CAPACITY SPILLOVERS FROM PRIVATE SUBSTITUTION: EVIDENCE FROM HOSPITAL-AT-HOME

Alon Bergman
University of Pennsylvania

Guy David
University of Pennsylvania & NBER

October 31, 2025

[DRAFT TO BE REFINED – DO NOT CIRCULATE]

Abstract

Capacity constraints are pervasive in public systems, yet evidence on how private alternatives affect those who remain is limited. We study capacity spillovers arising when high-resource patients substitute from hospital care to home-based hospitalization under Medicare's Hospital-at-Home program. Using patient-level data and an event-study design, we show that each transfer to home care increases the number and share of low-resource inpatients in the originating department, operating through both higher admissions and longer lengths of stay. Effects triple when hospitals operate above 95% occupancy and are absent for other transfer types, confirming a capacity-relief mechanism. We develop a theoretical framework showing how private exit from congested systems can generate equity-enhancing spillovers for underserved populations. The findings generalize to other capacity-constrained sectors, such as education or transportation, where private substitution can expand access for those left behind.

1. Introduction

Hospital capacity represents a binding constraint in health care delivery across developed economies. In the United States, hospital occupancy rates increased from 64% pre-pandemic to 75% in 2023-2024, with some states already exceeding the critical 85% threshold, above which hospitals struggle to manage demand surges and emergency capacity (Leuchter et al., 2025). During these high-occupancy periods, capacity constraints create negative spillover effects across patient populations, degrading quality indicators such as length of stay (Lim et al., 2023). The COVID-19 pandemic starkly revealed these capacity limits, as

hospitals struggled to accommodate surges in acutely ill patients while maintaining routine care (Tona et al., 2020). Yet capacity constraints are not merely episodic crises. They reflect persistent structural imbalances driven by aging populations, rising prevalence of chronic diseases, and years of constrained hospital investment (Navathe et al., 2024).

Traditional policy responses to capacity constraints offer limited solutions. Building new hospital infrastructure requires substantial capital investment, multi-year construction timelines, and generates fixed costs that hospitals must carry even when demand ebbs (Finkelstein 2007; Gaynor et al., 2015; Einav et al., 2018). Demand management through utilization review and prior authorization can reduce inappropriate admissions but offers a limited scope for addressing legitimate care needs (Doshmangir et al., 2022). Process optimization can generate efficiency gains but encounters diminishing returns in already lean systems (Call et al., 2013; Chandra et al., 2016). Expanding capacity without physical construction requires fundamentally different approaches.

Hospital-at-Home (HaH) programs represent one such approach. Under Medicare's Acute Hospital Care at Home waiver, launched in November 2020 during the COVID-19 pandemic, HaH allows clinically complex patients who would otherwise require inpatient admission to receive hospital-level care in their homes (CMS, 2024). By mid-2023, over 125 health systems and 290 hospitals across 37 states had implemented HaH programs, serving more than 31,000 patients (Pandit et al., 2024; Levine et al., 2024). Unlike traditional home health services that provide post-acute care, HaH delivers acute care: intensive monitoring through wearable devices, clinical visits, 24/7 access to care teams, intravenous medications, imaging, and laboratory services. Importantly, HaH maintains hospital billing status while shifting the location of care delivery (Leff et al., 2009; Federman et al., 2018).

Existing evidence demonstrates that HaH can deliver clinical outcomes comparable to or better than traditional hospitalization for appropriately selected patients. The seminal randomized controlled trial by Leff and colleagues (2005) across three sites with 455 older adults found that HaH patients experienced shorter lengths of stay (3.2 vs. 4.0 days), lower rates of confusion and falls, and costs approximately one-third lower than conventional hospitalization. Subsequent trials have consistently reported similar or superior outcomes: Levine et al.'s (2020) randomized trial at Brigham and Women's Hospital demonstrated that HaH reduced acute care costs by 38% while lowering 30-day readmissions from 23% to 7%. Systematic reviews and meta-analyses confirm these patterns across diverse settings (Shepperd et al., 2016; Caplan et al., 2012; Arsenault-Lapierre et al., 2021). The recent national evaluation of Medicare's waiver found mortality rates below 1%, escalation to

traditional hospital care in fewer than 7% of cases, and lower readmission rates compared to matched inpatient controls (CMS, 2024; Levine et al., 2024).

However, this growing literature has focused almost exclusively on direct outcomes for HaH recipients themselves. No prior work has examined system-level spillover effects: when high-resource patients transfer to HaH, freeing physical hospital beds, how does this affect patients who remain in traditional inpatient care? This gap matters for three interconnected reasons.

First, it speaks to fundamental questions in public economics about private substitution in capacity-constrained systems. When private alternatives exist to congested public goods, whether private schools, toll roads, or home-based hospital care, private exit by advantaged groups can generate positive externalities for those who remain. Finkelstein's (2007) landmark study of Medicare's introduction demonstrated that public insurance expansion increased hospital capacity with substantial spillovers to the non-elderly population, effects six times larger than partial-equilibrium predictions would suggest. Conversely, White (2013) showed that Medicare payment cuts reduced hospital discharges not only for Medicare beneficiaries but also for the non-elderly, as hospitals adjusted capacity system-wide. These general equilibrium effects highlight that understanding health care interventions requires examining not just direct treatment effects but also how one group's behavior affects another group's outcomes (Chandra & Staiger, 2007; Baker & Shankarkumar, 2015).

Second, spillover analysis directly addresses equity concerns about HaH access. Our descriptive analysis reveals that HaH eligibility depends not only on clinical appropriateness but also on social determinants—specifically housing quality, caregiver availability, and neighborhood stability. Program guidelines require functioning utilities, adequate space for medical equipment, and stable housing tenure (Chua et al., 2022; Williams et al., 2023). These requirements systematically exclude patients experiencing housing instability, those in multi-unit buildings lacking elevators, and individuals without caregivers—populations disproportionately low-income and non-white (CMS, 2024). If HaH primarily serves advantaged patients while capacity constraints harm disadvantaged patients, the program could exacerbate existing disparities. But if HaH generates capacity spillovers that disproportionately benefit disadvantaged patients, then unequal access need not imply inequitable outcomes.

Third, our findings inform ongoing Medicare policy debates. The Acute Hospital Care at Home waiver, initially authorized as a temporary pandemic response, has been extended multiple times, most recently through December 2025 (AHA, 2024). Permanent

authorization hinges partly on whether HaH generates benefits beyond direct patient outcomes. If capacity spillovers substantially expand access for vulnerable populations, payment rates should reflect both direct and spillover effects (MedPAC, 2024). Ignoring spillovers would lead to underpayment and suboptimal adoption of HaH.

This paper provides the first causal evidence on capacity spillovers from Hospital-at-Home programs. We ask: When high-resource patients transfer to HaH, does this create capacity spillovers that benefit lower-resource patients who remain hospitalized? Using patient-level administrative data from a multi-hospital health system and an event-study design that exploits the timing of individual HaH transfers, we trace out dynamic effects on low-resource patient census, admissions, length of stay, and clinical outcomes.

We make four primary contributions to the literature. First, we provide causal estimates of capacity spillovers resulting from private substitution in healthcare. Using an event-study framework, we show that each HaH transfer increases both the number and share of low-resource patients in the originating hospital department, with effects emerging within 1-2 days and persisting through five days post-transfer. Second, we decompose mechanisms: spillovers operate through increased admissions of low-resource patients (expanding access) and extended lengths of stay among existing low-resource patients (improving treatment completion). Third, we demonstrate that effects are three times larger when hospitals operate above 95% occupancy compared to lower occupancy levels, confirming the capacity-relief channel. Falsification tests using other transfer types—psychiatric transfers, hospice discharges—show no similar spillover patterns, ruling out alternative mechanisms unrelated to physical capacity. Fourth, we develop a theoretical framework formalizing how private exit from capacity-constrained public systems can generate equity-enhancing spillovers even when access to private alternatives is unequally distributed.

Our theoretical model builds on insights from both health economics (Einav et al., 2018) and public economics (Epple & Romano, 1998; Besley & Ghatak, 2001). We consider a hospital facing binding capacity constraints, patients who differ in resource intensity, and a private alternative (HaH) available to high-resource patients. When capacity binds and the cost of the private alternative falls below a threshold, high-resource patients exit the public system. This exit mechanically increases the share of low-resource patients served and, under plausible assumptions about how congestion affects quality, improves service quality for remaining patients. Three predictions follow: spillovers should increase with capacity utilization, operate through both admissions and length-of-stay, and arise specifically from capacity-relieving (not generic) transfers.

Our empirical findings support the model's predictions. Event-study estimates show that HaH transfers increase the census and share of low-resource patients in the same department during the days following transfer, with effects building over the first two to three days and persisting through day five. HaH transfers raise the low-resource patient share of census and admissions while modestly extending length of stay, with no comparable changes for high-resource patients. The effects are concentrated under high occupancy ($\geq$95%), where estimated impacts on census, share, and admissions are largest. Placebo analyses of non-HaH transfers show no such patterns, reinforcing that the observed effects are specific to capacity-relieving transfers rather than general patient-flow dynamics

Falsification tests using alternative transfer types confirm the mechanism's specificity. Psychiatric transfers—which also remove high-resource patients from general medical/surgical departments—generate similar spillover patterns, consistent with capacity relief. However, observation-to-inpatient status changes—which alter billing codes without freeing physical beds—show no spillover effects (point estimate: -0.02, 95% CI: -0.11, 0.07). This negative result is critical: it rules out explanations based on general patient flow dynamics, administrative reporting artifacts, or other mechanisms unrelated to physical capacity constraints.

Our findings connect to broader theoretical and empirical literatures on private provision in capacity-constrained public systems. In education, researchers have long debated whether private school vouchers harm public schools by facilitating exit of engaged families or benefit them by reducing class sizes and concentrating resources (Hsieh & Urquiola, 2006). A randomized evaluation of public-school grants in Pakistan found that improving public schools increased test scores not only in public schools but also in competing private schools—an "education multiplier" where public investment generated spillovers across sectors (Andrabi et al., 2024). In infrastructure, studies document that public investment in roads and utilities can crowd in private investment by reducing bottlenecks (Aschauer, 1989; Pereira, 2001). In hospital markets, vertical integration and selective contracting create spillover effects through referral networks and capacity reallocation (Ho and Pakes, 2014; Arnold et al., 2025).

Our contribution to these literatures is threefold. First, we demonstrate that the spillover mechanism operates in hospital settings, where capacity constraints are binding and private alternatives (HaH) are increasingly viable. Second, we provide granular evidence on mechanisms: spillovers work through both access (more admissions) and quality (longer stays permitting treatment completion) channels. Third, we show that spillovers

concentrate when constraints bind most tightly—a capacity gradient consistent with theory but rarely demonstrated empirically.

The equity implications are nuanced. HaH access is demonstrably unequal: patients from higher-income zip codes with better housing quality and greater caregiver availability are more likely to receive HaH (Saenger et al., 2020; Williams et al., 2023; CMS, 2024). Our machine learning analysis confirms these patterns: among clinically comparable high-resource patients, those from zip codes with newer housing, more single-family homes, and higher median incomes have significantly greater HaH probability. This access inequality raises legitimate concerns about HaH exacerbating disparities. However, our spillover results complicate this narrative: the low-resource patients least likely to access HaH benefit most from capacity relief when others do. HaH is inequitable in access but equity-enhancing in effects—a tension that pervades debates about private alternatives in public systems (Epple & Romano, 1998).

This tension has direct policy implications. If policymakers evaluate HaH solely on access equity, the program appears problematic: it systematically serves advantaged populations while excluding vulnerable groups facing housing instability and lacking caregivers. However, if evaluation incorporates spillover effects—expanded access and improved care for disadvantaged patients remaining in traditional settings—the equity calculus shifts. The normatively optimal policy may involve both expanding HaH capacity to serve advantaged patients (generating spillovers) and simultaneously investing in supports (housing assistance, caregiver subsidies, technology access) to broaden HaH eligibility for disadvantaged populations. Our results suggest that capacity spillovers are substantial enough to justify considering HaH as an equity-enhancing intervention despite unequal access.

The remainder of the paper proceeds as follows. Section 2 describes the institutional background of Hospital-at-Home programs and our study setting. Section 3 presents data and descriptive evidence on patient characteristics, hospital capacity utilization, and neighborhood socioeconomic factors. Section 4 develops our theoretical framework. Section 5 outlines the empirical strategy. Section 6 presents our empirical results. Section 7 discusses implications for policy, equity, and generalizability. Section 8 concludes.

2. Institutional Background

The Hospital-at-Home concept has been in existence for over two decades, preceding the COVID-19 pandemic, which catalyzed its rapid expansion. Bruce Leff and colleagues at Johns Hopkins University pioneered the modern U.S. Hospital-at-Home model in the late

1990s, conducting initial feasibility studies that demonstrated the safety of providing hospital-level care to selected acutely ill older patients at home (Leff et al., 1999). Their 1999 pilot study, involving 17 patients, established proof of concept, demonstrating that home-based acute care was both clinically feasible and potentially cost-saving.

Building on this foundation, Leff and colleagues launched a landmark three-site randomized controlled trial, published in 2005, which enrolled 455 older adults across three medical centers (Leff et al., 2005). This seminal study demonstrated that HaH patients experienced shorter lengths of stay, significantly lower rates of delirium and confusion, reduced functional decline, and costs approximately one-third lower than conventional hospitalization. The trial established that selected patients with conditions like congestive heart failure, chronic obstructive pulmonary disease, cellulitis, and community-acquired pneumonia could receive hospital-level care at home without compromising safety or clinical outcomes.

Despite these promising results, HaH adoption remained limited in the pre-pandemic era due to regulatory and payment barriers. Medicare's inpatient prospective payment system (IPPS) did not recognize home-based acute care as qualifying for hospital reimbursement, creating fundamental financial disincentives (Leff, 2009). Hospitals faced substantial infrastructure investments without adequate payment mechanisms to support these costs (DeCherrie et al., 2019). State licensure requirements, liability concerns, and workflow integration challenges further impeded scaling beyond pilot programs at academic medical centers (Federman et al., 2018; Clarke et al., 2021).

The Mount Sinai Health System in New York City represented one notable exception, developing its Hospital-at-Home program into a sustained operational model beginning in 2014. By 2018, the program had cared for over 685 individuals, demonstrating that HaH could be sustained outside of research settings with appropriate institutional support (Federman et al., 2018). Internationally, Spain and Australia developed widespread HaH models beginning in the 1980s and 1990s respectively, though differences in financing and regulatory environments limited direct transferability to the United States context.

Medicare's Acute Hospital Care at Home Waiver as Policy Catalyst

The COVID-19 pandemic fundamentally transformed HaH policy in the United States. As hospitals faced unprecedented capacity pressures in spring 2020, the Centers for Medicare & Medicaid Services (CMS) recognized the urgent need for capacity expansion mechanisms (Pandit et al., 2024). On November 25, 2020, CMS announced the Acute Hospital Care at

Home initiative, granting hospitals the ability to treat eligible patients in their homes while maintaining acute inpatient status and full IPPS reimbursement (CMS, 2020).

The waiver eliminated the primary regulatory barrier that had constrained pre-pandemic HaH growth: Medicare payment. Hospitals could now bill HaH episodes using the same MS-DRG codes as traditional inpatient admissions, receiving identical reimbursement despite fundamentally different cost structures. CMS established program requirements including twice-daily in-person clinical visits, continuous monitoring via mobile health technology, 24/7 access to registered nurses, same-day or next-day physician visits, and the ability to deliver hospital-level diagnostics and treatments (CMS, 2024).

The expansion was rapid and geographically widespread. Within six months, 43 health systems had received approval (Zychlinski et al., 2024). By December 2022, over 124 health systems encompassing 290 hospitals across 37 states had implemented HaH programs (Pandit et al., 2024). As of July 2024, participating hospitals had treated over 31,000 patients through the waiver, with mortality rates below 1%, escalation to traditional hospital care in fewer than 7% of cases, and readmission rates comparable to or lower than matched inpatient controls (CMS, 2024; Levine et al., 2024).

The waiver's success prompted multiple extensions beyond its initial emergency authorization. Initially tied to the COVID-19 Public Health Emergency declaration, the waiver was extended through December 31, 2024, and subsequently through December 31, 2025 (AHA, 2024). The Medicare Payment Advisory Commission (MedPAC) has recommended continued extension to gather additional evidence on cost-effectiveness, appropriate payment levels, and equity in program access (MedPAC, 2024). Permanent authorization remains under active policy debate, with stakeholders divided on payment methodology, quality oversight, and whether HaH represents a sustainable transformation in acute care delivery.

Hospital-at-Home Program Operations and Eligibility Criteria

Contemporary HaH programs admit patients who meet specific clinical and social eligibility criteria. Clinical criteria focus on conditions amenable to home-based treatment—primarily heart failure, COPD exacerbations, cellulitis, community-acquired pneumonia, urinary tract infections, and asthma—and exclude patients requiring intensive care, high-flow oxygen, invasive monitoring, or procedures unavailable at home (Levine et al., 2020). Social criteria include safe home environment (functioning utilities, adequate space, absence of hazards), reliable caregiver presence, telecommunications access enabling video visits and remote monitoring, and patient/family willingness to participate (Pandit et al., 2024). Programs

vary in caregiver requirements, with some requiring 24/7 presence while others accept intermittent availability or remote family support.

The clinical care model maintains hospital-level intensity while adapting to home environments. Patients receive twice-daily visits from registered nurses who conduct assessments, administer medications (including intravenous antibiotics and diuretics), draw blood for laboratory testing, and coordinate with physicians (Leff et al., 2009). Remote monitoring via wearable devices transmits continuous data on vital signs to command centers staffed 24/7 by registered nurses and physicians (Levine et al., 2020). Video consultation enables real-time clinical decision-making without requiring physical presence (Pandit et al., 2024).

Mobile diagnostic capabilities include portable ultrasound, electrocardiogram machines, and point-of-care laboratory testing (Levine et al., 2020). Most programs partner with agencies to provide chest radiographs at home within hours of physician orders. Mobile pharmacies enable same-day medication delivery, and durable medical equipment suppliers provide oxygen concentrators, hospital beds, and other equipment as needed (DeCherrie et al., 2019).

Physician involvement typically includes daily virtual rounds, same-day or next-day home visits for clinical changes, and 24/7 on-call availability. Care coordination is intensive, with dedicated coordinators facilitating communication across providers, managing logistics, and serving as primary contacts for patients and families (Brody et al., 2019). The average HaH length of stay typically ranges from 3-5 days, comparable to or slightly longer than traditional hospitalization for similar conditions (Levine et al., 2020; Pandit et al., 2024).

Study Setting and Context

Our analysis focuses on a multi-hospital community health system operating five community hospitals in the Northeastern United States. Unlike the academic medical centers (Johns Hopkins, Brigham and Women's, Mount Sinai) that dominate published HaH research, this community hospital setting serves a more heterogeneous patient population across socioeconomic dimensions, with greater racial/ethnic diversity and broader income distribution. This setting enhances the generalizability of findings to the majority of U.S. hospitals, which are community-based rather than academic institutions (AHA, 2023).

[FIGURE 1 HERE]

Figure 1 displays the cumulative growth of the HaH program across study hospitals. The HaH program was rolled out sequentially across system hospitals, starting with Hospital 1, the largest hospital in the system, on January 14, 2022. Following Hospital 1, other system hospitals joined the program every 2-3 months, with Hospital 5 being the last to join on October 26, 2022. By the end of our study period, the HaH program had treated 517 patients, with the majority (237, or 46%) being treated in Hospital 1.

The program provided system-developed remote monitoring technology, care coordination platform, and mobile diagnostic capabilities. Clinical teams included hospitalist physicians, registered nurses with emergency or intensive care experience, paramedics for mobile response, care coordinators, and pharmacists. The staffing model allocated one physician to approximately X HaH patients, one nurse to X patients, and one care coordinator to X patients, enabling twice-daily nursing visits, same-day physician response, and continuous 24/7 monitoring.

Eligibility criteria closely followed CMS waiver requirements with some system-specific refinements. Clinical criteria focused on diagnosis (CHF, COPD, cellulitis, pneumonia, UTI, asthma) and severity (moderate illness appropriate for medical-surgical floor, not requiring ICU). Social criteria required functioning utilities, telephone/internet access, and identified caregiver. Approximately 67% of screened patients meeting clinical and social criteria accepted the proposal to enter the HaH program.

The study period coincided with substantial and sustained capacity pressures across the health system. Average hospital occupancy rate ranged from 76% to 87%, with 15.4% of patient days occurring under high-occupancy conditions (defined as >95% occupancy). Occupancy frequently exceeded 95%, a critical threshold above which emergency department boarding times increase sharply, surgical case delays multiply, and quality indicators deteriorate (Lim et al., 2023; Weissman et al., 2007).

These capacity constraints reflected persistent structural pressures beyond pandemic artifacts. The study region experienced population aging, growth in chronic disease prevalence (particularly diabetes, heart failure, and COPD among Medicare beneficiaries), and nursing workforce shortages that limited effective bed capacity despite physical bed availability (MedPAC, 2024). Additionally, the post-pandemic period saw surges in delayed presentations of acute illness and deferred elective procedures requiring hospitalization, creating sustained demand pressures (Pandit et al., 2024).

This capacity-constrained environment provides an ideal natural experiment setting for studying spillover effects from capacity-relieving interventions. When baseline capacity

utilization is high, marginal capacity adjustments, such as individual HaH transfers freeing single beds, should generate larger effects on other patients' access and care quality. Conversely, in unconstrained settings with substantial excess capacity, HaH may represent pure substitution with negligible spillover benefits. Our empirical strategy exploits variation in capacity utilization over time and across hospitals to test whether spillover effects indeed concentrate when capacity binds most tightly, as our theoretical model predicts.

The intersection of several factors makes this setting particularly policy-relevant. First, community hospitals facing capacity pressures represent the modal U.S. hospital environment, not the exception. Second, the HaH program operated as a commercial, sustained model rather than a research demonstration, reflecting real-world implementation challenges. Third, the socioeconomically heterogeneous patient population enables examination of equity concerns about differential HaH access and spillover benefits. Fourth, the high-capacity-utilization context creates conditions under which capacity spillovers should be most visible and consequential. These features position our analysis to generate findings directly informative for policy decisions about Medicare waiver permanence, payment design, and strategies for equitable HaH expansion.

3. Data and Descriptive Evidence

Our analysis draws on administrative data from the health system, covering January 1, 2022, through December 4, 2023. For the 517 patients who participated in HaH during our study period, we obtained complete episode data including admission and discharge dates, MS-DRG codes, primary diagnoses, primary payer, age, and residential zip code. For all 83,980 inpatient cases across the health system, we obtained comprehensive data including dates of admission and discharge, MS-DRG classifications, diagnoses, payer, hospital, department, discharge disposition, age, and 30-day readmission indicators. We also received detailed cost accounting data capturing direct and indirect costs at the patient episode level.

From these patient-level data, we constructed hospital-level and department-level measures of daily census and occupancy rates by patient type and payer category. Occupancy rates were computed as the ratio of daily census to our constructed estimate of hospital capacity, estimated at the 95^{th} percentile of the occupancy count measured at each hospital during our study period.

We merged patient residential zip codes with U.S. Census Bureau American Community Survey 5-year estimates (2017-2021) to incorporate socioeconomic context. The ACS data provide zip code-level measures of demographics (race/ethnicity, age), socioeconomic status

(income, poverty, education), and housing characteristics (number of units in dwelling, number of rooms in unit).

Our final analytical sample spans 704 days across 74 departments in five hospitals, encompassing 83,980 unique patients, including 517 Hospital-at-Home episodes. The data structure supports panel analyses exploiting within-department temporal variation in HaH utilization and capacity constraints to identify spillover effects on wait times, length of stay, readmissions, costs, and other outcomes.

We classify patients as "low-resource" (LR) if their primary payer is Medicaid, self-pay, or charity; by contrast, high-resource patients are either privately insured or have Medicare/Medicare Advantage. Importantly, during our study period only privately insured and Medicare patients were considered eligible for the HaH program. Therefore, all HaH patients are “high resource” (HR) patients by construction.

Summary Statistics

[TABLE 1 HERE]

Table 1 presents summary statistics for the full sample and key patient subgroups. Our sample includes 83,980 inpatient episodes across the five-hospital system, of which 13,749 (16.4%) are classified as low-resource patients and 69,714 (83.6%) as high-resource patients. Low-resource patients are substantially younger (mean age 48.63) compared to high-resource patients (71.84) and HaH patients (76.23), reflecting the Medicare eligibility age threshold and the concentration of Medicaid beneficiaries among working-age adults. Insurance coverage patterns align with our classification: low-resource patients are predominantly covered by Medicaid (91.22%), charity care (6.31%), or self-pay (2.47%), while high-resource patients are covered by Medicare (75.21%) or private insurance (22.35%). Hospital-at-Home patients are almost exclusively Medicare beneficiaries (97.10%), consistent with the CMS waiver requirements.

Length of stay is similar across groups (5.59-5.72 days), with HaH patients averaging 5.58 days. However, total costs and cost per day differ: HaH patients incur higher total episode costs ($13,915) and higher daily costs ($2,515) compared to the full sample ($12,058 and $2,321, respectively), potentially reflecting the intensive monitoring and twice-daily nursing visits required by the HaH care model. Discharge disposition patterns differ sharply between HaH and traditional inpatient care. Nearly all HaH patients (97.49%) discharge to home or self-care, with one-quarter (25.15%) receiving home health services, compared to only 67.83% of the full sample discharging home. Conversely, traditional inpatients are far more

likely to require skilled nursing facility placement (18.10% versus 0.39% for HaH). The 30-day readmission rate is slightly higher for HaH patients (14.70%) than for high-resource (12.02%) or low-resource patients (10.24%), though differences are modest and likely reflect case-mix variation rather than quality differences.

A central concern for our analysis is understanding the systematic differences across patient populations, both between low-resource and high-resource patients and between high-resource patients who do and do not receive Hospital-at-Home care. These differences matter for two reasons: first, they establish the need to account for patient heterogeneity when estimating HaH effects; second, they inform whether HaH selection introduces systematic bias that could confound our spillover estimates.

To characterize multidimensional differences across patient populations, we conduct principal components analysis (PCA) on the full set of patients' residence zip code-level socioeconomic, demographic, and housing characteristics described in Appendix Table A2, along with patient age. This approach reduces the high-dimensional covariate space into a smaller set of principal components that capture the primary axes of variation in patient characteristics. We focus on the first four principal components, which collectively explain 63% of the total variance in the underlying characteristics.

[FIGURE 2 HERE]

Figure 2 plots the distributions of these four principal components separately for low-resource and high-resource patients. The distributions diverge sharply across all four components, revealing systematic differences in the multidimensional covariate space. Kolmogorov-Smirnov tests reject the null hypothesis that low-resource and high-resource patients are drawn from the same distribution for each component ($p < 0.001$ for all four components). The magnitude of the K-S statistics, ranging from 0.057 to 0.283, indicates substantial separation between these populations along multiple dimensions.

[TABLE 2 HERE]

To provide economic interpretation of these component differences, Table 2 presents results from a LASSO logistic regression predicting low-resource status from the full set of zip code characteristics and patient age. The LASSO procedure selects the most important predictive variables while regularizing to prevent overfitting. The results reveal that racial and ethnic composition drives much of the separation between low-resource and high-resource patients: zip codes with higher percentages of Hispanic/Latino residents and lower percentages of white residents are strongly associated with low-resource status. Economic disadvantage is

also prominent, with poverty rates and SNAP benefit receipt emerging as key predictors. The odds ratios are substantial in magnitude, indicating economically meaningful differences. For example, a 1 percentage point increase in SNAP benefit receipt in a patient's zip code is associated with a 12% decrease in the odds of them being a high-resourced.

In contrast to the sharp differences between low-resource and high-resource patients, we find minimal systematic variation between high-resource patients who receive Hospital-at-Home care and those who receive traditional inpatient care. Figure 3 presents the same principal component distributional analysis, now comparing high-resource inpatients who were not treated via HaH to the 517 HaH patients in our sample. The component distributions are nearly identical. Kolmogorov-Smirnov tests fail to reject equality of distributions for three of the four principal components ($p > 0.10$), and the first component shows only a marginally significant difference. This visual and statistical evidence suggests that HaH selection within the high-resource population does not systematically favor patients from socioeconomic or demographic contexts.

[TABLE 3 HERE]

Table 3 reinforces this conclusion through LASSO logistic regression predicting HaH receipt among high-resource patients. In stark contrast to Table 2's numerous significant predictors and large odds ratios distinguishing between low-resource and high-resource patients, Table 3 reveals that far fewer characteristics predict outcomes, and the odds ratios are modest in magnitude. This suggests that, conditional on being a high-resource patient meeting clinical eligibility criteria, selection into HaH versus traditional hospitalization is not strongly determined by the socioeconomic, demographic, or housing characteristics we observe.

The contrast between Tables 2 and 3 and between Figures 2 and 3 carries implications for our empirical strategy. The substantial differences between low-resource and high-resource patients justify our approach of analyzing these populations separately and attending carefully to potential differential effects. However, the minimal systematic differences between HaH and non-HaH patients within the high-resource group suggest that unobserved confounding related to neighborhood socioeconomic context is unlikely to be a major threat to identification. While HaH selection certainly depends on clinical factors and home safety considerations not fully captured in our zip code-level measures, the absence of strong socioeconomic gradients within the high-resource eligible population provides some assurance that our spillover estimates are not confounded by sorting of HaH patients from particularly advantaged or disadvantaged contexts.

4. Theoretical Framework

This section lays out a stylized model to describe how private opt-outs from publicly financed services, though inequitable in access, can generate equity-enhancing spillovers for low-resourced individuals. This framework applies to public education, healthcare, and transit, where demand may exceed public capacity and where private alternatives exist.

We model a population with heterogeneous income levels and derive conditions under which high-resourced individuals choose to exit the public system. We examine two utility specifications – logarithmic and linear – and study the resulting equilibrium, comparative statics, and equity implications. We show that private opt-outs reduce congestion in the public sector, raise the share of low-resourced beneficiaries, and improve overall public service quality.

We begin by considering publicly financed services, prevalent in education and healthcare, which are often capacity-constrained and subject to crowding-related reduction in quality. While high-resource individuals (HRs) may opt out using private alternatives, doing so can actually benefit low-resource users (LRs) by reducing crowding. We constructed a model to study how equilibrium participation and equity respond to private cost, quality, demand, and capacity.

Consider the number of HRs, n_H, number of LRs, n_L, and fraction of HRs opting into private settings, $\alpha \in [0,1]$. Public quality is given by: $q^{pub}(\alpha) = \frac{1}{n_L+(1-\alpha)n_H}$. Note that the quality in the public sector is always $\frac{1}{n_L} \geq q^{pub} \geq \frac{1}{n_L+n_H}$. Assume private sector quality is fixed at $q^{priv}$and comes at a cost C.

High-resource individuals compare the utility from public $u^{pub} = v(q^{pub}(\alpha))$ and the utility from private $u^{priv} = v\left(q^{priv}\right) - C$. Therefore, the indifference condition for the marginal high-resource individual is: C= $v\left(q^{priv}\right) - v(q^{pub}(\alpha))$. We can now solve for the equilibrium α^*under the two utility specifications: logarithmic utility $v(q) = \ln(q)$ and linear utility $v(q) = q$.

For logarithmic utility we have $C = \ln\left(q^{priv}\right) + \ln(n_L + (1-\alpha)n_H)$ leading to:

$$\alpha^* = \frac{1}{n_H}\left[(n_L + n_H) - \frac{e^C}{q^{priv}}\right]$$

For linear utility we have $C = q^{priv} - \frac{1}{n_L+(1-\alpha)n_H}$ leading to:

$$\alpha^* = \frac{1}{n_H}\left[(n_L + n_H) - \frac{1}{q^{priv} - C}\right]$$

In both specifications the comparative statics are identical. The fraction of HRs opting into private setting, α^*, is decreases with cost, $\frac{\partial \alpha^*}{\partial C} < 0$, increases with the quality of private, $\frac{\partial \alpha^*}{\partial q^{priv}} < 0$, increases with the number of low-resource individuals, $\frac{\partial \alpha^*}{\partial n_L} > 0$, and decreases with the number of high-resource individuals, $\frac{\partial \alpha^*}{\partial n_H} < 0$.

Now introduce a public capacity constraint, K. For simplicity, start with the case of non-binding capacity constraint, $K \geq n_L + n_H$. For this case, we will find a level of private cost $C \geq \underline{C}$ such that $\alpha^* = 0$. We now take the equilibrium $\alpha^*$for both utility specifications and find $\underline{C}$ for both cases. $\underline{C} = ln\left[q^{priv}(n_L + n_H)\right]$ for the logarithmic case and for the linear case: $\underline{C} = q^{priv} - \frac{1}{n_L + n_H}$.

Now assume that $C \geq \underline{C}$, but public capacity constraint is binding, i.e. $K < n_L + n_H$. Further assume that access is rationed regardless of resources such that the number of LRs served is βn_L and the number of HRs served is βn_H. We defined the proportion β as: $\beta = \frac{K}{n_L + n_H}$. Introducing private opt-outs, the number of individuals served by public outlets is given by: $K_{pub} = n_L + (1 - \alpha^*)n_H$ where all desired public users are served: $K_{pub} \leq K$.

The key prediction of this model are that both the quality of public outlet and the fraction of low-resource individuals served by public outlets is and increasing function of α^*.

$$q^{pub}(\alpha^*) = \frac{1}{n_L + (1 - \alpha^*)n_H} > \frac{1}{K}$$

$$Share_{LR}(\alpha^*) = \frac{n_L}{n_L + (1 - \alpha^*)n_H} > \frac{n_L}{n_L + n_H}$$

Note that even when $C = \underline{C}$ and the capacity constraint binds $K < n_L + n_H$, not all individuals can be accommodated by the public system. In this case, at least some HRs must opt out, not because of preference, but because of lack of access. Thus, even at the threshold $C = \underline{C}$, we observe a positive opt-out rate $\alpha^* > 0$ induced by the constraint rather than utility differences. This highlights that under constrained capacity, even perfectly equitable cost thresholds do not ensure equitable outcomes, reinforcing the value of private alternatives in expanding access for low-resourced individuals. Private opt-outs increase quality and representation of low-resourced individuals when public systems are overburdened. Even if private access is inequitable, it creates room for those who need public services the most.

This model shows that under both log and linear utility, private opt-outs by high-resourced individuals can benefit the public system, by raising quality and expanding access for those with fewer resources. Policy should recognize this spillover and design funding and access mechanisms accordingly.

5. Empirical Strategy

Our identification strategy exploits the timing of individual HaH transfers using an event-study framework. The unit of analysis is the department-by-date. Let HAH_{hjt} denote the number of high-resource patient transferring from hospital h, department j, on date t. We estimate:

$$Y_{hjt} = \sum_{\tau=-5}^{5} \beta_\tau HAH_{hjt-\tau} + \theta_{hj} + \delta_t + \varepsilon_{hjt}$$

where Y_{hjt} is the department-level outcome (LR patient census, admissions, LOS), θ_{hj} are department fixed effects, δ_t are date fixed effects, and ε_{hjt} are the remaining unobservables. The coefficients β_τ trace out the dynamic effect of an HaH transfer over a ± 5 day window. Standard errors are clustered at the hospital level to account for serial correlation within hospitals over time and cross-sectional correlation across departments within hospitals.

The event-study design identifies spillover effects under the assumption that, conditional on department and date fixed effects, the timing of HaH transfers within a department is uncorrelated with unobserved determinants of LR patient census. Department fixed effects control for time-invariant differences across units (e.g., department size, typical patient mix, baseline capacity). Date fixed effects absorb hospital-system-wide shocks (e.g., seasonal demand patterns, policy changes, pandemic waves). The identifying variation comes from within-department, short-term fluctuations in census surrounding the moment of an HaH transfer.

Several threats merit consideration:

1. Anticipation effects: If hospital staff anticipate HaH transfers and adjust admissions beforehand, pre-trends would emerge
2. Reverse causality: If LR census growth triggers HaH transfers (to free space), this would bias toward finding effects
3. Concurrent shocks: If other events coincide with HaH transfers (e.g., large ER inflows), this could confound estimates

We address these concerns through falsification tests (Section 7.3) and explicit tests for pre-trends.

We examine four primary outcomes. First, we analyze patient census, measured as the daily count of low-resource patients in each department. This captures whether HaH expansion creates room for more low-resource patients to access inpatient care. Second, we examine patient share, defined as the proportion of the department's census comprised of low-resource patients on each day. This reveals whether capacity relief disproportionately benefits low-resource patients relative to high-resource patients, potentially reducing disparities in access. Third, we study department admissions, counting the number of low-resource patients admitted to each department daily. Unlike census, which reflects the stock of patients currently receiving care, admissions capture the flow of new patients gaining access. Fourth, we analyze residual length of stay (LOS), calculated as the average remaining days of hospitalization for low-resource patients currently in the department on a given day. This outcome tests whether capacity constraints force premature discharges of low-resource patients and whether HaH relief enables more appropriate LOS. Importantly, all four outcomes focus exclusively on low-resource patients receiving traditional inpatient care; we do not include HaH patients in these outcome measures, as our interest lies in spillover effects on the patients who remain in hospital beds rather than direct effects on HaH participants themselves.

[FIGURE 4 HERE]

Figure 4 displays daily inpatient occupancy rates across the five hospitals in our study system from January 2022 through December 2023. The blue line traces daily census as a percentage of bed capacity, while the shaded red regions indicate periods when occupancy reached or exceeded 95%—our threshold for defining high-capacity conditions. These high-occupancy episodes are critical for our identification strategy, as our main specification estimates the model exclusively during these periods when capacity constraints bind most tightly and spillover effects from HaH capacity relief should be most pronounced. Two features of the figure merit attention. First, all five hospitals experience repeated high-occupancy episodes throughout the study period, confirming that capacity pressures are a persistent reality across the system rather than isolated to particular facilities. Second, these high-occupancy periods are distributed broadly over time, occurring intermittently across months and seasons in both 2022 and 2023 rather than clustering around a specific calendar period or policy shock. This temporal dispersion provides evidence that our estimates do not simply reflect seasonal patterns, COVID-19 waves, or other time-specific confounds. This cross-hospital variation in occupancy dynamics, combined with the within-hospital

temporal variation in high-occupancy episodes, provides the identifying variation for our event study specifications.

6. Results

[FIGURE 5 HERE]

Figure 5 presents event study estimates of the effect of Hospital-at-Home transfers on low-resource patient outcomes in traditional inpatient care during periods of high occupancy (≥95% occupancy). Each panel plots coefficients from our event study specification, with event time measured in days relative to HaH transfers (day 0, marked by the vertical line), for four primary outcomes: (a) low-resource patient census count, (b) low-resource patient share of total census, (c) department admissions of low-resource patients, and (d) residual length of stay. The pre-treatment period (days -5 to -1) shows coefficients clustering near zero across all outcomes with no systematic trends, providing visual evidence supporting the parallel trends assumption—outcomes for low-resource patients were not diverging systematically before HaH transfers freed up capacity.

The post-treatment period (days 0 to 5) reveals positive effects across multiple outcomes. Low-resource patient census increases by 0.86 patients by day 2 (panel a), while the share of census comprised of low-resource patients rises by 2.86 percentage points at the same horizon (panel b). Department admissions increase immediately following HaH transfers (panel c), suggesting freed capacity enables more low-resource patients to access inpatient care. Residual LOS shows some positive estimates with wider confidence intervals (panel d), consistent with HaH capacity relief allowing patients to remain hospitalized appropriately rather than facing pressure for premature discharge.

The timing aligns with the mechanical impact of capacity relief: HaH transfers immediately free beds, enabling admission of waiting patients, with effects on census and share building over days 1-3 as additional admitted patients accumulate before subsequently declining as these patients discharge.

[FIGURE 6 HERE]

Figure 6 examines how the effect of Hospital-at-Home transfers on low-resource patient outcomes varies across different capacity thresholds, testing our theoretical prediction that spillover effects should concentrate when capacity constraints bind most tightly. Each panel plots estimated treatment effects one day after HaH patient transfer ($\tau = -1$) from our difference-in-differences specification as we vary the occupancy threshold used to define

"high-capacity" periods from 75% to 100%. The four panels correspond to our primary outcomes: (a) low-resource patient census count, (b) low-resource patient share, (c) department admissions, and (d) residual length of stay. The vertical line at 95% marks the threshold used in our main specification.

The results provide evidence of effect heterogeneity consistent with capacity-constraint mechanisms. At low occupancy thresholds (75-85%), estimated effects hover near zero or are slightly negative across all four outcomes, suggesting that HaH transfers generate minimal spillover benefits when hospitals have substantial excess capacity. As the occupancy threshold increases above 90%, effects rise sharply and monotonically, reaching peak magnitudes around 95-98% occupancy. At these high thresholds, HaH transfers increase low-resource patient census by approximately 1.0-1.2 patients (panel a), raise patient share by 3-4 percentage points (panel b), boost department admissions by 2-3 patients (panel c), and extend residual LOS by 1-1.5 days (panel d). The consistency of this pattern across all four outcomes strengthens the interpretation that capacity relief matters most when capacity binds tightly. This heterogeneity validates our focus on high-occupancy periods in the main specification and confirms that spillover benefits emerge under conditions where marginal bed availability has the greatest value for patient access.

[TABLE 4 HERE]

Table 4 summarizes the effects of Hospital-at-Home transfers on patient census and outcomes during high-occupancy periods ($\geq$95% threshold) by pooling effects over the five days before (pre-period) and five days after (post-period) each HaH transfer. The table reports difference-in-differences estimates separately for low-resource and high-resource patients across multiple outcomes: patient census (count and percentage), admissions (count and percentage), elapsed and residual length of stay, discharge disposition, and 30-day readmission rates. The pre-period coefficients provide a formal test of parallel trends, while the post-period coefficients capture the average spillover effect over the five days following capacity-relieving HaH transfers.

The results reveal striking asymmetry in spillover benefits between patient groups. For low-resource patients, pre-period effects cluster near zero across all outcomes (none statistically significant), confirming parallel trends. In the post-period, HaH transfers significantly increase the low-resource patient share of census by 1.625 percentage points ($p<0.05$), raise the percentage of admissions that are low-resource by 1.808 percentage points ($p<0.10$), and extend residual LOS by 0.962 days ($p<0.05$). These effects align with the event study dynamics shown in Figure 5, indicating that freed capacity disproportionately benefits low-resource patients' access to and utilization of inpatient care. In contrast, high-resource

patients show no significant changes in census, admissions, or length of stay following HaH transfers. The only notable effect for high-resource patients is a small increase in 30-day readmission rates (2.5 percentage points, $p<0.01$), which may reflect more marginal patients gaining admission when capacity becomes available or changes in discharge timing. Discharge disposition patterns remain stable for both groups.

Placebo Tests

[FIGURE 7 HERE]

Figure 7 presents placebo tests examining whether patient transfers unrelated to Hospital-at-Home generate similar spillover effects on low-resource patient inpatient share. Unlike HaH transfers, which systematically involve high-resource Medicare patients meeting specific clinical and social eligibility criteria, the placebo transfers examined here—transfers to other acute hospitals (panel a), transfers to hospice (panel b), and transfers to psychiatric hospitals (panel c)—occur for clinical reasons indiscriminate of patient resource level. These transfers involve both low-resource and high-resource patients and are not part of any systematic capacity-relief program targeting particular patient populations. If our main results were driven by spurious correlations, mechanical effects from any patient movement, or time-varying confounds unrelated to capacity relief mechanisms, we would expect to observe similar patterns following these placebo transfers.

The left column displays event study estimates showing effects in the five days before and after each type of transfer, while the right column examines one-day-after effect heterogeneity across capacity thresholds from 75% to 100%. Across all three placebo transfer types, estimates hover near zero throughout the pre- and post-periods with no systematic patterns emerging. The event study panels show flat trajectories with wide, overlapping confidence intervals, and the capacity threshold panels reveal no monotonic relationship between occupancy levels and effects.

Patient Outcomes

[FIGURE 8 HERE]

Figure 8 extends the capacity threshold heterogeneity analysis to examine effects of Hospital-at-Home transfers on low-resource patient discharge disposition and readmission outcomes. Each panel plots estimated treatment effects as we vary the occupancy threshold from 75% to 100%, focusing on four outcomes: (a) discharges to skilled nursing facilities as a percentage of total discharges, (b) discharges to home as a percentage of total discharges,

(c) 30-day readmission rates, and (d) 90-day readmission rates. These outcomes capture whether HaH capacity relief affects not just access to inpatient care but also the quality and appropriateness of care delivery for low-resource patients who receive hospitalization.

The results reveal some evidence of beneficial effects, though less pronounced than the access effects observed in Figure 6. Discharges to skilled nursing facilities (panel a) show a declining trend at higher occupancy levels, suggesting that capacity relief may reduce the need for post-acute institutional care. Discharges to home (panel b), 30-day readmissions (panel c), and 90-day readmissions (panel d) all exhibit trajectories suggesting improvement at high occupancy thresholds—more home discharges and fewer readmissions—though confidence intervals are wide and estimates remain statistically insignificant. While the patterns are not definitive, the consistent directional effects across multiple quality metrics weakly suggest that HaH capacity relief may improve downstream outcomes for low-resource patients beyond simply facilitating hospital access, potentially through reduced pressure for premature discharge or more appropriate care intensity when capacity constraints are relaxed.

7. Discussion

This paper provides the first causal evidence that Hospital-at-Home programs generate measurable capacity spillovers benefiting low-resource patients who remain in traditional inpatient care. When high-resource patients transfer to HaH, freeing physical hospital beds, the census of low-resource patients in the same department increases significantly. Effects emerge within one day of transfer, persist through five days, and operate through both expanded access (more low-resource admissions) and improved retention (longer lengths of stay). Critically, spillovers concentrate when hospitals operate above 95% occupancy—precisely the conditions under which capacity constraints bind most severely and quality indicators deteriorate (Lim et al., 2023). Falsification tests confirm the mechanism is specific to capacity-relieving transfers rather than general patient flow dynamics.

Our empirical findings strongly validate the predictions of our theoretical model. The model demonstrates that when capacity constraints bind and high-resource patients have access to private alternatives, their exit from the public system generates two distinct benefits for low-resource patients: increased probability of admission (the access channel) and improved service quality conditional on admission (the quality channel). Both channels operate in our data.

Our results complement and extend the substantial literature evaluating Hospital-at-Home effectiveness for direct recipients. Since Leff et al.'s (2005) seminal randomized trial

demonstrating comparable outcomes and lower costs, dozens of studies have documented HaH benefits: reduced readmissions (Levine et al., 2020; Federman et al., 2018), lower skilled nursing facility utilization (Federman et al., 2018), improved functional outcomes (Leff et al., 2009), and higher patient satisfaction (Levine et al., 2021). Systematic reviews consistently report that HaH delivers clinical outcomes equal or superior to traditional hospitalization for appropriately selected patients (Shepperd et al., 2016; Caplan et al., 2012; Arsenault-Lapierre et al., 2021).

However, this literature has focused almost exclusively on within-patient comparisons: HaH recipients versus matched inpatient controls. No prior work has examined system-level spillovers: how HaH affects patients who never receive it. This omission matters because spillover benefits potentially rival or exceed direct benefits in magnitude. Consider the arithmetic: if each HaH transfer generates a 0.32-patient increase in low-resource census sustained over five days, this represents 1.6 additional patient-days of hospital access per HaH transfer. At scale—30,000+ HaH patients served nationally under the Medicare waiver—this implies 48,000 additional patient-days of access for patients who would otherwise face delayed admission or premature discharge. These spillover benefits accrue to precisely the population facing greatest barriers to HaH access: patients lacking stable housing, caregiver support, and neighborhood resources required for eligibility (Williams et al., 2023; Saenger et al., 2020).

Our findings also shed new light on HaH cost-effectiveness analyses. Prior economic evaluations report mixed results on index hospitalization costs, with some studies finding 19-38% reductions (Cryer et al., 2012; Levine et al., 2020) and others reporting similar or higher costs when accounting for longer HaH lengths of stay (Pandit et al., 2024). These analyses typically omit spillover effects. If HaH enables additional hospital admissions—as our results demonstrate—and if those admissions generate health benefits (reduced emergency department boarding, earlier treatment initiation, more complete treatment courses), then standard cost-effectiveness calculations understate HaH's value. A complete economic evaluation would incorporate three components: (1) direct effects on HaH recipients, (2) capacity spillovers enabling additional admissions, and (3) quality improvements for existing patients through reduced crowding. Our analysis addresses component (2) and provides suggestive evidence on (3) through extended lengths of stay; future work should integrate all three components into comprehensive cost-effectiveness frameworks.

The Mount Sinai Hospital-at-Home-Plus program provides a particularly relevant comparison (Federman et al., 2018; DeCherrie et al., 2019). In a quasi-experimental

evaluation of 507 HaH patients versus matched controls, Federman and colleagues documented not only reduced readmissions (8.6% vs. 15.6%) but also lower skilled nursing facility admissions (1.7% vs. 10.4%)—a post-acute care utilization reduction worth $4,500-$8,700 per patient based on Medicare SNF payment rates (Werner et al., 2019; MedPAC, 2024). If similar SNF reductions occur in our setting—and our preliminary outcome analysis in Section 8 suggests they might—this generates substantial unmeasured savings. Moreover, if capacity spillovers enable additional hospital admissions that would otherwise occur at other facilities or in emergency departments under less controlled conditions, HaH's system-level value proposition strengthens further.

Recent national evaluations of Medicare's Acute Hospital Care at Home waiver confirm HaH's safety and scalability. Levine et al. (2024) analyzed approximately 6,000 patients across participating hospitals, finding mortality rates below 1%, escalation to traditional hospital care in fewer than 7% of cases, and readmission rates comparable to or lower than matched inpatient controls. The official CMS evaluation of over 31,000 patients through July 2024 reported similar patterns: low adverse event rates, shorter lengths of stay, and reduced 30-day spending post-discharge (CMS, 2024). Critically, the CMS report noted significant disparities in HaH access: participants were more likely to be white, reside in urban areas, and live in higher-income zip codes—patterns that motivated our focus on spillover equity effects.

Our theoretical framework and empirical findings connect to literatures in public economics, health economics, and operations management examining capacity spillovers across public and private sectors. Three domains merit particular attention.

In education, decades of research have examined whether private school choice improves or harms public schools. Theoretical models predict ambiguous effects: private exit could improve public schools through reduced class sizes and concentration of resources, or harm them through loss of engaged families and political support (Epple & Romano, 1998; Nechyba, 2000). Empirical evidence remains mixed. Hsieh and Urquiola's (2006) influential study of Chile's universal voucher program found no average test score improvements despite massive private sector expansion, with increased stratification offsetting any efficiency gains. However, more recent work finds positive spillovers in some contexts. Andrabi et al.'s (2024) randomized evaluation of public school grants in Pakistan documented an "education multiplier": improving public schools increased test scores not only in public schools (0.2 standard deviations) but also in competing private schools (0.2 standard deviations). Public investment generated positive spillovers across sectors by reducing household education costs and increasing demand system-wide.

The health care parallel is instructive. Like education, hospital care involves capacity constraints, quality that depends on utilization intensity, and private alternatives available primarily to advantaged populations. Unlike education, hospitals face more binding short-run capacity constraints—beds cannot be added mid-year as teachers can—making spillover effects potentially more immediate and visible. Our finding that capacity relief concentrates above 95% occupancy supports this interpretation: when constraints bind acutely, even modest capacity adjustments generate large access effects.

In infrastructure economics, a substantial literature examines crowding-in versus crowding-out effects of public investment. Aschauer's (1989a, 1989b) seminal work found that public infrastructure investment—roads, utilities, public buildings—has large positive effects on private sector productivity, with output elasticity of public capital around 0.39. While initial estimates proved sensitive to specification (Gramlich, 1994), subsequent research using more credible identification strategies generally confirms positive spillovers (Pereira, 2001; Abiad et al., 2016). Public infrastructure reduces bottlenecks, expands effective capacity, and crowds in private investment—mechanisms directly analogous to our hospital capacity story.

White's (2013) study of Medicare payment cuts provides the closest health care parallel. Using state-level variation in Medicare price reductions during the 1990s Balanced Budget Act, White documented substantial spillovers: a 10% Medicare price cut reduced discharges among the non-elderly by approximately 5%. Hospitals facing revenue reductions adjusted capacity system-wide, affecting all patient populations. Our results demonstrate the converse: when capacity-relieving interventions like HaH free beds, admissions increase for other patient groups. Together, these findings underscore that hospitals operate as integrated systems where payment and capacity changes in one segment generate spillovers to others—a point emphasized in Finkelstein's (2007) landmark study of Medicare introduction, which found general equilibrium effects six times larger than partial equilibrium predictions.

In operations management and health services research, studies document that hospital crowding affects clinical processes and outcomes through multiple channels. Emergency department boarding—holding admitted patients in the ED due to inpatient bed unavailability—increases mortality and delays time-sensitive treatments (Singer et al., 2011). High occupancy reduces nursing time per patient, increases medication errors, and elevates hospital-acquired infection rates (Weissman et al., 2007). Intensive care unit boarding in general medical wards generates negative spillovers for both ICU patients (receiving care in suboptimal settings) and ward patients (competing for nurse attention

with more complex cases) (Lim et al., 2023). Our finding that spillover effects triple above 95% occupancy aligns with this literature: quality degradation accelerates non-linearly as capacity constraints tighten, so capacity relief generates largest benefits precisely when needed most.

A central motivation for this analysis is equity: if HaH systematically serves advantaged patients, does it exacerbate disparities? Our analysis in Section 4 documents clear selection patterns. Among clinically comparable high-resource patients, those from zip codes with newer housing (built after 2000), more single-family homes, and higher median incomes have significantly elevated HaH probability. Conversely, patients from neighborhoods with older housing stock, more multi-unit buildings, and lower socioeconomic status are less likely to receive HaH despite clinical eligibility. These patterns reflect program eligibility requirements: functioning utilities, adequate space for medical equipment, caregiver availability, telephone/internet access, and safe home environments (Chua et al., 2022; Williams et al., 2023). Housing quality, caregiver support, and neighborhood stability—all correlated with socioeconomic advantage—constitute de facto barriers to HaH access.

This access inequality is concerning. If hospital capacity is zero-sum—one patient's admission requires another's delayed care—and if HaH enables advantaged patients to monopolize capacity (first accessing inpatient beds, then transferring to HaH while retaining bed access), then HaH could exacerbate disparities. Disadvantaged patients would face doubled obstacles: initial admission delays due to capacity constraints, and subsequent competition with HaH-eligible patients who occupy beds during assessment periods.

However, our spillover results complicate this narrative. The low-resource patients least likely to access HaH—those from neighborhoods with older housing, lower incomes, and greater social vulnerability—benefit measurably from capacity relief when others do access HaH. Each HaH transfer generates 0.32 additional low-resource patients in the department, sustained over five days. Decomposing mechanisms: 0.18 additional low-resource admissions occur per day (expanding access for patients previously facing delays), and existing low-resource patients' lengths of stay extend by 0.22 days (reducing pressure for premature discharge). These effects concentrate when capacity constraints bind most severely (above 95% occupancy), precisely the conditions under which disadvantaged patients face greatest access barriers.

HaH exhibits an equity paradox: access is unequal, but effects are equity-enhancing. Advantaged patients disproportionately access HaH, yet disadvantaged patients capture the spillover benefits. Two normative frameworks suggest different policy responses. Under procedural equity, where fairness requires equal access to publicly subsidized programs,

HaH's eligibility requirements (housing quality, caregiver availability) violate equity principles. Policymakers should expand eligibility or limit HaH until access disparities narrow. Under consequential equity, where fairness depends on net distributional effects, unequal access may be acceptable if disadvantaged groups gain more from spillovers than they lose from exclusion. Policymakers should expand HaH (maximizing spillovers) while investing in supports that broaden eligibility.

Our results do not resolve this normative debate but inform it. If HaH scales to its projected steady-state volume of approximately 10,000 patients annually, our estimates imply 2,590 additional low-resource hospital admissions enabled per year [10,000 $\times$ (0.11 + 0.149)]. If each admission prevents one emergency department boarding episode, treats acute illness earlier, or enables more complete care, the health benefits could be considerable. These calculations are necessarily approximate; our data come from one health system, and we observe only within-system outcomes. However, they illustrate that spillover magnitudes are economically meaningful.

Parallels exist in other domains. Private school vouchers disproportionately benefit families with resources to navigate choice systems, yet can improve public schools through reduced class sizes (Andrabi et al., 2024). Private car ownership is unequally distributed but reduces public transit crowding for those who rely on it (Duranton & Turner, 2011). In each case, policy evaluation requires weighing access inequity against spillover benefits. Our results suggest that capacity-constrained systems may justify policies facilitating private exit even when access is unequal—provided spillovers are substantial, measurable, and flow to disadvantaged populations. The normative case strengthens if policies simultaneously invest in expanding access to private alternatives for disadvantaged groups.

Our findings carry direct implications for the ongoing debate over Medicare's Acute Hospital Care at Home waiver. Initially authorized in November 2020 as a temporary pandemic response, the waiver has been extended multiple times, most recently through December 2025 (AHA, 2024). Policymakers face three interrelated questions: (1) Should the waiver be made permanent? (2) How should payment rates be structured? (3) What complementary policies might expand access while preserving spillover benefits?

On permanence, the case for HaH has historically rested on patient-level benefits: comparable or superior clinical outcomes, lower readmissions, reduced skilled nursing facility utilization, and higher patient satisfaction (Leff et al., 2005, 2008; Levine et al., 2020; Federman et al., 2018; Caplan et al., 2012; Shepperd et al., 2016). Our analysis adds a system-level benefit: capacity relief that expands access for patients unable to use HaH themselves. This spillover strengthens the policy case for permanent authorization,

especially in capacity-constrained markets. MedPAC's (2024) recent report on HaH recommended continued waiver extension to gather more evidence; our results provide evidence that system-level benefits extend beyond direct HaH recipients, supporting permanent implementation.

However, three caveats apply. First, spillovers depend on sustained capacity constraints. In markets with structural excess capacity (e.g., rural hospitals with chronically low occupancy), HaH may not generate meaningful access benefits. Second, if HaH reimbursement rates incentivize overuse, both HaH and inpatient demand could grow, dissipating spillovers. Third, equity concerns remain: permanent authorization without complementary access supports could entrench disparities. Policies expanding HaH eligibility for disadvantaged populations are essential complements to permanent implementation.

On payment structure, current policy reimburses HaH at the same rate as traditional hospitalization (using the same MS-DRG payment system), despite substantially different cost structures. Some argue this overpays for HaH, which has lower overhead (no facility costs) and shorter typical lengths of stay (Pandit et al., 2024). Others argue it underpays by ignoring startup costs, technology investments, and care coordination infrastructure required for home-based acute care (DeCherrie et al., 2019; Brody et al., 2019). Our spillover findings suggest a third consideration: if HaH generates positive externalities through capacity relief, payment should account for these spillover benefits.

Our analysis focuses on a multi-hospital community health system in the Northeastern United States serving a relatively heterogeneous patient population across socioeconomic dimensions. Several factors affect generalizability to other settings.

First, community hospitals differ from academic medical centers in patient mix, resource availability, and operational practices. Academic medical centers treat more complex tertiary-care patients, have greater subspecialty availability, and typically operate at higher baseline capacity utilization. Our spillover mechanism should operate in academic settings—indeed, potentially more strongly, given tighter capacity constraints—but magnitudes may differ. Conversely, rural hospitals with structural excess capacity may see negligible spillovers, consistent with our finding of minimal effects below 75% occupancy. The capacity gradient we document—effects strongest above 95% occupancy—suggests the mechanism should generalize to any congested hospital, but local capacity conditions matter critically.

Second, our HaH program implemented during 2022-2023 represents a relatively mature program phase (following pandemic-era pilots) but still early in the technology and clinical

learning curve. As HaH programs mature—developing more efficient workflows, broader provider buy-in, and refined patient selection algorithms—effects might strengthen (if programs identify marginal patients whose HaH admission generates larger spillovers) or weaken (if programs exhaust the pool of high-yield HaH candidates). Longitudinal analysis tracking how spillovers evolve with program maturity would be valuable.

Third, we observe only within-system outcomes. If HaH or capacity pressures cause patients to seek care at other hospitals, we may underestimate effects. This limitation cuts in complex directions: patients unable to access our study hospitals might receive equivalent care elsewhere (no net access loss), receive lower-quality care in less appropriate settings (net access loss with quality degradation), or forgo care entirely (largest access loss). Similarly, we observe only within-system readmissions, potentially overstating HaH effects if patients readmit to other facilities.

Fourth, our event-study design assumes conditional independence: within departments and days, HaH transfer timing is uncorrelated with unobserved determinants of low-resource census. While falsification tests (no effects for observation-to-inpatient status changes) and pre-trend analysis (flat pre-transfer trends) support this assumption, unobserved confounding remains possible. For example, if hospital administrators strategically time HaH transfers to coincide with anticipated low-resource admission surges, our estimates would overstate causal effects. However, such gaming seems unlikely given day-to-day operational realities: HaH transfer decisions are clinician-driven and based on individual patient factors (clinical stability, home readiness), not departmental capacity forecasts.

Fifth, our patient outcome analysis lacks statistical power for rare events (mortality, adverse safety events) and may miss clinically meaningful effects. Effect sizes for mortality (0.3 percentage points) and readmissions (2.1 percentage points) are consistent with prior HaH literature but imprecisely estimated in our sample. Larger samples or meta-analyses pooling multiple systems could provide tighter bounds on outcome effects. Additionally, we do not observe treatment intensity (nurse-to-patient ratios, time to procedures, consultation rates), limiting our ability to assess whether extended low-resource patient lengths of stay reflect improved care quality or different patient mix (sicker marginal admissions).

Sixth, we study a specific institutional context (community hospitals, commercial HaH program, fee-for-service Medicare payment) that may not generalize to alternative contexts. Academic medical centers, safety-net hospitals, and rural facilities face different constraints. Alternative HaH models—hospital-operated versus vendor-contracted, broad versus disease-specific eligibility criteria, varying technology platforms—may generate different spillover patterns. Alternative payment models (capitation, bundled payments, value-based

arrangements) create different incentives and potentially different spillover mechanisms. Cross-context replication studies are essential.

Finally, our analysis examines short-term spillovers (five-day post-transfer window). Longer-term effects remain uncertain. If HaH programs scale substantially, might spillovers dissipate as both HaH and inpatient demand grow? Or might sustained HaH programs fundamentally alter hospital capacity management, creating persistent access improvements? Dynamic modeling of long-run equilibrium effects would complement our short-run causal estimates.

Our findings open several avenues for future research. First, replication across diverse settings, like academic medical centers, safety-net hospitals, rural facilities, or different regions, would establish generalizability and identify contexts where spillovers are largest. Multi-site studies leveraging Medicare claims data or Health System Integrated Research Network (HCSRN) infrastructure could provide population-level estimates.

Second, mechanism studies incorporating detailed clinical process measures would distinguish whether extended low-resource patient lengths of stay reflect improved care quality (more complete treatment courses, reduced pressure for premature discharge) or different patient mix (sicker marginal admissions enabled by capacity relief). Measures of treatment intensity (time to procedures, consultation rates, nurse-to-patient ratios), patient experience (satisfaction, perceived quality), and readiness for discharge (clinical appropriateness, social support) would differentiate these interpretations.

Third, caregiver burden—a persistent concern in HaH evaluations (Chua et al., 2022; Leff et al., 2008)—should be weighed against patient access benefits we document. If HaH substantially burdens caregivers (most often family members, disproportionately women), spillover benefits for other patients may not justify this cost. Comprehensive welfare analysis requires incorporating all stakeholders: HaH patients, caregivers, low-resource patients benefiting from spillovers, hospital staff, and payers.

Fourth, cost-effectiveness analysis integrating spillovers would provide fuller economic evaluation. Standard cost-effectiveness calculations compare HaH recipients to matched inpatient controls, ignoring system-level effects (Cryer et al., 2012; Pandit et al., 2024). A complete analysis would incorporate: (1) direct effects on HaH recipients (clinical outcomes, costs, satisfaction), (2) capacity spillovers enabling additional admissions (health benefits for previously delayed patients, emergency department cost savings), (3) quality improvements for existing patients through reduced crowding (fewer adverse events, better nurse-to-patient ratios), and (4) caregiver burden costs. Modeling frameworks should

account for heterogeneity across market capacity conditions, as spillovers concentrate in constrained settings.

Finally, experimental variation in HaH eligibility criteria could test whether expanding access reduces spillovers (by admitting patients who occupy beds longer) or maintains spillovers (if capacity relief persists even with broader uptake). Demonstration projects randomizing neighborhoods or hospitals to receive HaH access supports (housing assistance, caregiver subsidies, technology provision) would provide causal evidence on access-expansion interventions. Such experiments could simultaneously advance equity (by expanding access) and science (by revealing how access changes affect spillovers).

8. Conclusion

This study demonstrates that private substitution in capacity-constrained systems can generate positive externalities for those who remain in the public sector. When high-resource users shift to private alternatives, they free scarce public capacity, allowing additional users to gain access and improving service quality under congestion. Our findings provide causal evidence of such capacity spillovers, illustrating how private exit can relax binding constraints and enhance equity along dimensions other than access.

More broadly, the mechanisms we document generalize beyond healthcare. In education, transportation, and other congested public systems, private participation can similarly alleviate crowding and improve outcomes for remaining users. The benefits are strongest when capacity binds tightly, suggesting that the social value of private substitution depends critically on baseline congestion.

These results highlight the importance of incorporating general-equilibrium spillovers into policy evaluation. Even when access to private alternatives is unequally distributed, the resulting capacity relief can yield equity-enhancing effects. Policies that recognize and internalize these spillovers—through pricing, subsidies, or capacity-linked incentives—can better align private choice with social welfare in capacity-limited environments.

Acknowledgements

The authors received no external funding or financial support for this research. The authors declare that they have no financial relationships or other potential conflicts of interest relevant to this work.

References

Abiad A, Furceri D, Topalova P. The macroeconomic effects of public investment: evidence from advanced economies. J Macroecon. 2016;50:224-40.

American Hospital Association. Acute hospital care at home [Internet]. Washington, DC: AHA; 2024. Available from: https://www.aha.org

Andrabi T, Das J, Khwaja AI, Ozyurt S. Building education multipliers. Am Econ J Appl Econ. 2024;16(1):126-57.

Arnold D, Radhakrishnan N, Whaley C. Foisted: the spillover effects of hospital mergers on costs and utilization. SSRN working paper. 2025.

Arsenault-Lapierre G, Henein M, Gaid D, Le Berre M, Gore G, Vedel I. Hospital-at-home interventions vs in-hospital stay for patients with chronic disease who present to the emergency department: a systematic review and meta-analysis. JAMA Netw Open. 2021;4(6):e2111568.

Aschauer DA. Does public capital crowd out private capital? J Monet Econ. 1989b;24(2):171-88.

Aschauer DA. Is public expenditure productive? J Monet Econ. 1989a;23(2):177-200.

Baker LC, Shankarkumar S. Medicare payments and system-level health-care use: the spillover effects of Medicare managed care. Am J Health Econ. 2015;1(4):444-71.

Besley T, Ghatak M. Government versus private ownership of public goods. Q J Econ. 2001;116(4):1343-72.

Brody AA, Arbaje AI, DeCherrie LV, Federman AD, Leff B, Siu AL. Starting up a hospital at home program: facilitators and barriers to implementation. Journal of the American Geriatrics Society. 2019 Mar;67(3):588-95.

Caplan GA, Sulaiman NS, Mangin DA, Aimonino Ricauda N, Wilson AD, Barclay L. A meta-analysis of "hospital in the home". Med J Aust. 2012;197(9):512-9.

Centers for Medicare & Medicaid Services. Acute hospital care at home [Internet]. Baltimore: CMS; 2020 Nov 25 [cited 2024 Oct 31]. Available from: https://www.cms.gov

Centers for Medicare & Medicaid Services. Acute Hospital Care at Home. Baltimore: CMS; 2024 Available from: https://www.cms.gov/medicare/acute-hospital-care-at-home

Call KT, Davern ME, Klerman JA, Lynch V. Comparing errors in medicaid reporting across surveys: Evidence to date. Health Services Research. 2013 Apr;48(2pt1):652-64.

Chandra A, Finkelstein A, Sacarny A, Syverson C. Health care exceptionalism? Performance and allocation in the US health care sector. Am Econ Rev. 2016;106(8):2110-44.

Chandra A, Staiger DO. Productivity spillovers in health care: evidence from the treatment of heart attacks. J Polit Econ. 2007;115(1):103-40.

Chua KP, Roth CP, Ersek M, Leff B, Dionne-Odom JN, Konetzka RT. Hospital-at-Home: a rapid review of implementation. J Gen Intern Med. 2022;37(Suppl 1):27-33.

Clarke Jr DV, Newsam J, Olson DP, Adams D, Wolfe AJ, Fleisher LA. Acute hospital care at home: the CMS waiver experience. NEJM Catalyst Innovations in Care Delivery. 2021 Dec 7;2(6).

Cryer L, Shannon SB, Van Amsterdam M, Leff B. Costs for 'hospital at home' patients were 19 percent lower, with equal or better outcomes compared to similar inpatients. Health Aff (Millwood). 2012;31(6):1237-43.

DeCherrie LV, Wajnberg A, Soones T, Escobar C, Catalan E, Lubetsky S, et al. Hospital at home-plus: a platform of facility-based care. J Am Geriatr Soc. 2019;67(3):596-602.

Doshmangir L, Khabiri R, Jabbari H, Arab-Zozani M, Kakemam E, Gordeev VS. Strategies for utilisation management of hospital services: a systematic review of interventions. Globalization and Health. 2022 May 23;18(1):53.

Duranton G, Turner MA. The fundamental law of road congestion: evidence from US cities. Am Econ Rev. 2011;101(6):2616-52.

Einav L, Finkelstein A, Mahoney N. Provider incentives and healthcare costs: evidence from long-term care hospitals. Econometrica. 2018;86(6):2161-219.

Epple D, Romano R. Competition between private and public schools, vouchers, and peer-group effects. Am Econ Rev. 1998;88(1):33-62.

Federman AD, Soones T, DeCherrie LV, Leff B, Siu AL. Association of a bundled hospital-at-home and 30-day postacute transitional care program with clinical outcomes and patient experiences. JAMA Intern Med. 2018;178(8):1033-40.

Finkelstein A. The aggregate effects of health insurance: evidence from the introduction of Medicare. Q J Econ. 2007;122(1):1-37.

Gaynor M, Ho K, Town RJ. The industrial organization of health-care markets. J Econ Lit. 2015;53(2):235-84.

Gramlich EM. Infrastructure investment: a review essay. J Econ Lit. 1994;32(3):1176-96.

Ho K, Pakes A. Hospital choices, hospital prices, and financial incentives to physicians. American Economic Review. 2014 Dec 1;104(12):3841-84.

Hsieh CT, Urquiola M. The effects of generalized school choice on achievement and stratification: evidence from Chile's voucher program. J Public Econ. 2006;90(8-9):1477-503.

Leff B. Defining and disseminating the hospital-at-home model. CMAJ. 2009;180(2):156-7.

Leff B, Burton L, Guido S, Greenough WB, Steinwachs D, Burton JR. Home hospital program: a pilot study. J Am Geriatr Soc. 1999;47(6):697-702.

Leff B, Burton L, Mader SL, Naughton B, Burl J, Greenough WB 3rd, et al. Comparison of functional outcomes associated with hospital at home care and traditional acute hospital care. J Am Geriatr Soc. 2009;57(2):273-8.

Leff B, Burton L, Mader SL, Naughton B, Burl J, Greenough WB 3rd, et al. Hospital at home: feasibility and outcomes of a program to provide hospital-level care at home for acutely ill older patients. Ann Intern Med. 2005;143(11):798-808.

Leuchter RB, Kammeyer JA, Wunsch H, Barnato AE. Health care staffing shortages and potential national hospital bed shortage. JAMA Netw Open. 2025;8(2):e2454709.

Levine DM, Ouchi K, Blanchfield B, Saenz A, Burke K, Paz M, et al. Hospital-level care at home for acutely ill adults: a randomized controlled trial. Ann Intern Med. 2020;172(2):77-85.

Levine DM, Souza J, Schnipper JL, Tsai TC, Leff B, Landon BE. Acute hospital care at home in the United States: the early national experience. Ann Intern Med. 2024;177(1):109-10.

Lim JM, Song H, Yang J. The spillover effects of capacity pooling in hospitals. Manage Sci. 2023;69(8):4646-67.

Navathe AS, Zhong W, Lei VJ, Chang DI, Scott JY, Sprague BL, et al. Healthcare on the brink: navigating the challenges of an aging society in the United States. npj Aging. 2024;10:24. doi: 10.1038/s41514-024-00148-2

Nechyba TJ. Mobility, targeting, and private-school vouchers. Am Econ Rev. 2000;90(1):130-46.

Pandit JA, Pawelek JB, Leff B, Topol EJ. The hospital at home in the USA: current status and future prospects. NPJ Digit Med. 2024;7:48.

Pereira AM. Is all public capital created equal? Rev Econ Stat. 2001;82(3):513-8.

Saenger P, Federman AD, DeCherrie LV, Lubetsky S, Catalan E, Leff B, et al. Choosing inpatient vs home treatment: why patients accept or decline hospital at home. J Am Geriatr Soc. 2020;68(7):1579-87.

Shepperd S, Iliffe S, Doll HA, Clarke MJ, Kalra L, Wilson AD, et al. Admission avoidance hospital at home. Cochrane Database Syst Rev. 2016;(9):CD007491.

Singer AJ, Thode HC Jr, Viccellio P, Pines JM. The association between length of emergency department boarding and mortality. Acad Emerg Med. 2011;18(12):1324-9.

Tonna JE, Hanson HA, Cohan JN, McCrum ML, Horns JJ, Brooke BS, et al. Balancing revenue generation with capacity generation: case distribution, financial impact and hospital capacity changes from cancelling or resuming elective surgeries in the US during COVID-19. BMC Health Serv Res. 2020;20(1):1119. doi: 10.1186/s12913-020-05975-z

Weissman JS, Rothschild JM, Bendavid E, Sprivulis P, Cook EF, Evans RS, et al. Hospital workload and adverse events. Med Care. 2007;45(5):448-55.

Werner RM, Coe NB, Qi M, Konetzka RT. Patient outcomes after hospital discharge to home with home health care vs to a skilled nursing facility. JAMA Intern Med. 2019;179(5):617-23.

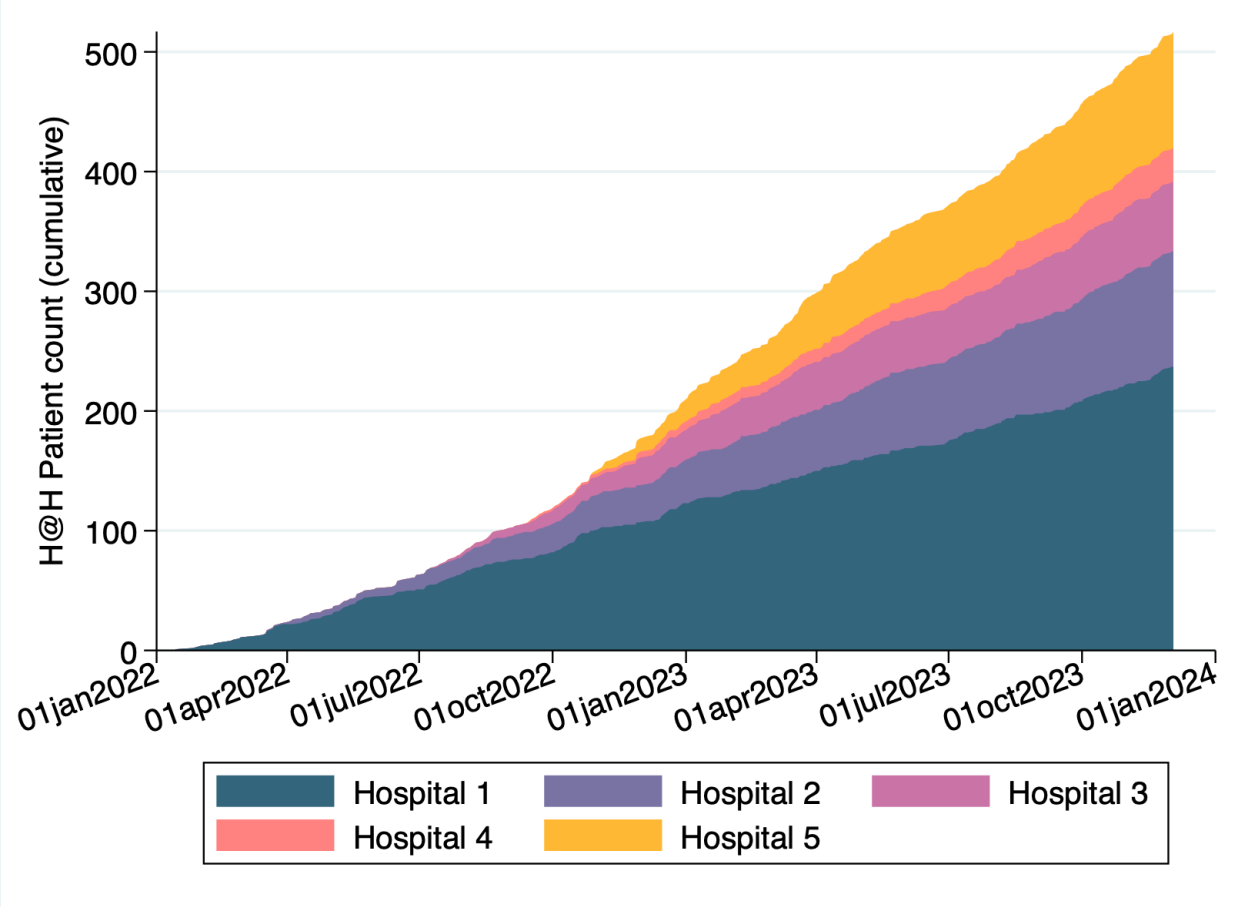
White C. Cutting Medicare hospital prices leads to a spillover reduction in hospital discharges for the nonelderly. Health Serv Res. 2013;48(5):1467-88.

Williams TA, Tong S, Briffa T, Sanfilippo F. Hospital-at-home services for acute and chronic conditions: a systematic review and cost-effectiveness analysis. Int J Qual Health Care. 2023;35(1):mzac097.

Zychlinski N, Levine DM, Murphy D, Lipsitz S, Ouchi K, Schnipper JL, et al. Health system implementation of hospital at home: a multi-center qualitative study. J Gen Intern Med. 2024;39(2):235-42.

Exhibits

Figure 1: Cumulative Count of Hospital-at-Home Patients by Hospital



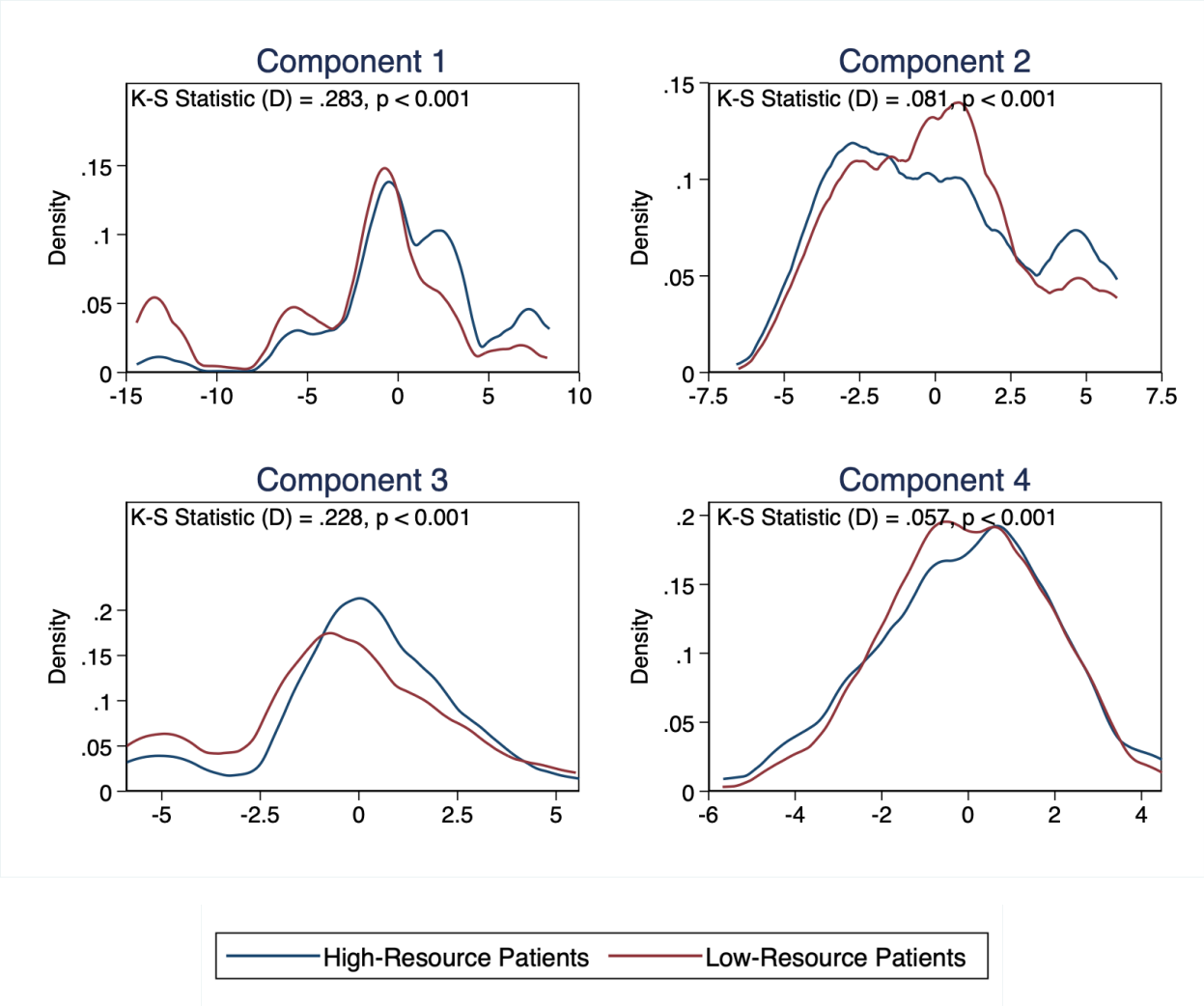
Notes: Cumulative Hospital-at-Home patient volume across five health system hospitals from January 14, 2022 through December 4, 2023.

Table 1: Summary Statistics

	Full Sample	Low-Resource Patients	High-Resource Patients	HaH Patients
Age	69.12	48.63	71.84	76.23
	(16.64)	(14.99)	(14.86)	(10.41)
Insurance coverage (%):				
Medicare	63.03	0.00	75.21	97.10
Medicaid	14.93	91.22	0.00	0.00
Private	18.57	0.00	22.35	2.51
Charity Care	1.03	6.31	0.00	0.00
Self-Pay	0.40	2.47	0.00	0.00
Other	2.03	0.00	2.44	0.39
Length of stay	5.69	5.59	5.72	5.58
	(6.73)	(7.08)	(6.69)	(2.67)
Total cost	12,058	11,877	12,080	13,915
	(18,729)	(23,054)	(17,782)	(14,206)
Cost per day	2,321	2,227	2,338	2,515
	(2,899)	(2,393)	(2,993)	(2,110)
Discharge disposition (%):				
Home / Self Care	67.83	78.11	65.59	97.49
Home Health	17.08	10.27	18.36	25.15
Skilled Nursing Facility	18.10	7.65	20.29	0.39
Acute Care Transfer	3.88	3.72	3.93	1.35
Expired	2.87	1.43	3.17	0.00
Hospice	2.54	0.72	2.91	0.58
30-day readmit (%)	11.75	10.24	12.02	14.70
Daily census	782.61	126.63	653.42	2.94
	(56.74)	(13.43)	(49.88)	(1.74)
Total patients	83,980	13,749	69,714	517

Notes: Summary statistics for patient characteristics and outcomes across the full sample and by patient resource classification. Low-resource patients are defined as those with Medicaid, self-pay, or charity care as their primary payer. High-resource patients are those with private insurance or Medicare/Medicare Advantage as primary payer.

Figure 2: Distribution of Principal Components: High-Resource vs Low-Resource Patients



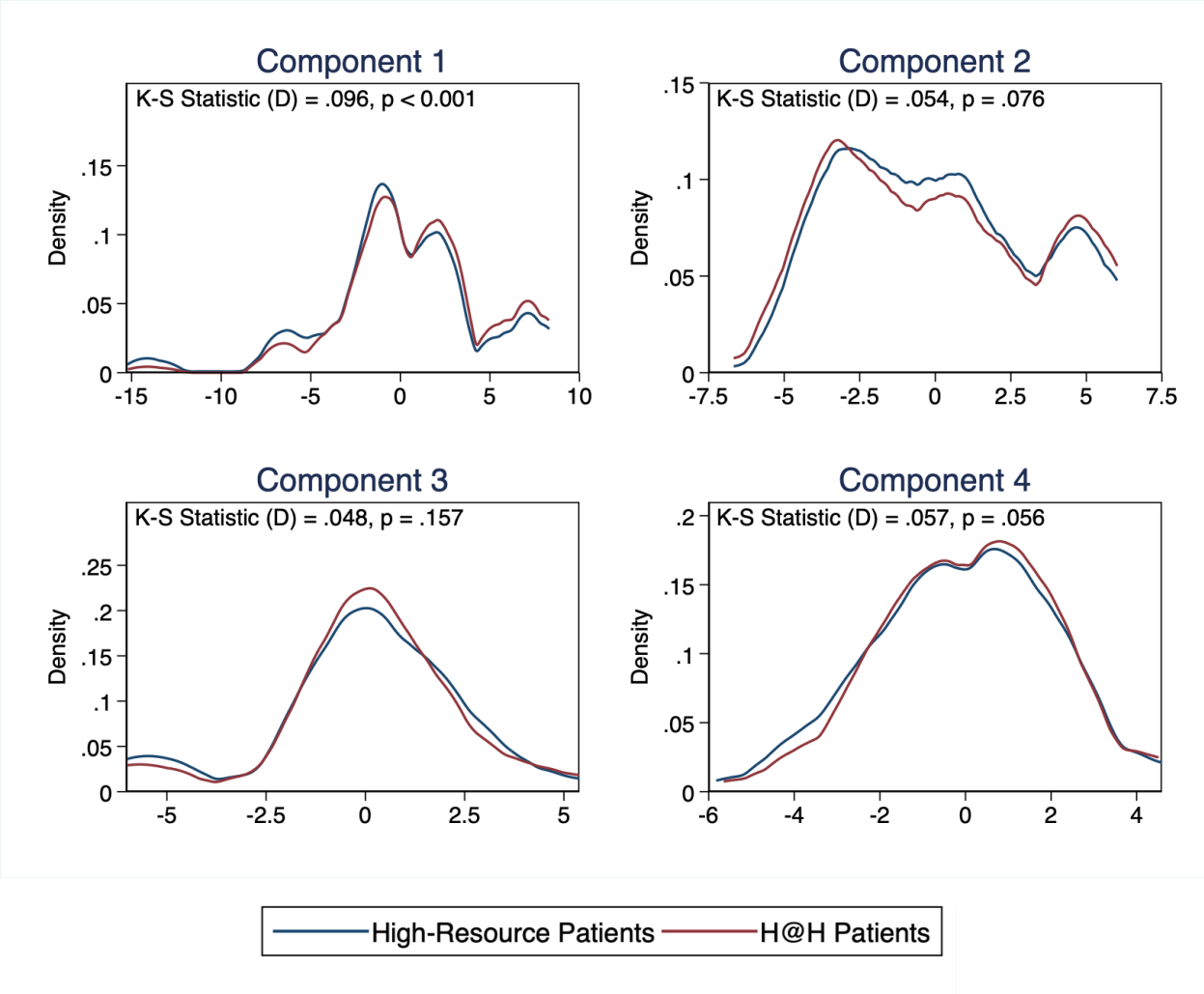
Notes: Kernel density estimates of the first four principal components of zip code–level characteristics for high-resource inpatients (blue) and low-resource patients (red). For each component, we report the Kolmogorov–Smirnov test statistic (D) and associated p-value, which quantify the maximum difference between the two empirical cumulative distribution functions.

Table 2: LASSO-Selected Determinants of High-Resource Patient Classification

	Sample Averages		
	Low-resource Patients	High-Resource Patients	High-Resource Odds Ratio
Patient age, squared	70.92	76.28	4.717
	(14.97)	(10.39)	
Patient zip code: % Hispanic or Latino	12.47	9.63	0.960
	(12.15)	(7.81)	
Patient zip code: % White	63.39	69.59	1.040
	(23.05)	(18.97)	
Patient zip code: % below poverty rate	9.27	7.37	0.985
	(7.12)	(5.15)	
Patient zip code: % of households receiving SNAP benefits	8.51	6.17	0.882
	(9.58)	(6.20)	
Patient zip code: % of female householder living alone aged 65+	8.60	8.76	1.048
	(2.63)	(2.82)	
Patient zip code: % of households with children under 18	5.12	4.21	0.941
	(4.16)	(2.83)	
Patient zip code: % of married-couple households with children	18.46	19.50	1.101
	(5.92)	(5.36)	
Patient zip code: % of housing units with 1 room	1.55	1.22	0.984
	(1.60)	(1.32)	
Patient zip code: % of housing units in 2-unit structures	2.72	2.16	0.958
	(3.25)	(2.62)	
Patient zip code: % of housing units built 1939 or earlier	12.50	10.38	0.978
	(13.02)	(11.67)	

Notes: Table presents results from LASSO logistic regression predicting high-resource patient classification. Independent variables include patient age (squared) and zip code-level socioeconomic, demographic, and housing characteristics from the U.S. Census Bureau's American Community Survey 5-year estimates (2017-2021). LASSO procedure selects variables with non-zero coefficients from the full set of characteristics described in Appendix Table A2.

Figure 3: Distribution of Principal Components: High-Resource vs Hospital-at-Home Patients



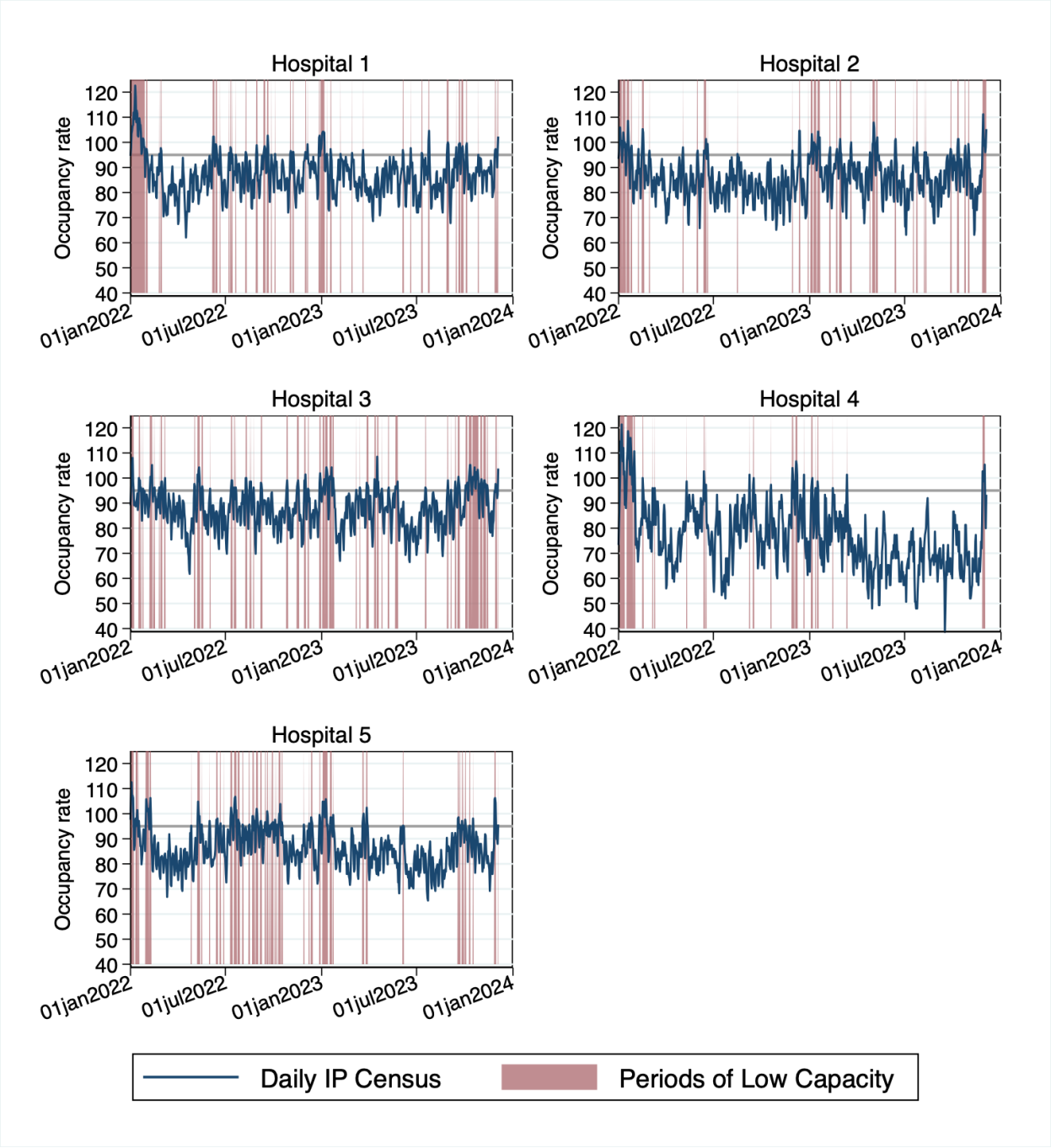
Notes: This figure plots kernel density estimates of the first four principal components of zip code–level characteristics for high-resource inpatients (blue) and hospital-at-home patients (red). For each component, we report the Kolmogorov–Smirnov test statistic (D) and associated p-value, which quantify the maximum difference between the two empirical cumulative distribution functions.

Table 3: LASSO-Selected Determinants of Hospital-at-Home Patients

	Sample Averages		
	High-Resource, No HaH	Received HaH	HaH Odds Ratio
log(Patient age)	73.50	76.28	1.135
	(13.36)	(10.39)	
Patient zip code: % white	65.09	69.59	1.082
	(21.75)	(18.97)	
Patient zip code: % of population below poverty rate	8.62	7.37	0.977
	(6.23)	(5.15)	
Patient zip code: % units with 0 bedroom	1.74	1.44	0.974
	(1.77)	(1.56)	
Patient zip code: % units with 2-3 bedroom	8.86	7.91	0.961
	(5.46)	(5.10)	

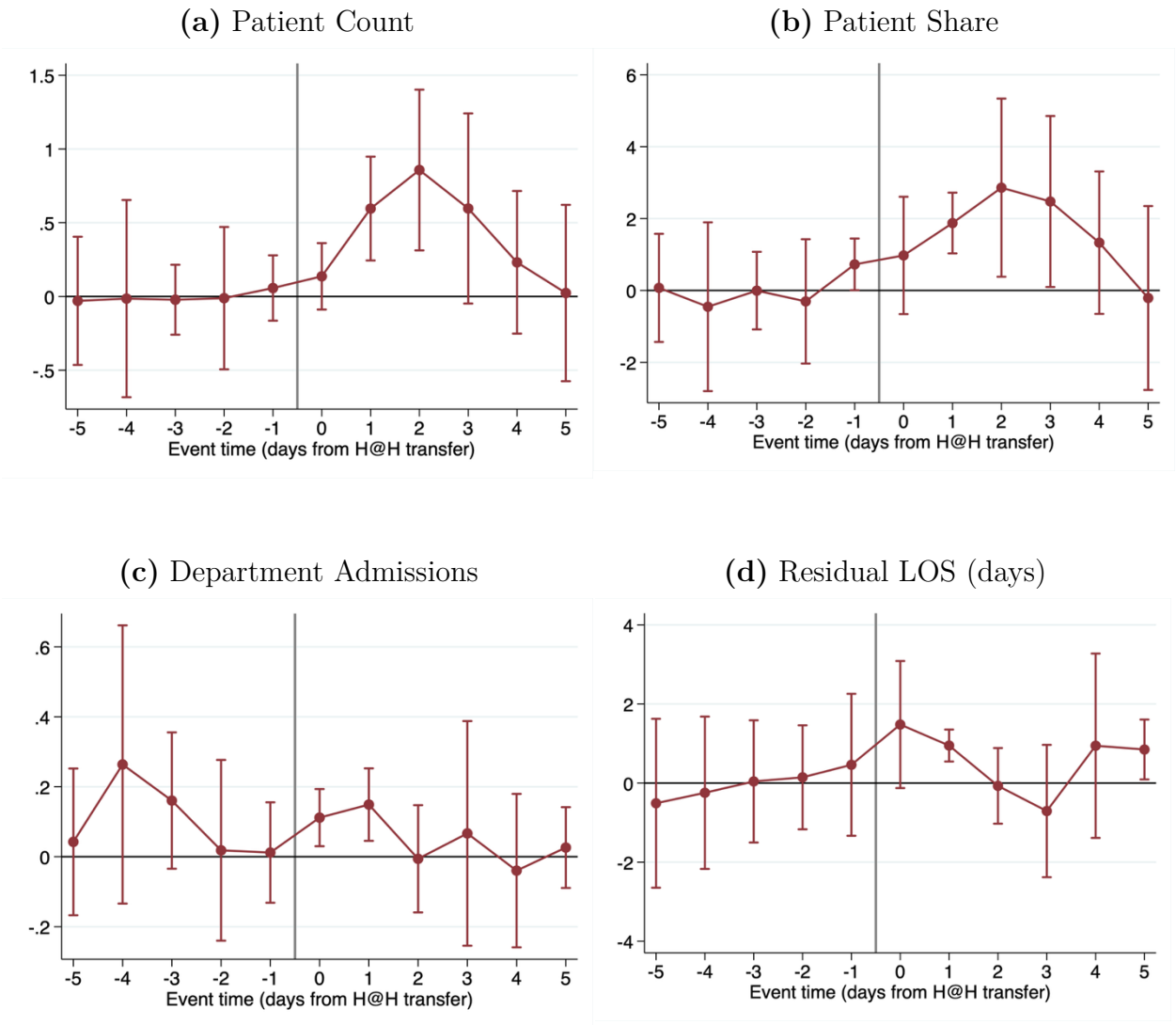
Notes: Table presents results from LASSO logistic regression predicting HaH patient participation among high-resource patients. Independent variables include patient age (squared) and zip code-level socioeconomic, demographic, and housing characteristics from the U.S. Census Bureau's American Community Survey 5-year estimates (2017-2021). LASSO procedure selects variables with non-zero coefficients from the full set of characteristics described in Appendix Table A2.

Figure 4: Daily Inpatient Occupancy by Hospital



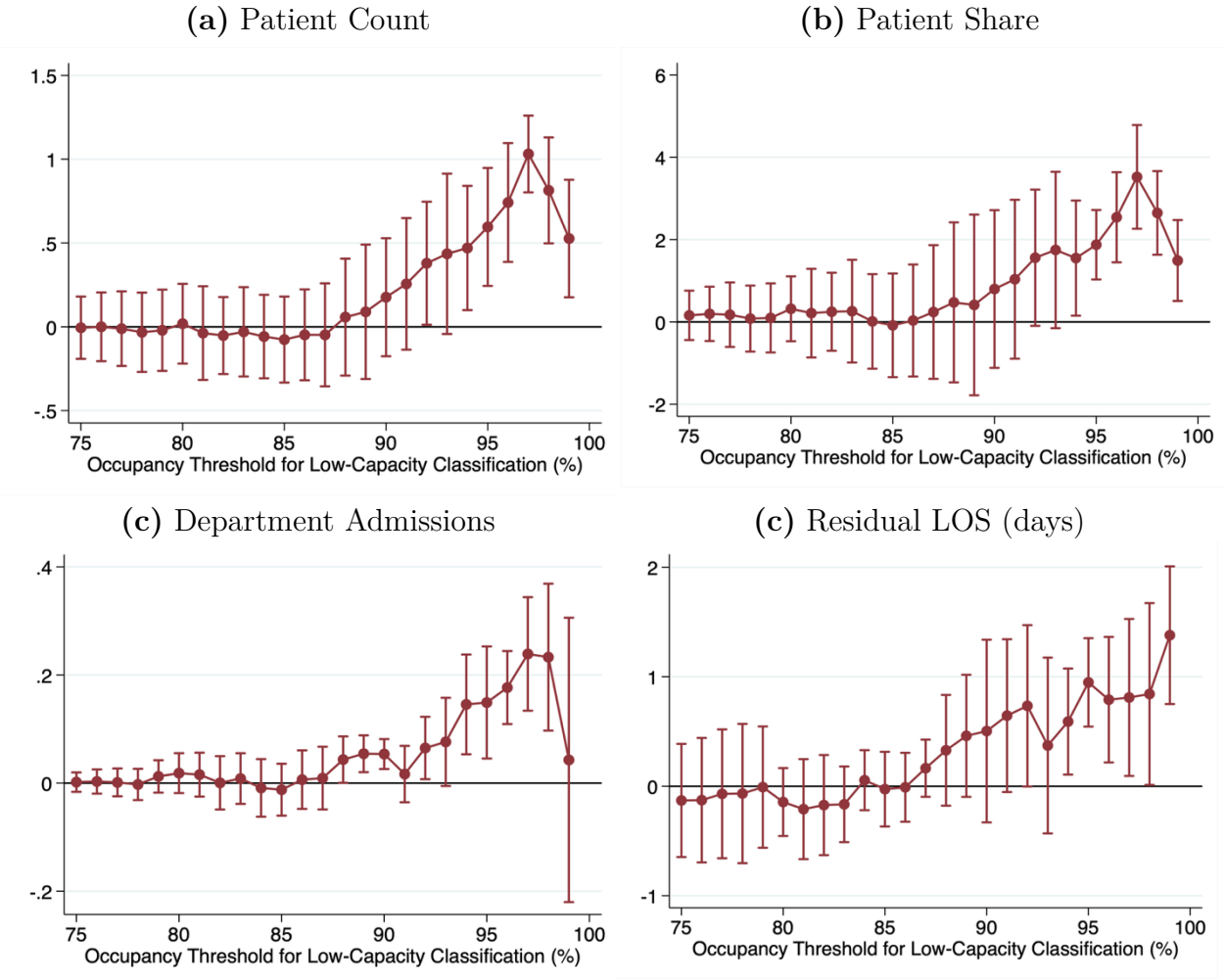
Notes: Daily inpatient occupancy rates (as percentage of licensed bed capacity) for each of the five health system hospitals from January 1, 2022 through December 4, 2023. Blue line shows daily census. Red shaded regions indicate periods when occupancy reached or exceeded 95%, the threshold used to define high-capacity conditions in the main specification.

Figure 5: Low-Resource Patient Census Following HaH Transfers



Notes: event study estimates of Hospital-at-Home transfer effects on low-resource patient outcomes during high-occupancy periods (≥95% occupancy). Event time measured in days relative to HaH transfer. Four panels show effects on: (a) low-resource patient census count, (b) low-resource patient share of total census, (c) department admissions of low-resource patients, and (d) average residual length of stay in days. Estimates include 95% confidence intervals.

Figure 6: Effect of HaH Transfers on Low-Resource Patient Census Across Capacity Thresholds



Notes: Hospital-at-Home transfer effects at one day after transfer ($\tau = -1$) on low-resource patient census across varying occupancy thresholds (75% to 100%). Four panels show effects on: (a) low-resource patient census count, (b) low-resource patient share of total census, (c) department admissions of low-resource patients, and (d) average residual length of stay in days. Estimates include 95% confidence intervals.

Table 4: Effect of HaH Transfers on Patient Census and Outcomes Under 95% Occupancy Threshold

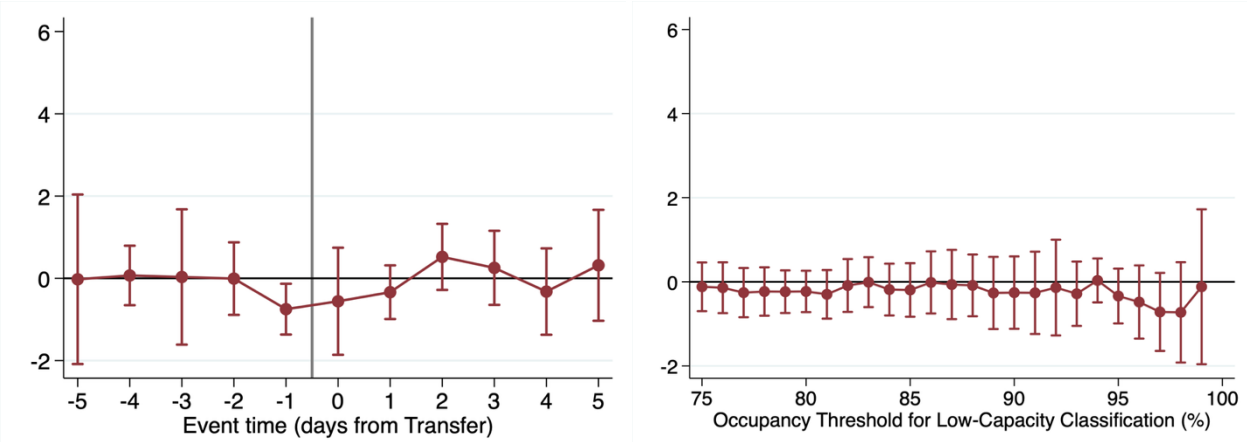
	Low-Resource Patients		High-Resource Patients	
	Pre-Period	Post-Period	Pre-Period	Post-Period
Patient census (count)	-0.018	0.438*	0.048	-0.448
	(0.091)	(0.194)	(0.382)	(0.560)
Patient census (%)	-0.026	1.625**	-2.118	-1.587
	(0.613)	(0.627)	(0.612)	(0.666)
Admissions (count)	0.075	0.050	-0.093	-0.035
	(0.046)	(0.039)	(0.125)	(0.197)
Admissions (%)	1.034	1.808*	-6.280	-1.379
	(0.896)	(0.821)	(0.792)	(0.964)
Elapsed LOS (days)	-0.545	0.109	0.420	0.250
	(0.907)	(0.600)	(0.738)	(0.540)
Residual LOS (days)	0.078	0.962**	-0.404	-0.185
	(0.646)	(0.297)	(0.454)	(0.296)
Discharges to Home	0.036	0.024	-0.057	0.011
	(0.025)	(0.022)	(0.029)	(0.017)
Discharges to SNF	-0.032	0.004	0.047	-0.007
	(0.017)	(0.014)	(0.024)	(0.011)
30-day Readmission Rate	-0.004	0.002	-0.007	0.025**
	(0.035)	(0.045)	(0.010)	(0.008)

Notes: Difference-in-differences estimates of Hospital-at-Home transfer effects on patient outcomes during high-occupancy periods (≥95% occupancy threshold). Pre-period coefficients pool effects over 5 days before HaH transfers; post-period coefficients pool effects over 5 days after transfers. Results shown separately for low-resource patients (Medicaid, self-pay, or charity care) and high-resource patients (private insurance or Medicare/Medicare Advantage). Standard errors in parentheses. * $p<0.05$, ** $p<0.01$.

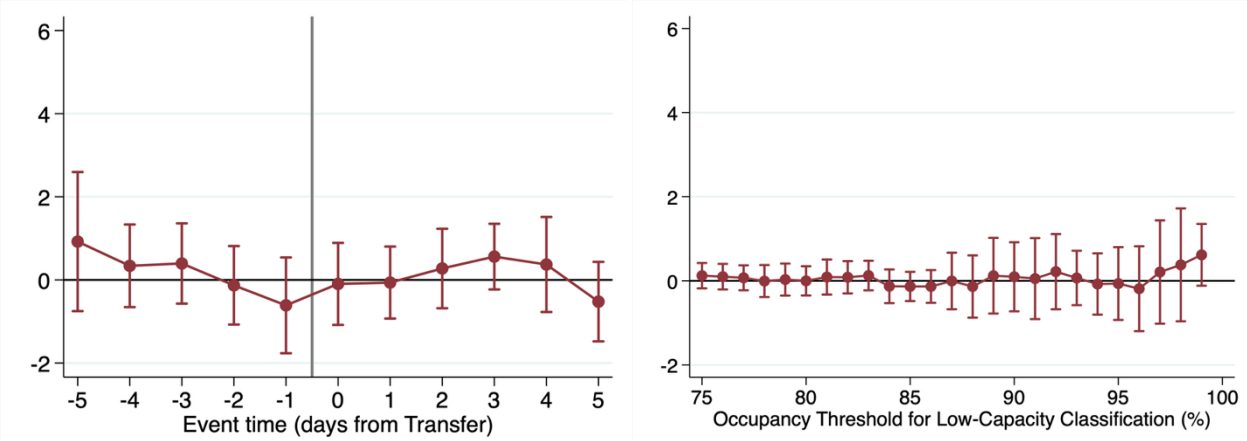
Figure 7: Effect of Other Transfers on Low-Resource Patient Inpatient Share

Following Discharge **Across Capacity Threshold**

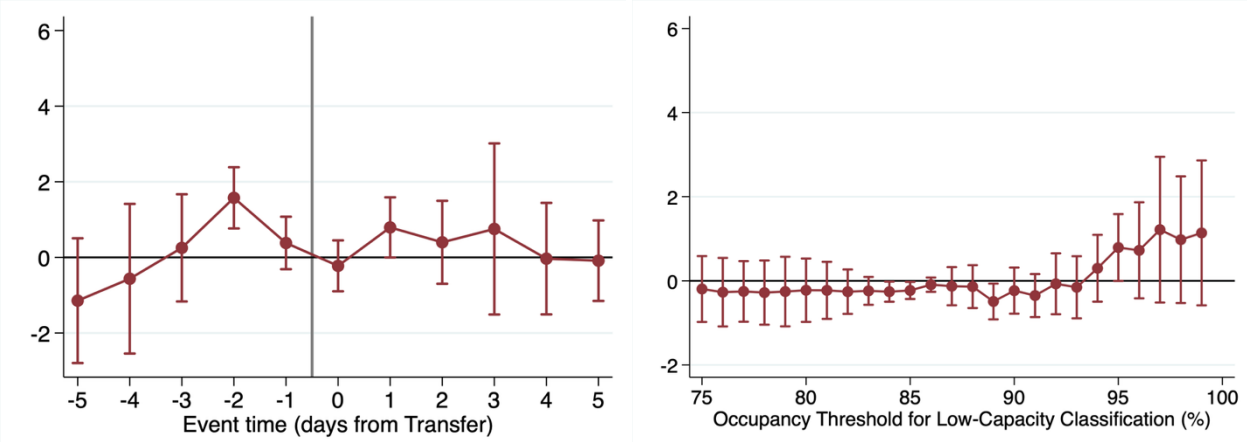
(a) Transfer to Other Acute Hospital



(b) Transfer to Hospice

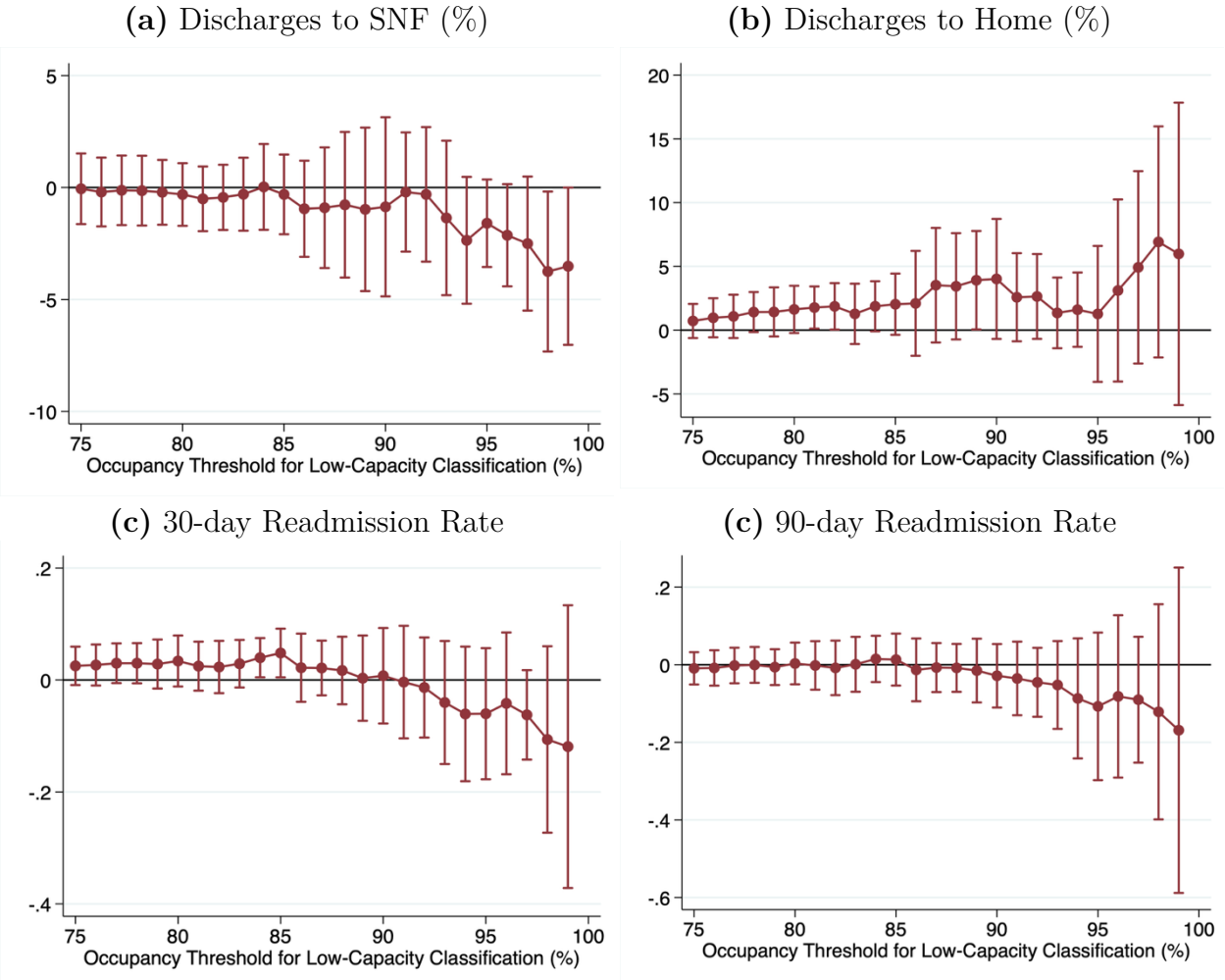


(b) Transfer to Psychiatric Hospital



Notes: Placebo tests examining effects of non-HaH patient transfers on low-resource patient inpatient share. Three transfer types examined: (a) transfers to other acute hospitals, (b) transfers to hospice, and (c) transfers to psychiatric hospitals. Left column displays event study estimates with event time measured in days relative to transfer (day 0, marked by vertical line). Right column shows treatment effect heterogeneity across occupancy thresholds from 75% to 100%. Estimates include 95% confidence intervals.

Figure 8: Effect of HaH Transfers on Low-Resource Patient Outcomes Across Capacity Thresholds



Notes: Hospital-at-Home transfer effects at one day after transfer ($\tau = -1$) on low-resource patient outcomes across varying occupancy thresholds (75% to 100%). Four panels show effects on: (a) % of patients discharged to skilled-nursing facilities (SNF), (b) % of patients discharged home, (c) 30-day readmission rates, and (d) 90-day readmission rates. Estimates include 95% confidence intervals.

Appendix

Table A1: Distribution of Top Diagnosis-Related Groups (DRG) by Patient Type

DRG	DRG Description	Full Sample		Low-Resource Patients		High-Resource Patients		HaH Patients	
		Count	Share (%)	Count	Share (%)	Count	Share (%)	Count	Share (%)
291/292/293	Heart Failure and Shock With/Without CC/MCC	3,692	4.40	381	2.77	3,232	4.64	79	15.28
177/178/179	Respiratory Infections and Inflammations With/Without CC/MCC	3,274	3.90	325	2.36	2,872	4.12	77	14.89
193/194/195	Simple Pneumonia and Pleurisy With/Without CC/MCC	2,061	2.45	256	1.86	1,738	2.49	67	12.96
190/191/192	Chronic Obstructive Pulmonary Disease With/Without CC/MCC	1,605	1.91	226	1.64	1,312	1.88	67	12.96
602/603	Cellulitis With/Without MCC	2,109	2.51	476	3.46	1,587	2.28	46	8.90
689/690	Kidney and Urinary Tract Infections With/Without MCC	2,278	2.71	237	1.72	2,001	2.87	40	7.74
202/203	Bronchitis and Asthma With/Without CC	941	1.12	247	1.80	666	0.96	28	5.42
871/872	Septicemia or Severe Sepsis Without MV >96 Hours With/Without MCC	4,404	5.24	708	5.15	3,668	5.26	28	5.42
698/699/700	Other Kidney and Urinary Tract Diagnoses With/Without CC/MCC	1,392	1.66	184	1.34	1,195	1.71	13	2.51
637/638/639	Diabetes With/Without CC/MCC	1,417	1.69	431	3.13	980	1.41	6	1.16
189	Pulmonary Edema and Respiratory Failure	827	0.98	107	0.78	714	1.02	6	1.16
659/660/661	Kidney and Ureter Procedures For Non-Neoplasm With/Without CC/MCC	825	0.98	141	1.03	679	0.97	5	0.97
853/854/855	Infectious and Parasitic Diseases with O.R. Procedures With/Without CC/MCC	940	1.12	184	1.34	753	1.08	3	0.58
Other DRGs	-	58,215	69.32	9,846	71.61	48,317	69.31	52	10.06
Total Patients		83,980	100.00	13,749	100.00	69,714	100.00	517	100.00

Notes: This table reports the frequency of the most common diagnosis-related groups (DRGs) for patients, by type, during the sample period. The table is sorted by descending frequency within the HaH Patients group.

Table A2: Patient Zip Code Characteristics by Patient Group

	Low-Resource Patients		High-Resource Patients		HaH Patients	
	Mean	S.D.	Mean	S.D.	Mean	S.D.
Total population	25,779	13,617	26,167	13,389	26,217	14,205
Ratio of males to females in the population	94.40	18.18	95.72	14.99	95.25	6.52
Median age of the population	39.20	5.35	41.73	4.81	42.30	4.25
Percent of population age 65 and over	16.01	6.44	18.10	6.25	18.29	3.85
Percent of population age 85 and over	1.91	0.99	2.37	1.08	2.39	0.94
Percent White	51.76	28.09	65.22	21.85	69.59	19.10
Percent Black or African American	25.44	20.49	17.01	17.35	14.39	15.46
Percent Asian	4.31	4.05	5.72	5.13	5.36	4.64
Percent Hispanic or Latino	19.64	18.41	11.39	10.63	9.63	7.86
Total number of households	9,705	5,345	10,058	5,347	10,131	5,642
Average household size	2.64	0.26	2.59	0.22	2.58	0.19
Average family size	3.24	0.24	3.17	0.20	3.15	0.17
Total number of occupied housing units	9,705	5,345	10,058	5,346	10,131	5,642
Percent of households that are married-couple households	41.95	15.25	50	11.39	52.16	10.43
Percent of married-couple households with children	15.45	6.74	18.83	5.79	19.50	5.40
Percent of cohabiting households	7.79	2.94	6.74	2.85	6.56	2.66
Percent of cohabiting households with children	2.82	1.90	2.10	1.52	2.00	1.65
Percent of male householder households (no spouse present)	17.60	5.57	15.66	5.28	14.99	4.31
Percent of male householder households with children	1.34	1	1.12	1.07	1.03	0.75
Percent of male householder living alone	11.93	4.92	11.24	4.61	10.85	3.52
Percent of male householder living alone aged 65+	3.83	3.96	3.63	3.82	3.37	1.48
Percent of female householder households (no spouse present)	32.66	10.97	27.59	7.45	26.29	6.49
Percent of female householder households with children	7.64	6.24	4.75	3.74	4.21	2.85
Percent of female householder living alone	15.72	3.67	15.64	3.89	15.57	4.03
Percent of female householder living alone aged 65+	7.90	2.65	8.68	2.70	8.76	2.84
Percent of households with children under 18	31.88	6.38	30.19	5.23	29.85	4.36
Percent of households with a person aged 65 or older	31.26	7.23	33.43	6.97	33.70	5.80
Median household income	81,473	29,669	98,227	25,558	102,653	23,964
Mean household income	103,216	35,799	124,113	36,032	128,121	33,227
Percentage of population below poverty level	13.75	10.53	8.62	6.44	7.37	5.18
Percent of households with income over $200,000	11.31	7.98	15.81	9.14	16.82	8.71
Percent of households receiving Social Security income	33.54	6.42	33.86	6.94	33.66	5.87
Percent of households receiving retirement income	24.27	8.97	27.56	7.42	28.19	5.77
Percent of households receiving SNAP benefits	14.81	14.88	7.57	8.18	6.17	6.24
Percent of housing units: single-family detached	54.21	26.30	64.50	18.68	67	16.60
Percent of housing units: single-family attached	20.93	19.30	13.85	12.01	12.74	9.63

Table A2 (Continued)

	Low-Resource Patients		High-Resource Patients		HaH Patients	
	Mean	S.D.	Mean	S.D.	Mean	S.D.
Percent of housing units in 2-unit structures	4.09	4.35	2.51	3.01	2.16	2.64
Percent of housing units in 3–4 unit structures	3.95	2.97	3.36	2.71	3.16	2.73
Percent of housing units in 5–9 unit structures	3.54	3.01	3.64	3.13	3.63	3.11
Percent of housing units in structures with ≥10 units	12.27	10.43	11.16	8.63	10.22	7.83
Percent of housing units that are mobile homes	1.01	2.61	0.98	2.42	1.10	2.96
Percent of housing units built in 2020 or later	0.23	0.36	0.28	0.36	0.31	0.38
Percent of housing units built 2010–2019	3.50	2.71	3.45	2.86	3.67	2.50
Percent of housing units built 2000–2009	8.05	6.93	8.82	7.09	9.73	8.09
Percent of housing units built 1980–1999	20.51	15.24	26.01	16.78	27.79	17.09
Percent of housing units built 1960–1979	30.48	14.72	32.77	14.03	32.44	13.18
Percent of housing units built 1940–1959	19.48	9.92	16.83	10.31	15.67	10.26
Percent of housing units built 1939 or earlier	17.76	15.42	11.83	12.55	10.38	11.75
Percent of housing units with 1 room	2.06	2.10	1.47	1.52	1.22	1.33
Percent of housing units with 2–3 rooms	10.23	6.26	8.83	5.50	7.91	5.13
Percent of housing units with 4–5 rooms	27.69	9.01	23.93	7.17	23.19	6.40
Percent of housing units with 6–7 rooms	33.10	6.82	31.46	7.36	31.30	6.20
Percent of housing units with 8 or more rooms	26.93	13.44	34.30	12.45	36.39	11.73
Percent of housing units with 0 bedrooms	2.32	2.42	1.74	1.79	1.44	1.57
Percent of housing units with 1 bedroom	12.32	8.05	10.33	7.06	9.40	6.75
Percent of housing units with 2–3 bedrooms	60.01	10.60	56.65	10.36	56.60	9.60
Percent of housing units with ≥4 bedrooms	25.35	13.55	31.29	12.82	32.55	12.04
Percent of occupied housing owner-occupied	65.27	19.06	73.47	13.50	75.99	12.05

Notes: Reported values are means and standard deviations of zip-code level characteristics, calculated separately for the zip codes of low-resource inpatients, high-resource inpatients, and hospital-at-home patients. All statistics are weighted by the number of patients residing in each zip code.