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

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Abstract

This paper examines the misallocation of Medicaid funds arising from "creative financing." Combining two decades of administrative, audit, and survey data on U.S. nursing homes with reduced-form and structural approaches, we show that states use creative financing schemes to maximize federal matching funds and divert them. Our theoretical and empirical analyses demonstrate that creative financing distorts the quality–quantity tradeoff in healthcare use. In Indiana, exploiting variation in the rollout of a creative financing scheme, we find a disproportionate expansion of Medicaid-funded care for dementia patients in the lowest-quality nursing facilities.

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1 Introduction

Joint funding of public programs is a cornerstone of U.S. federalism. The federal government provides local governments $1.1 trillion in grants—more than one-third of state budgets—to support a wide range of public policies, including health care (Congressional Research Service, 2025). Funding often takes the form of "federal matching grants." Matching grants aim to improve efficiency by internalizing spillover effects across states and providing insurance against economic shocks (Oates, 1999). However, they can also generate principal–agent problems when the federal government cannot perfectly monitor how federal matching funds are ultimately used. States can then use "creative financing" schemes to maximize federal funding but then redirect funds away from the intended purpose to obscure actual program spending (Committee for a Responsible Federal Budget, 2023b; Clemens and Veuger, 2025).

This paper examines how creative financing may affect the quantity-quality tradeoff in the health care sector. To our knowledge, it is the first paper to identify creative financing as a driver of institutional bias and quality shortfalls. We focus on Medicaid, the joint federal-state public health insurance program for low-income Americans, projected to cost one trillion in federal spending by 2033 (Keehan et al., 2025). The analysis centers on the nursing home industry, which accounts for $211 billion of U.S. health care spending and will become even more important, given increased longevity and demographic change. The nursing home industry relies heavily on Medicaid funding (Centers for Medicare & Medicaid Services, 2023) and has long faced quality concerns (Grabowski, 2001; Rau, 2018; Hackmann, 2019), while patients overwhelmingly prefer to age in place (Fields and Dabelko-Schoeny, 2015).

We begin by developing a simple theoretical framework that illustrates how creative financing arises from imperfect federal monitoring of state spending. The core assumption of our principal–agent model is that the federal government cannot fully observe how states ultimately use federal funds. This assumption appears realistic, given the widespread use of creative financing across states and the documented difficulty of regulators in curbing these practices. Although a 2003 reform sought to limit creative financing, such activities have persisted (Office of Inspector General, 2014; MACPAC, 2021a). Moreover, contemporaneous federal audits reveal the difficulty of tracking complex financial flows: the

Department for Health and Human Services (2025) concluded that it was "nearly impossible" to identify and follow these streams. In our model, the federal government observes quantities of care and nominal reimbursement rates, but not effective rates after funds are diverted. As a result, states have incentives to inflate nominal rates that qualify for matching funds while reducing effective provider payments through mechanisms such as "intergovernmental transfers." The ability to divert funds also incentivizes states to expand the volume of care that qualifies for matching, a phenomenon we term "public moral hazard."

We then test the model's predictions empirically. First, we present new evidence on the scope of creative financing and the diversion of Medicaid funds. By digitizing dozens of audit reports and along with representative state-level data, we document that between 2000 and 2002, 16 states used creative financing to divert at least $17 billion in Medicaid funds away from nursing homes. We estimate that nominal reimbursement rates were inflated by roughly 30% relative to effective rates, increasing the implied federal cost share of Medicaid spending—the Federal Medical Assistance Percentage (FMAP)—by 16 percentage points, substantially more than previously reported (MACPAC, 2021a).

In response to audit reports on the use of creative financing, Congress enacted legislation in 2003 to restrict its use. Under the reform, states could no longer redirect funds from *private* nursing homes through intergovernmental transfers, effectively limiting such practices to the small share of *public* nursing homes. However, Indiana responded by inducing county hospitals to acquire and municipalize private nursing homes, thereby even expanding its creative financing activities.[1] As a result, the share of publicly owned nursing homes in Indiana rose from 5% to 95% between 2000 and 2017. We combine the exact acquisition dates with administrative microdata on the universe of nursing homes in Indiana.

Employing Callaway–Sant'Anna event studies and quasi-experimental variation in the timing of these municipalizations, we then estimate the causal effect on the quantity and quality of care. Consistent with our model predictions, we find clear evidence of "public moral hazard": Medicaid days increase by 5% following municipalization, driven by dementia patients and nursing homes adding Alzheimer units. Dementia patients are especially conducive to expansion of institutional care, given their long lengths of stay, the

[1] Technically, only private nursing home licenses were acquired and assets leased, which was sufficient to trigger a change in ownership status.

limited availability of specialized dementia units, and impairments in their ability to express complaints (Mitchell et al., 2009).

However, ultimately, the welfare implications hinge on how increased nursing home use affects patient health (Baicker, Mullainathan, and Schwartzstein, 2015). Greater access to institutional care may improve outcomes (Hackmann, Pohl, and Ziebarth, 2024; Gandhi, 2023). At the same time, experience in treating patients with dementia is a key determinant of care quality (Mukamel et al., 2023), and expansion by low-quality providers may harm patients (Estrada et al., 2024). We therefore assess patient welfare by examining changes in nursing home quality following municipalization and shifts in patient sorting between nursing homes and home health care.

Specifically, building on Dubin and McFadden (1984) and Einav, Finkelstein, and Mahoney (2025), we estimate structural nursing home value-added models using distance to facilities as an instrument for provider choice (Olenski and Sacher, 2026; Einav, Finkelstein, and Mahoney, 2025). Using one-year survival and hospital readmission rates as quality measures, we first find no evidence of changes in nursing home quality following municipalization. Second, quality differences across nursing homes are large; dementia patients treated in facilities in the bottom quality quintile die sooner than similar patients who age in their community. Third and crucially, we show that lowest-quality providers overproportionally expand capacity and drive the increase in inpatient use by low-income dementia patients. This is even more concerning, given that mortality effects, although objective, solely measure extreme health outcomes.

In the final section, we assess allocative efficiency by connecting these empirical findings to our conceptual framework. Importantly, we show that creative financing distorts the quality–quantity tradeoff by encouraging expansion of low-quality care. In contrast, the efficient allocation would devote more resources to quality improvements or to expanding higher-quality facilities. Absent creative financing, Medicaid spending on institutionalized dementia patients could be two percent lower.

Our findings contribute to three strands of literature. First, we add to research on strategic behavior in fiscal federalism (Gordon, 1983; Dahlby, 1996; Knight, 2002; Agrawal, 2015; Clemens and Veuger, 2025) by showing how states use creative financing to obscure spending and divert Medicaid funds. While these practices have been examined in health policy

(Coughlin and Zuckerman, 2003b; Mitchell, 2018; Sharma and Xu, 2023), law (Hatcher, 2017), 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 payments. We show how creative financing distorts the quality–quantity margin toward lower-quality care. Our results also inform debates on Medicaid financing reform, including limits on creative financing (Kaiser Family Foundation, 2025a), changes to cost sharing (Clemens and Ippolito, 2018; LoSasso, 2025), and enhanced federal oversight (Federal Register, 2019).

Second, we contribute to the rich literature on moral hazard under asymmetric information in health care (Baicker, Mullainathan, and Schwartzstein, 2015; Eliason et al., 2018; Einav, Finkelstein, and Mahoney, 2018; Alexander and Schnell, 2024). We highlight imperfect monitoring between federal and state governments as a driver of creative financing, and study how public ownership structures can induce the expansion of low-quality care (Duggan, 2000). We also contribute to the relevance of ownership structures and organizational changes in health care more broadly (Dafny, 2019; Beaulieu et al., 2020).

Third, we contribute to research on payer design and long-term care quality (Grabowski, 2001; Werner, Konetzka, and Polsky, 2013; Dafny, 2005; Lin, 2015; Hackmann, 2019; Gandhi et al., 2026; Gandhi, Olenski, and Shi, 2025; 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). We show that creative financing lowers states' effective cost of institutional care, potentially encouraging policies that favor nursing homes over alternative care settings (Grabowski and Gruber, 2007; Mommaerts, 2018; Einav, Finkelstein, and Mahoney, 2023). Using recent advances in nursing home value-added estimation (Cheng, 2024; Einav, Finkelstein, and Mahoney, 2025; Cheng, 2025; Olenski and Sacher, 2026) and plausibly exogenous variation in ownership changes (Gupta et al., 2023; Gandhi, Song, and Upadrashta, 2026), we document that Indiana's creative financing scheme led to a disproportionate increase in Medicaid-funded care in the lowest-quality nursing facilities.

The next section discusses institutional details. Section 3 develops our simple theoretical framework and Section 4 presents reduced-form and structural empirical results.

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, as detailed below, 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. It is not clear whether creative financing is legal, leading 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 creating financing. For example, a former senior official from the Department of Health and Human Services writes:[2]

> "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

[2]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.

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, resulting in lower quality of care (Grabowski, 2001; Hackmann, 2019). Thus, states can top up Medicaid base rates through Supplemental Payments (SP) 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).[3] Supplemental Payments account for about seven percent of total Medicaid fee-for-service nursing facility payments; in 2019, $3.3 billion were disbursed to 25 states (MACPAC, 2021b).

However, states use creative financing to divert nursing home payments. Before 2003, states could divert funds from public *and* private nursing homes to county-owned nursing homes and then redirect them via "Intergovernmental Transfers." The pre-2003 regulations left states with considerable discretion in allocating Supplemental Payments across providers. States could pay hundreds of millions in Medicaid funds to nursing homes, triggering hundreds of millions more in federal matching funds for those same nursing homes. As these payments were not tied to specific services, states could redirect large portions for other purposes.

Panel A of Appendix Figure A1 illustrates such a scheme (Coughlin and Zuckerman, 2003b). 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. This illustrates one key creative financing scheme in simple terms.

[3]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 equaled $515 ($427 for managed Medicare) compared to only $209 for Medicaid (Spanko, 2019).

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 in 2003, a federal reform banned states from redirecting funds from *private* nursing homess which only had a market share of 7% at the time (Gabrel, 2000).

However, the reform affected states differently depending on their pre-reform creative financing activities. Coughlin, Bruen, and King (2004) report that 23 out of 34 states that responded to their survey used creative financing in FY 2002. Of those, 16 states used Supplemental Payment schemes in the nursing home industry, whereas 16 states did not, see Figure A2. Section 4.1 defines treatment and control groups for the 2003 reform bite accordingly. Using a simple difference-in-differences model, we then estimate the effect of the 2003 reform on the diversion of Medicaid funds.

2.4 Creative Financing 2.0: Evidence from Indiana

After the 2003 reform, Indiana implemented a scheme that expanded pre-2003 reform practices. This scheme is the focus of our empirical analysis. We exploit it to estimate the causal effects of creative financing on patient volume and health.

Specifically, to bypass the 2003 reform, Indiana induced county-owned hospitals to acquire private nursing homes, thereby municipalizing them. Once public, the state reinstated Intergovernmental Transfers to continue 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)).

In particular, Indiana provided per diem and supplemental payments to newly acquired county-owned nursing homes of an integrated hospital-nursing home system. Federal matching funds then augmented these payments. The county-owned hospitals would then redirect funds from the nursing homes, with a portion returned to the state budget (Hatcher, 2017). Panel B of Appendix Figure A1 illustrates the scheme in Indiana: Under a contractual agreement, county hospitals repaid the state's share of supplemental pay-

ments while retaining the federal match, which was divided between hospitals and nursing homes. Because federal matching funds were proportional to Medicaid service days, the integrated hospital-nursing home system had strong incentives to increase patient volume.

Pioneering the model was the Health and Hospital Corporation (HHC) of Marion County—a government entity. In 2003, it acquired and municipalized 17 nursing homes. By 2009, HHC owned 40 nursing homes, see Figure 1a.

[Insert Figure 1 about here]

In 2010, conversion activities accelerated as shown in Figure 1. The Indiana legislature passed Senate Bill 292, explicitly allowing county hospitals to own, operate, or contract with nursing homes as "health facilities" (Indiana Legislature, 2010). This broadened the legal authority for such acquisitions by removing uncertainty about whether a county hospital could legally own a nursing home. It also clarified that doing so was a permissible health care activity. Overall, Bill 292 effectively lowered legal barriers to municipalization.

Instead of directly acquiring nursing homes to facilitate, Indiana enabled HHC to use a "lease structure" to technically convert nursing homes on paper (Pahud and Myers, 2016). It allowed HHC to acquire the nursing home license while leasing the remaining assets. Such as lease structure still triggered a change of ownership without altering the nursing home management, which typically retained 5-20% of the additional Medicaid payments (Hatcher, 2017). As seen in Figure 1, by 2017, over 90% of nursing homes were county-owned.

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, investiga-

tions by The Indianapolis Star revealed that, of these $4.3 billion, between $1 and $3 billion have 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

The previous section shows that, despite reforms aimed at containing them, states continue to develop sophisticated creative financing schemes. These schemes allow lower-level jurisdictions to divert funds from their intended purposes.

This section develops a unifying theoretical framework to study how creative financing distorts the allocation of care between quality and quantity. Building on Holmstrom and Milgrom (1991), we analyze a multitask principal–agent problem with monitoring frictions. The Principal is the federal government, and the Agent is the state or county health care system. The Agent exerts effort along two dimensions—care volume and effective spending—but the Principal can only imperfectly monitor the latter. As a result, the Agent inflates the monitored dimension while reducing the non-monitored one, see Appendix B for details.

3.1 State and Federal Payoffs

State ("The Agent"): The state derives utility $B(\theta, Q)$, measured in dollars, from the quality (θ) and quantity (Q) of nursing home care. Due to cross-state spillovers, the state internalizes only a fraction $\tau \leq 1$ of these benefits.[4] The federal government reimburses a fraction of nominal Medicaid spending ($P \times Q$) through the FMAP, where P denotes the nominal reimbursement rate.[5] Providers, however, receive the *effective* reimbursement rate R, net of diverted funds, with $(P - R) \times Q$ redirected. We assume that quality increases

[4] Alternatively, τ may capture competing budget priorities.

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

with effective reimbursement, i.e., $\partial\theta(R)/\partial R > 0$.[6] The state then chooses (P, R, Q), but only P and Q are observable to the federal government. State utility is therefore:

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

Federal Government ("The Principal"): The federal government internalizes externalities across states, net of the federal reimbursement costs, and has utility:[7]

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

3.2 Social Welfare

Social welfare is $W = U^a + U^p = B(\theta(R), Q) - R \times Q$.[8] Maximizing welfare yields:[9]

$$B_R(\theta(R), Q)/Q = 1 \tag{3}$$
$$B_Q(\theta(R), Q)/R = 1 . \tag{4}$$

At the optimum, the marginal benefits of effective spending and care volume equal marginal costs.

3.3 Optimal Contracting Under Perfect Monitoring ($P \times Q = R \times Q$)

With perfect monitoring, $P \times Q$ can be replaced by $R \times Q$ in (1), yielding:

[6] Here, quality is an unspecified function of R , following the literature. Below, in the empirical part, quality may change because (a) a higher patient volume may induce more patients to select higher quality nursing homes, (b) care quality may increase among existing patients, the mechanism implied by $\partial\theta(R)/\partial R > 0$, and (c) lower-quality nursing homes may increase volume overproportionally, which is another theoretical prediction, see H3. We will provide empirical evidence for (a) to (c).

[7] An alternative formulation of the Principal's payoff is $U_p = B(\theta(R), Q) -$ State Utility.

[8] In general, the federal government's objective function differs from the social welfare function (Sieg and Yoon, 2025). Also note that we refrain from explicitly modeling the distortionary costs of taxation (or debt) to fund R at the state level and the matching funds at the federal level.

[9] $B_R \equiv B_Q(\theta(R), Q) \times \frac{\partial\theta(R)}{\partial R}$.

$$\tau \times B_R(\theta(R), Q)/Q = 1 - FMAP \quad (5)$$
$$\tau \times B_Q(\theta(R), Q)/R = 1 - FMAP\,. \quad (6)$$

Setting $\tau = 1 - FMAP$ implements the first-best. The FMAP acts as a Pigouvian subsidy internalizing the externality $(1 - \tau)$.[10]

3.4 Optimal Contracting Under Imperfect Monitoring ($P \neq R$)

We now consider the empirically relevant case where the federal government observes care volume Q 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:

$$\max_{P \leq \bar{P}, R, Q} \tau \times B(\theta(R), Q) + FMAP \times P \times Q - R \times Q\,. \quad (7)$$

with first-order conditions:

$$P = \bar{P} \quad (8)$$
$$\tau \times B_R(R, Q)/Q = 1 \quad (9)$$
$$\tau \times B_Q(R, Q)/R = 1 - FMAP \times \frac{\bar{P}}{R} = 1 - FMAP \times \mu. \quad (10)$$

Three predictions follow. First, imperfect monitoring induces states to inflate nominal rates to the cap, creating a wedge between P and R—a "public markup." This lowers health care quality as $\partial\theta(R)/\partial R > 0$.

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 cost share. The effective FMAP equals $FMAP \times \mu$, which incentivizes states to expand care volume Q—a mechanism we term "public moral hazard."

[10] Allowing τ to vary with fiscal capacity rationalizes income-based FMAP formulas.

Hypothesis 2 (H2) ***Public Moral Hazard****: The possibility to divert* $(P - R) \times Q$ *encourages state expansion of jointly funded care volume* Q*, raising the effective federal cost share to* $FMAP \times \mu$*.*

Third, higher public markups amplify public moral hazard. Since lower R implies lower quality, volume expansion is strongest among lower-quality programs.

Hypothesis 3 (H3) ***Complementarity of Public Markup and Public Moral Hazard****: Higher public markups, and ceteris paribus lower* R *and* θ*, imply stronger incentives to expand jointly funded care volume* Q*.*

[Insert Figure 2 about here]

Graphical Illustration. Figure 2 illustrates these mechanisms. The vertical axis denotes quality (θ), increasing in effective rates (R). The horizontal axis denotes quantity (Q).[11] Convex curves represent state indifference curves. Under perfect monitoring, the budget constraint 'C' is independent of the FMAP, and the expansion path 'I' reflects aligned incentives. Under imperfect monitoring, creative financing rotates the budget constraint outward to 'D'. The slope depends on $FMAP \times \mu$ and equals $-(1 - FMAP \times \mu)$. The new expansion path 'II' reflects increased volume and reduced incentives to raise effective rates, generating socially inefficient allocations.

Social Welfare. Finally, we maximize social welfare, $\max_{\tilde{P},FMAP} B(\theta(R), Q) - R \times Q$, subject to equations (9) and (10). States maximize nominal rates, $P = \bar{P}$; thus, we focus on $\tilde{P} = \bar{P} \times FMAP$ as the relevant case. The first order condition with respect to $\tilde{P}$, see Appendix Section B.2, implies:

$$(1 - \tau) \cdot \underbrace{\frac{d(R \times Q)}{d\tilde{P}}}_{\text{Positive Externality}} - \underbrace{\tilde{P} \cdot \frac{dQ}{d\tilde{P}}}_{\text{Public Moral Hazard}} = 0 \,. \tag{11}$$

On the one hand, a 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, a higher $\tilde{P}$ distorts the price-quantity tradeoff through public moral hazard, as captured by the second term.

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

Discussion. When effective spending cannot be monitored, creative financing distorts the quality-quantity tradeoff by encouraging low-cost volume expansion. In long-term care, this biases policy toward low-quality institutional care and away from home- and community-based alternatives. More broadly, our framework illustrates how imperfect monitoring in joint funding arrangements can systematically distort policy choices toward instruments that expand volume at relatively low fiscal cost.

4 Data, Empirical Approaches, and Results

The following three subsections examine the impact of creative financing on provider reimbursement ("public markups"), publicly funded inpatient care volume ("public moral hazard"), and quality of care. We organize the discussion of the data, the empirical strategy, and the results within each subsection accordingly.

4.1 How does Creative Financing Affect Effective Provider Reimbursement (H1)?

This subsection studies how creative financing may create a wedge between nominal and effective reimbursement rates, the "public markup", see Hypothesis **H1**. It produces empirical estimates of nominal spending qualifying for federal matching funds ($P \times Q$), effective spending ($R \times Q$), and an estimate for the diversion of fund:, $(P - R) \times Q$. We then assess the public markup $\mu = P/R$. To estimate these parameters, we combine several data sources, see Data Appendix C.

Data & Empirical Approach: First, we employ the On-Line Survey, Certification, and Reporting (OSCAR) system at the state-year level from 2000-2007 (Long-Term Care: Facts on Care in the U.S., 2025). The data cover all U.S. Medicaid and Medicare-certified nursing homes (98% of all nursing homes) and provide, at the state-year level (a) average Medicaid base per diem rates, and (b) total Medicaid days in nursing homes. The product of the two is a measure of effective nursing home spending, $R_{st} \times Q_{st}$, for state s in year t.

Second, we use the Medicaid Budget and Expenditure System (MBES), at the state-year level for the same time period. The dataset provides Medicaid spending data (Centers for Medicare & Medicaid Services, 2020a) with summaries from Form CMS-64. We use the

data to measure total nominal spending on nursing homes by state and year, $P_{st} \times Q_{st}$. Combining the two data sources, the public markup is $\mu_{st} = \frac{P_{st} \cdot Q_{st}}{R_{st} \cdot Q_{st}} = \frac{P_{st}}{R_{st}}$.

To test hypothesis **H**1, we use a simple 2x2 difference-in-differences (DD) model comparing the markups among the 15 states with pre-2003 creative financing schemes (treatment group) to those 16 states without pre-2003 creative financing schemes (control group), see Figure A2: $Y_{st} = \gamma_s + \gamma_t + \beta \times CF_s \times Post_t + \epsilon_{st}$ where Y_{st} is the markup in state s of year t and γ_s and γ_t denote state and year fixed effects. CF is one for states with a creative financing pre-2003 and $Post$ is one for post 2003 years. Then, β measures the differential impact of the 2003 reform for states with a pre-existing creative financing scheme. We will test the plausibility of the common time-trends assumption graphically and hypothesize that the markup Y_{st} will decrease following the 2003 reform.

Results: Figure 3 displays our public markup measure ($\frac{P}{R}$) over time, separately for the treatment and control groups. The x-axis shows calendar years from 2000 to 2007. We interpret Figure 3 as showing a "reverse" DD design with reasonably stable, similar, and parallel time trends in the post-2003 years, showing only minor differences in the markup in post-reform years between treated and controls. After 2003, we observe a significantly lower markup of less than 1.1, suggesting that the reform worked nationally as intended.

[Insert Figure 3 about here]

Importantly, consistent with **H**1, we find a public markup of about 1.3 among states that engaged in creative financing pre-reform, implying that the effective FMAP was 30% higher than the nominal FMAP. The validity of our markup measure and the research design is reinforced by the absence of a wedge for the control states. Concurrent with the 2003 reform, the treatment states markup decreased swiftly.

More formally, Panel A of column (1) in Table C2 (Appendix) shows a 0.27 decrease in the markup and a 16 pp reduction in the effective FMAP through the reform. Considering nominal Medicaid spending on nursing home care between 2000 and 2002 among states in the treatment group, states diverted about 0.3×\$58bn=\$17bn (≈\$30bn in 2026 dollars) over just three years. Equivalently and reassuringly, columns (3) and (4) of Table C2 (Appendix) show reductions in nominal federal and state expenditures on Medicaid inpatient long-term care by \$167 and \$118 million per year and state.

Panel B of Table C2 (Appendix) shows no evidence for significant changes in staffing levels that accompanied the reduction in the markup. The last column in Panel B shows a test of **H**2). It shows suggestive evidence that Medicaid days decreased by 3% in treatment states when the scope of creative financing was reduced. However, some states quickly adjusted to the new realities, closing their funding gaps. For instance, in September 2003, Pennsylvania passed the Nursing Facility Assessment Law (Commonwealth of Pennsylvania, 2005) in response to the 2003 reform: The bill says "*To forestall rate reductions and to avoid significant changes in eligibility or covered services, or both, the General Assembly passed Act 25 to enable the Commonwealth to qualify for a new source of increased federal funds.*" Likewise, Indiana introduced new creative financing operations, see Section 4.2.

Evidence from OIG Audit Reports. Next, we digitize 24 audit reports from 18 states to provide additional evidence on effective provider reimbursement, see Appendix Section C. These Office of Inspector General (OIG) audit reports by the Department for Health and Human Services (2025) provide direct estimates of the size of intergovernmental transfers and the amounts of redirected funds away from nursing homes. Appendix Figure C1a shows an average markup of 24% in states with creative financing schemes. This estimate is close to the DD estimate in column (1) of Appendix Table C2. Furthermore, Appendix Figure C1b indicates that the effective FMAP was up to 33 percentage points higher than the nominal FMAP. Furthermore, Appendix C provides additional consistent evidence on the magnitude of markups and creative financing operations from the Health and Hospital Corporation of Marion County in Indiana, see Section 2.4.

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

This subsection studies how creative financing may affect the volume of nursing home care, coined "public moral hazard" in Section 3, see Hypothesis **H**2. To do so, we zoom into the state of Indiana.

After the 2003 reform, Indiana continued and even intensified its creative financing activities. Specifically, the Health and Hospital Corporation (HHC) pioneered this model in collaboration with state representatives; see Section 2.4. In 2003, HHC began to acquire nursing homes to continue and even expand its creative financing activities and maxi-

mize revenue from federal taxpayers. Consequently, the number of county-owned nursing homes skyrocketed from 5 to 95% between 2000 and 2017, see Figure 1.

In what follows, we exploit the municipalization of formerly private nursing homes in a staggered DD design to study its impact on Medicaid volume. As only the ownership status changed on paper through a transfer of licences, but the management generally did not change, we view the change in ownership status as a clear indicator for implementing a creative financing scheme.

Data & Empirical Strategy: To do so, we combine three data sources, see Appendix D. First, we extract information on municipalizations—that is, ownership status changes—from (i) Nursing Home Compare, (ii) Indiana Department of Health (2020) data and (iii) reports by the IndyStar newspaper (Centers for Medicare & Medicaid Services, 2020b; Gillers et al., 2010). Second, we use LTC Focus data as above, but now at the *nursing-home*-year level from 2000 to 2015. As discussed, these data include nursing home characteristics. Third, we aggregate administrative patient-level data from the Long-Term Care Minimum Data Set (MDS) to the nursing home-year level to merge it with the other data sources. MDS is administrative data containing all Indiana Medicaid- and Medicare-certified nursing homes from 1999 to 2015.

To keep the sample composition stable over time, we balance our sample in calendar time at the nursing home-year level. Further, we focus on nursing homes with at least one Medicaid patient in 2000. As such, we obtain a sample of 368 nursing homes, which we follow for 17 years (1999-2015). Table D1 shows that, on average, nursing homes have 108 beds and an occupancy of 80%. Occupancy is also the only indicator that is substantially imbalanced between early and late acquisition status (Table D2), according to the normalized difference measure of Imbens and Wooldridge (2009). Nursing homes acquired after 2011 have significantly higher occupancy rates (78% vs. 70%) but a similar share of Alzheimer Special Care Units (39% vs. 42%), a similar acuity index (11.1 vs. 11.1), and a similar Registered Nurse hours-per-resident-day ratio (0.25 vs. 0.22).

Tracking 368 nursing homes from 1999 to 2015 ensures sufficient event-time coverage at the annual level and allows us to estimate medium- to long-term effects in Callaway and Sant'Anna (2021) event studies, see Appendix Section E. The CS-DD model compares changes in municipalized nursing homes with those in non-municipalized nursing homes.

In other words, since 95% of nursing homes were eventually municipalized, we omit the select group of never-treated and use the not-yet-treated as controls. Standard errors are clustered at the nursing home level.

Results: Figure 4 contains four CS event studies visualizing the impact of creative financing (via municipalization) on (a) for-profit status, (b) Medicaid days, (c) Medicaid days by dementia patients and (d) Alzheimer's units. As seen, we find no pre-trends in the years leading up to municipalization, but tight estimates around zero.

[Insert Figure 4 about here]

First, Figure 4a serves as a falsification exercise and shows a sharp decline in for-profit status beginning at event time 0, the year of municipalization. The effect size is approximately -0.6 three years post-acquisition, consistent with the fact that 59% of all nursing homes are for-profit on average (Table D1). The average treatment effect on the treated (ATT) is -0.54 and highly significant, see column (1) of Panel A in Table 1, which displays all pooled and averaged CS-DD regression estimates for Figure 4.

Figure 4b shows the impact on the number of Medicaid days per year. Starting in year 1 after the acquisition, the number of Medicaid days increases, confirming hypothesis **H**2. In fact, four years post-acquisition, converted nursing homes provided about three thousand additional Medicaid days, corresponding to 8.2 full-year residents and 11% of the mean (Table D1). Pooled over the post-reform years, we estimate an increase of 1,360 Medicaid days per year, see column (2) of Panel A in Table 1, or a 4.9% increase.

[Insert Table 1 about here]

Investigating the underlying mechanisms in Figures 4c and d, we find that patients with Alzheimer's disease and Alzheimer's disease-related dementias (AD/ADRD) drive the increase in Medicaid days.[12] Figure 4c shows the change in Medicaid days for the subpopulation of AD/ADRD patients. As seen, it mirrors the pattern in Figure 4b, with an

[12]We identify AD/ADRD patients based on their initial health assessment in nursing homes. To do so, we integrate MDS 2.0 with MDS 3.0 data, selecting patients with the Section I diagnosis indicators I1q or I1u active (MDS 2.0).

average post-acquisition effect of 1178 more Medicaid days per year and nursing home, a 12% increase, see column (3) of Panel A in Table 1.[13]

Note that dementia patients are a suitable target group for expanding public inpatient care, given their low discharge probabilities, long lengths of stay, and shortage of nursing home beds for dementia patients. Furthermore, note that 38% of all Medicaid days in our sample are among patients with dementia and that Medicaid reimbursement is risk-adjusted via the Case Mix Index. Consistent with more nursing home utilization by dementia patients, Figure 4d shows an increase in the share of nursing homes with Alzheimer's special care units by 9 pp, see Figure 4d and column (4) of Panel A in Table 1.

4.3 How Does Creative Financing Affect Quality of Care?

This subsection studies how creative financing may affect quality of care and, by extension, patient health, see Section 3 and Hypothesis **H**3. To do so, we continue to study Indiana's creative financing activities as proxied by the conversion of private nursing homes.

Following municipalization, *ceteris paribus*, care quality could increase or decrease, for instance, through more specialization via the addition of Alzheimer's special care units. Moreover, volume expansions may cause patient relocation between (i) nursing homes of different qualities as well as (ii) home health care and nursing home care.

To disentangle the underlying mechanisms and assess them separately, building on Dubin and McFadden (1984); Abdulkadiroğlu et al. (2020); Einav, Finkelstein, and Mahoney (2025), we specify and estimate a model of patient health value added that accounts for patient selection. In particular, we enhance the standard nursing home value-added models by modeling home health care as an outside option. To control for selection into nursing homes, we use the distance from the patient's residence to all nursing homes within a 50-mile radius as an instrument. Appendix F provides further details on the method and sample.

[13] Long stays surpassing 100 days drive this increase, see Appendix Figure D1. Concurrently, we find no change within 100 days—the maximum number of days covered by Medicare, see Appendix Figure D2. This suggests that the prolonged stays are not due to longer survival.

Choice sets: Given the findings above, we focus on dementia patients, discharged from hospitals *after acute care stays*. We do so for the following reasons. First, two-thirds of dementia patients in nursing homes are admitted from an acute care hospital, a central admission channel. Second, 12% of dementia patients have Medicaid as a payer (Table D4). Third, following a hospital discharge, patients or their surrogates have to make an active choice about follow-up care. Our administrative data record this nursing home vs. home health care choice, as well as subsequent health outcomes. The patients' choice sets comprise all nursing homes within a 50-mile radius of the patient's pre-hospitalization address. An average patient has 74 nursing homes and the outside good (home health care) in her choice set.[14]

Data & Sample: We again use administrative claims data, but keep the data at the *patient-stay* level as we intend to follow patients, not nursing homes. We then identify all hospital stays with Clinical Classification Software 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. To identify subsequent nursing home stays, we merge these index hospital stays with MDS data, yielding 206,833 hospital index stays; see Table D4. The final dataset comprises patients with an average age of 83 years, who are 90% white and have a 1-year survival rate of 67%. After the acute hospital stay, 37% were discharged to a nursing home, and the 90-day hospital readmission rate was 31%.

Mixed Logit Model (First Stage): We estimate a mixed logit model, enhanced with an outside good for home health care. This first stage models the nursing home choice and specifies patients' utility, see equation (F1) (Appendix). The random coefficient captures substitution between inside goods (nursing homes) and the outside good (home care).

Health Outcomes (Second Stage): The second stage models patients' health outcomes, given the nursing home choice in the first stage. We measure health via one-year survival and hospital readmission rates. Underlying latent health m_{ijt} is given by:

[14] We drop a small share of patients who choose a nursing home more than 50 miles away from the centroid of their home addresses' zip codes.

$$m_{ijt} = \alpha_j + \alpha_t + x'_{ijt}\alpha^x + \epsilon_{it}, \tag{12}$$

where x_{ijt} denotes observable patient (i), nursing home (j), and year-specific (t) characteristics. Further, α_t denotes year fixed effects and α_j denotes the value-added of nursing home j to patient health. As usual, ϵ_{it} is the normally distributed error term.

Instrument: As we only observe outcomes at endogenously chosen nursing homes, we need an instrument shifting variation in choice. Importantly, the instrument must affect patient health only through the choice of nursing home ("validity of exclusion restriction"). Following the literature, we use the distance between a patient's home address and any nursing home in her choice set as an instrument. As shown below, distance is a key determinant of provider choice ("relevance"). For a discussion on distance as a valid instrument, see Einav, Finkelstein, and Mahoney (2025), Dubin and McFadden (1984) and Appendix Section F. We first estimate the mixed logit choice model, construct control functions, and estimate the parameters of equation (12) via simulated maximum likelihood.

First Stage Results: Panel A of Table F1 (Appendix) presents select parameter estimates from the first stage, all statistically significant at the 95% level. Distance to nursing homes is an important predictor of choice and thus a relevant instrument. Consistent with the previous findings, discharges to a municipalized nursing home become more likely after a hospital stay, by about 5%.[15] Further, after a hospital stay, older dementia patients are more likely to be admitted to a nursing home, as are women, white patients, and patients with longer hospital index stays. The random coefficient, σ, carries a large standard deviation, implying large heterogeneity in choice preferences, consistent with the literature.[16]

[15] Using the point estimate from Table F1, we have $\frac{\frac{\partial s_{ij}}{\partial Post}}{s_{ij}} = 0.05 \times (1 - s_{ij})$. 37% choose nursing homes, divided by 74 nursing homes in the average choice set, suggesting $s_{ij} \approx (37\%)/74 = 0.5\%$. This suggests an average effect size from municipalization on admissions from acute care hospitals of $5\% \times (1 - 0.005) \approx 5\%$.

[16] A one standard deviation drop in the random coefficient corresponds to the effect size of an extra 42 life years (0.42×18.01=7.6).

Second Stage Results: Panel B of Table F1 presents estimates for equation (12). Importantly, municipalizations do *not* significantly increase survival. The 95% confidence interval indicates that survival is unlikely to increase by more than 3.7% or decrease by more than 1.6%.

Nursing Home Valued-Added: Figure F1a (Appendix) shows the value-added estimates, α_j from equation (12), based on one-year survival as shown on the vertical axis. Eighty percent of nursing homes have higher survival rates than the outside good. Further, consistent with Einav, Finkelstein, and Mahoney (2025), we find substantial heterogeneity in value added across nursing homes. The difference between the 10^{th} and 90^{th} percentiles is similar to the differences in one-year survival between a 65-year-old and a 100-year-old.

Figure F2 (Appendix) shows a scatterplot of the valued-added estimates (α_j) and the control function coefficients (ϕ_k) of equation (F4). We find a strong negative relationship, again as in Einav, Finkelstein, and Mahoney (2025), consistent with adverse selection. Robustness checks in Appendix F validate our value-added measures using other indicators such as readmission rates, staffing ratios and CMS star ratings (Figure F5 and Tables F2, F3). We also replicate the structural estimates using 30 and 90-day hospital readmission rates as health outcomes (Figure F4 and Table F4).

4.4 Does Creative Financing Induce Low Quality Providers to Expand (H3)?

To test **H**3, we now investigate whether lower-quality nursing homes drive the expansion of publicly funded nursing home care. To recall, **H**3 hypothesizes that, *ceteris paribus*, institutions with higher markups—implying low effective reimbursement rates and thus low quality—have stronger incentives to expand Medicaid-funded nursing home care. Having already focused on a state with documented creative financing activities, we now test whether, within this state, lower-quality nursing homes are more likely to increase volume following municipalization. Figure 5 shows clear evidence in line with **H**3.

[Insert Figure 5 about here]

After municipalization, lower-quality nursing homes (Figure 5b) show disproportionately larger increases in Medicaid days compared to higher-quality nursing homes (Figure

5a). Specifically, Panel B of Table 1 shows an increase of 1952 dementia-related Medicaid days per year in lower-quality nursing homes, a 19% increase (column (1)). In higher-quality nursing homes, the increase is 11% (column (2)). One contributing factor is excess capacity. The third and fourth columns of Table 1 indicate that the volume increase is concentrated in nursing homes with less than 90% occupancy in 2000, before municipalization, when volume expansion incentives were still muted.

One-Year Survival. When connecting the differential volume expansions with the one-year survival estimates in Table F5, it yields two effects: First, a (i) "volume expansion effect" that *reduces* aggregate mortality as average nursing home mortality is lower than for the outside good.[17] Second, a (ii) "relocation effect" that *increases* aggregate mortality as lower-quality nursing homes expand volume overproportionally. To quantify the net effect, we cross-multiply the mortality with the volume effect, resulting in a one percentage point net *decrease* in aggregate survival due to municipalization.[18] This implies a reduction in allocative efficiency due to creative financing.

4.5 Misallocation

In a very final step, we connect the empirical findings to the conceptual framework in Figure 2 to assess allocative efficiency in health care. We treat the public hospital-nursing home system as "the Agent" and the federal government as "the Principal."

Agent's Benefits and Costs: First, the benefit function of a representative hospital-nursing home system is approximated via a translog function:[19]

[17] Assume a 10% volume expansion across all nursing homes. As only about 16.6% of the volume expansion results "from outside" patients who would have otherwise chosen home health care (Table F5), we expect a 16.6%/10%=1.66% increase in Medicaid days. Taking a weighted average from the last row in Table F5, the mortality effect is then -1.9 pp: 0.2×-15.9 pp (high) + 0.6×-3.2pp (medium) + 0.2×16.1 pp (low) ≈ -1.9 pp.

[18] Specifically, we calculate 11% × -15.9 pp (high) + 9% × -3.2pp (medium) + 19% × 16.1pp (low)= 1 pp

[19] Appendix Section G.1 uses CES preferences, which can explain the ratio of quality to cost, but not levels.

$$B(\theta, Q) = v(\theta, Q) + \pi(\theta, Q) \tag{13}$$

$$\approx \gamma \left[\alpha_0 log(Q) + \alpha_0 log(\theta) + \alpha_1 log(Q)^2 + \alpha_2 log(\theta)^2 + \alpha_3 log(Q) log(\theta) \right] \tag{14}$$

Equation (13) includes benefits, $v(\theta, Q)$, and revenues, $\pi(\theta, Q)$, both depending on volume, Q, and quality, θ. Quality is the one-year survival rate and proportional to average variable costs: $log(\theta) = 1 - m_{NH} = \beta \times log(AC)$. We model diverted revenues via creative financing in the cost function: Without creative financing, total costs equal variable costs (AC) multiplied by volume (Q). With creative financing, $FMAP \times (P - R) \times Q$ is diverted.[20]

$$log(Costs) = \begin{cases} log(Q) + log(AC) & \text{No CF} \\ log(Q) + log(AC - FMAP \times (P - R)) & \text{CF}. \end{cases} \tag{15}$$

Calibration: In Appendix G, we calculate a 0.3 ppt decrease in one-year survival rates, suggesting that about 50 patients per year die earlier due to allocative inefficiencies triggered by creative financing, given 16,000 dementia patients in Indiana nursing homes (Kaiser Family Foundation, 2025d; for Disease Control and Prevention, 2025). NRZ: Martin, ich blick hier selbst nicht mehr genau durch, wieso sind es jetzt 0.3 ppt, wenn es in der Vorsection 1 ppt waren?

Next, we solve for the first-order conditions and combine them with the estimated changes in volume and mortality to calibrate the unknown model parameters. With creative financing, the slope of the cost curve flattens from -1 to $-(1 - FMAP \times \frac{P-R}{AC})$.[21] Figure 6 illustrates the quality-quantity tradeoff based on the empirical evidence from Indiana.

[20] We assume that only the federal share can be diverted.

[21] The base Medicaid reimbursement is cost-based. Following the literature, we assume they are approximately equal to average costs, $AC = R$, and use the estimates from Section 4.2 to arrive at a slope of $-(1 - 0.68 \times \frac{5.5-3.2}{3.2}) = -0.51$. In equation (14), we set $\gamma = 20$ and $\beta = 0.64$, such that $AC = R$. Further, we normalize log volume without creative financing to one, and calibrate the four α parameters to match model predictions, yielding: $\alpha_0 = 1.57, \alpha_1 = -0.8, \alpha_2 = -1.02$ and $\alpha_3 = 0.68$.

The horizontal axis denotes log Medicaid dementia patient days per nursing home and year. The vertical axis denotes one-year survival rates. The red circle denotes the allocation without creative financing, and the solid gray upward-sloping line denotes the expansion path without creative financing. The red diamond denotes the allocation with creative financing, situated below the optimal expansion path, and the dashed black upward-sloping line denotes the expansion path with creative financing.

[Insert Figure 6 about here]

To connect the figure to the theory in Section 3.4, we have added the allocations in blue, with the nominal reimbursement rate increasing gradually from R (at the red circle) to P (at the red diamond). The figure shows that one could achieve the same benefit at 1.7% lower costs when choosing a quality-quantity bundle on the expansion path without creative financing, see the black pentagon-shaped point NRZ: Ist nicht so ganz klar, wie man zu den 1.7% geringeren Kosten kommt Martin. R1 wollte auch gerade ein anderes Framing in "wie viel mehr Qualität, also weniger Tote, für denselben Preis. Scaled by Indiana's $1.8 billion annual Medicaid spending on dementia stays, this amounts to $310 million over a decade.[22]

Moreover, although objective, mortality is an extreme outcome, whereas measures of quality of life are systematically unavailable for dementia patients due to obvious issues with self-reported measures. However, investigative reporting has documented severe quality shortfalls in Indiana's nursing home industry, which only ranks 33^{rd} among U.S. states (Gillers et al., 2010; Evans, Hopkins, and Cook, 2020c; US News & World Report, 2025). Given the estimated increase of 1952 Medicaid days per year for *each* of the roughly 90 (one-fifth of 450, see Figure 1) lower-quality nursing homes in Indiana, dementia patients spent 176,000 additional days per year in lower-quality nursing homes.

NRZ: Hier brauchen wir m.E. 1-3 konkrete Policy proposals, sonst ist die Ref Reaktion eher "okay so what?" Wir hatten ja schon (i) UPL auf R setzen (ist aber inkonsistent, wenn R unobserved), (ii) SP ganz abschaffen, (iii) block grants, (iv) besteuern. Vielleicht

[22] In Indiana, the daily Medicaid base rate for nursing homes is $298, plus a $108 supplemental rate (Stulick, 2025). At least 90% of the state's 500 nursing homes participate in creative financing, each providing 10,000 Medicaid dementia days annually. Thus, total annual spending is $90\% \times 500 \times 10,000 \times (\$297.4 + \$108.3) \approx 1.8$ billion.

ist der Steuervorschlag der interessanteste und praktischste, solange die Feds die Tax Base beobachten können...

5 Conclusion

This paper shows that "creative financing" can induce low-quality health care providers to expand capacities. It can bias the quantity-quality tradeoff within inpatient facilities and reinforce other existing biases toward institutionalized long-term care in the United States.

We first document that many states do employ creative financing. Specifically, we find that such practices inflated nominal Medicaid spending on nursing homes by about 30%. As states systematically diverted funds from nursing homes, the actual (or effective) federal cost share (FMAP) was 16 percentage points higher than the nominal one, significantly more than previously documented.

Next, we zoom into the state of Indiana to document consequences for allocative efficiency. To circumvent a 2003 federal reform that aimed to restrict the scope of creative financing, Indiana aggressively municipalized formerly private nursing homes to continue and expand their creative financing practices. Consequently, the share of public nursing homes in the state increased from 5% to 95% in less than two decades. Using reduced-form Callaway and Sant'Anna (2021) difference-in-differences models, we find that, following the municipalizations and in line with our theoretical predictions, the care volume increased significantly and in the long run, an effect we coin "public moral hazard."

Importantly, to assess welfare consequences, we evaluate the Indiana scheme's impact on patients' health. Specifically, we enhance the standard nursing home value-added model by including home health care as an outside option. We then structurally estimate the mixed logit model using administrative microdata. Holding patient composition constant, we find no notable change in nursing home quality following municipalization. However, quality heterogeneity is substantial. Consistent with our theoretical predictions, the largest volume expansion occurred among the bottom 20% of nursing homes.

Studying the implications for allocative health care efficiency, in the final part, we show that creative financing can alter the quality-quantity tradeoff by promoting the expansion of low-quality programs. Reallocating Medicaid funds to improve quality or increase use

at higher-quality facilities could produce the same quality-quantity distribution at two percent lower costs in this specific case; effects are potentially much larger if one could consider broader quality-of-life measures, which, however, is nearly impossible among dementia patients.

The central insight from our analysis is that creative financing schemes can redirect federal and state funds earmarked for improving care quality while encouraging the expansion of low-quality public health care. Creative financing thus helps explain the persistently low effective Medicaid reimbursement rates, which contribute to systematic quality shortfalls in the nursing home industry (Grabowski, 2001; Hackmann, 2019). Despite widespread preferences among older adults to age at home (AP-NORC, 2021), *"[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 is the first paper to identify creative financing as a driver of this institutional bias and quality shortfalls. This explanation complements other policy factors contributing to this bias, including Medicaid's fee-for-service reimbursement (Hackmann, Pohl, and Ziebarth, 2024), eligibility standards (Grabowski and Gruber, 2007; Mommaerts, 2018), and lack of home and community-based care alternatives (Muramatsu et al., 2007; Guo, Konetzka, and Manning, 2015; Wang et al., 2020).

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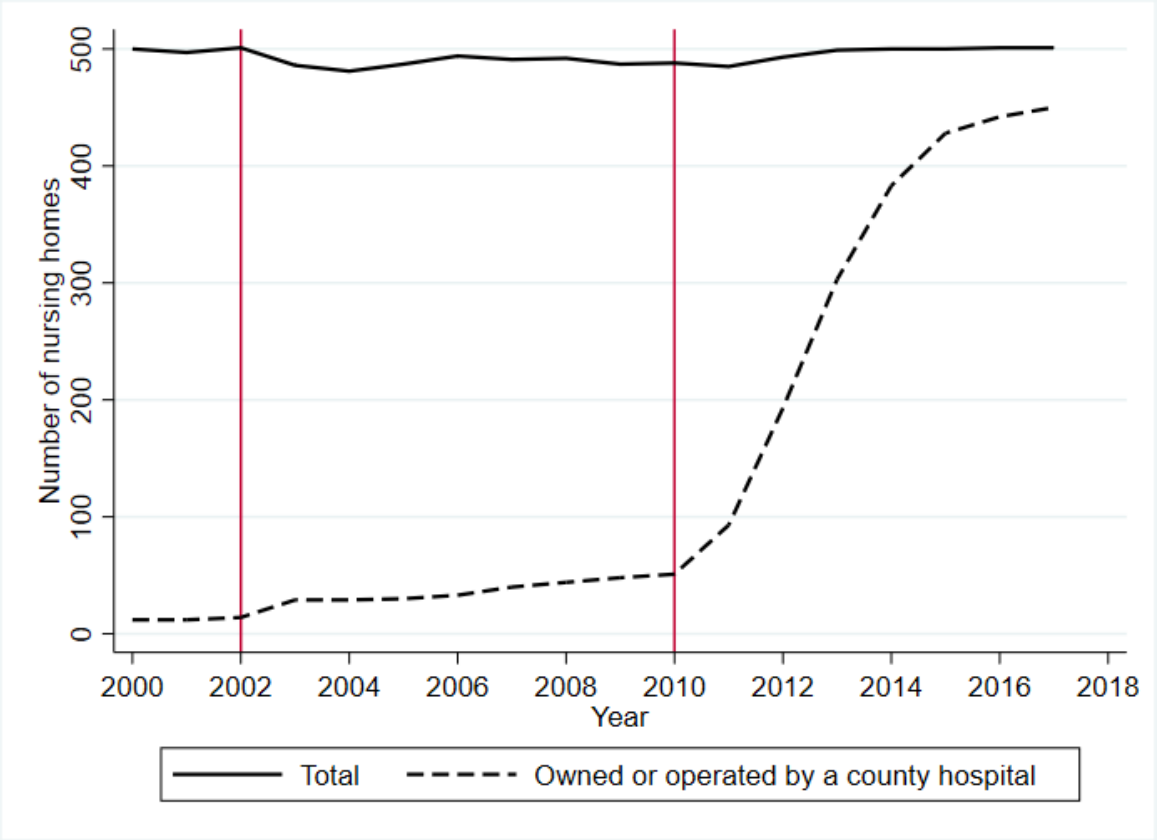
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Figure 1: Development of County-Owned Nursing Homes in Indiana



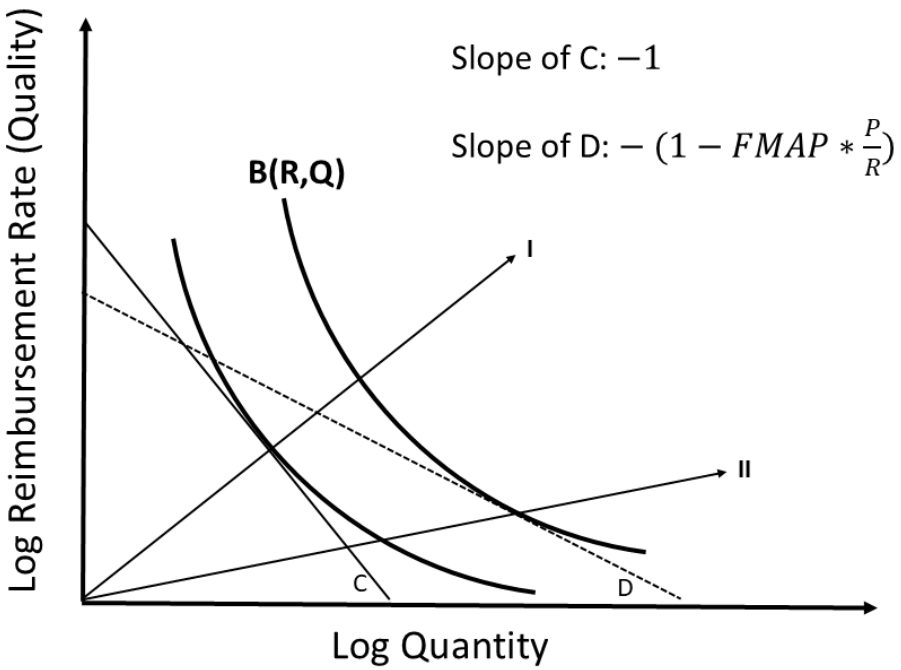
Source: Centers for Medicare & Medicaid Services (2020b) and Indiana Department of Health (2020).

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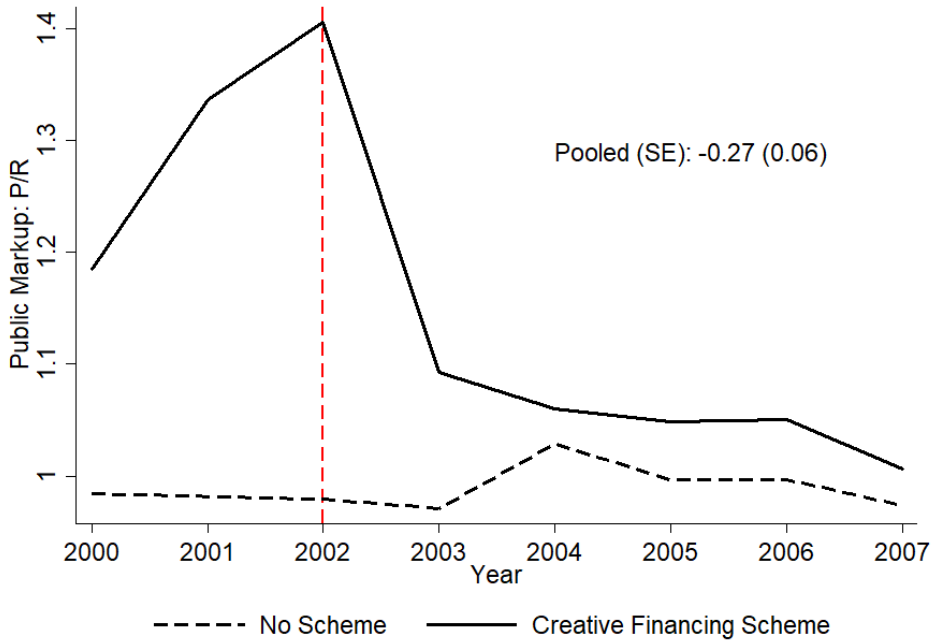
NRZ: Martin, hier muessen wir optimieren, was wir zeigen. Es sollte def nur eine Grafik sein. Ich hab die Institutional Section zum Senate Bill in 2010 ergaenzt. Eine Frage, die aufkam und zu der ich auch keine Antwort weiss: wieso hoeren wir bei den CMS Mikrodaten in 2015 auf? Gibt es da einen harten Grund, bestimmt oder? Denn sollten wir knapp erwaehnen. Entsprechend wuerde ich diese Grafik auch in 2015 enden lassen. (Im Patient stay sample gehen wir ja sogar nur bis 2012, was ist das der Grund?)

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 creative financing (CF). The convex curves denote indifference curves for different benefit levels. Line 'C' denotes the budget constraint for the state without CF. 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 and line 'II' denotes the corresponding expansion path.

Figure 3: 2003 Reform and Public Markups

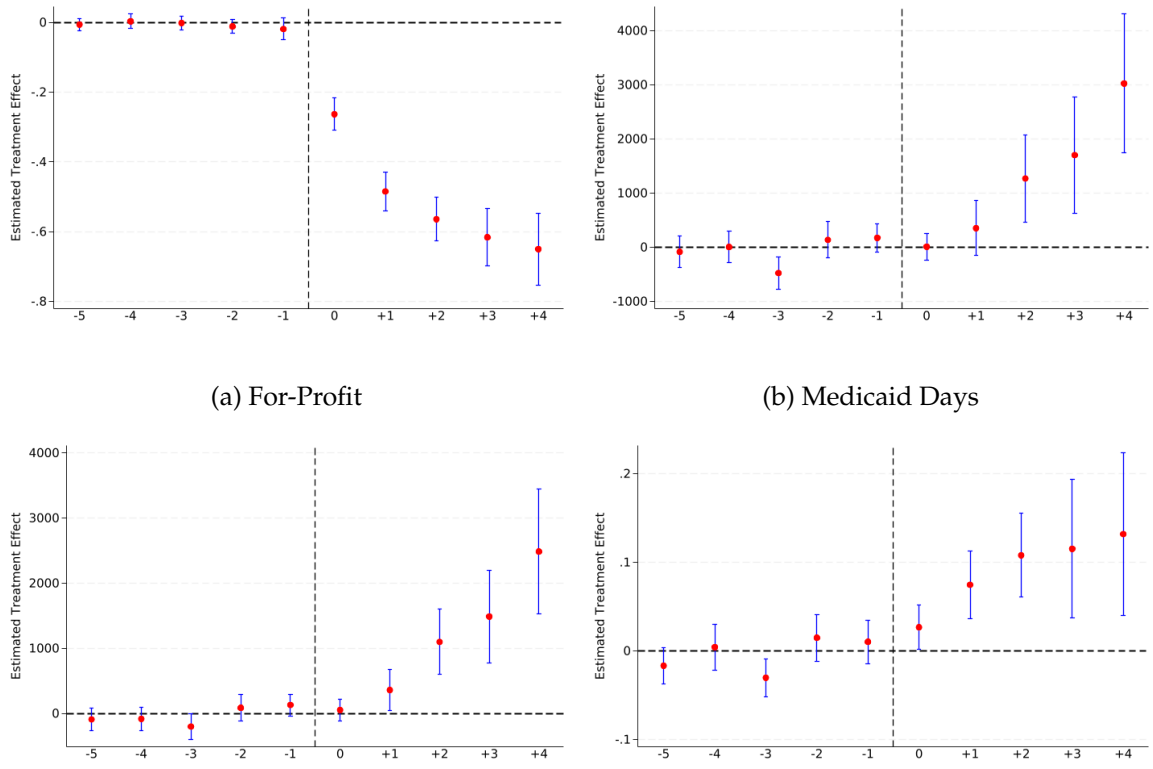


Source: Long-Term Care: Facts on Care in the U.S. (2025); Centers for Medicare & Medicaid Services (2020a). This figure presents the public markup, $\frac{P}{R}$, the wedge between the nominal (P) and the effective Medicaid reimbursement rate, R. The vertical line denotes the time of the 2003 reform; see the main text for details. The categorization of treatment and control states is depicted in Figure A2 and described in Coughlin and Zuckerman (2003a); Coughlin, Bruen, and King (2004).

NRZ: Martin, könntest du hier den Font Type und die Font Size, insbesondere an den Achsen und den anderen Figures, anpassen?Oder ich mache es, wenn du mir sagst, wo der Source-File zu der Grafik ist. Ich wuerde auch quality auf der y Achse rausnehmen und im Text erwaehnen, das ist ja nur per Annahme so. Koennten auch Log Effective Reimbursement Rate schreiben oder einfach log R und log Q, faende ich am besten.)

NRZ: Hier sollen die y-Achasen identisch sein.

Figure 4: Creative Financing and Medicaid-Funded Nursing Home Expansion (H 2)



(a) For-Profit

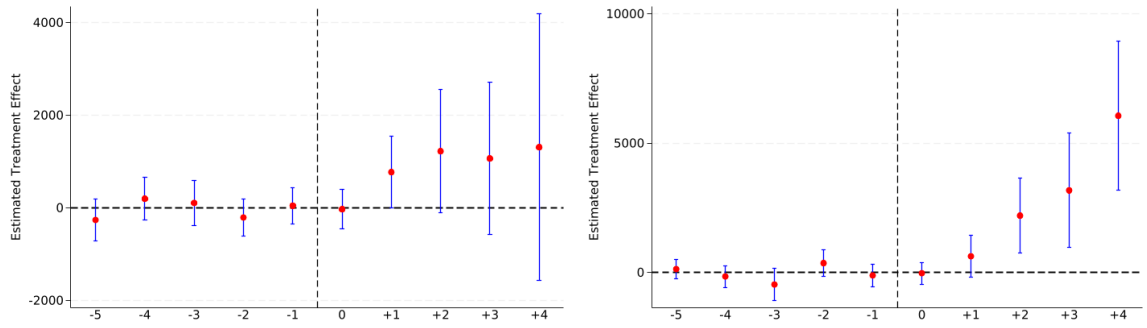
(b) Medicaid Days

(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 municipalization of nursing homes. Subgraph captions indicate the outcome variable of a Callaway Sant'Anna event study. 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: Medicaid Nursing Home Expansion (H 2) by Quality of Care

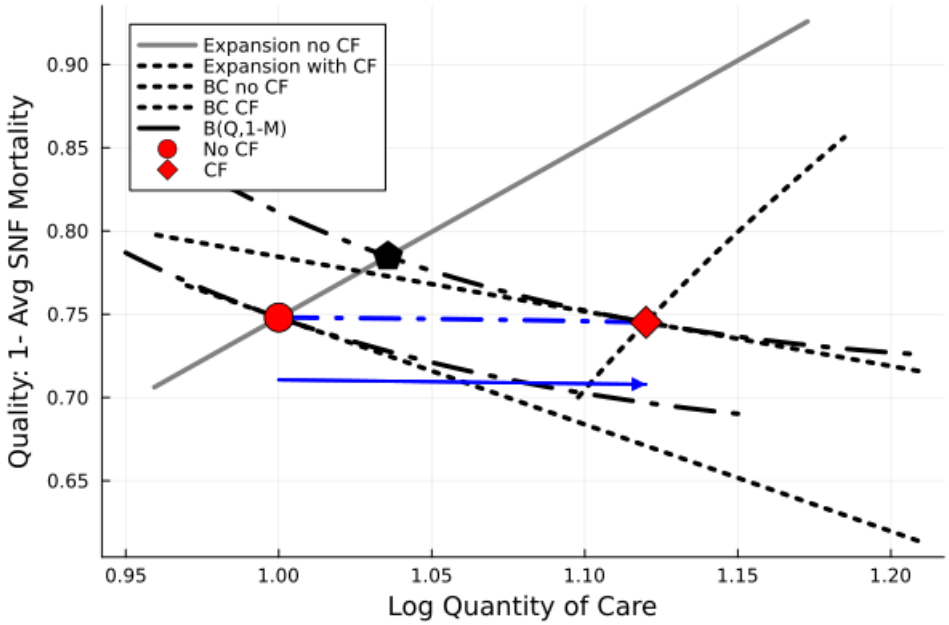


(a) Higher Quality SNFs

(b) Lower Quality SNFs

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 (Callaway and Sant'Anna, 2021). They present results on cumulative Medicaid days among nursing home residents with dementia at the nursing home-year level. Figure 5a focuses on higher-quality nursing homes, whose value-added estimate for one-year survival is in the top quintile. Figure 5b focuses on lower-quality nursing homes, whose value-added estimate is in the bottom quintile.

Figure 6: Medicaid Quantity-Quality Tradeoff—Theory and Evidence



Notes: Using the empirical evidence from Indiana, the figure illustrates the theoretical framework in Figure 2. The horizontal axis displays log quantity of nursing home days, and the vertical axis denotes log average costs per patient day, which is further averaged across nursing homes. The grey upward sloping line denotes the expansion path without creative financing (CF), and the red circle 'no CF' denotes the allocation before municipalization. The red diamond 'CF' denotes the allocation with creative financing. The intersection between the indifference curve and the expansion path, the black pentagon point, denotes the allocation that achieves the same hospital-nursing home objective at lower costs.

NRZ: Wir hatten viel zu viele Akronyme. Wenn du mir sagt, wo die sources files liegen, mache ich das, aber siehe comment Figure 2. Die Achsen wuerde ich hier mit "One-Year Survival" und "Medicaid Volume" bezeichnen bzw "Log Q" etc. je nachdem was dir lieber ist. Das sollte aber alles konsistent sein, der Style und die Beschriftungen etc.

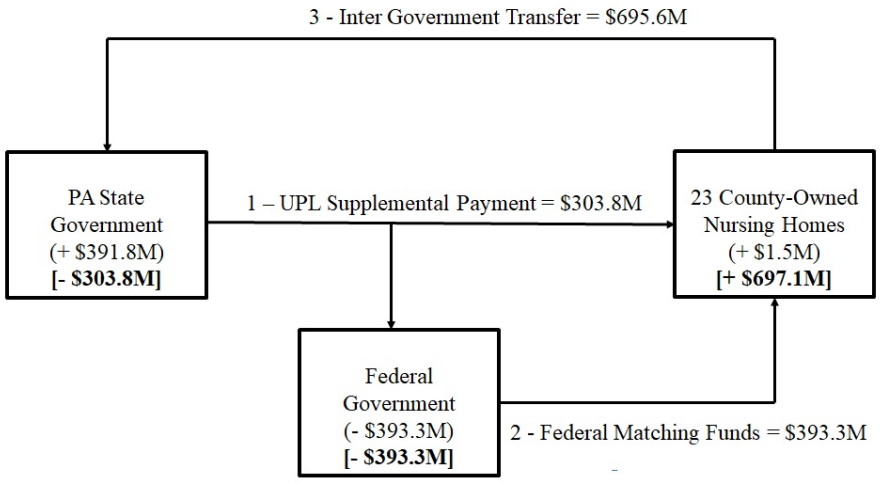
Table 1: Creative Financing and Medicaid-Funded Nursing Home Expansion (H 2)

Panel A	**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	**Dementia Medicaid Days**			
	Low Quality	High Quality	Occu<90% (2000)	High Occu >90% (2000)
	(1)	(2)	(3)	(4)
	1952***	1106**	1389***	300
	(687)	(556)	(299)	(449)
Sample Mean	10,150	10,020	9,620	10,070
Observations	1,037	986	4,828	1,428
Year FE	X	X	X	X
SNF FE	X	X	X	X

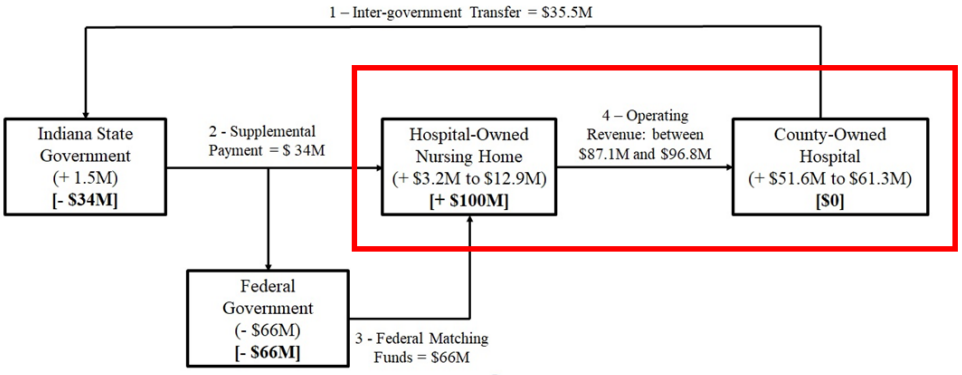
Sources: Long-Term Care: Facts on Care in the U.S. (2025), MDS (2020), Centers for Medicare & Medicaid Services (2020b); Indiana Department of Health (2020), CMS Skilled Nursing Facility Provider Information, State of Indiana (2025), authors' calculation. See Section 4.2 and Appendix D for more details. Sample is at the nursing-home-year-level from 1999-2015. ***, **, 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; also see the main text. In Panel A, column (1) presents CS DD results using for-profit ownership as the dependent variable. Column (2) uses the cumulative number of Medicaid days, and column (3) uses Medicaid days for patients diagnosed with dementia. The last column presents results for an indicator that denotes whether the nursing home has an Alzheimer's unit. Panel B always uses cumulative Medicaid days among patients diagnosed with dementia as a dependent variable and conditions on specific subsamples as indicated. The first and second columns of Panel B condition the sample on the bottom (column (1)) and the top quantile (column (2)) of the one-year mortality value-added distribution; see Figure F1. Columns (3) and (4) of Panel B condition on SNFs with occupancy rates of less and more than 90% in the year 2000, respectively.

A Online Appendix

Figure A1: Schemes using UPL Supplemental Payments for Nursing Facilities



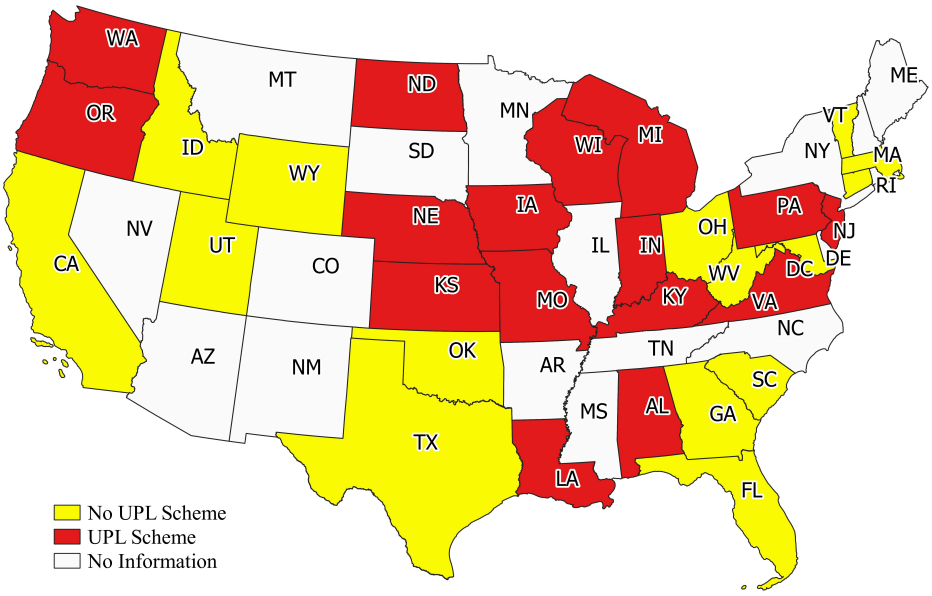
(a) Panel A: Pennsylvania in FY2002



(b) Panel B: Indiana after 2003

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 (2003b). Figures for Panel B are based on Hatcher (2017)

Figure A2: States Use of UPL-SPs in Nursing Homes in FY 2002



Notes: This map illustrates states that used creative financing in the form of an upper payment limit supplemental payment (UPL-SP) scheme in FY 2002 based on the survey from Coughlin, Bruen, and King (2004). Pennsylvania is listed as using a UPL-SP scheme according to Coughlin and Zuckerman (2003b).

B Theoretical Framework

B.1 Principal-Agent Basic Model

Consider a Principal p and an Agent a. The Agent produces output $\Pi(e_1, e_2)$ for the Principal through costly efforts $e_1 \in [\underline{e_1}, \overline{e_1}]$ and $e_2 \in \mathbf{R}^+$, where $C(e_1, e_2)$ denotes the cost of effort borne by the agent. Output and costs are strictly increasing in effort levels.

Key is that the Principal cannot perfectly monitor actual effort e_j, and takes reported effort $\hat{e}_j$ for $j \in \{1, 2\}$ as given. Thus, the Principal compensates the Agent based on reported effort: $w(\hat{e}_1, \hat{e}_2)$.

The Principal's payoff is then $U^p = \Pi(e_1, e_2) - w(\hat{e}_1, \hat{e}_2)$ and the Agent's payoff is $U^a = w(\hat{e}_1, \hat{e}_2) - C(e_1, e_2)$.

Further, we define social welfare as the sum of the payoffs:

$$W = U^p + U^a = \Pi(e_1, e_2) - C(e_1, e_2) \tag{B1}$$

Perfect Monitoring: Under perfect monitoring, $e_j = \hat{e}_j$ for $j \in \{1, 2\}$. In this case, the Principal pays the Agent for the full output $\Pi(e_1, e_2) = w(\hat{e}_1, \hat{e}_2)$ and the Agent chooses socially efficient effort levels:

$$e^{*,opt} = \underset{e_1, e_2 \in [\underline{e_1}, \overline{e_1}] \times \mathbf{R}^+}{\arg\max} \; \Pi(e_1, e_2) - C(e_1, e_2) \, . \tag{B2}$$

Imperfect Monitoring: Under imperfect monitoring, the Principal can monitor e_2, hence $e_2 = \hat{e}_2$, but not e_1. To facilitate comparisons, we assume that the Principal pays the 'reported' profits to the Agent: $\Pi(\hat{e}_1, \hat{e}_2) = w(\hat{e}_1, \hat{e}_2)$. This yields two predictions:[23]

1. *Shirking in effort of type 1:* $e_1^* = \underline{e_1} \leq e_1^{*,opt}$; $\hat{e}_1^* = \overline{e_1} \geq e_1^{*,opt}$, when $\frac{\partial w(\hat{e}_1, e_2)}{\partial \hat{e}_1} \geq 0$
2. *Overexertion in effort of type 2:* $e_2^* = \hat{e}_2^* \geq e_2^{*,opt}$ when $\frac{\partial^2 w(\hat{e}_1, e_2)}{\partial \hat{e}_1 \partial e_2} > 0$ and $\frac{\partial^2 U^a}{\partial^2 e_2} < 0$.

Intuitively, the Agent shirks in type 1 effort, reporting maximum but only providing minimum effort. This, in turn, induces additional effort of type 2 when higher reported

[23] Taking the total differential over the Agent's first order condition for effort type 2 and reorganizing yields: $\frac{\Delta e_2}{\Delta \hat{e}_1} = -\frac{\frac{\partial^2 w(\hat{e}_1, e_2)}{\partial \hat{e}_1 \partial e_2}}{\frac{\partial^2 U^a}{\partial^2 e_2}}$.

effort of type 1 increases the marginal returns on type 2, $\frac{\partial^2 w(\hat{e}_1,e_2)}{\partial \hat{e}_1 \partial e_2} > 0$ (and the overall Agent payoff is concave in type 2 effort).[24]

In summary, under imperfect monitoring and when the Agent's compensation is complementary to reported efforts, actual and reported efforts are distorted in opposing directions.

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

$$\max_{\tilde{P}} V(\tilde{P}) = B(R(\tilde{P}), Q(\tilde{\tilde{P}})) - R(\tilde{P})Q(\tilde{P}) \tag{B3}$$

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 (B3), 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

[24] The latter is a necessary condition for an interior solution for effort of type 2.

$$Q = \tau \frac{\partial B}{\partial R} \Rightarrow \frac{\partial B}{\partial R} = \frac{Q}{\tau}$$
$$R - \tilde{P} = \tau \frac{\partial B}{\partial Q} \Rightarrow \frac{\partial B}{\partial Q} = \frac{R - \tilde{P}}{\tau}$$

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

$$\begin{aligned}
\frac{dV}{d\tilde{P}} &= \left(\frac{Q}{\tau} - Q\right) \cdot \frac{dR}{d\tilde{P}} + \left(\frac{R - \tilde{P}}{\tau} - R\right) \cdot \frac{dQ}{dP} \\
&= \left(\frac{1-\tau}{\tau}\right) Q \cdot \frac{dR}{d\tilde{P}} + \left(\frac{-\tilde{P} + (1-\tau)R}{\tau}\right) \cdot \frac{dQ}{d\tilde{P}} \qquad \text{(B4)} \\
&= \left(\frac{1-\tau}{\tau}\right) \cdot \frac{d(R * Q)}{d\tilde{P}} - \frac{\tilde{P}}{\tau} \cdot \frac{dQ}{d\tilde{P}} \,. \qquad \text{(B5)}
\end{aligned}$$

Multiplying equation (B5) by τ yields

$$(1-\tau) \cdot \underbrace{\frac{d(R \times Q)}{d\tilde{P}}}_{\text{Positive Externality}} - \underbrace{\tilde{P} \cdot \frac{dQ}{d\tilde{P}}}_{\text{Public Moral Hazard}} = 0 \,. \qquad \text{(B6)}$$

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.[25]

[25] By contrast, without public moral hazard, $dQ/d\tilde{P} = 0$ and $dR/d\tilde{P} = 0$, diverted funds represent a non-distortionary transfer from the federal government to states.

B.3 Alternative 2-Stage Game Framework

This section abstracts from instruments that allow states to directly influence care volume. Instead, in equilibrium, volume is determined by the intersection of demand and supply and states can only influence care provision through Medicaid reimbursement rates. This setup presents states with a tradeoff: (a) lower reimbursement rates to contain costs vs. (b) higher reimbursement rates to expand access.

We model the market for Medicaid nursing home patients as a two-stage game. In the first stage, the state bargains with providers over Medicaid reimbursement rates. In the second stage, providers take rates as given and compete in service quality over patients in a differentiated products market. The main result is that creative financing results in higher volume of publicly funded care when:

$$\frac{\bar{P} - R}{R} \geq \frac{1}{\epsilon_{Q,R}},$$

where $\frac{\bar{P}-R}{R} = \mu - 1$ denotes the public markup μ minus one. $\epsilon_{Q,R}$ denotes the elasticity of equilibrium quantities with respect to changes in the effective reimbursement rate R. In words, states design reimbursement rates to increase volume when the public markup is large, or when quantities respond elastically to changes in effective rates.

B.3.1 Second Stage

Demand: The indirect utility function describes patient preferences over nursing home care:

$$u_{ijt} = \begin{cases} \delta_j + \eta_{ij} & \text{for nursing homes} \\ \eta_{io} & \text{otherwise} \end{cases} \tag{B7}$$

where o denotes an outside good. δ_j denotes the quality of the nursing home j and we assume idiosyncratic taste shocks η that are i.i.d. extreme value. Given quality, nursing home market shares and overall demand are given by:

$$s_j(\delta) = \frac{\exp\{\delta_j\}}{1+\sum_k \exp\{\delta_k\}} \tag{B8}$$

$$Q_j^D(\delta) = s_j(\delta) \times N, \tag{B9}$$

where N denotes the population size.

Supply: Nursing homes solve a quality-quantity tradeoff governed by their production function

$$Q_j^S = A_j \times h(Q_j, \delta_j) \times I_j \,. \tag{B10}$$

Here, I_j denotes a variable input factor with an input price w; for example, the wage, whereas $h(\cdot)$ captures the costs of producing higher quality allowing for economies of scale. A captures total factor productivity, which implies the following cost function:

$$C(Q_j, \delta_j) = \frac{Q_j}{A_j \times h(Q_j, \delta_j)} \times w \tag{B11}$$

In this stage, nursing homes take R as given and choose the profit-maximizing quality level:

$$\delta_j^* = \arg\max_{\delta_j} \Pi_j = \arg\max_{\delta_j} \left(R Q_j^D(\delta) - C(Q_j^D(\delta), \delta_j) \right) . \tag{B12}$$

Analysis: We impose the following simplifying assumption:

$$\frac{w}{A \times h(Q, \delta)} = c_\delta \times \delta + c_m + c_q \times Q^\gamma, \;\; \gamma \geq 0 \,. \tag{B13}$$

$$\leftrightarrow \quad C(Q, \delta) = Q \times \left(c_\delta \times \delta + c_m + c_q \times Q^\gamma \right) \tag{B14}$$

where c_δ denotes the effects of higher quality on the marginal cost of production, and γ allows for decreasing returns to scale.

NRZ: Brauchen wir hier nicht eine knappe Diskussion der Annahme.

FOC and Optimality Condition: Solving the first order condition, we get:

$$\delta_j^* = \underbrace{\frac{1}{c_\delta}\Big(R - c_m - (1+\gamma) \times c_q \times Q_j^\gamma\Big)}_{\text{Perfect Competition}} - \underbrace{\frac{Q_j}{\partial Q_j / \partial \delta_j}}_{\text{Quality Markdown}} \quad . \tag{B15}$$

The first term denotes quality under perfect competition, whereas the second term refers to lower quality ("quality markdown") due to nursing home market power.

Overall, the first order condition produces a positive relationship between quality δ_j and the effective reimbursement rate R. As qualities are strategic complements in this setting, provider competition will reinforce the positive relationship. As a result, increases in reimbursement rates will result in higher quality and higher quantities consumed. Specifically, we expect:

$$\frac{\partial Q_j^*}{\partial R} \geq 0 \, . \tag{B16}$$

B.3.2 First Stage: Rate Setting (w/o Creative Financing)

In the first stage, states negotiate with nursing homes over the effective reimbursement rate R, considering the quantity and quality effects in the second stage. The state trades off marginal benefits from increased nursing home access against costs. States value quality and quantity of care, which are both determined by R.

Netting out spending, the state's payoff is

$$V(R) = \sum_j \tau B_j(R, Q) - \sum_j R \times Q_j^*(R) \times [1 - FMAP] \, . \tag{B17}$$

Note that the state pays only a fraction $(1 - FMAP)$ of total Medicaid spending; the federal government pays the remaining share, $FMAP$. States and nursing homes engage in Nash Bargaining to determine R:

$$R^* = \underset{R \leq UPL}{\arg\max} \, V(R)^\alpha \times \Big(\sum_j \Pi_j(R)\Big)^{1-\alpha}, \tag{B18}$$

where α denotes the state's bargaining weight and $1 - \alpha$ denotes the bargaining weights of nursing homes.

FOC and Optimality Condition: Consider a single monopoly nursing home. Abstracting from a binding upper payment limit and taking logs, the first order condition yields:

$$\frac{\alpha}{V(R)} \times \Big((\tau B_Q(R,Q) - R \times [1 - FMAP]) \times \frac{\partial Q^*}{\partial R} + (\tau B_R(R,Q) - [1 - FMAP]) \times Q^* \Big) + \frac{(1-\alpha)}{\Pi(R)} \times Q^* = 0, \tag{B19}$$

where $B_R(R,Q) = \partial B/\partial R$ and $B_Q(R,Q) = \partial B/\partial Q$. Here, we have used the nursing home's first-order condition on profits. Rearranging, we find

$$R^* \times [1 - FMAP] = \underbrace{\tau B_Q(Q,R)}_{\text{Quantity Motive}} + \underbrace{\frac{(\tau B_R(Q,R) - [1 - FMAP]) \times Q^*}{\frac{\partial Q^*}{\partial R}}}_{\text{Quality Motive}} + \underbrace{\frac{(1-\alpha)}{\alpha} \times \frac{V(R)}{\Pi(R)} \times \frac{Q^*}{\frac{\partial Q^*}{\partial R}}}_{\text{NH Bargaining Power}} = 0. \tag{B20}$$

The first term represents quantities, capturing the state's interest in expanding access and saving on substitute care. The second term represents quality, capturing that higher rates produce higher quality. The FMAP rate implicitly subsidizes both motives. The last term represents the bargaining power of nursing homes, which is only relevant for $\alpha < 1$. The higher the bargaining power of nursing homes, the higher the reimbursement rates.

B.3.3 Creative Financing Step 1: Introducing Transfers

We introduce creative financing in two steps. First, we allow states to extract surplus from nursing homes via a transfer T. This turns the problem into one of transferable utilities. States now solve:

$$\Big(T^{*,T}, R^{*,T} \Big) = \underset{T, R \leq UPL}{\arg\max} \Big(V(R) + T \Big)^{\alpha} \times \Big(\Pi(R) - T \Big)^{1-\alpha}. \tag{B21}$$

Reimbursement rates are now set to maximize joint surplus; transfers divide the surplus between the state and providers. Specifically, optimal rates under transfers, $R^{*,T}$, satisfy:

$$R^{*,T} = \underset{R \leq UPL}{\arg\max}\, V(R) + \Pi(R)\,. \tag{B22}$$

Optimality Condition: After reorganizing the first order condition, we have:

$$R^{*,T} \times [1 - FMAP] = \tau B_Q(Q, R) - \frac{(\tau B_R(Q, R) - [1 - FMAP]) \times Q^*}{\frac{\partial Q^*}{\partial R}} + \frac{Q^*}{\frac{\partial Q^*}{\partial R}} = 0. \quad \text{(B23)}$$

This optimality condition is closely related to equation (B20) but differs in the implicit weight imposed on provider profits. Specifically, we define the cutoff value $\underline{\alpha}$ such that $\frac{(1-\underline{\alpha})}{\underline{\alpha}} \times \frac{V(R)}{\Pi(R)} = 1$. Equations (B20) and (B23) equal for $\alpha = \underline{\alpha}$. Provided that the support for $V(R)$ and $\Pi(R)$ is compact and convex, we have the following two cases:

1. *States have upper hand*: When states hold the upper hand, $\alpha > \underline{\alpha}$, the reimbursement rate R and volume increase as states adopt creative financing mechanisms.

2. *Providers have upper hand*: Conversely, when providers hold the upper hand, $\alpha < \underline{\alpha}$, reimbursement rate R and volume decrease as states adopt creative financing mechanisms.

States hold all bargaining power: $\alpha = 1$

Although this is not the empirically relevant case, to understand changes in incentives, we assume that states hold all bargaining power.

FOC and Optimality Condition: With $\alpha = 1$, we simplify the first-order conditions with and without transfers:

$$\Big[\tau B_Q(Q, R) - R \quad + R \times FMAP\Big] \frac{\partial Q}{\partial R} + \Big[\tau B_R(Q, R) - Q \qquad + FMAP \times Q\Big] \quad = \quad 0 \quad \text{(B24)}$$

$$\underbrace{\Big[\tau B_Q(Q, R) - \frac{\partial C}{\partial Q} + R \times FMAP\Big] \frac{\partial Q}{\partial R}}_{\text{Quantity Incentive}} + \underbrace{\Big[\tau B_R(Q, R) - \frac{\partial C}{\partial \delta} \frac{\partial \delta}{\partial R} + FMAP \times Q\Big]}_{\text{Quality Incentive}} \quad = \quad 0 \quad \text{(B25)}$$

where equation (B24) denotes the case without transfers, discussed in Appendix Section B.3.2, and equation (B25) denotes the case with transfers. The first term in each equation captures the incentives to increase quantities, and the second term captures the incentives regarding the quality of care.

The middle summand highlights how transfers alter incentives for setting rates and quantities: The ability of nursing homes to extract funding increases the costs of improving quality due to leakage. The regulator pays R, but only a fraction is passed on, and the rest

is extracted. By extracting funding, states reduce the cost of a higher volume from R to $\frac{\partial C}{\partial Q}$ and the cost of a better quality (through rate increases) from Q to $\frac{\partial C}{\partial \delta}\frac{\partial \delta}{\partial R}$, see equations B24 vs. B25.

In summary, with transfers, states set a higher reimbursement rate than without—as long as $\alpha > \underline{\alpha}$—resulting in a higher care volume.

B.3.4 Creative Financing Step 2: Introducing Nominal and Effective Rates

We now introduce a nominal reimbursement rate P, in addition to the effective rate R. Importantly, P qualifies for federal matching funds. Providers receive a marginal reimbursement rate R and a lump sum payment $(P - R) \times \bar{Q}$. However, states may redirect these payments through a transfer. Provider profits before transfers are now:

$$\Pi(R, P, \bar{Q}) = R * Q - C(\delta, Q) + (P - R) \times \bar{Q} \tag{B26}$$

Providers continue to choose Q optimally, determined by the optimal quality choice δ, holding $\bar{Q}$ fixed. States solve:

$$\left(T^{*,T}, R^{*,T}, P^{*,T}, \bar{Q}^{*,T}\right) = \underset{T, R \leq UPL, P \leq UPL, \bar{Q} \leq Q^{*,CF}}{\arg\max} \left(V(P) + T\right)^{\alpha} \times \left(\Pi(R, P, \bar{Q}) - T\right)^{1-\alpha}. \tag{B27}$$

The ability to transfer funds implies that states will max out nominal provider payments $P \times Q$, implying that $P = \bar{P} = UPL$ and $\bar{Q} = Q^{*,CF}$. Further, and as in Appendix Section B.3.3, states choose rates R that maximize the sum of surpluses:

$$R^{*,T} = \underset{R \leq UPL}{\arg\max}\, V(\bar{P}) + \Pi(R, \bar{P}, Q^{*,T}) = \tau B(Q, R) - C(Q, \delta) + \bar{P} \times FMAP \times Q^{*}\,. \tag{B28}$$

Optimality Condition: Taking the first order condition and rearranging yields, similar to equation (B25):

$$\underbrace{\left[\tau B_Q(Q, R) - \frac{\partial C}{\partial Q} + \bar{P} \times FMAP\right]\frac{\partial Q}{\partial R}}_{\text{Quantity Incentive}} + \underbrace{\left[\tau B_R(Q, R) - \frac{\partial C}{\partial \delta}\frac{\partial \delta}{\partial R}\right]}_{\text{Quality Incentive}} = 0\,. \tag{B29}$$

Thus, introducing nominal rates beyond effective rates changes the quality and quantity incentives. Compared to the case with just transfers (equation (B25)), states have more incentives to increase quantities as $\bar{P} > R$, and expand volume. Conversely, states have less incentives to raise quality through higher R because it does not trigger additional matching funds tied to P. As a result, the quality incentive term in equation (B29) misses $FMAP \times Q$ from equation (B25).

Discussion: Consistent with the main text, creative financing incentivizes higher volume but weakens the incentive to improve quality. In contrast to the main text, however, the changes in incentives have opposing effects on optimal reimbursement rates: higher effective rates R increase quality *and* quantity, leaving the net effect ambiguous.

To see this, after subtracting equation (B25) from equation (B29), creative financing results in higher R and Q, when $(\bar{P} - R) \times FMAP \times \frac{\partial Q}{\partial R} \geq Q \times FMAP$. Rearranging yields:

$$\frac{\bar{P} - R}{R} \geq \frac{1}{\epsilon_{Q,R}} \tag{B30}$$

where $\epsilon_{Q,R}$ denotes the elasticity of volume with respect to R. States raise reimbursement rates, and hence program costs, when $\mu - 1 = \frac{\bar{P}}{R} - 1 = \frac{\bar{P}-R}{R}$ exceeds $\frac{1}{\epsilon_{Q,R}}$.

In words, when rate increases have a small effect on volume, the cost-saving motive dominates and results in lower Medicaid rates. Conversely, states increase rates when they have a large effect on volume or when the markup is large.

NRZ: Martin, gg den mit Abstand Hauptkommentar aus meiner Sicht "you do too much", sollten wir auch diskutieren, ob wir die Provider Taxes nicht rausnehmen; ich wuerde auch das Nash Bargaining rausnehmen; im Zweifel machen wir mit den state-year effects ein separates Paper und schicken es zu Jeff und JPubE...hier geht das alles total unter, verwirrt und/oder veraergert die Leser...

B.4 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 setting up intergovernmental transfers, provider taxes then redirect provider revenues away from the 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).

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.[26] 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).

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

[26]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.

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.[27]

Discussion: Provider taxes aim to reduce the state's cost share. They generally incentivize capacity expansions. For instance, the most common provider taxes are levied on nursing homes (46 states) and hospitals (45 states), thereby biasing— ceteris paribus— Medicaid care toward institutional care. Specifically, only three states have a tax on home health long-term care providers (Kaiser Family Foundation, 2025a).[28] In summary, provider taxes disproportionately subsidize the state's cost share for inpatient long-term care, incentivizing an institutional bias toward institutionalized care.

B.4.1 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:

$$\max_{R,Q} \tau \times B(\theta(R), Q) - (1 - FMAP) \times (R + t) \times Q + t \times Q \,. \tag{B31}$$

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:

$$\tau \times B_R(R, Q)/Q = 1 - FMAP \tag{B32}$$

$$\tau \times B_Q(R, Q)/R = 1 - FMAP \cdot \frac{R + t}{R} = 1 - FMAP \cdot \frac{P}{R} \,. \tag{B33}$$

Intergovernmental transfers and provider taxes induce slightly different incentives. First, Hold Harmless Tests typically limit the amount of the tax. Most states calibrate the

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

[28] This includes Kentucky, New York, and Minnesota, who reports having a provider tax on all regulated health care providers.

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).

The cap on provider taxes also reduces the public markup to $\mu = \frac{R+t}{R}$.[29] Nevertheless, consistent with hypothesis **H**2, the provider tax increases the effective FMAP and incentivizes states to increase the volume eligible for joint funding, thereby distorting the quality-quantity tradeoff.

[29]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.

C Data Appendix to Provide Evidence on H1

This section describes the primary data sources used to generate a panel of state-year observations from 2000 to 2007. The panel comprises 17 states with pre-2003 creative financing schemes (treatment group) and 16 states without such schemes (control group); see Figure A2 and Coughlin and Zuckerman (2003a); Coughlin, Bruen, and King (2004). In total, we have 264 observations for most outcomes and produce simple Difference-in-Differences (DD) estimates, see Section 4.1 of the main text. Subsequently, this appendix presents supporting evidence from 24 digitized audit reports from 18 states, along with financial nursing home reports from Indiana.

C.1 State-Year CMS Data

First, we use public data from the Medicaid Budget and Expenditure System (MBES) by Centers for Medicare & Medicaid Services (2020a). These data contain Medicaid expenditures at the state and federal levels by service categories based on Form CMS-64. We use these data to measure total nominal spending (P) on nursing home care by state and year.

Second, we use public data on the Federal Medical Assistance Percentage (FMAP) for Medicaid by state and year (Kaiser Family Foundation, 2025d). We merge them with the CMS data e at the state-year level.

Third, we use public data from LTC Focus at the state-year level (Long-Term Care: Facts on Care in the U.S., 2025). It covers all U.S. Medicaid and Medicare-certified nursing homes and includes patient and facility characteristics such as staffing levels, the number of beds, occupancy or special care units. The data also provide Medicaid per diem rates and the number of Medicaid days in nursing homes at the state-year level; thus, we use their product to measure effective spending (R).

Table C1: Summary Statistics State-Year CMS Data

Variable	**Mean**	**Std. Dev.**	**N**
Treatment states	0.4848	(0.5007)	264
Markup	1.0738	(0.2431)	256
Effective FMAP	66.24	(17.77)	256
Federal Expenditures	688.81	(603.55)	264
State Expenditures	492.86	(514.17)	264
RN Ratio	0.5078	(0.2013)	264
LPN Ratio	0.8295	(0.1749)	264
CNA Ratio	2.3133	(0.2591)	264
Medicaid days	7,562,009	(6,302,317)	264
log Medicaid days	15.4319	(1.0002)	264

Source: Centers for Medicare & Medicaid Services (2020a); Kaiser Family Foundation (2025d); Long-Term Care: Facts on Care in the U.S. (2025), data are from 2000-2007 at the state-year level. The markup is $\frac{P}{R}$, the ratio of the nominal, P, to the effective Medicaid rate, R. The effective FMAP is $FMAP \times (1 + markup)$. Federal and state expenditures are in million dollars. Registered nurse (RN), licensed practical nurse (LPN), and certified nurse assistant (CNA) to patient ratios are displayed. Medicaid days are calculated by multiplying the total number of beds by the occupancy rate and the share of Medicaid patients for each nursing home and year. "Markup" and "effective FMAP" has only 256 observations because Hawaii does not have an LTC Focus estimate of the average Medicaid rate.

Table C2: Effects of 2003 Reform on Nursing Home Spending

	Markup	**Effective FMAP**	**Federal Expenditures**	**State Expenditures**
$CF \times Post$	-0.2702***	-15.86***	-167.09***	-118.29***
	(0.0577)	(3.6793)	(47.59)	(35.22)
	RN Ratio	**LPN Ratio**	**CNA Ratio**	**Lg MA Days**
$CF \times Post$	-0.0090	0.0018	-0.0072	-0.0307**
	(0.0275)	(0.0254)	(0.0403)	(0.0142)
Year Fixed Effects	X	X	X	X
NH Fixed Effects	X	X	X	X

Source: Source: Centers for Medicare & Medicaid Services (2020a); Kaiser Family Foundation (2025d); Long-Term Care: Facts on Care in the U.S. (2025), data are from 2000-2007 at the state-year level. The sample has 264 state-year observations from 17 treated and 16 nontreated states over 8 years (Federal and State Expenditures only have 256 observations). See the main text for more details. ***, **, and * = statistically different from zero at the 1%, 5%, and 10% level. Standard errors are clustered at the state level and reported in parentheses. Each column in each panel corresponds to one standard DD model, with CF flagging states with a pre-reform creative financing scheme in place and $Post$ taking the value 1 for years after 2002. The markup is $\frac{P}{R}$, the ratio of the nominal, P, to the effective Medicaid rate, R. The effective FMAP is $FMAP \times (1 + markup)$. Federal and state expenditures are in million dollars. The second panel shows results for the registered nurse (RN), licensed practical nurse (LPN), and certified nurse assistant (CNA) to patient ratios. "NH" abbreviates nursing home. The last column presents results for the log number of annual Medicaid days (Lg MA Days).

C.2 Audit Reports by the Office of Inspector General (OIG)

To provide additional information on how creative financing may drive a wedge between nominal and effective nursing home reimbursement rates, we digitize and analyze 24 audit reports from 18 states between 1997 and 2003, during the pre-reform era.

CMS requested all reports that were drafted by the Office of Audit Services of the Office of Inspector General (OIG). OIG is mandated to protect the integrity of the Department of Health and Human Services (HHS) programs and the well-being of its beneficiaries (Department for Health and Human Services, 2025). The reports provide information on the extent of creative financing in each state, including the amounts expropriated via Intergovernmental Transfers (IGTs).

They thus provide independent estimates and hard evidence of fund diversion. It allows us to calculate the public markup for a subset of states using this alternative source. Specifically, we combine the IGT amounts with information on total nominal Medicaid spending (*Total MHEX*) separately for states (*State MHEX*) and the federal government (*Total MHEX - State MHEX*), from CMS-64 forms. We then construct the markdown as

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

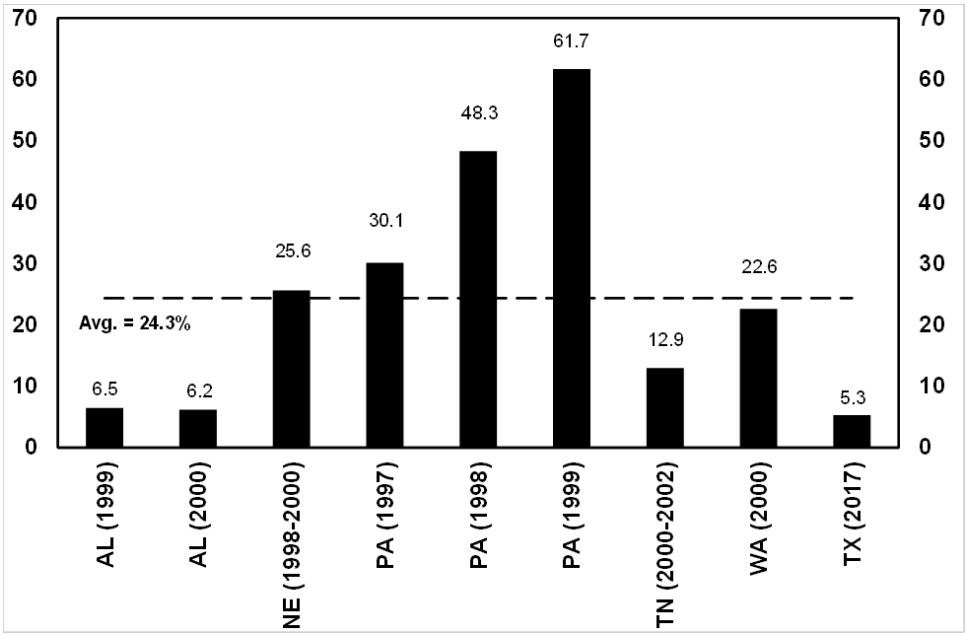
Figure C1a shows an average markup of 24% in states with creative financing schemes. This estimate is very close to the DD estimate in column (1) of Appendix Table C2.

Appendix Figure C1b presents evidence that the "effective FMAP" was up to 33 percentage points higher than the nominal one, for example, in Pennsylvania in 1999, where the effective FMAP was 87% instead of the official 54%.

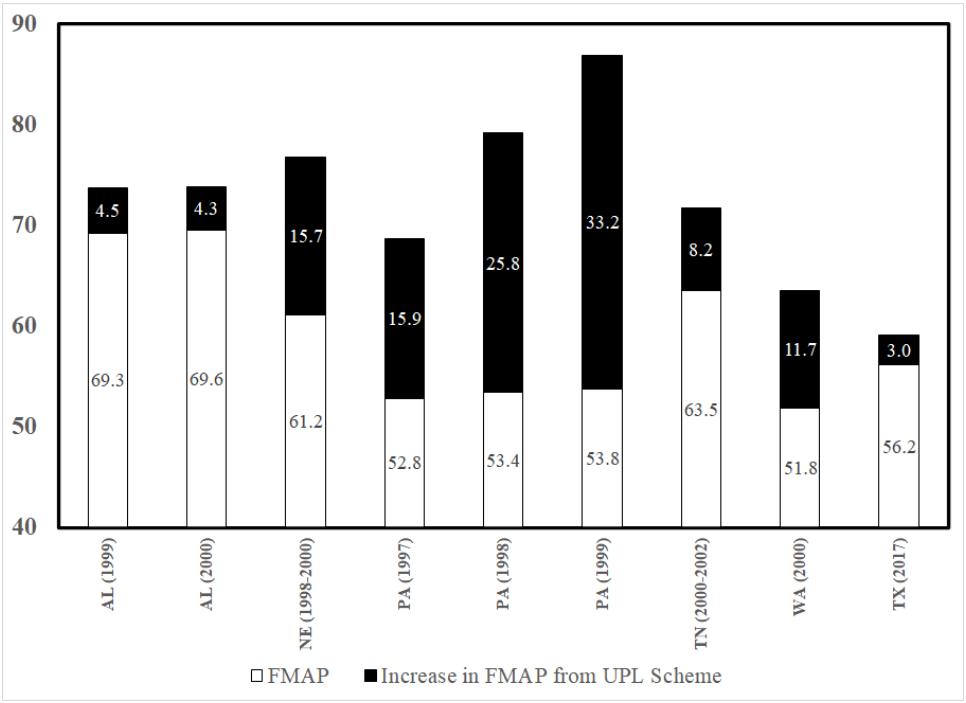
C.3 Financial Statements by Health and Hospital Corporation (HHC)

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

Figure C1: Public Markups and the Effective FMAP—Evidence from Audit Reports



(a) Public Markups



(b) Effective vs. Nominal FMAP

Notes: Figure C1a shows the public markup, $\frac{P}{R}$, indicating the wedge between the nominal Medicaid reimbursement rate, P, and the effective Medicaid reimbursement rate, R. Figure C1b contrasts the nominal vs the effective 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).

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 C3, 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.

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 to its "general fund" (column (7)). The monies were used to finance HHC's hospital operations.

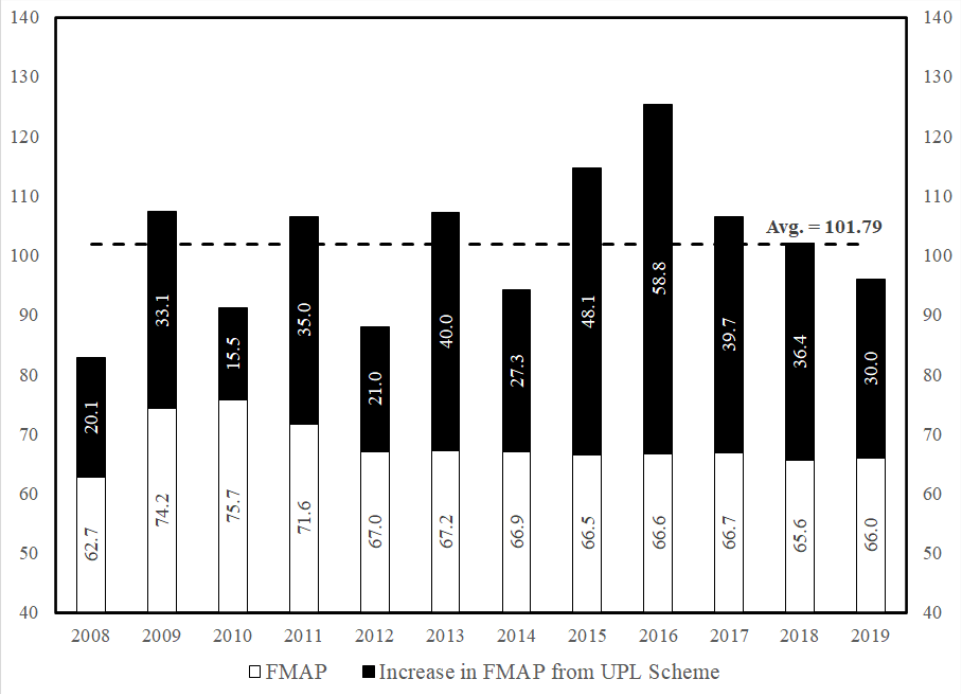
While we cannot quantify the amount transferred back to the state, independent sources suggest that it roughly recovered its share in supplemental payments. We thus, conservatively, assume that only the Medicaid base payments of $3.2 billion remained at the nursing homes. This corresponds to a markup of 72%:

$$\mu_{HHC} = \frac{P_{HHC} \times Q_{HHC}}{R_{HHC} \times Q_{HHC}} = \frac{\$5.5bn}{\$3.2bn} = 1.72 \tag{C2}$$

Thus, the effective FMAP was 68% (nominal FMAP) $\times 1.72 = 117\%$. Put differently, the federal cost share of Medicaid spending exceeds 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, as above, we assess the effective FMAP over time to bolster the claim that Indiana continued to run sophisticated financial schemes at least until 2019. To do so, we approximate Medicaid nursing home spending (*Reg MHEX*) from published HHC revenue from its long-term care division, along with its share of Medicaid patients. Between 2008 and 2019, none of the diverted funds from nursing homes to the General Fund were transferred back to fund nursing homes. Further, two-thirds of diverted funds went to the inpatient hospital division under *Wishard Health Services* (before 2013) and *Eskenazi*

Figure C2: 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.

Health Services (starting in 2013). The remainder was transferred to *Capital Projects and Debt Service Funds*. We calculate the markup and effective FMAP as:

Effective FMAP = FMAP $\times \frac{RegMHEX+SupMHEX}{RegMHEX} = FMAP \times \mu$, see Figure C2.

Table C3: 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	102

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

D Data Appendix to Provide Evidence on H2

Here, we describe in more detail the primary data sources to generate a panel at the nursing home-year level in Indiana from 1999 to 2015. The panel is based on 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 municipalization 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.[30]

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

[30] 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 codes are posted in the Supplementary Materials and describe 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.

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. 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. 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 4.3 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

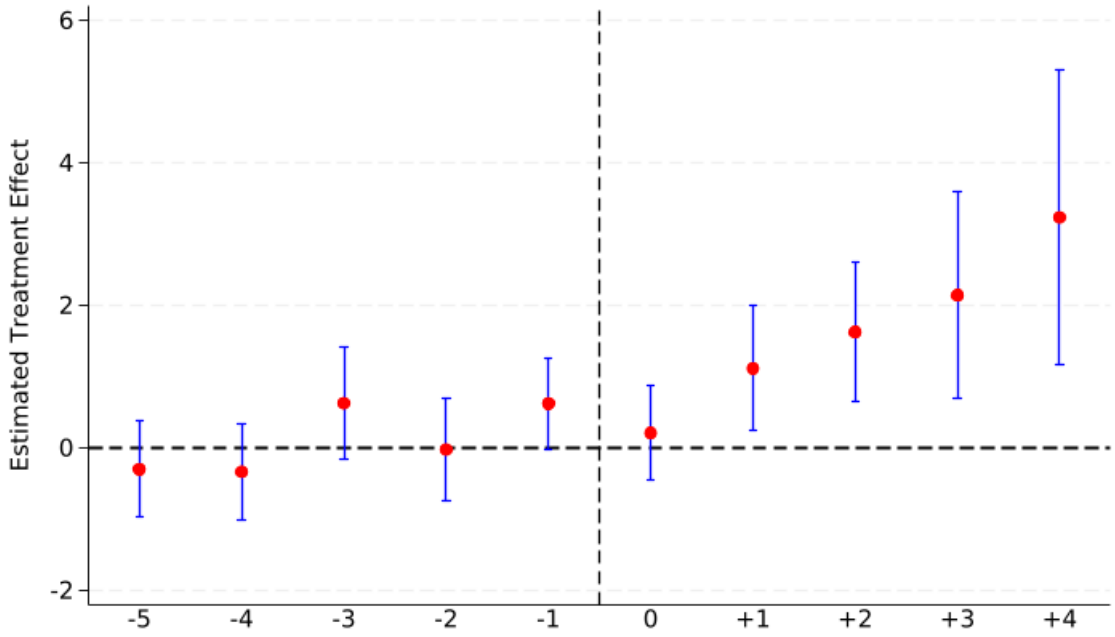
Source: Long-Term Care: Facts on Care in the U.S. (2025), MDS (2020), Centers for Medicare & Medicaid Services (2020b); Indiana Department of Health (2020), CMS Skilled Nursing Facility Provider Information, State of Indiana (2025), authors' calculation. The sample is based on AD/ADRD patients in acute 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	0.8994	(0.3007)	206,833
Black	0.0872	(0.2822)	206,833
Female	0.6207	(0.4852)	206,833
Index hospital stay in days	5.5642	(4.5465)	206,833
1-year survival rate	0.6707	(0.47)	206,833
30-day hospital readmission rate	0.1743	(0.3794)	206,833
90-day hospital readmission rate	0.3111	(0.4629)	206,833
Discharged to			
Home	0.3257	(0.4686)	206,833
Nursing home	0.3685	(0.4824)	206,833
Intermediate Care Facility	0.0332	(0.1793)	206,833
Hospice	0.0215	(0.145)	206,833
Nursing Home Matches MDS Claims			
Distance to next nursing home (in miles)	5.8902	(7.0849)	77,794
Medicaid days	185.8092	(469.9024)	76,272
Any Medicaid days	0.1238	(0.3293)	77,794

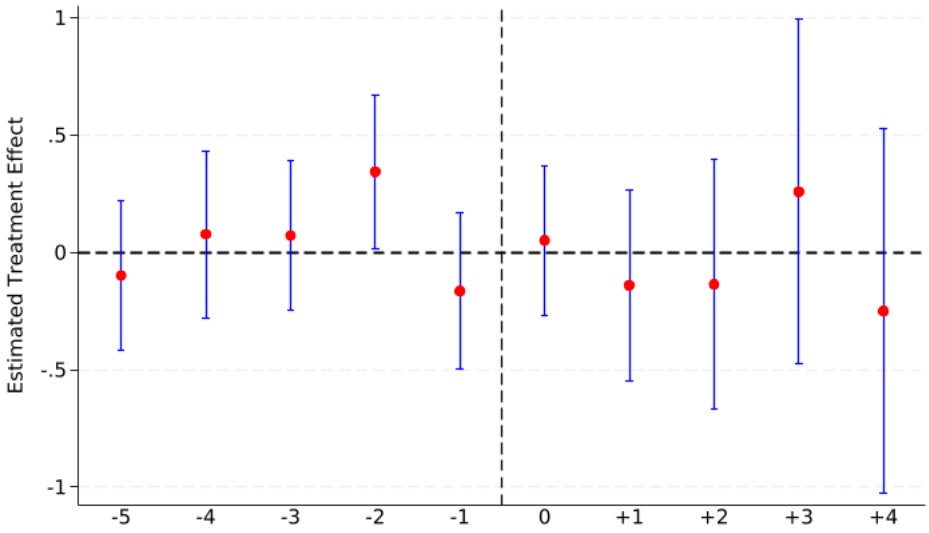
Source: Long-Term Care: Facts on Care in the U.S. (2025), MDS (2020), Centers for Medicare & Medicaid Services (2020b); Indiana Department of Health (2020), CMS Skilled Nursing Facility Provider Information, State of Indiana (2025), authors' calculation. The sample is based on AD/ADRD patients in acute 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 4.2 and Appendix D for details. Discharged home comprises community discharges in which patients may receive care at home.

Figure D1: Dementia Patients: Long Nursing Home Stays of 100+ Days



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 municipalization. All event studies show 90% confidence intervals.

Figure D2: Mortality Results



(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, where event time 0 indicates the municipalization. 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).[31]

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

which is estimated via the sample analogues:

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

[31] 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 municipalization of nursing homes, the quality of care may change because of the municipalization 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 .[32]

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.[33] 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).

[32]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.

[33]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 value-added 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 value-added 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 stand for selection on the 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: Municipalizations 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
Municipalized	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)			
Municipalized	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 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 (12). Estimates are based on the same dementia-related index hospital stays described in Appendix Table D4.

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

$\gamma_{ik}(j) = E[\eta_{ik} - \mu_\eta | x_{jt(i)}, \pi_i, c_i]$ 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

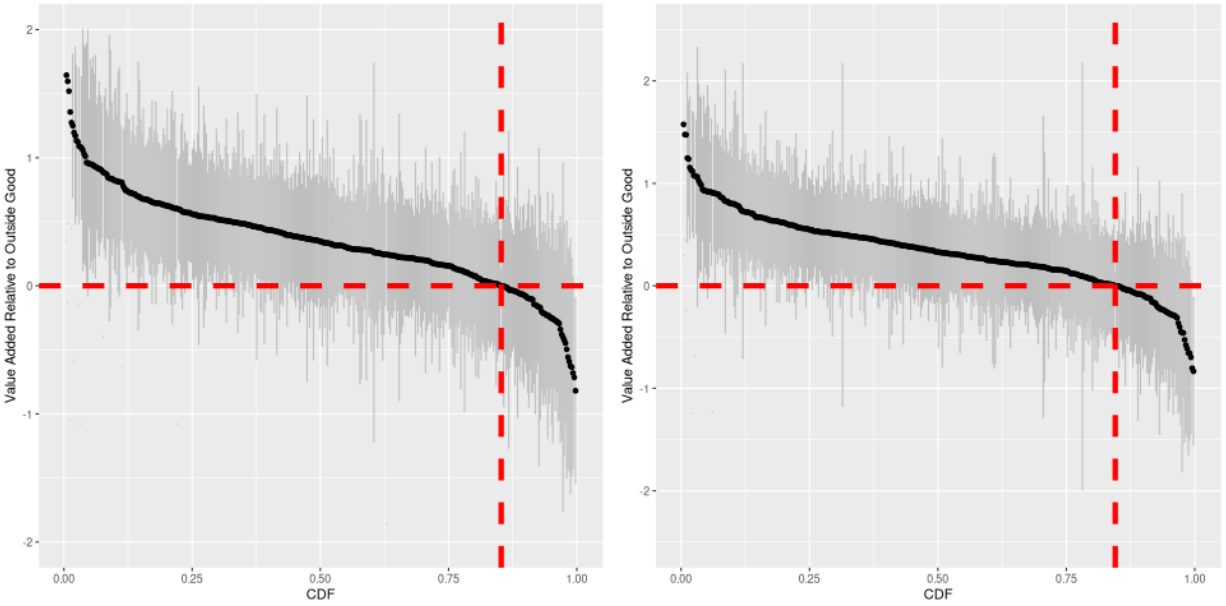
$$w_\pi = \hat{p}_{ik}(\pi) \times \frac{\phi(\frac{\pi}{\sigma_\pi})}{\int \hat{p}_{ik}(\pi)\phi(\frac{\pi}{\sigma_\pi})d\pi} \tag{F9}$$

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

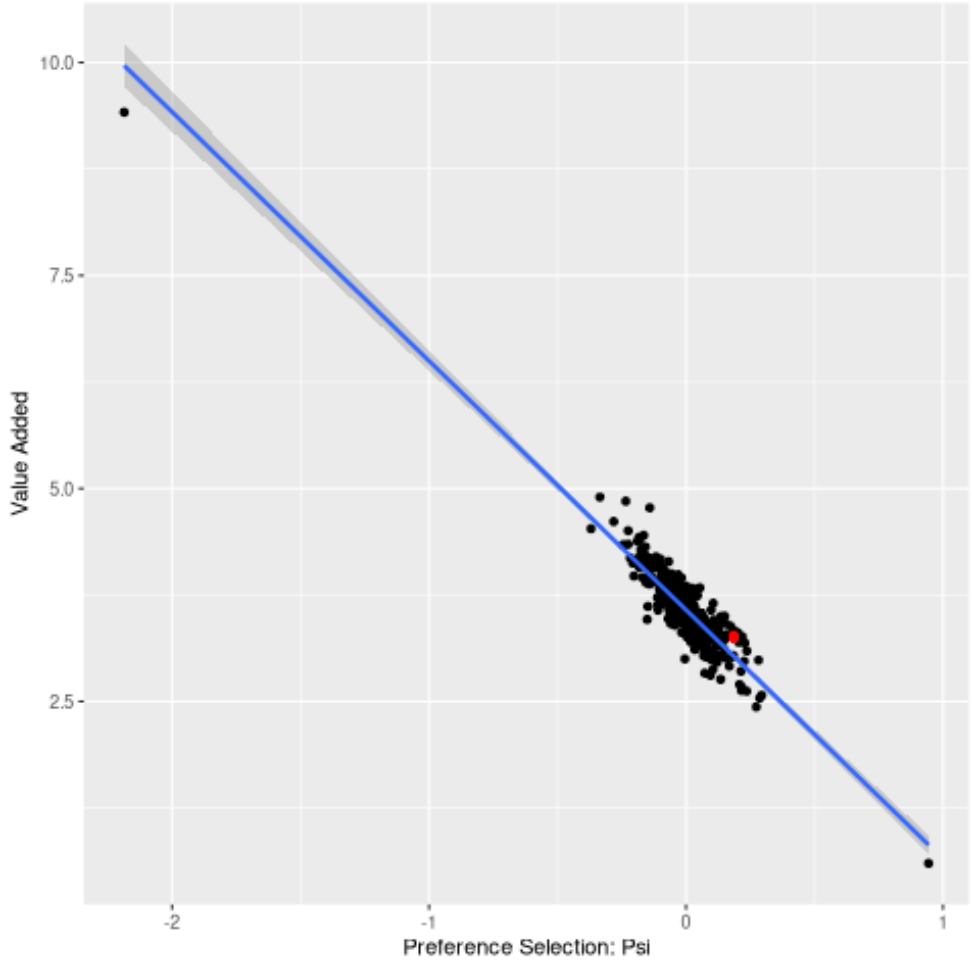
(b) One-Year Survival: Shrinkage Adjusted

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 value-added estimates α_j, see equation (12) 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).

First, Figure F2 shows clear evidence for selection into nursing homes via the strong correlation between our value-added estimates and the preference selection coefficient Ψ.

Figure F3 provides a binned scatter plot with value-added 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 value-added 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 = value-added) estimates, α_j, in equation (12), for one-year survival on the vertical axis.

F.3 Validation of Nursing Home Quality Measures:

Naturally, the nursing home-specific value-added estimates carry noise. To validate our value-added 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.[34] 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).

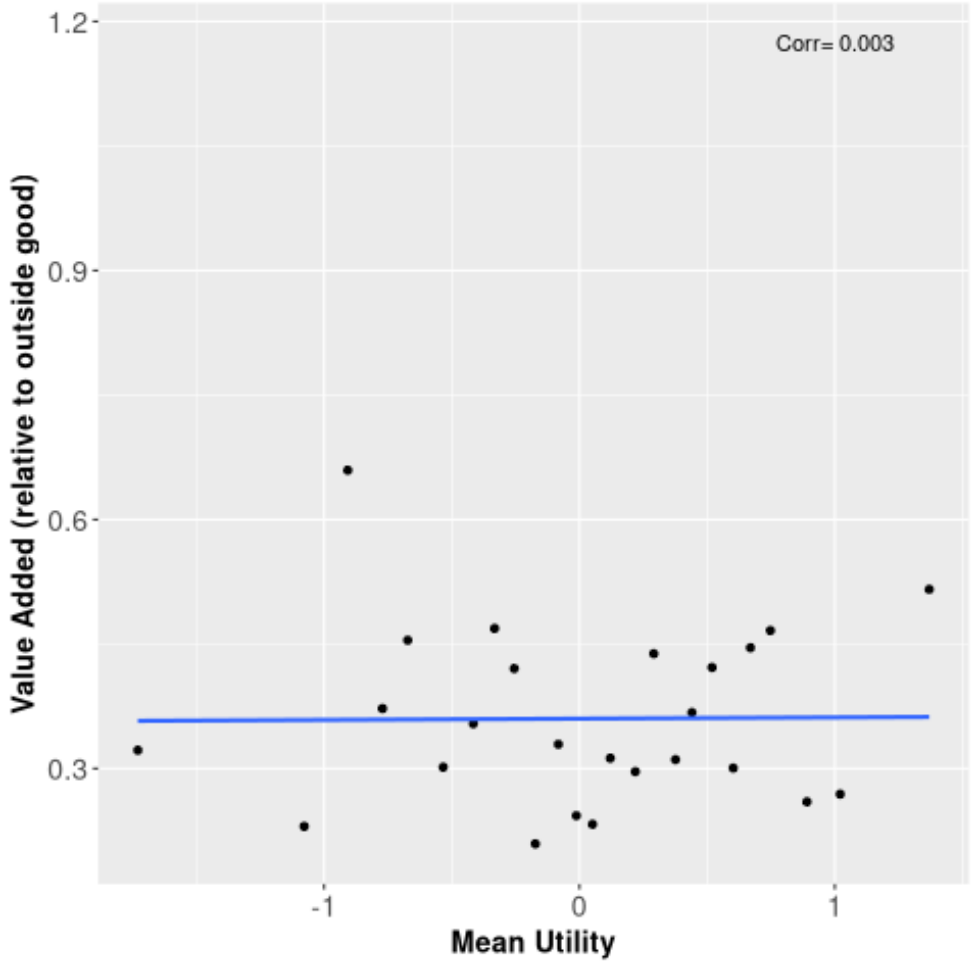
Panel B of Table F1 shows nursing home characteristics and the CMS star rating. These provide alternative quality of care measures. As seen, nursing homes with high value-added estimates also have higher registered nurse (RN)-to-patient staffing ratios and a higher RN-to-nurse ratio, which are key determinants 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.

Next, we validate our quality measures by correlating the value-added 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 shows the correlation between our three quality measures and nursing home characteristics, such as staffing ratios or star ratings. Finally, following Panel B of Table

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

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) value-added estimates, α_j, in equation (12), for one-year survival on the vertical axis.

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

	NH Value Added 1-Year Survival		
	High (top 20%)	Low (bottom 20%)	Medium
Standard. Value-Added			
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)

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 value-added estimates fall in the top quintile of the value added 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%.

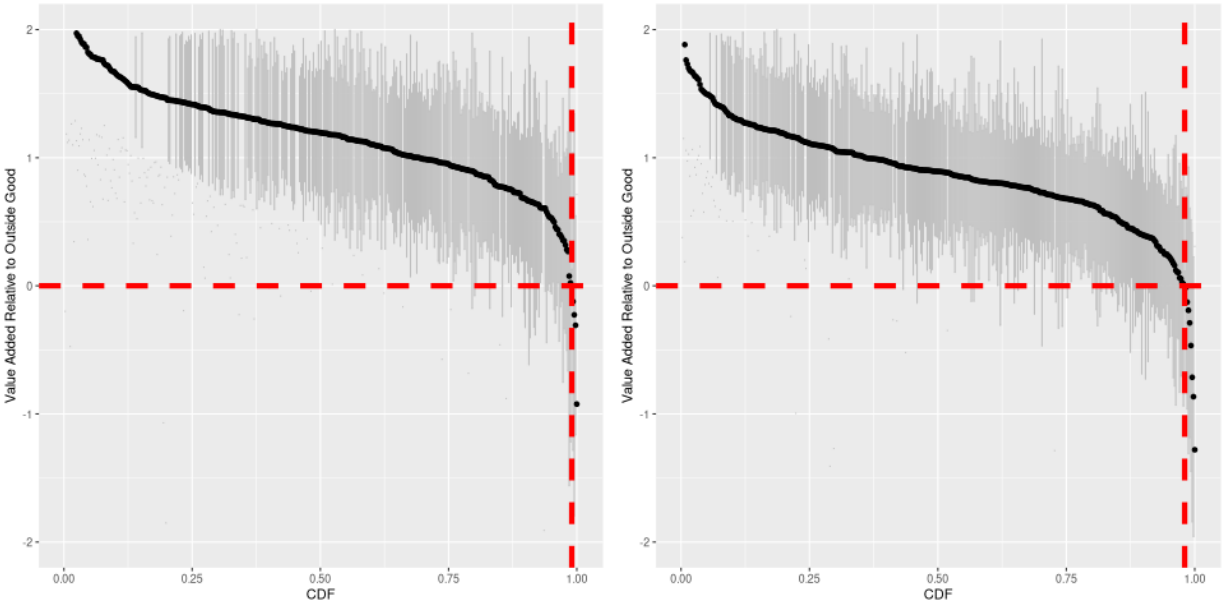
F1, Table F4 shows estimates for the health outcome equation using readmission rates instead of mortality.

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	-0.03
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.

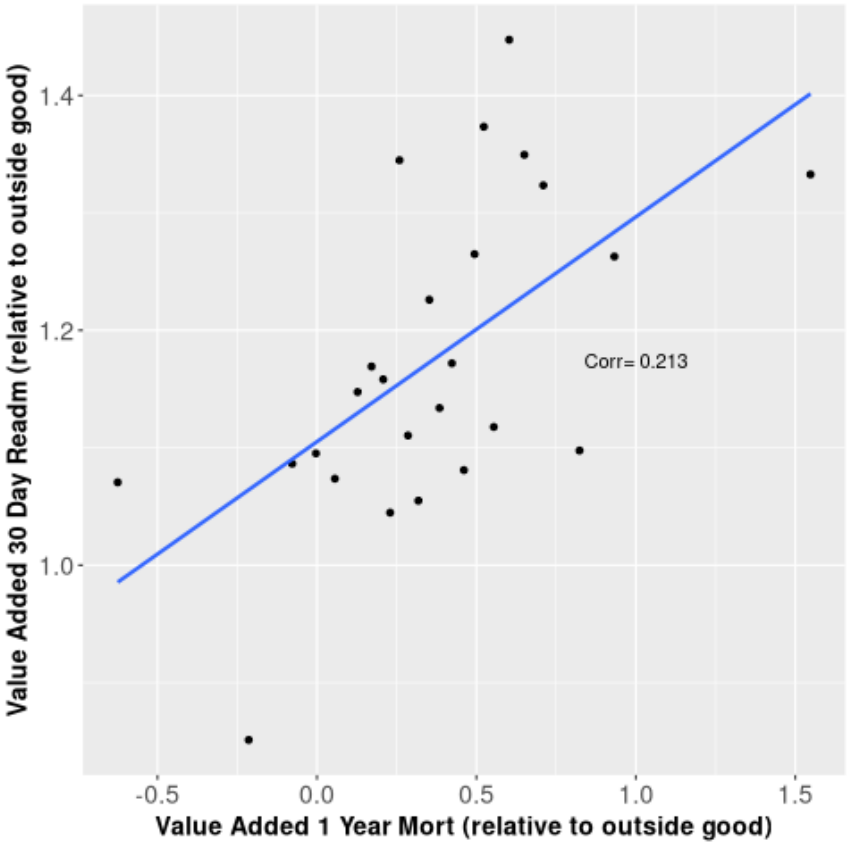
Figure F4: Value Added Estimates—Hospital Readmission Rates



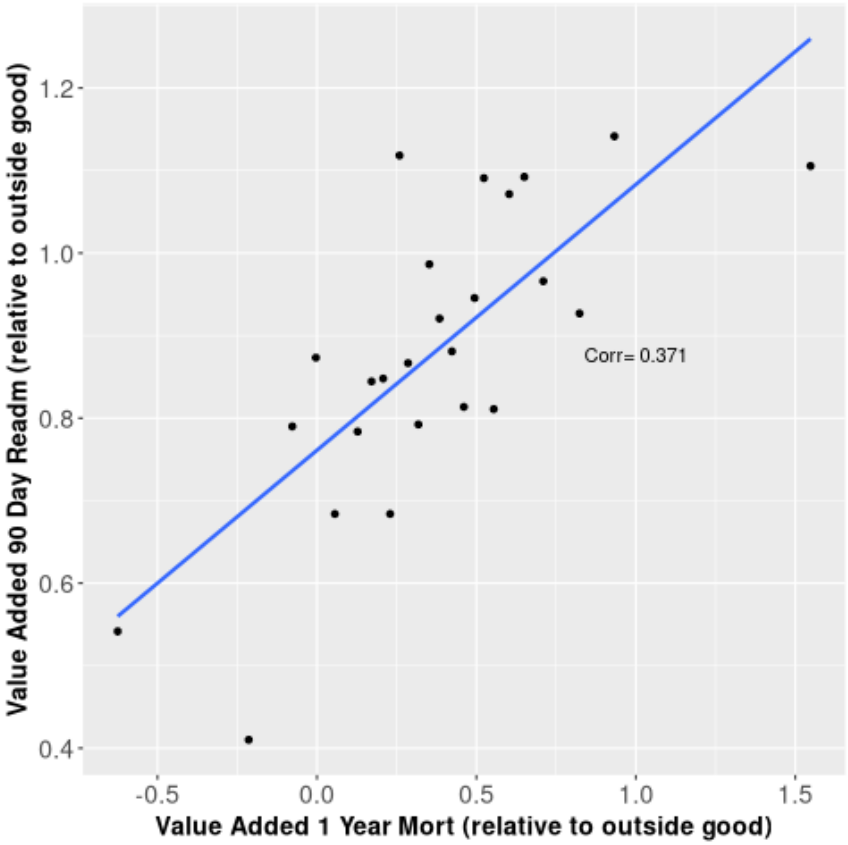
(a) 30-Day Readmission Rate

(b) 90-Day Readmission Rate

Figure F5: Valued Added—Mortality vs Readmission Rate



(a) Mortality Against 30-Day readmission



(b) Mortality Against 90-Day readmission

Table F4: 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 of dementia related index hospital stays described in Appendix Table D4.

F.4 Patient Relocation and Mortality:

We also probe the mortality 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 mortality effects of different care choices.

Let s_j denote the share of patients choosing nursing homes 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 municipalization. We aggregate the diversion ratios across groups of nursing homes, based on the value-added 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 F5 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 municipalization. 16.7% would have chosen the outside good, 15.0% a different nursing home of higher quality, 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 municipalization would have chosen a different nursing home.

The second panel of Table F5 considers implications for mortality. The first row, denoted "Post", presents the average one-year mortality rate at the destination nursing home (borrowed from Table F2). The second row, denoted "Pre", presents the average one-year mortality rate among marginal patients for the origin care choices. Intuitively, it presents the average mortality had the patients not chosen the destination facility.[35] As seen, the pre-post difference for

[35] Mathematically, this is determined by the weighted average over the "Post" mortality rates, including the mortality rate of 35.9% for the outside good, weighted by the diversion ratios in the first panel.

Table F5: Patient Relocation and One-Year Survival Rates

	By Value Added 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%
Mortality			
Post	11.5%	24.0%	42.5%
Pre	27.4%	27.2%	26.4%
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 mortality rate for an 85-year-old white female with a 6-day index hospital stay. The first row presents the average mortality rate in the destination nursing home. The second row presents the counterfactual mortality rate for marginal residents had they not chosen the destination nursing home. The last row presents the difference.

high-quality nursing homes is $27.4 - 11.5\% = 15.9\%$. Thus, expanding higher-quality nursing homes reduces the one-year mortality rate by 15.9 percentage points among marginal residents. In contrast, expansions of lower-quality nursing homes increase mortality by 16.1 percentage points among marginal residents.

G Details on Calibration

G.1 CES Approximation

First, we construct the average one-year survival rate over the three quintile groups in Table F2, based on their quintile shares (20%, 20%, and 60%). Pre-municipalization, we calculate an average one-year survival rate of 74.8%.[36] Second, and following municipalization, we estimate a 19% volume increase in lower-quality nursing homes, and 9 and 11% increases in middle and higher-quality nursing homes, respectively (see Table 1). Combined with the diversion ratios from Table F5, these compositional changes reduce the average one-year survival rate to 74.5%.[37]

For robustness, we consider the following benefit function featuring CES preferences,

$$B(\theta, Q) = v(\theta, Q) + \pi(\theta, Q) \approx \left[\gamma \times log(Q)^{\rho} + (1-\gamma) \times \theta^{\rho}\right]^{\frac{1}{\rho}} \tag{G1}$$

but maintain the same specifications for costs and health production. Note that, here, the parameter γ captures the relative importance of care volume.[38]

Calibration: We focus on Medicaid dementia patients using the estimated overall 12% increase in Medicaid volume (see Section 4.2).[39] We then calculate survival, pre- and post-municipalization, as follows: First, we take one-year mortality in each of the three groups in Table F2. Pre-municipalization, survival is the weighted average over the three estimates and implies a one-

[36] We have $1 - (0.2 * 11.5\% + 0.6 * 24\% + 0.2 * 42.5\%) = 74.8\%$.

[37] Here, we consider the nursing home type's own expansion effect and then net out the substitution effects as given by the diversion ratios. Let $g \in \{low, middle, high\}$ denote the type and $\Delta\%_g$ be the direct expansion effect as in Table 1. Finally, let $D_{gg'}$ denote the diversion ratios denoted in the top panel of Table F5. The relative market shares among nursing homes (ignoring the outside good) with creative financing are then given by $s_g^{CF} = (1 + \Delta\%_g) \times s_g^{NoCF} - \left[\sum_k \Delta\%_k \times s_k^{NoCF} \times \frac{D_{gk}}{\sum_m D_{mk}}\right]$, where s_g^{NoCF} denotes the baseline market shares for nursing home groups.

[38] Consistent with the theory, we abstract from changes in preferences following the acquisition of nursing homes. We note that the management of nursing homes typically remained unchanged following the acquisition, motivating this assumption.

[39] Absent a natural unit volume, we normalize log volume without creative financing to one and consider robustness around different values.

year survival rate of 74.8%.[40] We find a 19% increase in volume in lower-quality nursing homes and a 9 and 11% increase in middle and higher-quality nursing homes, respectively (see Table 1). Using the diversion ratios from Table F5, we estimate that the compositional changes reduce the average one-year survival rate to 74.5%.[41]

Next, we solve for the first-order conditions and use the estimated changes in volume and mortality to calibrate the unknown model parameters. The marginal rate of substitution is:

$$MRS = MB_q / MB_m = \frac{\gamma}{(1-\gamma)\times\beta} \times \left(\frac{\beta \times log(AC)}{log(\sum_j q_j)}\right)^{1-\rho} \tag{G2}$$

Following the discussion in Section 3, this implies that, in the optimum:

$$MRS = 1 \quad \Leftrightarrow \quad \frac{(1-\gamma)\times\beta}{\gamma} = \left(\frac{\beta \times \overline{log(AC_j)}}{log(\sum_j q_j)}\right)^{1-\rho}\Bigg|_{no\ CF} \tag{G3}$$

$$MRS = 1 - FMAP \times \frac{P-R}{AC} \quad \Leftrightarrow \quad \frac{(1-\gamma)\times\beta}{\gamma} \times (1 - FMAP \times \frac{P-R}{AC}) = \left(\frac{\beta \times \overline{log(AC_j)}}{log(\sum_j q_j)}\right)^{1-\rho}\Bigg|_{with\ CF} \tag{G4}$$

In words, the ratio of log average costs over log volume (with and without creative financing) is informative about the relative importance of volume in the planner's objective function and the elasticity of substitution, ρ. With estimates of average costs, mortality, volume, and the effective FMAP under creative financing, we can back out the parameters β, γ, and ρ.

With creative financing, the slope of the cost curve flattens from -1 to $-(1 - FMAP \times \frac{P-R}{AC})$ (Figure 2).[42] With two conditions and three unknown parameters (β, γ, ρ), we need to impose

[40] We have $1 - (0.2 * 11.5\% + 0.6 * 24\% + 0.2 * 42.5\%) = 74.8\%$.

[41] For this calculation, we consider the nursing home type's own expansion effect and then net out the substitution effects as given by the diversion ratios. Let $g \in \{low, middle, high\}$ denote the type and $\Delta\%_g$ be the direct expansion effect as indicated in Table 1. Finally, let $D_{gg'}$ denote the diversion ratios denoted in the top panel of Table F5. The relative market shares among nursing homes (ignoring the outside good) with creative and then given by $s_g^{CF} = (1 + \Delta\%_g) \times s_g^{NoCF} - \left[\sum_k \Delta\%_k \times s_k^{NoCF} \times \frac{D_{gk}}{\sum_m D_{mk}}\right]$, where s_g^{NoCF} denotes the baseline market shares for nursing home groups.

[42] The base Medicaid reimbursement rates are cost-based and often assumed to be approximately equal to average costs. We therefore assume $AC = R$ and use the estimates from Section 4.2 to arrive at a slope of $-(1 - 0.68 \times \frac{5.5-3.2}{3.2}) = -0.51$.

one additional normalization and set $\beta = 1$. We then set $\gamma = 0.84$ and $\rho = -4.73$ to match the first order conditions pre and post-creative financing.

Results: Figure G1 illustrates the quality-quantity tradeoff based on the empirical evidence from Indiana. The horizontal axis denotes log Medicaid dementia patient days per nursing home and year. The vertical axis denotes one-year survival rates. The red circle represents the allocation without creative financing, and the gray upward sloping line denotes the expansion path. The red diamond indicates the allocation with creative financing, which is below the optimal expansion path.

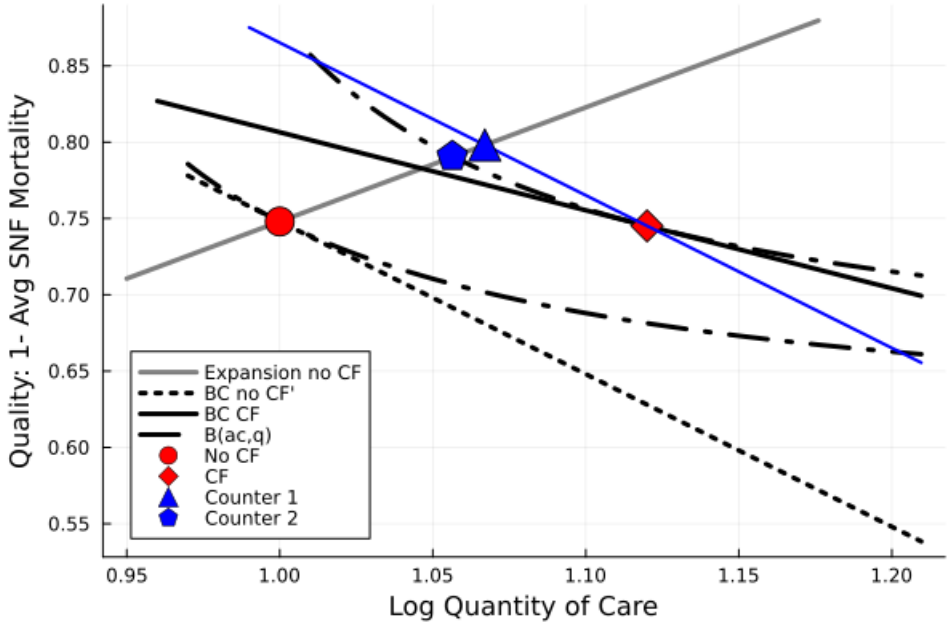
To measure distortions, we add two curves to the framework. First, we add the social budget constraint with a slope of -1, going through the allocation with creative financing, denoted by the blue line. The triangular point denotes the optimal bundle, the intersection between this line and the expansion path, holding total effective costs (under creative financing) fixed. Second, we add the indifference curve, going through the allocation with creative financing. The intersection between the indifference curve and the expansion path, the blue pentagon point, denotes the allocation that achieves the same social objective but at lower costs. Based on the calibrated parameters, we find cost savings of about 3.3% (the difference between the points denoted by the triangle and the pentagon).

According to our estimates from Table F5, only 16.6% of new residents would otherwise choose outpatient care. That means that the aggregate quantity effects are accordingly smaller. While it is unclear whether nursing homes internalize the effects of business stealing from other nursing homes, the federal government would. We, therefore, also consider a specification with a smaller quantity expansion of only 16.6%$\times$12%=2%[43]. The results are qualitatively similar, but the cost savings are proportionally smaller and equal 0.3% (without holding benefits fixed). We note, however, that it is unlikely that the entire increase in patient days can be attributed to increases in admissions from acute care hospitals. To the extent that nursing homes also prolong stays and delay discharges to the community following increases in Medicaid rates (Hackmann, Pohl, and Ziebarth, 2024), increases in total nursing home days will be larger. Hence, we view this second estimate as a lower bound.

Taking stock, we estimate that Medicaid days among dementia patients increase by between 2 and 12% because of public moral hazard. In Indiana, at least 90% of the state's 500 nursing

[43]Considering the average 12% increase in Medicaid days across all nursing homes.

Figure G1: Quality and Quantity Tradeoffs—Evidence from Indiana



Source: The figure provides an empirical illustration of the theoretical framework in Figure 2 using the empirical evidence from Indiana. The horizontal axis displays log quantity of nursing home days, and the vertical axis denotes log average costs per patient day, which is further averaged across nursing homes. The grey upward-sloping line denotes the expansion path without creative financing (CF), and the red circle 'no CF' denotes the allocation prior to the municipalization of nursing homes. The red diamond point 'CF' denotes the allocation with CF. The social budget constraint has a slope of -1, denoted by the blue line. The intersection between this budget constraint and the expansion path, the triangular blue point, denotes the optimal bundle, holding total costs under creative financing fixed. The intersection between the indifference curve and the expansion path, the blue pentagon point, denotes the allocation that achieves the same hospital-nursing home objective but at lower costs.

homes participate in the creative financing scheme, each providing 10,000 Medicaid-covered dementia days annually on average. Indiana nursing homes are reimbursed at a $297.4 base rate plus a $108.3 supplemental rate per resident and day (Stulick, 2025). This translates to an additional Medicaid spending of $42-$255 million per year.[44] Hence, between 0.3 and 3.3% of overall ADRD spending can be considered wasteful; in Indiana alone, this amounts to between $55 and $600 million over 10 years. To put it further into context, the amount corresponds to roughly 20% of the increased spending. It is attributable to lower-quality nursing homes that held a 20% market share before the scheme's introduction.

[44] We have 450 nursing homes $\times$ 10k days per NH $\times$ ($297.4 + $108.3) $\times$ (0.02 to 0.12) =$37 - $219 million.