)	No Alzheimer's Unit (4)
Assigned to Room with No Roommate	-0.003	-0.016***	0.001	-0.011***
	(0.005)	(0.006)	(0.008)	(0.004)
Assigned to Roommate with AD/ADRD	0.002	-0.010*	-0.001	-0.003
	(0.005)	(0.006)	(0.009)	(0.005)
First Stage F-statistic	9,846	8,992	3,059	14,937
Dependent Variable Mean	0.140	0.148	0.146	0.144
Number of Observations	937,652	865,482	363,022	1,440,112

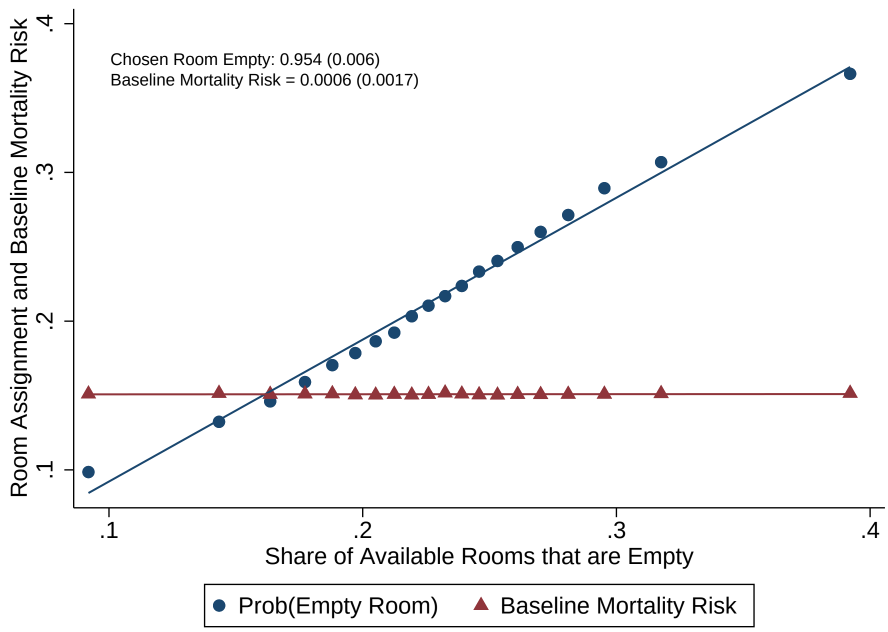
Notes: This table shows heterogeneity in room effects by whether the nursing home has above- or below-median staffing (in columns 1 and 2), and whether the nursing home has an Alzheimer's special care unit (in columns 3 and 4). Panel A shows the results for all patients, while Panels B and C show results for the subsample of patients with AD/ADRD and without AD/ADRD respectively. Controls include nursing home-by-year fixed effects and controls for capacity strain and overall patient composition. Standard errors are clustered at the nursing home level. $^{*}p < 0.10$, $^{**}p < 0.05$, ***

Figure I: First stage and Balance in Mortality Risk

(a) Assignment to Roommate with AD/ADRD Diagnosis



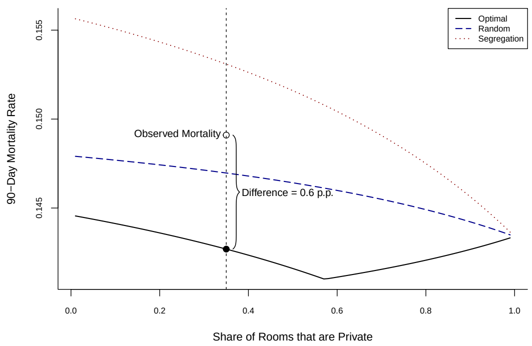
(b) Assignment to Room Without a Roommate



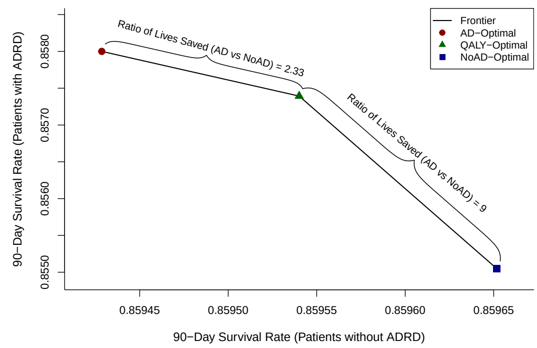
Notes: Panel (a) plots the probability of being assigned a roommate with AD/ADRD and baseline mortality risk as a function of the share of available rooms with a patient that has AD/ADRD at the time of admission, controlling for the other instrument, nursing-home-by-year fixed effects and short-run variation in occupancy rates and patient composition at the time of admission. Panel (b) plots the probability of being assigned to an empty room as a function of the share of available rooms that are empty at the time of admission, controlling for the other instrument, nursing-home-by-year fixed effects and short-run variation in occupancy rates and patient composition at the time of admission. Coefficient estimates and standard errors are based on linear regressions with the same outcomes and regressors, with standard errors clustered at the nursing home level. Each circle and triangle corresponds to a bin containing 5 percent of the sample (20 bins in total).

Figure II: Gains and Tradeoffs Under Different Room Assignment Policies

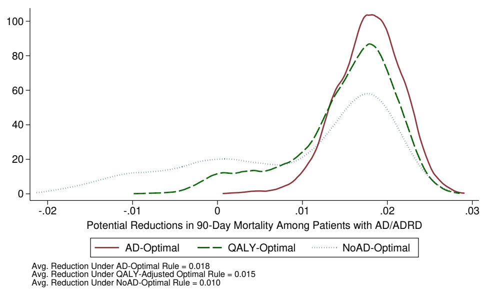
(a) Mortality Under Diff. Assignment Rules



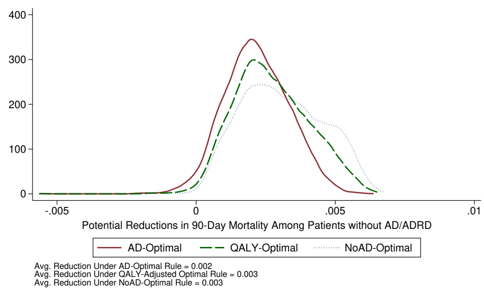
(b) Survival Frontier for Average Facility



(c) Nursing-Home-Level Gains for Patients with AD/ADRD



(d) Nursing-Home-Level Gains for Patients without AD/ADRD



Notes: The black, blue, and red lines in panel (a) plot the simulated 90-day mortality rate under the mortality-minimizing (optimal) assignment rule, random assignment rule, and segregated assignment rule respectively, as a function of the fraction of rooms that are private, assuming full capacity. The fraction of the resident population with AD/ADRD is assumed to be 0.3 (reflecting the observed rate in the data), and simulated mortality is constructed based on the IV estimates in columns 3 and 4 of Table II. The dashed vertical line reflects the empirically observed fraction of rooms that are private (35%), the open circle shows the observed 90-day mortality rate in the sample, and the solid point shows the simulated 90-day mortality rate under the optimal assignment rule (when the fraction of rooms that are private is 35%). Panel (b) plots the survival frontier for the representative nursing home (with 30% of patients with AD/ADRD and 35% of rooms private), and 85% occupancy rate (the average observed in the data). The red point, green triangle, and blue square respectively show outcomes under the AD-optimal assignment rule, QALY-adjusted optimal assignment rule, and NoAD-optimal assignment rule respectively. Panels (c) and (d) show kernel density plots of potential reductions in mortality at the nursing home level for patients with and without AD/ADRD respectively, under three assignment rules along the survival frontier: the AD-optimal assignment rule, the QALY-adjusted optimal assignment rule, and the NoAD-optimal assignment rule.

Appendix Tables and Figures

Table A.1: Relationship Between Resident and Roommate Characteristics at Admission

	AD/ADRD (1)	Female (2)	Post-Acute Care (3)	Medicaid (4)	Bachelor's Degree (5)	Age ≤ 80 (6)	Race: White (7)
Share of Roommates with AD/ADRD	0.096***						
	(0.002)						
Share of Roommates that are Female		0.644***					
		(0.003)					
Share of Roommates that are Post-Acute Care			0.052***				
			(0.001)				
Share of Roommates on Medicaid				0.057***			
				(0.001)			
Share of Roommates with Bachelor's Degree					0.013***		
					(0.002)		
Share of Roommates Aged ≤ 80						0.048***	
						(0.001)	
Share of Roommates that are White							0.072***
							(0.002)
Number of Observations	2,011,580	2,011,580	2,011,580	2,011,580	2,011,580	2,011,580	2,011,580
R-squared	0.102	0.401	0.284	0.223	0.100	0.119	0.380

Notes: This table shows regressions of patient characteristics at admission on the average value of these characteristics among the patient's roommate(s) at the time of the patient's admission, nursing-home-by-year fixed effects, as well as capacity strain and patient composition fixed effects. The sample is limited to patients who are assigned a roommate, and standard errors are clustered at the nursing home level. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table A.2: Robustness of Main IV estimates

Panel A. Full Sample	Death Within 90 Days of Admission					
	(1)	(2)	(3)	(4)	(5)	(6)
Assigned No Roommate	-0.007**	-0.002	-0.010***	-0.010***	-0.018***	-0.016***
	(0.003)	(0.003)	(0.004)	(0.004)	(0.004)	(0.004)
Assigned Roommate with ADRD	0.012***	0.009***	0.009***	0.009***	0.009***	0.006
	(0.003)	(0.003)	(0.003)	(0.003)	(0.004)	(0.004)
F-statistic	25,736	25,470	16,396	16,404	21,679	21,655
Nursing Home × Year FE	X	X	X	X	X	X
Capacity Strain and Case-Mix Controls		X	X	X	X	X
County × Year × Month FE			X	X	X	X
Day of Week FE				X	X	X
Room FE					X	X
Baseline Patient Characteristics						X
Dependent Variable Mean	0.149	0.149	0.149	0.149	0.149	0.149
Number of Observations	2,568,824	2,568,824	2,566,344	2,566,344	2,453,858	2,453,858

Panel B. Patients with AD/ADRD	Death Within 90 Days of Admission					
	(1)	(2)	(3)	(4)	(5)	(6)
Assigned No Roommate	0.011*	0.014**	-0.001	-0.001	-0.014	-0.013
	(0.006)	(0.007)	(0.008)	(0.008)	(0.011)	(0.011)
Assigned Roommate with ADRD	0.047***	0.034***	0.029***	0.029***	0.027***	0.025***
	(0.006)	(0.006)	(0.006)	(0.006)	(0.009)	(0.008)
F-statistic	10,123	9,942	4,701	5,766	5,766	5,766
Nursing Home × Year FE	X	X	X	X	X	X
Capacity Strain and Case-Mix Controls		X	X	X	X	X
County × Year × Month FE			X	X	X	X
Day of Week FE				X	X	X
Room FE					X	X
Baseline Patient Characteristics						X
Dependent Variable Mean	0.161	0.161	0.161	0.161	0.161	0.161
Number of Observations	762,322	762,322	758,449	758,449	601,990	601,990

Panel C. Patients without AD/ADRD	Death Within 90 Days of Admission					
	(1)	(2)	(3)	(4)	(5)	(6)
Assigned No Roommate	-0.012***	-0.009**	-0.014***	-0.014***	-0.023***	-0.020***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.005)	(0.004)
Assigned Roommate with ADRD	-0.005	-0.003	-0.002	-0.002	-0.006	-0.010**
	(0.004)	(0.004)	(0.004)	(0.004)	(0.005)	(0.005)
F-statistic	18,072	17,707	13,609	13,613	13,791	13,776
Nursing Home × Year FE	X	X	X	X	X	X
Capacity Strain and Case-Mix Controls		X	X	X	X	X
County × Year × Month FE			X	X	X	X
Day of Week FE				X	X	X
Room FE					X	X
Baseline Patient Characteristics						X
Dependent Variable Mean	0.144	0.144	0.144	0.144	0.144	0.144
Number of Observations	1,803,134	1,803,134	1,800,307	1,800,307	1,680,948	1,680,948

Notes: Column 2 presents our baseline specification. Controls include nursing home-by-year fixed effects and controls for capacity strain and overall patient composition. Column 1 presents a more parsimonious specification, only controlling for nursing-home-by-year fixed effects. Columns 3–6 gradually add additional control variables to our baseline specification, including county-by-year-by-month fixed effects, day-of-the-week fixed effects, room fixed effects, and controls for patient health and demographics, which include baseline demographic and health variables from the MDS, as well as baseline chronic conditions from Medicare claims data. Standard errors are clustered at the nursing home level.$^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table A.3: OLS Estimates with Different Sets of Controls

Panel A. Full Sample	Death Within 90 Days of Admission					
	(1)	(2)	(3)	(4)	(5)	(6)
Assigned No Roommate	0.006***	0.006***	0.006***	0.006***	-0.004***	-0.004***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Assigned Roommate with ADRD	0.001	0.001	0.001	0.001	0.004***	0.003***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Nursing Home × Year FE	X	X	X	X	X	X
Capacity Strain and Case-Mix Controls		X	X	X	X	X
County × Year × Month FE			X	X	X	X
Day of Week FE				X	X	X
Room FE					X	X
Baseline Patient Characteristics						X
Dependent Variable Mean	0.149	0.149	0.149	0.149	0.149	0.149
Number of Observations	2,568,824	2,568,824	2,566,344	2,566,344	2,453,858	2,453,858

Panel B. Patients with AD/ADRD	Death Within 90 Days of Admission					
	(1)	(2)	(3)	(4)	(5)	(6)
Assigned No Roommate	0.000	0.001	0.001	0.001	0.004	0.003
	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)
Assigned Roommate with ADRD	-0.008***	-0.009***	-0.009***	-0.009***	0.020***	0.018***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)
Nursing Home × Year FE	X	X	X	X	X	X
Capacity Strain and Case-Mix Controls		X	X	X	X	X
County × Year × Month FE			X	X	X	X
Day of Week FE				X	X	X
Room FE					X	X
Baseline Patient Characteristics						X
Dependent Variable Mean	0.161	0.161	0.161	0.161	0.161	0.161
Number of Observations	762,322	762,322	758,449	758,449	601,990	601,990

Panel C. Patients without AD/ADRD	Death Within 90 Days of Admission					
	(1)	(2)	(3)	(4)	(5)	(6)
Assigned No Roommate	0.007***	0.008***	0.008***	0.008***	-0.007***	-0.007***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Assigned Roommate with ADRD	0.003***	0.003***	0.003***	0.003***	-0.002***	-0.004***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Nursing Home × Year FE	X	X	X	X	X	X
Capacity Strain and Case-Mix Controls		X	X	X	X	X
County × Year × Month FE			X	X	X	X
Day of Week FE				X	X	X
Room FE					X	X
Baseline Patient Characteristics						X
Dependent Variable Mean	0.144	0.144	0.144	0.144	0.144	0.144
Number of Observations	1,803,134	1,803,134	1,800,307	1,800,307	1,680,948	1,680,948

Notes: Column 2 presents OLS estimates conditional on our baseline set of control variables including nursing-home-by-year fixed effects and controls for capacity strain and overall patient composition. Column 1 presents OLS estimates when only controlling for nursing home by year fixed effects. OLS estimates in columns 3-5 gradually add additional control variables to our baseline specification, including county-by-year-by-month fixed effects, day-of-the-week fixed effects, room fixed effects, and controls for patient health and demographics which include baseline demographic and health variables from the MDS, as well as baseline chronic conditions from Medicare claims data. Standard errors are clustered at the nursing home level.$^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table A.4: Effect of Roommate Assignment on Mortality at Different Time Horizons

	Death Within 30 Days (1)	Death Within 90 Days (2)	Death Within 180 Days (3)	Death Within 360 Days (4)
Panel A. Full Sample				
Assigned to Room with No Roommate	0.002	-0.002	-0.005	-0.002
	(0.002)	(0.003)	(0.004)	(0.004)
Assigned to Roommate with AD/ADRD	-0.000	0.009***	0.011***	0.012***
	(0.002)	(0.003)	(0.004)	(0.004)
F-statistic	25,473	25,473	25,473	25,473
Dependent Variable Mean	0.057	0.149	0.221	0.308
Number of Observations	2,568,901	2,568,901	2,568,901	2,568,901
Panel B. Patients with AD/ADRD				
Assigned to Room with No Roommate	0.011**	0.014**	0.012	0.012
	(0.004)	(0.007)	(0.008)	(0.009)
Assigned to Roommate with AD/ADRD	0.008**	0.034***	0.045***	0.043***
	(0.004)	(0.006)	(0.007)	(0.008)
F-statistic	9,942	9,942	9,942	9,942
Dependent Variable Mean	0.059	0.161	0.248	0.358
Number of Observations	762,350	762,350	762,350	762,350
Panel C. Patients Without AD/ADRD				
Assigned to Room with No Roommate	-0.002	-0.009**	-0.012***	-0.009*
	(0.002)	(0.004)	(0.004)	(0.005)
Assigned to Roommate with AD/ADRD	-0.004	-0.003	-0.005	-0.004
	(0.003)	(0.004)	(0.005)	(0.005)
F-statistic	17,708	17,708	17,708	17,708
Dependent Variable Mean	0.056	0.144	0.210	0.286
Number of Observations	1,803,183	1,803,183	1,803,183	1,803,183

Notes: All regressions include nursing home-by-year, capacity strain and patient composition fixed effects. Standard errors are clustered at the nursing home level.$^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table A.5: Heterogeneity by Admission Source

	Death Within 90 Days of Admission					
	Post-Acute Care			Not Post-Acute Care		
	All (1)	ADRD (2)	No AD (3)	All (4)	ADRD (5)	No AD (6)
Assigned No Roommate	-0.001	0.015	-0.008*	-0.003	0.011	-0.009
	(0.004)	(0.010)	(0.004)	(0.006)	(0.010)	(0.007)
Assigned Roommate with ADRD	0.010**	0.041***	-0.004	0.004	0.020**	-0.006
	(0.004)	(0.009)	(0.005)	(0.006)	(0.009)	(0.008)
F-statistic	16,249	5,211	12,032	11,043	4,228	5,831
Dependent Variable Mean	0.150	0.180	0.140	0.147	0.137	0.154
Number of Observations	1,667,556	417,565	1,241,471	896,607	330,849	553,643

Notes: This table shows IV estimates of equation (1) separately for patients who are admitted from acute care hospitals in columns 1–3 (for all post-acute care patients in column 1, post-acute patients with AD/ADRD in column 2, and post-acute patients without AD/ADRD in column 3), and for patients who are not admitted from acute care hospitals in columns 4–6 (for all non-post-acute care patients in column 4, non-post-acute patients with AD/ADRD in column 5, and non-post-acute patients without AD/ADRD in column 6). Controls include nursing home-by-year fixed effects and controls for capacity strain and overall patient composition. Standard errors are clustered at the nursing home level.$^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table A.6: Heterogeneity by Vaccination Status

	Flu Vaccine (1)	No Flu Vaccine (2)	PPV Vaccine (3)	No PPV Vaccine (4)
Assigned to Room with No Roommate	-0.010*	-0.011*	-0.007	-0.016***
	(0.006)	(0.006)	(0.005)	(0.006)
First Stage F-statistic	8,528	9,412	12,200	9,086
Dependent Variable Mean	0.110	0.119	0.115	0.119
Number of Observations	587,357	695,534	758,919	622,923

Notes: This table shows results from IV regressions for different subsamples of patients based on vaccination status. All regressions include nursing home-by-year, capacity strain and patient composition fixed effects. Standard errors are clustered at the nursing home level. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table A.7: Peer Effects for Other Patient Characteristics

Panel A. Peer Effects in Cognitive Impairment (CPS)						
	Death Within 90 Days of Admission					
	All	CPS≥3	CPS<3	All	CPS≥4	CPS<4
	(1)	(2)	(3)	(4)	(5)	(6)
Assigned No Roommate	-0.002	0.000	-0.008**	-0.004	0.017	-0.008***
	(0.003)	(0.007)	(0.004)	(0.003)	(0.011)	(0.003)
Assigned Roommate with CPS≥3	0.009***	0.015***	-0.001			
	(0.003)	(0.006)	(0.004)			
Assigned Roommate with CPS≥4				0.010**	0.046***	-0.006
				(0.004)	(0.011)	(0.005)
F-statistic	25,206	12,194	15,844	17,758	4,072	14,387
Dependent Variable Mean	0.149	0.193	0.127	0.149	0.242	0.135
Number of Observations	2,568,901	869,175	1,696,735	2,568,901	329,165	2,230,382
Panel B. Peer Effects in Physical Impairment (ADL)						
	Death Within 90 Days of Admission					
	All	ADL≥14	ADL<14	All	ADL≥21	ADL<21
	(1)	(2)	(3)	(4)	(5)	(6)
Assigned No Roommate	-0.001	0.001	-0.008*	-0.002	-0.004	-0.009***
	(0.003)	(0.005)	(0.004)	(0.003)	(0.009)	(0.003)
Assigned Roommate with ADL≥14	0.010***	0.007*	-0.001			
	(0.003)	(0.004)	(0.004)			
Assigned Roommate with ADL≥21				0.016***	0.019**	-0.002
				(0.004)	(0.009)	(0.004)
F-statistic	23,370	14,994	11,770	22,019	6,611	16,584
Dependent Variable Mean	0.149	0.179	0.103	0.149	0.261	0.118
Number of Observations	2,568,901	1,563,253	1,002,457	2,568,901	552,626	2,010,501

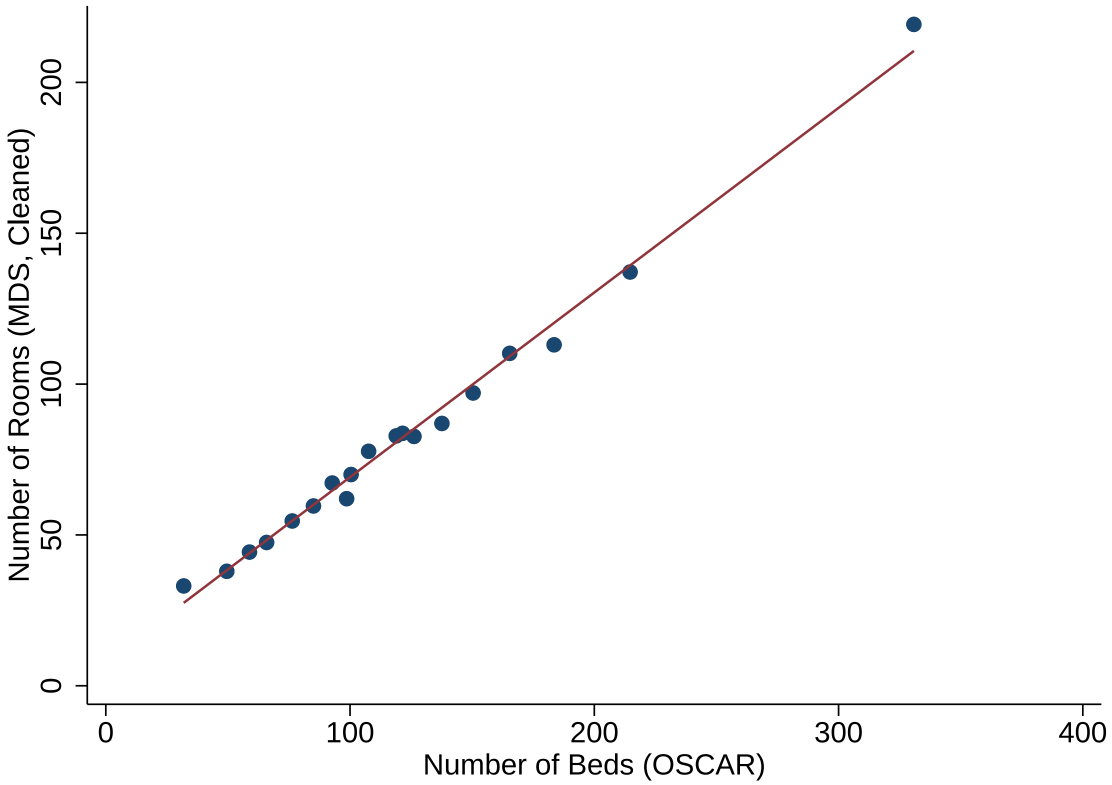
Notes: This table shows IV regressions of the effects of being assigned no roommate or a roommate with characteristic X on 90-day mortality, where the instruments are the share of available rooms that are empty, and the share of available rooms with a patient that has characteristic X, at the time of the focal patient's admission. The characteristic X represents cognitive impairment as proxied by CPS in Panel A, and physical impairment as proxied by ADL in Panel B, where higher CPS and ADL scores indicate greater impairment. All regressions include nursing home-by-year, capacity strain and patient composition fixed effects. Standard errors are clustered at the nursing home level.$^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table A.8: IV bounds Under Potential Violations of Conditional Independence

	Baseline Estimate	Controlled Estimate	Bounds with $\delta = 1$, $R^2_{\max} = 1.3R^2_{rich}$	Bounds with $\delta = 1$, $R^2_{\max} = 1$
Panel A. Full Sample				
	(1)	(2)	(3)	(4)
Assigned to Room with No Roommate	-0.002 (0.003)	-0.016 (0.004)	[-0.022, 0.004]	[-0.067, 0.055]
Assigned to Roommate with AD/ADRD	0.009 (0.003)	0.006 (0.004)	[0.003, 0.011]	[-0.016, 0.029]
Panel B. Patients with AD/ADRD				
	(1)	(2)	(3)	(4)
Assigned to Room with No Roommate	0.014 (0.007)	-0.013 (0.011)	[-0.026, 0.027]	[-0.064, 0.066]
Assigned to Roommate with AD/ADRD	0.034 (0.006)	0.025 (0.008)	[0.021, 0.037]	[0.011, 0.047]
Panel C. Patients without AD/ADRD				
	(1)	(2)	(3)	(4)
Assigned to Room with No Roommate	-0.009 (0.004)	-0.020 (0.004)	[-0.026, -0.003]	[-0.060, 0.036]
Assigned to Roommate with AD/ADRD	-0.003 (0.004)	-0.010 (0.005)	[-0.014, 0.000]	[-0.038, 0.022]

Notes: This table shows bounds for the treatment effect estimates under the equal selection assumption ($\delta = 1$), as recommended by Oster (2019). Columns (1) and (2) report the baseline estimates and estimates with even more controls, respectively. Columns (3) and (4) show bounds assuming either $R^2_{max} = 1.3R^2_{rich}$ as recommended by Oster (2019), or $R^2_{max} = 1$ respectively.

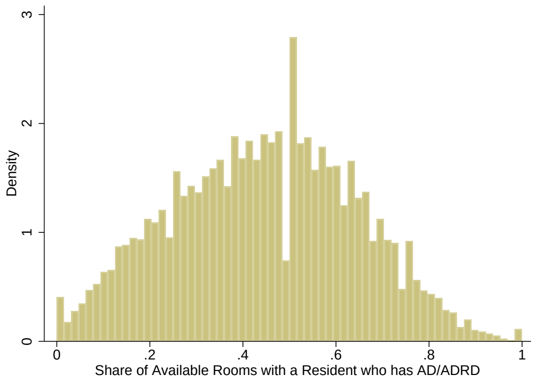
Figure A.1: Relationship Between Number of Rooms and Number of Beds



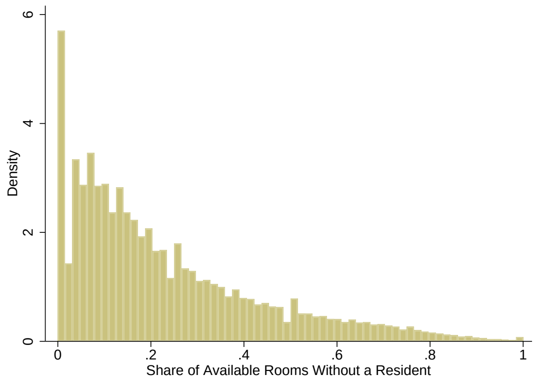
Notes: This figure shows a binscatter of the relationship between number of rooms in each nursing home each year based on the room identifier in the MDS data, and the number of beds in the same nursing-home-year according to the OSCAR data.

Figure A.2: Distribution of Share of Available Rooms with a Patient that has AD/ADRD or Without a Patient

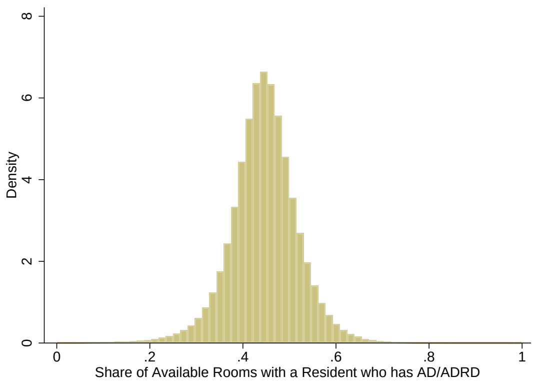
(a) Rooms with a Patient that has AD/ADRD



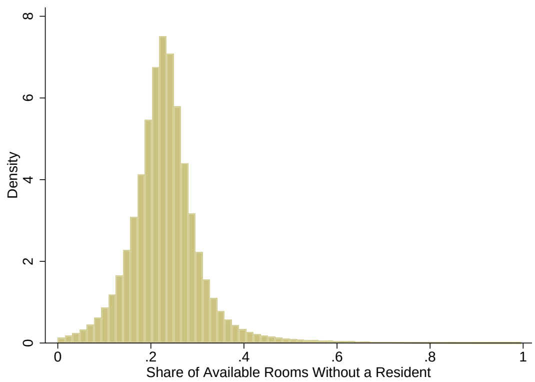
(b) Rooms Without a Patient



(c) Rooms with a Patient that has AD/ADRD (Residualized of Nursing-Home-by-Year Fixed Effects and Patient Composition)



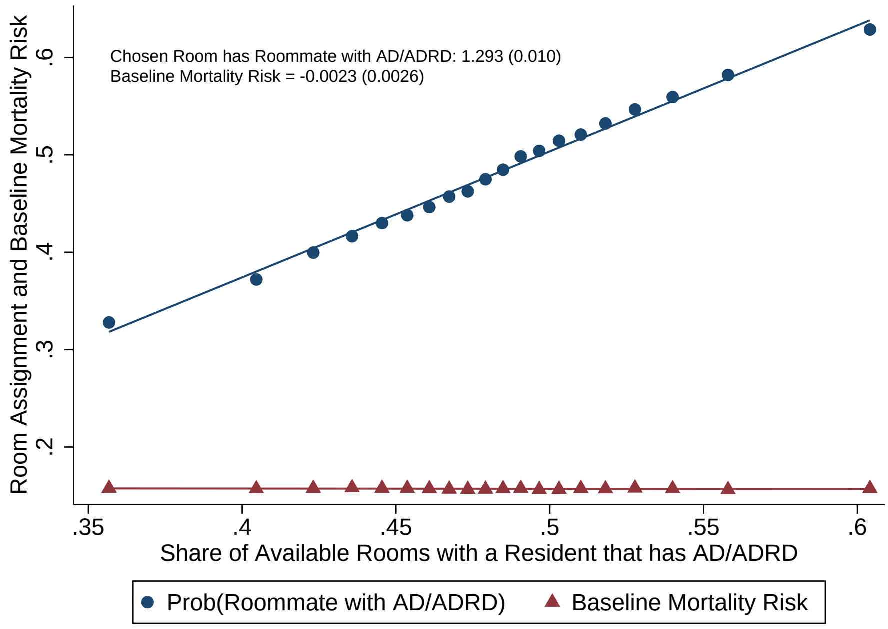
(d) Rooms Without a Patient (Residualized of Nursing-Home-by-Year Fixed Effects and Patient Composition)



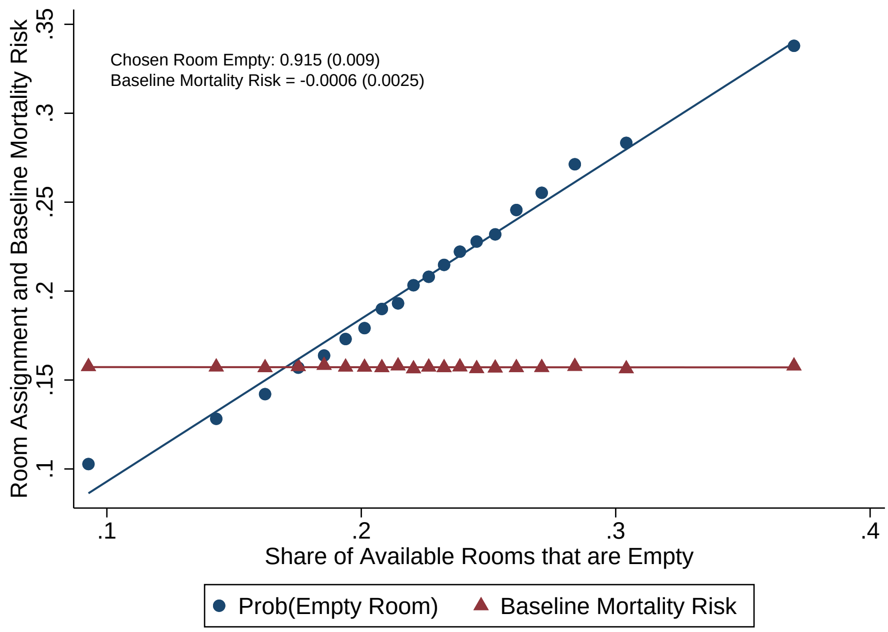
Notes: This figure plots histograms showing the distributions of our instruments – share of available rooms with a patient that has AD/ADRD and share of available rooms that are empty – both unconditionally in panels (a) and (b), and controlling for nursing-home-by-year fixed effects and short-run variation in occupancy rates and patient composition in panels (c) and (d). Specifically, in panels (c) and (d), we first residualize the instruments of the controls before adding back their overall means (dropping the small number of observations that have values outside of the unit interval).

Figure A.3: First stage and Balance in Mortality Risk for Patients with AD/ADRD

(a) Assignment to Roommate with AD/ADRD Diagnosis



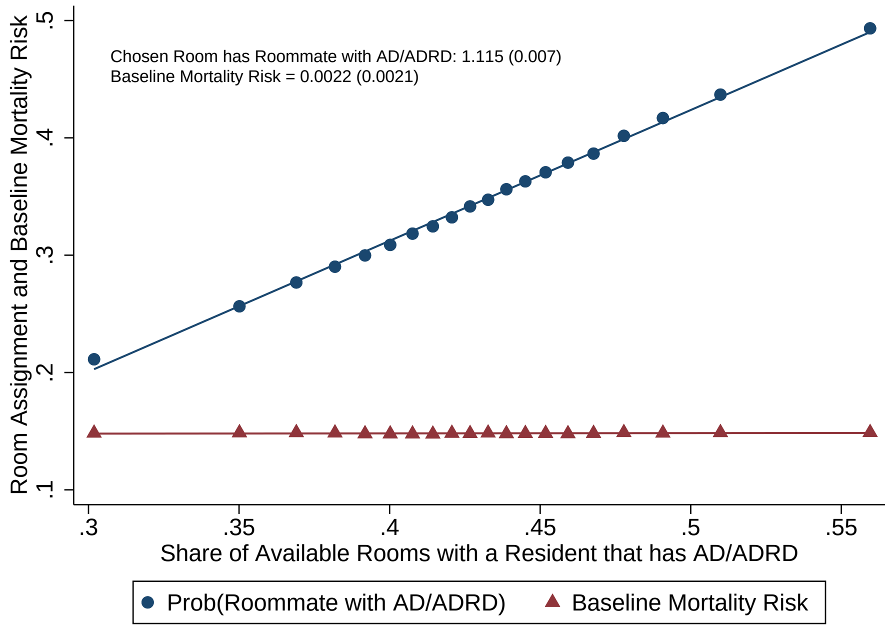
(b) Assignment to Room Without a Roommate



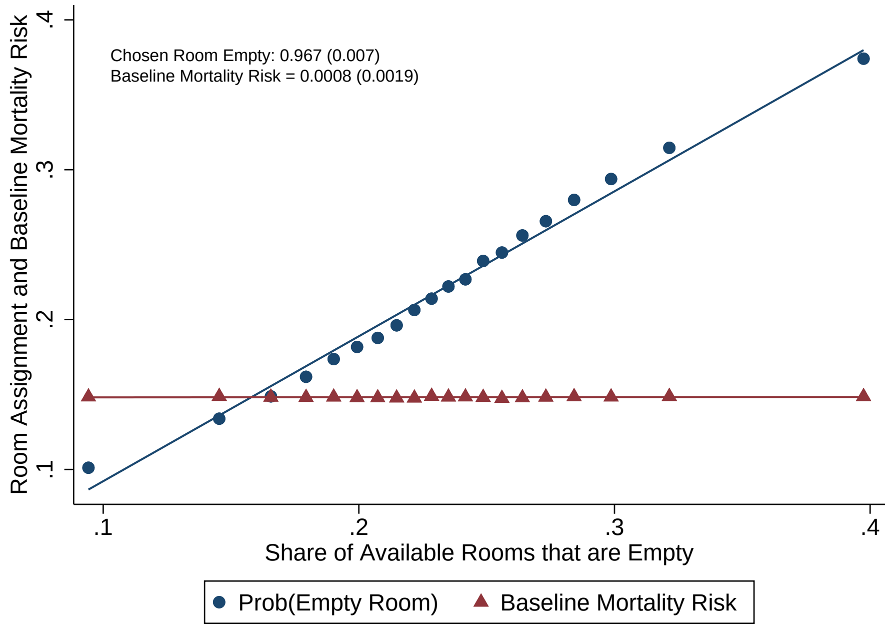
Notes: Panel (a) plots the probability for patients with AD/ADRD of being assigned a roommate with AD/ADRD and baseline mortality risk as a function of the share of available rooms with a patient that has AD/ADRD at the time of admission, controlling for the other instrument, nursing-home-by-year fixed effects and short-run variation in occupancy rates and patient composition at the time of admission. Panel (b) plots the probability for patients with AD/ADRD of being assigned to an empty room as a function of the share of available rooms that are empty at the time of admission, controlling for the other instrument, nursing-home-by-year fixed effects and short-run variation in occupancy rates and patient composition at the time of admission. Coefficient estimates and standard errors are based on linear regressions with the same outcomes and regressors, with standard errors clustered at the nursing home level. Each circle and triangle corresponds to a bin containing 5 percent of patients with AD/ADRD (20 bins in total).

Figure A.4: First stage and Balance in Mortality Risk for Patients without AD/ADRD

(a) Assignment to Roommate with AD/ADRD Diagnosis



(b) Assignment to Room Without a Roommate

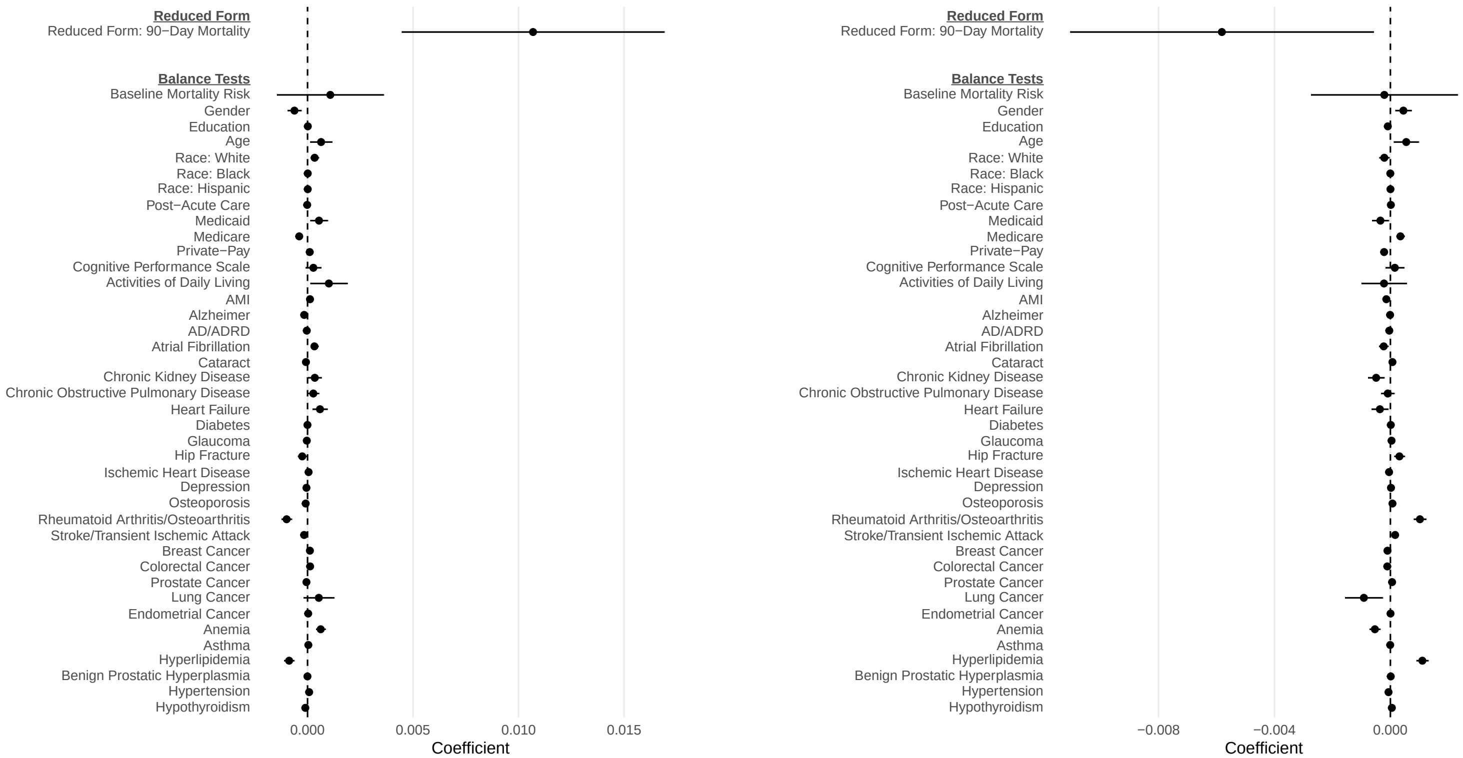


Notes: Panel (a) plots the probability for patients without AD/ADRD of being assigned a roommate with AD/ADRD and baseline mortality risk as a function of the share of available rooms with a patient that has AD/ADRD at the time of admission, controlling for the other instrument, nursing-home-by-year fixed effects and short-run variation in occupancy rates and patient composition at the time of admission. Panel (b) plots the probability for patients without AD/ADRD of being assigned to an empty room as a function of the share of available rooms that are empty at the time of admission, controlling for the other instrument, nursing-home-by-year fixed effects and short-run variation in occupancy rates and patient composition at the time of admission. Coefficient estimates and standard errors are based on linear regressions with the same outcomes and regressors, with standard errors clustered at the nursing home level. Each circle and triangle corresponds to a bin containing 5 percent of patients without AD/ADRD (20 bins in total).

Figure A.5: Reduced Form and Balance for All Patients

(a) Share of Available Rooms with a Patient that has AD/ADRD

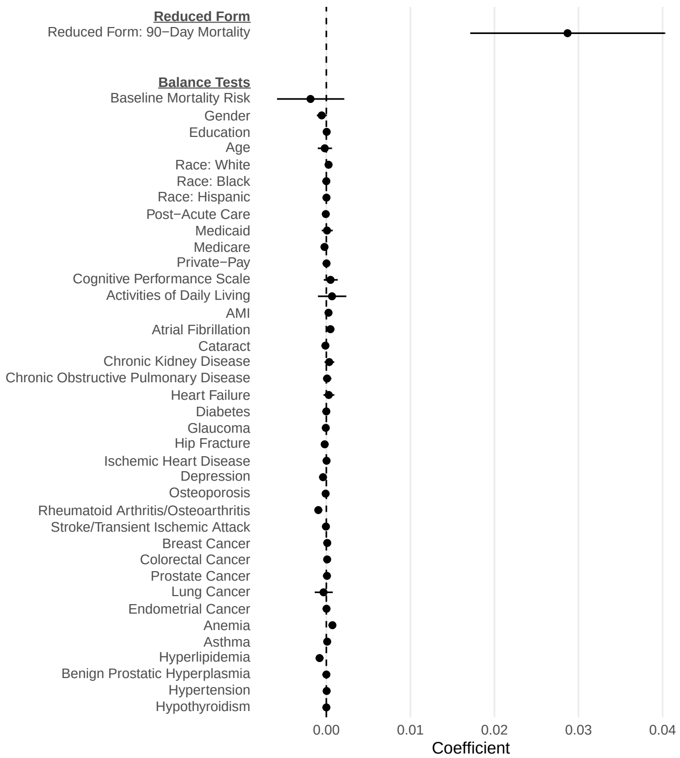
(b) Share of Available Rooms Without a Roommate



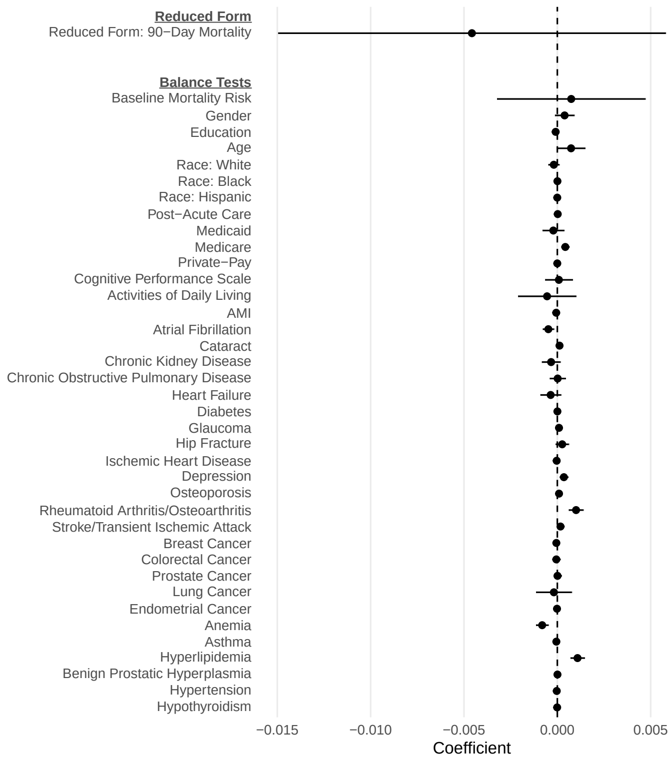
Notes: This figure provides evidence on the conditional independence/exclusion restriction assumption by comparing regression estimates of baseline characteristics on the instruments (from the second row onwards) with the reduced form estimate (of the outcome on the instrument) in the first row, where baseline characteristics are scaled according to their associations with 90-day mortality. Specifically, panels (a) and (b) plot coefficient estimates and 95 percent confidence intervals from regressions of 90-day mortality (in the first row) and baseline patient characteristics (in the remaining rows) on the share of available rooms with a patient that has AD/ADRD and the share of available rooms that are empty respectively, controlling for nursing-home-by-year fixed effects and short-run variation in occupancy rates and patient composition at the time of admission, and with standard errors clustered at the nursing home level.

Figure A.6: Reduced Form and Balance for Patients with AD/ADRD

(a) Share of Available Rooms with a Patient that has AD/ADRD



(b) Share of Available Rooms Without a Roommate

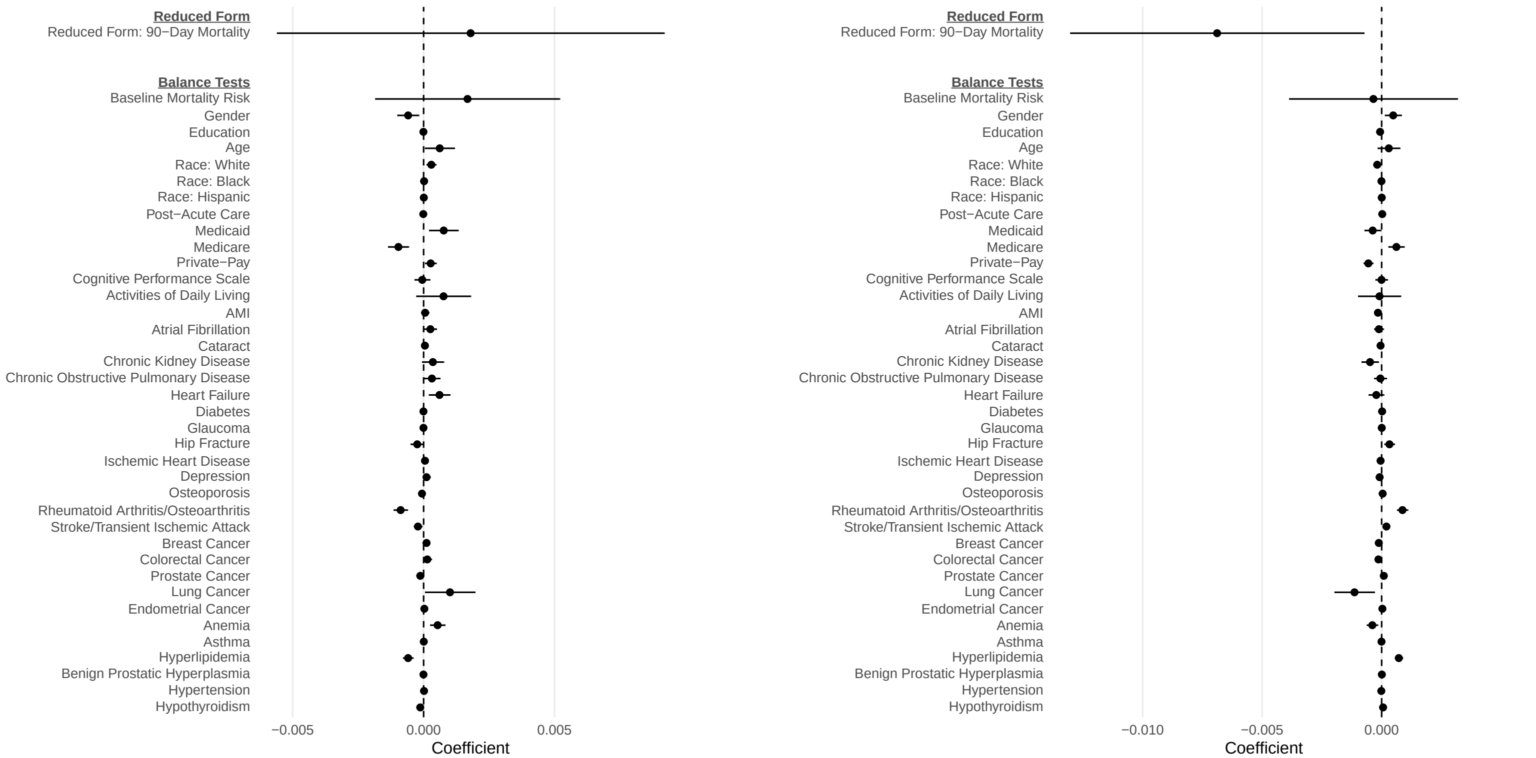


Notes: This figure provides evidence on the conditional independence/exclusion restriction assumption for patients with AD/ADRD by comparing regression estimates of baseline characteristics on the instruments (from the second row onwards) with the reduced form estimate (of the outcome on the instrument) in the first row, where baseline characteristics are scaled according to their associations with 90-day mortality. Specifically, panels (a) and (b) plot coefficient estimates and 95 percent confidence intervals from regressions of 90-day mortality (in the first row) and baseline patient characteristics (in the remaining rows) on the share of available rooms with a patient that has AD/ADRD and the share of available rooms that are empty respectively, controlling for nursing-home-by-year fixed effects and short-run variation in occupancy rates and patient composition at the time of admission, and with standard errors clustered at the nursing home level.

Figure A.7: Reduced Form and Balance for Patients without AD/ADRD

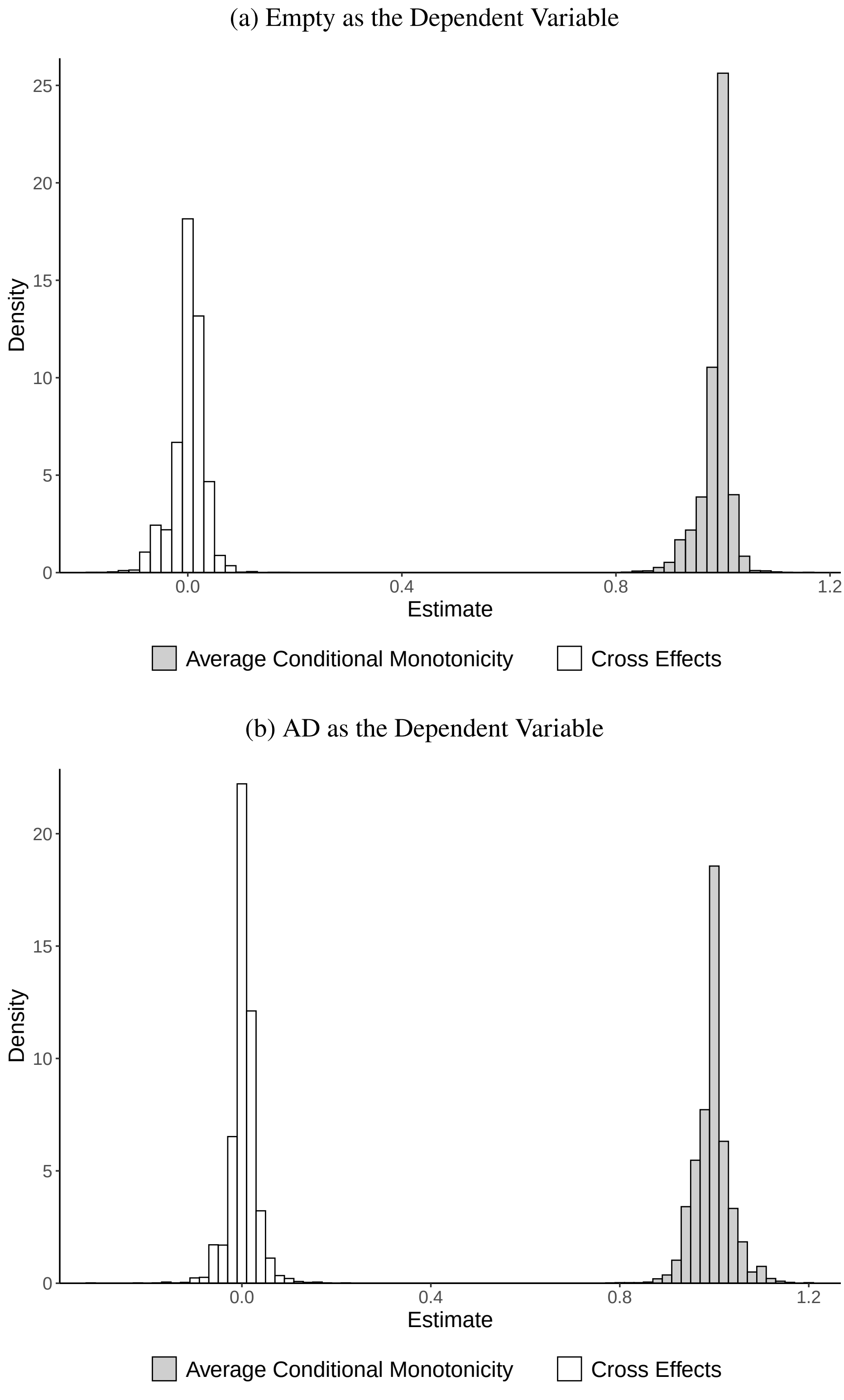
(a) Share of Available Rooms with a Patient that has AD/ADRD

(b) Share of Available Rooms Without a Roommate



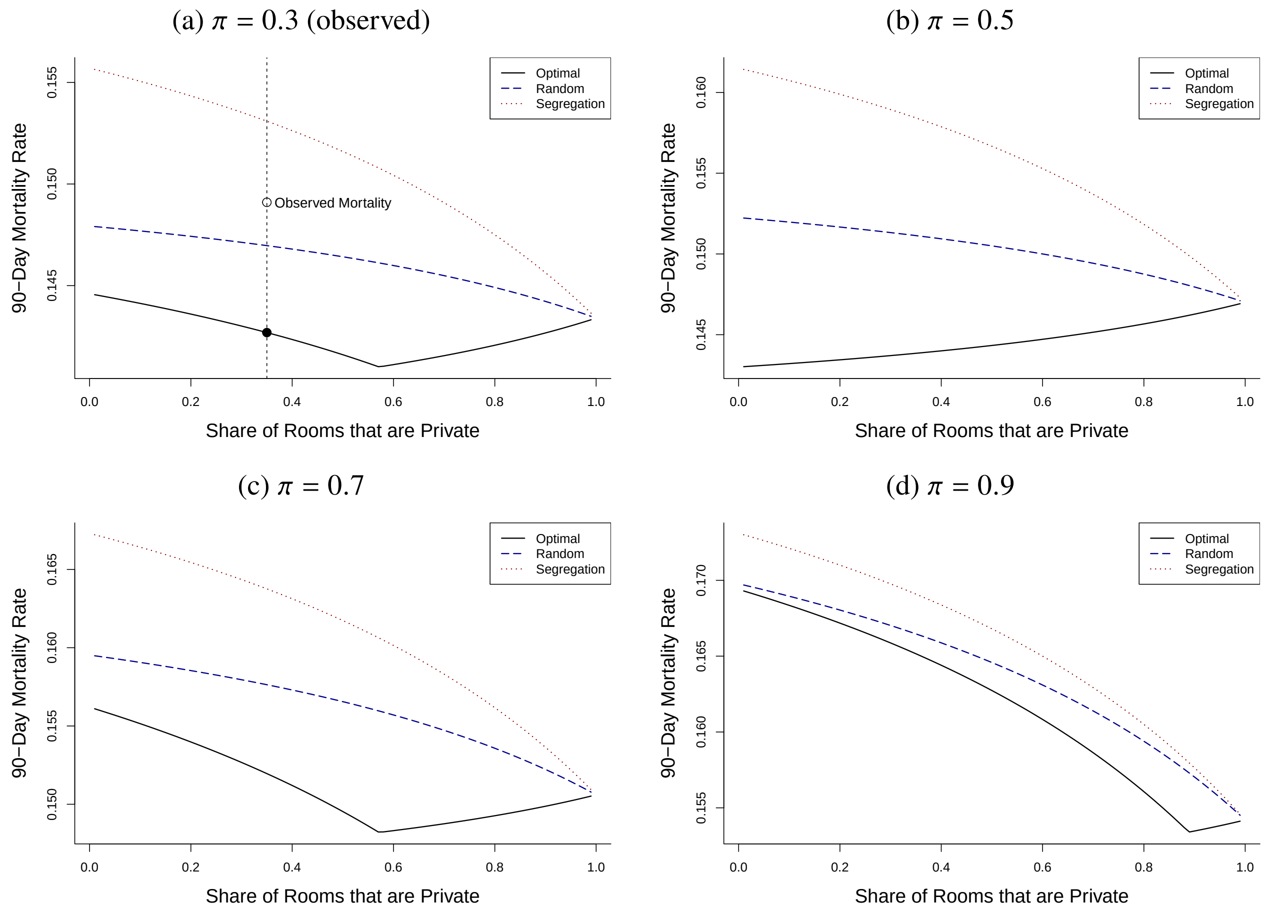
Notes: This figure provides evidence on the conditional independence/exclusion restriction assumption for patients without AD/ADRD by comparing regression estimates of baseline characteristics on the instruments (from the second row onwards) with the reduced form estimate (of the outcome on the instrument) in the first row, where baseline characteristics are scaled according to their associations with 90-day mortality. Specifically, panels (a) and (b) plot coefficient estimates and 95 percent confidence intervals from regressions of 90-day mortality (in the first row) and baseline patient characteristics (in the remaining rows) on the share of available rooms with a patient that has AD/ADRD and the share of available rooms that are empty respectively, controlling for nursing-home-by-year fixed effects and short-run variation in occupancy rates and patient composition at the time of admission, and with standard errors clustered at the nursing home level.

Figure A.8: Average Conditional Monotonicity and No Cross-Effects



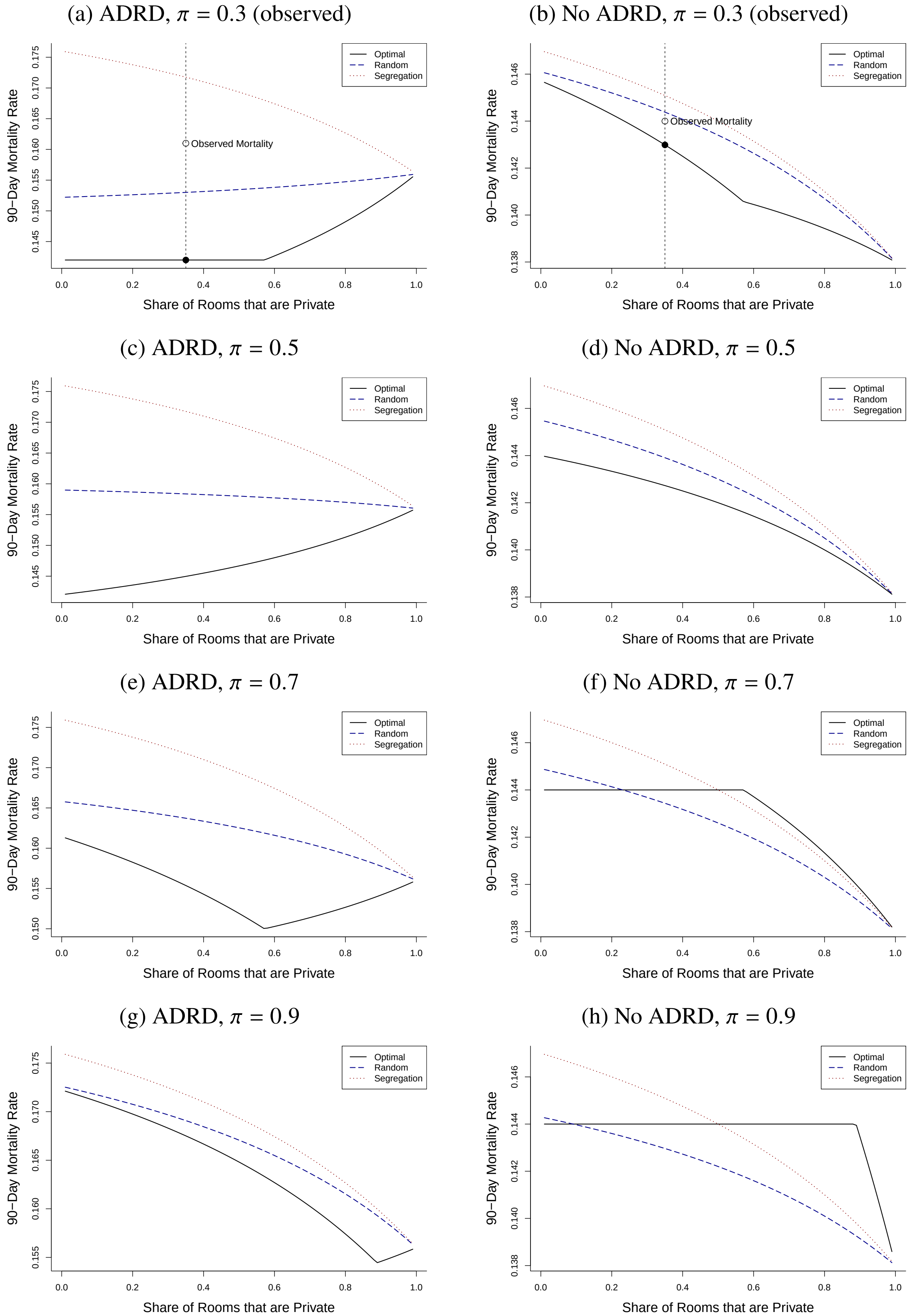
Notes: These figures show histograms of coefficient estimates from regressions of $\text{Empty}_{r,j,t}$ and $\text{AD}_{r,j,t}$ on both $P^{\text{Empty}}_{j,t}$ and $P^{\text{AD}}_{j,t}$ for different subsamples (controlling for nursing-home-by-year fixed effects and short-run variation in occupancy rates and patient composition at the time of admission). The dependent variable in panel (a) is $\text{Empty}_{r,j,t}$ and the dependent variable in panel (b) is $\text{AD}_{r,j,t}$. The subsamples are defined based on 42 baseline characteristics as well as their pairwise interactions. We consider all possible pairwise combinations except for when the sample restriction leads to less than 10,000 observations, resulting in a total of more than 3,800 different subsamples. The grey bars (respectively, white bars) correspond to estimates on the transformed instrument that matches (does not match) the dependent variable.

Figure A.9: Simulated Mortality Under Different Assignment Rules Assuming Full Capacity



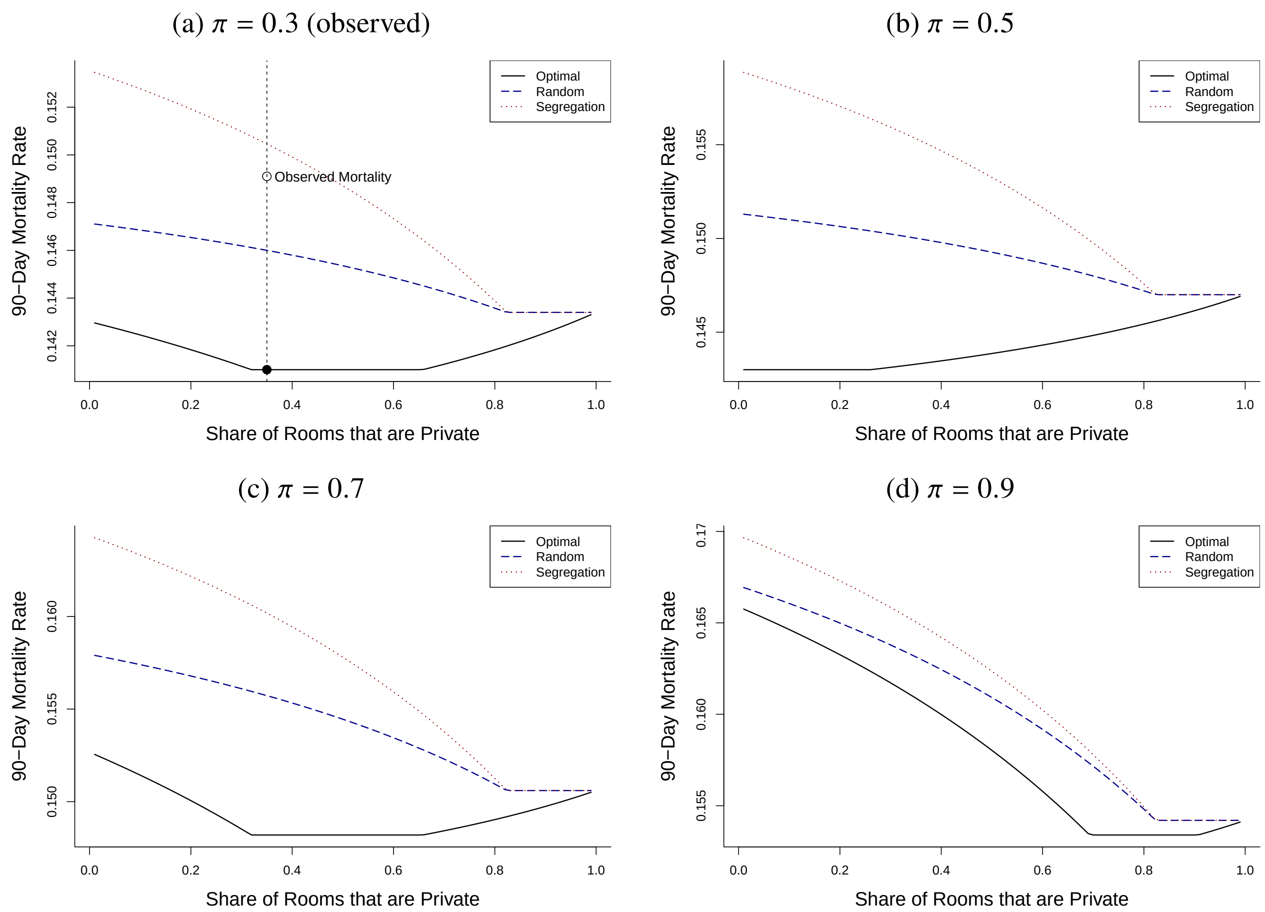
Notes: The black, blue, and red lines in this figure plot the simulated 90-day mortality rate under the mortality-minimizing (optimal) assignment rule, random assignment rule, and segregated assignment rule respectively, as a function of the fraction of rooms that are private, assuming full capacity. The different panels represent different fractions of the resident population with AD/ADRD, and simulated mortality is constructed based on the IV estimates in columns 3 and 4 of Table II.

Figure A.10: Simulated Mortality Under Different Assignment Rules for Different Groups Assuming Full Capacity



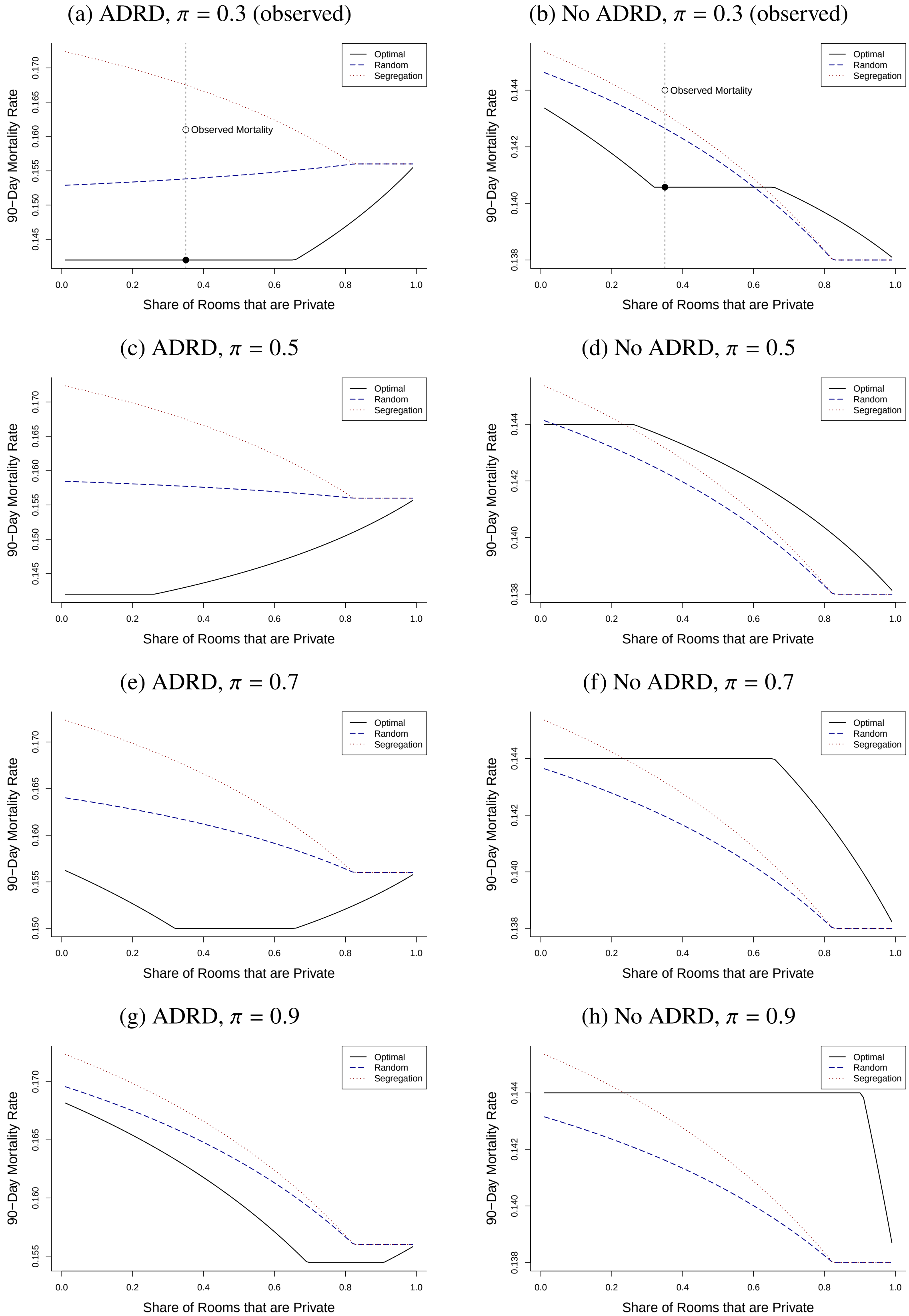
Notes: The black, blue, and red lines in this figure plot the simulated 90-day mortality rate separately for patients with and without AD/ADRD under the mortality-minimizing (optimal) assignment rule, random assignment rule, and segregated assignment rule respectively, as a function of the fraction of rooms that are private, assuming full capacity. The different panels represent different fractions of the resident population with AD/ADRD and plotting either simulated mortality for patients with AD/ADRD or for patients without AD/ADRD. Simulated mortality is constructed based on the IV estimates in columns 3 and 4 of Table II.

Figure A.11: Simulated Mortality Under Different Assignment Rules Assuming 85% Occupancy Rate



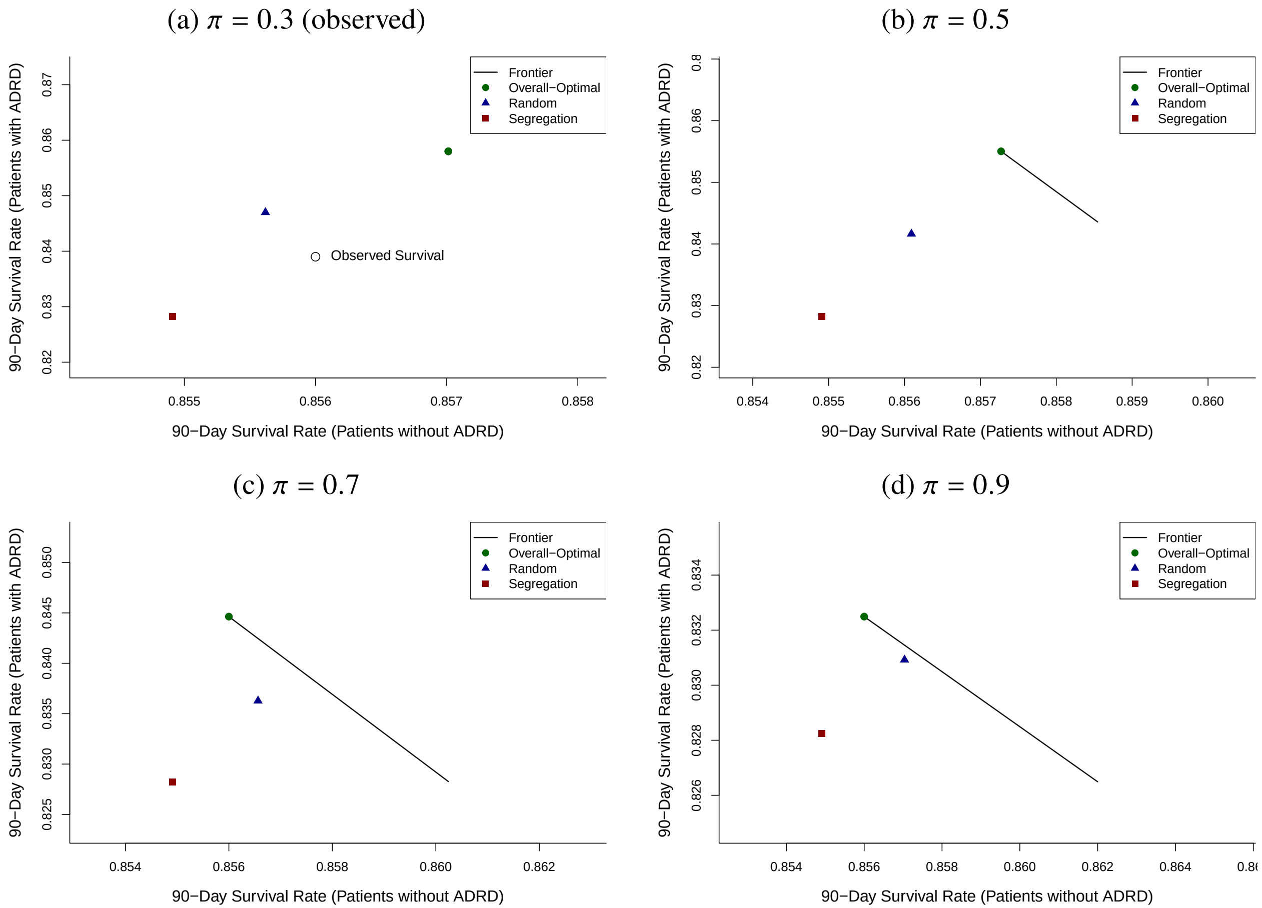
Notes: The black, blue, and red lines in this figure plot the simulated 90-day mortality rate under the mortality-minimizing (optimal) assignment rule, random assignment rule, and segregated assignment rule respectively, as a function of the fraction of rooms that are private, assuming 85% occupancy rate (the average in our sample). The different panels represent different fractions of the resident population with AD/ADRD, and simulated mortality is constructed based on the IV estimates in columns 3 and 4 of Table II.

Figure A.12: Simulated Mortality Under Different Assignment Rules for Different Groups Assuming 85% Occupancy Rate



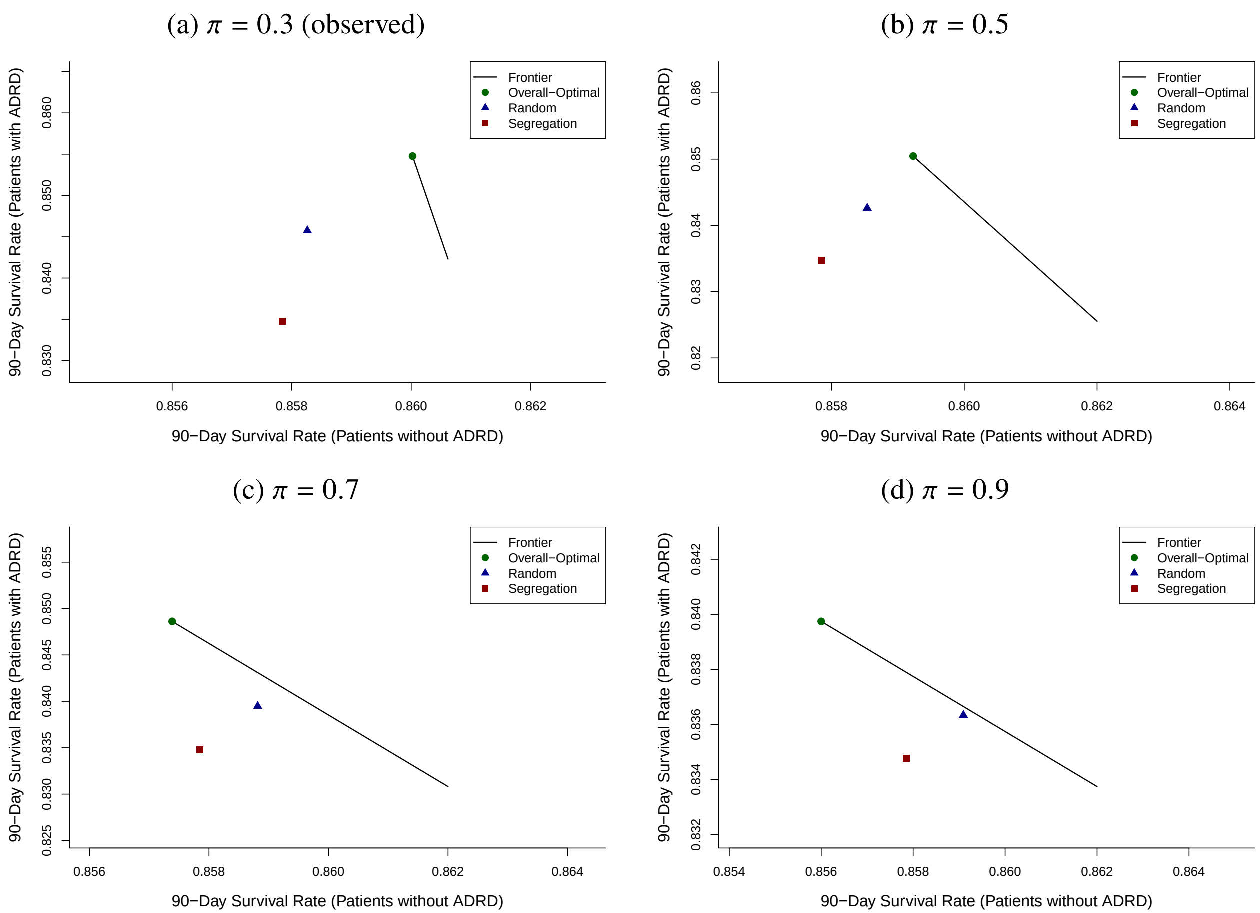
Notes: The black, blue, and red lines in this figure plot the simulated 90-day mortality rate separately for patients with and without AD/ADRD under the mortality-minimizing (optimal) assignment rule, random assignment rule, and segregated assignment rule respectively, as a function of the fraction of rooms that are private, assuming 85% occupancy rate (the average in our sample). The different panels represent different fractions of the resident population with AD/ADRD and plotting either simulated mortality for patients with AD/ADRD or for patients without AD/ADRD. Simulated mortality is constructed based on the IV estimates in columns 3 and 4 of Table II.

Figure A.13: Survival Frontier for Patients with and without AD/ADRD Assuming Full Capacity and 35% of Rooms Private



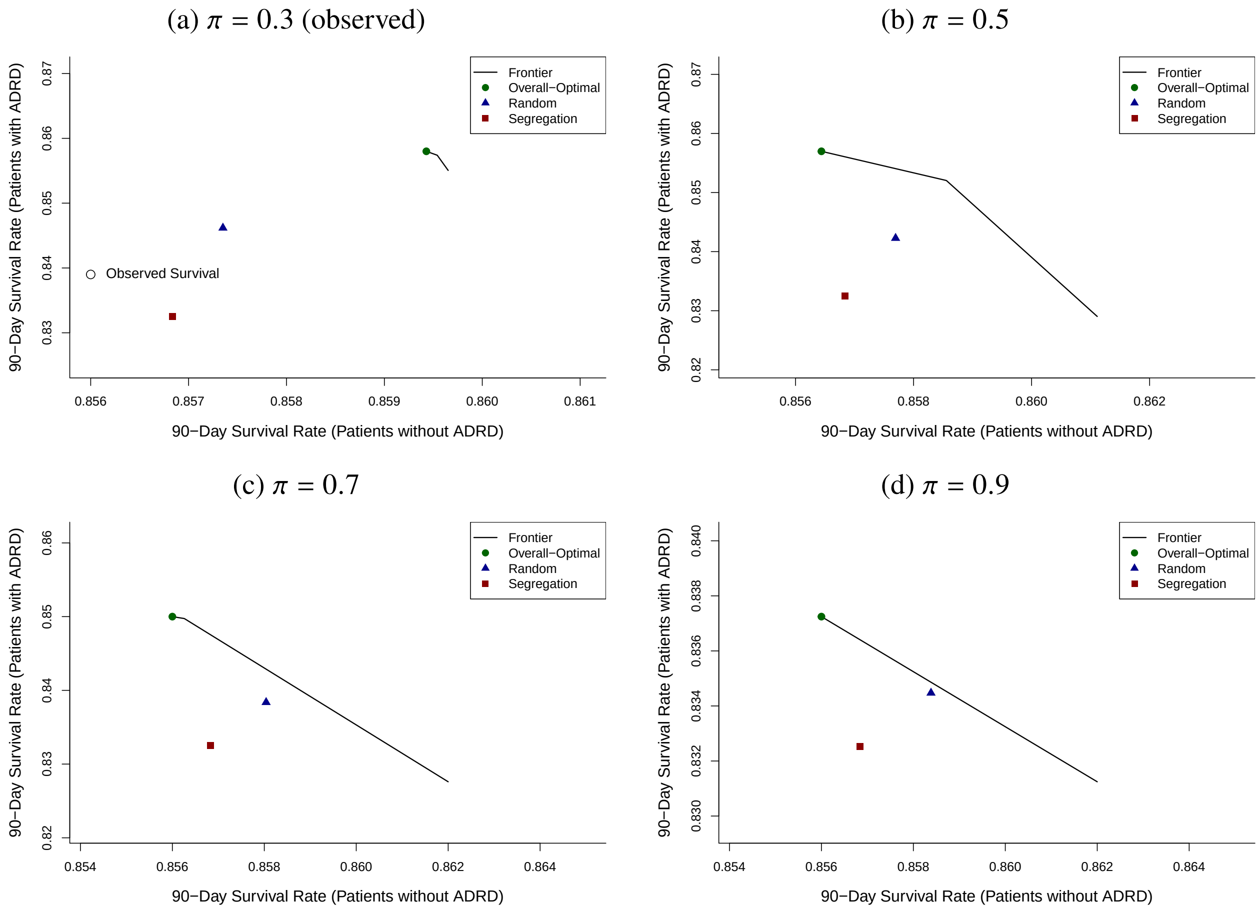
Notes: The line in each of these figures shows the maximum achievable pairs of survival rates for patients with AD/ADRD and for patients without AD/ADRD (i.e., the survival frontier), assuming full capacity. The fraction of rooms that are private is assumed to be 35% (the average fraction in our sample), and different panels correspond to different fractions of the resident population having AD/ADRD. Simulated mortality is constructed based on the IV estimates in columns 3 and 4 of Table II. The survival rates for these two groups under assignment that minimizes overall mortality (respectively, the random assignment rule and segregated assignment rule) are shown using a green point (blue triangle and red square).

Figure A.14: Survival Frontier for Patients with and without AD/ADRD Assuming Full Capacity and 70% of Rooms Private



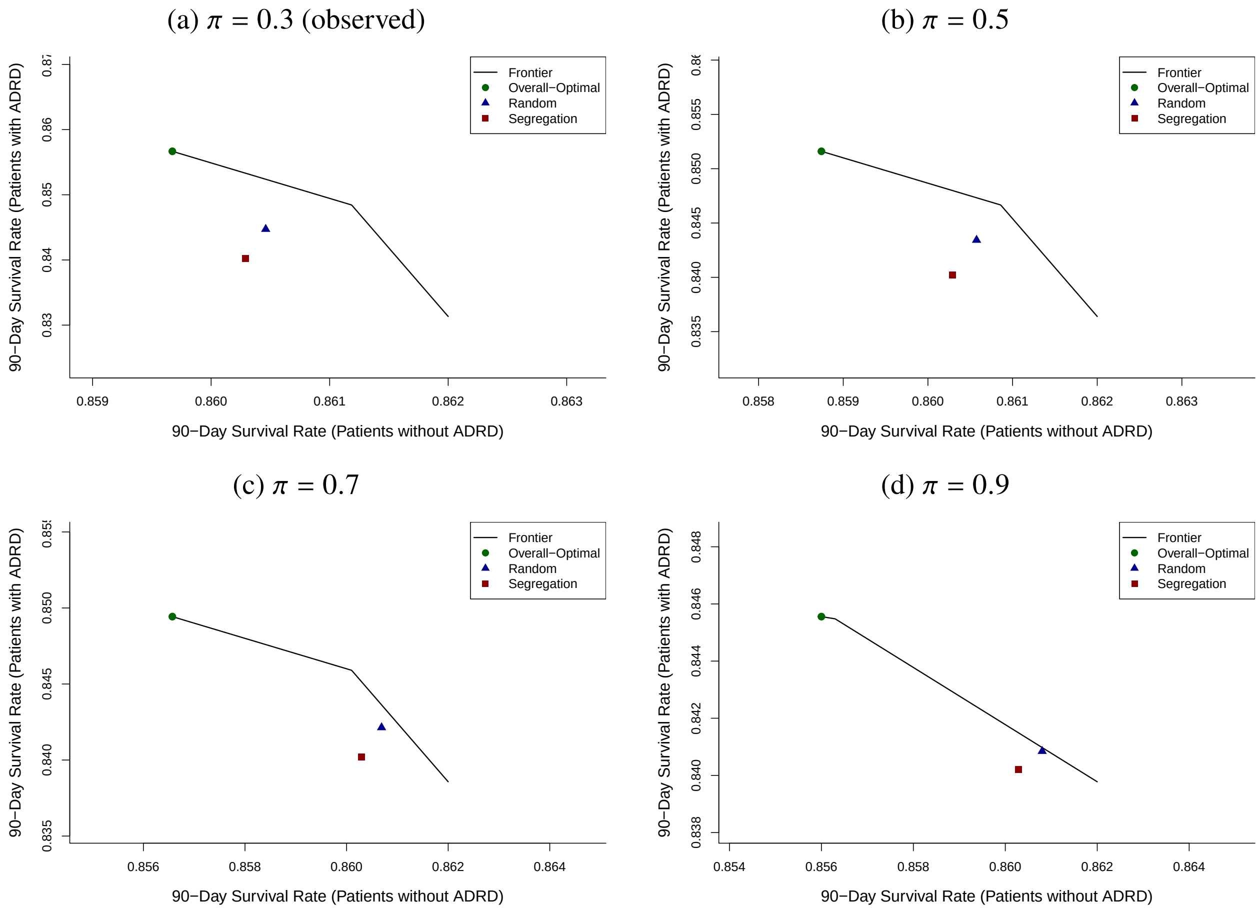
Notes: The line in each of these figures shows the maximum achievable pairs of survival rates for patients with AD/ADRD and for patients without AD/ADRD (i.e., the survival frontier), assuming full capacity. The fraction of rooms that are private is assumed to be 70%, and different panels correspond to different fractions of the resident population having AD/ADRD. Simulated mortality is constructed based on the IV estimates in columns 3 and 4 of Table II. The survival rates for these two groups under assignment that minimizes overall mortality (respectively, the random assignment rule and segregated assignment rule) are shown using a green point (blue triangle and red square).

Figure A.15: Survival Frontier for Patients with and without AD/ADRD Assuming 85% Occupancy Rate and 35% of Rooms Private



Notes: The line in each of these figures shows the maximum achievable pairs of survival rates for patients with AD/ADRD and for patients without AD/ADRD (i.e., the survival frontier), assuming an 85% occupancy rate (the average in our sample). The fraction of rooms that are private is assumed to be 35% (the average fraction in our sample), and different panels correspond to different fractions of the resident population having AD/ADRD. Simulated mortality is constructed based on the IV estimates in columns 3 and 4 of Table II. The survival rates for these two groups under assignment that minimizes overall mortality (respectively, the random assignment rule and segregated assignment rule) are shown using a green point (blue triangle and red square).

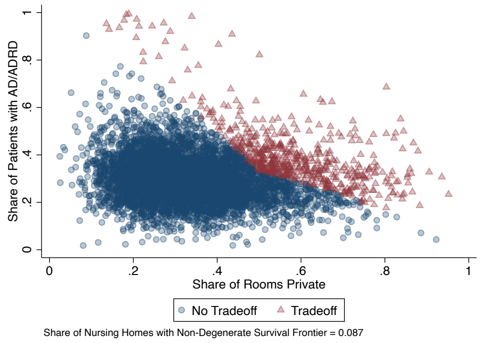
Figure A.16: Survival Frontier for Patients with and without AD/ADRD Assuming 85% Occupancy Rate and 70% of Rooms Private



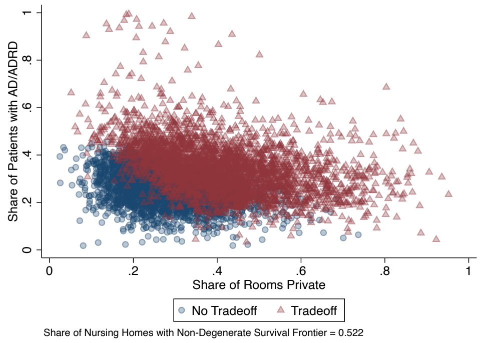
Notes: The line in each of these figures shows the maximum achievable pairs of survival rates for patients with AD/ADRD and for patients without AD/ADRD (i.e., the survival frontier), assuming an 85% occupancy rate (the average in our sample). The fraction of rooms that are private is assumed to be 70%, and different panels correspond to different fractions of the resident population having AD/ADRD. Simulated mortality is constructed based on the IV estimates in columns 3 and 4 of Table II. The survival rates for these two groups under assignment that minimizes overall mortality (respectively, the random assignment rule and segregated assignment rule) are shown using a green point (blue triangle and red square).

Figure A.17: Variation in Share of Patients with AD/ADRD, Room Configurations and Tradeoffs Faced by Nursing Homes in our Sample

(a) Scatterplot of π_j against p_j with Tradeoffs Assuming Full Capacity



(b) Scatterplot of π_j against p_j with Tradeoffs Based on Actual Occupancy Rates

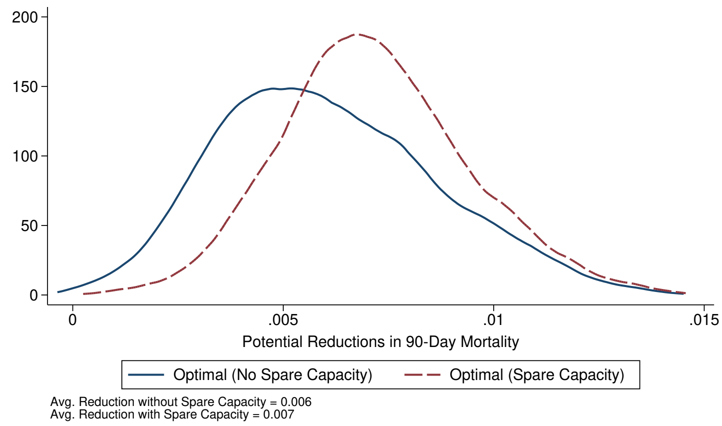


(c) Scatterplot of π_j against p_j with Different Tradeoff Types Based on Actual Occupancy Rates

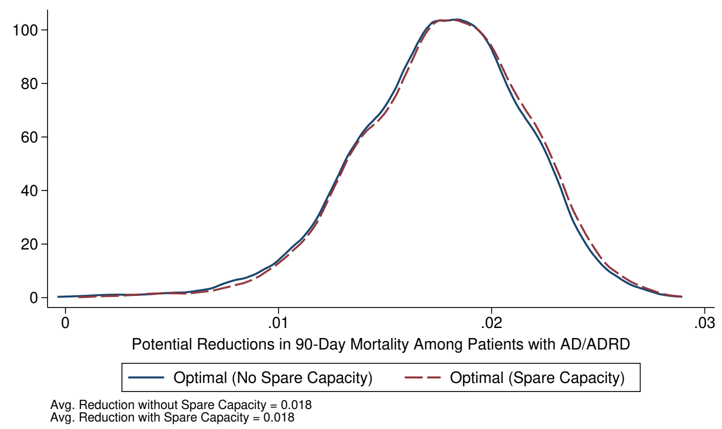
Notes: These figures show scatterplots of the share of patients with AD/ADRD (π_j) against the share of rooms private (p_j) for nursing homes in our sample with at least 100 patients. The blue circles show nursing homes where there is no tradeoff between outcomes of patients with and without AD/ADRD on the survival frontier, assuming full capacity in panel (a) and using actual occupancy rates in panels (b) and (c). In panels (a) and (b), the red triangles show nursing homes that do face a tradeoff. In panel (c), the red triangles, green squares, and orange diamonds respectively show nursing homes facing a tradeoff where the survival frontier has a kink, the survival frontier only has the flatter segment, and the survival frontier only has the steeper segment respectively.

Figure A.18: Variation in Potential Gains at the Nursing Home Level Under the Assignment Rule that Minimizes Overall Mortality

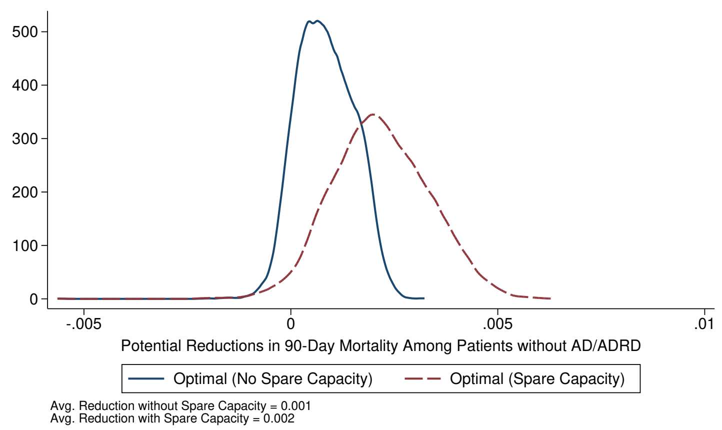
(a) Overall Survival Gains



(b) Survival Gains for Patients with AD/ADRD



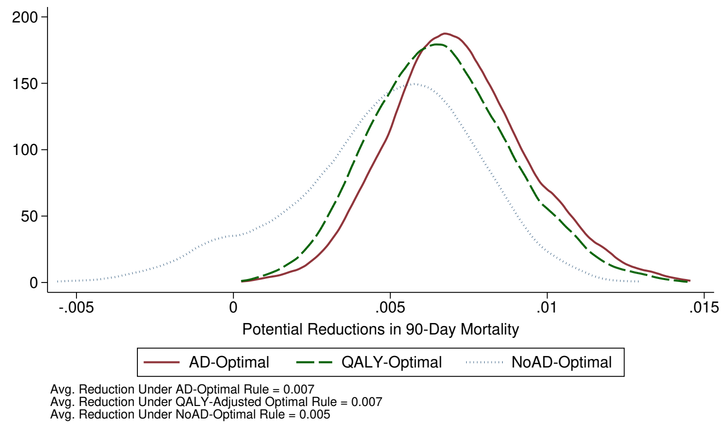
(c) Survival Gains for Patients without AD/ADRD



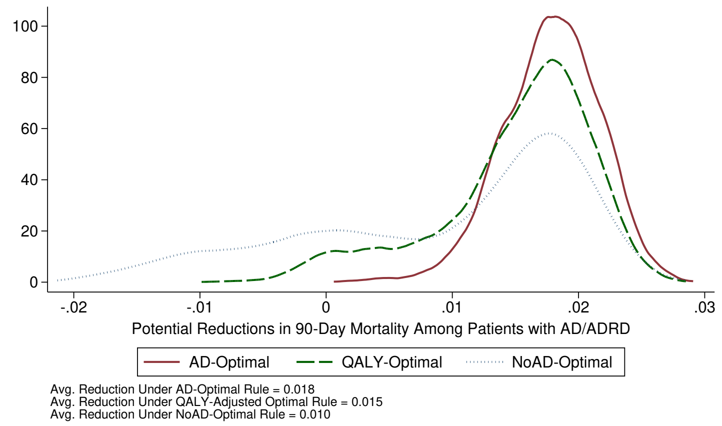
Notes: These kernel density plots show the distributions of potential reductions in the 90-day mortality rate at the nursing home level by comparing simulated mortality under the (optimal) mortality-minimizing assignment rule with observed mortality at the nursing home. The blue solid line assumes full capacity for simulating 90-day mortality under the optimal assignment rule, whereas the red dashed line uses actual occupancy rates for simulating 90-day mortality under the optimal assignment rule. Panels (a), (b), and (c) show potential reductions in 90-day mortality for all patients, patients with AD/ADRD, and patients without AD/ADRD respectively.

Figure A.19: Variation in Potential Gains at the Nursing Home Level Under the AD-Optimal, QALY-Optimal, and NoAD-Optimal Assignment Rules

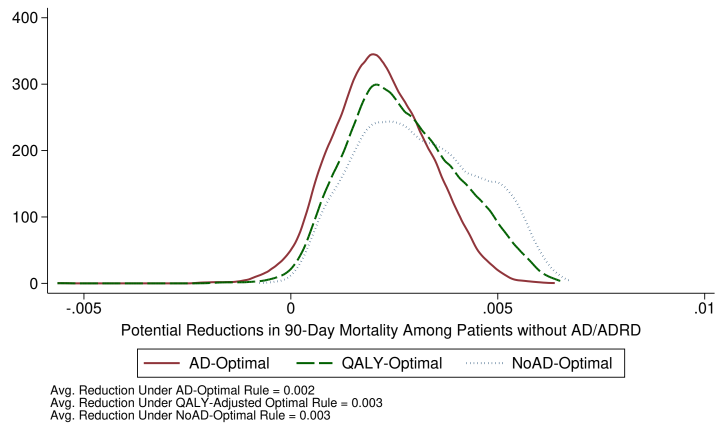
(a) Overall Survival Gains



(b) Survival Gains for Patients with AD/ADRD



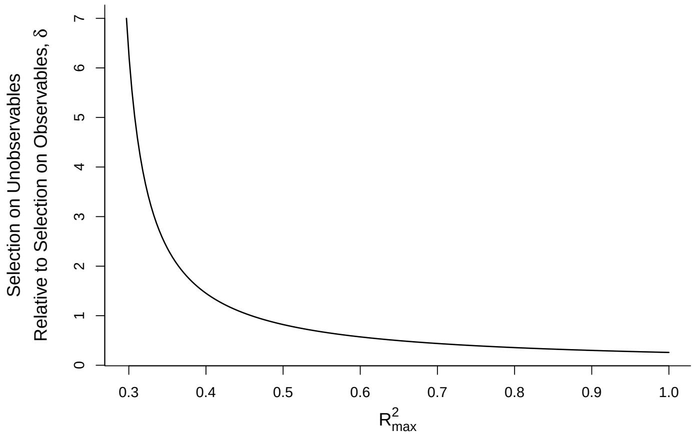
(c) Survival Gains for Patients without AD/ADRD



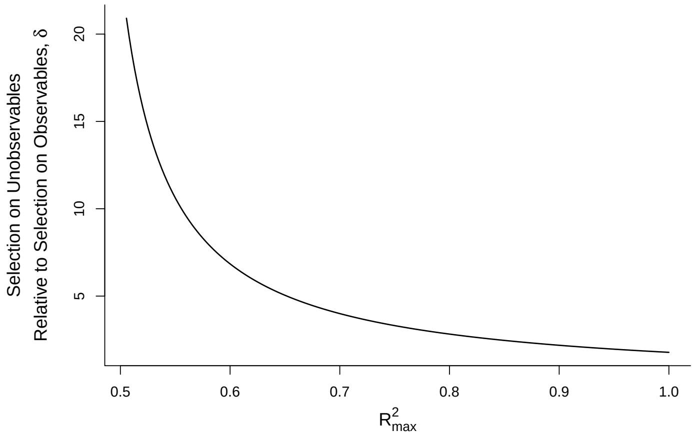
Notes: These kernel density plots show the distributions of potential reductions in the 90-day mortality rate at the nursing home level by comparing simulated mortality under three efficient assignment rules with observed mortality at the nursing home level. The red solid line is based on the assignment rule minimizing overall mortality, the green dashed line is based on the assignment rule minimizing QALY-adjusted mortality, and the blue dotted line is based on the assignment rule minimizing mortality among patients without AD/ADRD. Panels (a), (b), and (c) show potential reductions in 90-day mortality for all patients, patients with AD/ADRD, and patients without AD/ADRD respectively.

Figure A.20: Values of $R^2_{\max}$ and δ Required to Explain Treatment Effect Estimates

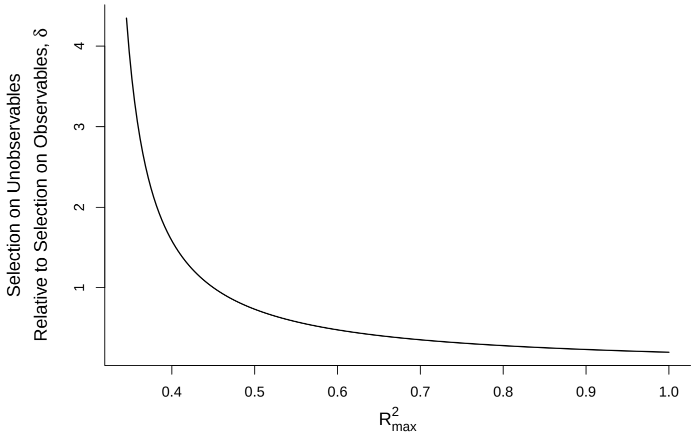
(a) Effect of Being Assigned Roommate with AD/ADRD in the Full Sample



(b) Effect of Being Assigned Roommate with AD/ADRD for Patients with AD/ADRD



(c) Effect of Being Assigned No Roommate for Patients without AD/ADRD



Notes: Each panel of this figure plots values of (R^2_{max}, δ) under which one of the endpoints of the bounds for the IV estimates contains zero. Panel (a) shows robustness for the estimate of being assigned an AD/ADRD roommate in the full sample, panel (b) shows robustness for the estimate of being assigned an AD/ADRD roommate for patients with AD/ADRD, and panel (c) shows robustness for the estimate of being assigned no roommate for patients without AD/ADRD.