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Creative Financing and Public Moral Hazard: Evidence from Medicaid and the Nursing Home Industry

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Abstract

Medicaid finances U.S. nursing home care through federal matching grants that reward verifiable volume, not quality. We show that states exploit this through creative financing, diverting funds earmarked for nursing homes. This turns the federal match into a pure volume subsidy and generates a novel allocative distortion we term public moral hazard. We develop the mechanism theoretically and test its predictions using 24 federal audits and administrative microdata from Indiana. Event studies show Medicaid dementia volume rises 12%; structural quality estimates show the expansion concentrates in the lowest-quality facilities, reallocating patients toward worse providers and reducing one-year survival.

JEL classification

H51, H75, I11, I13, I18, J14

Keywords

fiscal federalism, moral hazard, Medicaid, nursing homes, quality of care, joint funding, misallocation of matching funds

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1 Introduction

Joint funding of public programs is a cornerstone of U.S. federalism. The federal government provides local governments more than $1.1 trillion annually in grants—over one-third of state budgets—to support public policies ranging from infrastructure to health care (Congressional Research Service, 2025). Much of this funding takes the form of federal matching grants, matching state contributions in a fixed proportion. Matching grants can improve efficiency by internalizing spillovers across jurisdictions and providing insurance against local fiscal shocks (Oates, 1999). At the same time, they may generate principal-agent problems when the federal government cannot perfectly monitor how states ultimately spend federal funds, as states may then employ "creative financing schemes." Creative financing exploits federal matching formulas to increase federal transfers while altering the ultimate use of the associated funds (Committee for a Responsible Federal Budget, 2023b; Clemens and Veuger, 2025).

This paper studies how creative financing affects the quantity-quality tradeoff in publicly funded health care. To our knowledge, it is the first paper to identify creative financing as a driver of quantity and quality distortions in long-term care. We focus on Medicaid, the joint federal-state public insurance program for low-income Americans, which is projected to exceed one trillion dollars in annual federal spending by 2033 (Keehan et al., 2025). Our empirical setting is the nursing-home industry, which accounts for $211 billion in annual U.S. health care expenditures and will become increasingly important as the population ages (Centers for Medicare & Medicaid Services, 2023). Nursing homes rely heavily on Medicaid reimbursement and have long faced concerns about chronic underfunding and low-quality care (Grabowski, 2001; Rau, 2018; Hackmann, 2019). At the same time, most older Americans overwhelmingly prefer to age at home rather than in institutions (Fields and Dabelko-Schoeny, 2015; AP-NORC, 2021).

We begin by developing a simple theoretical framework illustrating how creative financing arises under imperfect monitoring and distorts reimbursement rates and the volume of care provided. In our principal-agent model, the federal government observes care quantities and nominal reimbursement rates, but cannot perfectly monitor effective reimbursement, which providers keep. States, therefore, have incentives to first inflate nominal reimbursement that qualifies for federal matching funds (here: Medicaid rates), to then redirect some of these enhanced provider revenues through ”intergovernmental transfers.” Such ”creative financing” creates a wedge between nominal and effective reimbursement—we term the ratio of nominal over effective reimbursement *public markup*. This mechanism thus reduces the states’ effective cost share for Medicaid-funded care, thereby encouraging states to expand the volume of such care—a phenomenon we term *public moral hazard*. One main contribution of this paper is to theoretically define and empirically identify this novel allocative distortion in jointly funded public programs.

The model further implies that creative financing may alter the joint distribution of care quality and utilization across providers. Providers differ in occupancy, Medicaid specialization, and marginal expansion costs. As a result, the response to creative financing may vary systematically across nursing homes. Several channels shape these heterogeneous responses. First, providers differ in the potential fiscal gains they can generate from additional Medicaid-funded care. Facilities that can generate larger fiscal surpluses may expand Medicaid volume more strongly. Second, providers with greater unused capacity may respond more strongly because marginal expansion costs are lower. At the same time, the relationship between utilization and quality is theoretically ambiguous. Higher occupancy and treatment volume may improve quality through specialization and learning-by-doing, but may also reduce quality through congestion and binding capacity constraints. Moreover, because providers may respond differently, creative financing may reallocate patients across providers, potentially shifting market shares toward either higher- or lower-quality facilities. Ultimately, the net relationship between creative financing, utilization, and provider quality is therefore an empirical question.

We then test the model’s predictions empirically. First, we provide new evidence on the scope of creative financing and the diversion of Medicaid funds. By manually digitizing 24 federal audit reports, we document the scale of creative financing schemes in the nursing home sector across multiple states. We estimate that nominal Medicaid reimbursement rates exceed effective reimbursement rates by roughly one-quarter in states employing such schemes. As a consequence, the effective Federal Medical Assistance Percentage (FMAP) exceeds the nominal FMAP by approximately 14 percentage points on average, much more than prior calculations have suggested (MACPAC, 2021a).

We then exploit a unique natural experiment in Indiana. A federal reform in 2003 essentially banned creative financing activities in private nursing homes. However, in response and to circumvent the reform, Indiana aggressively municipalized formerly private nursing homes. It is crucial to note that these conversions were solely paper transactions used to execute creative financing, while the private company that operated nursing homes remained exactly the same, pre- and post-municipalization. Thus, we exploit the timing of the license acquisition as a high-quality empirical measure of the onset of creative financing activities in Indiana nursing homes. As a result of the license acquisitions, the share of publicly owned nursing homes increased from 5% to 90% between 2000 and 2017.

Next, we combine exact acquisition dates with administrative microdata covering the universe of Indiana nursing homes. We do so to study the effect of license acquisition—measuring the start of creative financing—-on Medicaid volume and quality of care. Using staggered-adoption Callaway–Sant'Anna event studies, consistent with the model's predictions, we find clear evidence of *public moral hazard*: Medicaid nursing-home days increase by approximately 5% following license acquisition. The increase is primarily driven by dementia patients and the expansion of Alzheimer's special care units. Dementia patients are particularly conducive to expansion of institutional care given their long lengths of stay, low discharge probabilities, and limited availability of specialized dementia facilities (Mitchell et al., 2009). We validate the creative financing mechanism through placebo estimates and real ownership conversions in states without creative financing activities.

We then study how creative financing changes the allocation of care across providers. Guided by the theoretical framework, we investigate heterogeneity in this paper's newly identified allocative distortion of public moral hazard across nursing homes. Specifically, we investigate differential expansions by initial Medicaid specialization, unused capacity, and pre-conversion ownership type. We find that the volume expansions are concentrated in formerly for-profit nursing homes with higher baseline shares of Medicaid patients and greater unused capacity prior to license acquisition.

Finally, we examine how creative financing affects provider quality and care quality consumed across nursing homes. Recall that the theoretical quality predictions are ambiguous. Building on Dubin and McFadden (1984) and Einav, Finkelstein, and Mahoney (2025), we estimate structural nursing-home-quality models using patient-level administrative data and distance-based instruments for provider choice (Olenski and Sacher, 2026; Einav, Finkelstein, and Mahoney, 2025). Further, we augment the nursing-home quality model by considering home health care as an outside option. Using one-year survival and hospital readmission rates as outcome measures, we find no evidence that license acquisition systematically affects the quality of care provided by a given nursing home. That is, holding patient composition fixed, we find no conclusive evidence that engaging in creative financing changes provider quality.

Importantly, however, we document substantial heterogeneity in provider quality and show that the resulting volume expansions are disproportionately concentrated among lower-quality facilities. In particular, the largest volume expansions occur among the bottom quintile in terms of facility quality. Combining the estimated volume responses with our quality estimates, we find that this reallocation raises one-year mortality by roughly 0.8 percentage points among the 11% of dementia patients whose care choice changes. Because quality within a given nursing home is unchanged, the decline in quality operates in our setting through where the marginal Medicaid day is provided.

In sum, we find that creative financing increases publicly funded nursing home utilization while reallocating vulnerable patients toward lower-quality providers. Our results thus imply that creative financing contributes to an institutional bias of U.S. long-term care policy. By lowering states' effective cost share for nursing home care, creative financing encourages additional institutionalization, with much of the resulting volume expansion occurring in lower-quality nursing homes. Our broader insight is that joint funding formulas can only condition on what the federal government can verify. When it observes the volume of care and the nominal reimbursement rate, but not the payment providers ultimately retain, the federal match operates as a subsidy to verifiable quantity alone. Federal matching funds are then quality-blind by construction: they flow toward whichever providers generate the most Medicaid days, not toward those delivering the best care. The resulting distortion is therefore allocative rather than a matter of spending levels, and, to our knowledge, we are the first to document it in long-term care.

Our findings contribute to three strands of literature. First, we contribute to work on strategic behavior in fiscal federalism (Gordon, 1983; Dahlby, 1996; Knight, 2002; Agrawal, 2015; Clemens and Veuger, 2025; Clemens and Mahajan, 2026) by showing how states use creative financing to obscure spending and divert Medicaid funds. While such practices have been discussed in health policy (Coughlin and Zuckerman, 2003; Mitchell, 2018; Sharma and Xu, 2023), law (Hatcher, 2016), and the popular press (Evans, Hopkins, and Cook, 2020b), they have received limited attention in economics. An important exception is Baicker and Staiger (2005), who study the diversion of Medicaid matching funds through Disproportionate Share Hospital (DSH) payments, and Duggan (2000), who shows that private (but not public) providers respond to the incentives created by DSH payments, cream-skimming the most profitable indigent patients. Duggan (2000) attributes the muted public response to a soft budget constraint: local governments reduce their subsidies roughly one-for-one as DSH revenues arrive, leaving public hospitals without a financial stake. Our framework characterizes incentives at a more aggregated level than the individual facility, where fiscal gains are internalized rather than clawed back.

Second, we contribute to the literature on moral hazard and asymmetric information in health care (Baicker, Mullainathan, and Schwartzstein, 2015; Einav, Finkelstein, and Mahoney, 2018; Eliason et al., 2018; Cabral and Cullen, 2017; Alexander and Schnell, 2024). We highlight imperfect monitoring between federal and state governments as a source of allocative distortions and show how health care reimbursement design can induce the expansion of lower-quality care.

Third, we contribute to research on long-term care financing and nursing-home quality (Grabowski, 2001; Werner, Konetzka, and Polsky, 2013; Lin, 2015; Hackmann, 2019; Gandhi et al., 2026; Gandhi, Olenski, and Shi, 2026; Olenski, 2026). Although 88% of older Americans generally prefer to age at home (AP-NORC, 2021), institutional and policy biases toward nursing home care persist (Chidambaram and Burns, 2023). Existing work emphasizes reimbursement design, eligibility rules, and limited home-care alternatives as drivers of institutional bias (Grabowski and Gruber, 2007; Mommaerts, 2018; Einav, Finkelstein, and Mahoney, 2023). We show that creative financing provides an additional mechanism by artificially lowering states' effective cost of institutional care and encouraging the expansion of lower-quality nursing-home services. Our setting also speaks to work on ownership and health care quality (Dafny, 2019; Beaulieu et al., 2020; Gupta et al., 2024; Gandhi, Song, and Upadrashta, 2026): unlike conversions that transfer operational control, Indiana's municipalizations changed licenses only, isolating the financial incentive created by creative financing from the ownership change itself. To measure nursing home quality, we build on and contribute to recent advances in nursing home value-added estimation (Cheng, 2024; Einav, Finkelstein, and Mahoney, 2025; Cheng, 2025; Olenski and Sacher, 2026).

The next section discusses institutional details. Section 3 develops the conceptual framework, and Section 4 presents the empirical analysis.

2 Institutional Setting

2.1 Medicaid Funding

Medicaid provides public health insurance to nearly 80 million low-income individuals, with total annual spending of approximately 1 trillion dollars, expected to increase to 1.6 trillion by 2033 (Keehan et al., 2025). The Medicaid program operates under a federal-state partnership: states administer the program with significant discretion while sharing costs with the federal government (Kaiser Family Foundation, 2025c). The federal cost share is the "Federal Medical Assistance Percentage" (FMAP), which decreases in the state's per capita income according to a formula bounded by the statutory limits of 50% (from below) and 83% (from above), see Kaiser Family Foundation (2025b).

However, states use creative financing to increase federal matching funds, thereby effectively shifting costs to the federal government. The Committee for a Responsible Federal Budget (2023a) estimates that the federal government currently covers 5% more Medicaid spending than without creative financing. In the context of Medicaid, the Committee for a Responsible Federal Budget (2023b) defines creative financing as states using provider taxes, intergovernmental transfers, and supplemental payment arrangements to increase their effective federal matching rate and reduce the amount of state general funds needed to finance Medicaid. This paper focuses on supplemental payments and intergovernmental transfers; see Appendix B.3 for a discussion on provider taxes. Note that it is unclear whether creative financing is legal, which has led to heated debates among legal scholars and in lawsuits, audits, and legislative initiatives, as discussed throughout this paper.

The Centers for Medicare and Medicaid Services' (CMS) limited oversight and monitoring capacities help explain the scale and persistence of creative financing. For example, a former senior official from the Department of Health and Human Services writes:[1]

> "CMS is tasked with administering massive cooperative spending programs that represent substantial federal investment to provide or expand access to quality health services. Administering Medicaid alone requires CMS to oversee 56 individual state and territorial plans that receive nearly three-quarters of a trillion dollars in annual federal expenditures. Yet CMS has only a few hundred employees, operating on a relatively modest budget, dedicated to supervising Medicaid programs. As constituted, it [CMS] simply does not have the capacity to fill the void if the private enforcement mechanisms on which the agency has come to rely were suddenly stripped away."

2.2 Creative Financing in Nursing Homes: Pre-2003

The nursing home industry, the focus of our analysis, relies heavily on Medicaid, with two-thirds of the 1.5 million nursing home patients covered by Medicaid, totaling $59 billion in annual Medicaid spending (Kaiser Family Foundation, 2024). State Medicaid programs reimburse nursing homes on a "per diem" basis (MACPAC, 2019); these base rates are lower than for private payers or Medicare beneficiaries, and can result in lower quality of care (Grabowski, 2001; Hackmann, 2019). Thus, states can top up Medicaid base rates through Supplemental Payments to avoid lower-quality care for Medicaid beneficiaries.

The total reimbursement rate, per diem plus Supplemental Payments, is then matched with federal funds using the FMAP, provided the total rate remains below the "Upper Payment Limit" (UPL) (Mitchell, 2018).[2] Supplemental Payments account for about seven percent of total Medicaid fee-for-service nursing facility payments (MACPAC, 2021b).

However, some states used creative financing to divert payments intended for nursing homes. The pre-2003 regulations left states considerable discretion in allocating Supplemental Payments across providers: states could accrue payments on Medicaid days provided in *private* nursing homes but direct them to county-owned homes, which then returned the funds to the state via Intergovernmental Transfers. Because these payments were not tied to specific services, little of the money had to remain with providers.

[1] See, Brief Amici Curiae in Support of Respondent. Hospital Corporation of Marion County v. Talevski, No. 21-806. U.S. Supreme Court, filed September 23, 2022.

[2] The UPL corresponds to the rate that Medicare would pay for the service. Typically, it is at least twice the Medicaid per diem rate. In 2018, the average Medicare rate per patient-day was $515 ($427 for managed Medicare), compared to only $209 for Medicaid (Spanko, 2019).

Panel A of Appendix Figure A1 illustrates such a scheme (Coughlin and Zuckerman, 2003). Pennsylvania paid \$300 million (figures rounded) in Supplemental Payments to 23 county-owned nursing homes. Given the state's FMAP of 56%, this triggered \$400 million in federal matching funds, bringing the total to \$700 million for the county's nursing facilities. Yet only \$1.5 million actually remained with the providers, as the large majority was transferred to the Pennsylvania government.

2.3 The 2003 Reform

In 2001, 29 states ran creative financing via intergovernmental transfers, many of which served nursing homes (U.S. Department of Health and Human Services, 2001). In response, Congress directed the Department of Health and Human Services to limit federal tax dollars that could be diverted (Ku and Park, 2001; Federal Register, 2001).

Effective 2003, a federal reform thus banned states from redirecting funds from *private* nursing homes, restricting the practice to publicly owned homes, which had only a 7% market share at the time (Gabrel, 2000).

2.4 Creative Financing 2.0: Evidence from Indiana

In response to the 2003 reform, Indiana implemented a creative financing scheme, which is the focus of our empirical analysis. The scheme was implemented at the nursing home level; we exploit its precise timing to estimate its causal effects on patient volume and health.

Specifically, to bypass the 2003 reform, Indiana induced county-owned hospitals to acquire private nursing homes, thereby municipalizing them on paper. Once public, the state used Intergovernmental Transfers to redirect federal matching funds. The stated purpose of these municipalizations, codified in law, was to "*maximize the amount of federal financial participation that the state can obtain through the intergovernmental transfer or other payment mechanism*" (Indiana Code § 12-15-14-1(b)).

Panel B of Appendix Figure A1 illustrates the resulting flow of funds for the Health and Hospital Corporation (HHC) of Marion County in 2019. Indiana paid per diem and Supplemental Payments to the newly acquired county-owned nursing homes, and federal matching funds augmented these payments. Under a contractual agreement, the county hospitals then repaid the state's share while retaining the federal match, which was divided between hospitals and nursing homes; the homes themselves often kept only a small share of the enhanced Medicaid revenues (Hatcher, 2016). Because federal matching funds were proportional to Medicaid service days, the integrated hospital-nursing home system had strong incentives to increase patient volume.

The HHC of Marion County pioneered this model in Indiana, acquiring and municipalizing 17 nursing homes in 2003 and owning 40 by 2009. Conversions accelerated in 2010, when the Indiana legislature passed Senate Bill 292, which explicitly allowed county hospitals to own, operate, or contract with nursing homes as "health facilities" (Indiana Legislature, 2010). By removing the legal uncertainty about whether a county hospital could own a nursing home, the bill lowered the barriers to municipalization, and several other county hospitals began acquiring nursing homes following the HHC model. As Figure 1 shows, over 90% of Indiana nursing homes were county-owned by 2017.

[Insert Figure 1 about here]

These conversions were paper transactions. Rather than acquiring the nursing homes outright, HHC used a "lease structure": it purchased the nursing home *license* while leasing the remaining assets (Pahud and Myers, 2016). Ownership therefore changed without any change in the management or operation of the home, as Hatcher (2016) documents:

> "To implement its revenue strategy, the agency [HHC] started buying for-profit nursing homes [...]. The agency worked with state officials to turn [...] nursing homes into a revenue opportunity, taking advantage of federal Medicaid funding policies.[...] When the agency started purchasing the nursing facilities, it did not actually take over operations. Rather, HHC simply bought the nursing home licenses, leased the properties from the private companies that owned the rights, and then hired a private company to operate the nursing homes. American Senior Communities was the company running the private nursing homes prior to the initial HHC purchases in 2003, and after the purchases, HHC hired the same company to keep operating them."

This agreement essentially allows private entities to transfer funds as Intergovernmental Transfers (Congressional Budget Office, 2026). CMS has harshly criticized such arrangements, noting that *"everyone wins—except perhaps the patient and the federal taxpayer"* (Evans, Hopkins, and Cook, 2020a). The Indianapolis Star described Indiana county hospitals as *"an absentee landlord primarily concerned with using this collection of nursing homes to generate much-needed cash."* (Gillers et al., 2010).

Nevertheless, the Indiana scheme was highly effective in maximizing federal Medicaid revenues. In FY 2020, Indiana received $996 million in supplemental payments for nursing homes, more than any other state (Medicaid and CHIP Payment and Access Commission, 2021). From 2003 to 2020, Indiana county hospitals extracted approximately $4.3 billion in additional Medicaid funds for nursing homes from federal taxpayers. However, investigations by The Indianapolis Star revealed that, of these $4.3 billion, between $1 and $3 billion had been diverted (Evans, Hopkins, and Cook, 2020b).

In our empirical analysis below, we exploit the timing of nursing home acquisitions in a difference-in-differences framework to estimate the causal effect of this scheme on the volume and quality of care.

3 Conceptual Framework

This section develops a unifying theoretical framework to study how creative financing distorts the allocation of care. Building on the multitask principal-agent paradigm (Holmstrom and Milgrom, 1991), we study a setting with monitoring frictions. The Principal is the federal government, and the Agent is the state or county health care system. The Principal observes care volume and nominal reimbursement but cannot fully monitor effective provider payments, that is, how much of the nominal reimbursement is actually spent. This creates scope for a wedge between nominal and effective spending. When such a wedge can be monetized and funding diverted, the Agent inflates the monitored margin (observable care volume) while shirking on the unmonitored one (effective spending).

The broader insight is that, under imperfect monitoring, a matching subsidy is a quantity subsidy: public funds expand the volume of care without necessarily raising, and potentially lowering, the effective rates paid to providers. This logic applies to any jointly financed program with an unmonitored margin. We conclude with a discussion of how these distortions may affect the quality of care through changes within providers and the market reallocation between providers.

3.1 State and Federal Payoffs

State ("The Agent"): The state values the quality (θ) and quantity (Q) of nursing home care through a dollar-denominated benefit function $B(\theta, Q)$, increasing and concave in both arguments. We consider that the state internalizes only a fraction $\tau \leq 1$ of these benefits, creating a wedge between the state's valuation, τB, and the full valuation, B. We remain agnostic about the source of this wedge: it may reflect fiscal spillovers across jurisdictions, competing state budget priorities, or a lower welfare weight that the state places on Medicaid beneficiaries seeking nursing home care.

The federal government reimburses a fraction of nominal Medicaid spending ($P \times Q$) through the FMAP, where P denotes the nominal reimbursement rate.[3] Providers, however, receive the *effective* reimbursement rate R, net of redirected funds, with $(P - R) \times Q$ captured by the state. We assume that the state chooses (P, R, Q), allowing $P \neq R$, as we detail below. In the theoretical discussion, we assume that quality θ is increasing in R, i.e., $\partial\theta(R)/\partial R > 0$, considering that more resources can improve quality.[4]

We define the state's indirect conditional utility as:

$$U^a = \underbrace{\tau \times B(\theta(R), Q) + FMAP \times P \times Q}_{\text{State Utility}} - \underbrace{R \times Q}_{\text{Costs}}. \tag{1}$$

Federal Government ("The Principal"): While not central to our main predictions, we assume that the federal government internalizes externalities across states, net of the federal reimbursement costs, and has utility:

$$U^p = \underbrace{(1 - \tau) \times B(\theta(R), Q)}_{\text{Fed Utility}} - \underbrace{FMAP \times P \times Q}_{\text{Costs}}. \tag{2}$$

3.2 Perfect Monitoring ($P = R$)

We start by considering the case with perfect monitoring. In this scenario, $P \times Q$ can be replaced by $R \times Q$ in (1), eliminating the scope for creative financing. The state's first-order conditions with respect to R and Q yield:

[3] Including per diem and supplemental rates; see Section 2.

[4] If not, states choose the minimum rate R_{min} in our model, determined by a participation constraint of the provider.

$$\begin{aligned} \tau \times B_R(\theta(R), Q)/Q &= 1 - FMAP && (3) \\ \tau \times B_Q(\theta(R), Q)/R &= 1 - FMAP\,. && (4) \end{aligned}$$

It follows that setting $FMAP = 1 - \tau$ maximizes the joint surplus between the state and the federal government: $U^a + U^p$, meaning that the FMAP acts as a Pigouvian subsidy internalizing the externality $(1 - \tau)$.

3.3 Imperfect Monitoring ($P \neq R$)

We now consider the empirically relevant case where the federal government observes care volume Q and the nominal rate P, but not the effective rate R. While Q and the nominal rate P are publicly observed (Centers for Medicare & Medicaid Services, 2025), the share of funds reaching providers is difficult to trace, even in detailed audits (Office of Inspector General, 2001a). By statute, P is capped at the upper payment limit, $\bar{P} = UPL$.

The state's problem is then:

$$\max_{P \leq \bar{P}, R, Q} \tau \times B(\theta(R), Q) + FMAP \times P \times Q - R \times Q\,. \quad (5)$$

with first-order conditions:

$$\begin{aligned} P &= \bar{P} && (6) \\ \tau \times B_R(\theta(R), Q)/Q &= 1 && (7) \\ \tau \times B_Q(\theta(R), Q)/R &= 1 - FMAP \times \frac{\bar{P}}{R} = 1 - FMAP \times \mu. && (8) \end{aligned}$$

where we define $\mu = \frac{\bar{P}}{R}$ as the *"public markup."*

Three key predictions follow from the first-order conditions. First, states have incentives to inflate the nominal rate P. In the extreme case considered here, states increase P up to the cap $\bar{P}$, equation (6). In practice, increasing P all the way to the cap may raise suspicions of creative financing and trigger audits, preventing some states from fully exploiting the cap.[5]

[5]Adding an expected auditing cost C that increases in the nominal rate P can capture such 'soft limits.' In that case, the optimal nominal rate P^* is determined by the condition $\frac{dC}{dP} = \frac{dU^a}{dP}$, where $\frac{dU^a}{dP}$ captures the marginal benefit of increasing P through higher federal subsidies. Expected auditing costs thus create a soft limit on P, which may be below the statutory cap $\bar{P}$.

Conversely, because the effective rate R does not qualify for matching funds, states have an incentive to reduce R, equation (7).[6] This creates a wedge between P and R, the public markup $\mu = \frac{P}{R}$.

Hypothesis 1 (H1) ***Public Markup:*** *Under imperfect monitoring of R, states inflate nominal relative to effective rates, creating a public markup $\mu = \frac{P}{R}$ that enables diversion of $(P - R) \times Q$.*

Second, the public markup increases the effective federal subsidy, encouraging expansion of jointly funded care volume Q. This mechanism, which we term *"public moral hazard,"* arises because the effective FMAP exceeds the nominal FMAP by a factor equal to the public markup μ, equation (8).[7]

Hypothesis 2 (H2) ***Public Moral Hazard****: The presence of a public markup increases the effective federal subsidy to care, encouraging expansion of jointly funded care volume Q.*

Finally, the markup and public moral hazard responses are complementary: because the effective FMAP rises with the markup μ, programs facing larger markups have the strongest incentives to expand volume. Whether programs and firms with higher markups are higher- or lower-quality is theoretically ambiguous and ultimately an empirical question, which we discuss in more detail below.

Hypothesis 3 (H3) ***Complementarity and Differential Expansion****: Higher public markups amplify public moral hazard and thus allocative distortions. That implies that volume expansions concentrate among providers with the largest markups.*

Graphical Illustration. Figure 2 illustrates how creative financing distorts the reimbursement rates and the quantity of care in opposing directions. The vertical axis denotes the reimbursement rate, R, which may positively affect the quality of care. The horizontal axis denotes the quantity of care, Q.[8] The convex curves represent indifference curves for dif-

[6] This abstracts away from an income effect discussed below.

[7] Note that the relative distortions between rate-quality and quantity are independent of τ: equations (7)–(8) raise the effective price of quality relative to volume regardless of the welfare weight, since τ scales marginal benefits but not the wedge in effective prices. Creative financing therefore distorts the rate-quality-quantity mix even when evaluated against the state's own objective, τB.

[8] Q and R are expressed in logs, yielding linear budget constraints.

ferent benefit levels, up to the scaling factor τ. We can now distinguish between perfect and imperfect monitoring.

Under perfect monitoring, absent creative financing, the downward-sloping line 'C' denotes the state's budget constraint. The slope equals -1 and does not depend on the FMAP. A one percent increase in rates must be offset by a one percent increase in volume to balance the state budget. The expansion path 'I' illustrates the state's optimal rate-quantity mix. As τ increases, states choose higher rates and volumes along this path. Allocations along this path minimize both state and federal costs of achieving a given benefit level.

Under imperfect monitoring and with creative financing, the downward-sloping curve 'D', now rotated outward, denotes the state's budget constraint. The slope depends on the FMAP, scaled by the markup $\mu = \frac{P}{R}$ and is $-(1 - FMAP \times \mu)$.[9] States have stronger incentives to increase care volume, reflecting public moral hazard, and weaker incentives to increase rates and thus quality, as indicated by the allocations along the new expansion path 'II'.

Note that creative financing also yields a positive income effect on the state's budget. Although not the focus of our analysis, policy discussions indicate that states perceive reimbursement rates and quantity as 'normal' goods, meaning that the positive income effects will further increase quantity setting. This suggests that the income and substitution effects for rate-setting work in opposing directions, leaving the net effect of creative financing on rate-setting ambiguous.

The allocations along the new expansion path 'II' are cost-efficient for the state, but not for the federal government. The wedge between the two expansion paths 'I' and 'II' represents the distortionary effect of creative financing on the quantity of care, public moral hazard, and scales with the magnitude of the public markup μ.

[9]To derive the slope of the budget constraint, we start with the state's costs under creative financing, given by $Costs = R \times Q - FMAP \times P \times Q$. Taking logs of costs and solving for $\log(Q)$, we get $\log(Q) = \log(\text{costs}) - \log(R - FMAP \times P)$. Taking the derivative w.r.t. $\log(R)$ (or the derivative w.r.t. R and then multiplying by $\frac{\partial R}{\partial \log(R)} = R$), we get $\frac{\partial \log(Q)}{\partial \log(R)} = -\frac{1}{1 - FMAP \times \frac{P}{R}}$

3.4 Implications for the Quality of Care

So far, the theory has highlighted that creative financing is not only a transfer between the federal and state governments, but also distorts the volume of care. However, central to patient welfare is also the quality of care received. In this subsection, we discuss channels through which creative financing may generate heterogeneous provider responses and heterogeneous quality effects. We distinguish between within-provider responses and patient-relocation effects across providers that differ in quality of care. Appendix B.1 extends the baseline model to allow for heterogeneity in provider quality and provides more discussion of how variation in quality and capacity shapes provider responses to creative financing.

Within-Provider Quality Responses. The substitution effects, highlighted above, suggest that creative financing may reduce rate-setting and thus the quality of care. On the other hand, the income effect of creative financing may increase rate-setting and, in turn, quality. The net effect on quality is therefore theoretically ambiguous.

Between-Provider Quality Reallocation. As discussed under H3, we expect heterogeneous responses to creative financing based on the markup of nominal over effective rates, and thus a reallocation of patients across providers. Providers with higher markups have stronger incentives to expand volume. These providers could be lower quality to the extent that lower effective rates compromise quality. On the other hand, low effective rate providers could be more efficient, offering higher quality of care. It is therefore an empirical question whether higher-markup providers are of higher or lower quality.

Reallocation—Capacity Channel. While not modeled above, the response to creative financing also depends on providers' capacity constraints. Providers operating below capacity can expand care volume more easily because they face flatter marginal cost curves. However, the relationship between capacity and quality is again ambiguous. Lower occupancy may reflect weaker demand due to lower quality or reputation, but it may also reflect higher quality if providers avoid congestion that may lower quality.

Implications. In sum, these operating channels imply that creative financing may directly affect the quality of care, with the direction of the effect shaped by income and substitution effects. Furthermore, the effect of creative financing on care volume is likely heterogeneous across providers, which affects the distribution of care quality. Whether expansion is concentrated among higher- or lower-quality providers is ultimately an empirical question that depends on how markup incentives and capacity constraints interact.

4 Data, Empirical Approaches, and Results

The following subsections examine the impact of creative financing on provider reimbursement (*public markup*), publicly funded nursing home volume (*public moral hazard*), and quality of care received, across and within providers. We organize the discussion of the data, empirical strategy, and results accordingly.

4.1 How Does Creative Financing Affect Effective Reimbursement (H1)?

Testing H1 (Public Markup). This subsection provides empirical evidence on the existence and magnitude of the public markup, $\mu = P/R$, by comparing nominal and effective reimbursement rates. We estimate nominal spending that qualifies for federal matching funds ($P \times Q$), effective provider reimbursement ($R \times Q$), and the implied redirected funds $(P - R) \times Q$. We then quantify the public markup, $\mu = P/R$, and the implied effective FMAP: $\mu \times FMAP$.

To do so, we digitize and calculate these parameters from two sets of reports. First, we digitized 24 audit reports from 18 states between 1997 and 2017. CMS commissioned these reports from the Office of Audit Services of the Office of Inspector General (OIG). OIG is mandated to protect the integrity of Department of Health and Human Services (HHS) programs and the well-being of beneficiaries (Department for Health and Human Services, 2025). The reports provide information on the extent of creative financing in each state, including the amounts transferred through Intergovernmental Transfers (IGTs) and redirected from nursing homes, corresponding to $(P - R) \times Q$. We complement the reports with CMS-64 forms to obtain nominal Medicaid nursing home spending ($P \times Q$).

Figure 3a displays the implied public markups for the six states whose audits report IGT amounts that can be matched to nursing-home-specific Medicaid spending: AL, NE, PA, TN, WA, and TX. Figure 3b contrasts nominal and effective FMAP rates in these states.

Appendix Section C provides further details on the data sources, calculations, and assumptions.

Figure 3 therefore provides direct evidence for Hypothesis H1 by comparing nominal Medicaid spending, $P \times Q$, to effective provider reimbursement, $R \times Q$, and quantifying the implied public markup $\mu = P/R$. Figure 3a shows that nominal Medicaid reimbursement rates are, on average, 24% higher than effective reimbursement among states with creative financing schemes, implying a markup of $\mu = 1.24$. Markups vary across states, reaching 1.62 in Pennsylvania in 1999. Consistent with this, Figure 3b shows that the effective FMAP, $\mu \times FMAP$, exceeded the nominal FMAP by as much as 33 percentage points. Across the audit reports, the average increase in the nominal-to-effective FMAP is 14 percentage points.

[Insert Figure 3 about here]

Second, we manually review, digitize, and calculate redirected funds using the financial statements of the Health and Hospital Corporation (HHC) of Marion County, the central actor in Indiana's creative financing scheme, see Section 2. We focus on the years 2008 to 2019, a period when Indiana intensified its nursing home municipalizations and, thus, its creative financing. Appendix Table C2 reports detailed financial indicators disclosed by HHC for each calendar year. Appendix Figure C1 presents the corresponding effective FMAP calculations.

As shown in column (7) of Table C2, HHC redirected (at least) \$1.9 of \$5.5 billion in nursing-home-related payments through IGTs to finance hospital operations from 2008 to 2019. We estimate an average markup of $\mu = \frac{\$5.5bn}{\$5.5bn - \$1.9bn} = 1.53$ and an effective FMAP of 104%, compared to a nominal FMAP of 68%. An effective FMAP above 100% implies that the combined state-local system receives more in federal reimbursements than it spends on effective provider payments. Aggressive creative financing thus generated substantial net fiscal gains from Medicaid-funded nursing home care through federal supplemental matching payments. Appendix Section C.2 provides additional details on the underlying calculations and assumptions.

In summary, a systematic review and quantification of 24 OIG audit reports and 12 annual HHC financial statements provide clear evidence that creative financing schemes are a widespread phenomenon. Across states, where creative financing was in effect, we calculate public markups of approximately $\mu = 1.24$ and effective FMAPs exceeding nominal FMAPs by 14 percentage points. In Indiana, between 2008 and 2019, the scheme redirected at least \$1.9 billion from nursing homes, producing an effective FMAP of 104%. Overall, these findings clearly confirm Hypothesis H1: creative financing generates substantial public markups, increasing nominal relative to effective reimbursement rates.

4.2 How Does Creative Financing Affect Public Health Care Volume (H2)?

Testing H2 (Public Moral Hazard). This subsection tests whether the higher public markups documented in Section 4.1 indeed cause nursing homes to expand Medicaid volume, Q, consistent with public moral hazard. To do so we turn to Indiana, which implemented its creative financing scheme at the nursing home level.

After the 2003 reform, HHC pioneered a creative financing scheme in close cooperation with state officials; see Section 2.4. Beginning in 2003, it acquired private nursing homes to preserve and expand access to supplemental federal matching funds, raising the share of county-owned nursing homes from roughly 5% to 90% between 2000 and 2017 (Figure 1). Crucially, these conversions occurred only on paper: HHC purchased nursing home licenses while operating management remained unchanged. Unlike the ownership conversions studied in Gupta et al. (2024) and Gandhi, Song, and Upadrashta (2026), which alter production technology and management, the Indiana case therefore isolates a shift in financial incentives of the kind modeled in Section 3. Our empirical strategy exploits the staggered timing of these license acquisitions.

Data & Empirical Strategy. To do so, we combine three data sources; see Appendix D for details. First, we identify license acquisitions (”municipalizations”) using (i) Nursing Home Compare, (ii) Indiana Department of Health (2020), and (iii) reports by the *IndyStar* newspaper (Centers for Medicare & Medicaid Services, 2020b; Gillers et al., 2010). Second, we merge in LTC Focus data on facility characteristics at the nursing-home-year level from 2000 to 2015. Third, we aggregate patient-level administrative data from the Long-Term Care Minimum Data Set (MDS) to the nursing-home-year level. MDS covers all Medicaid- and Medicare-certified nursing homes. Our sample thus includes (almost) the universe of nursing home stays in Indiana from 1999 to 2015.

To maintain a stable sample composition over time, we balance the panel in calendar time at the nursing-home-year level. We then restrict attention to nursing homes with at least one Medicaid patient in 2000, yielding a panel of 368 nursing homes over 17 years.

Table D1 shows that nursing homes have, on average, 108 beds and an occupancy rate of 80%. Occupancy is also the only characteristic that is substantially imbalanced between early and late municipalization cohorts, according to the normalized difference metric of Imbens and Wooldridge (2009), see Table D2. Nursing homes municipalized after 2011 exhibit higher occupancy rates (78% vs. 70%) but similar shares of Alzheimer Special Care Units (39% vs. 42%), similar acuity indices (11.1 vs. 11.1), and similar registered nurse hours per resident day (0.25 vs. 0.22). Below, we investigate occupancy as one key characteristic to facilitate public moral hazard, in addition to the pre-conversion share of Medicaid patients and for-profit status.

We note that tracking nursing homes from 1999 to 2015 provides sufficient event-time coverage to estimate medium- and long-run effects using Callaway and Sant'Anna (2021) event studies; see Appendix Section E. The Callaway–Sant'Anna DD estimator compares changes in outcome measures between municipalized and non-municipalized nursing homes. Because 90% of nursing homes are eventually municipalized, we use not-yet-treated facilities as controls. Standard errors are clustered at the nursing-home level.

Results. Figure 4 presents four Callaway–Sant'Anna event studies showing the effect of license acquisition on (a) for-profit status, (b) Medicaid days, (c) Medicaid days among dementia patients, and (d) Alzheimer's special care units. As seen, across outcomes, there is no evidence of pre-trends prior to municipalization.

[Insert Figure 4 about here]

First, Figure 4a serves as a falsification exercise. It shows a sharp decline in for-profit status beginning in the year when HHC acquired the license. To recap, the change in license ownership is supposed to trigger a change in private-to-public ownership. Three years after license acquisition, the effect size is approximately -0.6, broadly consistent with the fact that 67% of nursing homes are for-profit on average (Table D1). The pooled average treatment effect on the treated (ATT) equals -0.54 and is statistically significant at the one percent level; see column (1) of Panel A in Table 1.

Figure 4b shows the effect on annual Medicaid days per nursing home to test for the existence of public moral hazard. Beginning one year after license acquisition, Medicaid days increase significantly, consistent with Hypothesis H2. Four years post-acquisition, converted nursing homes provide roughly 3,000 additional Medicaid days annually, corresponding to approximately 8.2 full-year residents and 11% of the sample mean (Table D1). Averaging across all post-treatment years, the Indiana creative financing activities increased Medicaid days by 1,360 days, a 4.9% increase (column (2) of Panel A in Table 1).

[Insert Table 1 about here]

Figures 4c and d investigate the underlying mechanisms. They show that dementia-related care drives much of this expansion.[10] Figure 4c shows the effect on Medicaid days among patients with Alzheimer's disease and related dementias (AD/ADRD). The pattern closely mirrors Figure 4b: The average post-acquisition effect equals 1,178 additional Medicaid days per year and nursing home, corresponding to a 12% increase (column (3) of Panel A in Table 1).[11]

Dementia patients are a particularly attractive target group for expanding publicly financed inpatient care because they exhibit low discharge probabilities, long lengths-of-stay, and face shortages of specialized nursing-home capacity. Moreover, 38% of Medicaid days in our sample involve dementia patients. Consistent with increased specialization to accommodate the volume expansion, Figure 4d shows a nine percentage point increase in the probability that a nursing home operates an Alzheimer's special care unit (column (4) of Panel A in Table 1).

Placebo Test. We next verify that the volume expansion reflects creative financing rather than the ownership change itself. Applying the Indiana research design and treatment definition to states without creative financing schemes, we identify 93 genuine municipalizations across 19 such states between 2005 and 2015, following Coughlin, Bruen, and

[10]We identify AD/ADRD patients based on their initial nursing-home health assessments by integrating MDS 2.0 and MDS 3.0 records and selecting patients with active Section I diagnosis indicators I1q or I1u (MDS 2.0).

[11]Long stays exceeding 100 days drive this increase; see Appendix Figure D2. We find no increase within the first 100 days of a stay, the maximum period typically covered by Medicare; see Appendix Figure D3.

King (2004), and estimate the same Callaway–Sant'Anna event study on Medicaid days. If public ownership *per se* drove the Indiana result, a comparable post-acquisition expansion should appear here. It does not: the pooled ATT is statistically indistinguishable from zero (-73 Medicaid days, standard error 359), with flat pre- and post-acquisition trends, and the 95% confidence interval excludes effects larger than roughly half the Indiana estimate (Appendix Figure D1). Municipalization thus expands Medicaid volume only where it unlocks creative financing, consistent with public moral hazard (H2) rather than a mechanical consequence of public ownership.

In summary, consistent with Hypothesis H2, Medicaid care volume increased significantly when nursing homes started their creative financing activities. These findings directly identify *public moral hazard*, a novel allocative bias as derived in Section 3. Further, the findings suggest that this newly identified distortion affects not only the aggregate level of care provision, but also its composition across patient groups and provider types; it biases health care use towards more nursing home care for Alzheimer's patients.

4.3 Heterogeneity in Public Moral Hazard (H3)

Next, we test for complementarities between the *public markup* and *public moral hazard*. One natural empirical challenge is that effective and nominal spending are both endogenously determined through creative financing.

Medicaid share. We note, however, that creative financing is inherently tied to Medicaid revenues, implying that changes in the markup should be largest for nursing homes with a higher baseline share of Medicaid patients. We thus test for differential volume expansion effects between providers whose Medicaid share is above or below the median across providers. Panels (a) and (b) in Figure 5 present the corresponding Callaway–Sant'Anna event studies with Medicaid days as the outcome, splitting nursing homes by their pre-conversion Medicaid share in the year 2000. Consistent with Hypothesis H3, we find that the increase in Medicaid days following license acquisition is larger among nursing homes with above-median pre-conversion Medicaid shares.

[Insert Figure 5 about here]

Pre-conversion ownership. Because management remained unchanged, formerly for-profit nursing homes became public providers in disguise, with profit incentives intact. We therefore expect them to respond more strongly to the new creative financing incentives, placing greater weight on financial returns. Panels (c) and (d) of Figure 5 split the sample by for-profit status prior to conversion. Consistent with this reasoning, expansion effects are larger among formerly for-profit homes.

Excess Capacity: Capacity may be another key driver of the novel allocative distortion that this paper identifies. Nursing homes with greater unused capacity may expand more easily in response to fiscal incentives from creative financing. On the other hand, it is not clear how excess capacity relates to the markup. In any case, Figure 5e–f show a larger volume expansion among nursing homes with pre-conversion occupancy rates below 90%, consistent with the idea that capacity slack facilitates stronger volume responses. While the event-study point estimates consistently point to stronger expansion among for-profit, higher-Medicaid-share, and lower-occupancy nursing homes, the corresponding differences in pooled ATTs are imprecise for Figures 5 (a) vs. (b) and (c) vs. (d), see figure notes. We therefore read the Medicaid-share and for-profit patterns as suggestive.

4.4 Creative Financing and the Quality of Care

Finally, we assess how creative financing affects quality of care. We start by assessing quality of care using state-of-the-art methods that account for patient selection. Building on these estimates, we then explore how creative financing affects quality within and across providers along with the patient-weighted distribution in our empirical setting.

4.4.1 Estimating Provider Quality

This subsection estimates nursing-home quality and examines whether creative financing affects patient outcomes. We then use estimated nursing-home quality for each nursing home to test whether care was disproportionately expanded among lower-quality providers.

In principle, as discuss in the theory section, creative financing could improve or deteriorate patient outcomes in nursing homes. By adding Alzheimer's special care units, nursing homes may specialize, potentially improving care. On the other hand, volume expansions reallocate patients across nursing homes of different quality or between nursing homes and home health care.

To investigate these margins while accounting for patient selection, we estimate a model of nursing-home quality, building on Dubin and McFadden (1984); Abdulkadiroğlu et al. (2020) and Einav, Finkelstein, and Mahoney (2025). We extend standard nursing-home value-added models by explicitly modeling home health care as an outside option, and follow Einav, Finkelstein, and Mahoney (2025) in instrumenting nursing home choice with distance. Appendix F provides further details. Estimating demand and quality jointly allows us to ask where the marginal Medicaid patient goes. Creative financing may improve access to higher-quality care, or it may expand lower-quality providers.

Data & Sample. Motivated by the previous findings, we focus on dementia patients discharged from acute-care hospitals, for two reasons. First, roughly two-thirds of dementia patients entering nursing homes are admitted following an acute-care hospitalization. Second, following hospital discharge, patients or their surrogates must actively choose between nursing-home care and home health care, and our administrative claims data observe both this choice and subsequent outcomes. We first identify hospital stays associated with Clinical Classification Software diagnosis code 653 ("Delirium, dementia, and amnestic and other cognitive disorders") (CCS, 2017), exclude out-of-state and missing ZIP codes, and restrict the sample to patients aged 65 or older; see Appendix Table D3. We then merge hospital discharges with MDS nursing-home records, yielding 206,833 hospital index stays. Table D4 shows that patients have an average age of 83 years, 90% are white, one-year survival is 67%, and 12% have Medicaid as the primary payer. Following hospital discharge, 37% enter nursing homes, and the 90-day readmission rate equals 31%.

We now use administrative claims data at the patient-stay level. We first identify hospital stays associated with Clinical Classification Software diagnosis code 653 ("Delirium, dementia, and amnestic and other cognitive disorders") (CCS, 2017), exclude out-of-state and missing ZIP codes, and restrict the sample to patients aged 65 or older; see Appendix Table D3. We then merge hospital discharges with MDS nursing-home records, yielding 206,833 hospital index stays. In Table D4, the summary statistics show that patients have an average age of 83 years, 90% are white, and one-year survival is 67%. Following hospital discharge, 37% enter nursing homes, and the 90-day readmission rate equals 31%.

Mixed Logit Model (First Stage). The first stage models nursing-home choice and patient utility; see equation (F1) in the Appendix. Patient choice sets include all nursing homes within a 50-mile radius of the patient's pre-hospitalization residence, plus home health care as the outside option.[12] On average, patients face 74 nursing homes. We estimate a mixed logit model, allowing for flexible substitution between nursing homes and this outside option.

Health Outcomes (Second Stage). The second stage models patient health outcomes conditional on provider choice. We measure health using one-year mortality and hospital readmission. The latent index m_{ijt} for patient i at nursing home j in year t is specified as:

$$m_{ijt} = \alpha_j + \alpha_t + x'_{ijt}\alpha^x + \epsilon_{it}, \tag{9}$$

where x_{ijt} denotes observable patient, nursing-home, and year characteristics; α_t denotes year fixed effects; and α_j captures nursing-home quality. The error term ϵ_{it} is normally distributed. We observe the realized event rather than the latent index: $m_{ijt} > 0$ indicates that patient i died within one year of admission or, in the readmission specification, was readmitted to an acute-care hospital. We report $-\alpha_j$ below so that higher values denote better providers.

Instrument. Because outcomes are only observed at endogenously chosen nursing homes, identification requires an instrument shifting provider choice. Following the literature, we use the distance between a patient's residence and each nursing home in the patient's choice set. Distance strongly predicts provider choice and therefore satisfies the relevance criterion. The key identifying assumption is that distance affects patient outcomes only through nursing home choice; see Einav, Finkelstein, and Mahoney (2025), Dubin and McFadden (1984), and Appendix Section F for a discussion. We estimate the mixed logit demand model, construct control functions, and estimate equation (9) via simulated maximum likelihood.

[12]We exclude the small share of patients selecting nursing homes located more than 50 miles from the centroid of their residential ZIP code.

Results. Panel A of Table F1 (Appendix) reports the first-stage estimates. As mentioned, distance strongly predicts nursing home choice, confirming the instrument's relevance. Consistent with the evidence on public moral hazard, patients become approximately 5% more likely to enter nursing homes following hospital discharge once they are municipalized.[13] Further, older dementia patients, women, white patients, and patients with longer hospital stays are more likely to enter nursing homes. The random coefficient exhibits substantial dispersion, implying considerable heterogeneity in preferences.[14]

Panel B of Table F1 reports estimates of equation (9). Importantly, license acquisition does not significantly shift average one-year survival rates. The 95% confidence interval rules out survival gains larger than 3.7 percentage points and declines larger than 1.6 percentage points.

Nursing Home Quality. Figure F1a (Appendix) shows the estimated nursing-home quality coefficients, $-\alpha_j$, from equation (9), based on one-year survival (shrinkage adjusted estimates are presented in F1b). We normalize the estimates relative to the outside option (home health care), whose value is set to zero in the figure. The figure then ranks nursing homes from highest to lowest estimated value added and reports 95% confidence intervals.

Figure F1a yields two important insights. First, approximately 80% of nursing homes exhibit positive estimated survival relative to the outside option, implying better average one-year survival than home-based care, conditional on observables. Conversely, roughly 20% of nursing homes exhibit lower estimated survival than the outside option. Second, we find substantial heterogeneity in qualitý across nursing homes, consistent with the recent literature (Einav, Finkelstein, and Mahoney, 2025).

Because nursing-home quality estimates are naturally noisy, we group providers into broader categories for the analysis below. Motivated by Figure F1a, we classify nursing homes in the bottom quintile as "lower-quality" providers and nursing homes in the top quintile as "higher-quality" providers. Appendix F validates the quality estimates using

[13] Using the estimates in Table F1, the implied proportional increase in the probability of selecting a municipalized nursing home is approximately 5%. Since individual nursing homes account for only a small share of a patient's overall choice set, the standard logit adjustment term $(1 - s_{ij})$ is close to one.

[14] A one-standard-deviation decrease in the random coefficient corresponds to the utility equivalent of approximately 42 additional life years.

alternative outcome measures, including readmission rates, staffing ratios, and CMS star ratings (Figure F5 and Tables F2, F3). We additionally replicate the structural estimates using 30- and 90-day hospital readmission rates as outcomes (Figure F4 and Table F5).

4.4.2 Effects on the Quality of Care

As discussed, we find no significant change in one-year survival following initiation of creative financing, suggesting that within-provider quality adjustments are limited. Turning now to between-provider effects, we examine whether the expansion in Medicaid-funded care is concentrated among lower-quality providers. Specifically, informed by Section 4.4.1, we define nursing homes in the bottom quintile of the quality distribution as ”lower-quality” providers and nursing homes in the top quintile as ”higher-quality” providers.

[Insert Figure 6 about here]

Figure 6 compares Medicaid-volume responses across these two categories. As seen, lower-quality nursing homes increase Medicaid volume more than higher-quality nursing homes. Specifically, Panel B of Table 1 shows dementia-related Medicaid days increase in lower-quality nursing homes by 1,952 days annually, corresponding to a 19% increase (column (1)). Higher-quality nursing homes exhibit an 11% increase (column (2)).

Further, the heterogeneity findings above suggest that for-profit providers with excess capacity and higher Medicaid shares exhibit stronger volume responses to creative financing. Here, we find that lower-quality providers exhibit stronger volume responses. To reconcile these findings, we explore the correlation between quality and (pre-determined) nursing-home characteristics in 2000 in Table F4. As seen, for-profit status is strongly associated with quality—lower-quality homes are disproportionately for-profit. We also see a higher Medicaid share among the lowest-quality providers. Taking stock, for-profit nursing homes serve higher shares of Medicaid and tend to be of lower quality. At the same time, after license acquisition, they overproportionally expand volume, leading to a reallocation of patients toward lower-quality facilities.

Allocative Implications. Finally, we combine the differential volume responses with the one-year survival estimates to assess the allocative implications of creative financing. Two forces operate in opposite directions. An expansion effect increases aggregate survival, because municipalization draws patients into nursing homes who would otherwise have received home health care, which carries higher average mortality. A composition effect decreases aggregate survival, because the expansion is concentrated in lower-quality nursing homes. Weighting each quality group by its baseline share of Medicaid dementia days, we estimate the two effects at 0.16 percentage points (expansion) and -0.25 percentage points (composition), respectively, for a net decrease in one-year survival of approximately 0.09 percentage points; Appendix Section F.4 provides the derivation. This corresponds to a 0.8 percentage point decrease in one-year survival among patients whose care choice actually changes in response to creative financing. Applied to the roughly 16,000 AD/ADRD patients in Indiana nursing homes, this implies that about $16,000 * 0.0009 \approx 14$ patients die earlier each year. The composition effect thus dominates: creative financing does not reduce quality within a given nursing home, but by reallocating Medicaid volume toward lower-quality providers it lowers the quality of care patients actually receive.

4.5 Within- and Between-Program Distortions

Our results show that creative financing can generate substantial public markups, increase Medicaid-funded nursing home volume, and expand providers with lower quality and greater excess capacity. These findings have broader implications for the allocation of public long-term care spending.

The key mechanism is that creative financing lowers the state's effective net-of-match price of institutional care. By inflating nominal above effective provider reimbursement rates, states can increase federal matching funds without proportionally increasing effective spending. Because these financing arrangements rely on institutional reimbursement systems, public ownership, intergovernmental transfers, and supplemental payment mechanisms such as UPL payments, they are considerably less available for most home- and community-based services (HCBS). Consequently, creative financing increases the relative fiscal attractiveness of institutional care.

This mechanism generates two distinct distortions. First, it creates a *within-program distortion* by directing Medicaid-funded nursing home volume toward providers that have stronger incentives or greater ability to engage in creative financing. Second, it creates a *between-program distortion* by shifting public long-term care spending toward institutional care and away from HCBS.

5 Conclusion

This paper shows that creative financing can distort the allocation of public health care use and spending. We first document that creative financing practices exist and are economically relevant. Using manually digitized audit reports from multiple states, we show that such schemes inflate nominal publicly funded nursing home spending by roughly one-quarter in states with creative financing. Because states systematically redirect funds away from nursing homes, the effective federal cost share exceeds the nominal FMAP by approximately 14 percentage points on average—substantially more than previously documented.

Using high-quality administrative data, we then zoom in and study a unique setting in Indiana. To circumvent a 2003 federal reform intended to restrict the use of creative financing, Indiana aggressively acquired licenses of formerly private nursing homes, municipalizing them. However, the conversion occurred only on paper, through license purchases by government institutions, while the management remained unchanged. This setup allows us to measure the timing of creative financing activities precisely at the nursing home level, and to study their consequences.

As a result of this unique setup, the share of (on paper) publicly-owned nursing homes increased from 5% to 90% within less than two decades. Exploiting the staggered license acquisition process in difference-in-differences designs of Callaway and Sant'Anna (2021), we show that creative financing activities significantly increase Medicaid-funded nursing-home volume. To our knowledge, this is the first paper to define and identify this novel allocative distortion theoretically and empirically—*public moral hazard* or an expansion of publicly funded care due to an open-ended federal cost share.

We next investigate implications for the quality of care received by vulnerable elderly with long-term care needs in a state whose nursing homes have consistently ranked poorly among all U.S. nursing homes. Recall that, while volume expansions are a clear theoretical prediction of creative financing, the impact on the quality of care is theoretically ambiguous and thus an empirical question. Consequently, we first estimate nursing home quality using administrative microdata and a structural mixed-logit framework with home health care as an outside option. Holding patient composition constant, we find no evidence that creative financing activities improve the average quality of nursing homes. In line with the literature, however, we document substantial heterogeneity in quality. Further, we show that the strongest volume expansions occur in nursing homes in (i) the bottom quintile of the quality distribution, (ii) that operate below capacity and (iii) with a higher share of Medicaid patients at baseline. Creative financing, therefore, can weaken allocative efficiency by redirecting care toward providers with comparatively poor patient outcomes.

More broadly, our analysis highlights how imperfect monitoring in jointly funded federal-state programs can generate systematic distortions in the provision of public services. By linking federal reimbursements to nominal rather than effective spending, current Medicaid rules create incentives to maximize reimbursable volume rather than effective care quality. These mechanisms help explain persistently low effective Medicaid reimbursement rates and chronic quality shortfalls documented in the nursing home sector in the United States (Grabowski, 2001; Hackmann, 2019). Moreover, these findings are likely generalizable to jointly funded public programs under fiscal federalism when the federal funder cannot perfectly monitor effective spending.

The results also speak to the broader institutional bias of U.S. long-term care policy. Despite widespread preferences among older adults to age at home (AP-NORC, 2021), creative financing makes institutional care more fiscally attractive than home- and community-based alternatives, which are less amenable to revenue extraction. As summarized by the Evans, Hopkins, and Cook, *"[Indiana's] elder care system is now so skewed to nursing homes [...] that the expansion of alternative options such as in-home care has been stifled."* (Evans, Hopkins, and Cook, 2020b).

To our knowledge, this paper is the first to identify creative financing as an element of both institutional bias and allocative distortions in long-term care. This mechanism complements existing explanations emphasizing Medicaid reimbursement design (Hackmann, Pohl, and Ziebarth, 2024), eligibility rules (Grabowski and Gruber, 2007; Mommaerts, 2018), and limited access to home- and community-based care (Muramatsu et al., 2007; Guo, Konetzka, and Manning, 2015; Wang et al., 2020). To remove these incentives to artificially expand inpatient long-term care volume in low-quality facilities, policymakers could consider providing incentives towards effective nursing home spending, possibly through value-based payment models, or limiting the scope of creative financing via more stringent upper payment limits.

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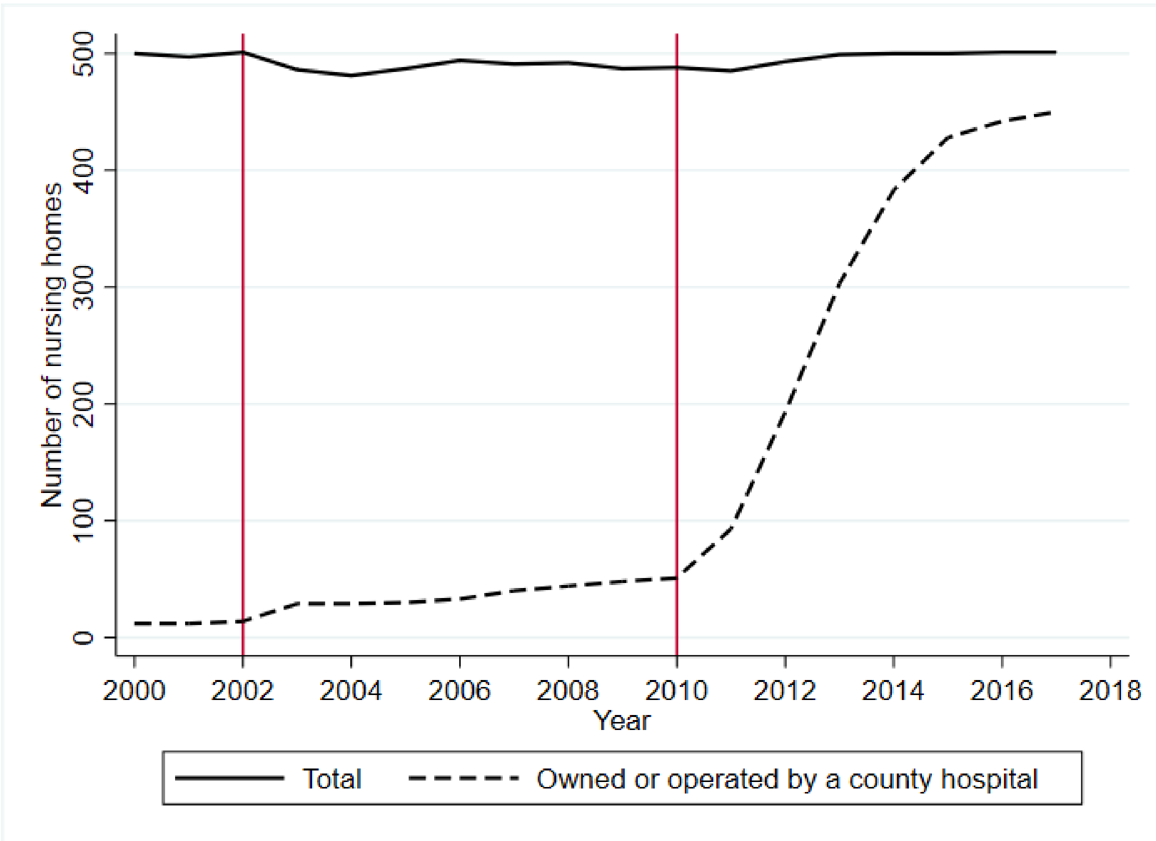
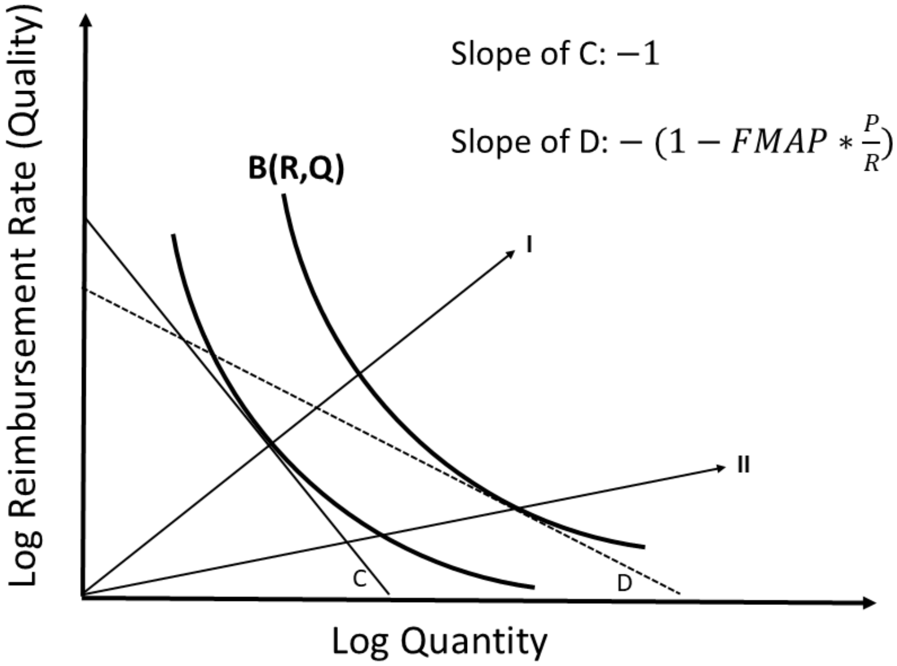
Figure 1: Development of County-Owned Nursing Homes in Indiana



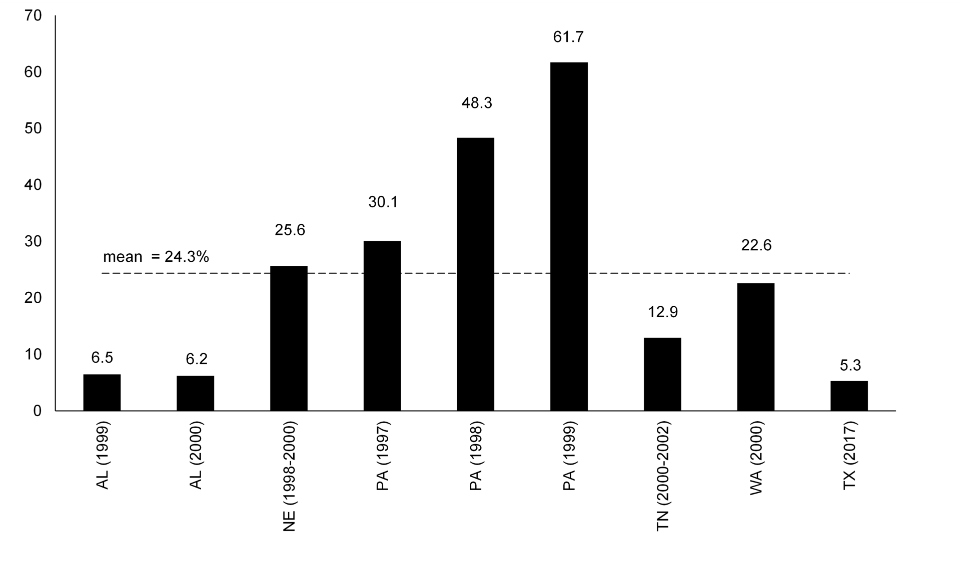
Source: Centers for Medicare & Medicaid Services (2020b) and Indiana Department of Health (2020).

Figure 2: Creative Financing and the Medicaid Quantity-Quality Tradeoff

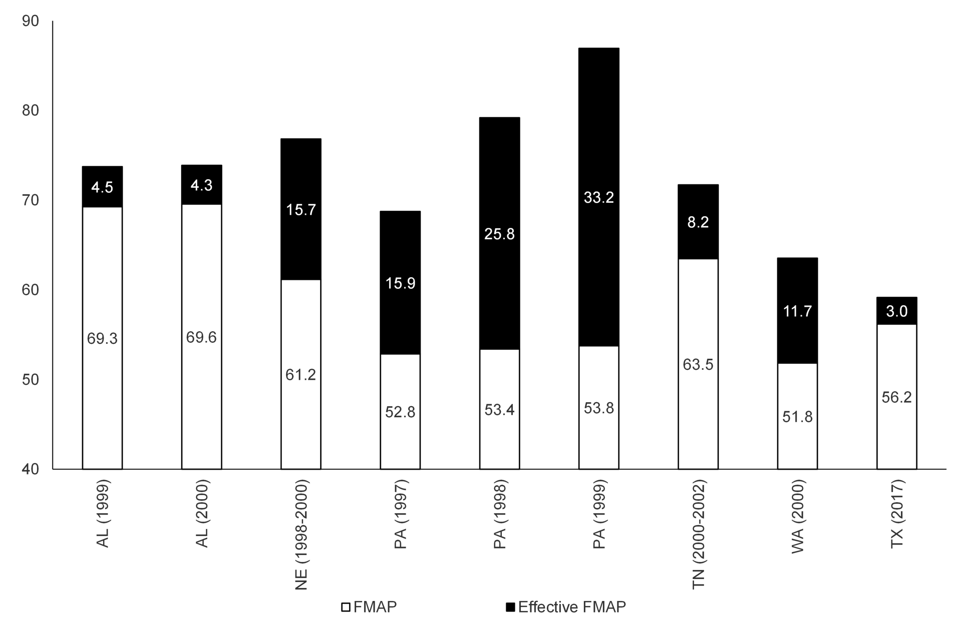


Notes: This figure illustrates policy tradeoffs between states' Medicaid reimbursement rates and volume under joint financing, with and without imperfect monitoring of effective spending R, see Section 3 for details. Imperfect monitoring leads to creative financing (CF) by the states and municipalization of providers ($M = 1$) to enable fund diversion. The convex curves denote indifference curves for different benefit levels. Line 'C' denotes the budget constraint for the state without CF and perfect monitoring ($R = P$). Line 'I' denotes the corresponding expansion path providing the optimal rate and quantity mix without CF. Line 'D' denotes the budget constraint for the state with CF due to imperfect monitoring of effective spending ($PneqR$); line 'II' denotes the corresponding expansion path.

Figure 3: Public Markups and Effective FMAPs—Evidence from Audit Reports (H 1)



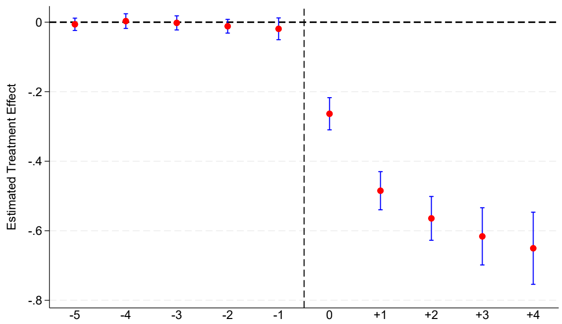
(a) Difference Between Nominal and Effective Nursing Home Medicaid Spending



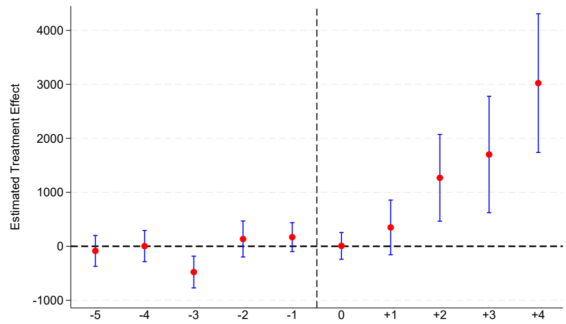
(b) Effective vs. Nominal FMAP

Sources: Office of Inspector General (2001a,b,d,c, 2004b,a, 2005e,a,b,d,c, 2014); Centers for Medicare & Medicaid Services (2020a), calculated using equations (C1). Figure 3a shows the percentage difference between nominal spending, $P \times Q$, and effective spending, $R \times Q$, as $\frac{P \times Q}{R \times Q} - 1$. This corresponds to $\frac{P}{R} - 1$, where $\mu = \frac{P}{R}$ denotes the public markup. The underlying calculation uses IGT amounts from OIG audit reports with nominal Medicaid spending (*Total MHEX*) for states (*State MHEX*) and the federal government (*Total MHEX - State MHEX*) from CMS-64 forms. We then construct the markup as $\mu = \frac{P}{R} = \frac{Total MHEX}{Total MHEX - IGT}$. Figure 3b contrasts the nominal vs the effective FMAP, where the latter is $\mu \times FMAP$. See also Appendix C.1 for details.

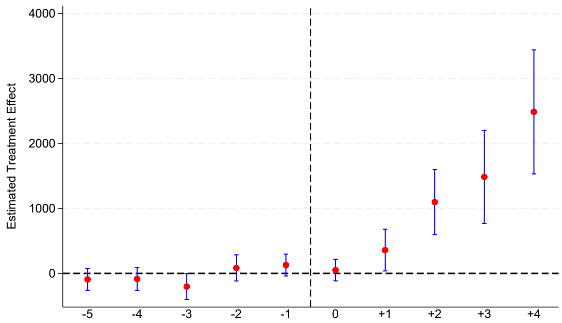
Figure 4: Creative Financing and Public Moral Hazard (H 2)



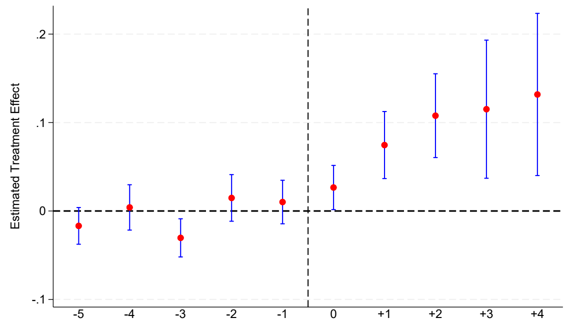
(a) For-Profit



(b) Medicaid Days



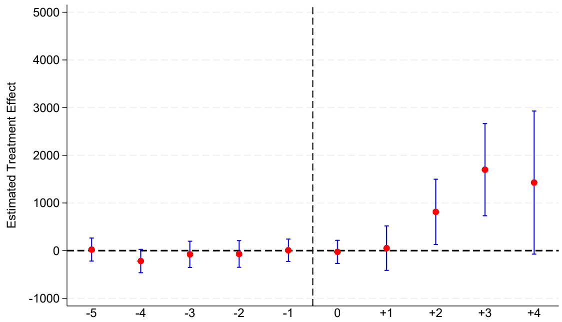
(c) Dementia-Related Medicaid Days



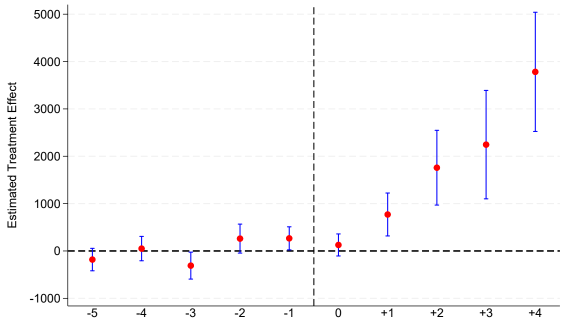
(d) Nursing Homes w/ Alzheimer Unit

Sources: Long-Term Care: Facts on Care in the U.S. (2025), MDS (2020); Centers for Medicare & Medicaid Services (2020b); Indiana Department of Health (2020), CMS Skilled Nursing Facility Provider Information, State of Indiana (2025), authors' calculation. The sample is balanced in calendar time at the nursing home-year level from 1999 to 2015; see Appendix D for more details on the sample and the summary statistic in Table D1. The four subgraphs present Callaway-Sant'Anna event-study estimates, with event time 0 denoting the license acquisition and beginning of creative financing. Subgraph captions indicate the outcome variable. The CS DD pooled estimates over the entire post-reform period are in Table 1. All event studies show 90% confidence intervals. See main text.

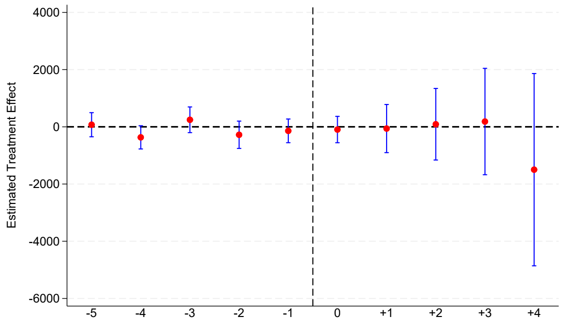
Figure 5: Public Moral Hazard Heterogeneity by Pre-Conversion Characteristics



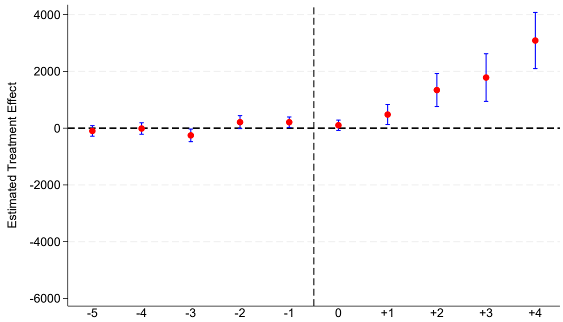
(a) Below Median Medicaid Share



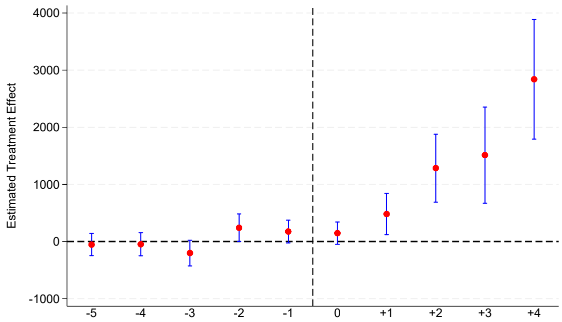
(b) Above Median Medicaid Share



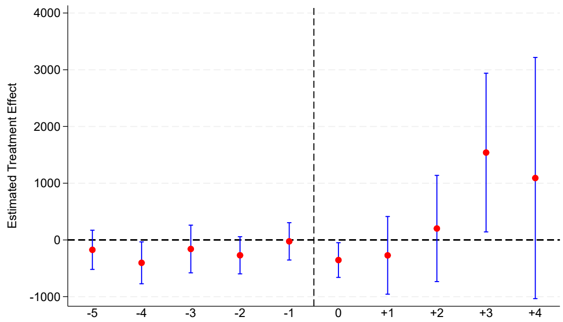
(c) Not-For-Profit



(d) For-Profit



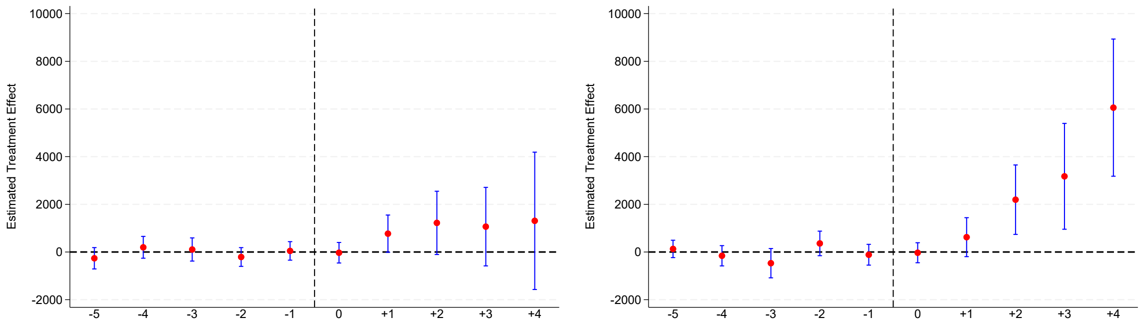
(e) Occupancy $< 90\%$



(f) Occupancy $> 90\%$

Sources: Long-Term Care: Facts on Care in the U.S. (2025), MDS (2020); Centers for Medicare & Medicaid Services (2020b); Indiana Department of Health (2020), CMS Skilled Nursing Facility Provider Information, State of Indiana (2025), authors' calculation. The figure presents Callaway-Sant'Anna event studies of the effect of license acquisition on Medicaid days, estimated separately within subgroups defined by pre-conversion (Year 2000) characteristics: the share of Medicaid beneficiaries (Panels a and b), for-profit ownership (Panels c and d), and the occupancy rate (Panels e and f). Event time 0 denotes the license acquisition. The CS-DD pooled estimates over the entire post-reform period are in Table 1, Panels B and C. All event studies show 90% confidence intervals. When formally testing the difference between the differences in the ATT estimates between the right and left column, (b)-(a) produces -1089 (t-value -2.019); (d)-(c) produces 790 (t-value 0.833); (f)-(e) produces -1089 (t-value -2.019). See main text and Appendix D for details.

Figure 6: Public Moral Hazard by Quality of Care (H 3)



(a) High Quality Nursing Homes

(b) Low Quality Nursing Homes

Source: Long-Term Care: Facts on Care in the U.S. (2025); Centers for Medicare & Medicaid Services (2020b) and Indiana Department of Health (2020). The figures show Callaway Sant'Anna event studies of the effect of license acquisition on Medicaid days, estimated separately by high and low-quality nursing homes. Event time 0 denotes the license acquisition. The CS-DD pooled estimates over the entire post-reform period are in Table 1, Panels B. All event studies show 90% confidence intervals. The sample consists of nursing home residents with dementia at the nursing home-year level. Figure 6a focuses on high-quality nursing homes, whose quality estimate for one-year survival is in the top quintile of the nursing home quality distribution. Figure 6b focuses on nursing homes whose quality estimate is in the bottom quintile of the quality distribution.

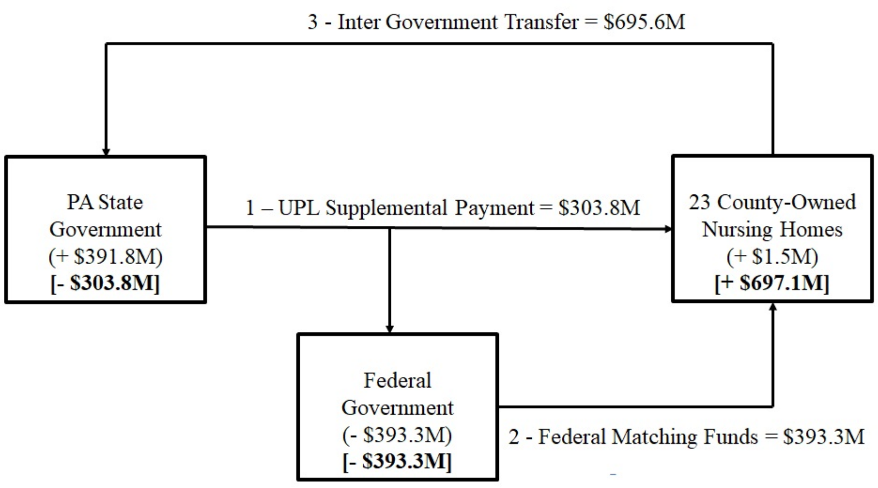
Table 1: Creative Financing and Medicaid-Funded Nursing Home Expansion

Panel A: Main Outcomes	**For-Profit**	**Total Medicaid Days**	**Dementia Medicaid Days**	**Alzheimer Unit**
	(1)	(2)	(3)	(4)
	-0.54***	1,360***	1,178***	0.09***
	(0.03)	(449)	(255)	(0.03)
Mean	0.67	28,040	9,720	0.37
N	5,888	6,256	6,256	5,888
Panel B: Heterogeneity	**Dementia Medicaid Days**			
	Low Quality	High Quality	Occupancy<90%	Occupancy >90%
	1952***	1106**	1389***	300
	(687)	(556)	(299)	(449)
Sample Mean	10,150	10,020	9,620	10,070
N	1,037	986	4,828	1,428
Panel C: Heterogeneity	**Dementia Medicaid Days**			
	Not-For-Profit	For-Profit	Below Median Medicaid Share	Above Median Medicaid Share
	613	1403***	1078***	1589***
	(907)	(275)	(416)	(340)
Sample Mean	10,955	9,463	10,187	9,258
Observations	1,088	5,168	3,128	3,128
Year FE	X	X	X	X
SNF FE	X	X	X	X

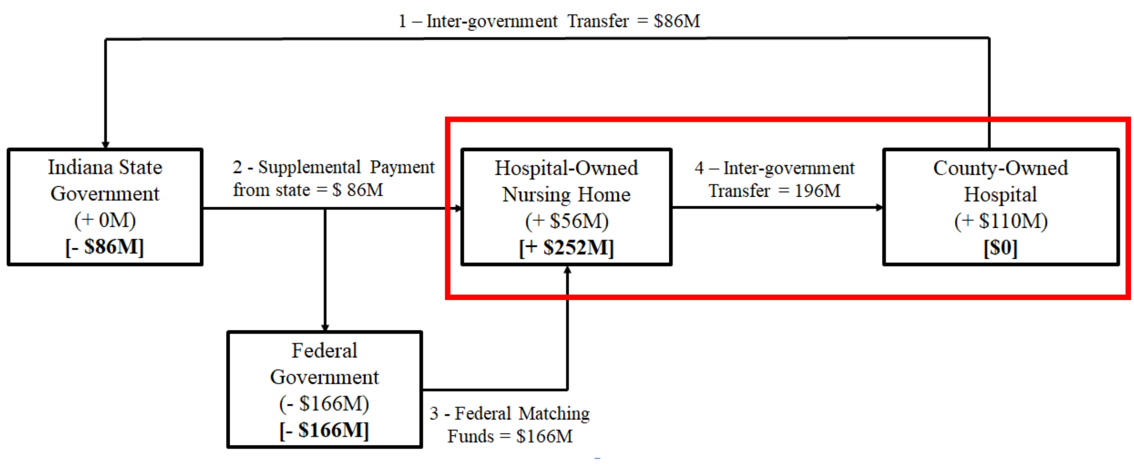
Sources: Long-Term Care: Facts on Care in the U.S. (2025), MDS (2020), Centers for Medicare & Medicaid Services (2020b); Indiana Department of Health (2020), CMS Skilled Nursing Facility Provider Information, State of Indiana (2025), authors' calculation. See Section 4.2 and Appendix D for more details. The sample is at the nursing-home-year level from 1999 to 2015, balanced in calendar time. ***, **, and * = statistically different from zero at the 1%, 5%, and 10% level. This table presents ATT estimates based on Callaway and Sant'Anna (2021). Figure 4 shows the equivalent event studies for the four outcomes in Panel A, where the column headers indicate the dependent variables; see the main text. In Panel A, column (1) presents CS-DD results using for-profit ownership as the dependent variable. Column (2) uses overall Medicaid days, and column (3) uses Medicaid days for dementia patients diagnosed as the dependent variable. Column (4) uses whether the nursing home has an Alzheimer's unit as the dependent variable. Figures 5 and 6 show the equivalent CS-DD event studies for Panels B and C, which always use Medicaid days among dementia patients as the dependent variable and condition on subsamples as indicated. Columns (1) and (2) of Panel B condition on the bottom and top quantiles of the nursing home quality distribution, respectively; see Figure F1. Columns (3) and (4) of Panel B condition on nursing homes with occupancy rates of less than and more than 90% in the year 2000, respectively. Columns (1) and (2) of Panel C condition on not-for-profit and for-profit ownership in 2000, and columns (3) and (4) condition on a Medicaid patient share below and above the sample median in 2000.

A Online Appendix

Figure A1: Schemes using UPL Supplemental Payments for Nursing Facilities



(a) Panel A: Pennsylvania in FY2002



(b) Panel B: Indiana in 2019

Notes: Figures in round brackets reflect the net payment position. Figures in bold and square brackets reflect reported Medicaid expenditures to CMS. Figures for Panel A are based on Mangano (2001) and as depicted in Coughlin and Zuckerman (2003). Figures for Panel B are based on the financial statements of the Health and Hospital Corporation (HHC) of Marion County, see Section 2.4

B Theoretical Framework

B.1 Heterogeneity and Differential Expansion

This appendix extends the baseline model to allow for heterogeneity across providers. The goal is to provide microfoundations for the differential expansion in care volume documented in the empirical analysis (Hypothesis H3), and to clarify how variation in quality and capacity shapes provider responses to creative financing.

B.1.1 Setup

Consider providers indexed by $g \in \{L, M, H\}$, corresponding to low-, medium-, and high-quality nursing homes. Providers differ along three dimensions: effective reimbursement rates R_g, baseline utilization $u_g^0 \in (0,1)$, and quality $\theta_g = \theta(R_g)$. Each provider operates at fixed capacity $\bar{Q}_g$ and chooses care volume $Q_g \leq \bar{Q}_g$.[15] Utilization is defined as:

$$u_g = \frac{Q_g}{\bar{Q}_g}.$$

Expanding care volume becomes increasingly costly as utilization rises. Marginal costs are given by:

$$MC_g(Q_g) = R_g \cdot c'(u_g), \quad \text{with } c''(u_g) > 0, \tag{B1}$$

where $c(\cdot)$ is a convex cost function. Each provider chooses Q_g to maximize:

$$U_g = \tau B(\theta(R_g), Q_g) + FMAP \cdot P \cdot Q_g - \int_0^{Q_g} MC_g(q)\, dq. \tag{B2}$$

B.1.2 First-Order Condition

The first-order condition for optimal care volume is:

$$\tau B_Q(\theta(R_g), Q_g) + \tau B_\theta(\theta(R_g), Q_g) \cdot \theta'(R_g) = MC_g(Q_g) - FMAP \cdot P. \tag{B3}$$

[15] When using the total number of beds as an outcome, a CS event study yields a non-significant estimate of 0.733, providing little evidence for general increases in the number of beds.

The left-hand side captures the marginal benefit of expanding care volume, including both the direct benefit of additional care (B_Q) and the indirect effect through quality ($B_\theta \cdot \theta'(R_g)$). The right-hand side reflects the net marginal cost, adjusted for the federal subsidy.

B.1.3 Comparative Statics

Comparative statics characterize how optimal choices change in response to shifts in key parameters. In this setting, we study how an increase in the public markup affects incentives to expand care volume ("public moral hazard"). Starting from the state's objective, the marginal fiscal return to an additional unit of care is given by federal reimbursements minus effective costs, $FMAP \cdot P - R_g$. Using the definition of the public markup, $\mu = \frac{P}{R_g}$, this can be rewritten as:

$$FMAP \cdot P = FMAP \cdot \mu \cdot R_g$$

An increase in the public markup raises the marginal return to expanding care volume. However, the response differs across providers due to two key channels:

(i) Markup Channel. Providers with lower effective reimbursement R_g face a larger wedge between nominal and effective rates. For a given nominal rate P, this implies a higher markup μ and therefore a larger increase in the fiscal return to care volume. The relationship between reimbursement and quality is, however, theoretically ambiguous. Lower reimbursement may reflect lower quality, but it may also reflect greater efficiency.

(ii) Capacity Channel. Providers with lower baseline utilization u_g^0 operate further from capacity and therefore face flatter marginal cost curves, allowing them to expand more easily. However, the relationship between utilization and quality is also ambiguous. Lower occupancy may reflect weaker demand due to lower quality, but it may also reflect higher quality if providers avoid congestion or maintain excess capacity.

B.1.4 Level and Composition Effects

An increase in the public markup generates both a level effect and a composition effect.

The *level effect* refers to the increase in aggregate care volume:

$$Q = \sum_g Q_g.$$

The *composition effect* reflects changes in the distribution of care across providers. Because providers differ in both effective reimbursement and capacity constraints, the response to the markup varies across g, implying:

$$\frac{\partial Q_g}{\partial \mu} \neq \frac{\partial Q_{g'}}{\partial \mu}.$$

If lower-quality providers are characterized by lower effective reimbursement and greater excess capacity, the markup and capacity channels reinforce each other, implying disproportionately large expansion among lower-quality providers:

$$\frac{\partial Q_L}{\partial \mu} > \frac{\partial Q_M}{\partial \mu} > \frac{\partial Q_H}{\partial \mu}. \tag{B4}$$

B.1.5 Connection to the Empirical Analysis

This extension provides a microfoundation for Hypothesis H3. The empirical analysis separately identifies both the level effect (aggregate expansion in Medicaid-funded care) and the composition effect (differential expansion across providers).

The evidence suggests that creative financing leads to disproportionate care volume expansions among providers at the bottom of the quality distribution and among facilities operating at intermediate occupancy levels. These findings are consistent with the interaction of three mechanisms emphasized in the model: higher fiscal returns from public markups, heterogeneous capacity constraints, and heterogeneous responses during the rollout of license acquisitions.

More broadly, the results imply that public moral hazard affects not only the overall level of care provision, but also the allocation of care across providers.

B.2 Optimal Contract under Incomplete Monitoring

Now we turn to the optimal linear contract between the Principal and the Agent under incomplete monitoring. We aim to maximize social welfare

$$\max_{\tilde{P}} V(\tilde{P}) = B(R(\tilde{P}), Q(\tilde{\tilde{P}})) - R(\tilde{P})Q(\tilde{P}) \tag{B5}$$

where $R(\tilde{P})$ and $Q(\tilde{P})$ are implicitly defined by the Agent's first-order conditions:

$$\begin{aligned} Q &= \tau \frac{\partial B}{\partial R} \\ R &= \tilde{P} + \tau \frac{\partial B}{\partial Q}. \end{aligned}$$

Note that $\tilde{P} = FMAP \times P$ is the federal contribution to the nominal rate P. Taking the first order condition of equation (B5), we have:

$$\begin{aligned} \frac{dV}{d\tilde{P}} &= \frac{\partial B}{\partial R} \cdot \frac{dR}{d\tilde{P}} + \frac{\partial B}{\partial Q} \cdot \frac{dQ}{d\tilde{P}} - \left(Q \cdot \frac{dR}{d\tilde{P}} + R \cdot \frac{dQ}{d\tilde{P}} \right) \\ &= \left(\frac{\partial B}{\partial R} - Q \right) \cdot \frac{dR}{d\tilde{P}} + \left(\frac{\partial B}{\partial Q} - R \right) \cdot \frac{dQ}{d\tilde{P}}. \end{aligned}$$

Using the constraints

$$\begin{aligned} Q = \tau \frac{\partial B}{\partial R} &\Rightarrow \frac{\partial B}{\partial R} = \frac{Q}{\tau} \\ R - \tilde{P} = \tau \frac{\partial B}{\partial Q} &\Rightarrow \frac{\partial B}{\partial Q} = \frac{R - \tilde{P}}{\tau} \end{aligned}$$

and substituting them into the first-order condition, we have:

$$
\begin{aligned}
\frac{dV}{d\tilde{P}} &= \left(\frac{Q}{\tau} - Q\right) \cdot \frac{dR}{d\tilde{P}} + \left(\frac{R - \tilde{P}}{\tau} - R\right) \cdot \frac{dQ}{dP} \\
&= \left(\frac{1-\tau}{\tau}\right) Q \cdot \frac{dR}{d\tilde{P}} + \left(\frac{-\tilde{P} + (1-\tau)R}{\tau}\right) \cdot \frac{dQ}{d\tilde{P}} \qquad \text{(B6)} \\
&= \left(\frac{1-\tau}{\tau}\right) \cdot \frac{d(R * Q)}{d\tilde{P}} - \frac{\tilde{P}}{\tau} \cdot \frac{dQ}{d\tilde{P}} \,. \qquad \text{(B7)}
\end{aligned}
$$

Multiplying equation (B7) by τ yields

$$
(1-\tau) \cdot \underbrace{\frac{d(R \times Q)}{d\tilde{P}}}_{\text{Positive Externality}} - \underbrace{\tilde{P} \cdot \frac{dQ}{d\tilde{P}}}_{\text{Public Moral Hazard}} = 0 \,. \qquad \text{(B8)}
$$

Intuitively, higher federal contributions (higher $\tilde{P}$) may encourage higher effective spending, $R \times Q$, internalizing the positive externality $(1-\tau)$, as captured by the first term. On the other hand, higher federal contributions distort the price-quantity tradeoff through quantity expansions, as indicated by the second term.

An interesting case is $dQ/d\tilde{P} > 0, dR/d\tilde{P} = 0$, namely with a zero pass-through rate from nominal to effective rates (and hence no effect on quality): $\tilde{P}^* = FMAP^* \times \bar{P}^* = (1-\tau) \times R$. Setting $FMAP^* = (1-\tau)$ implies $\bar{P}^* = R$. In other words, unless higher federal contributions translate into higher effective provide reimbursement (and by extension quality), the upper payment limit should be set to R which, however, is unobserved.[16]

B.3 Provider Taxes

Another creative financing tool is provider taxes. States use them to reduce their Medicaid cost share (MACPAC, 2021a) because they allow them to increase nominal reimbursement rates, thereby triggering federal matching funds. Similar to intergovernmental transfers, provider taxes redirect provider revenues away from their intended purpose. Provider taxes must satisfy the following federal legal requirements: They must be (a) broad-based, (b) uniform, and (c) not hold providers harmless (Congressional Research Service, 2024).

[16]By contrast, without public moral hazard ($dQ/d\tilde{P} = 0$ and $dR/d\tilde{P} = 0$), diverted funds are a pure transfer from the federal government to the state. Even then the transfer is not welfare-neutral: federal matching funds are raised through distortionary taxation, so each diverted dollar carries the marginal deadweight loss of public funds. Creative financing is thus costly even absent the moral-hazard distortion we emphasize.

Requirements. An (a) broad-based tax must apply to all providers within a defined class—states, meaning it cannot single out providers. The tax must also be (b) uniform, meaning the same rate must apply to all providers within the class.[17] Lastly, states are (c) must not hold providers "harmless"—that is, they cannot guarantee that providers will be reimbursed for their tax payments. Under current rules, the "Hold Harmless Test" is waived if tax revenue accounts for 6% or less of net patient revenue, a threshold known as the "safe harbor" (42 CFR § 433.68).

Hold Harmless Test. States have devised arrangements to circumvent the Hold Harmless Test, e.g., through "pooling agreements." Pooling agreements mean that providers contribute taxes to a shared pool, which then disburses funds to providers in proportion to their tax burden. Like intergovernmental transfers, pooling agreements are a legal grey area and currently contested; federal regulators have had difficulties tracking and monitoring these schemes (Young, 2023). In California, for instance, hospitals have effectively neutralized provider taxes through a redistribution mechanism, holding them harmless. Hospitals serving a high share of low-income patients receive more in Medicaid payments than they contribute in taxes. They then donate a portion of this surplus to a charity affiliated with the California Hospital Association. That charity, in turn, distributes grants to hospitals with fewer low-income patients to offset their net losses under the tax scheme.

Tax Types and Incentives: Provider taxes vary across states and providers, particularly in their tax base. This affects provider incentives. First, provider taxes could be a percentage of revenues, incentivizing higher volume and Medicaid rates. Second, they could be a flat tax on the number of inpatient beds, incentivizing higher capacity, but not directly higher utilization. Third, other states impose a flat tax on the number of inpatient days (Kaiser Family Foundation, 2025a), providing incentives to expand volume, see below. For example, California's provider tax on nursing homes is a flat tax per resident day. Its tax on Managed Care Organizations is a flat tax per enrollee per month.[18]

[17] CMS defines 19 provider classes to evaluate whether state tax programs are broad-based and uniform (42 CFR § 433.56). States may also seek waivers from the broad-based and uniformity requirements if they demonstrate that the tax is generally redistributive and not directly tied to Medicaid payments.

[18] See https://www.dhcs.ca.gov/provgovpart/Pages/SkilledNursingFacilities.aspx, last accessed April 17th, 2025.

Discussion: Similar to Intergovernmental Transfers (IGT), Provider Taxes aim to reduce the state's cost share. Similar to IGTs but not identical, they incentivize capacity expansions, that is, public moral hazard; see below for a formal discussion. The most common provider taxes are levied on nursing homes (46 states) and hospitals (45 states), thereby incentivizing—*ceteris paribus*—institutional long-term care expansions. Only three states (KY, NY, MN) have a tax on home health long-term care providers (Kaiser Family Foundation, 2025a).[19]

B.3.1 Quality-Quantity Tradeoff Under Volume-Based Provider Taxes

Finally, we formalize the impact of a volume-based flat provider tax on the state's quality-quantity tradeoff. Building on the notation and our preferred model in Section 3, the state maximizes:

$$\max_{R,Q} \tau \times B(\theta(R), Q) - (1 - FMAP) \times (R + t) \times Q + t \times Q \,. \tag{B9}$$

Here, t denotes the flat tax. The effective reimbursement rate becomes $R = P - t$. Taking the first order conditions with respect to R and Q, we have:

$$\tau \times B_R(R, Q)/Q = 1 - FMAP \tag{B10}$$

$$\tau \times B_Q(R, Q)/R = 1 - FMAP \cdot \frac{R + t}{R} = 1 - FMAP \cdot \frac{P}{R} \,. \tag{B11}$$

Intergovernmental transfers and provider taxes induce slightly different incentives. First, Hold Harmless Tests typically limit the amount of the tax. Most states calibrate the tax to follow the "Below 6% of Revenues" rule, such that nominal rates are linearly related to effective rates via $P = R + t$. As a result, increases in effective rates still qualify for matching funds on the margin, leaving the incentives for rate-setting unaffected (compared with the case of perfect monitoring).

Further, the cap on provider taxes reduces the public markup to $\mu = \frac{R+t}{R}$.[20] Nevertheless, consistent with hypothesis **H2**, provider taxes increase the effective FMAP and

[19] These states report having a provider tax on all regulated health care providers.

[20] We note that the cap provides a separate dynamic incentive to increase overall revenues, allowing for higher flat taxes on volume in the future. This incentive would apply equally to rate-setting increases and volume increases.

incentivize states to increase the care volume eligible for joint funding, thereby distorting the quality-quantity tradeoff.

C Data Appendix for Empirical Evidence on H1

C.1 Audit Reports by the Office of Inspector General (OIG)

This section details the construction of the public markups reported in Figure 3; see Section 4.1 for the provenance of the underlying 24 Office of Inspector General (OIG) audit reports. The audits provide independent, state-level estimates of the amounts that jurisdictions expropriated from nursing homes through Intergovernmental Transfers (IGTs). Of the 18 audited states, six report IGT amounts that can be matched to nursing-home-specific Medicaid spending; these are the states in Table C1 and Figure 3.

We construct nominal and effective spending in three steps. First, we extract the IGT amount for each state and audit period from the OIG reports, reported in column (8) of Table C1. Second, we use CMS-64 forms to obtain nominal Medicaid nursing home spending, $P \times Q$ or "TotalMHEX", as the sum of base per diem payments, column (3), and Supplemental Payments, column (6); columns (5) and (7) report the corresponding federal matching funds at the nominal FMAP in column (4). Third, we treat the IGT as the portion of nominal spending that does not reach providers, so that effective provider reimbursement is $R \times Q = P \times Q - IGT$. The public markup is therefore

$$\mu = \frac{P}{R} \quad = \quad \frac{TotalMHEX}{TotalMHEX - IGT} \tag{C1}$$

Pennsylvania in 1999 illustrates the calculation. Total Medicaid spending comprises \$2.47 billion in base payments and \$1.52 billion in Supplemental Payments, for nominal spending of \$3.99 billion. The audit reports that the entire \$1.52 billion in Supplemental Payments was returned through IGTs, leaving \$2.47 billion in effective provider reimbursement. The implied markup is $\mu = 3.99/2.47 = 1.62$, and the effective FMAP is $53.8\% \times 1.62 = 86.9\%$, against a nominal FMAP of 53.8% (column (4))

Figure 3a shows the percentage difference between nominal spending, $P \times Q$, and effective spending, $R \times Q$, as $\frac{P \times Q}{R \times Q} - 1$. Figure 3b shows the implied "effective FMAP".

C.2 Financial Statements by Health and Hospital Corporation (HHC)

Finally, we provide similar evidence from hand-collected financial reports from one of the main stakeholders in Indiana's scheme, the Health and Hospital Corporation (HHC) of Marion County (see Section 2.4). As discussed in Section 2.4, starting in 2003, HHC became the pioneer of nursing home acquisitions in Indiana. By 2009, HHC owned the licenses for 40 nursing homes and received more than 80% of the state's supplemental payments to nursing homes. By 2019, they held the license of 78 (out of the 450) nursing homes that a county hospital had acquired. We limit our analysis to the HHC of Marion County, as the other hospitals did not disclose the size of IGTs in their financial statements, nor how much of it was used for nursing home patients.

Specifically, HHC's financial reports show that they received $3.2 billion in base Medicaid revenues for nursing home services, see column (2) of Table C2, jointly funded by the federal government and the state at an average nominal FMAP of 68%, see column (3): $2.1 billion paid by the federal government (column (4)), and $1.1 billion paid by the state (not shown in a separate column, the difference).

In addition, the state initiated $750 million in supplemental payments for nursing home services, generating an extra $1.5 billion in federal payments (column (6)), for a total of $2.3 billion in supplemental payments; see column (5). Total nominal Medicaid payments for nursing home services thus amounted to $3.2+$2.3=$5.5 billion. HHC redirected $1.9 billion of those from nursing homes via intergovernmental transfers (IGTs) to its "general fund" (column (7)).[21] The money was used to finance HHC's hospital operations.

As above with the OIG reports, we conservatively assume that solely the published IGT amounts from HHC's financial reports were diverted. Overall, we estimate a markup of $\mu = 1.53$.

$$\mu_{HHC} = \frac{P_{HHC} \times Q_{HHC}}{R_{HHC} \times Q_{HHC}} = \frac{\$5.5bn}{\$5.5bn - \$1.9bn} = 1.53 \tag{C2}$$

[21] This figure is consistent with a 2025 IndyStar article based on data obtained through a public records lawsuit. (Cook, 2025) reports that at least $2.6 billion has been diverted from nursing homes since 2000.

Thus, the effective FMAP was 68% (nominal FMAP) $\times 1.53 = 104\%$. Put differently, federal payments exceed effective spending on nursing homes, implying that the state and HHC jointly generated a net surplus from providing Medicaid-funded nursing home care.

As a last step, we calculate the effective FMAPs by calendar years to cross-check whether Indiana continued to run sophisticated creative schemes during our sample period. Between 2008 and 2019, two-thirds of diverted funds went to the inpatient hospital division under *Wishard Health Services* (before 2013) and *Eskenazi Health Services* (starting in 2013). The remainder was transferred to *Capital Projects and Debt Service Funds*.

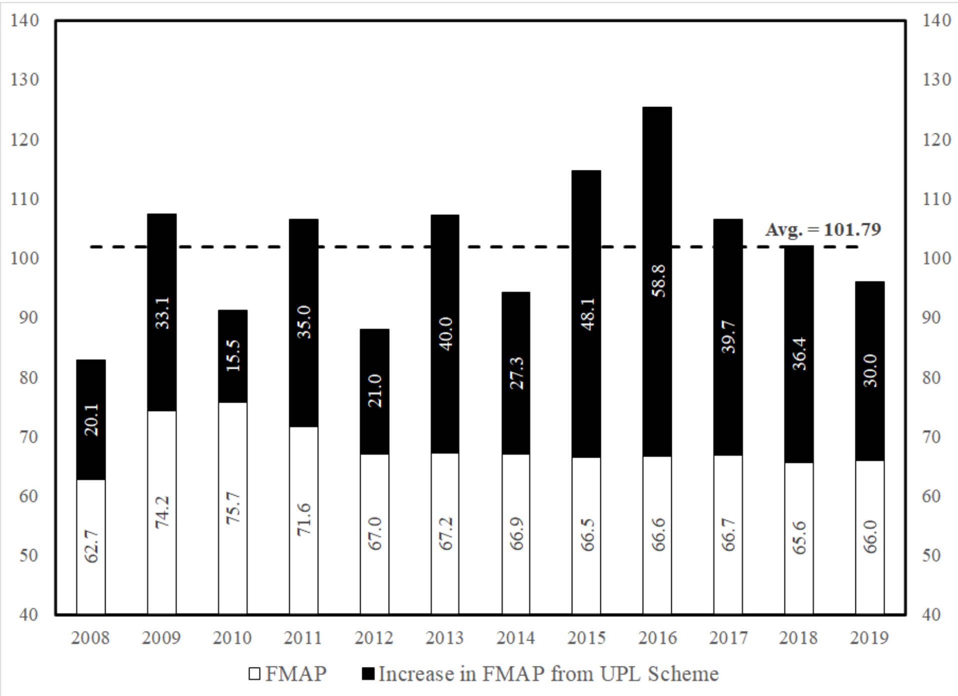
For each year between 2008 and 2019, using the sum of column (2) [Total base payments] and (5) [Total SP payments] as nominal spending P and subtracting column (7) [IGTs] to obtain effective spending R, we obtain high effective FMAP rates of between 83% (83%) and 125%, see Table C2 and Figure C1.

Table C1: Creative Financing by Audited States—OIG Reports 1997-2017

State (1)	**Year** (2)	**Total Base Medicaid NH Payments** (3)	**Nominal FMAP in %** (4)	**Matching Funds Federal Govt.** (5)	**Total Medicaid SP** (6)	**Federal Matching Funds SP** (7)	**IGT** (8)	**Effective FMAP in %** (9)
AL	1999	$590,316,720.00	69.3	$408,911,552.16	$39,556,368.00	$27,400,639.84	$38,171,895.12	73.7
AL	2000	$684,473,216.00	69.6	$476,188,827.84	$44,000,000.00	$30,610,852.16	$42,460,000.00	73.9
NE	1998-2000	$879,075,904.00	61.2	$537,694,852.59	$227,000,000.00	$138,846,635.41	$225,500,000.00	76.8
PA	1997	$2,603,652,424.00	52.8	$1,375,995,098.63	$783,011,000.00	$413,810,725.37	$783,011,000.00	68.7
PA	1998	$2,335,975,088.00	53.4	$1,247,177,376.12	$1,128,818,000.00	$602,676,063.88	$1,128,818,000.00	79.2
PA	1999	$2,466,321,952.00	53.8	$1,326,141,226.75	$1,521,004,000.00	$817,843,797.25	$1,521,004,000.00	86.9
TN	2000-2002	$3,075,248,128.00	63.5	$1,952,322,897.85	$398,000,000.00	$252,670,510.15	$398,000,000.00	71.7
WA	2000	$597,935,165.00	51.8	$309,893,512.64	$147,023,043.00	$76,198,039.36	$137,223,043.00	63.5
TX	2017 (2nd Half)	$2,633,491,015.33	56.2	$1,479,490,745.74	$193,682,943.00	$108,810,745.93	$141,574,583.00	59.1

Sources: CMS-64, audit reports from the HHS Office of Inspector General (OIG), see Appendix C.1 and main text for details. NH stands for "Nursing Home." SP stands for "Supplemental Payments."

Figure C1: Effective FMAP—Evidence from Digitized Financial Reports



Notes: This figure presents the nominal and effective FMAP: $FMAP \times \frac{P}{R}$. The estimates refer to nursing homes operated by HHC of Marion County and build on the HHC's financial reports.

Table C2: Creative Financing at HHC—Financial Reports 2008-19

Year	**Total Base Medicaid NH Payments to HHC**	**Nominal FMAP in %**	**Matching Funds from Federal Government**	**Total Medicaid SP**	**Federal Matching Funds SP**	**IGT NH to HHC**	**Effective FMAP in %**
(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**
2008	$73,295,398.08	62.7	$45,948,885.06	$51,423,940.00	$32,237,667.99	$30,300,000.00	82.8
2009	$103,972,717.74	74.2	$77,158,153.83	$74,421,268.00	$55,228,022.98	$55,000,000.00	107.3
2010	$146,408,300.97	75.7	$110,816,443.00	$71,102,472.00	$53,817,461.06	$37,000,000.00	91.2
2011	$175,031,206.98	71.6	$125,272,003.31	$155,821,249.00	$111,523,198.39	$108,597,652.00	106.5
2012	$294,135,500.45	66.9	$196,953,131.10	$153,550,441.00	$102,817,375.29	$106,700,000.00	87.9
2013	$281,597,415.00	67.2	$189,120,823.91	$198,664,337.00	$133,422,968.73	$179,392,756.00	107.2
2014	$299,855,988.18	66.9	$200,663,627.29	$217,764,223.00	$145,727,818.03	$150,000,000.00	94.2
2015	$344,433,166.70	66.5	$229,116,942.49	$239,393,167.00	$159,244,334.69	$245,000,000.00	114.6
2016	$332,350,340.00	66.6	$221,345,326.44	$309,998,000.00	$206,458,668.00	$301,100,000.00	125.4
2017	$365,596,740.00	66.7	$243,999,264.28	$279,213,000.00	$186,346,756.20	$240,329,000.00	106.4
2018	$371,053,100.00	65.6	$243,373,728.29	$292,579,000.00	$191,902,566.10	$236,700,000.00	101.9
2019	$375,686,640.00	65.9	$247,802,907.74	$251,916,000.00	$166,163,793.60	$196,359,000.00	95.9
	$3,163,416,514.10	68.1	$2,131,571,236.74	$2,295,847,097.00	$1,544,890,631.05	$1,886,478,408.00	

Sources: Financial Reports of Health and Hospital Corporation of Marion County, see Appendix C.1 and Section 2.4 for details. NH stands for "Nursing Home." SP stands for "Supplemental Payments." The last row shows the sum of the annual dollar amounts or the average FMAP across all years displayed.

D Data Appendix for Empirical Evidence on H2

Here, we describe in more detail the primary data sources used to construct a panel dataset at the nursing home-year level in Indiana from 1999 to 2015. The panel uses administrative data, linked to data from Long-Term Care: Facts on Care in the U.S. (2025) and hand-collected data as described in Section C. The administrative data are MDS compiled by CMS and include all Medicaid- and Medicare-certified nursing homes in Indiana from 1999 to 2015. As discussed, we use this nursing home-year data to study the impact of creative financing on care volume. Specifically, we exploit the license acquisitions of nursing homes in a staggered CS-DD setting.

D.1 Nursing Home-Year Data from LTC Focus and MDS

We used information from various sources to create the nursing-home-year data; see Section 4.2 and the README file for more details.

Ownership Data. The ownership data, including nursing home identifiers and exact dates when nursing homes were acquired, come from three data sources:

1. CMS Skilled Nursing Facility Provider Information. The archived data snapshot was downloaded on October 28, 2024, from https://data.cms.gov/provider-data/archived-data/nursing-homes using the December 2017 file.
2. Manual searches of Indiana Consumer Reports from July 2019. When the consumer report showed an acquisition by a publicly owned hospital that preceded the CMS report, the consumer report date was used.[22]
3. Reporting from Indystar in an article titled ”Money Flowed, Care Lagged (Evans, Hopkins, and Cook, 2020b). The article was downloaded on August 29, 2019, from https://www.newspapers.com/image/126265325.
4. Legacy data from CMS Compare from 2000 to 2017, downloaded in July 2018. Note that we set the acquisition year to 2000 when nursing homes were owned by a county

[22] A sample of is available at https://secure.in.gov/health/reports/reports/QAMIS/cr000016.htm.

hospital before the sample start. We use this assumption only when all the sources above are unavailable. It only affects five nursing homes in the balanced sample used for the analysis.

LTC Focus. This is the main Long-Term Care: Facts on Care in the U.S. (2025) data and includes all nursing homes in Indiana by provider number (PROVNUM), provider name, address, zip code, and year, along with additional information on facilities.

Indiana Population. We use population data for counties in Indiana between 2000 and 2018, downloaded on October 28, 2024 from State of Indiana (2025). Similarly, we use data on the county population aged 65 and older.

Long Term Care Minimum Data Set (MDS) 2.0. To produce the main working dataset, we merge administrative microdata from MDS (2020), aggregated at the nursing-home-year level, with the datasets above. CMS owns these data, which cannot be made publicly available. The code is posted in the Supplementary Materials and describes how we generate our primary dataset at the nursing-home-year level. Among other things, the MDS measures the health of all nursing home residents in all U.S. Medicaid or Medicare-certified nursing homes (98% of all U.S. nursing homes) in a standardized manner. The data also contain the exact admission and discharge dates, as well as the discharge destination.

To produce the dataset for the placebo test in Figure D1, we primarily relied on LTC Focus. The placebo replicates the Indiana nursing-home-year panel in the set of non-creative-financing states following the survey in Coughlin, Bruen, and King (2004): AK, CA, CT, DC, FL, GA, HI, ID, MD, MA, MS, OH, OK, SC, TX, UT, VT, WV, WY (19 jurisdictions). Treatment follows the Indiana definition exactly: a facility is municipalized in the first year a county or city hospital holds a 5%-or-greater direct ownership interest, identified from CMS ownership records (role ”5% or greater direct ownership interest”; the association date gives the conversion year). Treatment is absorbing; once public, the facility remains coded public in all subsequent years. Outcomes come from the national LTC Focus facility-year files, constructed identically to Indiana (e.g., Medicaid days = total beds × occupancy × Medicaid share × 365 ⁄ 10,000). The event studies control for county population aged 65+ (SEER, age bins 14–18), merged by county and year; see README for more details.

Like the Indiana sample, the panel is balanced in calendar time—facilities observed in every year 2000–2017—and restricted to facilities with at least one Medicaid patient in 2000. Cohorts span 2005–2015, yielding a final estimation sample of 93 municipalized and 4,834 never-treated nursing homes. As with Indiana, we run Callaway–Sant'Anna event studies with not-yet-treated controls and regression adjustment; the pooled ATT uses the simple aggregation and the dynamic path uses the event-study aggregation, with standard errors clustered at the nursing-home level.

Table D1: Summary Statistics Nursing-Home-Year

Variable	**Mean**	**Std. Dev.**	**N**
Panel A			
For-profit	0.67	0.22	5888
Total Medicaid days in '000	28.04	12.56	6256
Alzheimer's Medicaid days in '000	9.72	6.52	6256
Alzheimer's Special Care Unit	0.37	0.48	5888
Panel B			
Occupancy rate in %	80.36	12.85	5888
Total beds	108.2	45.94	5888
Registered Nurse hours per resident day	0.30	0.29	5888
LPN hours per resident day	0.88	0.27	5888

Source: Long-Term Care: Facts on Care in the U.S. (2025), MDS (2020), Centers for Medicare & Medicaid Services (2020b); Indiana Department of Health (2020), CMS Skilled Nursing Facility Provider Information, State of Indiana (2025), authors' calculation. See Section 4.2 and Appendix D for more details. The sample is at the nursing home year level from 1999-2015. LTC Focus data are available only from 2000, which is why variables from this dataset only have 5888 observations. The sample is otherwise at the nursing-home-year level from 1999 to 2015.

Table D2: Characteristics of Early (<2011) vs. Late Nursing Home Acquisitions (>=2011)

Variable Names	Early (mean)	Early (sd)	Late (mean)	Late (sd)	Norm Diff
Panel A: Main outcomes					
For-profit	0.889	0.316	0.854	0.353	0.073
Occupancy rate	69.572	14.236	78.523	12.587	0.471
Medicaid days	21,563	9,685	20,066	8,912	0.114
Alzheimer's Special Care Unit	0.422	0.497	0.394	0.489	0.041
Has Nurse Practitioner or Physician Assistant	0.244	0.432	0.312	0.464	0.107
Panel B: Controls					
County population	247,939	295,987	189,492	266,149	0.147
County population above 65	27,709	31,413	22,700	28,720	0.118
Average Acuity Index	11.115	1.147	11.112	1.344	0.001
Registered Nurse/Nurse Ratio	0.175	0.071	0.207	0.109	0.248
Direct-care staff hours per resident day	3.063	1.049	3.171	0.682	0.086
Registered Nurse hours per resident day	0.224	0.210	0.250	0.146	0.100
Licensed Practical Nurse hours per resident day	0.972	0.431	0.949	0.250	0.046
Certified Nursing Assistant hours per resident day	1.866	0.553	1.971	0.585	0.131
Share restrained	6.638	7.129	3.485	4.556	0.373

Source: Long-Term Care: Facts on Care in the U.S. (2025), MDS (2020), Centers for Medicare & Medicaid Services (2020b); Indiana Department of Health (2020), CMS Skilled Nursing Facility Provider Information, State of Indiana (2025), authors' calculation. See Section 4.2 and Appendix D for more details. The sample is at the nursing-home-year-level, balanced in event time and includes nursing homes with valid observations for all variables that were acquired by a county hospital between 2005 and 2012. The normalized difference is calculated as in Imbens and Wooldridge (2009) where values above 0.25 indicate substantial imbalances.

D.2 Patient-Stay Data

As in Section D.1, we use various sources to create a dataset at the patient-stay level in Indiana from 2000-2012; Section 4.4 and the README file contain more details.

Table D3: Sample Selection for Dementia Patient Sample

Sample	Observations
Dementia Patients in Indiana Hospitals	313,133
Drop if Zip Code Missing or Outside Indiana	285,843
Restrict to 2000-2012	218,645
Keep Patients 65+ in Acute Care Hospitals	208,825
Drop nursing homes outside 50 miles or haven't entered	206,833

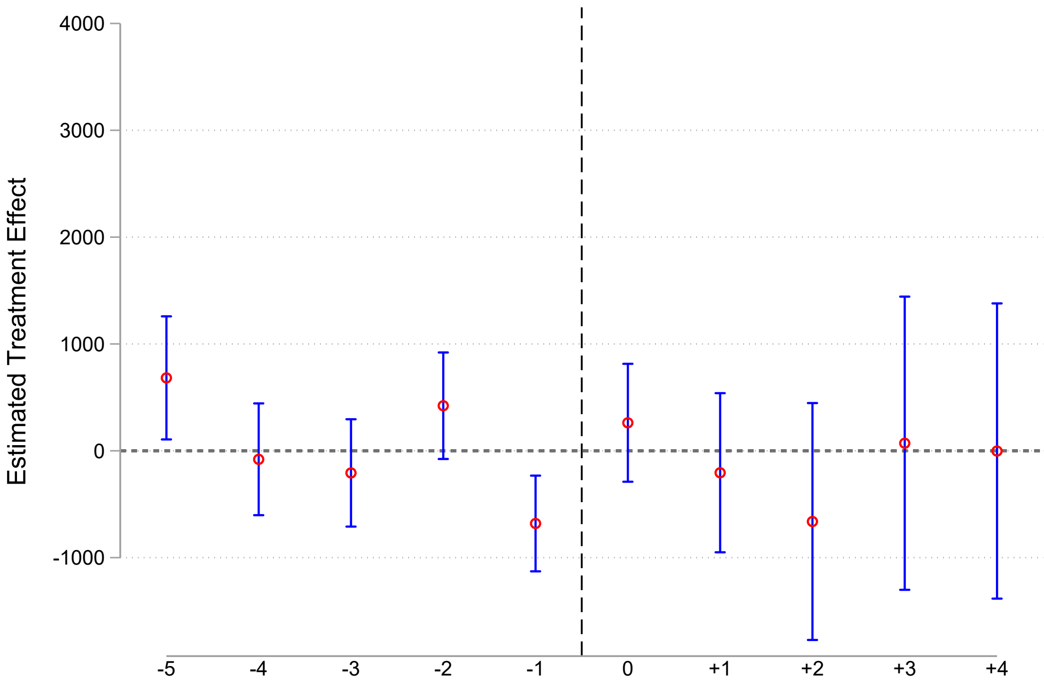
Source: Long-Term Care: Facts on Care in the U.S. (2025), MDS (2020), Centers for Medicare & Medicaid Services (2020b); Indiana Department of Health (2020), CMS Skilled Nursing Facility Provider Information, State of Indiana (2025), authors' calculation. The sample is based on AD/ADRD patients in acute care hospitals and at the patient-stay level in Indiana from 2000-2012.

Table D4: Summary Statistics for Dementia Patient Sample

Variable	Mean	(Std. Dev.)	N
Age	82.58	(7.2)	206,833
White	0.899	(0.301)	206,833
Black	0.087	(0.282)	206,833
Female	0.621	(0.485)	206,833
Index hospital stay in days	5.564	(4.547)	206,833
1-year survival rate	0.671	(0.47)	206,833
30-day hospital readmission rate	0.174	(0.379)	206,833
90-day hospital readmission rate	0.311	(0.463)	206,833
Discharged to			
Home	0.326	(0.469)	206,833
Nursing home	0.369	(0.482)	206,833
Intermediate Care Facility	0.033	(0.179)	206,833
Hospice	0.022	(0.145)	206,833
Nursing Home Matches MDS Claims			
Distance to next nursing home (in miles)	5.890	(7.085)	77,794
Medicaid days	186	(470)	76,272
Any Medicaid days	0.124	(0.329)	77,794

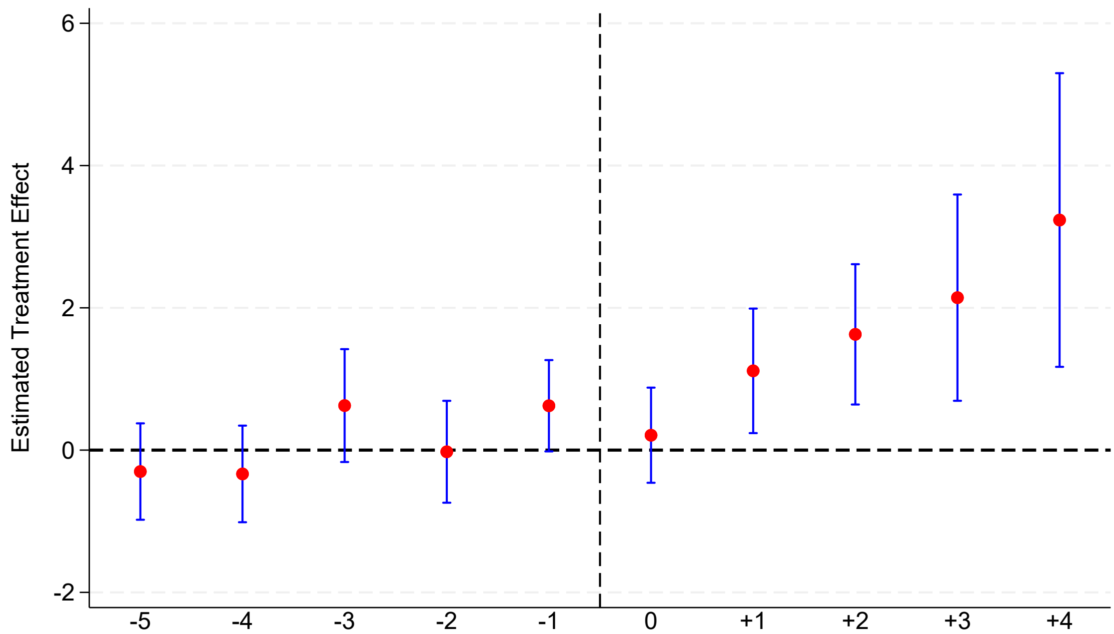
Source: Long-Term Care: Facts on Care in the U.S. (2025), MDS (2020), Centers for Medicare & Medicaid Services (2020b); Indiana Department of Health (2020), CMS Skilled Nursing Facility Provider Information, State of Indiana (2025), authors' calculation. The sample is based on AD/ADRD patients in acute care hospitals in Indiana at the patient-stay level from 2000-2012; see Table D3 for the sample selection. We flag patients as AD/ADRD when the Section I diagnosis indicators I1q or I1u are active, per MDS 2.0 definitions. See Section 4.4.1 and Appendix D for details. Discharged home comprises community discharges in which patients may receive care at home.

Figure D1: Placebo: Medicaid Volume after Municipalization in Non-CF States



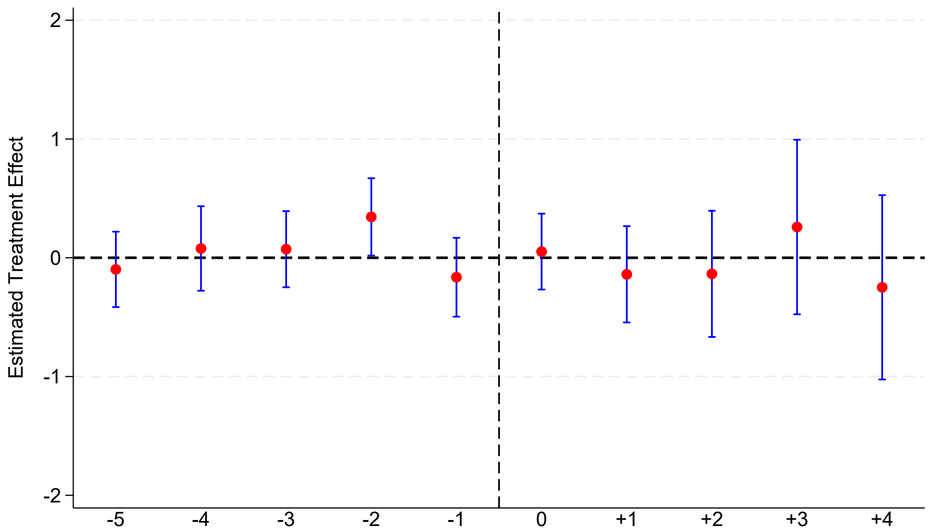
Long-Term Care: Facts on Care in the U.S. (2025), Centers for Medicare & Medicaid Services (2026), National Cancer Institute (2026), authors' calculation. The sample is balanced in calendar time at the nursing home-year level from 1999 to 2015; see Appendix D for more details on the dataset. Notes: The figure presents a Callaway and Sant'Anna (2021) event study of the effect of license acquisition on annual Medicaid days per nursing home, estimated in states without a nursing-home creative-financing scheme following Coughlin, Bruen, and King (2004). Event time 0 denotes the year a county hospital first acquires an ownership interest in the facility; estimates use not-yet-treated facilities as controls, and standard errors are clustered at the nursing-home level. Bars are 90% confidence intervals. Estimates at +3 to +5 rest on the earlier cohorts only, as the 2013–2015 acquisition wave cannot reach those horizons by 2017. See Appendix D and main text for details.

Figure D2: Creative Financing and Nursing Home Stays of 100+ Days among Dementia Patients



Source: Long-Term Care: Facts on Care in the U.S. (2025), MDS (2020), Centers for Medicare & Medicaid Services (2020b); Indiana Department of Health (2020), CMS Skilled Nursing Facility Provider Information, State of Indiana (2025), authors' calculation. The sample is based on AD/ADRD patients in acute care hospitals in Indiana at the patient-stay level from 2000-2012; see Table D3 for the sample selection. The graph shows Callaway Sant'Anna event studies, with event time 0 indicating license acquisitions. All event studies show 90% confidence intervals.

Figure D3: Creative Financing and One-Year Survival



(a) 100 Day Mortality

Source: Long-Term Care: Facts on Care in the U.S. (2025), MDS (2020), Centers for Medicare & Medicaid Services (2020b); Indiana Department of Health (2020), CMS Skilled Nursing Facility Provider Information, State of Indiana (2025), authors' calculation. The sample is based on AD/ADRD patients in acute care hospitals in Indiana at the patient-stay level from 2000-2012; see Table D3 for the sample selection. The graph shows Callaway Sant'Anna event study estimates, with event time 0 indicating license acquisitions. All event studies show 90% confidence intervals.

E Details on Callaway and Sant'Anna (2021) Estimator

To avoid the pitfalls with two-way fixed effects estimators in staggered difference-in-differences setups, we implement the estimator from Callaway and Sant'Anna (2021). Specifically, while the simple 2x2 DD design in Section 4.1 has a single treatment group, the staggered Callaway-Sant'Anna (CS) DD defines each treatment group (here, municipalized nursing homes) by its year of conversion, g, and yields T-1 event-study parameters.

The average treatment effects on the treated are then: $ATT(g,t) = \mathbb{E}\left[Y_{i,t}(g) - Y_{i,t}(\infty) \mid G_i = g\right]$ where each ATT(g, t) is the average treatment effect of being converted at period g relative to period g' for every eventually converted group, g, not-yet-treated group, g', and time periods, t, such that $t \geq g$ and $g' > t$. $\mathbb{E}\left[Y_{i,t}(\infty) \mid G_i = g\right]$ are untreated potential outcomes for each treatment group in each period, that is, unobserved counterfactuals.

ATT(g, t) can be identified by comparing the expected outcome change for g between periods $g-1$ and t to that for the not-yet-treated at period t (Roth et al., 2023).[23]

$$ATT(g,t) = \mathbb{E}\left[Y_{i,t} - Y_{i,g-1} \mid G_i = g\right] - \mathbb{E}\left[Y_{i,t} - Y_{i,g-1} \mid G_i = g'\right] \tag{E1}$$

which is estimated via the sample analogs:

$$\widehat{ATT(g,t)} = \frac{1}{N_g} \sum_{i:G_i=g} \left[Y_{i,t} - Y_{i,g-1}\right] - \frac{1}{N_{g'}} \sum_{i:G_i=g'} \left[Y_{i,t} - Y_{i,g-1}\right]$$

[23] Our setting uses the not-yet-treated nursing homes as controls as eventually almost all nursing homes are converted, resulting in the crucial parallel trends assumption (under no anticipation effects), see also Baker et al. (2025): $\mathbb{E}\left[Y_{i,t}(\infty) - Y_{i,t}(\infty) \mid G_i = g\right] = \mathbb{E}\left[Y_{i,t}(\infty) - Y_{i,t}(\infty) \mid G_i = g'\right]$

F Mixed Logit Model with Selection Correction

This appendix section outlines the data, sample selection, and econometric approach used to estimate the relationship between creative financing and quality of care. Following license acquisition of nursing homes, the quality of care may change because of creative financing activities themselves or because the patient allocation across nursing homes (and between nursing homes and home health care) changes, given that nursing homes expanded care volumes ("public moral hazard").

F.1 Dataset and Sample

To study these questions, we use the dataset in Table D4 that identifies AD/ADRD patients in acute care hospitals in Indiana using administrative Medicare claims data from 2000 to 2012, see Section D.2. Compared to the sample in Section 4.2, we leave the data at the *patient (hospital)-stay* level and flag hospital stays with Clinical Classification Software (CCS) diagnosis code 653 "Delirium, dementia, and amnestic and other cognitive disorders"(CCS, 2017), drop patients from out-of-state or missing zip codes, and only keep patients 65 and older, see Appendix Table D3 .[24]

Sample The final sample includes 206,833 hospital index stays with information on patient demographics such as age (82.6 years), race (90% white), one-year mortality (33%), and discharge destinations after the acute care stay (37% to a nursing home) as well as hospital readmission rates (31% within 90 days). We merge these index hospital stays with MDS data to identify subsequent nursing home stays.[25] We find successful nursing home matches for 37.6% of all index stays—–nearly identical to the 36.9% of patients reported as discharged to any nursing home in the hospital claims. We assume that patients not matched to a nursing home choose an outside good. In what follows, we interpret the outside good as outpatient care provided in the community—specifically, home care—as it is the most common alternative discharge destination (see Table D4).

[24]We also identify and drop a small share of patients who choose a nursing home more than 50 miles away from the centroid of their home addresses' zip code.

[25]For a successful merge, we require that the hospital stay precedes the nursing home stay by at most two weeks. The ID of the merged nursing home uniquely identifies the destination nursing home.

Furthermore, we assume that patients who are not matched to a nursing home choose an outside good. In what follows, we interpret the outside good as outpatient care provided in the community—specifically, home care—-as it is the most common alternative discharge destination (see Table D4).

Choice sets: To ensure sufficient observations per nursing home for the quality estimations below, we pool nursing homes with fewer than 50 admissions throughout the sample period with the outside good. In addition to the outside good, the patients' choice sets comprise all nursing homes within 50 miles of the patient's former address. The average discharge patient has 74 nursing homes, and the outside good, in her choice set.

F.2 Estimation

In the first step, we estimate a mixed logit choice model of nursing home choice, enhanced with an outside option representing home healthcare. In a second step, we construct control functions and estimate the parameters of a health outcome equation via simulated maximum likelihood.

We index patients by i and providers by j, and denote by t the year of the hospital discharge. Patients maximize the following indirect conditional utility function:

$$u_{ijt} = \begin{cases} \delta_j + x'_{ijt}\beta^x + z'_{ij}\beta^z + \eta_{ij} & \text{for nursing home } j \text{ in } i\text{'s choice set} \\ \pi_i + \gamma_t + \eta_{io} & \text{if outside good} \end{cases} \tag{F1}$$

$$\eta_{ij} \sim \text{i.i.d. extreme value}$$

$$\pi_i \sim N(0, \sigma^2)$$

where x_{ijt} denotes observable patient, nursing home, and year-specific characteristics. z_{ij} denotes preference shifters (instruments), excluded from the health outcome equation below. Our instrument is the distance between a patient's home address and any nursing home in the choice set. Further, δ_j denotes a nursing home fixed effect and captures vertical differentiation between choice options, conditional on x and z. γ_t denotes year fixed effects, capturing intertemporal changes in preferences for nursing home care. η_{ij} captures a horizontal taste shock, distributed i.i.d. extreme value.

Finally, we add a random coefficient to the logit choice framework to capture substitution patterns between inside goods (nursing homes) and the outside good (home care). This preference shock for the outside good is π_i and follows a normal distribution. We estimate the demand model via simulated Maximum Likelihood Estimation.

Health Outcomes: We model health outcomes, measured via survival and hospital readmission probabilities, as a binary outcome. The underlying latent health index m_{ijt} is given by:

$$m_{ijt} = \alpha_j + \alpha_t + x'_{ijt}\alpha^x + \epsilon_{it}, \tag{F2}$$

where x_{ijt} is defined as above. α_t denotes year fixed effects, and α_j denotes the quality of provider j to patient health. Finally, ϵ_{it} are unobserved differences in patient health, following a standard normal distribution.

A key challenge in estimating equation (F2) is that we observe outcomes only at endogenously selected nursing homes. To account for selection on unobservables, we follow Dubin and McFadden (1984) and adopt a control function approach. We assume the control function is linear in the demeaned preference shocks η_{ij} and π_i. Conditional on unobserved preference shifters $\{\eta_{ij}, \pi_i\}$ and the provider choice c_i, expected health can be written as:

$$E[m_{ijt}|x_{ijt}, \eta_i, \pi_i, c_i = j] = \alpha_j + \alpha_t + x'_{ijt}\alpha^x + \Big[\sum_{k \in J_i} \phi_k(\eta_{ik} - \mu_\eta) + \psi(\eta_{ij} - \mu_\eta)\Big] + \rho\pi_i + \rho_\psi\pi_i. \tag{F3}$$

Following Einav, Finkelstein, and Mahoney (2025), the terms in squared brackets represent selection on extreme-value preference shocks, where μ_η is the mean of the taste shock (Euler's constant). The first term $(\eta_{ik} - \mu_\eta)$ considers the shock to any option in the choice set, including the outside good, whereas the second term, $\eta_{ij} - \mu_\eta$, only turns on if the patient chooses alternative j. We extend this linearization to the random coefficient for the outside good by adding two analogous terms at the end of the expression, $\rho\pi_i + \rho_\psi\pi_i$. Here, the second term is nonzero only if the patient chooses the outside good.

As shown by Dubin and McFadden (1984) and Einav, Finkelstein, and Mahoney (2025), integrating out the η's yields:

Table F1: Structural Estimates: License Acquisitions and Health

Panel A: Mixed Logit	Coefficient Estimate	Lower Bound CI	Upper Bound CI
Inside Good (SNF)			
Log Distance	-1.51	-1.51	-1.50
License acquired	0.05	0.01	0.09
Outside Good (Home health)			
Age	-18.01	-18.91	-17.10
Female	-0.65	-0.74	-0.56
White	-1.82	-1.99	-1.66
Hospital LOS	-0.29	-0.30	-0.28
σ_π^2	7.63	7.32	7.94
Panel B: Health Outcome (1-Year Survival)			
License acquired	0.02	-0.03	0.07
Age	-0.04	-0.04	-0.03
Female	0.29	0.27	0.30
White	-0.05	-0.07	-0.03
Hospital LOS	-0.02	-0.02	-0.02
$Corr(\pi, \epsilon)$	0.40	0.27	0.53
Roy Selection SNFs	0.02	-0.00	0.04
Roy Selection Outside good	-0.25	-0.34	-0.16

Sources: Long-Term Care: Facts on Care in the U.S. (2025), MDS (2020), Centers for Medicare & Medicaid Services (2020b); Indiana Department of Health (2020), CMS Skilled Nursing Facility Provider Information, State of Indiana (2025), authors' calculation. The sample comprises AD/ADRD patients in acute care hospitals in Indiana from 2000-2012, at the patient-stay level, and is described in Appendices D.2 and F. The outcome is the one-year survival rate. Columns (2) and (3) show the 95% confidence interval (CI). Panel A estimates equation (F1) and Panel B equation (9). Estimates are based on the same dementia-related index hospital stays described in Appendix Table D4.

$$E[m_{ijt}|x_{ijt}, \pi_i, c_i = j] = \alpha_j + \alpha_t + x'_{ijt}\alpha^x + \left[\sum_{k \in J_i} \phi_k \gamma_{ik}(j) + \psi \gamma_{ij}(j)\right] + \rho\pi_i + \rho_\psi \pi_i \,, \tag{F4}$$

$\gamma_{ik}(j) = E[\eta_{ik} - \mu_\eta | x_{jt(i)}, \pi_i, c_i]$ are the (mixed) logit choice probabilities:

$$\gamma_{ij}(j) = \begin{cases} -log\ \hat{p}_{ik} & k = j \\ \frac{\hat{p}_{ik}}{1-\hat{p}_{ik}} log\ \hat{p}_{ik} & otherwise \end{cases} \tag{F5}$$

where $\hat{p_{ij}}$ is the predicted probability that patient i chooses nursing home j conditional on x, z and π given by

$$\hat{p}_{ij} = \frac{\exp(\delta_j + x'_{jt(i)}\beta^x + z'_{ij}\beta^z)}{\exp(\pi_i + \gamma_{t(i)}) + \sum_{k/o}\exp(\delta_k + x'_{kt(i)}\beta^x + z'_{ik}\beta^z)} \,. \tag{F6}$$

Importantly, and as stated above, $\hat{p}_{ik}$ is conditional on random coefficient shock π_i. The parameters of the control terms in equation (F4) have economic interpretations. As discussed in Einav, Finkelstein, and Mahoney (2025), ϕ_k stands for the control function coefficients correcting for the unobservable correlation between demand shocks for nursing home k and the value added at nursing home k. These terms would correct, for example, for the bias that would arise if patients who are (unobservably) in poor health systematically select high-quality nursing homes. The $\psi\gamma_{ij}(j)$ term would correct for any remaining potential correlation between demand shocks for nursing home j and the value added at nursing home j—beyond $\phi_k\gamma_{ik}(j)$'s. The terms $\rho\pi_i$ and $\rho_\psi\pi_i$ capture analogous types of selection on the random coefficient shock π for the outside good, that is, home health care.

Integrating Out the Random Coefficient: Finally, we integrate out the random coefficient π_i:

$$E[m_{ijt}|x_{ijt}, c_i] = \int \left(\alpha_j + \alpha_t + x'_{ijt}\alpha^x + \sum_{k\in J_i}\phi_k\gamma_{ik}(\pi) + \psi\gamma_{ij}(\pi) + \rho\pi + \rho_\psi\pi\right) dF_{\pi|x_{ijt},c_i} \,, \tag{F7}$$

where $F_{\pi|x_{ijt},c_i}$ denotes the distribution of π conditional on x_{ijt}, c_i. From Bayes' rule, we have:

$$f_{\pi|x_{ijt},c_i} = \frac{f_{\pi,c_i|x_{ijt}}}{f_{c_i|x_{ijt}}} = f_{c_i|\pi,x_{ijt}} \times \frac{f_{\pi|x_{ijt}}}{f_{c_i|x_{ijt}}} = \hat{p}_{ik}(\pi) \times \frac{\phi(\frac{\pi}{\sigma_\pi})}{\int \hat{p}_{ik}(\pi)\phi(\frac{\pi}{\sigma_\pi})d\pi} \,, \tag{F8}$$

where $\phi(\cdot)$ denotes the standard normal density. Hence, and building on the demand model, we construct the weights

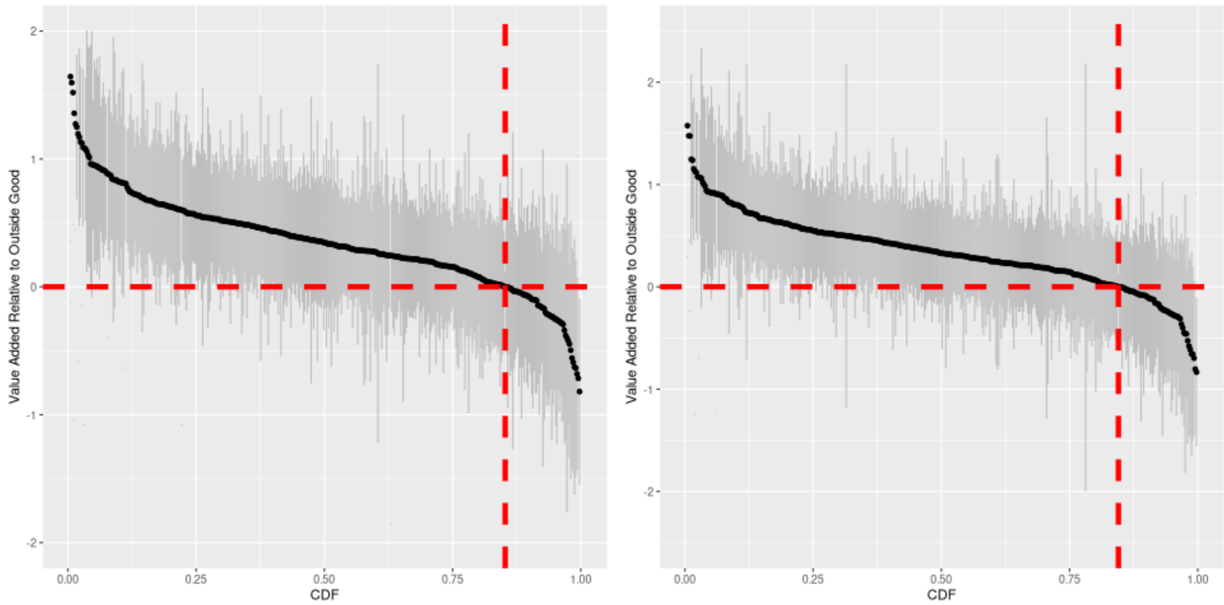
$$w_\pi = \hat{p}_{ik}(\pi) \times \frac{\phi(\frac{\pi}{\sigma_\pi})}{\int \hat{p}_{ik}(\pi)\phi(\frac{\pi}{\sigma_\pi})d\pi} \tag{F9}$$

such that

$$E[m_i|x_{jt(i)}, c_i] = \int \left(\alpha_j + \alpha_t + x'_{ijt}\alpha^x + \sum_{k\in J_i}\phi_k\gamma_{ik}(\pi) + \psi\gamma_{ij}(\pi) + \rho\pi + \rho_\psi\pi\right) w_\pi \, d\pi \,, \tag{F10}$$

and estimate downstream mortality outcome parameters via (weighted) Maximum Likelihood Estimation.

Figure F1: Value Added Estimates



(a) One-Year Survival (b) One-Year Survival: Shrinkage Adjusted

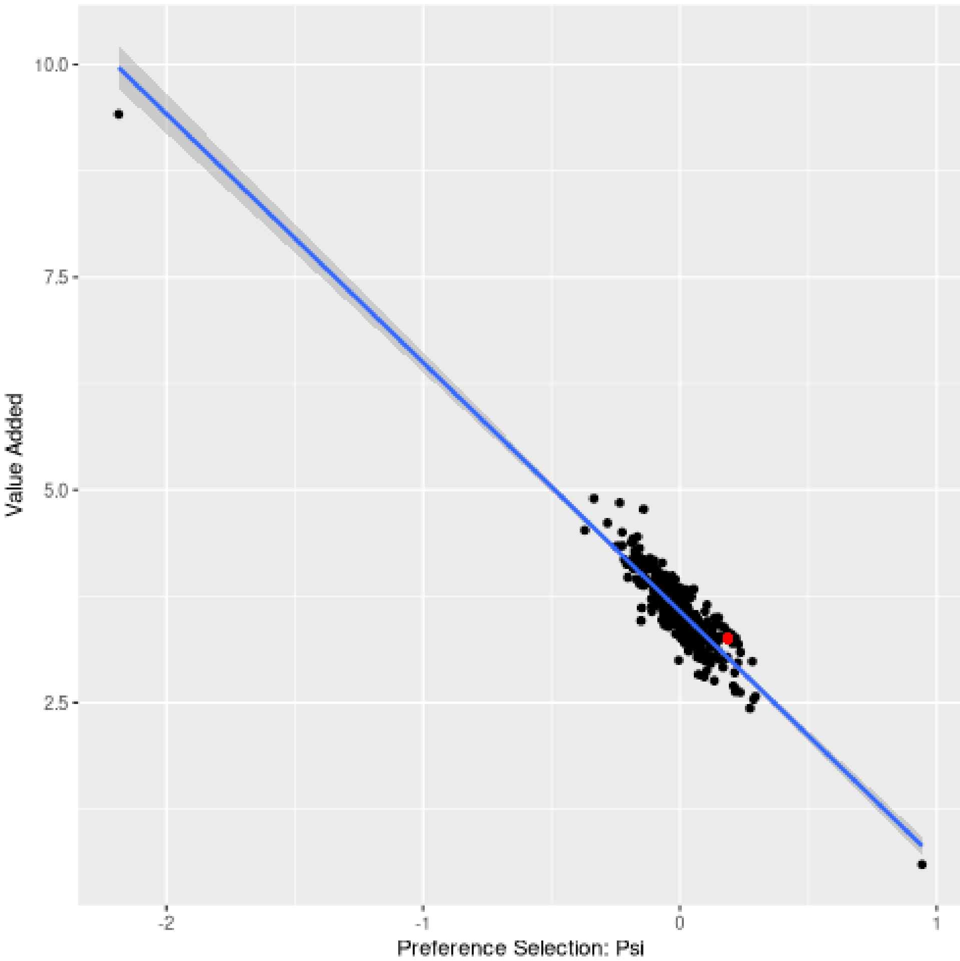
Source: Long-Term Care: Facts on Care in the U.S. (2025), MDS (2020), Centers for Medicare & Medicaid Services (2020b); Indiana Department of Health (2020), CMS Skilled Nursing Facility Provider Information, State of Indiana (2025), authors' calculation. The sample comprises AD/ADRD patients in acute care hospitals in Indiana from 2000-2012, at the patient-stay level and Appendices D.2 and F. The figure shows the redirected quality estimates α_j, see equation (9) for one-year survival on the vertical axis. Estimates are presented relative to the outside good $\alpha_j - \alpha_0$, in descending order, along with the 95% confidence interval (grey bars). The horizontal axis denotes the cumulative density, and the vertical line separates nursing homes whose value added exceeds that of the outside good (mostly home-based care) from those whose value added falls short of it. The right graph applies a shrinkage technique from the empirical Bayes literature, following Chandra et al. (2016).

Figure F2 shows clear evidence for selection into nursing homes via the strong correlation between our quality estimates and the preference selection coefficient Ψ.

Figure F3 provides a binned scatter plot with quality on the y-axis and (binned) mean utility on the x-axis. We find no systematic relationship between the two variables, with a correlation of close to zero. Apparently, consumers (or their surrogates) do not account for differences in health outcomes produced by nursing homes, for example, due to asymmetric information or capacity constraints.

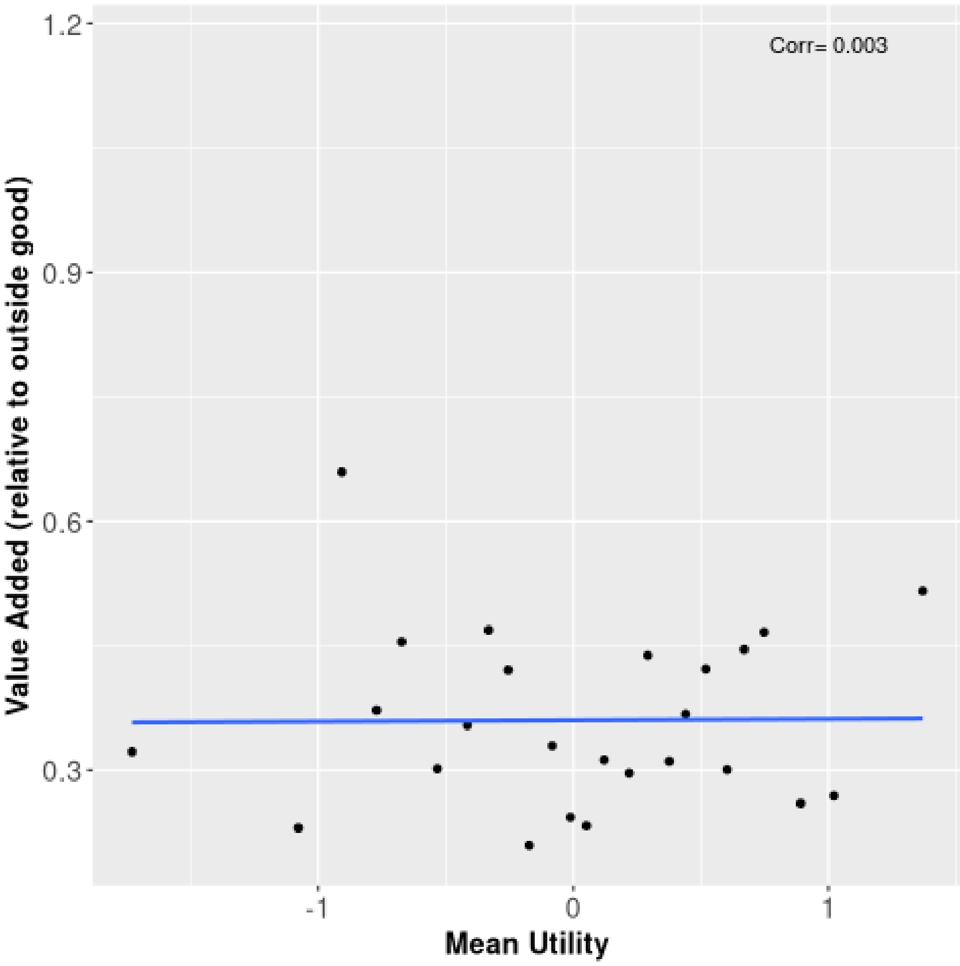
Below, we find no link between occupancy and our quality estimates, suggesting that rationing alone is unlikely to reconcile the lack of a statistical link. Further, rationing alone cannot explain why patients choose low-quality providers over the outside good. We, therefore, interpret Figure F3 as evidence for asymmetric information over the quality of nursing homes.

Figure F2: Selection and Value Added



Source: Long-Term Care: Facts on Care in the U.S. (2025), MDS (2020), Centers for Medicare & Medicaid Services (2020b); Indiana Department of Health (2020), CMS Skilled Nursing Facility Provider Information, State of Indiana (2025), authors' calculation. The sample comprises AD/ADRD patients in acute care hospitals in Indiana from 2000-2012, at the patient-stay level and Appendices D.2 and F. The figure shows a correlation between the preference selection coefficient, Ψ, on the horizontal axis and the (redirected = quality) estimates, α_j, in equation (9), for one-year survival on the vertical axis.

Figure F3: Utility and Valued-Added



Source: Long-Term Care: Facts on Care in the U.S. (2025), MDS (2020), Centers for Medicare & Medicaid Services (2020b); Indiana Department of Health (2020), CMS Skilled Nursing Facility Provider Information, State of Indiana (2025), authors' calculation. The sample is based on AD/ADRD patients in acute care hospitals in Indiana at the patient-stay level from 2000-2012; see Table D3 for the sample selection and Appendices D.2 and F. The figure shows a correlation between mean utility on the horizontal axis and the (redirected) quality estimates, α_j, in equation (9), for one-year survival on the vertical axis.

F.3 Validation of Nursing Home Quality Measures:

Naturally, the nursing home-specific quality estimates carry noise. To validate our quality measures, we first group nursing homes into higher- and lower-quality nursing homes, and then compare the results to other quality outcome markers.

Motivated by Figure F1, we flag the bottom quintile of nursing homes—those whose mortality impact falls short of the outside option—and label them ”lower-quality.” Conversely, we label the top quintile ”higher-quality.” The first row of Table F2 reports the average (standardized) one-year survival rate across the two nursing home groups. Survival is 1.16 (1.12) standard deviations higher (lower) among higher (lower) quality nursing homes compared to quintiles two to four.

To put these estimates into perspective, we calculate the average one-year mortality rate for a representative patient across quality quintiles.[26] For the highest quality nursing homes, we estimate an average one-year mortality rate of 11.5%, and for the lowest quality nursing homes, a one-year mortality rate of 42.5%. For the outside good, we estimate a mortality rate of 35.9%, see Panel B of Table F2. In robustness exercises, we use 30- and 90-day hospital readmissions as health outcomes, yielding qualitatively similar results. Nursing homes with the highest estimated survival rates also have lower 30- and 90-day readmission rates, validating our categorization (see second and third row of Table F2).

Panel B of Table F1 shows nursing home characteristics and the CMS star rating. These provide alternative measures of quality of care. As seen, nursing homes with high quality estimates also have higher registered nurse (RN)-to-patient staffing ratios and a higher RN-to-nurse ratio, which are key determinants of nursing home quality (Friedrich and Hackmann, 2021). Further, they have higher CMS star ratings. These comparisons confirm that our proposed method and categorization capture actual and meaningful differences in the quality of care. When stratifying low- and high-quality nursing homes by their baseline characteristics in the year 2000 (Table F4), characteristics are relatively balanced as judged by Imbens and Wooldridge (2009)'s normalized difference or t-tests. The Medicaid payer share is higher in low-quality nursing homes (69% vs. 64%) and lower-quality nursing homes are substantially more likely to be for-profit (89% vs. 72%).

[26]The mortality estimates apply to an 85-year-old, white female patient with a 6-day index hospital stay.

Table F2: Validation—One-Year Survival vs. Alternative Quality Measures

	NH Value Added 1-Year Survival		
	High (top 20%)	Low (bottom 20%)	Medium
Standard. quality			
One Year Survival	1.163 (1.288)	-1.117 (0.709)	-0.015 (0.298)
1- (30-Day Readmission)	0.247 (1.198)	-0.359 (0.938)	0.037 (0.917)
1-(90-Day Readmission)	0.429 (1.071)	-0.537 (1.194)	0.036 (0.813)
Other: Quality of Care			
Avg One Year Mortality*	11.5%	42.5%	24.0%
RN to Nurse Ratio	0.265 (0.129)	0.213 (0.065)	0.244 (0.132)
RN hours per Patient-Day	0.680 (1.075)	0.325 (0.383)	0.522 (0.731)
CMS Star Rating	2.870 (1.334)	2.486 (1.096)	2.544 (1.263)
Occupancy Rate	78.91 (12.67)	81.58 (9.112)	78.68 (10.30)
Share occupancy $< 90\%$	0.827 (0.380)	0.802 (0.401)	0.910 (0.287)
For-profit	0.604 (0.436)	0.821 (0.320)	0.668 (0.415)
Medicaid payer share	50.64 (25.01)	63.18 (15.14)	51.66 (25.66)

Table shows descriptive statistics based on the sample of dementia related index hospital stays described in Appendix Table D4. The first column presents results for nursing homes whose quality estimates fall in the top quintile of the quality distribution shown in Figure F1. The second column pools nursing homes in the bottom quintile of the distribution, and the third column pools the remaining nursing homes situated in the second to fourth quintile of the distribution. * The one-year mortality rate in Panel B is for an 85-year-old white female with a 6-day index hospital stay. For comparison, the corresponding one-year mortality rate for individuals choosing the outside good is 35.9%.

Next, we validate our quality measures by correlating the quality estimates generated by the one-year mortality vs. 30-day (Figure F4a) and 90-day (Figure F4b) hospital readmission rates in Figure F5.

Moreover, Table F3 presents correlations between our three quality measures and nursing home characteristics, such as staffing ratios and star ratings. Finally, following Panel B of Table F1, Table F5 presents estimates for the health outcome equation using readmission rates rather than mortality.

Table F3: Correlation with Other Markers

Variable	Mean Utility	VA: Mort	VA: Read 30	VA: Read 90
Nurse Practitioner	0.098	-0.038	-0.076	-0.072
Alzheimer's Unit	0.179	-0.042	-0.025	-0.030
RN Staffing Ratio	0.207	0.071	0.049	0.043
LPN Staffing Ratio	0.268	0.049	0.015	0.006
Occupancy Rate	-0.025	0.008	-0.053	-0.024
Total Beds	0.106	-0.123	-0.052	-0.019
Hospital Based	0.242	0.065	0.043	0.023
Overall Rating	0.172	0.112	0.109	0.162
Survey Rating	0.193	0.119	0.081	0.118
Quality Rating	-0.024	0.011	-0.021	0.025
Staffing Rating	0.118	0.015	0.079	0.109
RN Staffing Rating	0.053	0.054	0.137	0.146

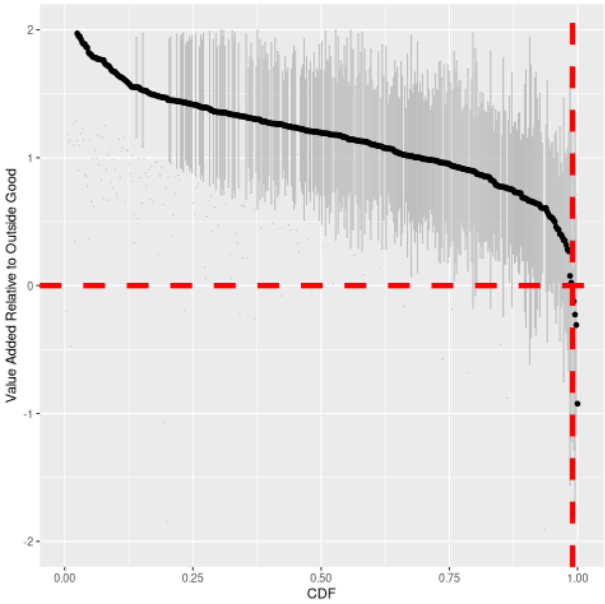
Table shows correlations based on the sample of dementia related index hospital stays described in Appendix Table D4.

Table F4: Baseline (Year 2000) Characteristics by Bottom and Top Quintile Quality

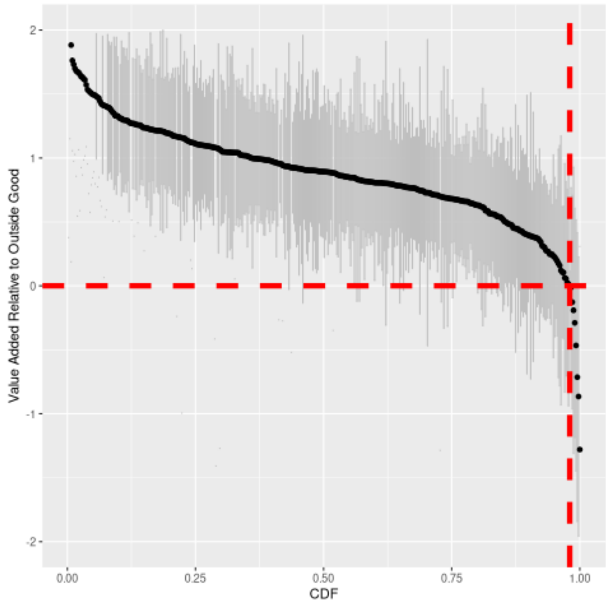
	Low (bottom 20%)	High (top 20%)	Difference	Normalized difference	T-stat
Occupancy rate	81.14	77.80	-3.350	-0.170	1.338
Share occupancy $< 90\%$	0.682	0.719	0.037	0.057	-0.449
Medicaid payer share	68.87	64.06	-4.812	-0.218	1.714
For-profit	0.894	0.719	-0.175	-0.318	2.521
Total beds	116	113	-3.242	-0.048	0.380
Acuity index	10.66	10.46	-0.203	-0.143	1.117
RN hrs/patient day	0.268	0.273	0.005	0.027	-0.213
LPN hrs/patient day	0.763	0.835	0.072	0.156	-1.233
CNA hrs/patient day	1.511	1.643	0.132	0.198	-1.576
RN-to-nurse ratio	0.259	0.255	-0.003	-0.023	0.177

Table shows descriptive statistics based on the sample of dementia related index hospital stays described in Appendix Table D4. The first column presents results for nursing homes whose quality estimates fall in the bottom quintile of the quality distribution shown in Figure F1. The second column pools nursing homes in the top quintile of the distribution. All variables are measured at the year 2000 baseline within the estimation sample. The difference is high minus low quality nursing homes; the normalized difference follows Imbens and Wooldridge (2009); the t-statistic is from a two-sample t-test assuming equal variances. Sample sizes: N(Low) = 66 SNFs, N(High) = 57 SNFs. See main text for more details.

Figure F4: Value Added Estimates—Hospital Readmission Rates



(a) 30-Day Readmission Rate



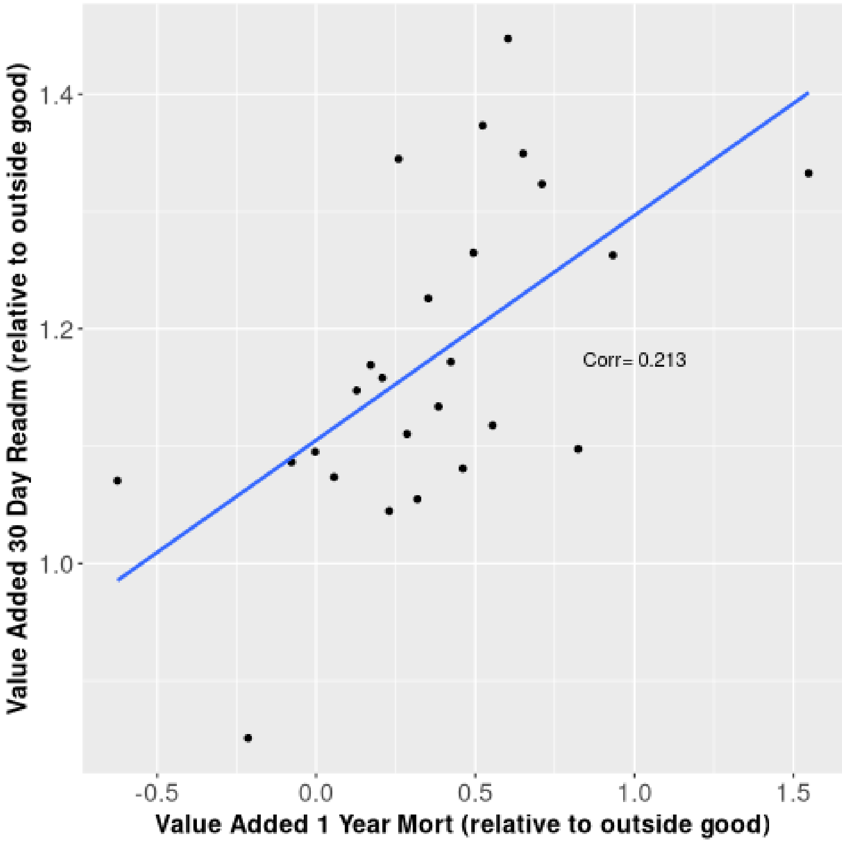
(b) 90-Day Readmission Rate

Table F5: Health Outcome Estimates Using Readmission Rates

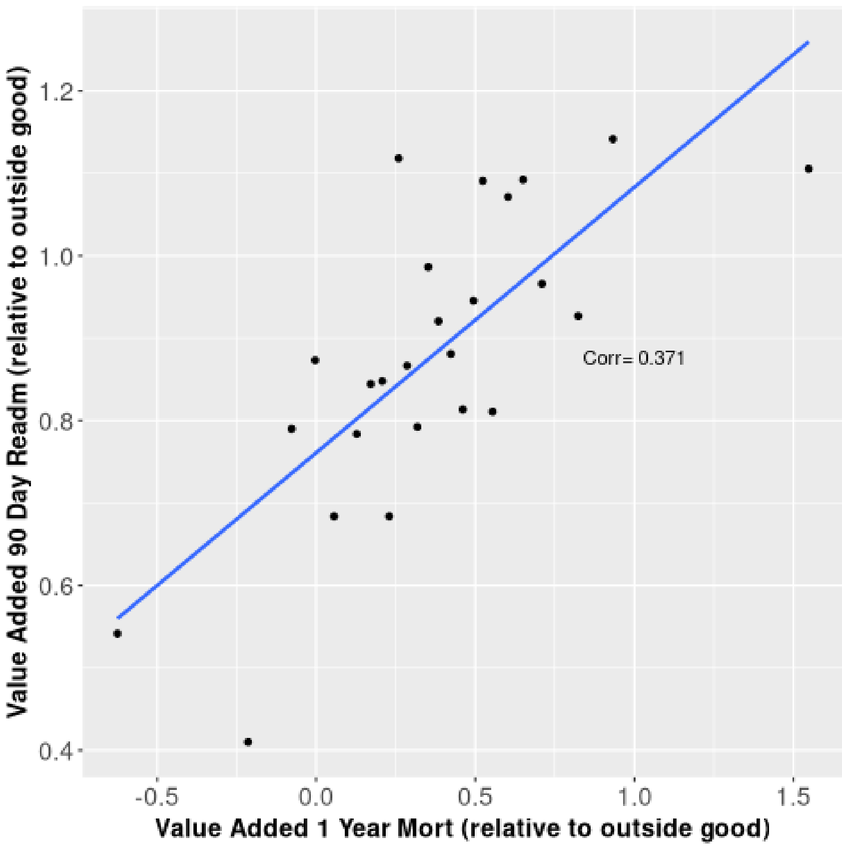
	30-Day			90-Day		
	Coefficient	Lower CI	Upper CI	Coefficient	Lower DI	Upper CI
Municipalized	0.01	-0.05	0.06	0.03	-0.02	0.07
Age	0.55	0.44	0.65	0.53	0.44	0.62
Female	0.10	0.08	0.11	0.10	0.08	0.11
White	0.10	0.07	0.12	0.15	0.13	0.17
Hospital LOS	0.01	0.01	0.01	-0.00	-0.00	-0.00
Ψ_η	0.03	0.01	0.05	0.02	0.00	0.04
ρ	0.43	0.27	0.58	0.11	-0.04	0.25
ρ_ψ	-0.98	-1.07	-0.90	-0.62	-0.70	-0.54

Sources: Long-Term Care: Facts on Care in the U.S. (2025), Centers for Medicare & Medicaid Services (2020b); Indiana Department of Health (2020), CMS Skilled Nursing Facility Provider Information, State of Indiana (2025), authors' calculation. See Appendix C and Appendix Tables D3 and D4 for details on data sources and the sample at the nursing home-year level. Equation (F4) is estimated. The outcome is the 30-day and the 90-day readmission rate. All coefficients are multiplied by -1 to reflect effects on positive health. Estimates are based on the same dementia-related index hospital stays described in Appendix Table D4.

Figure F5: Valued Added—Mortality vs Readmission Rate



(a) Mortality Against 30-Day readmission



(b) Mortality Against 90-Day readmission

F.4 Patient Relocation and One-Year Survival:

We also probe the survival effects of patient relocation between care choices due to public moral hazard. To this end, we use our model estimates to quantify ”diversion ratios”, and then relate them to the survival consequences of different care choices.

Let s_j denote the share of patients choosing nursing home j. Diversion ratios then measure substitution between care choices:

$$D_{kj} = -\frac{\partial s_k}{\partial \delta_j} / \frac{\partial s_j}{\partial \delta_j} .$$

They capture the share of new residents at nursing home k that are diverted from care choice j as j changes its mean utility δ_j, e.g., after license acquisition. We aggregate the diversion ratios across groups of nursing homes, based on the quality group $g \in \{0, low, middle, high\}$, separating out the outside good. Specifically, we consider

$$D_{gg'} = -\frac{1}{\#g} \sum_{j \in g} \left[\sum_{k \in g', k \neq j} \frac{\partial s_k}{\partial \delta_j} / \frac{\partial s_j}{\partial \delta_j} \right]. \tag{F11}$$

The first panel of Table F6 presents diversion ratio estimates. The columns show the destination nursing homes by groups, and the rows present the corresponding origins. The first column considers new residents in higher-quality nursing homes following license acquisitions. 16.7% would have chosen the outside good, 15.0% a higher-quality nursing home, and 50.3% a nursing home of ’average’ quality. Lastly, 17.9% would have chosen a nursing home of much lower quality in the lowest quality group. Put differently, the estimates suggest that 83.3% of patients who choose a focal nursing home after license acquisitions would have chosen a different nursing home.

The second panel of Table F6 considers implications for survival. The first row, denoted “Post,” presents the average one-year survival rate at the destination nursing home (borrowed from Table F2). The second row, denoted “Pre,” presents the average one-year survival rate among marginal patients for the origin care choices. Intuitively, it presents the average survival had the patients not chosen the destination facility.[27] As seen, the pre-post difference

[27] Mathematically, this is the diversion-ratio-weighted average of the “Post” survival rates, including the rate of 64.1% for the outside good. For the middle group, for instance, $0.169(64.1) + 0.127(88.5) + 0.555(76.0) + 0.149(57.5) = 72.8\%$.

Table F6: Patient Relocation and One-Year Survival Rates

	By Quality Estimates		
	High	Middle	Low
Diversion Ratios			
From Outside	16.7%	16.9%	15.5%
From High VA	15.0%	12.7%	16.2%
From Middle VA	50.3%	55.5%	54.3%
From Low VA	17.9%	14.9%	14.1%
One-Year Survival			
Post	88.5%	76.0%	57.5%
Pre	72.6%	72.8%	73.6%
Difference	15.9ppt	3.2ppt	-16.1ppt

The top panel shows estimated diversion ratios based on equation (F11) using the estimates in Table F1. The columns present the destination nursing homes, grouped by value added into top quintile ("High"), bottom quintile ("Low") and three middle quintiles ("Middle"). The rows present the origin nursing homes as well as the outside good. The bottom panel shows the one-year survival rate for an 85-year-old white female with a 6-day index hospital stay. The first row presents the average survival rate in the destination nursing home. The second row presents the counterfactual survival rate for marginal residents had they not chosen the destination nursing home. The last row presents the difference.

for high-quality nursing homes is $88.5 - 72.6\% = 15.9$ percentage points. Thus, expanding higher-quality nursing homes raises the one-year survival rate by 15.9 percentage points among marginal residents. In contrast, expansions of lower-quality nursing homes reduce survival by 16.1 percentage points among marginal residents.

Aggregation. Finally, we combine the estimates to assess the aggregate effects of creative financing on survival among dementia patients. There are two forces that operate in opposite directions. First, there is an *expansion effect*, which arises because municipalization draws patients into nursing homes who would otherwise have received home health care. Because one-year survival is lower under the outside option than in the average nursing home, this margin *increases* aggregate survival. Second, there is a *composition effect*, which arises because the expansion is concentrated in lower-quality nursing homes. Holding total volume fixed, this shifts care toward worse providers and *decreases* aggregate survival. As a benchmark, the volume-weighted one-year survival rate among nursing home residents before municipalization is $20\% \times 88.5\% + 60\% \times 76.0\% + 20\% \times 57.5\% = 74.8\%$.

Starting with the expansion effect, we first calculate the survival difference between nursing home care (by quality) and home care. The former is presented in Table F6 under "Post" and the latter is estimated to be 64.1%. We then multiply the difference with the increase in Medicaid days attributable to residents originating from home care. Note that we estimate increases in Medicaid volume of 11%, 9%, and 19% at high-, middle-, and low-quality nursing homes, that comprise 20%, 60%, and 20% of all nursing homes (and hence approximately days), respectively. Building on this, we calculate:

$$\begin{aligned} \Delta^{Expansion} &= 16.7\% \times 20\% \times 11\% \times (88.5\% - 64.1\%) \\ &+ 16.9\% \times 60\% \times 9\% \times (76.0\% - 64.1\%) \\ &+ 15.5\% \times 20\% \times 19\% \times (57.5\% - 64.1\%) \\ &= +0.16 \text{ ppt} \end{aligned}$$

Here, the first row corresponds to high-quality nursing homes, followed by middle- and low-quality nursing homes. Note that the third row enters with a negative sign: survival in bottom-quintile nursing homes (57.5%) falls short of survival under home health care (64.1%), so institutionalizing marginal patients in the lowest-quality facilities lowers their survival. Only the top two quality groups outperform the outside option. On net, the expansion of institutional care raises aggregate survival by 0.16 percentage points.

Turning to the composition effect, we repeat the calculation over rows 2–4 of Table F6, which record flows between nursing home groups. Within-group moves do not contribute to the calculation, since origin and destination survival coincide, leaving six terms:

$$\begin{aligned} \Delta^{Composition} &= 20\% \times 11\% \times \left[50.3\% \times (88.5\% - 76.0\%) + 17.9\% \times (88.5\% - 57.5\%)\right] \\ &+ 60\% \times 9\% \times \left[12.7\% \times (76.0\% - 88.5\%) + 14.9\% \times (76.0\% - 57.5\%)\right] \\ &+ 20\% \times 19\% \times \left[16.2\% \times (57.5\% - 88.5\%) + 54.3\% \times (57.5\% - 76.0\%)\right] \\ &= -0.25 \text{ ppt} \end{aligned}$$

The first two rows are positive: expansions at high- and middle-quality facilities draw residents from worse providers and raise survival. The third row dominates, at -0.57 percentage points, because bottom-quintile nursing homes expand fastest (19%) and draw 54.3% of their marginal residents from middle-quality facilities, a gap of 18.5 percentage points in one-year survival. Middle-quality providers are thus the principal source of the patients flowing into both tails, and the composition effect is governed by the asymmetry between those two flows.

Net effect. Combining the two margins,

$$\Delta = \Delta^{Expansion} + \Delta^{Composition} = 0.16 - 0.25 \approx -0.09 \text{ percentage points,} \tag{F12}$$

we find that creative financing lowers one-year survival among Medicaid dementia residents on net, implying that the composition effect dominates the expansion effect. The effect size is small, however, and corresponds to roughly one tenth of a percentage point.[28] Applying it to the estimated 16 thousand AD/ADRD patients in Indiana nursing homes (Kaiser Family Foundation, 2025d; for Disease Control and Prevention, 2025) would suggest that, every year, about $16{,}000 \times 0.0009 \approx 14$ patients die earlier because of the allocative inefficiencies triggered by creative financing.

This aggregate figure averages over all Medicaid dementia residents, most of whom are inframarginal. Creative financing raises Medicaid volume by 11.4% ($20\% \times 11\% + 60\% \times 9\% + 20\% \times 19\%$), so the effect among the patients whose care choice actually changes is $-0.09/0.114 \approx -0.8$ percentage points. The two margins are individually far larger than either figure suggests: among the 1.9% of baseline volume drawn out of home health care, one-year survival *rises* by 8.5 percentage points, while among patients relocated between nursing homes it *falls* by 2.6 percentage points. The small net effect thus reflects two substantial and largely offsetting reallocations rather than a uniformly small response.

[28] An alternative, and more direct, way to characterize the net effect is given by the product of each group's expansion rate, its baseline volume share, and its pre-post survival difference from the last row of Table F6. Summed across groups, we have $11\% \times 20\% \times (15.9) + 9\% \times 60\% \times (3.2) + 19\% \times 20\% \times (-16.1) \approx -0.09$ percentage points.