Patient Peer Effects: Evidence from Nursing Home Room Assignments*

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Abstract

We provide causal evidence on patient peer effects in inpatient care using data from U.S. nursing homes. Drawing on administrative records covering 2.6 million stays (2000–2010) from the Minimum Data Set linked to Medicare claims, we exploit plausibly exogenous roommate assignments identified through unique room identifiers. Our instrumental variables approach addresses reflection and selection concerns, showing that roommate health significantly impacts 90-day mortality. The estimated peer effects are large—equivalent to 0.6-0.8 standard deviations in facility-level value-added differences. We document patient substitutability in health production: healthier patients experience smaller health gains when paired with healthier roommates. Room type (private versus shared) and patient health interact in production, acting as complements or substitutes depending on peer health. Our peer effect estimates imply meaningful differences in aggregate health outcomes under different counterfactual room assignment policies.

*We thank Yiqun Chen, Chris Cronin, Ashvin Gandhi, Devin Pope, and Tamara Konetzka for helpful comments and suggestions

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1 Introduction

One of the central objects of inquiry in health economics and health care delivery is the production of health (Grossman, 1972). Efficient care delivery requires understanding how key inputs—patients, health care professionals, capital, and technology—combine to shape health outcomes. Seminal contributions have thus studied the extent of substitutability and complementarities between capital/technology and health care professionals (Pauly, 1980; Jensen and Morrisey, 1986; Acemoglu and Finkelstein, 2008; Chandra and Staiger, 2020), technology and organizational practices (Dranove et al., 2014), and health care occupations (Reinhardt, 1972; Brown, 1988; McGrath et al., 2000), as well as match effects between patients and providers (Alsan, Garrick, and Graziani, 2019a). Yet, despite this progress, we know remarkably little about how patients themselves interact as inputs in the production of health. While it is well established that communicable diseases spread through contact between patients and caregivers, the potential for non-communicable patient spillovers—where one patient's health, behavior, or recovery influences another's—remains largely unexplored. Understanding these interactions is crucial, as they shape treatment effectiveness, recovery trajectories, and the efficiency of resource allocation within care facilities.

This paper provides some of the first empirical evidence on patient peer effects in shared inpatient care rooms, documenting interpersonal spillovers that extend beyond the transmission of infectious disease and highlighting a previously overlooked dimension of the health production process. We construct a novel database with high-frequency patient-to-room assignments and exploit plausibly exogenous roommate assignment to quantify the causal effect of peer effects on patient health. Using administrative data on millions of patient stays, we quantify the causal effects of peer health on patient health and quantify the substitutability and complementarities of patient and peer health as well as patient health and room accommodation (shared vs. private room) in health care production. Finally, we explore counterfactual room-assignment policies that incorporate these peer and room-type interactions.

We study these questions in the context of the U.S. nursing home industry. Nursing facilities care for nearly 1.2 million Americans and account for almost 1% of GDP (Chidambaram et al., 2024). Demographic shifts, including declining fertility, rising child-

lessness, and increased geographic dispersion of families, have weakened informal caregiving networks and accelerated demand for formal long-term care (LTC). This demand is especially acute among individuals with Alzheimer's disease and related dementias (AD/ADRD), who constitute a rapidly growing share of the LTC population. Between 2017 and 2019, more than 3 million U.S. nursing home residents were diagnosed with AD/ADRD or cognitive impairment (Mukamel et al., 2023), a number projected to rise sharply with continued population aging. Understanding the drivers of cognitive decline and identifying scalable, non-pharmacologic interventions within institutional settings is thus central to improving patient outcomes, containing public costs, and advancing dementia care.

Peer interactions are a natural but understudied mechanism in this setting. Many residents share rooms and spend extended time in close proximity, yet the health consequences of these roommate dynamics remain largely unexplored. For residents with limited family involvement or external supports, roommates may provide critical sources of cognitive and emotional stimulation. At the same time, residents and their families often prefer single rooms to safeguard privacy, autonomy, and personalized care (Herr, Lückemann, and Reichert, 2025). This tension is particularly salient for AD/ADRD patients, for whom some facilities provide special care units. However, while a substantial portion of nursing home residents are diagnosed with AD/ADRD, fewer than 5% of nursing home beds are in such units (Gaugler et al., 2022). Motivated by these facts, we investigate peer effects among nursing home roommates, focusing on how residents' outcomes vary with the presence of a roommate, and whether the resident and their roommate has AD/ADRD.

Our empirical analysis yields four main findings. First, we find that patient peer effects are quantitatively large and result in substantial variation in risk-adjusted patient outcomes within providers, conditional on aggregate provider labor and capital inputs. Second, we find evidence of patient substitutability in health production, whereby the presence of a healthier roommate is associated with weaker individual health gains for healthier patients. Third, we find that sharing a rooms and patient health can be substitutes or complements in health production, depending on peer health. Fourth, we find that counterfactual room-assignment policies imply meaningful shifts in aggregate health outcomes once peer and room-type interactions are accounted for.

To reach these conclusions, we leverage administrative records covering millions of nursing home stays from 2000–2010, combining the Minimum Data Set (MDS) with linked Medicare claims. The MDS provides detailed admission-to-discharge assessments for the near-universe of U.S. nursing home residents. A unique feature of these data is the presence of a room identifier, which enables us to observe patient-to-room assignments. To our knowledge, we are among the first to exploit this identifier for research, and we present extensive validation evidence to support its use. Specifically, we document a high correlation in roommate gender within rooms, conditional on nursing home and year fixed effects, and show that the number of distinct rooms is consistently smaller than the number of beds—both patterns consistent with the identifier capturing true room assignments. While we devote substantial effort to cleaning the variable and refining the analytic sample, some measurement error likely remains. Importantly, such error would bias against detecting peer effects, suggesting that our estimates understate their full magnitude.

Using this identifier, we classify residents into three room arrangements: (i) empty rooms, (ii) rooms shared with at least one resident diagnosed with AD/ADRD, and (iii) rooms shared with residents not diagnosed with AD/ADRD. Empty rooms include both single-bed rooms and temporarily vacant multi-bed rooms; we assess differences between these cases in supplemental analyses. Comparing outcomes across empty versus shared rooms provides new evidence on the role of privacy in patient health and contributes to ongoing policy debates over mandates for single-room provision in several countries. Comparisons across shared rooms, in turn, isolate the role of peer composition and speak directly to our central question of patient peer effects.

To establish a causal relationship between patient peers' health and patient outcomes, we need to address three empirical challenges.

The first is the so-called reflection problem when two roommates A and B affect each other simultaneously (Manski, 1993), making it difficult to separate out the actual causal effect that A's health has on B's health. To address this challenge, we take advantage of the panel data structure and measure the roommates (A's) predetermined health, measured at the time of B's admission.

The second challenge concerns the endogenous assignment of new patients to rooms by demographics or health. To address the selection into rooms, we adopt an instrumental

variables approach using high-frequency variation in room-specific occupancy. Intuitively, if all rooms with a vacant bed are empty on the day of admission, then any newly admitted resident will be assigned to an empty room. Likewise, if all rooms with a vacant bed are shared with an already admitted resident with AD/ADRD, then the probability that a newly admitted resident is matched with a roommate with AD/ADRD is one. Conversely, if all rooms with residents with AD/ADRD are already fully occupied, then this probability drops to zero. Our identifying assumption is that, conditional on year-by-facility fixed effects, this day-to-day variation in occupancy is orthogonal to unobserved health of new admissions. We provide extensive balancing tests across a broad set of predetermined outcomes to support this claim. While some differences remain statistically significant given our large sample size, they are quantitatively negligible and point in opposite directions across key outcomes—if anything biasing us against finding peer effects.

The last challenge concerns the endogenous selection out of nursing homes determined by upstream discharges (e.g. hospital discharges), downstream discharges (e.g. returning back to the community), or mortality. This is potentially concerning because the MDS only collects data for nursing home residents and not post discharge. To address this limitation, we focus our analysis on outcomes that we can measured independently of nursing home residence. Specifically, our main outcome measure is the 90-day (since admission) mortality rate, measured in Medicare claims data. The claims data report mortality dates for all elderly individuals and are thus not affected by censoring problems related to nursing home discharges.

Our primary sample considers first stays of nursing home residents in 12 large states between 2000-2010, providing more than 2.6 million observations. We estimate the effect of being assigned to an empty room or a room shared with a roommate diagnosed with AD/ADRD using TSLS, using the share of empty rooms and share of available rooms co-shared with roommates diagnosed with AD/ADRD in the nursing home at the time of admission as instrumental variables.

Our instruments are highly predictive of room assignment, with first stage F-statistics in the tens of thousands. In addition, we find that room availability at the time of admission is not systematically related with baseline health and demographic characteristics of residents, supporting the notion that the instruments are as-good-as-randomly assigned.

Our IV estimates indicate that being assigned to a room without a roommate reduces 90-day mortality by 0.8 percentage points (5.2%) on average, relative to being assigned to roommates without an AD/ADRD diagnosis. In addition, being assigned a roommate with AD/ADRD increases 90-day mortality relative to being assigned roommates without an AD/ADRD by 1.3 percentage points (8.4 %). For comparison, Cheng (2023) estimates differences in value-added to 90-day mortality between nursing homes in California and finds a standard deviation of 2 percentage points. This means that the effect of moving from an empty room to one shared with a resident diagnosed with AD/ADRD has a quantitatively similar effect on 90-day mortality (+2.1 percentage points), to switching to a nursing home with one standard deviation lower value-added. By contrast, OLS estimates have the opposite sign, suggesting that room assignment is correlated with unobservable determinants of health and highlighting the value of our IV strategy for identifying causal effects.

To assess whether patient health and peer health interact as complements or substitutes in health care production, we split the analysis sample into two subsamples comprising only residents with AD/ADRD and without AD/ADRD at admission. We find that patients with AD/ADRD at baseline benefit from a roommate without AD/ADRD but we find no statistically significant mortality difference by peer health among for patients without AD/ADRD at admission. This suggests that patient and peer health are substitutes in health care production (submodular in production in the sense of Milgrom and Roberts (1990)), pointing to potential outcome gains from mixing patient health within rooms. The interactions between room sharing and patient health is more subtle. When potential peers have an AD/ADRD diagnosis at admission, we find diminishing benefits, meaning that patients with AD/ADRD would benefit more from a private room, suggesting the a private room and patient health are submodular (substitutes) in production. However, when potential peers do not have an AD/ADRD, diagnosis at admission, we find that patients without AD/ADRD would benefit more from a private room, suggesting increasing benefits and that a private room and patient health can also be supermodular (complementary) in production.

Our empirical findings imply that differences in room composition, holding the overall patient census fixed have meaningful effects on aggregate nursing home mortality, accounting for up to 0.75 standard deviations in quality between nursing homes.

Finally, we study potential mechanisms underlying our results. Our results are consistent with roommates without AD/ADRD playing a support role, e.g., potentially alerting staff when their roommate is in danger or needs help. In particular, we find that residents with AD/ADRD at baseline – the type of resident who is most likely to need support from their roommates – do not seem to benefit from being assigned to a room without roommates, in contrast to residents without AD/ADRD, who are less likely to need such support and thus benefit from not having a roommate.

Second, we find suggestive evidence that lower risk of disease contagion may partially explain the benefits of being assigned to a room without a roommate. In particular, the estimated effect of being assigned to an empty room is smaller among residents who received a PPV vaccine compared to those who did not receive a PPV vaccine (although the estimated effect does not differ between residents who did or did not receive flu vaccinations).

Finally, we find that nursing home inputs may also contribute to our peer effect estimates. One possible explanation for the room effects we find is that residents living without a roommate may receive more attention from staff, whereas roommates with AD/ADRD may take away staffing time/attention from their roommates. Our peer effect estimates are muted when we limit the sample to nursing homes with above-median staffing, compared to estimates based on the sample of nursing homes with below-median staffing, consistent with this explanation assuming that the effect of staffing on health outcomes is concave. In addition, we find that the effect of being assigned a roommate with AD/ADRD on future mortality is much smaller in nursing homes with an Alzheimer's unit, which is consistent with staff in these nursing homes being more experienced in caring for such residents.

This paper contributes to several strands of literature. First, it contributes to a vast literature on peer effects. Most of this literature focuses on education settings and on relatively young individuals (Sacerdote, 2001; Carrell, Fullerton, and West, 2009; Abdulkadiroğlu, Angrist, and Pathak, 2014), so we add to this body of work by showing that peer effects matter for an important outcome among a much older population. Another contribution we make to this literature is our identification strategy. Most well-identified papers in this setting leverage random assignment of individuals into groups. While residents are rarely randomly assigned to rooms in nursing homes, we leverage high-frequency variation in

the composition of available rooms stemming from admissions and discharges to obtain quasi-experimental variation in room assignment.

Second, we add to a literature studying the health production function. Previous studies have documented substantial differences in value-added 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, 2023). Our focus lies on heterogeneity in outcomes and care received within a given provider. Previous work has demonstrated important complementarities between providers and patients arising from communication frictions, issues of trust, or biases ((Chandra and Staiger, 2010; Alsan and Wanamaker, 2018; Alsan, Garrick, and Graziani, 2019b; Cabral and Dillender, 2024; Obermeyer et al., 2019; Greenwood et al., 2020; Frakes and Gruber, 2022; Cabral and Dillender, 2024). Our paper adds to this body of work by identifying a separate piece of the health production function – complementarities and substitutabilities between patients and their room types– and showing its quantitative importance for an important health outcome: 90-day mortality.

Third, we add to a growing literature on the economics of nursing homes. Previous work has studied provider quality, provider behavior, and consumer choice (Einav, Finkelstein, and Mahoney, 2025; Hackmann, 2019; Friedrich and Hackmann, 2021; Gandhi, 2023; Gandhi et al., 2024). A common assumption in these papers is that provider quality is a common good. Our paper contributes to this literature by adding nuance to this assumption: nursing home "quality" (in terms of the causal effect of a nursing home on resident outcomes) by vary depend on the type of room one is assigned to, and that room "quality" also varies depending on resident characteristics.

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 Setting and Data

2.1 Data

We use national longitudinal MDS 2.0 data from 2000–2010 for twelve large states: California, New York, Florida, Texas, Pennsylvania, Ohio, Illinois, New Jersey, Massachussetts, Indiana, Michigan, and North Carolina. This data contains admission and discharge assessments as well as quarterly assessments in between, for nearly all residents in Medicaid or Medicare-certified nursing homes ($\approx$ 96% coverage). These assessments contain detailed information on resident' demographics and health status, and crucially for our analysis, room identifiers. 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 resident is assigned to at admission, as well as the room composition at the nursing home she is assigned to.

We supplement the MDS with two additional data sets. We link the MDS to Medicare data in order to track changes in residents' health status over time, even after they are discharged from nursing homes. In addition, we merge our data with the Online Survey Certification and Reporting (OSCAR) data set, which contains information about annual staffing levels and the number of certified beds for each nursing home (which we use as a validation check for the room identifier in the MDS data). We also add information on whether the provider has an Alzheimer's special care unit, which we explore in our mechanism section.

Our main health outcome measure is risk-adjusted mortality, given that it is relevant, is well-measured, and has been commonly used in the health economics literature (Chandra et al., 2016b; Finkelstein, Gentzkow, and Williams, 2021). We measure mortality using the beneficiary death date in the Medicare beneficiary summary files.

We also use several other variables on residents' health status, either as controls for baseline health at admission, or as outcomes. These include 27 chronic conditions from the Medicare data, as well as the Cognitive Performance Scale (CPS) and Activities of Daily Living (ADL) from the MDS (higher values of which indicate worse health), which have been used as measures of cognitive and physical impairment in numerous studies

(Grabowski, Gruber, and Angelelli, 2008; Rahman, Norton, and Grabowski, 2016; Cornell et al., 2019). Finally, to measure whether roommates have AD/ADRD, we use Alzheimer's disease or dementia diagnosis from the MDS.

We limit the sample to residents on Medicare during our sample period, since the Medicare data allows us to observe health outcomes for residents even after they are discharged from nursing homes. In addition, for our main specifications, we focus on the first stay observed in our sample for each resident. This is because factors influencing room assignment in subsequent stays may differ from the first stay (e.g., due to bed hold policies)[1], and subsequent stays can only occur if residents survive their initial stay so that including all resident-stays may affect the representativeness of our sample.

A crucial variable for our analysis is the room identifier in the MDS. In practice, the format in which this variable is recorded differs across nursing homes and even within nursing homes over time. Hence, we take several steps to clean the room identifier.

A common issue with the room identifier is that it does not always identify the room. In many cases, this variable records the *bed* the resident is assigned to rather than the room, as can be inferred from the presence of a suffix which identifies the bed inside a given nursing home room. Examples include "15-1" or "15/A", where 15 corresponds to the room number and 1 or A corresponds to the bed within the room. In such cases, we simply strip the bed identifier suffix to obtain the room number. A more problematic scenario is when the information recorded in the room identifier is too coarse – referring to an entire section of a nursing home (e.g., "SOUTH") – or invalid (e.g., "ROOM"), in which case we drop residents who are assigned to these rooms from the analysis.

Another complication is that the way in which a nursing home refers to the same room may change over time: for instance, a room initially referred to as room "15" in a nursing home may be later referred to as "A15" due to the nursing home expanding and adding another section/wing, or simply due to inconsistencies in data entry by different nurses. If we treat all rooms that ever appeared in MDS assessments as always available throughout the entire sample period, we will end up with many "phantom" rooms, which seem to be available but in fact have become obsolete or do not yet exist (due to changes in data entry

[1]Specifically, if a resident is discharged from the nursing home to a hospital and is expected to return, the nursing home may hold her bed during the intervening period

practices, or nursing home expansions/contractions). To avoid this, we define the set of nursing home rooms on an annual basis.

Even after these cleaning steps, some room outliers with very large values for maximum occupancy remain. For our primary analysis, we drop nursing home rooms with maximum recorded occupancies of more than four. Nonetheless, we check that our main results are robust to alternative thresholds.[2]

As a check on the quality of our room identifier, we compare the number of distinct room identifiers in the MDS to bed counts in OSCAR in Appendix Figure A.1. In line with our expectations, the expected number of rooms is smaller than number of beds and is increasing with beds, and the numbers are consistent with most rooms having one or two beds. In addition, Appendix Table A.1 shows that there is strong homophily in roommate characteristics, particularly along gender lines, but also for other demographic and health characteristics.

Taken together, this evidence suggests that our room measures capture meaningful information on actual room assignments. While measurement error cannot be entirely ruled out, such error would bias estimates toward zero, implying that our findings represent a conservative lower bound on peer effects.

2.2 Summary Statistics

The columns 1–4 of Table 1 provides summary statistics on baseline characteristics for the full sample, residents assigned to rooms without a roommate, residents assigned roommate(s) with AD/ADRD, and residents assigned roommate(s) none of whom have AD/ADRD respectively. In order to focus on within-nursing-home-year differences in baseline characteristics between residents assigned to different types of rooms, these variables are residualized of nursing-home-by-year fixed effects (with the overall mean added back). Columns 5 and 6 show difference in means for the baseline characteristic for different subsamples along with standard errors for these differences clustered at the nursing home level.

The first six rows show summary statistics for some basic demographic variables. We observe that more than half of residents are female, the average age is 78, and that the

[2]Results available from authors upon request.

majority are white, have less than a Bachelor's degree, are post-acute care, and are not on Medicaid at admission.

The last four rows show baseline health of residents. For easier interpretation, we start by combining the many health variables into a single summary index: baseline mortality risk. We do so by considering the regression of 90-day mortality on the demographic variables, each of the 27 chronic conditions (as defined by the CMS Chronic Conditions Data Warehouse), fixed effects for CPS and ADLs, indicators for whether the resident is assigned to an empty room and whether the resident is assigned a roommate with AD/ADRD, as well as nursing-home-by-year fixed effects. We define baseline mortality risk as the predicted values from this regression, net of the room effects and the nursing-home-by-year fixed effects, and we obtain these predicted values using k-fold cross-validation with $k = 10$.

In columns 5 and 6, we observe that residents assigned to rooms without a roommate as well as residents assigned to a room where at least one roommate has AD/ADRD tend to have a slightly higher baseline mortality risk than residents assigned to rooms with roommates who do not have AD/ADRD. We also see statistically significant differences in CPS scores, ADL scores, and number of chronic conditions for residents assigned to different types of rooms, suggesting that room assignment is not random and that naive OLS regressions will not recover the causal effect of roommates on future health.

Table 1: Summary Statistics

	Full Sample	Assigned to Empty Room	Assigned Roommate(s) with AD/ADRD	Assigned Roommate(s) All Without AD/ADRD	Difference: (2) - (4)	Difference: (3) - (4)
	(1)	(2)	(3)	(4)	(5)	(6)
Female	0.623	0.606	0.642	0.615	-0.012***	0.031***
	(0.470)	(0.476)	(0.464)	(0.472)	(0.001)	(0.001)
Education: Bachelor's Degree	0.082	0.088	0.078	0.082	0.008***	-0.004***
	(0.260)	(0.277)	(0.249)	(0.260)	(0.001)	(0.000)
Age	78.229	77.991	78.676	77.928	-0.004***	-0.026***
	(11.555)	(11.704)	(11.226)	(11.771)	(0.001)	(0.001)
Race: White	0.813	0.817	0.810	0.813	0.004***	-0.004***
	(0.310)	(0.301)	(0.310)	(0.314)	(0.001)	(0.001)
Post-Acute Care	0.656	0.653	0.643	0.669	-0.018***	-0.029***
	(0.405)	(0.408)	(0.415)	(0.393)	(0.001)	(0.001)
Medicaid	0.117	0.113	0.126	0.110	0.003***	0.018***
	(0.286)	(0.278)	(0.303)	(0.272)	(0.001)	(0.001)
Baseline Mortality Risk	0.155	0.157	0.156	0.154	0.003***	0.002***
	(0.103)	(0.104)	(0.102)	(0.103)	(0.000)	(0.000)
Cognitive Performance Scale	1.805	1.785	1.923	1.701	0.086***	0.247***
	(1.539)	(1.531)	(1.560)	(1.514)	(0.004)	(0.004)
Physical Impairment (ADLs)	14.457	14.400	14.490	14.457	-0.061***	0.046***
	(7.304)	(7.325)	(7.353)	(7.245)	(0.015)	(0.014)
Number of Chronic Conditions	6.595	6.555	6.621	6.591	-0.044***	0.036***
	(3.859)	(3.838)	(3.842)	(3.886)	(0.008)	(0.007)
Nursing Home x Year Fixed Effects	X	X	X	X	X	X
Number of Observations	2,666,256	579,005	1,024,846	1,062,405	-	-

Notes: Columns 1-4 shows summary statistics (mean and standard deviation) for the full sample of (first stays of) residents, residents assigned to empty rooms, residents assigned to a room where at least one roommate has AD/ADRD, and residents assigned to a (non-empty) room where none of the roommates have AD/ADRD at admission respectively. Each variable in columns 1-4 is first residualized of nursing-home-by-year fixed effects, before having the overall mean for the variable added back. Baseline mortality risk is calculated using k-fold cross-validation for k=10, based on regressions of 90-day mortality on baseline health and demographic characteristics, net of nursing home x year fixed effects and room assignment. Columns 5 (and 6) show difference in mean characteristics between residents assigned to empty rooms (assigned roommate with AD/ADRD respectively) and residents assigned to roommates without AD/ADRD, with the standard error for this difference being shown in parentheses. Standard errors are obtained from regressions of each baseline characteristic on indicators for being assigned to an empty room and being assigned a roommate with AD/ADRD, along with nursing-home-by-year fixed effects, with standard errors being clustered at the nursing home level.

3 Empirical Strategy

To measure the causal effects of nursing home roommates on patient health, we need to address two central challenges: (1) simultaneity in peer influence (a reflection problem), and (2) endogenous, non-random roommate assignments that can confound sorting with peer effects.

3.1 Reflection Problem

To address the challenge of simultaneity in peer influence, we examine the effect of roommates' predetermined AD/ADRD diagnoses on residents' subsequent health. Our primary model is:

$$Y_{irjt} = \beta_0 + \beta_1 \,\text{Empty}_{r(i),j,t(i)} + \beta_2 \,\text{AD}_{r(i),j,t(i)} + X_i'\gamma + \delta_{j,y(t)} + \varepsilon_{irjt}, \tag{1}$$

where Y_{irjt} is a future health outcome (90-day mortality in our main specifications) for a resident i who is admitted to room r in nursing home j on day t, $\text{Empty}_{r(i),j,t(i)}$ is an indicator for whether i is assigned to an empty room, $\text{AD}_{r(i),j,t(i)}$ is an indicator for whether at least one of i's roommates at admission has AD/ADRD, X_i is i's baseline characteristics, and $\delta_{j,y(t)}$ are nursing-home-by-year fixed effects. We measure roommate health at the time of i's admission in order to avoid reflection bias (since i's health cannot affect prior diagnoses).

3.2 Endogenous room assignments:

Given the evidence presented above that roommate assignment is unlikely to be random, we estimate the causal effects of roommates on future health using an IV strategy which leverages high-frequency variation in room composition.

We instrument room assignment – $\text{Empty}_{r(i),j,t(i)}$ and $\text{AD}_{r(i),j,t(i)}$ – with the share of rooms with a vacant bed at the nursing home that are empty – $s^{\text{Empty}}_{j,t(i)}$ – and the share of rooms with a vacant bed that have an existing resident with AD/ADRD – $s^{\text{AD}}_{j,t(i)}$ – at the time of i's admission. Intuitively, if all available rooms are empty (or already have an existing resident with AD/ADRD) on the day of admission, then any newly admitted resident

will be assigned to an empty room (respectively, a roommate with AD/ADRD). Hence, the first stage equations are:

$$\text{Empty}_{r(i),j,t} = \phi_{j,y(t)} + \tau_1 s^{\text{Empty}}_{j,t(i)} + \tau_2 s^{\text{AD}}_{j,t(i)} + X_i'\omega + \eta_{irjt} \tag{2a}$$

$$\text{AD}_{r(i),j,t} = \xi_{j,y(t)} + \alpha_1 s^{\text{Empty}}_{j,t(i)} + \alpha_2 s^{\text{AD}}_{j,t(i)} + X_i'\varphi + \nu_{irjt} \tag{2b}$$

Following equation (1), we again include nursing home-by-year fixed effects ($\phi_{j,y(t)}, \xi_{j,y(t)}$), and control for resident baseline characteristics (X_i).

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 resident that has AD/ADRD. However, this variation may also be due to differences between nursing-home-years (e.g., share of rooms with a resident who has AD/ADRD may be higher in nursing homes' that have Alzheimer's units), and our IV strategy leverages within-nursing-home-year variation. Indeed, panels (c) and (d) show that the within-nursing-home-year distributions of the instruments are tighter[3]. Nonetheless, substantial variation in the instruments remain, due to volatility in admissions and discharges (both in volume and composition).

3.2.1 Identification

To interpret β_1 and β_2 as the LATE of being assigned and empty room or a room shared with a resident with an AD/ADRD diagnosis, our instrumental variables need to be relevant and conditionally independent. In this section, we summarize empirical evidence supporting the validity of these identifying assumptions.[4]

[3]Specifically, we plot the distributions of the variables residualized of nursing-home-by-year fixed effects 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 resident 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 normalized variable would be $0 - 0.75 + 0.5 = -0.25$

[4]In ongoing work, we explore exclusion and monotonicity.

Relevance: Our approach requires that our instruments have strong predictive power for the endogenous variables[5]. We assess this by examining the relationships between Empty and $s^{\text{Empty}}_{j,t(i)}$ as well as between $\text{AD}_{r(i),j,t}$ and $s^{\text{AD}}_{j,t(i)}$, conditional on nursing-home-by-year fixed effects.

The blue dots in Figure 1 present the first stage results. Figure 1a presents results from the first stage regression for one of our instruments: the share of available rooms occupied with at least one resident with AD/ADRD at the time (day) of admission, $s^{AD}_{j,t}$ (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 $s^{AD}_{j,t}$ (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 p.p. increase in the share of available rooms with a resident diagnosed with AD/ADRD increases the probability of being assigned a resident diagnosed with AD/ADRD by 1.16 p.p, with a t-statistic of more than 200.

The blue dots in Figure 1b present corresponding evidence for the second instrument: the share of available empty rooms, $s^{Empty}_{j,t}$ (holding $s^{AD}_{j,t}$ fixed). The blue line (circle markers) shows again a positive linear relationship between the probability of being assigned to an empty room (vertical axis) and $s^{Empty}_{j,t}$ (horizontal axis), $\alpha_1 > 0$, providing again strong support for instrumental relevance. Moreover, the relationship is remarkably linear, which supports the linear specification in equation 2a. We find that a 1.p.p. increase in in the share of available empty rooms increases the probability of being assigned an empty room by 0.97, with a t-statistic greater than 170.

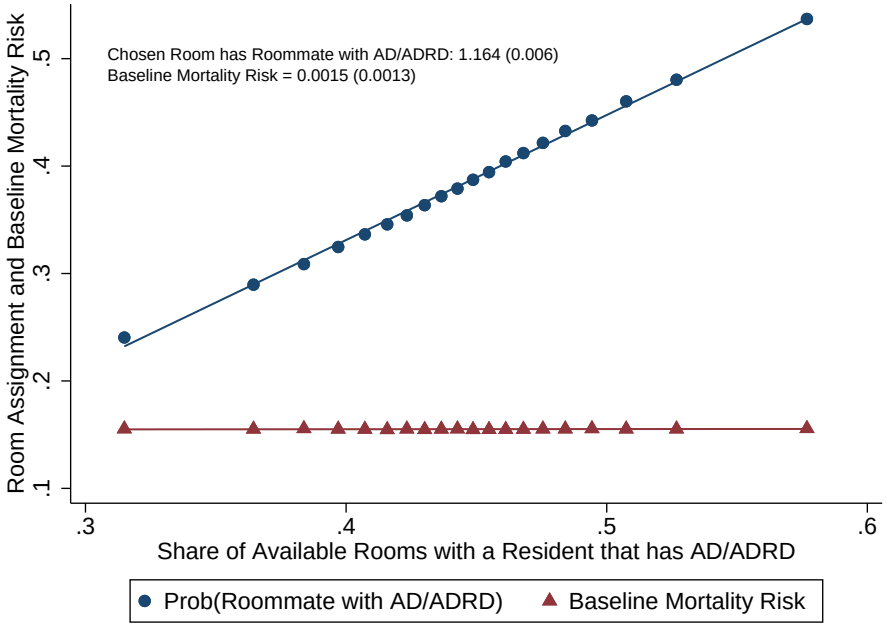
In the empirical evidence below, we show that patient characteristics are well-balanced across the share of available empty rooms or rooms occupied with a resident diagnosed with AD/ADRD, consistent with quasi-random variation in the instruments. Otherwise, e.g., if the variation is driven by patient hocks, we would observe systematic changes in patient characteristics with the instrument.

Conditional Independence: For our instrument to be valid, our instruments must be uncorrelated with patients' potential outcomes, conditional on the baseline controls including

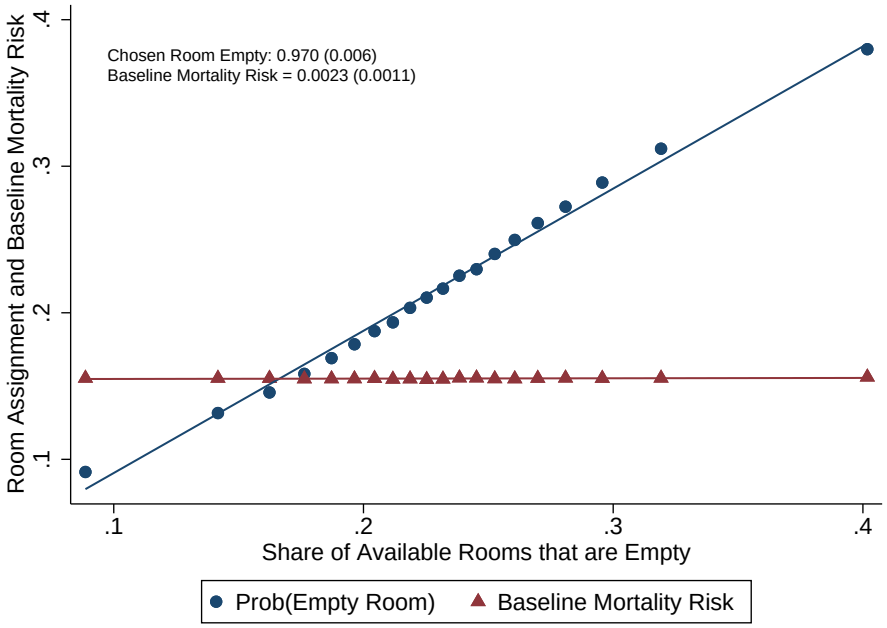
[5]Specifically, in the case with two endogenous variables and two excluded instruments, the 2×2 matrix of first stage coefficients must have rank 2.

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 resident that has AD/ADRD at the time of admission, controlling for nursing-home-by-year fixed effects and the share of available rooms that are empty 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 nursing-home-by-year fixed effects and the share of available rooms that have a resident with AD/ADRD 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.

nursing-home-by-year fixed effects and resident-level controls X_i. While the institutional features described above support conditional independence, this assumption may still be violated if residents delay their admission until a more preferred room type becomes available, or if they change their nursing home choice because their preferred room type is unavailable.

To address this concern, we present two sets of empirical evidence which provide strong support for the conditional independence assumption. First, we show that patients' observed characteristics are well balanced across the instruments, conditional on our baseline controls. As shown by the red dots and lines in Figure 1, predicted mortality constructed on baseline patient characteristics at admission remarkably stable across variation in the instruments. Specifically, the red line in Figure 1a plots the relationship between observable baseline mortality risk of resident i (vertical axis) and the share of empty rooms occupied with a resident diagnosed with AD/ADRD. The coefficient estimate is small in magnitude and not statistically significant at the five percent significance level.

The red line in Figure 1b revisits this for our second instrument, the share of empty rooms, $s_{j,t}^{Empty}$. Again, the coefficient estimate is small, and even though the estimate is statistically significant at the five percent level, given our later results that being assigned to an empty room reduces 90-day mortality on average, if anything this small bias from imbalance in baseline mortality risk may lead us to *underestimate* the effect of being assigned to an empty room.

To probe the conditional independence assumption for our instruments further, Appendix Figure A.3 explores balance for 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).[6] 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.

[6]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.

The results in Appendix Figure A.3 shows that for both instruments, we observe that 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 tend to have inconsistent signs. Indeed, when we combine the baseline characteristics into baseline mortality risk, this risk measure is essentially conditionally uncorrelated with $s^{\text{AD}}_{j,t(i)}$ in panel (a), and although its correlation with $s^{\text{empty}}_{j,t(i)}$ is barely statistically significant at the five percent significance level in panel(b), the sign of this correlation is the opposite of the reduced form estimate, suggesting that even if this imbalance results in bias, it is likely to attenuate the IV estimate of β_1 towards zero.

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 average of treatment effects across different residents (i.e., with non-negative weights and zero weights on the "wrong" treatment effect).[7] 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). Denoting these instruments by P^{Empty} and P^{AD}, at a high level 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 (controlling for Empty) 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 in different subsamples based on baseline characteristics, the regressions of Empty (AD) on P^{Empty} and P^{Empty} (and controls)

[7] 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.

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.4 shows histograms of coefficient estimates with Empty and Empty 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 Average Effects

Table 2 shows IV and OLS estimates of equation (1) for the full sample. Column 1 shows that being assigned to an empty room at admission reduces 90-day mortality by 1.4 ppts relative to being assigned a roommate, a 9 percent reduction relative to the mean. Column 2 shows that this effect depends on the characteristics of roommates residents are assigned to: relative to being assigned roommates that do not have dementia, being assigned to an empty room at admission reduces 90-day mortality by 0.8 ppts while being assigned a roommate that has dementia increases mortality by 1.3 ppts. In both IV specifications, the first-stage F-statistics are in the tens of thousands, so weak instruments are unlikely to be an issue.

Columns 3 and 4 of Table 2 show OLS estimates for comparison. The estimate in column 3 suggests that being assigned to an empty room *increases* 90-day mortality, while column 4 suggests 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 *reduces* mortality. The signs of these estimates are the opposite of the IV estimates, suggesting that room assignment is correlated with unobserved determinants of health, and highlighting the importance of our IV strategy for identifying causal effects. In addition, the magnitude of the OLS estimates are very small, which may be due to attenua-

Table 2: IV and OLS Estimates of Average Room Effects

	Death Within 90 Days of Admission			
	IV	*IV*	*OLS*	*OLS*
	(1)	(2)	(3)	(4)
Assigned to Room with No Roommate	-0.014***	-0.008***	0.003***	0.003***
	(0.003)	(0.003)	(0.001)	(0.001)
Assigned to Roommate with AD/ADRD		0.013***		-0.001**
		(0.003)		(0.001)
Baseline Mortality Risk	1.000***	1.000***	1.000***	1.000***
	(0.003)	(0.003)	(0.003)	(0.003)
F-statistic	36625	26553	-	-
Dependent Variable Mean	0.155	0.155	0.155	0.155
Number of Observations	2,666,256	2,666,256	2,666,256	2,666,256

Notes: Baseline mortality risk is calculated using k-fold cross-validation for k=10, based on regressions of 90-day mortality on baseline health and demographic characteristics, net of nursing home x year fixed effects and room assignment. Standard errors are clustered at the nursing home level.

tion bias caused by measurement error in room assignment, an issue that is also alleviated by IV.

4.2 Substitutability and Complementarities in Health Care Production

To explore the interaction between peer health and resident health, we revisit the analysis across different patient subsamples in Panel A of Table 3. In columns (1) and (2), we compare results between residents with or without a diagnosis of AD/ADRD at admission. We observe that being assigned to an empty room does not seem to reduce mortality for residents with AD/ADRD at admission but does reduce mortality for residents without AD/ADRD at admission, relative to being assigned roommates without AD/ADRD. At the same time, being assigned a roommate with AD/ADRD increases mortality for residents with AD/ADRD but not for residents without AD/ADRD at admission, relative to being assigned roommates without AD/ADRD. These patterns are consistent with roommates without AD/ADRD potentially playing a support role, alerting staff when their roommates are in danger or need help. This supportive role played my roommates may be especially valuable for residents with AD/ADRD, who may lack awareness of their surroundings. At the same time, roommates with AD/ADRD may be less capable of playing this support role, which explains why residents AD/ADRD benefit from having roommates without AD/ADRD, but not from having a roommate with AD/ADRD.

To explore the implications of these patterns for the substitutability and complemenentarities in production, we adopt the notation from Milgrom and Roberts (1990) and examine whether the health care production function is submodular or supermodular in its inputs. Formally, we define the resident's health outcome, in our case 90-day mortality, as a function of three inputs, a) own health H and b) peer health health H_p, which are indicators that turns on if the resident (pr their roommate) are diagnosed with AD/ADRD at baseline, and c) room type, R, an indicator that turns on when assigned to an empty room. Mortality is thus defined as:

$$Y = f(H, H_p, R) \,. \tag{2}$$

Holding room type fixed, our estimates from Panel A of Table 3 suggest that $f(\cdot)$ is submodular in resident and peer health, meaning that they are substitutes.[8] In words, increasing one input weakly reduces the marginal productivity of the other. Consider a shared room, with two AD/ADRD residents. Increasing peer health has a substantial positive spillover effect on health for residents with AD/ADRD (-3.3 p.p. in 90-day mortality). Conversely, there is almost no positive spillover effect on health when the residents does not have AD/ADRD at baseline (-0.3 p.p. in 90-day mortality). This provides an argument for mixing patient health within rooms, as we discuss below.

This framework also allows us to study the interaction between resident health and room type, holding (potential) peer health fixed. Here the results are more nuanced. Conditional a potential peer with AD/ADRD, we find that $f(\cdot)$ is submodular in resident health and room type, again meaning that they are substitutes. When resident health is lower (AD/ADRD at baseline), we find substantial benefits from being assigned an empty room (-3.3 p.p. =0.7 p.p. = -2.6 p.p. in 90-day mortality) due to avoid the negative peer effect in a shared room. When resident health is better (no AD/ADRD at baseline), the benefits are smaller (-0.3 p.p. - 1.5 p.p.=-1.8 p.p.).

However, this calculation is reversed when considering a potential peer without AD/ADRD. Here, we find that $f(\cdot)$ is supermodular in resident health and room type, meaning that resident health and room type can also be complements. When resident health is lower (AD/ADRD at baseline), we now find no benefit from being assigned an empty room. If anything, our estimates point to an increase in 90-day (+0.7 p.p.). Conversely, a resident in

[8] Details for these derivations are presented in Appendix Section B.

better health (no AD/ADRD at baseline) would benefit significantly from being assigned an empty room (-1.5 p.p.). This suggests that optimal assignment to empty rooms does not only depend on resident health but also on the distribution of peer health, assuming that the nursing home includes 90-day mortality in its considerations.

4.3 Room Assignments and Average Mortality

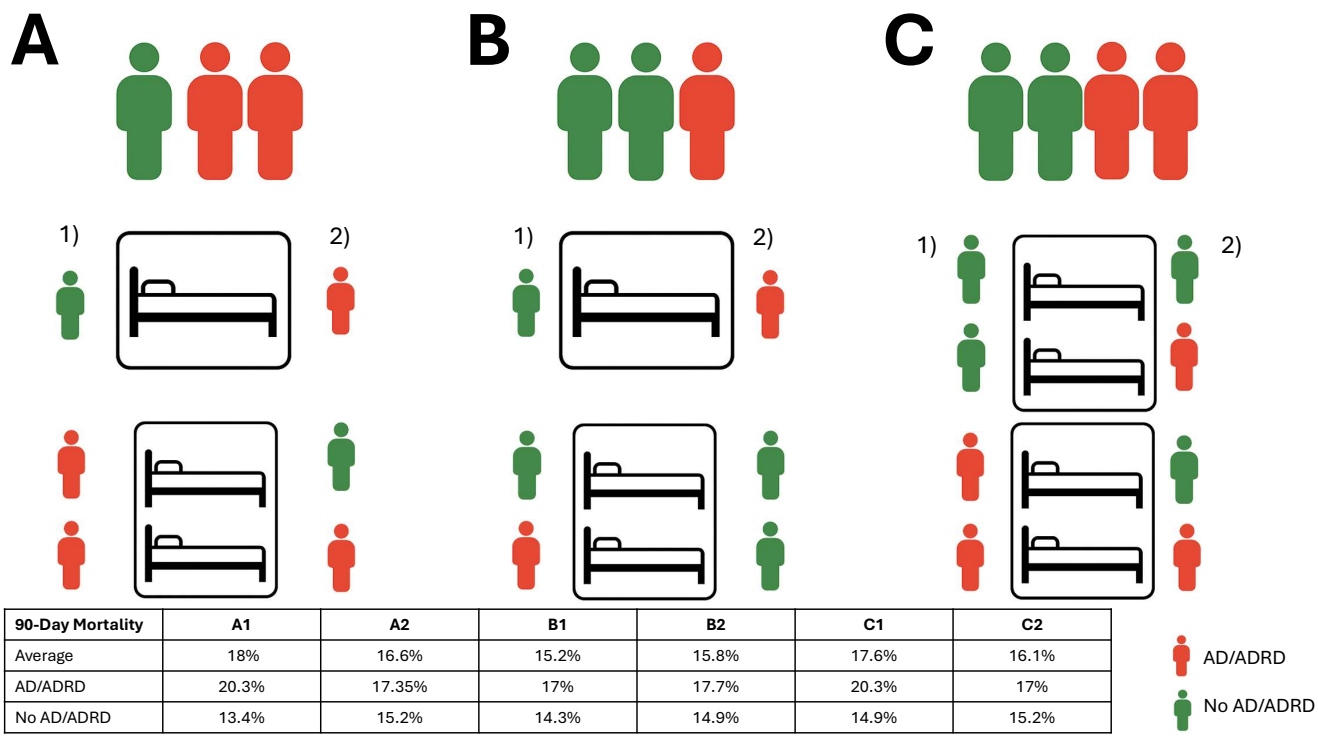
Appendix Section C presents a more general room assignment model, but in this subsection we illustrate the main insights around these interaction effects using three stylized examples, summarized in Figure 2. Example A considers a case with three residents, two have been diagnosed with AD/ADRD (red) and one has not (green). The nursing home operates two rooms. In the first case (A1), the resident without an AD/ADRD diagnosis is assigned the empty room. In the second case, a resident diagnosed with AD/ADRD is assigned an empty room (A2). The numbers presented in the table indicate that switching from A1 to A2 would reduce average 90-day morality by 1.6 p.p. While the resident without AD/ADRD is worse off, the large positive spillover effects to residents with AD/ADRD would result in a substantial net reduction in resident mortality. This exercise mirrors the case with a peer with AD/ADRD, where room type and patient health are substitutes.

Example B considers the case of a healthy peer. In this case, and as stated above, patient health and room type are complements, whereby assigning the empty room to a resident without AD/ADRD (B1) yields lower average mortality than assigning the empty room to a resident with AD/ADRD disgnosis (B2).

Example C holds the room type fixed and isolates the interaction between resident and peer health. As discussed, resident and peer health are substitutes. Thus mixing residents by health results in significantly lower average mortality.

In conclusion, our estimates imply the different room assignments of residents have first order implications on average patient mortality. Average mortality varies by up to 1.5 p.p. depending on the assignment. For comparison, Cheng (2023) estimates differences in value-added to 90-day mortality between nursing homes in California and finds a standard deviation of 2 percentage points. This suggests that differences in room assignments correspond to up to 1.5/2=3/4 standard deviations in quality between nursing homes. While 90-day mortality is almost certainly not the only outcome that nursing homes consider,

Figure 2: Room Assignments and 90-Day Mortality



90-Day Mortality	A1	A2	B1	B2	C1	C2
Average	18%	16.6%	15.2%	15.8%	17.6%	16.1%
AD/ADRD	20.3%	17.35%	17%	17.7%	20.3%	17%
No AD/ADRD	13.4%	15.2%	14.3%	14.9%	14.9%	15.2%

Notes: This figure illustrates the 90-day mortality rates by baseline health across different resident to room assignments. Panels A and B consider a single room (including multi-bed rooms with one assigned resident) and a two-bed room. Panel C considers two two-bed rooms. For each panel, we consider a census of residents shown at the top and illustrate two possible room assignments 1) and 2). Using the estimates from columns 1-2 in Panel A of Table 3, we calculate the corresponding average mortality rate and the mortality rates for residents with and without and AD/ADRD diagnosis at baseline and present them in the table below. Column A1, for instance, corresponds to Panel A's allocation 1).

our findings suggests that aggregate health outcomes can be very sensitive to room assignments.

4.4 Mechanisms

In this section, we consider several mechanisms that may help reconcile the large peer effects discussed above.

Length of Stay: A first contributing factor to the magnitude of peer effects is likely the length of stay. Since length of stay may in itself be an endogenous outcome (Einav, Finkelstein, and Mahoney, 2025), we explore differences based on the resident's admission channel instead. Specifically, residents admitted from an acute care hospital typically require primarily rehabilitative care and many of them have short stays, commonly referred to as stays of up to 100 days in length. In contrast, residents admitted from the community have lengths of stay. Columns 3 and 4 of panel A in Table 3 compare the mortality effects of room assignment for residents admitted from acute care hospitals with those admitted from other sources. We observe that the effects of room assignment tend to be smaller in magnitude for residents who are post-acute care compared to those who are not, consistent with the shorter average stay length of post-acute care residents.

Vaccination: While the results in panel A suggest that roommates without AD/ADRD may play a support role which can be especially valuable for residents with AD/ADRD, they do not explain why being assigned to an empty room leads to lower mortality rates for residents without AD/ADRD. Panel B explores 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 residents 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 residents who did or did not receive flu vaccines, the effect is smaller for residents who received a PPV vaccine compared to residents who did not receive a PPV vaccine. This provides suggestive evidence that disease contagion may partially explain the reduction in 90-day mortality for residents assigned to empty rooms.

Other Inputs: In panel C, we explore whether nursing home characteristics can explain the estimated room effects. An important determinant of resident health in nursing homes is staffing levels (Lin, 2014; Harrington et al., 2020), so a natural hypothesis is that the observed differences in health outcomes arise from differential staffing inputs devoted to residents in different types of room. For example, residents assigned to empty rooms may benefit from undivided attention from nursing staff, while nurses may devote less time to residents in shared rooms, especially if their roommates require more attention. To test this hypothesis, we estimate room effects for nursing homes with above-median and below-median staffing in columns 1 and 2 respectively, where staffing is defined as the sum of z-scores for RN, LPN, and CNA staffing. If we assume that resident outcomes are concave in staffing inputs, we may expect estimates of room effects to be muted for residents in nursing homes with high staffing. This is precisely the pattern we see in columns 1 and 2 of panel C – both for the effect of being assigned to an empty room, and the effect of roommate type – suggesting that differences in staffing may contribute to our peer effect estimates.

Finally, in columns 3 and 4 of panel C, we test whether peer effects vary by whether nursing homes have an Alzheimer's unit. In particular, staff at nursing homes with Alzheimer's units may be better trained or more experienced with caring for residents with AD/ADRD, which may ameliorate the negative estimated effect on health outcomes of being assigned a roommate with AD/ADRD seen above (Joyce et al., 2018). This is precisely the pattern we see in the final two columns of panel C: the effect of being assigned a roomate with AD/ADRD (relative to being assigned roommates without AD/ADRD) is small and statistically insignificant for residents in nursing homes with Alzheimer's units, but remain large and high statistically significant for residents in nursing homes without Alzheimer's units.

5 Conclusion

In this paper, we study peer effects among nursing home roommates. To identify causal effects of assignment to different types of roommates, we use an an IV strategy based on

Table 3: Heterogeneity in Room Effects

Panel A. Heterogeneity by Resident Baseline Characteristics

	Death Within 90 Days of Admission			
	AD/ADRD	*No AD/ADRD*	*Post-Acute Care*	*Not Post-Acute Care*
	(1)	(2)	(3)	(4)
Assigned to Room with No Roommate	0.007	-0.015***	-0.005	-0.011**
	(0.006)	(0.003)	(0.004)	(0.005)
Assigned to Roommate with AD/ADRD	0.033***	0.003	0.011***	0.013**
	(0.006)	(0.004)	(0.004)	(0.005)
Baseline Mortality Risk	0.945***	1.023***	1.038***	0.933***
	(0.005)	(0.004)	(0.004)	(0.005)
First Stage F-statistic	11410	18080	17117	11171
Dependent Variable Mean	0.17	0.149	0.157	0.152
Number of Observations	862,836	1,800,514	1,743,796	917,995

Panel B. Heterogeneity by Vaccination Status

	Death Within 90 Days of Admission			
	Flu Vaccine	*No Flu Vaccine*	*PPV Vaccine*	*No PPV Vaccine*
	(1)	(2)	(3)	(4)
Assigned to Room with No Roommate	-0.015***	-0.014***	-0.008*	-0.016***
	(0.006)	(0.005)	(0.004)	(0.005)
Baseline Mortality Risk	0.792***	0.872***	0.818***	0.889***
	(0.005)	(0.005)	(0.005)	(0.005)
First Stage F-statistic	9464	10521	14524	10595
Dependent Variable Mean	0.115	0.126	0.12	0.126
Number of Observations	607,450	723,669	785,853	649,954

Panel C. Heterogeneity by Facility Characteristics

	Death Within 90 Days of Admission			
	Above-Median Staffing	*Below-Median Staffing*	*Alzheimer's Unit*	*No Alzheimer's Unit*
	(1)	(2)	(3)	(4)
Assigned to Room with No Roommate	-0.006	-0.010**	-0.002	-0.009***
	(0.004)	(0.004)	(0.007)	(0.003)
Assigned to Roommate with AD/ADRD	0.010**	0.017***	0.002	0.016***
	(0.004)	(0.004)	(0.007)	(0.003)
Baseline Mortality Risk	0.985***	1.015***	1.011***	0.997***
	(0.004)	(0.004)	(0.006)	(0.004)
First Stage F-statistic	14685	13788	5287	21687
Dependent Variable Mean	0.154	0.157	0.152	0.156
Number of Observations	1,372,519	1,293,660	576,779	2,089,400

Notes: Baseline mortality risk is calculated using k-fold cross-validation for k=10, based on regressions of 90-day mortality on baseline health and demographic characteristics, net of nursing home x year fixed effects and room assignment. Standard errors are clustered at the nursing home level.

high-frequency variation in the composition of available rooms at the time of admission. We find an extremely strong first stage, and show evidence supporting conditional independence of our instruments in a battery of balance tests.

We estimate that being assigned to a room without a roommate reduces 90-day mortality on average relative to being assigned roommates without AD/ADRD, and that being assigned a roommate with AD/ADRD increases mortality (relative to roommates without AD/ADRD). We find suggestive evidence that these effects may be explained by roommates without AD/ADRD potentially playing a support role, lower risk of disease contagion for residents living by themselves, and the effect of one's roommate (or absence thereof) on the amount of staffing input one receives. In addition, we find heterogeneity in the effect of being assigned to different types of rooms by residents' baseline characteristics.

This last observation points to a novel channel for improving resident outcomes through optimal assignment of residents to rooms. A similar idea has been explored in education settings (Carrell, Sacerdote, and West, 2013), but has not been discussed as prominently in health settings, where most of the discussion has focused on patient-to-provider matches. In future work, we plan to combine well-identified peer effects estimates with a dynamic structural model to estimate the optimal assignment policy for nursing homes assigning residents to rooms.

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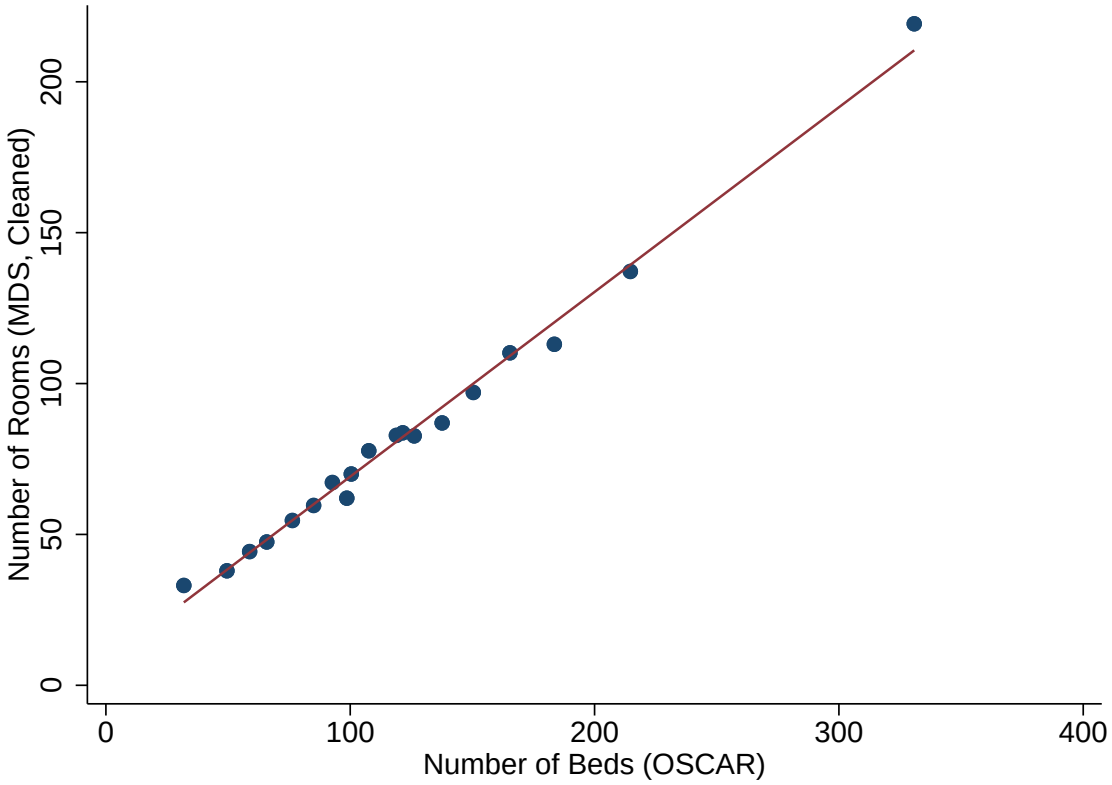
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A Appendix Figures and Tables

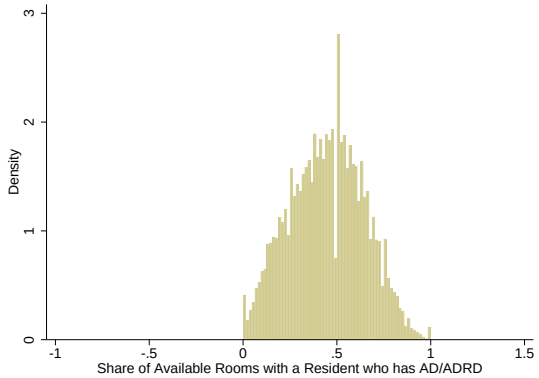
Figure A.1: Relationship Between Number of Rooms and Number of Beds



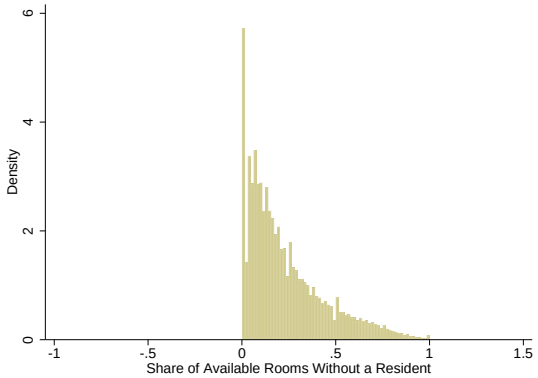
Notes: This figure plots the relationship between number of rooms in each nursing home each year based on the room identifier in the MDS data, and the number of beds in the same nursing-home-year according to the OSCAR data.

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

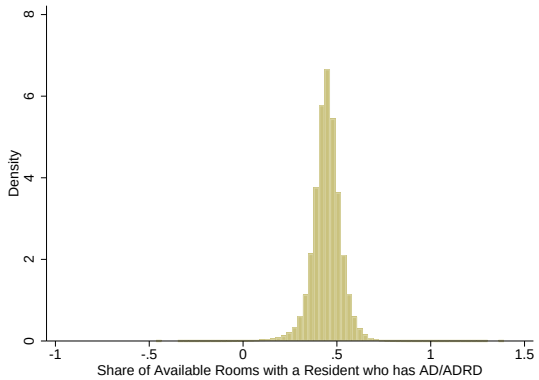
(a) Rooms with a Resident that has AD/ADRD



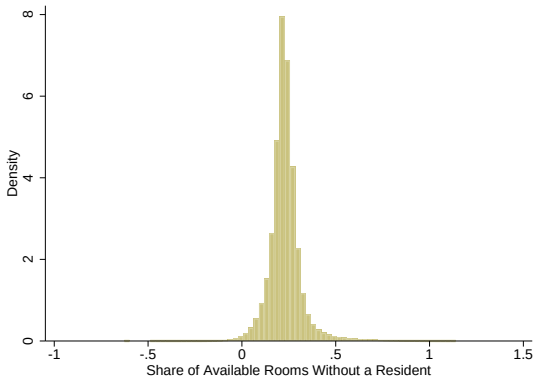
(b) Rooms Without a Resident



(c) Rooms with a Resident that has AD/ADRD (Within-Nursing-Home-Year)



(d) Rooms Without a Resident (Within-Nursing-Home-Year)

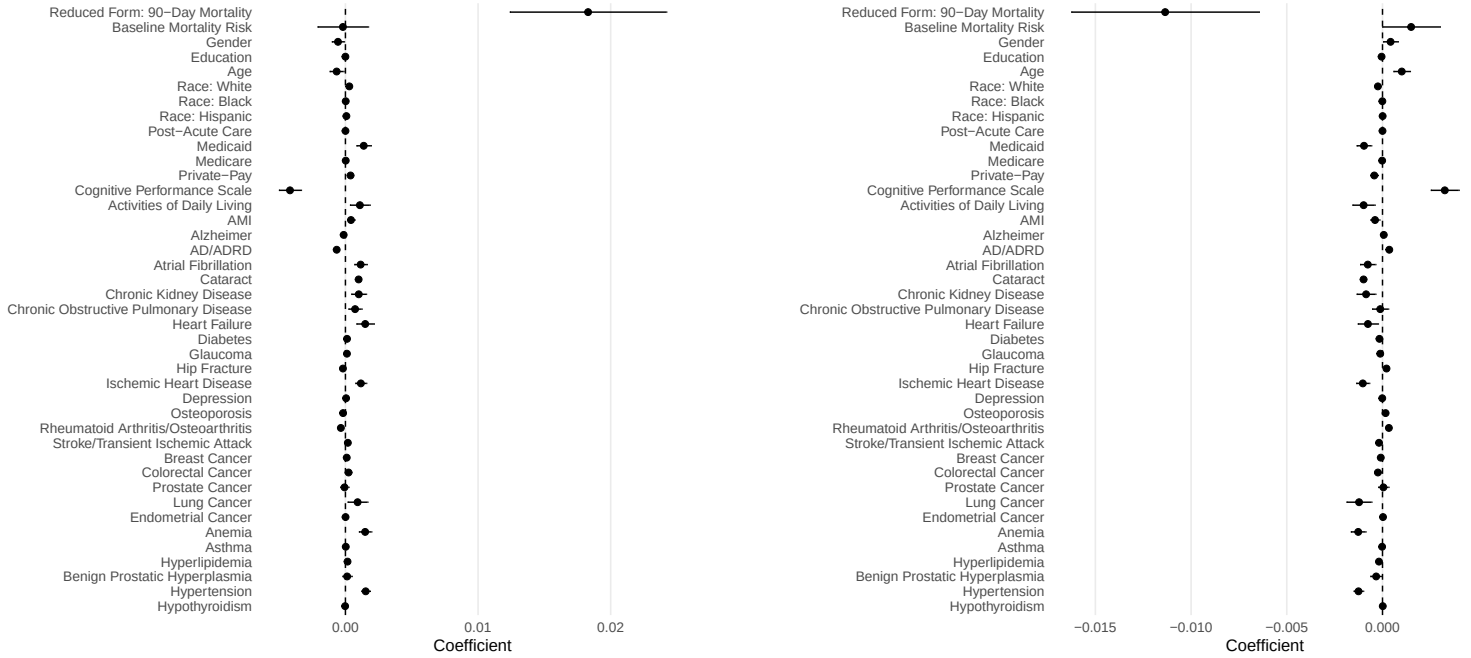


Notes: This figure plots histograms showing the distributions of our instruments – share of available rooms with a resident that has AD/ADRD and share of available rooms that are empty – both unconditionally in panels (a) and (b), and conditional on nursing-home-by-year fixed effects in panels (c) and (d). Specifically, for the within-nursing-home-year distributions of our instruments, we first residualize the instruments of nursing-home-by-year fixed effects, before before adding back their overall means.

Figure A.3: Reduced Form and Conditional Independence

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

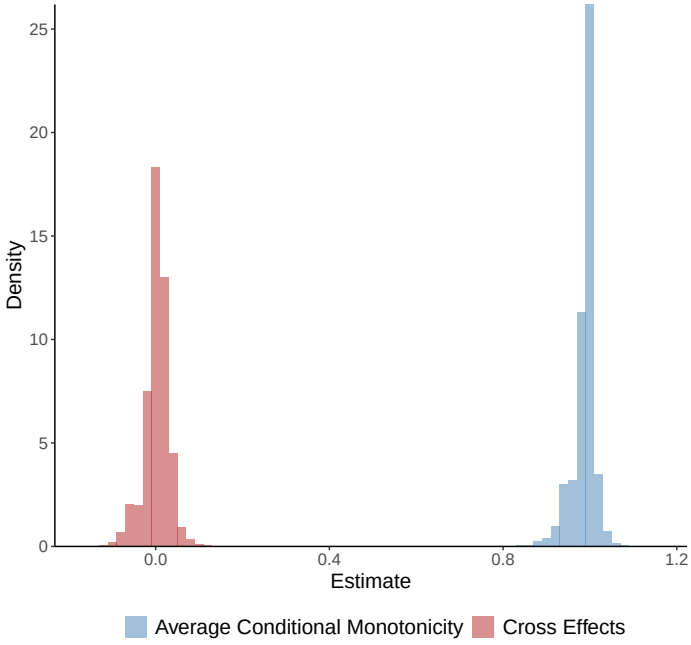
(b) Share of Available Rooms Without a Roommate



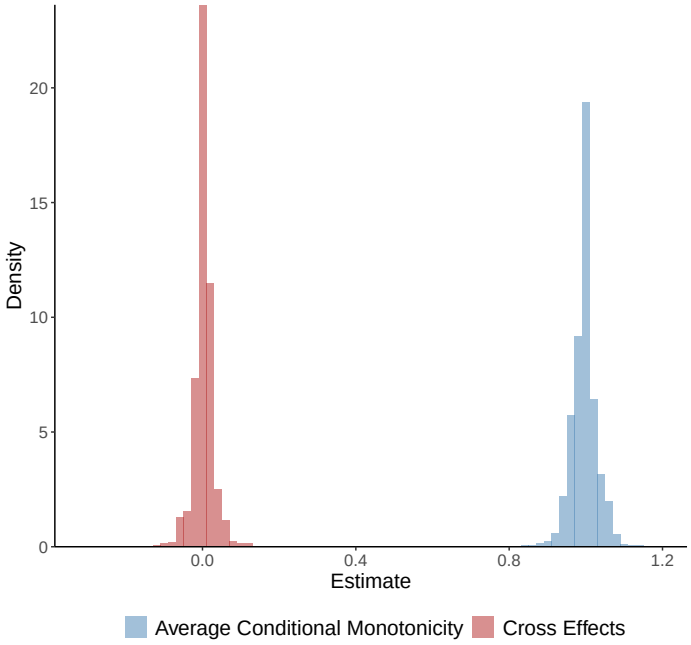
Notes: This figure provides evidence on the conditional independence assumption by comparing regression estimates of baseline characteristics on the instruments (from the second row onwards) with the reduced form estimate (of the outcome on the instrument) in the first row. Specifically, panel (a) and (b) plot coefficient estimates and 95 percent confidence intervals from regressions of 90-day mortality (in the first row) and baseline resident characteristics (in the remaining rows) on the share of available rooms with a resident that has AD/ADRD and the share of available rooms that are empty respectively, controlling for nursing-home-by-year fixed effects, and with standard errors clustered at the nursing home level.

Figure A.4: Average Conditional Monotonicity and No Cross-Effects

(a) Empty as the Dependent Variable



(b) AD as the Dependent Variable



Notes: These figure shows histograms of coefficient estimates from regressions of Empty and Empty on P^{Empty} and P^{AD} (and controls) for different subsamples. 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: Homophily in Roommate Characteristics

	AD/ADRD	Female	Post-Acute Care	Medicaid	Bachelor's Degree	Age ≤ 80	Race: White
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Share of Roommates with AD/ADRD	0.094***						
	(0.002)						
Share of Roommates that are Female		0.642***					
		(0.003)					
Share of Roommates that are Post-Acute Care			0.051***				
			(0.001)				
Share of Roommates on Medicaid				0.056***			
				(0.001)			
Share of Roommates with Bachelor's Degree					0.014***		
					(0.002)		
Share of Roommates Aged ≤ 80						0.048***	
						(0.001)	
Share of Roommates that are White							0.071***
							(0.002)
Nursing Home x Year Fixed Effects	X	X	X	X	X	X	X
Number of Observations	2,087,100	2,086,611	2,087,100	2,087,100	2,087,100	2,087,100	2,087,100
R-squared	0.093	0.397	0.280	0.219	0.099	0.115	0.380

Notes: This table shows regressions of resident characteristics at admission on the average value of this characteristics of the same characteristics among the resident's roommate(s) at the time of the resident's admission, and nursing-home-by-year fixed effects. The sample is limited to residents who are assigned a roommate, and standard errors are clustered at the nursing home level.

B Complements and Substitutes in Production

Submodularity and Supermodularity in Production: To study whether room design, patient, and peer health interact as substitutes in production, we borrow notation from Milgrom and Roberts (1990) and define a health production function:

$$f : X \to \mathbb{R} , \tag{B.1}$$

where $(X, \geq)$ is a lattice with

$$x \vee y \equiv inf\{z \in X | z \geq x, z \geq y\} = (max\{x_1, y_1\}, ..., max\{x_n, y_n\}) \tag{B.2}$$
$$x \wedge y \equiv sup\{z \in X | z \geq x, z \geq y\} = (min\{x_1, y_1\}, ..., min\{x_n, y_n\}) . \tag{B.3}$$

f is *supermodular* if for all $x, y \in X$:

$$f(x \vee y) + f(x \wedge y) \geq f(x) + f(y) . \tag{B.4}$$

Alternatively, f is *submodular* if $-f$ is *supermodular* meaning that for all $x, y \in X$:

$$f(x \vee y) + f(x \wedge y) \leq f(x) + f(y) . \tag{B.5}$$

Application to health care production: Turning to our specific application, we define:

$$X = (R, H, H_p) = \{0, 1\}^3 \tag{B.6}$$

where $R = 1$ denotes a private room, H denotes patient health, with $H = 0$ denoting an AD/ADRD diagnosis at admission. H_p denotes peer health, again with $H_p = 0$ denoting an AD/ADRD diagnosis for the roommate/peer at admission.

We can now explore sub- and supermodularity using our empirical estimates presented in Table 3. Table B.2 presents the results, where the first cell corresponds to the effects on patient health and the second cell corresponds to peer health. To provide an example, consider the last row (Panel F). In this case, we're holding peer health fixed, and consider a peer with an AD/ADRD diagnosis at admission, $H_p = 0$. We thus focus on room design, x_1 or y_1, and own patient health at admission, x_2 and y_2. The last row this considers a shared room with a healthy patient, $x = (0, 1)$, and a single room with an unhealthy patient $y = (1, 0)$, both conditional on an unhealthy peer. Column 1 then presents $f(1, 1; H_p = 0) - f(0, 1; H_p = 0)$. In words, we calculate the difference for a healthy patient moved a shared room, shared with an unhealthy peer, to a single room. The combined positive effect is 0.018 (0.015+0.003) according to the estimates in Table 3. Turning to the peer, we're considering the effect for an unhealthy patient $H_p = 0$, of moving from a shared room with a healthy peer to a single room. The estimate from Table 3 suggests that this would harm the patient if anything, resulting in a negative effect of -0.007. The second column repeats the calculations, and we take the difference of the two estimates in column 3. A negative difference suggests submodularity and a positive difference suggests super-modularity.

A few more comments are in order before interpreting the results. First, we can exclude pairs with $x = (0, 0)$ or $x = (1, 1)$ (and likewise for y). These calculations trivially yield a difference of 0 in the third column, consistent with both sub- and supermodularity. Second, to be internally inconsistent, the difference within each panel must equal across the two considered scenarios. It thus suffices to focus on just one of the two presented rows. This allows us to abstract away from harder to interpret objects Δ which denote the reduction

Table B.2: Submodularity and Supermodularity in Production

	$f(x \vee y) - f(x)$ $\Delta Y, \Delta Y^P$ (1)	$f(y) - f(x \wedge y)$ $\Delta Y, \Delta Y^P$ (2)	Difference (1)-(2) (3)	Modularity (4)
Panel A: R=1, (H, H_p)				
$x = (1,0),\ y = (0,1)$	0,Δ_1	0,Δ_1	0,0	SUB/SUPER,SUB/SUPER
$x = (0,1),\ y = (1,0)$	Δ_1, 0	Δ_1, 0	0,0	SUB/SUPER,SUB/SUPER
Panel B: R=0, (H, H_p)				
$x = (1,0),\ y = (0,1)$	0.003,$\Delta_{0,1}$	0.033,$\Delta_{0,1}$	-0.03, $\Delta_{0,1} - \Delta_{0,0}$	SUB,SUB
$x = (0,1),\ y = (1,0)$	$\Delta_{0,1}$, 0.003	$\Delta_{0,0}$, 0.033	$\Delta_{0,1} - \Delta_{0,0}$, -0.03	SUB,SUB
Panel C: H=1, (R, H_p)				
$x = (1,0),\ y = (0,1)$	0,Δ_1	0.003,$\Delta_{0,1}$	-0.003,$\Delta_1 - \Delta_{0,1}$	SUB/SUPER,SUPER
$x = (0,1),\ y = (1,0)$	0.015,0.015	0.018,-0.007	-0.003,0.022	SUB/SUPER,SUPER
Panel D: H=0, (R, H_p)				
$x = (1,0),\ y = (0,1)$	0,Δ_1	0.033,$\Delta_{0,0}$	-0.033,$\Delta_1 - \Delta_{0,0}$	SUB,SUB/SUPER
$x = (0,1),\ y = (1,0)$	-0.007, 0.018	0.026, 0.026	-0.033,-0.008	SUB, SUB/SUPER
Panel E: $H_p = 1$, (R,H)				
$x = (1,0),\ y = (0,1)$	Δ_1, 0	$\Delta_{0,1}$, 0.003	$\Delta_1 - \Delta_{0,1}$, -0.003	SUPER,SUB/SUPER
$x = (0,1),\ y = (1,0)$	0.015, 0.015	-0.007, 0.018	0.022,-0.003	SUPER,SUB/SUPER
Panel F: $H_p = 0$, (R,H)				
$x = (1,0),\ y = (0,1)$	Δ_1, 0	$\Delta_{0,0}$, 0.033	$\Delta_1 - \Delta_{0,0}$, -0.033	SUB/SUPER,SUB
$x = (0,1),\ y = (1,0)$	0.018, -0.007	0.026, 0.026	-0.008,-0.033	SUB, SUB

Notes: This table assess sub- and supermodularity in health care production based on based on patient health, peer health, and room design.

in 90-day mortality from transitioning between unhealthy to health in a single room Δ_1 or a shared room, shared with an unhealthy peer, $\Delta_{0,0}$, or a healthy peer $\Delta_{0,1}$. Third, and last, panels c and E and likewise D and F are symmetric. It thus suffices to focus just on the first cell.

Main results: As illustrated in panels A and B, and focusing on the first cell, we find that health production is submodular in patient and peer health, conditional on room arrangement. This suggests that patient and peer health are substitutes not complements.

We also find that health production is submodular in peer health and room design, conditional on own health at admission, panels C and D. This suggests peer health and room design are also substitutes.

Lastly, the interaction between own health and room design are more subtle. Conditional on an unhealthy peer, we find that health production is submodular in own health and room design (Panel F). However, conditional on a healthy peer, health production becomes supermodular in own health and room design (Panel E).

C Optimal Room Assignment

C.1 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 residents with and without AD/ADRD to rooms in a given nursing home. Denote the fraction of residents with AD/ADRD by π and types by $k \in \{\text{AD}, \text{No}\}$. Letting N be the total number of residents and N_k be the number of residents of each type, we thus have:

$$N_{\text{AD}} = \pi N, \qquad N_{\text{No}} = (1-\pi)N.$$

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 of the nursing home is equal to the number of residents. 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 residents (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 $r \in \{0, \text{AD}, \text{No}\}$. 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 AD residents in private rooms, x^0_{AD},
- The number of residents without AD in private rooms, x^0_{No},
- The number of shared rooms with two residents with AD, s_{AA},
- The number of shared rooms with two residents without AD, s_{NN}, and,
- The number of shared rooms with one resident who has AD and another who does not, s_{AN}.

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

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

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

Using the contraints and the fact that $x^0_{\text{No}} = pR - x^0_{\text{AD}}$, we can express s_{AA} and s_{NN} as:

$$s_{\text{AA}} = \tfrac{1}{2}\left(\pi N - x^0_{\text{AD}} - s_{\text{AN}}\right), \qquad s_{\text{NN}} = \tfrac{1}{2}\left((1-\pi)N - (pR - x^0_{\text{AD}}) - s_{\text{AN}}\right).$$

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

$$\begin{aligned}
\max_{x^0_{\text{AD}}, s_{\text{AN}}} \quad V = {} & C + \alpha x^0_{\text{AD}} + \beta s_{\text{AN}} \\
\text{s.t.} \quad & x^0_{\text{AD}} \in [L, U], \\
& s_{\text{AN}} \in \left[0, \min\{\pi N - x^0_{\text{AD}}, (1-\pi)N - (pR - x^0_{\text{AD}})\}\right],
\end{aligned}$$

where:

$$\begin{aligned}
\alpha &\equiv (u_{\text{AD},0} - u_{\text{AD,AD}}) - (u_{\text{No},0} - u_{\text{No,No}}), \\
\beta &\equiv (u_{\text{AD,No}} + u_{\text{No,AD}}) - (u_{\text{AD,AD}} + u_{\text{No,No}}), \\
C &\equiv \pi N u_{\text{AD,AD}} + (1-\pi) N u_{\text{No,No}} + pR(u_{\text{No},0} - u_{\text{No,No}}), \\
L &\equiv \max\{0, pR - (1-\pi)N\}, \quad U \equiv \min\{\pi N, pR\}.
\end{aligned}$$

The parameter α can be interpreted as the difference in privacy premium between residents with and without AD. On the other hand, β can be interpreted as the surplus from having a mixed room rather than homogeneous shared rooms. Moreover, we observe that β is almost identical to the expression defining supermodularity or submodularity (between residents with and without AD/ADRD in shared rooms), with negative values of β 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 β.

First, in the supermodular case ($\beta \leq 0$), homogeneous rooms is more efficient than mixed rooms, so we set $s^*_{\text{AN}} = 0$. In addition, we allocate as many private rooms to the

type with the greater privacy premium as possible: if $\alpha > 0$, set $x^{0*}_{\text{AD}} = U$, whereas if $\alpha \leq 0$, set $x^{0*}_{\text{AD}} = L$.

On the other hand in the submodular case ($\beta > 0$), 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 ($|\alpha| > \beta$), 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 $\beta \geq |\alpha|$. For a given choice of x^0_{AD}, the maximum feasible number of mixed rooms is:

$$s_{max}(x^0_{\text{AD}}) = \min\{ \overbrace{\pi N - x^0_{\text{AD}}}^{\text{Remaining Residents with AD}}, \underbrace{(1-\pi)N - (pR - x^0_{\text{AD}})}_{\text{Remaining Residents without AD}} \}.$$

This quantity is maximized when the two constraints bind simultaneously, which occurs when $x^0_{\text{AD}} = x_{bal}$:

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

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

C.2 Comparison of Counterfactual Mortality with Other Assignment Rules

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

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

$$\frac{x^0_{\text{AD}}}{\pi N} = \frac{x^0_{\text{No}}}{(1-\pi)N} = \frac{p}{p + 2(1-p)}.$$

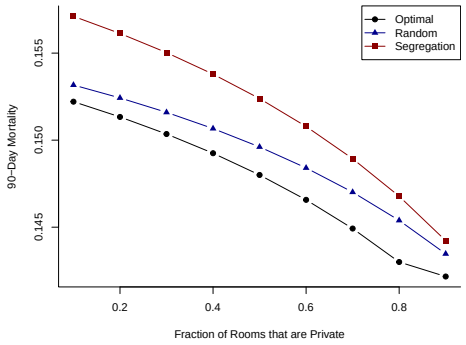
In addition, the fraction of shared rooms with two residents with (without) AD/ADRD is π^2 (respectively $(1-\pi)^2$), and the fraction of shared rooms that are mixed is $2\pi(1-\pi)$. Under counterfactual assignment with perfect segregation, we assume that private rooms are randomly assigned, but a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

Figure C.5 shows counterfactual 90-day mortality under different assignment rules, varying the proportion of the resident population having AD/ADRD (π) across different panels, and varying the proportion of rooms that are private in each panel. Average potential outcomes for different resident types under different room assignments $Y_k(r)$ are based on estimates in panel A of Table 3. We observe that different assignment rules can lead to quantitatively meaningful differences in mortality: when half of the resident population has AD/ADRD and 10 percent of rooms are private, optimal assignment leads to a 0.7 p.p. fall in 90-day mortality relative to random assignment, and a 1.4 p.p. fall relative to perfect segregation.

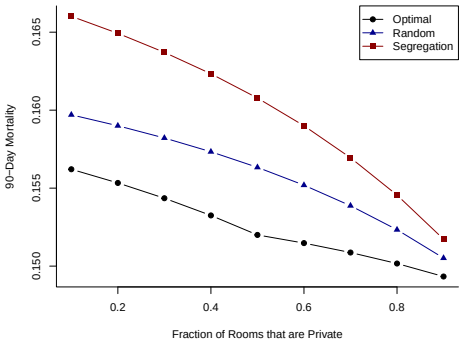
In addition, we observe four qualitative patterns. First, for all values of π and p, mortality is highest under perfect segregation, followed by random assignment and finally (by defintion) optimal assignment. Second, mortality is decreasing in the share of rooms that are private, consistent with assignment to private rooms reducing mortality on average. Third, differences in counterfactual mortality tend to be greater when a roughly even share of the population has AD/ADRD, consistent with there being the most scope for assignment rules to make a difference when there is more heterogeneity in the population. Fourth, differences across different assignment rules are greatest when a small share of rooms are private, pointing to the importance of submodularity in health production across patient types in shared rooms.

Figure C.5: Counterfactual Mortality Under Different Assignment Rules

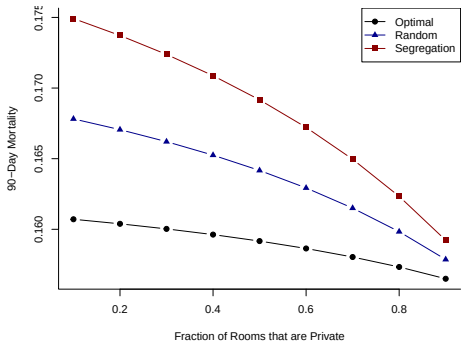
(a) $\pi = 1/6$



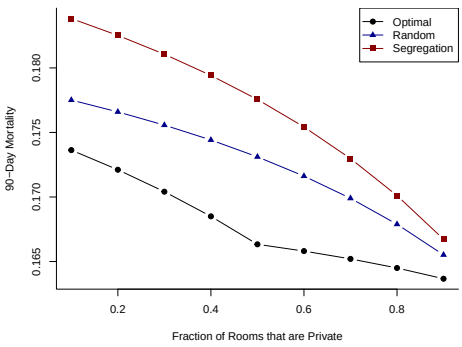
(b) $\pi = 1/3$



(c) $\pi = 1/2$



(d) $\pi = 2/3$



(e) $\pi = 5/6$

