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 (2000–2010) across 7,200 U.S. nursing homes, we exploit plausibly exogenous roommate assignments identified through unique room identifiers. We estimate that assignment to a roommate diagnosed with Alzheimer's disease (AD) or Alzheimer's disease related dementias (ADRD), relative to placement in a private room, 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. 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. In contrast, mortality of patients without AD/ADRD does not depend on roommate cognitive health but is reduced in private rooms. A simple assignment rule exploiting this heterogeneity could reduce overall mortality by 0.6 percentage points—saving roughly 1,400 life-years per year in our sample—without additional resources.

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1 Introduction

With declining fertility rates, rising childlessness, and increasing prevalence of Alzheimer's disease (AD) and Alzheimer's disease related dementias (ADRD) in the population, nursing homes have become an increasingly important part of the healthcare sector. Nearly 1.2 million Americans reside in nursing homes, supported by $91 billion in annual Medicaid and Medicare expenditures (Kaiser Family Foundation, 2025), and 56% of individuals currently aged 57–61 are projected to stay in a nursing home in the future (Hurd, Michaud, and Rohwedder, 2017). Accordingly, a growing body of work in economics studies the production of health in nursing homes, and incentives driving facilities' quality decisions (Hackmann, 2019; Gandhi et al., 2024; Einav, Finkelstein, and Mahoney, 2025). Yet a fundamental question has received surprisingly little attention: does your nursing home roommate affect your health? Nearly 80% of patients are assigned to shared rooms upon admission, yet beyond well-documented infection transmission (Brown et al., 2021; Konetzka, Grabowski, and Mor, 2024), we know very little about whether—and how—roommates influence each other's health.

This paper provides the first causal evidence that patient peer effects, operating largely through non-infectious channels, generate mortality impacts comparable to provider quality differences. Assignment to a roommate with AD/ADRD, relative to placement in a private room, 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. Moreover, these peer effects vary significantly by observable patient characteristics, and a simple room assignment rule may reduce overall mortality rates by 0.6 percentage points relative to the status quo, without additional staff or facility modifications. These findings reveal profound asymmetries in how patients interact as productive inputs, with immediate implications for care delivery, facility design, and $91 billion in annual public expenditures.

Understanding patient peer effects matters particularly because of what we do—and do not—know about quality variation in patient care. A substantial literature documents large mortality and quality differences between 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). Yet we know relatively little about what drives variation within facilities—whether pa-

tients receiving care from identical staff, in the same building, with the same aggregate inputs, experience systematically different outcomes. Recent evidence shows that most Black-white disparities in nursing home quality occur within rather than between facilities (Einav et al., 2025), underscoring that facility-level measures may mask important heterogeneity in patient experiences. Our findings reveal an important mechanism driving such within-facility variation: peer effects generate mortality differences comparable to between-facility quality gaps that have motivated decades of policy interventions such as minimum staffing regulations and inspections. This suggests micro-level assignment policies may be as consequential as macro-level facility choice—a margin entirely absent from current quality measurement, reimbursement policy, and consumer information systems.

The scarcity of credible evidence on patient peer effects is not without reason. Roommate assignment is rarely random; facilities may match roommates by acuity, diagnosis, or behavior. Separating peer effects from selection, common shocks, and reflection problems requires granular assignment data and credible exogenous variation—both scarce in existing research. We overcome these challenges using administrative data covering 2.5 million patient-stays across over 7,200 U.S. nursing facilities (2000–2010). We construct a novel database linking high-frequency patient-to-room assignments and exploit quasi-random variation in roommate characteristics driven by bed availability at admission. Conditional on facility-by-time fixed effects, as well as capacity strain and general patient composition at the facility, the types of rooms available at the precise time of admission generate plausibly exogenous variation in whether patients receive private rooms, and if not, their roommate's cognitive health and acuity. We present extensive evidence including balance tests and an array of robustness checks to support this assumption.

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 (7% relative to 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—but do not gain from private rooms. 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 explain by infection control, privacy preferences, or symmetric social interaction—it points to peer production of health through caregiving spillovers.

Third, these interaction effects have profound policy implications. 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.

Evidence on mechanisms supports the monitoring interpretation. Peer effects are substantially larger in facilities with below-median staffing, suggesting roommates substitute for professional supervision when care is inadequate. Effects are also concentrated among patients not in specialized Alzheimer's units, which provide enhanced monitoring and environmental accommodations. Both patterns indicate peer monitoring substitutes for formal care inputs—precisely what theory predicts if cognitively healthy roommates provide surveillance and behavioral regulation.

We contribute to three strands of literature. First, we extend the peer effects literature which has mostly focused on education and younger populations (Sacerdote, 2001; Carrell, Fullerton, and West, 2009; Abdulkadiroğlu, Angrist, and Pathak, 2014), by providing the first causal evidence that patient peer effects in healthcare among elderly pop-

ulations—operating largely through non-infectious channels—generate mortality impacts comparable to provider quality differences. Assignment to a roommate with AD/ADRD increases 90-day mortality by 1.1 percentage points (7% of baseline), equivalent to receiving care at a facility half a standard deviation worse in quality. Methodologically, while most peer effects studies exploit one-time random assignment, we leverage high-frequency variation in bed availability at admission—a novel identification strategy applicable to other institutional settings where assignment is endogenous but vacancies are quasi-random.

Second, we contribute to the health production function literature. Previous work documents substantial value-added differences between hospitals (Chandra et al., 2016a; Hull, 2018) and nursing homes (Olenski and Sacher, 2024; Einav, Finkelstein, and Mahoney, 2025; Cheng, 2025).[1] We identify a distinct margin: within-facility heterogeneity driven by peer interactions, holding aggregate inputs fixed. We show this margin is quantitatively comparable to between-facility quality differences that have motivated decades of policy interventions. This challenges the conventional focus on aggregate resources and suggests micro-level assignment policies may be as consequential as macro-level facility choice—a margin entirely absent from current quality measurement, reimbursement policy, and consumer information systems.

Third, we contribute to a small but growing literature documenting within-facility variation in nursing home care quality. Prior work has shown racial differences in inputs (medication use, feeding tubes, vaccinations) and outcomes (re-hospitalization, pressure ulcers, home discharges) among patients within the same facility (Einav et al., 2025). We identify a distinct source of within-facility variation: room assignments and peer effects.

Our analysis relates closely to concurrent work by McWilliam (2025), who examines a comprehensive set of outcomes for private versus shared rooms among post-acute nursing home patients, finding no significant improvements in mortality, hospital readmission, discharge to home, length of stay, or resident mood. Our findings complement and extend this work in two ways. First, we examine peer effects within shared rooms, showing that outcomes depend not just on room type but also on roommate characteristics—a margin absent from private-vs-shared comparisons. Second, we show the "private room effect"

[1] Prior work also documents provider-patient complementarities from communication frictions and bias (Alsan and Wanamaker, 2018; Alsan, Garrick, and Graziani, 2019; Greenwood et al., 2020).

is highly heterogeneous: beneficial for cognitively healthy patients, but neutral or even harmful for patients with AD/ADRD who gain more from cognitively healthy roommates.

This paper proceeds as follows. Section 2 describes the nursing home setting and our data. Section 3 outlines our IV strategy, discussing the identifying assumptions and providing evidence that they are satisfied. Section 4 presents our peer effect estimates and explores mechanisms. Section 5 concludes.

2 Background and Data

2.1 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 are roughly $140 billion annually, 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 dementia are significantly more likely to require nursing home care than those without cognitive impairment; between 2017 and 2019, more than three million nursing home patients have been diagnosed with Alzheimer's disease and related dementias (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 Alzheimer's disease or related dementias, understanding how facility practices shape outcomes for this population has become an urgent policy priority.

2.1.1 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. Un-

like 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 behavioural 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.

2.1.2 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 individual roommate characteristics on patient outcomes.

2.2 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. A key feature of our identification strategy is that we focus on assignments to three mutually exclusive room types: private rooms, shared rooms where the roommate has Alzheimer's disease or related dementias (AD/ADRD), and shared rooms where no roommate has 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.

2.2.1 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 when-

ever there is a significant change in status during nursing home stays.[2] The data have been widely 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 to at admission, as well as the room composition at the nursing home she is assigned to. Finally, we construct room capacity as the maximum number of patients co-residing in the room at any point during that year. This 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 age, and similar health status—patterns consistent with room assignments reflecting deliberate matching decisions rather than random measurement error.

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

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 (specifically, at the end of the day before the focal resident's admission). 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. In rooms with multiple roommates, we classify the room as having an AD/ADRD roommate if *any* roommate has the diagnosis. We measure room composition at the time of the focal patient's admission, which is pre-determined and 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.

Dementia 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. We measure cognitive impairment using 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 as controls in some specifications and to test for effect heterogeneity.

2.2.2 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 to control for baseline health differences in robustness exercises.

2.2.3 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.

2.2.4 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.[3]

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 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)[4], 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 B.

[3]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.

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

2.3 Summary Statistics

Columns 1–4 of Table 1 provide summary statistics on baseline characteristics 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 the baseline characteristic for 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 that 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 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.

3 Empirical Strategy

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

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

where $Y_{i,r,j,t}$ is a future health outcome (90-day mortality in our main specifications) for patient i admitted to room r in nursing home j 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

Table 1: Summary Statistics

	Full Sample	Assigned No Roommate	Assigned Roommate with AD/ADRD	Assigned Roommate Without AD/ADRD	Diff: (2)-(4)	Diff: (3)-(4)
	(1)	(2)	(3)	(4)	(5)	(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.

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.

$\Gamma_{j,t}$ is a vector of time-varying controls, including 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).[5] 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 assignment practices. Second, the 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).

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),[6] so that β_1 and β_2 isolate the incremental effects of the assigned roommate environment.

The coefficients of interest are β_1 and β_2. They denote the causal effects of the room type assigned at admission on outcomes. 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.[7]

[5] 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.

[6] 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.

[7] 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).

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 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 1 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.

3.1 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 – $s_{j,t}^{\text{Empty}}$ – and the share of rooms with a vacant bed that have an existing patient with AD/ADRD – $s_{j,t}^{\text{AD}}$ – 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 $s_{j,t}^{\text{Empty}}$

and $s_{j,t}^{\text{AD}}$ 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:

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

$$\text{AD}_{r,j,t} = \alpha_1 \, s_{j,t}^{\text{Empty}} + \alpha_2 \, s_{j,t}^{\text{AD}} + \Gamma_{j,t}' \alpha_\gamma + \nu_{irjt}. \tag{2b}$$

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 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[8]. We observe that substantial variation in the instruments remains, due to volatility in admissions and discharges (both in volume and composition).

3.1.1 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

[8]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.[9] We assess this by examining the relationships between $\text{Empty}_{r,j,t}$ and $s_{j,t}^{\text{Empty}}$ as well as between $\text{AD}_{r,j,t}$ and $s_{j,t}^{\text{AD}}$, 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).

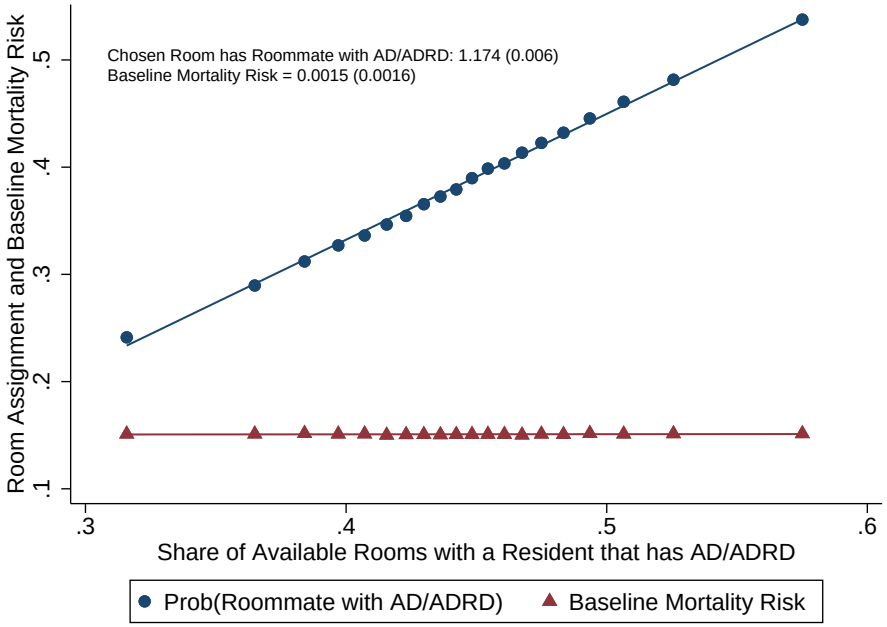
The blue dots in Figure 1 present the first stage results. Figure 1a presents results from the first stage regression in a binscatter plot for one of our instruments: the share of available rooms occupied with at least one patient with AD/ADRD at the time (day) of admission, $s_{j,t}^{AD}$ (holding the other instrument fixed). The blue line (circle markers) shows a positive linear relationship between the probability of being assigned to a roommate with AD/ADRD (vertical axis) and the instrument $s_{j,t}^{AD}$ (horizontal axis), $\alpha_2 > 0$, providing strong support for instrumental relevance. Moreover, the relationship is remarkably linear, which supports the linear specification in equation (2b). 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.

The blue dots in Figure 1b present corresponding evidence for the second instrument: the share of available empty rooms, $s_{j,t}^{Empty}$ (holding $s_{j,t}^{AD}$ fixed). The blue line (circle markers) shows again a positive linear relationship between the probability of being assigned to an empty room (vertical axis) and $s_{j,t}^{Empty}$ (horizontal axis), $\alpha_1 > 0$, providing strong support for instrumental relevance. The relationship is also remarkably linear, supporting the linear specification in equation (2a). 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.

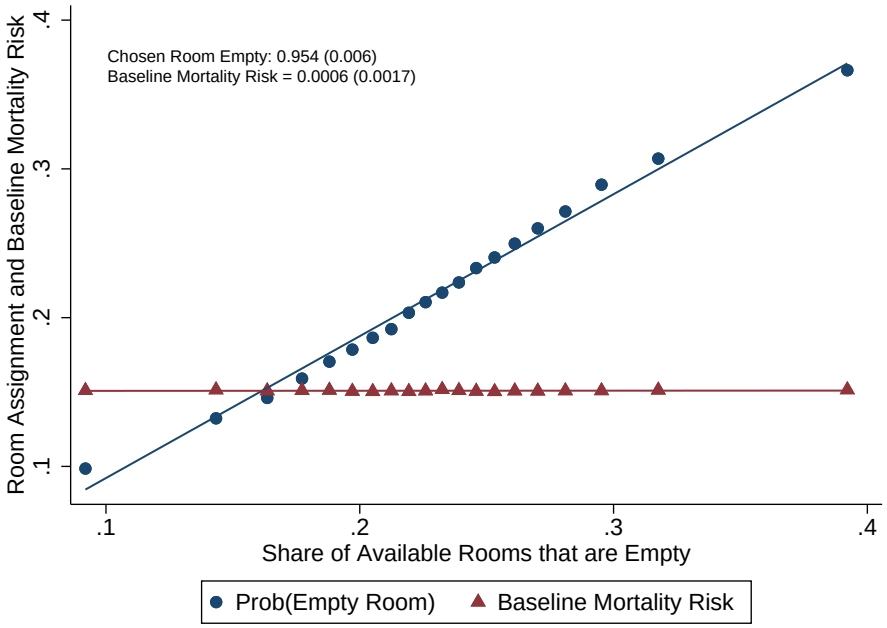
[9] Specifically, in the case with two endogenous variables and two excluded instruments, the 2×2 matrix of first stage coefficients must have rank 2.

Figure 1: 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).

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.

Conditional independence could fail if patients delay admission until a preferred room type becomes available or select nursing homes based on room availability. The exclusion restriction could fail if the instruments proxy for broader facility-level conditions—such as overall resident composition or operational strain—that directly affect mortality through peer effects outside the room or staffing constraints.

Our empirical strategy directly addresses both concerns. 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. The 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-level availability. By flexibly controlling for overall resident composition, the specification 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.

We further provide direct empirical evidence supporting these assumptions. First, we examine whether observed patient characteristics are balanced across the instruments, conditional on the full set of 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, and over 500 pairwise interactions between these variables, controlling for nursing-home–year fixed effects, room assignment, capacity strain, and patient composition.

The red triangles in Figure 1 plot the relationship between baseline mortality risk and the instruments—the shares of empty rooms and available rooms with an AD/ADRD pa-

tient at the time of admission ($s_{j,t}^{Empty}$ and $s_{j,t}^{AD}$). Baseline mortality risk is remarkably stable across variation in both instruments. In particular, the regression of baseline mortality risk on each instrument is statistically insignificant despite the large sample size.[10]

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).[11] To ensure comparability of the coefficients' scale and sign across regressions for different variables, we multiply the coefficient estimate (and standard error) by the dependent variable's association 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 strain. Instead, variation in the instruments reflects quasi-random room-level 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 as properly weighted averages of treatment effects across different patients (i.e., with non-

[10] 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.

[11] 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.

negative weights and zero weights on the "wrong" treatment effect).[12] 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^{Empty} and P^{AD}. Average conditional monotonicity requires that P^{Empty} (respectively, P^{AD}) only affects Empty (AD) weakly positively, while no cross-effects requires that P^{Empty} does not affect AD (conditional on P^{AD}) 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 Empty (AD) on P^{Empty} and P^{AD} (and controls) should result in a positive coefficient estimate on P^{Empty} (P^{AD}) and a zero estimate (up to statistical uncertainty) on P^{AD} (P^{Empty}). Appendix Figure A.8 shows histograms of coefficient estimates with Empty and AD as the dependent variables in panels (a) and (b) respectively, for over 3,300 subsamples defined based on 42 baseline characteristics and their pairwise interactions. The blue bars (respectively, red bars) correspond to estimates for the transformed instrument that matches (does not match) the dependent variable. We observe that all the blue bars are large and positive, supporting average conditional monotonicity, whereas all of the red bars are small and close to zero, supporting the no cross-effects assumption.

4 Results

4.1 IV Estimates of Room Effects

Table 2 shows IV estimates of equation (1) 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 as-

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

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

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

signed to an empty room 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 being assigned roommates that do not have AD/ADRD (the reference group), being assigned to an empty room 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 an empty room 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 health determinants 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. That means that moving from a room shared with a patient with AD/ADRD to an empty room reduces 90-day mortality is similar to a 0.5 standard deviation fall in the value added distribution of nursing homes. 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 2 examine patients with and without AD/ADRD at admission. The results reveal asymmetric effects. Empty room assignment reduces mortality for patients without AD/ADRD but increases mortality for those with AD/ADRD. Similarly, having 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 mortality benefit from cognitively intact roommates relative to private rooms. These findings suggest potential gains from pairing patients with AD/ADRD with cognitively intact roommates, as we discuss below.

Importantly, the identifying assumptions continue to hold 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—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 dementia 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 dementia 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 an AD/ADRD patient on a peer AD/ADRD patient it is difficult to reconcile with the absence of a negative effect on peers without AD/ADRD.

Table 2: 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.

4.2 Robustness Checks

Different Sets of Controls We test whether our IV estimates remain stable as we consider different sets of controls. First, in column 1, 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[13] 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 on the average effects of roommate assignment and heterogeneity in effects by baseline cognitive status remain qualitatively unchanged. Moreover, the magnitudes of the estimates in

[13]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.

our preferred specification tend to be smaller than the magnitudes from specifications with both fewer and more controls, suggesting that our estimates are conservative.

To better understand sources of bias in the OLS estimates, in Appendix Table A.3 we conduct the same exercise for the OLS estimates. 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 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 treatment effects are specific to the time horizon for mortality that we chose. 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 growing over time. 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 instance, if a patient or her family has strong preferences for private rooms, she may choose a different nursing home if her otherwise most-preferred nursing home has no empty rooms. The linearity of the first stage (even for the top and bottom 5% of the room composition instruments) as well as the balance tests for the instrument suggest that this type of selection is uncommon. Nonetheless, we address this possibility by estimating our main specifications on the sample of patients who are admitted from acute care hospitals. Given the time constraints around the discharge process, these patients are much less likely to be able to choose between nursing homes based on short-run fluctuations in room composition. Columns 1–3 of Appendix Table A.5 show that IV estimates for the effects of room assignment for post-acute-care patients are remarkably similar to the main estimates in Table 2: moving from an empty room

to a roommate with AD/ADRD increases 90-day mortality by 1.1 percentage points, patients with AD/ADRD benefit from having a roommate without AD/ADRD, and patients without AD/ADRD benefit from being assigned to private rooms. Estimates for patients not admitted from acute care hospitals in columns 4–6 of Appendix Table A.5 are less precise due to smaller sample sizes but 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 D explains these bounds in greater detail, with additional bounds under alternative assumptions shown in Appendix Table D.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 D.12.

"Power Asymmetry" in IV Finally, we address the issue of "power asymmetry" in 2SLS estimation when t-tests are used inference, as pointed out by Keane and Neale (2023).[14] The IV estimates in Table 2 indicate that on average, being assigned to an empty room reduces

[14]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, one with each treatment variable.

90-day mortality while being assigned a roommate with AD/ADRD increases mortality. On the other hand, the OLS estimates shown in Appendix Table A.3 bias us against finding these effects. 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 even less of an issue.

4.3 Room Assignments and Average Mortality

These findings raise a natural policy question: which room assignment rules would minimize overall mortality? In this subsection, we derive intuitive optimality conditions and use them to quantify the potential mortality reductions from optimal room assignments.

Formally, we consider a room-specific health production function

$$U = f(i, i', r) \tag{2}$$

where U as a positive outcome, here 90-day survival, i is patient health at admission, and i' is peer health at admission. r denotes the room, which accommodates up to two residents. Assignment to an empty room is captured by $f(i, r)$. We assume that total health production is additive in room-specific average survival.[15]

We define $\mathcal{A}$ to be the set of all feasible allocations, where each allocation $A \in \mathcal{A}$ consists of a set of such tuples satisfying capacity and feasibility constraints (e.g., each patient is assigned to exactly one room, room capacities, etc.). We treat the nursing home capacity, along with the 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.

We thus solve the following problem:

[15] As discussed earlier, our rich set of control variables in Γ purge the data of potential peer interaction effects outside of shared nursing home rooms.

$$A^* \in \arg\max_{A \in \mathcal{A}} \sum_{(i,i',r) \in A} f(i,i',r). \tag{3}$$

Motivated by our empirical setting, we consider a simpler version of this model with two types of patients (with or without AD/ADRD), two types of rooms (private room with one bed or shared room with two beds), and assume that the number of patients is equal to the nursing home's bed capacity, C. In this model, the feasible set of allocations is characterized by the share of patients with AD/ADRD, $\pi \in [0,1]$, the share rooms that are private, $p \in [0,1]$, and nursing home bed capacity, C: $\mathcal{A}(\pi, p, C)$. Furthermore, due to accounting balances, each feasible allocation $A \in \mathcal{A}$ is fully characterized by two decision variables: x_{priv}^{AD} and $x_{share}^{AD,noAD}$, which are the number of patients with AD/ADRD in private rooms and the number of shared rooms that are mixed (one patient with AD/ADRD, "AD", and one without, "noAD"), respectively. The feasible set of allocations can thus be written as $(x_{priv}^{AD}, x_{share}^{AD,noAD}) \in \mathcal{A}(\pi, p, C)$.

As we detail in Appendix Section C, the solution to this simpler version of the model boils down to a linear programming problem, which can be written as:

$$x_{priv}^{AD,*}, x_{share}^{AD,noAD,*} = \underset{x_{priv}^{AD}, x_{share}^{AD,noAD} \in \mathcal{A}(\pi,p,C)}{\arg\max} \psi x_{priv}^{AD} + \theta x_{share}^{AD,noAD}, \tag{4}$$

where:

$$\psi \equiv (u_{priv}^{\text{AD}} - u_{share}^{\text{AD,AD}}) - (u_{priv}^{\text{noAD}} - u_{share}^{\text{noAD,noAD}}),$$

$$\theta \equiv (u_{share}^{\text{AD,noAD}} + u_{share}^{\text{noAD,AD}}) - (u_{share}^{\text{AD,AD}} + u_{share}^{\text{noAD,noAD}}).$$

Here, $u_r^{i,i'}$ denotes 90-day survival for patient i with AD/ADRD (AD) or without (noAD), when assigned to a private room ($r = priv$), or a room shared ($r = share$) with or without a roommate with AD/ADRD.

The survival-maximizing allocation is governed by two key parameters, ψ and θ, each with a clear economic interpretation.

Privacy premium: The parameter ψ is the difference in the privacy premium across patient types. A positive ψ implies that, relative to sharing a room with a resident of their own type, AD/ADRD patients derive a larger survival benefit from private rooms than

cognitively intact patients. Using the estimates from Table 2, columns 3 and 4, imply (after flipping signs to capture effects on survival), we obtain:

$$\psi = (-1.4 + 3.4) - (0.9 - 0) = 1.1$$

percentage points. The parameter estimate combines two effects. On the one hand, cognitively intact residents benefit more from a private room than from sharing a room with another cognitively intact resident (columns 3 and 4, row 1 of Table 2). On the other hand, residents with AD/ADRD benefit from sharing a room with a cognitively intact resident relative to sharing with another AD/ADRD resident. Together, these imply that AD/ADRD residents gain more from a private room compared to sharing with a resident of their *own* type — than cognitively intact residents do, yielding $\psi > 0$.

Complementarity parameter: The parameter θ measures the net production gain from mixed relative to segregated shared rooms. 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. Our estimates from Table 2 imply that:

$$\theta = (0 + 0.3) - (-3.4 + 0) = 3.7$$

percentage points, suggesting that the production function in shared rooms is submodular, and that mixed rooms can increase average survival relative to segregated rooms.

Implications for room allocations: 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 privacy premium outweighs the gains from mixing, so average survival is higher when allocating AD/ADRD patients to private rooms, even at the cost of fewer mixed rooms. However, we find $|\psi| < \theta$: the benefit of mixing dominates,

and nursing-home-level survival increases by maximizing the number of mixed shared rooms.

We illustrate the difference between the survival-maximizing assignment rule and alternative assignment rules that impose random assignment or segregation by health in Figure 2, for different room configurations (specifically, varying the fraction of rooms that are private, p). We observe that regardless of the room configuration, simulated average 90-day mortality is lowest under the survival-maximizing assignment rule, followed by the random room assignment, and highest under segregated room assignment. The empirically relevant fraction of rooms that are private (25%) is illustrated with a dashed vertical line, and the observed mortality rate is shown using an open circle. The observed 90-day mortality rate is 14.9%, compared to the simulated mortality rate of 14.3% under the optimal assignment rule. This implies that better room assignments may reduce average 90-day mortality rates by 0.6 percentage point (a 4% reduction relative to baseline), which 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).[16]

Appendix Figure C.9 shows differences in the simulated mortality rate as a function of fractions of rooms private, for different patient compositions in the separate panels (varying the fraction of the patient population that has dementia, π). Again, for all values of p and π considered, average mortality is lowest under the optimal assignment rule, followed by the random assignment rule, and finally segregated rooms. We also observe that differences in mortality rates across different assignment rules tend to be largest when the patient population is relatively mixed ($\pi \approx 0.5$) and most rooms are shared ($p \approx 0$): in this case, 90-day mortality rate is about 0.9 (respectively, 1.8) percentage points higher under random assignment (segregated rooms) compared to the survival-maximizing assignment rule.

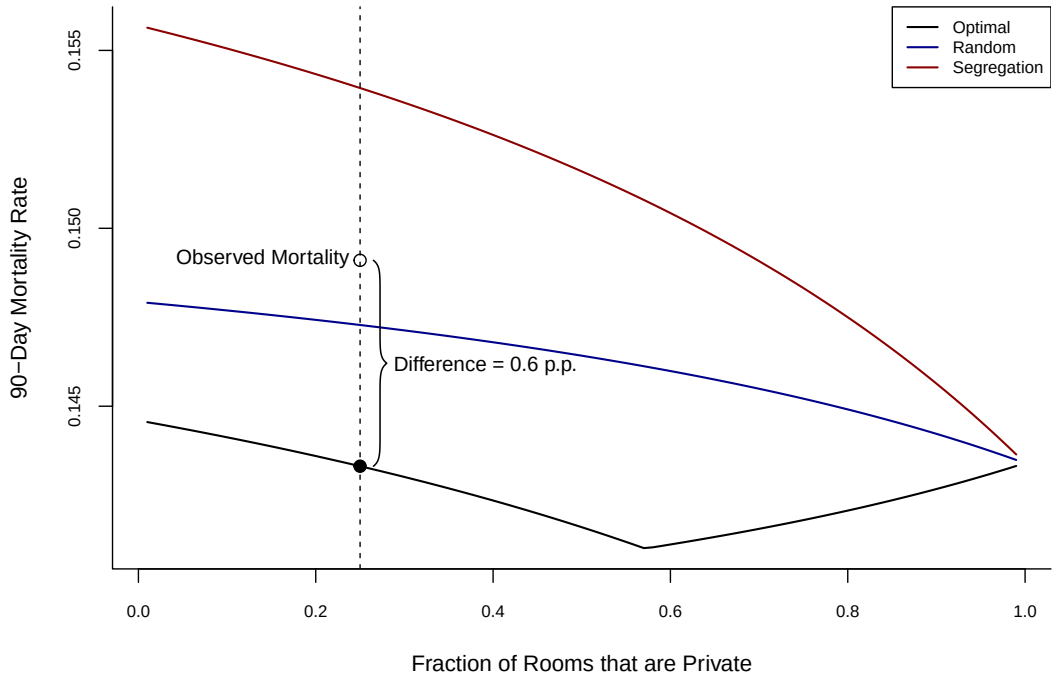
A concern with this room assignment policy is that it may potentially improve overall survival rates at the expense of a certain subgroup's outcomes. To test whether this is the

[16] 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:

$$0.006 \times 2,568,901/11 = 1,401.$$

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.

Figure 2: Simulated Mortality Under Different Assignment Rules



Notes: This 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 function of the fraction of rooms that are private. 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 2. The dashed vertical line reflects the empirically observed fraction of rooms that are private (25%), 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 25%).

case, Appendix Figure C.10 shows the simulated 90-day mortality rates under different assignment rules separately for patients with and without AD/ADRD. Panels (a) and (b) show that reductions in mortality under the optimal assignment rule relative to observed mortality rates is driven primarily by patients with AD/ADRD, while survival outcomes for patients without AD/ADRD are only slightly better than the status quo.

To explore potential tradeoffs between outcomes of patients with and without AD/ADRD in room assignment policies, Appendix Section C.2 considers a constrained room assignment problem that maximizes survival among patients with AD/ADRD subject to the constraint that survival among patients without AD/ADRD must be above a certain level. This allows us to trace out the survival frontier for these two groups of patients, which is shown in Appendix Figure C.11. In panel (a), we observe that under the observed share of patients with AD/ADRD and share of rooms private, there is no tradeoff between survival rates of the two groups, so the frontier is a singleton. Intuitively, this is because in this case, private rooms are all occupied by patients without AD/ADRD and mixing in shared rooms is not detrimental to the outcomes of these patients. By contrast, when a larger share of patients have AD/ADRD as shown in panels (b), (c), and (d), it is no longer possible to have maximal mixing in shared rooms while reserving all private rooms for patients without AD/ADRD, so the frontier is no longer a singleton. We observe that in these cases, the assignment rule that maximizes overall survival rates is on the point along the frontier that is most beneficial for patients with AD/ADRD, reflecting the fact that outcomes for these patients are more sensitive to room assignments.

4.4 Heterogeneity and Mechanisms

In this section, we consider heterogeneity along other dimensions of patient and facility characteristics, as well as several mechanisms that may drive the peer effects we estimate.

4.4.1 Heterogeneity within Facilities

Vaccination: While the results in Table 2 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 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.

4.4.2 Heterogeneity Between Facilities and the Scope for Patient Monitoring

As discussed above, one potential explanation for the large peer effects arise from patient monitoring by cognitively intact roommates. To explore this possibility further, we analyze effect sizes between nursing homes by staffing levels and the 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 3 compare residents in facilities with above- and below-median staffing levels, where staffing is defined as the sum of z-scores for RN, LPN, and CNA levels. Panel A compares outcomes between all patients, whereas panels B and C split the sample into residents with and without AD/ADRD. We find that positive externalities of cognitively intact residents on residents with AD/ADRD inside shared rooms 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. In contrast, the reduction amounts to only 2.2 percentage points in higher-staffed facilities. We also find that assigning a resident with AD/ADRD

to a private 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.

Interestingly, in lower-staffed facilities, cognitively healthy residents have a lower mortality rate when sharing a room with a resident with AD/ADRD compared to sharing a room with other cognitively intact residents. That said, cognitively healthy residents benefit even more from a private room, and our findings suggest that a private room is particularly valuable to cognitively intact residents in lower-staffed nursing homes.

Alzheimer's units: In columns 3 and 4 of Table 3, 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 AD/ADRD patients 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 residents with AD/ADRD inside shared rooms 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. In 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 a private room is detrimental to survival in facilities without Alzheimer's units. 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.

Table 3: Heterogeneity by Facility Characteristics

Panel A: All Patients

	Above-Median Staffing	Below-Median Staffing	Alzheimer's Unit	No Alzheimer's Unit
	(1)	(2)	(3)	(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	Below-Median Staffing	Alzheimer's Unit	No Alzheimer's Unit
	(1)	(2)	(3)	(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	Below-Median Staffing	Alzheimer's Unit	No Alzheimer's Unit
	(1)	(2)	(3)	(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.

4.4.3 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). 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 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 responses—because our instruments may correlate with the overall prevalence of AD/ADRD residents and with occupancy. We therefore interpret these specifications as suggestive evidence on beyond-room spillovers rather than as causal estimates of 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.

5 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.

Critically, we find substantial heterogeneity in these peer effects. Patients with AD/ADRD benefit from cognitively healthy roommates but not from private rooms, suggesting that peers provide important monitoring and support. In 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, our estimates reflect effects under current assignment practices; optimal assignment may generate different effect sizes through equilibrium effects on peer composition. Second, 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). Third, 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 based on cognitive and physical impairments of roommates. Fourth, the simple assignment policy considered in this paper is static (assigning all patients simultaneously), whereas in practice patients arrive and exit stochastically.

Future work will extend this analysis by developing a dynamic structural model to characterize optimal assignment policies accounting for the full distribution of patient characteristics, stochastic arrival patterns, and capacity constraints. Additionally, studying effects on falls, medication adherence, and staff response times using statistical methods to account for selection out would strengthen interpretation on mechanisms and guide implementation.

More broadly, our findings highlight that peer environments constitute a potentially important but understudied determinant of health outcomes in institutional settings. As policymakers seek to improve quality of care in nursing homes, hospitals, and other congregate care facilities, strategic peer assignment may offer meaningful gains at minimal cost.

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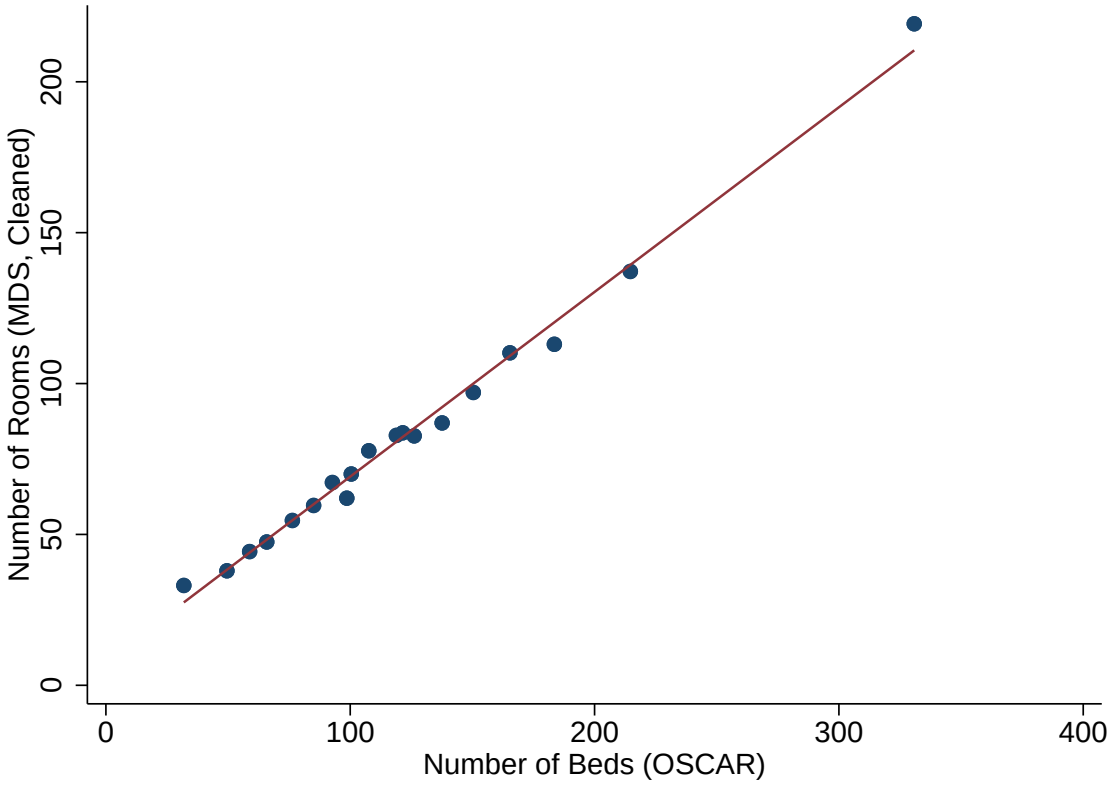
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A Appendix Figures and Tables

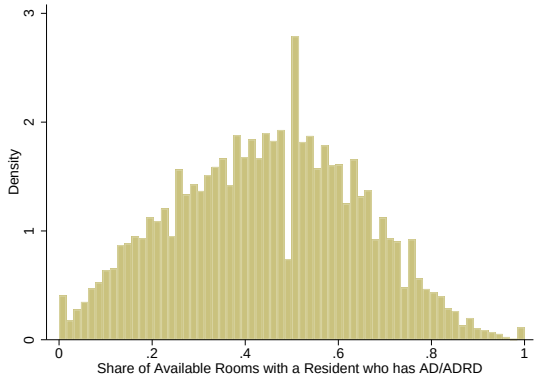
Figure A.1: Relationship Between Number of Rooms and Number of Beds



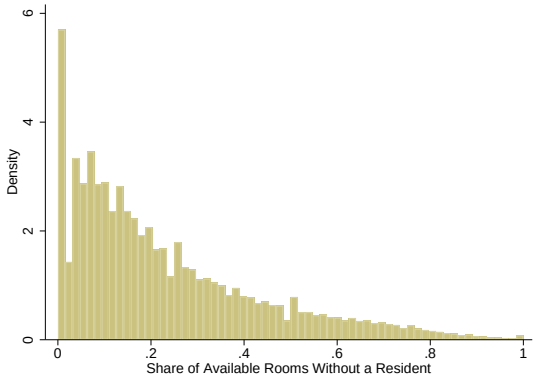
Notes: This figure plots the relationship between number of rooms in each nursing home each year based on the room identifier in the MDS data, and the number of beds in the same nursing-home-year according to the OSCAR data.

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

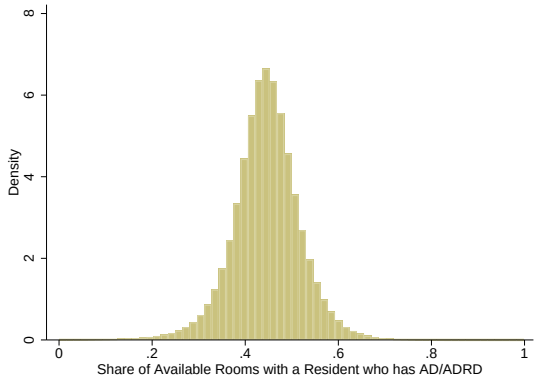
(a) Rooms with a Patient that has AD/ADRD



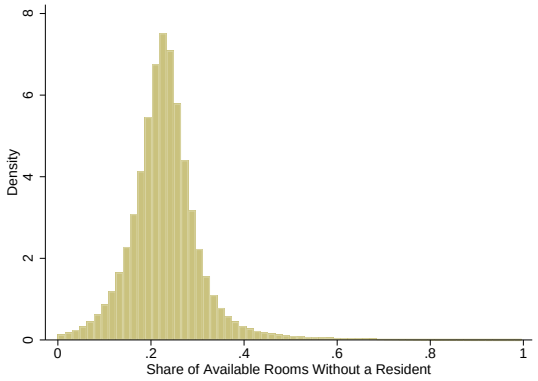
(b) Rooms Without a Patient



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



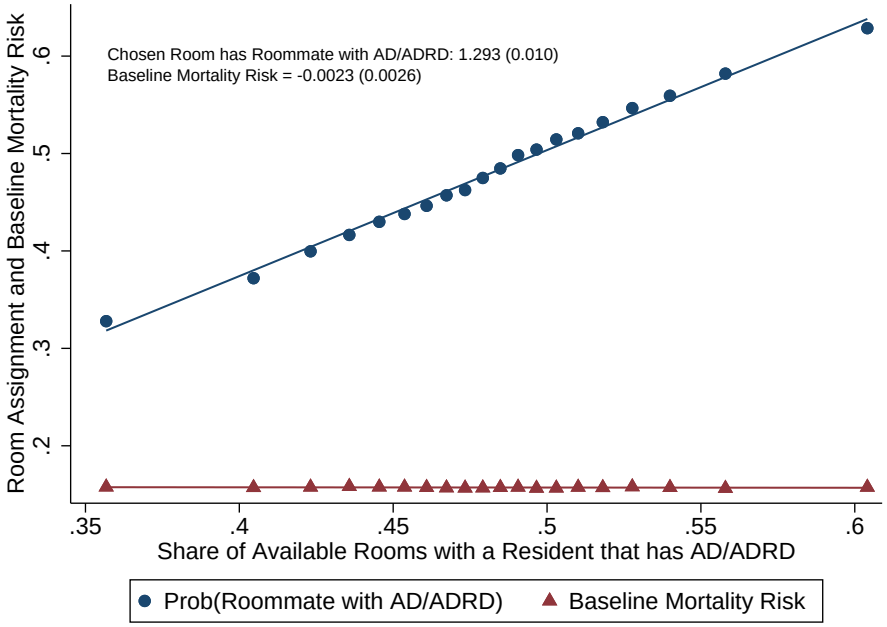
(d) Rooms Without a Patient (Residualized of Nursing-Home-by-Year Fixed Effects and Patient Composition)



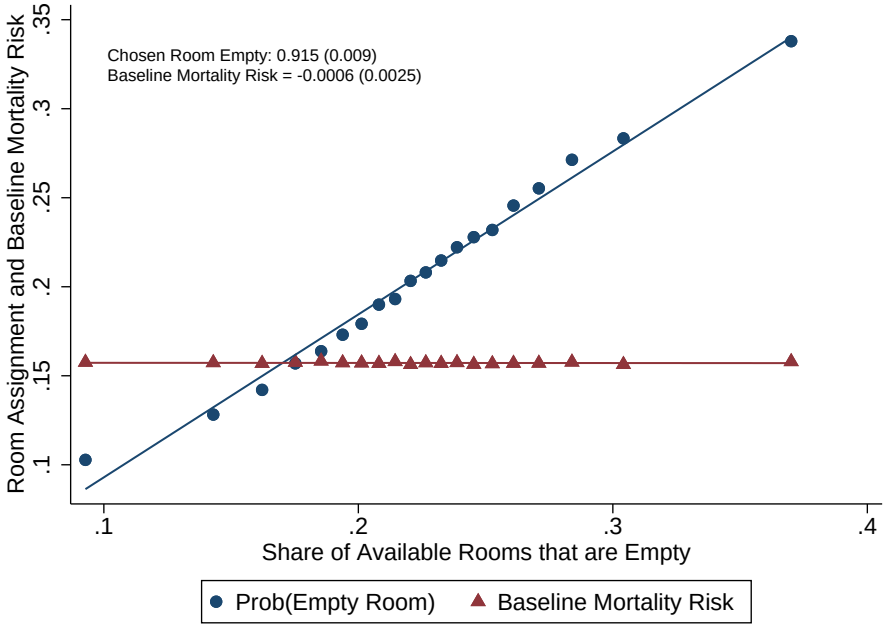
Notes: This figure plots histograms showing the distributions of our instruments – share of available rooms with a patient that has AD/ADRD and share of available rooms that are empty – both unconditionally in panels (a) and (b), and controlling for nursing-home-by-year fixed effects and short-run variation 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.

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

(a) Assignment to Roommate with AD/ADRD Diagnosis



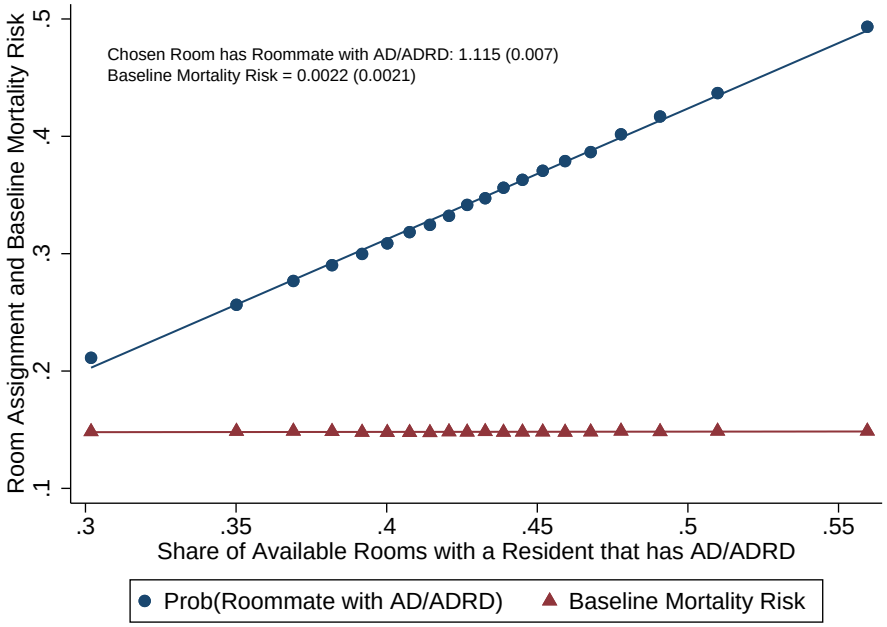
(b) Assignment to Room Without a Roommate



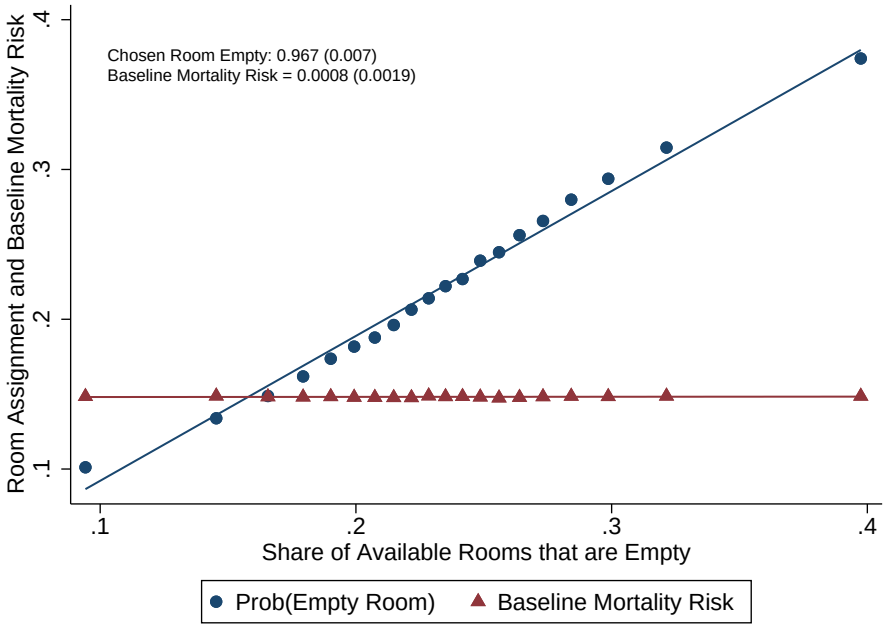
Notes: Panel (a) plots the probability for patients with AD/ADRD of being assigned a roommate with AD/ADRD and baseline mortality risk as a function of the share of available rooms with a patient that has AD/ADRD at the time of admission, controlling for the other instrument, nursing-home-by-year fixed effects and short-run variation in occupancy rates and patient composition at the time of admission. Panel (b) plots the probability 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

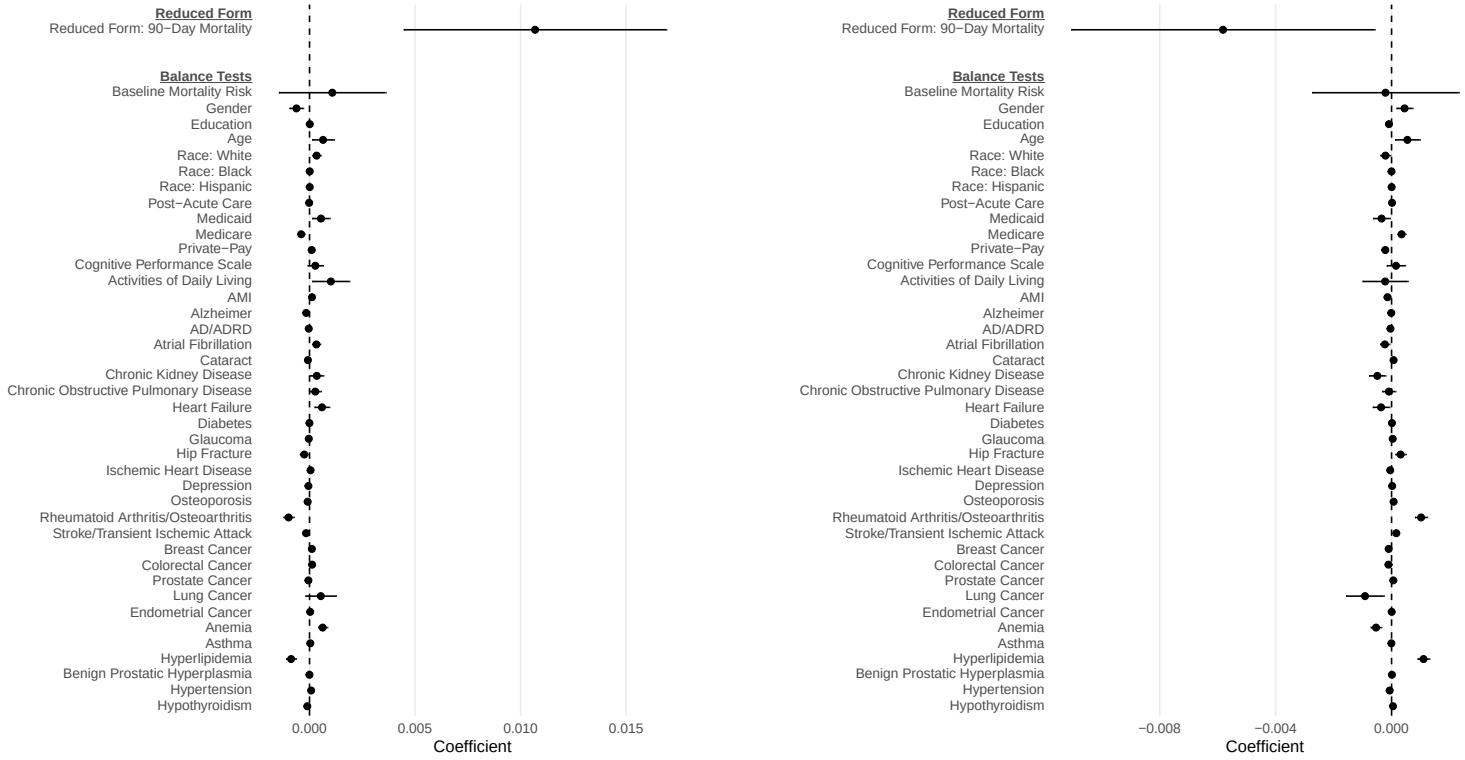


Notes: Panel (a) plots the probability for patients without AD/ADRD of being assigned a roommate with AD/ADRD and baseline mortality risk as a function of the share of available rooms with a patient that has AD/ADRD at the time of admission, controlling for the other instrument, nursing-home-by-year fixed effects and short-run variation in occupancy rates and patient composition at the time of admission. Panel (b) plots the probability 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

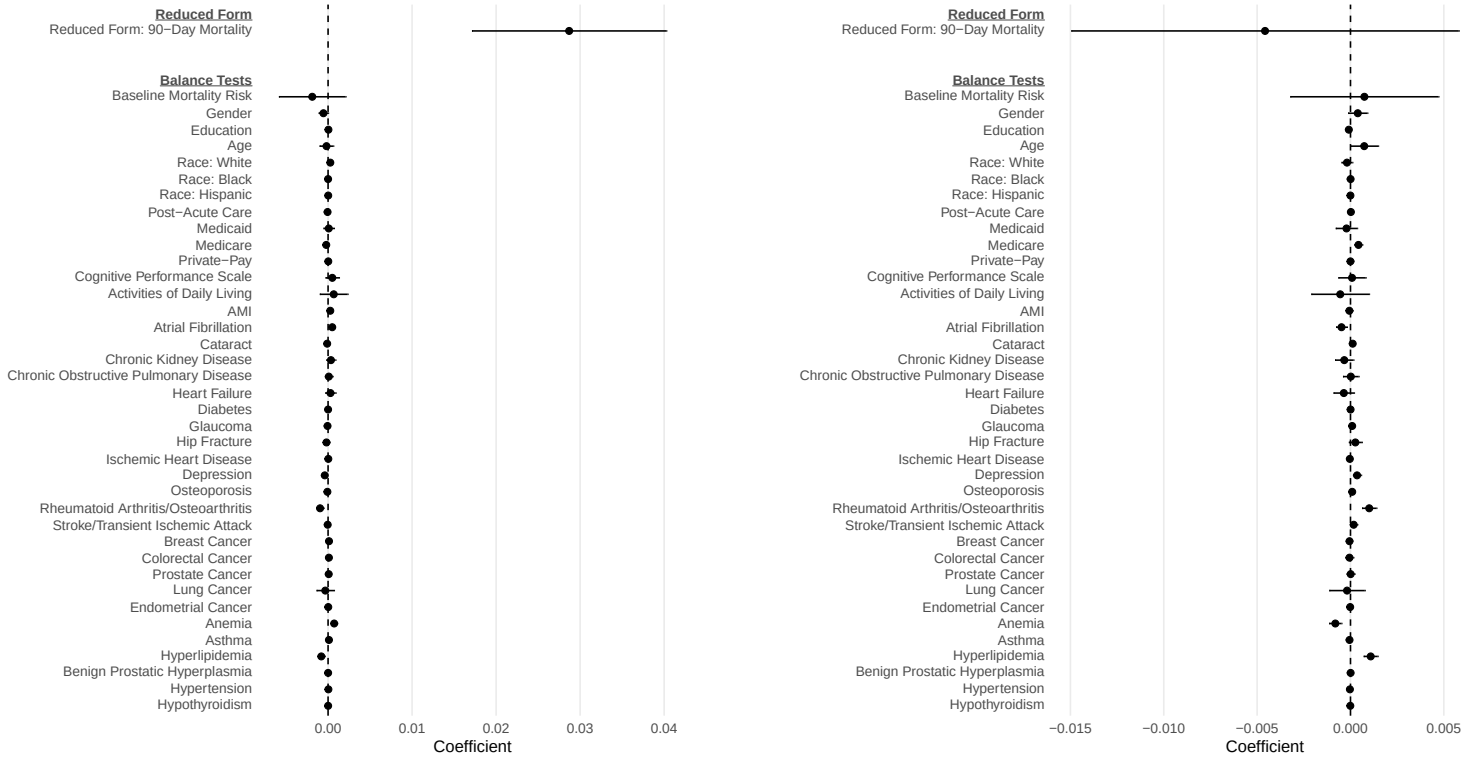


Notes: This figure provides evidence on the conditional independence/exclusion restriction assumption by comparing regression estimates of baseline characteristics on the instruments (from the second row onwards) with the reduced form estimate (of the outcome on the instrument) in the first row. Specifically, panel (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

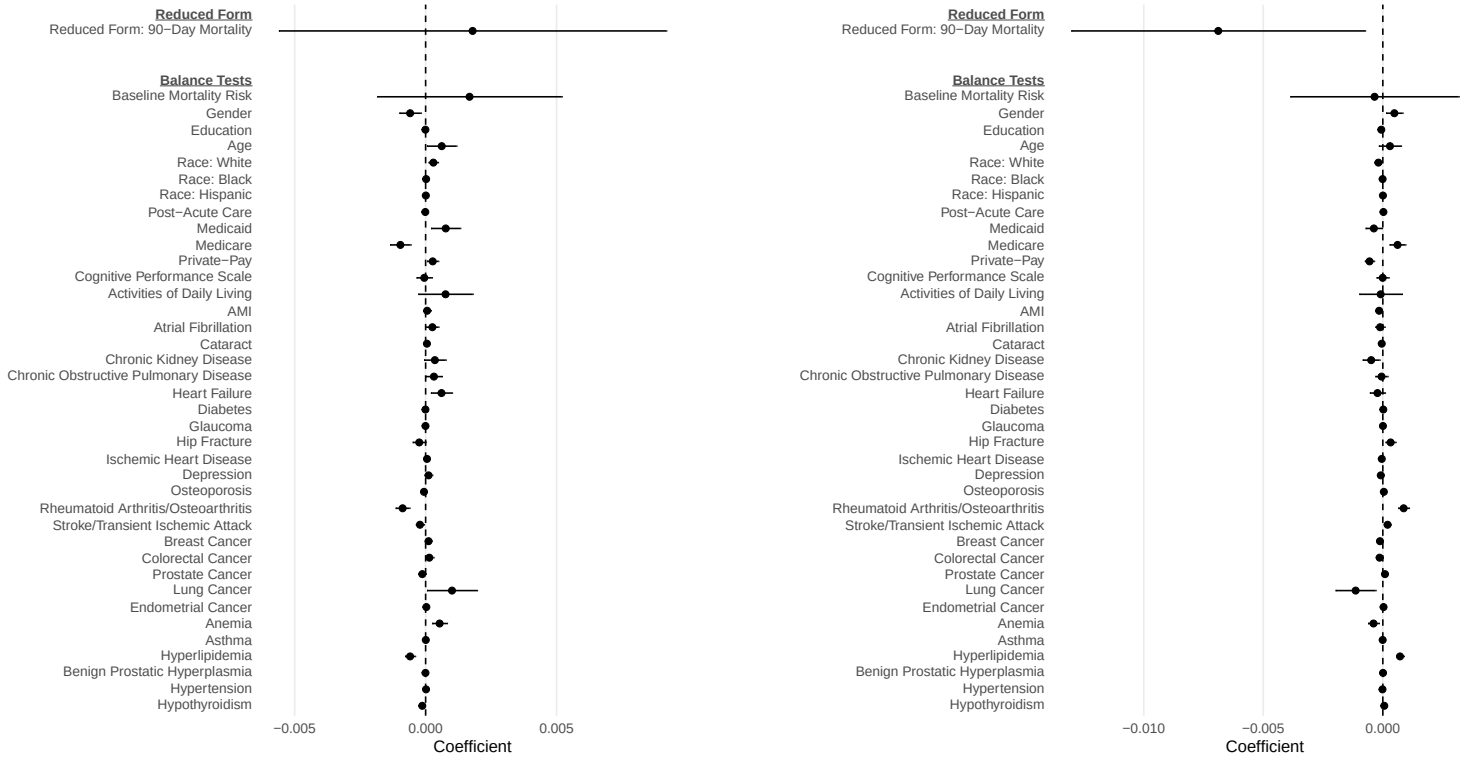


Notes: This figure provides evidence on the conditional independence/exclusion restriction assumption for patients with AD/ADRD by comparing regression estimates of baseline characteristics on the instruments (from the second row onwards) with the reduced form estimate (of the outcome on the instrument) in the first row. Specifically, panel (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

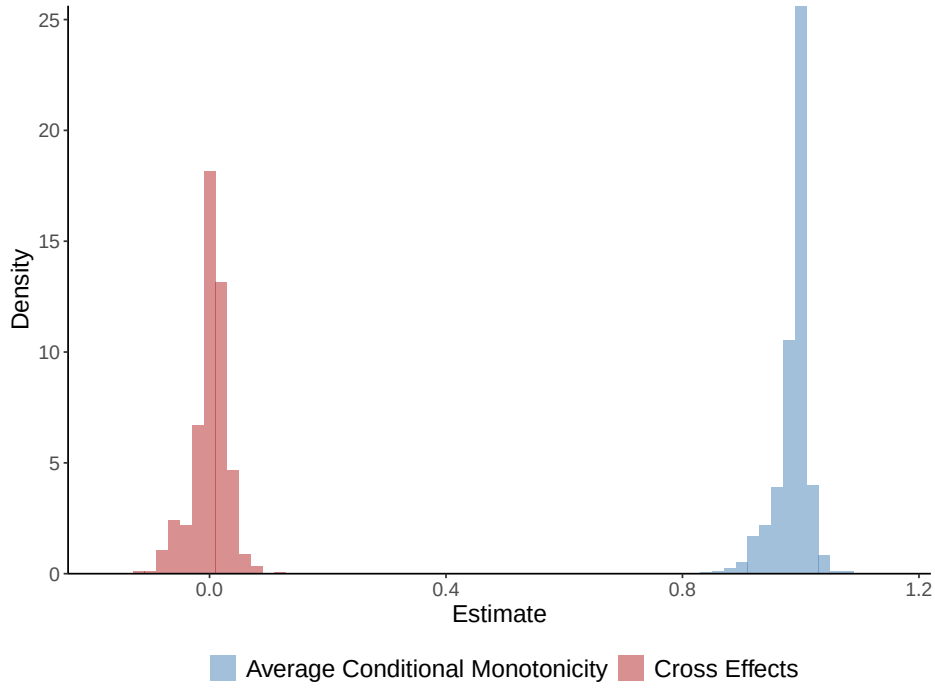
(b) Share of Available Rooms Without a Roommate



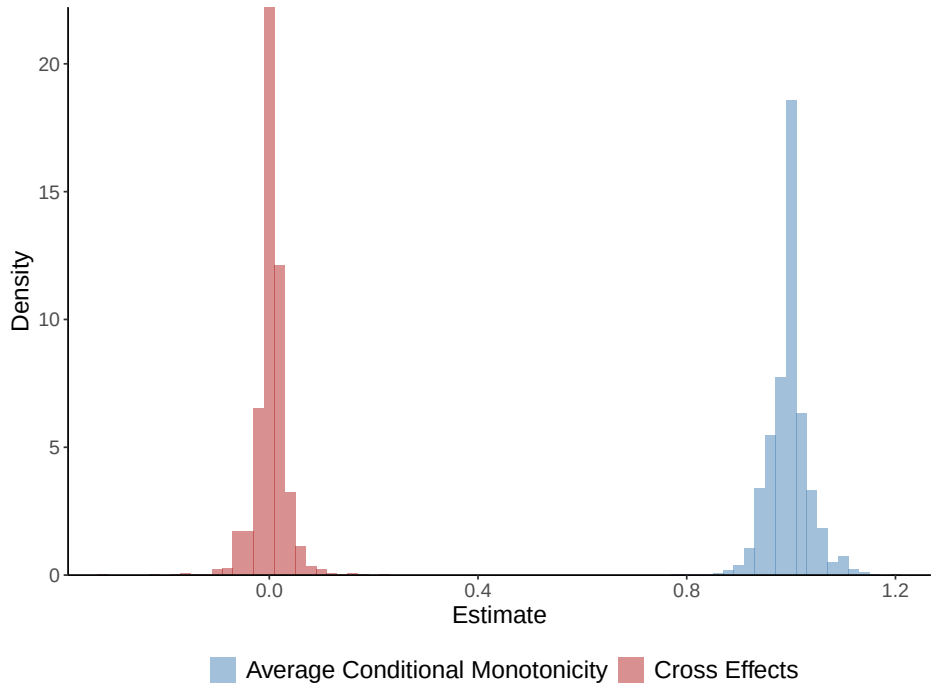
Notes: This figure provides evidence on the conditional independence/exclusion restriction assumption for patients without AD/ADRD by comparing regression estimates of baseline characteristics on the instruments (from the second row onwards) with the reduced form estimate (of the outcome on the instrument) in the first row. Specifically, panel (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

(a) Empty as the Dependent Variable



(b) AD as the Dependent Variable



Notes: These figures show histograms of coefficient estimates from regressions of Empty and AD on both p^{Empty} and p^{AD} 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 Empty and the dependent variable in panel (b) is AD. 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 3,300 different subsamples. The blue bars (respectively, red bars) correspond to estimates on the transformed instrument that matches (does not match) the dependent variable.

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 $\leq$ 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 $\leq$ 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.

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
Controls for Capacity Strain		X	X	X	X	X
Controls for Patient Composition		X	X	X	X	X
County × Year × Month FE			X	X	X	X
Day of Week FE				X	X	X
Room FE					X	X
Controls for Baseline 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
Controls for Capacity Strain		X	X	X	X	X
Controls for Patient Composition		X	X	X	X	X
County × Year × Month FE			X	X	X	X
Day of Week FE				X	X	X
Room FE					X	X
Controls for Baseline 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
Controls for Capacity Strain		X	X	X	X	X
Controls for Patient Composition		X	X	X	X	X
County × Year × Month FE			X	X	X	X
Day of Week FE				X	X	X
Room FE					X	X
Controls for Baseline 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: Controls for baseline characteristics 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.

Table A.3: OLS Estimates with Additional 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
Controls for Capacity Strain		X	X	X	X	X
Controls for Patient Composition		X	X	X	X	X
County × Year × Month FE			X	X	X	X
Day of Week FE				X	X	X
Room FE					X	X
Controls for Baseline 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
Controls for Capacity Strain		X	X	X	X	X
Controls for Patient Composition		X	X	X	X	X
County × Year × Month FE			X	X	X	X
Day of Week FE				X	X	X
Room FE					X	X
Controls for Baseline 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
Controls for Capacity Strain		X	X	X	X	X
Controls for Patient Composition		X	X	X	X	X
County × Year × Month FE			X	X	X	X
Day of Week FE				X	X	X
Room FE					X	X
Controls for Baseline 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: Controls for baseline characteristics 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.

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.

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.

Table A.6: Heterogeneity by Vaccination Status

	Flu Vaccine	No Flu Vaccine	PPV Vaccine	No PPV Vaccine
	(1)	(2)	(3)	(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.

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≥3	CPS<3
	(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.

B 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.[17]

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.[18]

Missing Discharge Dates. Some patient stays are missing discharge assessments (which nursing homes are required to fill in when patients leave the facility, be it due to discharge to hospital/community or due to death). In particular, no further assessments are recorded for a patient for a given 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.[19] 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 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 private 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.

[17] 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 $y(t)$.

[18] Results available from authors upon request.

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

C Optimal Room Assignment

C.1 Basic Model for Optimal Assignment Rule

In this section, 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). We will then quantify the importance of room assignment for mortality, by comparing counterfactual mortality under this optimal assignment rule relative to alternative assignment rules.

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 has a capacity of two. In addition, for simplicity assume that the total capacity C of the nursing home is equal to the number of patients: $C = N$. Assuming that N is large so we can ignore integer constraints, this implies that:

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

Note that if instead total capacity exceeds the number of patients (holding π and p constant), the extra degrees of freedom means that optimal assignment will generally be even more effective.

Denote the different types of room assignment — to a private room, a shared room with a roommate who has AD/ADRD, and a shared room with a roommate who does not have AD/ADRD — by $r \in \{0, AD, noAD\}$. We denote (average) potential outcomes for each type by:

$$Y_k(r) \equiv Pr\left(\text{Death Within 90 Days} | \text{Type} = k, \text{Assigned to Room of Type } r\right),$$

and let $u_{kr} \equiv 1 - Y_k(r)$ for convenience. 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:

$$\begin{aligned}
\max_{\substack{x_{priv}^{AD},\, x_{priv}^{noAD},\, x_{share}^{AD,AD},\\ x_{share}^{noAD,noAD},\, x_{share}^{AD,noAD}}} \quad V = \quad & \underbrace{x_{priv}^{AD} u_{priv}^{AD}}_{\text{AD in Private Rooms}} + \overbrace{x_{priv}^{noAD} u_{priv}^{noAD}}^{\text{No AD in Private Rooms}} \\
& + \underbrace{2x_{share}^{AD,AD} u_{share}^{AD,AD}}_{\text{Shared: (noAD,noAD)}} + \overbrace{2x_{share}^{noAD,noAD} u_{share}^{noAD,noAD}}^{\text{Shared: (noAD, noAD)}} + \underbrace{x_{share}^{AD,noAD}\left(u_{share}^{AD,noAD} + u_{share}^{noAD,AD}\right)}_{\text{Shared: (AD,noAD)}}, \\
\text{s.t.} \quad & x_{priv}^{AD} \geq 0, x_{priv}^{noAD} \geq 0, x_{share}^{AD,AD}, x_{share}^{noAD,noAD} \geq 0, x_{share}^{AD,noAD} \geq 0, \text{ (Non-Negativity)} \\
& x_{priv}^{AD} + x_{priv}^{noAD} = pR, \text{ (Balance for private rooms)} \\
& x_{share}^{AD,AD} + x_{share}^{noAD,noAD} + x_{share}^{AD,noAD} = (1-p)R, \text{ (Balance for shared rooms)} \\
& x_{priv}^{AD} + 2x_{share}^{AD,AD} + x_{share}^{AD,noAD} = \pi N, \text{ (Balance for Patients with AD)} \\
& x_{priv}^{noAD} + 2x_{share}^{noAD,noAD} + x_{share}^{AD,noAD} = (1-\pi)N, \text{ (Balance for Patients without AD)}
\end{aligned}$$

where the second and third lines of the constraints ensures 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:

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

where:

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

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 is almost identical to the expression defining supermodularity or submodularity (between patients with and without AD/ADRD in shared rooms), with negative values of θ corresponding to supermodularity, and positive values corresponding to submodularity.

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.

First, in the supermodular case ($\theta \leq 0$), homogeneous rooms is more efficient than mixed rooms, so we set $x_{share}^{AD,noAD} = 0$. In addition, we 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 $x_{priv}^{AD,*} = L$.

On the other hand in the submodular case ($\theta > 0$), mixed rooms is more efficient than homogeneous rooms. Hence, we want to maximize the number of shared rooms, except when the difference in privacy premium outweighs the gains from mixing ($|\psi| > \theta$), in which case we may want to 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 $x_{share}^{AD,noAD,*} = s_{max}(x_{priv}^{AD,*})$.

C.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.

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

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

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

We can write the constrained assignment problem as:

$$\max_{\substack{x^{AD}_{priv}, x^{noAD}_{priv}, x^{AD,AD}_{share}, \\ x^{noAD,noAD}_{share}, x^{AD,noAD}_{share}}} \bar{u}_{AD}$$

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

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^g and θ^g are the privacy premium and gains from mixing respectively for a patient from group g.

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:

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

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

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

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

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

$$(x_{priv}^{AD,\hat{AD}}, x_{share}^{AD,noAD,\hat{AD}})$$

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:

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

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:

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

where

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

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

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

with a kink at

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

which divides the upper boundary into two segments, as long as $x_{bal} \in [L, U]$.[20]

On the first segment, we have:

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

which implies

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

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:

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

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

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:

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

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

C.3 Comparison of Counterfactual Mortality Under Different Assignment Rules

To quantify potential gains from optimal assignment, we compare our optimal assignment rules to two other assignment rules: random assignment and perfect segregation.

Under random assignment, the fraction of patients of each type assigned to private rooms is equal to the fraction of total beds that are private:

$$\frac{x_{priv}^{AD}}{\pi N} = \frac{x_{priv}^{noAD}}{(1-\pi)N} = \frac{p}{p + 2(1-p)}.$$

In addition, the fraction of shared rooms with two patients with (without) AD/ADRD is π^2 (respectively $(1-\pi)^2$), and the fraction of shared rooms that are mixed is $2\pi(1-\pi)$. Under counterfactual assignment with perfect segregation, we assume that private rooms are randomly assigned, but a fraction π of shared rooms have two patients with AD/ADRD and the remaining shared rooms have two patients without AD/ADRD.

Figure C.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. Figure C.10 shows simulated 90-day mortality under the same assignment rules and parameters as Figure C.9, but separately for patients with AD/ADRD and patients without AD/ADRD. Average potential outcomes for different patient types under different room assignments $Y_k(r)$ are based on estimates in Table 2.

We observe that different assignment rules can lead to quantitatively meaningful differences in mortality: in particular, Figure C.9 shows that under the observed values of π and p in the population ($\pi = 0.3, p = 0.25$), 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 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 C.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 slightly higher but almost identical to simulated mortality for this group under the optimal assignment rule.

In addition, we observe several qualitative patterns. First, the difference 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 C.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 C.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 is 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.

To further explore potential tradeoffs between outcomes of patients with and without AD/ADRD in room assignment policies, Figure C.11 plots the survival frontier for these two types of patients, and compares it to various other room assignment policies. Each subfigure corresponds to a different fraction of patients having AD/ADRD, and the share of rooms that are private is assumed to be 25% (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 mortality rates for the two groups when the fraction of patients having AD/ADRD matches the fraction in the data ($\pi = 0.3$).

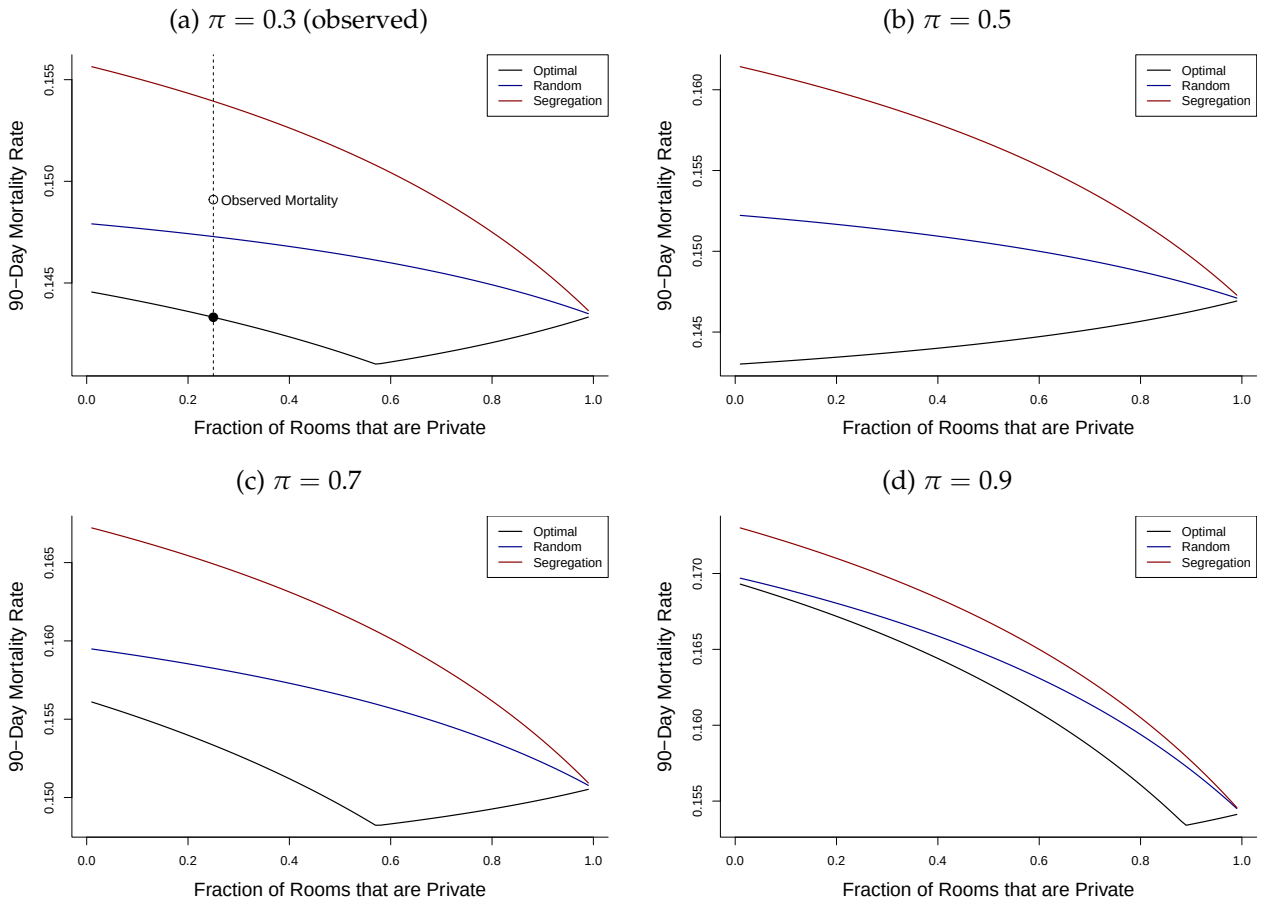
Panel (a) of Figure C.11 shows that for the empirically observed values of share of patients with AD/ADRD (π) and share of rooms private (p), there is essentially no tradeoff between the survival of patients with and without AD/ADRD. with the survival frontier collapsing down onto the green circle. This is because when π and p are small, one can as-

sign 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. Consistent with Figures C.10, observed survival is far lower than the optimal assignment rule for patients with AD/ADRD but only slightly lower for patients without AD/ADRD.

Panels (b), (c), and (d) of Figure C.11 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 reducing the number of these patients assigned to mixed shared rooms and assigning them instead to private rooms. However, this comes at a steep cost for patients with AD/ADRD, given that some shared rooms will then be occupied by two patients with AD/ADRD, which is not only the worst outcome for them but also one of the largest room effects we estimate in terms of magnitude. 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).

Finally, we observe in all panels of Figure C.11 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 $p = 0.25$ (a result seen earlier in Figure C.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.

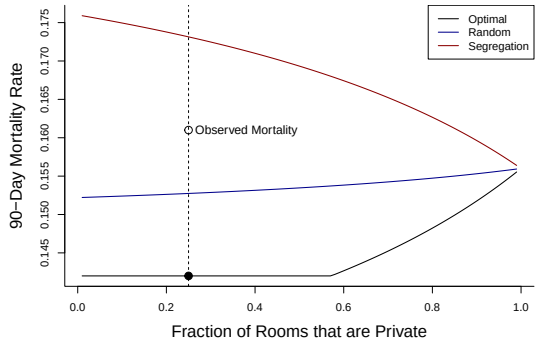
Figure C.9: Simulated Mortality Under Different Assignment Rules (for Different Shares of Residents with AD/ADRD)



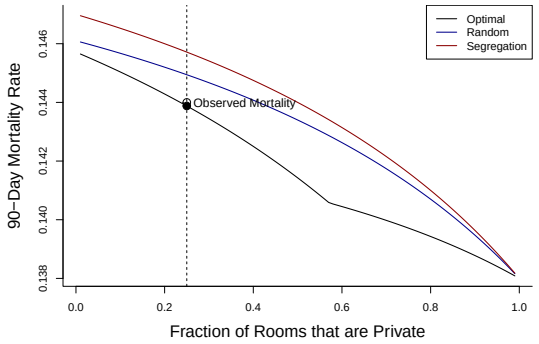
Notes: This black, blue, and red lines in this figure plot the simulated 90-day mortality rate under the mortality-minimizing (optimal) assignment rule, random assignment rule, and segregated assignment rule respectively, as function of the fraction of rooms that are private. The different panels represent 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 2.

Figure C.10: Simulated Mortality Under Different Assignment Rules for Different Groups (for Different Shares of Residents with AD/ADRD)

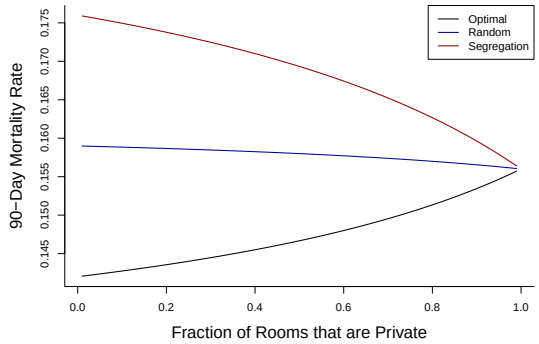
(a) ADRD, $\pi = 0.3$ (observed)



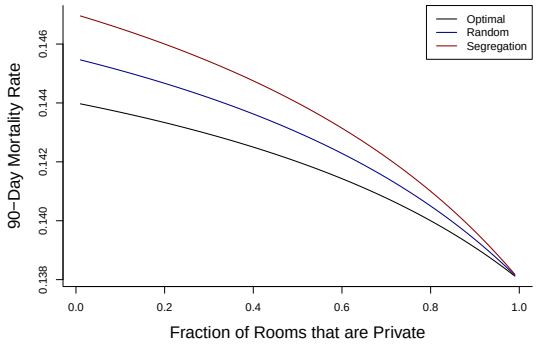
(b) No ADRD, $\pi = 0.3$ (observed)



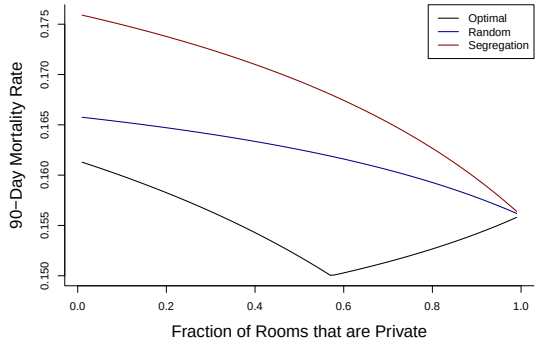
(c) ADRD, $\pi = 0.5$



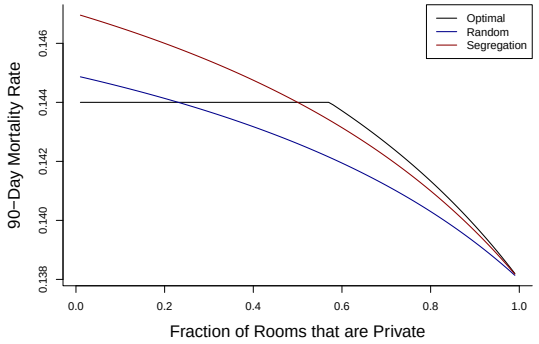
(d) No ADRD, $\pi = 0.5$



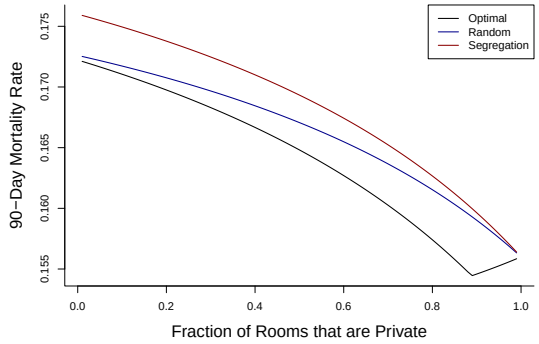
(e) ADRD, $\pi = 0.7$



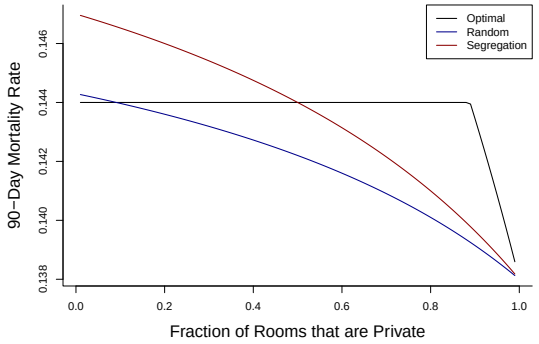
(f) No ADRD, $\pi = 0.7$



(g) ADRD, $\pi = 0.9$

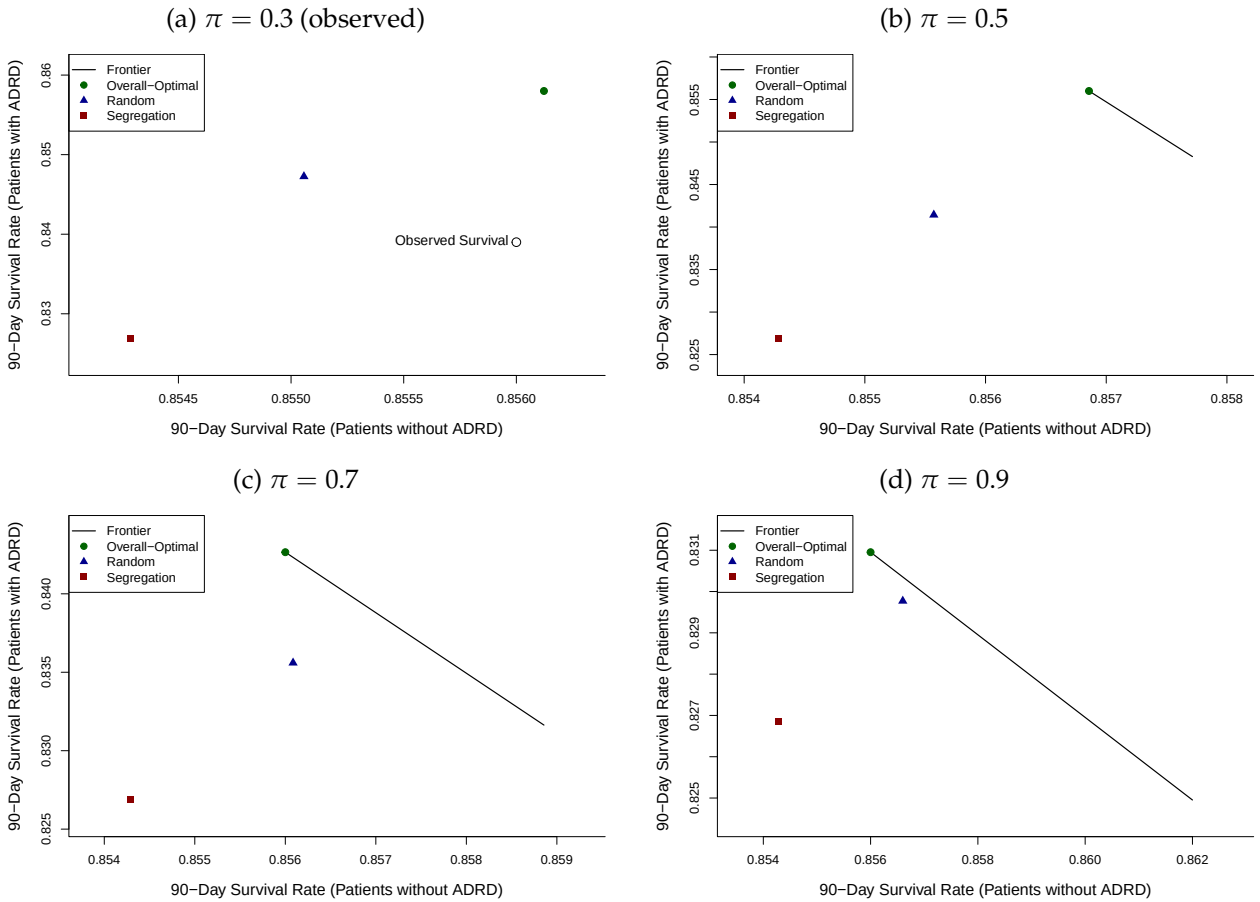


(h) No ADRD, $\pi = 0.9$



Notes: This 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 function of the fraction of rooms that are private. 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 2.

Figure C.11: Survival Frontier for Patients with and without AD/ADRD (25% of Rooms Private, for Different Shares of Residents with AD/ADRD)



Notes: The line in each of these figures show the maximum achievable pairs of survival rates for patients with AD/ADRD and for patients without AD/ADRD (i.e., the survival frontier). The fraction of rooms that are private is assumed to be 25% (the observed fraction in the data), 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 2. The survival rates for these two groups under assignment that minimizes overall mortality (respectively, the random assignment rule and segregated assignment rule) is shown using a green point (blue triangle and red square).

D 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 unobservables 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 specfication, 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 D.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 reproduces our treatment effect estimates with nursing home-by-year fixed effects or with a much richer set of fixed effects and controls for reference. 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 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 several estimates the addition of controls strengthens our results, suggesting that violations of the conditional independence assumption may 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 D.12 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 D.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 have to be about 20 times more important than selection on observables in order to explain the positive IV estimate.

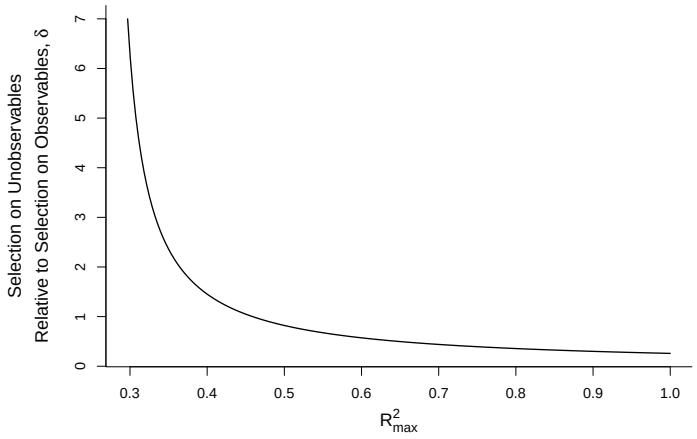
Table D.8: IV bounds Under Potential Violations of Conditional Independence

	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]

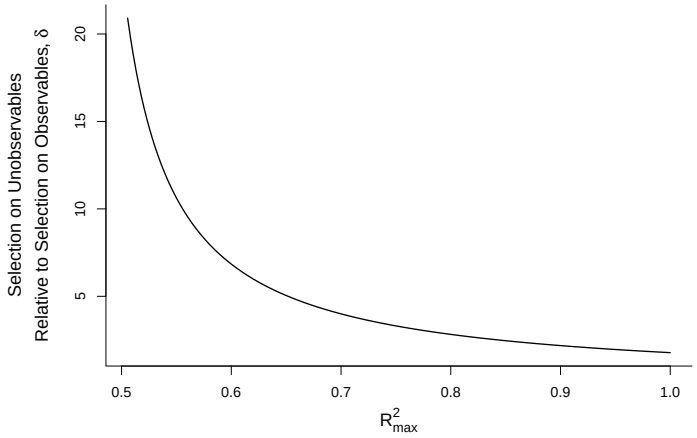
Notes: This table shows bounds for the treatment effect estimates allowing for different amounts of selection on unobservables relative to observables. Columns (1) and (2) report the baseline and controlled estimates, respectively. Columns (3) and (4) show bounds under alternative assumptions about the amount of variation in the outcome that can be explained by instruments, observed controls, and unobserved controls, as well as the maximum R^2 attributable to unobserved controls to explain all of the variation in the outcome.

Figure D.12: Values of R^2_{max} and δ Required to Explain Treatment Effect Estimates

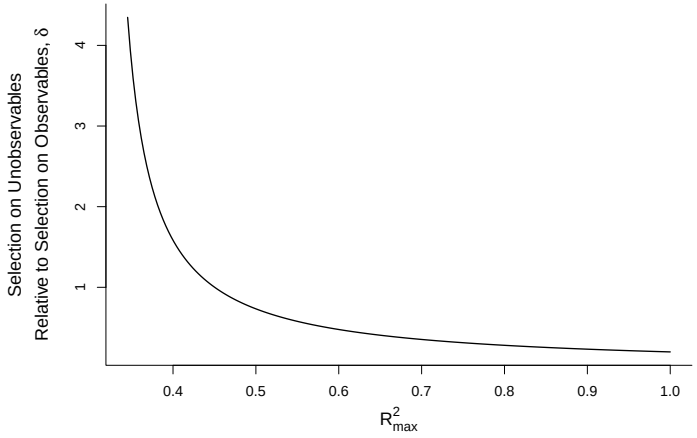
(a) Full Sample: Effect of Being Assigned Roommate with ADRD



(b) ADRD Sample: Effect of Being Assigned Roommate with ADRD



(c) Non-ADRD Sample: Effect of Being Assigned to an Empty Room



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 an empty room for patients without AD/ADRD.