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

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Abstract

This paper studies the misallocation of Medicaid funds, its consequences for reimbursement rates, and quantity and quality of care used. Combining two decades of administrative, audit, and survey data on U.S. nursing homes, we show that states employ creative financing schemes to divert federal matching funds from their intended purposes. Our theoretical and empirical analysis demonstrates that these schemes distort the quality-quantity tradeoff. In Indiana, exploiting plausibly exogenous variation in the rollout of a creative financing scheme, we find that these strategies result in a disproportionate expansion of Medicaid-funded care for dementia patients in the lowest-quality nursing facilities.

Keywords: fiscal federalism, distortions, moral hazard, Medicaid, nursing homes

JEL Codes: H51, H75, I11, I13, I18, J14.

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1 Introduction

Joint funding of public programs has been a cornerstone of U.S. federalism. In 2022, the federal government provided states and local governments $1.2 trillion in federal grants to fund a wide range of public policies, including health care, education, transportation, and environmental protection (House Budget Committee, 2023). Joint funding often includes federal matching grants that subsidize lower-level government spending. Federal matching grants help lower governments internalize externalities and provide them with insurance against aggregate enrollment fluctuations (Oates, 1999). However, they also create a principal-agent problem. Local jurisdictions may misallocate resources when the federal government cannot fully monitor effective program spending.

In this paper, we study the misallocation of federal matching funds and their implications for patients and providers in the context of the large and growing Medicaid program, projected to reach $799 billion in federal spending by 2033 (Congressional Budget Office, 2023). We document that states use complex creative financing schemes to obscure actual spending, enabling the diversion of funds from their intended uses. We present some of the first empirical evidence that these schemes distort the states' quality-quantity tradeoff, expanding lower-quality care services in order to maximize the revenue from federal matching grants. We do so in a crucial empirical setting: the U.S. nursing home industry, which heavily relies on Medicaid financing and has been plagued with concerns over the quality of care (Evans, Hopkins, and Cook, 2020b; Estrada et al., 2024). Combining two decades of administrative, audit, and survey data with quasi-experimental variation in the rollout of a creative financing scheme in Indiana, we document disproportionate increases in Medicaid-funded care in the lowest-quality nursing facilities, with potentially harmful consequences for patient mortality.

We begin by making a basic theoretical point in a principal-agent framework, representing the federal government and states, respectively. Central to this model is the federal government's inability to perfectly monitor state spending of federal funds. We argue that this is a reasonable assumption given widespread "creative financing" practices across states and federal regulators' documented inability to eliminate them. For instance, despite a 2003 reform intended to end such practices, creative financing activities continue to persist (Department for Health and Human Services: Office of Inspector General, 2014;

MACPAC, 2021) and new creative financing instruments have been developed in Indiana and many other states. Comprehensive federal audits in the late 1990s struggled to track complex financial flows at state levels and reports by Department for Health and Human Services (2025) concluded it was "nearly impossible" to identify and follow these financial streams.

We then examine how this incomplete monitoring affects the quality-quantity trade-off in the Medicaid program. Specifically, we assume the federal government can monitor care quantities and nominal reimbursement rates, but not effective rates paid after fund diversion. This creates incentives for states to inflate nominal rates (qualifying for federal subsidies) while reducing effective provider payments—likely degrading care quality, which is again difficult to monitor (Weisbrod, 1991). We term this gap between nominal and effective rates "public markup," which states divert elsewhere. Simultaneously, higher nominal rates drive increased care quantity, creating what we call "public moral hazard"—expanded public insurance utilization resulting from joint funding and incomplete monitoring.

We test these predictions in the context of Medicaid payments to U.S. nursing homes. First, we present new evidence on the prevalence of creative financing schemes in this vital industry, and quantify the public markup. Combining audit reports with survey data, we document that between 2000-2002, 16 states used intergovernmental transfers to divert at least $17bn in Medicaid funds away from nursing homes. Put differently, states inflated nominal reimbursement rates by 40% over the effective rate paid to nursing homes. When considering the diversion of funds, the implied federal cost share of Medicaid spending, the Federal Medicaid Assistance Percentage (FMAP), increases by 16 percentage points (pp), a much larger effect than previously reported (MACPAC, 2021).

In response to the audit reports, Congress directed the Secretary of Health and Human Services (HHS) to cap the scope of intergovernment transfers. Effective 2003, states could no longer redirect funds from private nursing homes, restricting intergovernmental transfers to the 7% public nursing homes. In response to the 2003 law, and to continue (and even expand) their creative financing scheme, Indiana systematically municipalized private nursing homes. We exploit this scheme in Indiana to study its causal effects on the quantity and quality of care.

As a result, in Indiana, the share of publicly owned nursing homes surged from 5% in 2000 to 95% by 2017. We combine the timing of these acquisitions with high-quality administrative micro data from the Centers for Medicare & Medicaid Services (CMS) to quantify the scheme's causal effects on the care volume. Our findings confirm a public moral hazard effect: we estimate a significant 5% increase in Medicaid days following the acquisitions. This increase in Medicaid days is driven by patients diagnosed with Alzheimer's disease and Alzheimer's disease-related dementias (AD/ADRD). For this patient group, the increase in Medicaid days is 14% and accompanied by a significant increase in Alzheimer's special care units. AD/ADRD patients have relatively long lengths of stay, are rarely discharged to home health care options, and require specialized treatment; quality of care for AD/ADRD patients is positively correlated with the share of AD/ADRD patients in nursing homes (Mukamel et al., 2023), suggesting that nursing homes without much experience provide lower quality of care, especially in economically deprived counties and among minorities (Travers et al., 2024; Estrada et al., 2024).

Central to patient welfare is how Indiana's scheme affects patient health. We examine two key mechanisms: changes in nursing home care quality post-municipalization, potentially attributable to the addition of Alzheimer's special care units, and patient relocation between nursing homes and other care settings. To this end, building on Dubin and McFadden (1984); Abdulkadiroğlu et al. (2020); Einav, Finkelstein, and Mahoney (2022), we estimate a nursing home health value-added model using patient distance to nursing homes as a plausibly exogenous source of variation in nursing home choices. We focus this exercise on AD/ADRD patients using the one-year survival rate as our primary health outcome measure. The analysis yields three main findings. First, holding the patient composition fixed, we find no significant change in nursing home quality following the municipalization. Second, we estimate large differences in quality between nursing homes. Moving a patient from the bottom quintile to the top quintile in the quality distribution decreases the one-year survival rate from more than 33% to less than 16%. Further, nursing homes in the bottom quintile provide lower quality care than outside goods, comprising mostly care provided at home. Third, we find quantity increases throughout the quality distribution, but that the increase is largest for nursing homes in the bottom quintile of the quality distribution.

In the last section of the paper, we connect our findings to our conceptual framework to assess the implications for allocative efficiency. We find that Indiana's scheme distorts the quality-quantity tradeoff towards an expansion of lower-quality nursing home care. In contrast, the optimal expansion path would allocate some of the incremental Medicaid spending towards improving the quality of care (e.g., increased nurse-to-patient staffing ratios) or towards expanding higher-quality nursing homes. Our calculations suggest that Medicaid spending on dementia patient stays could be reduced by 3.4% without compromising the quality-adjusted quantity of care.

Our findings contribute to several literatures. First, we add to research on strategic interactions in fiscal federalism (Gordon, 1983; Dahlby, 1996; Agrawal, 2015; Clemens and Veuger, 2023), arguing that states use creative financing schemes to obscure spending and divert Medicaid funds. Although these schemes have been examined in health policy (Coughlin and Zuckerman, 2003b; Mitchell, 2018), law (Hatcher, 2017), and the popular press (Evans, Hopkins, and Cook, 2020b), they have received little attention in the economics literature. An important exception is the seminal paper by Baicker and Staiger (2005), who document the diversion of Medicaid matching funds in the context of Disproportionate Share Hospital payments. We add to their analysis by highlighting that these schemes introduce a regulator bias, in the spirit of Averch and Johnson (1962), distorting the states' quality-quantity tradeoff towards expanding lower-quality programs. Our analysis informs the debates on Medicaid financing reform (Committee for a Responsible Federal Budget, 2023b), including increased surveillance (Federal Register, 2019), cost-sharing changes (Rudowitz, 2017; Clemens and Ippolito, 2018), monitoring for fraud (Shi, 2023) and broader fiscal impacts (Gruber and Sommers, 2020).

Second, we add to a large and growing health economics literature on patient and provider moral hazard under asymmetric information (Finkelstein et al., 2012; Baicker, Mullainathan, and Schwartzstein, 2015; McGuire, 2000; Miller, Johnson, and Wherry, 2021; Eliason et al., 2018; Einav, Finkelstein, and Mahoney, 2018; Clemens and Gottlieb, 2014; Hackmann, Pohl, and Ziebarth, 2024). We add to this discussion the role of asymmetric information between the federal government and local jurisdictions and show how it can result in "public" moral hazard. Consistent with evidence on Medicaid Disproportionate Share Hospital payments (Duggan, 2000), we find an increase in patient volume following an increase in nominal reimbursement rates. Interestingly, though, in our setting county-

owned hospitals are the key players and use diverted nursing home funds to finance their hospital operations.

Third, we contribute to the literature on the design of reimbursement models and the quality of care in U.S. long-term care. We find that several states systematically divert Medicaid funds earmarked for nursing home care, likely contributing to quality shortfalls that have plagued the industry for decades (Grabowski, 2001; Werner, Konetzka, and Polsky, 2013; Lin, 2015; Hackmann, 2019). At the same time, several critiques argue that policy biases toward institutional nursing home care continue to exist (Chidambaram and Burns, 2023) despite the fact that nursing home care is highly unpopular and the elderly prefer to age at home (The Associated Press-NORC Center for Public Affairs Research, 2021). We find that creative financing schemes can distort the quality-quantity trade-off in the design of long-term care policies, potentially contributing to the adoption of policies that favor institutional care (Grabowski and Gruber, 2007; Mommaerts, 2018). We combine recent advances in the estimation of nursing home value added Einav, Finkelstein, and Mahoney (2022); Olenski and Sacher (2024); Cheng (2023) with plausibly exogenous variation in the timing of nursing home acquisitions (Gupta et al., 2021; Gandhi, Song, and Upadrashta, 2023) to document that Indiana's creative financing scheme resulted in a disproportionate increase in Medicaid-funded care in the lowest-quality nursing facilities.

2 Institutional Setting

2.1 The Structure of Medicaid Funding

The Medicaid program, a cornerstone of the U.S. healthcare system, operates under the framework of federalism in health policy, with $880 billion in annual spending (Kaiser Family Foundation, 2024b). It provides public health insurance for 93 million low-income individuals, granting states significant administrative discretion while sharing costs with the federal government.

State and federal sources jointly fund Medicaid. Its financing model requires states to contribute funds to qualify for federal matching. The federal cost share of Medicaid spending is the Federal Medical Assistance Percentage (FMAP). The FMAP 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).

However, states often employ creative financing schemes, such as provider taxes or intergovernmental transfers (detailed below), to reduce their general fund obligations. All states but Alaska adopt provider taxes on primary care physicians, insurance plans, hospitals, and nursing homes and are now one of the largest funding sources for states' Medicaid costs. As we detail below, these instruments allow states to extract federal matching funds from these entities, thereby effectively shifting additional costs onto the federal government. The Committee for a Responsible Federal Budget (2023a) estimates that the federal government covers over 5% more in Medicaid costs than it would without creative financing. These sophisticated schemes are borderline legal. However, the Centers for Medicare and Medicaid Services' limited oversight and monitoring capacities help explain their scale and persistence.

A former senior official from the Department of Health and Human Services writes:[1]

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

2.2 Creative Financing in SNFs: Pre-2003

Our analysis focuses on the nursing home industry. It heavily relies on Medicaid spending, with two-thirds of all 1.5 million nursing home patients covered by Medicaid, totaling $59bn in overall Medicaid spending per year (Kaiser Family Foundation, 2024a). State Medicaid programs reimburse nursing homes on a "per diem" basis (MACPAC, 2019a); these base rates are lower than for private payers or Medicare, resulting in low quality of care (Grabowski, 2001; Hackmann, 2019). Consequently, states can top up Medicaid base rates via Supplemental Payments (SP) to avoid lower quality-of-care for Medicaid beneficiaries. The total reimbursement rate, per diem plus SP, is then matched with federal funds using the FMAP, as long as the total rate remains below the "Upper Payment Limit"

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

(UPL) (Mitchell, 2018).[2] In 2019, SPs accounted for seven percent of total Medicaid fee-for-service nursing facility payments (MACPAC, 2019b).

However, when states use creative financing to divert nursing home payments, these top-up payments are unlikely to improve the quality of care. Before 2003, states could divert funds accrued by public *and* private nursing homes to county-owned nursing homes and then redirect them to the state via Inter-Governmental Transfers (IGTs). Specifically, the pre-2003 regulations left states complete discretion on how to allocate SPs across providers. As a result, states could pay hundreds of millions in Medicaid funds to nursing homes, triggering further hundreds of millions in federal matching funds to the same nursing homes. As these payments were not tied to specific services, states could funnel large portions back into the state budget via IGTs and use the funds for other purposes.

Panel A of Appendix Figure A.1 illustrates such a scheme (Mangano, 2001; Coughlin and Zuckerman, 2003b). Pennsylvania paid $300 million (figures rounded) in UPL-SPs to 23 county-owned nursing homes. Given the FMAP of 56%, this triggered $400 million in federal matching funds and produced a total of $700 million for the county nursing facilities. Yet only $1.5 million remained with the providers as the rest was transferred to the Pennsylvania government via an IGT.

2.3 The 2003 Reform

In 2001, twenty-nine states operated IGT programs, many for nursing homes (U.S. Department of Health and Human Services, 2001). In response, Congress directed the Secretary of Health and Human Services (HHS) to cap federal Medicaid spending that could be diverted through IGTs (Ku and Park, 2001; Federal Register, 2001). Consequently, effective 2003, a reform banned states from redirecting monies from *private* nursing homes. While states could still set up IGTs from *public* nursing homes, public nursing homes only had a market share of 7% (Gabrel, 2000)).

[Insert Figure 1 about here]

Further, 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

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

responded to their survey used creative financing schemes in FY 2002; 16 states used UPL-SPs schemes in the nursing home industry, see Figure 1. Sixteen states did not use UPL-SPs schemes in the nursing home industry. In Section 4.1, using this information to define treatment and control groups, we estimate the effect of the 2003 reform on mark-ups, and thus effective reimbursement rates.

2.4 Creative Financing 2.0: Evidence from Indiana

After the 2003 reform, states explored alternative creative financing schemes to continue to redirect federal matching funds. One notable example is provider taxes, which function similarly to pre-reform IGT schemes (Miller and Wang, 2009).[3] By contrast, Indiana implemented an alternative scheme that mirrored pre-2003 reform practices. This scheme is the focus of our empirical analysis as we exploit it to estimate the causal effects of creative financing on various outcomes.

Specifically, to bypass the 2003 reform, Indiana induced county-owned hospitals to acquire private nursing homes. Once public, the state reinstated IGTs 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 payments and SPs to newly acquired county-owned nursing homes. Federal matching funds then augmented these payments. Next, county hospitals would redirect these funds from the nursing homes through IGTs (Hatcher, 2017), with a portion returned to the state budget. Panel B of Appendix Figure A.1 illustrates this post-2003 scheme in Indiana. Under a contractual agreement, county hospitals repaid the SPs to the state, while retaining the federal match, which was divided between the hospital and the SNF. Because federal matching funds were proportional to Medicaid service days, the integrated hospital-SNF 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 statewide as shown in Figure 2a.

[3] Fosdick (2007) describes Michigan's 1.8% provider tax on net hospital patient revenues, which generated $243 million in tax revenues in 2006/2007. Of this, Michigan retained $46 million ("gainsharing") and returned $197 million to hospitals via higher Medicaid rates, attracting $257 million in federal matching funds. Hospitals experienced a net revenue increase of $210 million, while the state gained $47 million.

[Insert Figure 2 about here]

In that context, it is noteworthy that Indiana permitted HHC to use a "lease structure" instead of directly acquiring SNFs to facilitate these purchases (Pahud and Myers, 2016). Unlike a direct acquisition, where a hospital buys providers' assets, the lease structure allowed HHC to acquire solely the nursing home license while leasing the remaining assets. This lease structure thus triggered a change of ownership without altering the nursing home management, which typically retained 5-20% of the additional UPL payments (Hatcher, 2017). The Indianapolis Star described the county hospital as "an absentee landlord primarily concerned with using this collection of nursing homes to generate much-needed cash." CMS has harshly criticized such arrangements, noting that "everyone wins—except perhaps the patient and the federal taxpayer" (Evans, Hopkins, and Cook, 2020a). In 2010, Indiana expanded the model to other county hospitals, and by 2017, over 90% of SNFs in the state were county-owned, see Figure 2b.

This scheme has been highly effective in maximizing federal Medicaid revenue. In fiscal year 2020, Indiana received $996.1 million in SPs for nursing facilities, making up over 30% of all federal SP funding, more than any other state, including states like California and New York (Medicaid and CHIP Payment and Access Commission, 2021). Through their scheme, since 2003, Indiana county hospitals have secured approximately $4.3 billion in additional Medicaid funding for nursing homes. However, investigations 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 the nursing home acquisitions to study the causal effect of this scheme on the volume and the quality of care.

3 Conceptual Framework

The previous discussion highlights that, even after reforms to stop such practices, states continue to develop sophisticated, creative financing schemes. These schemes make it difficult for the federal government to monitor effective program spending. This allows states (or county-owned hospitals) to divert funds from their intended purposes. In this section,

we develop a unifying theoretical framework that helps us understand how creative financing schemes can distort the quality and quantity of care provided.

We start with a general principal-agent framework with monitoring frictions and develop their economic implications. The framework considers two types of agent effort, but the Principal can only perfectly monitor one of them. Our main finding is that when the payment to the agent is complementary in both reported efforts, actual efforts will be distorted in opposing directions: the agents shirks in the non-monitored effort but inflates the monitored effort. The details are presented in Appendix B.

In what follows below, we apply the general insights to our institutional setting, where the Principal is the federal government and the Agent can be the state, as discussed below, or a publicly owned provider, which we detail in our empirical application. In the case with incomplete monitoring, we treat patient volume as monitored effort and effective spending as the non-monitored effort.

3.1 Payoffs

State ("The Agent"): We assume that the state values the quality, θ, and the quantity of nursing home care, Q, provided through the benefit function $B(\theta, Q)$, which we denote in dollars. State internalize only fraction $\tau \leq 1$ of the benefits because of free-riding on neighboring states.[4]

The federal government (the Principal) covers a fraction of total nominal Medicaid spending ($P \times Q$) according to the state's FMAP, where P denotes the nominal Medicaid reimbursement rate. In contrast, the state pays nursing homes *effective* reimbursement rates (net of diversion of funds), worth $R \times Q$, where R is the effective Medicaid reimbursement rate. We assume a positive relationship between the effective reimbursement rate and the quality of care, $\theta(R)$. The state's payoff is then:

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

Building on the notation from the principal-agent literature, we refer to the first term as the utility of participating in the program.The second term captures the costs of efforts,

[4] Alternatively, τ can be interpreted as a discount factor when states' prioritize spending on other programs, particularly when state budgets are tight.

namely resources that the agent could have invested in other programs. We assume that the agent chooses effort, in our case R and Q, as well as P under incomplete monitoring as we detail below.

Federal government ("The Principal"): The federal government internalizes the externalities across states, net of the federal reimbursement cost:[5]

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

3.2 Social Welfare and Efficiency

We define social welfare as the sum of the two payoffs:[6]

$$W = U^a + U^p = B(\theta(R), Q) - R \times Q. \tag{3}$$

Maximizing welfare with respect to R and Q yields two optimality conditions:[7]

$$B_R(\theta(R), Q)/Q = 1 \tag{4}$$
$$B_Q(\theta(R), Q)/R = 1\,. \tag{5}$$

Intuitively, the marginal benefit of increasing effective spending should be proportional between increases in rates and quantity. At the optimal R and Q, the marginal benefit of increasing either equals 1.

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

Suppose the federal government observes effective state spending, $R \times Q$. Replacing $P \times Q$ by $R \times Q$ in equation (1) and solving for the first-order conditions with respect to R and Q, we have:

[5] An alternative and equivalent formulation of the federal government's payoff, which connects closely with the principal-agent literature, is given by $U_p = B(\theta(R), Q) -$ State Utility.

[6] A Pareto efficient contract maximizes the payoff of one party, given a fixed payoff to the other party. Adding a transfer T paid by the Principal to the Agent, we can express agent utility as $\bar{u_0^a} = \tau \times B(\theta(R), Q) + FMAP \times P \times Q + T$. The Principal's payoff, holding the Agent's overall payoff fixed, can then be written as $U^f = B(\theta(R), Q) - R \times Q - \bar{u_0^a}$, which equals equation (3) minus a constant.

[7] Here, B_R is shorthand for $B_Q(\theta(R), Q) \times \frac{\partial \theta(R)}{\partial R}$.

$$\tau \times B_R(\theta(R), Q)/Q = 1 - FMAP \quad (6)$$
$$\tau \times B_Q(\theta(R), Q)/R = 1 - FMAP\,. \quad (7)$$

It is clear from here that setting $\tau = 1 - FMAP$ achieves the optimal allocation. Intuitively, the federal government chooses a Pigouvian subsidy $FMAP$ to internalize the positive externality $1 - \tau$ of the state's effective program spending.[8]

3.4 Distortions under Imperfect Monitoring ($P \neq R$)

We now turn to the empirically relevant case with incomplete monitoring. The state uses creative financing to divert nominal funds. Conceptually, these schemes arise from the inability of the federal government to monitor effective spending $R \times Q$, allowing states to divert $P \times Q - R \times Q$ towards other programs.

More specifically, we assume that the federal government can monitor the care volume, Q, but not the effective rate, R. The state can then set a nominal billing rate P, which qualifies for federal subsidies via the FMAP. By law, P is capped at the upper payment limit, $\bar{P} = UPL$. The state's optimization problem thus becomes:

$$\max_{P \leq \bar{P}, R, Q} \tau \times B(\theta(R), Q) + FMAP \times P \times Q - R \times Q\,. \quad (8)$$

This yields the following first-order conditions with respect to R and Q:

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

This yields two main predictions. First, when the federal government cannot monitor the effective reimbursement rate R, the state will inflate the nominal rate P beyond R. In the considered case, the state will optimally increase the nominal rate up to the cap, $P = UPL$. In contrast, the effective reimbursement rate, R, no longer qualifies for matching funds (equation (9)). The state internalizes effective rate changes in full, and not just $1 - FMAP$,

[8] Budget constraints may force states to cut back on program spending further. This can be captured by a discount factor τ that is increasing in the state budget and provides a rationale for tying the nominal FMAP to the state's fiscal capacity.

and has stronger incentives to reduce R, thereby lowering the quality of care. In other words, the "effective *price* FMAP" is zero. [9]

Hypothesis 1 (H1) *Public Markup: Under imperfect monitoring of creative financing schemes, states have incentives to inflate nominal reimbursement rates (P) beyond effective reimbursement rates (R), creating a public markup* $\mu = \frac{P}{R}$*, and allows them to divert* $(P - R) \times Q$*, away from the intended purpose.*

Second, the public markup reduces program costs for the states. Specifically, the "effective *quantity* FMAP" exceeds the nominal FMAP by a factor equal to the public markup $\frac{P}{R} = \mu$, as indicated by equation (10). This incentivizes states to expand the quantity of care, which we dub "public moral hazard." Note that the effective quantity FMAP may exceed 100%, in which case, from the state's perspective, the program pays for itself.

Hypothesis 2 (H2) *Public Moral Hazard: Under imperfect monitoring, creative financing increases the "effective quantity FMAP", the share of public programs funded by the federal government, to* $FMAP \times \mu = FMAP \cdot \frac{P}{R}$*. It incentivizes states to increase the volume of care eligible for joint funding.*

Graphical illustration: Figure 3 illustrates the opposing effects of creative financing on health care quality and quantity. The vertical axis denotes quality of care, a positive function of R. The horizontal axis denotes quantity of care, Q. We denote the volume of care in logs, and the underlying effective reimbursement rate in logs, yielding a linear budget constraint. The convex curves represent indifference curves for different benefit levels (up to the scaling factor τ). We can now differentiate between the two cases in Subsections 3.3 and 3.4.

First, the downward-sloping line 'C' denotes the state's budget constraint under perfect monitoring and without creative financing. The slope does not depend on the 'FMAP', and incentives are aligned between states and the federal government. For that case, the expansion path I illustrates the optimal rate and quantity mix. As τ increases, states will

[9] As we detail below, the substitution effect on R may be offset by an income effect, provided that diversion of funds increases the state's budget and that effective rates are a normal good. However, this does not compromise the key insight here, which is that states will inflate the nominal reimbursement, captured by a public markup defined as $\mu = \frac{P}{R}$, increasing the program's cost to the federal government.

choose higher rates and volumes along this path. Allocations along this path not only minimize the state's but also the social cost of achieving a given benefit level.

[Insert Figure 3 about here]

Second, the downward-sloping line 'D' denotes the state's budget constraint under imperfect monitoring and with creative financing. Compared to the case without creative financing, the budget constraint is rotated to the right on the horizontal axis.[10] The slope does now depend on the 'FMAP', scaled by the markup $\mu = P/R$ and is -(1-FMAP$\times\mu$).[11] Under imperfect monitoring, states engage in creative financing, have incentives to increase care volume, and engage in public moral hazard. They have relatively weaker incentives to increase rates, and thus quality, as indicated by the allocations along the new expansion path II. These allocations minimize state costs under creative financing, but they do not minimize federal costs and hence not the social cost of care.

3.5 Discussion

We characterize the distortions from imperfect monitoring under a specific information structure and a specific set of regulatory instruments.

Central is that the federal government can monitor volume but not effective spending. When the federal government can no longer monitor volume, reimbursements may take the form of block grants, in which case states have no incentives to increase the care volume. In contrast, states will have an incentive to lower the care volume. While this case (of not being able to monitor volume) is theoretically possible, we note that the federal government has several instruments to monitor nursing home days.[12] We are unaware of systematic reporting discrepancies in the volume of care between states and the federal government in the context of nursing home care.

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

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

[12] Nursing home residents are assessed on at least a quarterly basis and recorded in the Minimum Data Set, which we discuss later. Furthermore, patient assessments are conducted during nursing home inspections, implying a very accurate patient census.

We also assume that states choose not only the reimbursement rates (or effective spending per capita) but also the care volume. While the quantity of care is determined in equilibrium based on demand and supply, we note that states have several instruments to influence this equilibrium outcome. Such measures include nursing home capacity regulations, eligibility criteria as well as coverage and expansions of outpatient care substitutes such as waivers or Home- and Community-Based Services (HBCS). The broader insight from our theoretical framework is that states will prioritize instruments that increase volume at relatively low costs.[13] Nursing homes on the other hand, who act as agents in our main empirical analysis, can use targeted investments to attract new patients, expand advertising efforts, or skew their admission policies towards Medicaid patients when capacities are binding.

4 Data, Empirical Approaches, and Results

Our discussion of the data, empirical strategy, and results is organized into three subsections. They study the impact of creative financing schemes on prices (and "public markups"), quantities (and "public moral hazard"), and healthcare quality. Our analysis proceeds at different levels of aggregation, using various data sources and methods. We organize the discussion of the data, the empirical strategy, and results within each section accordingly.

4.1 How does Creative Financing affect Prices and the Public Markup?

This subsection studies how creative financing may bias Medicaid prices and create a wedge between nominal and effective reimbursement rate, the "public markup", see Hypothesis **H**1. The objective is to produce 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 funds, $(P - R) \times Q$. Ultimately, the goal is to produce estimates of the public markup $\mu = P/R$. We combine several data sources to measure these objects. The Data Appendix C provides more details.

[13] When states only have reimbursement rates as effective instruments, they face a tradeoff between cost savings and expanding access through higher rates. We discuss this in Appendix Section B2.4 and derive conditions under which the quantity motive dominates.

Data & Empirical Approach: First, we use Long-Term Care: Facts on Care in the U.S. (2025) (LTC Focus) data at the state-year level from 2000-2007. The data cover all U.S. Medicaid and Medicare-certified nursing homes (98% of all nursing homes). The data provide the average Medicaid base per diem rate (at the state-year level) and the total number of Medicaid days provided in nursing home care. We interpret the product of the two as a measure of effective SNF spending, $R_{st} \times Q_{st}$, for state s in year t, an assumption that we return to below.

Second, we use data from The Medicaid Budget and Expenditure System (MBES), which provides state-by-year expenditure data, including total Medicaid spending on various programs (Centers for Medicare & Medicaid Services, 2020a). These data include detailed summaries from Form CMS-64, which we use to construct total nominal spending on nursing home care by state and year, $P_{st} \times Q_{st}$.

Combining the two data sources we can construct the public markup as follows:

$$\mu_{st} = \frac{P_{st} \cdot Q_{st}}{R_{st} \cdot Q_{st}} = \frac{P_{st}}{R_{st}} \,. \tag{11}$$

To test hypothesis **H**1, we compare the derived 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 1. We do so over time, before and after the reform, using a simple difference-in-differences (DD) regression model:

$$Y_{st} = \mu_s + \mu_t + \beta \times CF_s \times Post_t + \epsilon_{st} \tag{12}$$

for outcome Y_{st} of state s in year t, where μ_s and μ_t denote state and year fixed effects. CF is a binary indicator for states with a creative financing scheme pre 2003. $Post$ is a binary indicator for the years 2003 onward. The parameter of interest is β, denoting the differential effect of the 2003 reform for states with a pre-existing creative financing scheme.

Further, we use the simple DD design to test for changes in additional outcome measures included in LTC Focus using information from Kaiser Family Foundation (2025). Specifically, we use our mark-up measure to calculate the "effective FMAP" rate along with measures of federal and state Medicaid nursing home expenditures as well as nurse-to-patient ratios and the total number of Medicaid days. While we use the latter primarily as an input to calculate markups and effective spending (Appendix C), evidence on whether

the 2003 reform is linked to changes in the Medicaid days at the SNF level also provides an outlook for our hypothesis on public moral hazard, **H**2.

Results: On the y-axis, Figure 4 displays the average public markup ($\frac{P}{R}$) over time, separately for the treatment and control group. The x-axis shows calendar years from 2000 to 2007. Note that the standard DD identifying assumption is the parallel time trends assumption. We interpret Figure 4 as showing a "reverse" DD design with reasonably stable, similar, and parallel trend times in the post-2003 years, showing only minor differences in our calculated mark-up in post-reform years. This first observation suggests that the 2003 reform was successful in producing an era where states with and without pre-reform creative financing schemes look alike. After 2003, overall, we see little evidence of a wedge between effective and nominal Medicaid nursing home spending, suggesting that the reform worked as intended at the national level.

[Insert Figure 4 about here]

Further, consistent with hypothesis **H**1, we find a public markup of about 1.3 among states with a CF scheme in the pre-reform years. This suggests that the effective quantity FMAP was initially 30% higher than the nominal FMAP in states with creative financing schemes. In contrast, we find no wedge between effective and nominal Medicaid nursing home spending in the control states. Concurrent with the 2003 reform, the markup observed in the treatment states decreases swiftly.

More formally, our DD estimates show a 0.27 decrease in Panel A of column (1) of Table C.2 (Appendix), and a reduction in the effective FMAP by 16pp through the reform. Considering the nominal Medicaid spending of \$58bn on nursing home care between 2000 and 2002 among states in the treatment group, the average pre-reform markup of 1.3 suggests that states diverted 0.3$\times$\$58bn=\$17bn per year. Equivalently and reassuringly, columns (3) and (4) of Table C.2 (Appendix) show reductions in (nominal) federal and state expenditures on Medicaid inpatient long-term care by \$150 and \$112 million per year and state.

Panel B of Table C.2 (Appendix) tests for changes in normalized staffing levels also provided in the LTC Focus data. Despite the lower state and federal nominal Medicaid spending following the reform (Panel A), we do not find evidence for such changes in staffing levels. This finding implicitly reinforces the idea that nominal pre-2003 nursing

spending was artificially inflated and substantially differed from effective spending as a result of creative financing.

The last column in Panel B of Appendix Table C.2 previews a much more detailed test of the public moral hazard channel (hypothesis **H**2) in Section 3. As seen, there is first evidence that the overall number of Medicaid days in nursing homes decreased by a significant 3% when the scope for creative financing was reduced in treatment states. However, note that not all states shut down their creative financing operations. Some states quickly adopted similar instruments to close their funding gap. For instance, in September 2003, Pennsylvania passed Act 25 in response to the federal reform.[14] Likewise, Indiana introduced a new creative financing scheme, see Section 4.2.

Evidence from ODI Audit Reports. Next, we make use of rather qualitative and descriptive evidence using 24 digitized audit reports from 18 states. We manually reviewed and digitized these, see Appendix Section C. These Office of Inspector General (OIG) audit reports by Department for Health and Human Services (2025) provide direct estimates of the size of intergovernmental transfers. They provide independent estimates, and hard evidence on the diversion of funds, and allow us to calculate the public markup for a subset of states. Appendix Figure C.1a shows an average markup of 24% in states with creative financing schemes. This estimate is very close to the DD estimate in Appendix Table C.2. Further, Appendix Figure C.1b suggests that the "effective FMAP" was up to 33ppt higher than the nominal one, for example in Pennsylvania where the effective FMAP was 84% instead of 54% in 1999.

Evidence from HHC Financial Reports. 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. Specifically, HHC's own financial reports show that HHC received a total of $3.2bn in base Medicaid revenues for nursing home services, see column 3 of Table C.4, jointly funded between the federal government and the state at an average nominal FMAP of 68% ($2.1bn paid the federal government, and $1.1bn paid by the state). In addition to that, the state initiated

[14] Also known as the Nursing Facility Assessment Law (Commonwealth of Pennsylvania, 2005), the act states that *"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."*

$750 million in supplemental payments for nursing home services, generating an extra $1.5bn in federal payments see column H, for a total of $2.3bn in supplemental payments, see column 6. Total nominal Medicaid payments for nursing home services amounted to $3.2bn+$2.3bn=$5.5bn. HHC then redirected $1.9bn from the nursing homes via intergovernmental transfers (IGT) to its general fund (column (7)) to finance its hospital operations. We conservatively assume that the state recovered $409 million of the full $750 million via IGTs. While we cannot quantify the amount transferred back to the state budget, independent sources suggest that the state recovered its share in supplemental payments. Essentially, this implies that only the Medicaid base payments of $3.2bn remained at the nursing homes. Interpreted through the lenses of our conceptual framework, this corresponds to a public markup of:

$$\mu_{HHC} = \frac{P_{HHC} \times Q_{HHC}}{R_{HHC} \times Q_{HHC}} = \frac{\$5.5bn}{\$3.2bn} = 1.72 \tag{13}$$

or 72%. As a result, the effective FMAP increases from 68% to $68\% * 1.72 = 117\%$. Put differently, the federal cost share of total Medicaid spending ($68\% * \$5.5$ billion=$3.74) billion exceeds total effective spending on nursing home services, implying that the state (and HHC) turn a net surplus from providing Medicaid nursing home services.

4.2 How does Creative Financing Affect Quantities and Pubic Moral Hazard?

This subsection quantifies the causal effects of creative financing on the volume of care ("public moral hazard"). To do so, we zoom into Indiana's scheme which was particularly refined and aggressive, turning a net surplus from providing nursing home care. To recall, Indiana first encouraged county hospitals to acquire private nursing homes to circumvent the 2003 reform. HHC pioneered the model and started to acquire nursing homes in 2003, see Section 2.4 and Figure 2b. To provide evidence on how the municipalization of nursing homes changed provider operations and affected patients, we again combine several data sources. Below and in Data Appendix C, we provide more details.

Data & Empirical Approach: To exploit the timing of the nursing home acquisitions in an event study framework, we extract the information on municipalizations from Nursing Home Compare (Centers for Medicare & Medicaid Services, 2020b), the Indiana Depart-

ment of Health (2020) data as well as reports by the IndyStar newspaper for validation. Second, we use LTC Focus data as in Section 4.1, but now at the nursing home-year level from 2000 to 2017. These data include nursing home characteristics, including staffing levels and whether the nursing home has a special care unit, along with information on utilization by types of insurance. Third, we aggregate patient-level data from the Long-Term Care Minimum Data Set (MDS) to the nursing home-year level. MDS is administrative data containing all Medicaid and Medicare-certified nursing homes in Indiana from 1999 to 2015. Our baseline sample is balanced in calendar time at the SNF-year level to keep the sample composition stable. This also implies that we omit the very first and the very last targeted nursing homes which may have been selectively targeted.[15] Further, as Medicaid-certified nursing homes were the target of these acquisitions, we focus on nursing homes with at least one Medicaid patient in 2000.

Then, we run Callaway and Sant'Anna (2021)'s staggered differences-in-difference and event study models comparing acquired to not-yet-acquired nursing homes, where the event time refers to the year of the acquisition:

$$Y_{nt} = \mu_n + \mu_t + \sum_{i=k}^{K} \alpha_k (Post_i t = k) + \epsilon_{nt} \tag{14}$$

for outcome Y_{nt} of nursing home n in year t, where μ_s and μ_t denote SNF and year fixed effects. The model avoids biases due to dynamic and heterogeneous treatment effects. It calculates average treatment effects for each event time, using the "not-yet-treated" as controls, where $Post_i t = k$ indicates the k-th year after the acquisition. α_k represents the coefficients for the treatment effect in the k-th year post treatment and ϵ_{nt} stands for the error term, clustered at the SNF level.

Results: Figure 5a shows an event study of the treatment (that is, municipalization) on for-profit status. Recall that public nursing homes are not-for-profit (by design) and that the share of for-profit nursing homes was 59% over the entire sample (see Table D.1). Thus, this first event study is our first stage and a validation of our identification approach. Figure 5a shows no pre-trend in the years leading up to the municipalization, but tight estimates around zero. Then we observe a sharp decline in the for-profit status starting in year 0, de-

[15] Table D.4 shows that SNFs acquired before 2011 had lower occupancy rates, more patients restrained and lower nurse-to-patient ratios.

noting the year of the municipalization. In line with expectations, the effect size is around -0.6 three years post acquisition. The average treatment effect on the treated (ATT) is -0.54 (se=0.03), shown in the first column of Panel A in Table 1.

[Insert Figure 5 about here]

Figure 5b shows an event study estimate on the total number of Medicaid days per year. Again, we find no evidence of a systematic pre-trend. Yet, starting in year 1 after the acquisition, the number of Medicaid days increases, confirming hypothesis **H**2. Four years after the acquisition, nursing homes provided an extra 3,000 Medicaid days, corresponding to 8.2 full-year residents. The effect size is relatively large, considering that nursing homes serve 18,591 Medicaid days per year on average (Table D.1). 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, which corresponds to a 5.2% increase. However, recall that the effect size is growing over time, where 3000 extra Medicaid days equal an effect size of about 16% four years after the acquisition.

Investigating the underlying mechanisms, we find that the rise in Medicaid days is primarily attributable to patients diagnosed with Alzheimer's disease and Alzheimer's disease-related dementias (AD/ADRD). To show this, we identify AD/ADRD patients based on the initial nursing home admission assessment.[16] Then we use the total number of Medicaid days spent by AD/ADRD patients in nursing homes as an outcome. As seen, Figure 5c mirrors the event study pattern in Figure 5b for Medicaid days by all patients. We calculate an ATT of 1178 days (se=255), which represents a 14% increase in Medicaid days for this group, as detailed in the third column of Panel A in Table 1.[17] This finding is not unexpected given that 38% of all Medicaid days in our sample are by dementia patients. Additionally, Medicaid reimbursements are risk-adjusted and thus higher for patients with cognitive impairments. Consequently, even greater incentives exist to expand care volumes for Medicaid dementia patients. We also find that the increase in dementia days is accompanied by an expansion in Alzheimer special care units, see 5d. Quantitatively, we estimate an ATT of 9pp (se=3pp) throughout the post-acquisition period.

[16]This involves integrating MDS 2.0 with MDS 3.0 data, specifically selecting patients with the Section I diagnosis indicators I1q or I1u active, as per MDS 2.0 definitions.

[17]In further robustness tests, we observe that the rise in dementia days stems from stays surpassing 100 days, see Appendix Figure D.1. Concurrently, there is no indication of reduced mortality within the first 100 days, see Appendix FigureD.2b, suggesting that the prolonged stays are not due to enhanced survival.

4.3 How does Creative Financing Affect Quality of Care?

Central to patient welfare is how Indiana's creative financing operations ultimately affected patient health. This subsection investigates this question. To do so, we consider two key mechanisms. First, even under a constant patient composition, the quality of nursing home care may change following municipalization, for instance, by adding Alzheimer's special care units. Second, the public moral channel identified in the previous subsection suggests patient relocation between nursing homes of different qualities and between nursing homes and home health care. To disentangle the two mechanisms, we specify and estimate a model of patient health value-added that takes patient selection into account, building on Dubin and McFadden (1984); Abdulkadiroğlu et al. (2020); Einav, Finkelstein, and Mahoney (2022). Below and in Data Appendix D, we provide more details on the sample and methods.

Given the previous findings on volume expansions being driven by dementia patients, here we focus on hospital discharge patients diagnosed with dementia. These patients typically require post-acute and long-term care. We focus on patients discharged from an acute care hospital for two reasons. First, two-thirds of dementia patients in nursing home care are admitted from an acute care hospital, making this a central admission channel.[18] Second, following a hospital discharge, patients (or their surrogates) have to make an active choice about follow-up care. Our data allow us to identify whether the selected inpatient long-term care and, if yes, which nursing home they chose. In other words, we model care choices and subsequent health outcomes.

Data: To study these questions, we build another unique dataset to identify AD/ADRD patients in acute care hospitals in Indiana using administrative Medicare claims data from 2000 to 2012. Specifically, compared to the sample in Section 4.2, we leave the data at the *patient 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.[19] We

[18] According to a federal whistleblower complaint, a county-owned hospital funneled millions annually to another hospital through disguised payments for patient referrals to its newly acquired nursing homes (Evans, Hopkins, and Cook, 2021).

[19] Using supplemental data detailed below, 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.

arrive at a sample of 206,833 hospital index stays, see Appendix Table D.2 and Table D.3 for summary statistics. The final dataset includes patient demographics such age (82.6 years), race (90% white), one-year mortality (33%) and discharge destinations after the acute care stay (37% to SNF) as well as hospital readmission rates (90-day readmission rate of 31%). We then merge these index hospital stays with MDS data to identify subsequent nursing home stays.[20] On average, 12% of allAD/ADRD patients discharged to a nursing home use have *any* SNF Medicaid days where the average number of Medicaid days is 186 (Table D.3).

Empirical Approach: To isolate changes in quality from changes in the patient composition, we develop and estimate a nursing home production model that considers the patient composition. First, we create choice sets for each AD/ADRD patient who was discharged from an acute care hospital stay. The patient's choice set comprises all nursing homes that are located within 50 miles of the patient's former address, in addition to the outside good, which is home health care. Then, we first estimate a mixed logit nursing home choice model, enriched by an outside good corresponding to home care. Indexing patients by i and providers by j and denoting by t the year of the hospital discharge, patients maximize the following indirect conditional utility function:

$$u_{ijt} = \begin{cases} \delta_j + x'_{ijt}\beta^x + z'_{ij}\beta^z + \eta_{ij} & \text{if j in } i\text{'s SNF choice } J_i^{SNF} \\ \pi_i + \gamma_t + \eta_{io} & \text{if outside good} \end{cases} \tag{15}$$

$$\eta_{ij} \sim \text{i.i.d. extreme value} \tag{16}$$

$$\pi_i \sim N(0, \sigma^2) \tag{17}$$

Where x_{ijt} denotes observable patient, nursing home, and year-specific characteristics. z_{ij} denotes preference shifters (instruments), excluded from the health outcome equation

[20] For a successful merge, the hospital stay precedes the nursing home stay by at most two weeks, and it ends before the SNF stay. Further, the ID of the discharged nursing home allows the identification of the destination nursing home. We find successful nursing home matches for 37.6% of all index stays, which is almost identical to the share of patients discharged to any nursing home (36.9%). We assume that patients not matched to a nursing home choose home care, considering that it is by far the most common alternative discharge destination, see Table D.3. To ensure a sufficiently large number of observations per nursing home for the value-added estimation below, we pool nursing homes with fewer than 50 admissions throughout the sample period with the outside good.

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 SNF fixed effects 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, which is distributed i.i.d. extreme value.

Finally, to capture substitution patterns between inside goods (nursing homes) and the outside good (home care), we add a random coefficient to the logit choice framework. 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.We model health outcomes, measured via mortality and readmission rates, as a binary outcome. The underlying latent health index m_{ijt} is given by:

$$m_{ijt} = \alpha_j + \alpha_t + x'_{ijt}\alpha^x + \epsilon_{it}, \tag{18}$$

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 to the estimation of equation (18) is that we only observe outcomes at (endogenously) chosen nursing homes. To correct for such selection, we exploit exogenous variation via an excluded instrument. Put differently, we require variation in preferences that only affect health through provider choice. Following the literature (Einav, Finkelstein, and Mahoney, 2022), we use the distance between a patient's home address and any nursing home in her choice set as an instrument. The key exclusion restriction is that distance to the next SNF only affects patient health through an increased probability of choosing that nursing home. As shown below, distance to nursing homes is a key determinant of provider choice and thus a relevant instrument while its validity is not formally testable. We then follow Dubin and McFadden (1984) and adopt a control function approach, detailed in Appendix Section E, where we proceed in two steps. First, we estimate the choice model. Second, we construct the control functions and estimate the parameters of equation 18 via simulated maximum likelihood.

Mixed Logit Results: Panel A of Table 2 presents select parameter estimates from equation (15), which are all statistically significant at the 95% level. Distance to nursing homes, our instrument, is an important choice predictor; the precisely estimated coefficient on log distance is -1.51. Further, consistent with the public moral hazard channel, nursing home admissions (after a hospital stay) become more likely after they are municipalized.

[Insert Table 2 about here]

The remaining rows summarize the marginal utility of select demographics for the outside good, that is, home health care instead of institutional SNF care. The negative coefficient on age suggests that older dementia patients are more likely to be admitted to a nursing home after a hospital stay. The same applies to women, white patients, and patients with longer hospital index stays. Finally, we estimate a large standard deviation on the random coefficient, σ. 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). This suggests that the random coefficient plays a vital role in capturing heterogeneity in preferences between the outside and the inside goods.

Panel B of Table 2 presents select parameter estimates for the health outcome equation (18). As discussed, we exclude log distance from this equation. Further, we redirect outcomes to give parameters a "positive" interpretation, meaning "better" outcomes. Older patients, white patients, and patients with longer hospital stays are in worse health and have a lower 1-year survival rate, whereas women have a higher survival rate. Importantly, we do *not* find that nursing home acquisitions improve health. The coefficient in the first row is positive but statistically insignificant. Applying 95% statistical confidence intervals, we can exclude that muncipalizations decrease survival rates by more than 4% or increase them by more than 9%, respectively. In other words, holding the patient composition fixed, we do not find evidence for systematic changes in the quality of nursing home care received following municipalizations.

Valued Added Results: To investigate whether higher patient volume ("public moral hazard") affects mortality or readmission rates, we turn to the estimated value-added coefficients, α_j, again redirected to denote positive effects. Figure 6a shows the distribution of these SNF value-added estimates concerning one-year survival rates in nursing homes

relative to home health care. To facilitate the interpretation, we display SNF value-added estimates net of the outside good, in descending order from highest to lowest (net-of-home-care) value-added. Hence, the dashed horizontal line corresponds to the value-added of the outside good.

[Insert Figure 6 about here]

Figure 6a provides several insights. First, 80% of nursing homes are situated in the upper half. They have a higher average value-added than outpatient long-term care. Conversely, 20% are situated in the bottom half, indicating a lower value-added compared to outpatient care.[21]

Second, heterogeneity in quality of care is very large, consistent with the recent literature (Einav, Finkelstein, and Mahoney, 2022). The value added drops from 0.5 to about -0.5 when moving from the 10th to the 90th percentile, which corresponds to comparing the life expectancy of a 65-year-old to a 100-year-old in a given nursing home (0.35*3.09≈1.).

Third, Figure E.2 (Appendix) shows a scatterplot between the valued-added estimates and the control function coefficients ϕ_k of equation (E.2). We find a strong negative relationship similar to Einav, Finkelstein, and Mahoney (2022). The negative preference selection ($\phi < 0$) for higher-quality nursing homes is consistent with an adverse selection mechanism, where sicker patients with higher mortality prefer higher value-added nursing homes. Further, the selection coefficient ψ is small compared to the ϕ estimates, see Ψ_η in Table 2.

Robustness: The value-added estimates naturally carry noise. We, therefore, pool nursing homes into higher and lower-quality nursing homes. Motivated by Figure 6, we pool the bottom quintile of nursing homes—those whose point estimate falls short of the outside option—and label them "low-quality." Conversely, we label the top quintile "high-quality." The first row of Table 3 shows the average (standardized) one-year survival rate across these two groups of nursing homes. Survival is 1.16 (1.12) standard deviations higher among high (low) quality nursing homes, compared to quintiles two to four.

[21] Figure 6b applies a shrinkage technique from the empirical Bayes literature to adjust for possible biases (Morris, 1983; McClellan and Staiger, 2000; Chandra et al., 2016). Shrinking reduces effect size differences, but effect heterogeneity remains large. Moreover, the qualitative comparisons to the outside good remain essentially unchanged. We, therefore, continue with our unadjusted estimates.

To put these estimates into perspective, the lowest value-added estimate in the group of higher-quality nursing homes implies a one-year mortality rate of 16%, see Panel B of Table 3. And the highest value-added estimate in the group of lower-quality nursing homes implies a one-year mortality rate of 32%.[22] In robustness exercises, we use 30 and 90-day hospital readmission rates as health outcomes, yielding qualitatively similar results. Moreover, 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 3).

[Insert Table 3 about here]

Panel B of Table 2 shows SNF characteristics and the CMS star rating. These provide alternative quality of care measures. Using data from LTC Focus, we document that "high-quality" nursing homes (based on value-added estimates) also have higher registered nurse (RN)-to-patient staffing ratios, and a higher RN-to-nurse ratio. Further, they have higher CMS star ratings. These checks illustrate that our proposed method and categorization into high and low-quality nursing homes capture actual and meaningful differences in the quality of care.

4.4 Quantity Expansions and Quality of Care

Building on Table 3, we now investigate whether low-quality or high-quality nursing homes drive the public moral hazard channel. Figure 7 presents changes in Medicaid days for dementia patients in high-quality (Figure 7a) and low-quality nursing homes (Figure 7b). While we also see volume increases in higher-quality nursing homes, they are disproportionately larger in lower-quality nursing homes. Further, Panel B of Table 1shows an increase of 1952 Medicaid days per nursing home and year in lower-quality nursing homes. In higher-quality nursing homes, the increase is 1106 days. One factor is access capacity. The third and fourth column of Table 1 show that the volume increase is concentrated in nursing homes with less than 90% occupancy.

Taking stock, we find that the identified public moral hazard channel is concentrated in nursing homes with excess capacity that are, on average, of lower quality.

[22] The mortality estimates are calculated for an 85-year-old white female patient with a 6-day index hospital stay.

4.5 Misallocation

Before we conclude, we connect our findings to our conceptual framework in Figure 3. The objective is to assess the implications for allocative health care efficiency. To recall, we view the public hospital-SNF system as "the Agent", playing a game against "the Principal", aka the federal government.

Agent's Benefit Function: We approximate the benefit function of a representative public state entity—the Agent—via CES preferences given by:

$$B(\theta, Q) = v(\theta, Q) + \pi(\theta, Q) \approx \left[\gamma \times log(Q)^{\rho} + (1-\gamma) \times \theta^{\rho}\right]^{\frac{1}{\rho}} \tag{19}$$

This benefit function combines non-pecuniary benefits, $v(\theta, Q)$, and nursing home revenues, $\pi(\theta, Q)$. To tie this subsection closely to the theoretical framework, we model diverted hospital transfers via provider costs, see below. The benefit function increases in the volume of nursing home care, Q, and the quality of care. We define quality by the one-year nursing home survival rate, $\theta = 1 - m_{SNF}$. The parameter γ captures the relative importance of care volume.[23]

Agent's Costs: Next, we specify the net costs for the SNF-hospital system, with and without creative financing (CF). Without creative financing, total costs are the product of average (variable) costs, AC, and overall volume of care, Q, see the first row of:

$$log(Costs) = \begin{cases} log(Q) + log(AC) & \text{No CF} \\ log(Q) + log(AC - FMAP \times (P - R)) & \text{CF} \end{cases} \tag{20}$$

With creative financing, the Agent diverts additional monies, denoted by $P - R$, the "markup", assuming that only $FMAP \times (P - R)$ can be diverted (see second row).[24]

[23] Consistent with the theoretical discussion, we abstract away from changes in preferences over outcomes following the acquisition of nursing homes. We note that the management of nursing homes typically remained unchanged following the acquisition, motivating this assumption.

[24] As discussed, Indiana redirected a significant fraction of its UP-SP contributions to the state budget.

Health Production: Producing higher care quality is costly, requiring, for instance, a higher nurse-to-patient ratio. To keep the exposition tractable, we assume that quality is proportional to the average variable costs per patient and day:

$$\theta = 1 - m_{SNF} = \beta \times log(AC)\,. \tag{21}$$

Similar to the discussion in Section 3, this allows us to express benefits and costs in terms of quality and quantity, that is, mortality and care volume.

Calibration: Section 4.2 finds a 14% increase in Medicaid days among dementia patients. Absent a natural unit volume, we normalize log volume without creative financing to one, and consider robustness around different values. We then calculate survival, pre- and post-municipalization: First, we take one-year survival in each of the three quintile groups in Table 3. Pre municipalization, survival is the weighted average over the three estimates, and implies a one-year survival rate of 75.5%. We find a 20% increase in volume in lower-quality nursing homes, and a 10% increase in the remaining nursing homes, reducing the average one-year survival rate to 75.1%.

Next, we solve for the first order conditions with and without creative financing, and use the estimated changes in volume and mortality to calibrate the unknown model parameters. The slope of the cost curve flattens from -1 to $-(1 - FMAP \times \frac{P-R}{AC})$ (Figure3) with creative financing. The base Medicaid reimbursements 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 $-(1 - 0.68 \times \frac{5.2-3.1}{3.1}) = -0.54$. With two conditions and three unknown parameters (β, γ, ρ), we need to impose one additional normalization and set $\beta = 1$. We then set $\gamma = 0.78$ and $\rho = -3.54$ to match the first order conditions pre and post creative financing.

Results: Figure 8 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 denotes the allocation without creative financing, and the gray upward sloping line denotes the

expansion path. The red diamond denotes the allocation with creative financing, which is situated 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 intersection between this line and the expansion path, the triangular point, denotes the optimal bundle, 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.

Note that the cost savings depend on the parametric restrictions on the objective function. Based on the calibrated parameters, we find costs savings of about 3.4%.

5 Discussion and Conclusion

This paper studies the misallocation of federal Medicaid matching funds and their implications for patients and providers in the context of the large and growing Medicaid program. Using digitized audit reports from 18 states and 2000-2017 data on the universe of nursing homes, we first document that many states use creative financing schemes. In the nursing home industry, these programs inflated nominal reimbursement rates by 40% while diverting at least $17 billion in Medicaid funds between 2000-2002. This diversion of funds increased the effective federal cost share (FMAP) by 16 percentage points, significantly more than previously documented.

Next, we focus on a specific creative financing scheme in Indiana. We document that it led to an expansion of nursing home care to maximize federal matching funds. We coin this expansion of public insurance use in response to the federal cost share "public moral hazard." Specifically, Indiana first municipalized private nursing homes, and then expanded Medicaid nursing home capacities. The intention was to reinstate creative financing in response to a federal reform. As a result, between 2000 and 2017, the share of public nursing homes increased from 5% to 95% in Indiana. Following the municipalization, in line with our theoretical predictions, the volume of Medicaid days increased significantly. We find that this volume expansion was driven by an increase in Medicaid inpatient days among

patients diagnosed with Alzheimer's disease and Alzheimer's disease-related dementias (AD/ADRD).

Third, we evaluate how the Indiana scheme affected patients by estimating a nursing home value-added model using administrative CMS microdata, focusing on dementia patients and their one-year survival rates. Our findings are threefold: First, there was no notable change in nursing home quality after municipalization. Second, quality disparities are significant; shifting patients from the lowest to highest-quality quintile would boost their survival rate by 17 percentage points. Third, while quantity increased across all five SNF quality quintiles, the largest expansion occurred in the lowest quintile.

In the paper's final section, we link our results to our theoretical framework. Our findings show that Indiana's policies skew the quality-quantity balance by promoting lower-quality nursing home care expansion. Optimally, reallocating some Medicaid funds to enhance care quality or usage at higher-quality facilities could cut costs on dementia care by 3.4% without compromising quality-adjusted quantity of care.

Going beyond our empirical setting, creative financing can explain the persistently low effective Medicaid reimbursement rates that contribute to the systematic quality shortfalls in the nursing home industry (Grabowski, 2001; Hackmann, 2019). Further, "public moral hazard" creates volume biases towards inpatient long-term care use. According to Evans, Hopkins, and Cook (2020b): *"The state's [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."* To our knowledge, this is the first paper that has carved out creative financing as one reason for such institutional bias, in addition to Medicaid's (i) fee-for-service reimbursement (Hackmann, Pohl, and Ziebarth, 2024), (ii) eligibility standards (Grabowski and Gruber, 2007; Mommaerts, 2018), and (iii) lack of home and community-based care alternatives to nursing home care (Muramatsu et al., 2007; Guo, Konetzka, and Manning, 2015; Wang et al., 2020).

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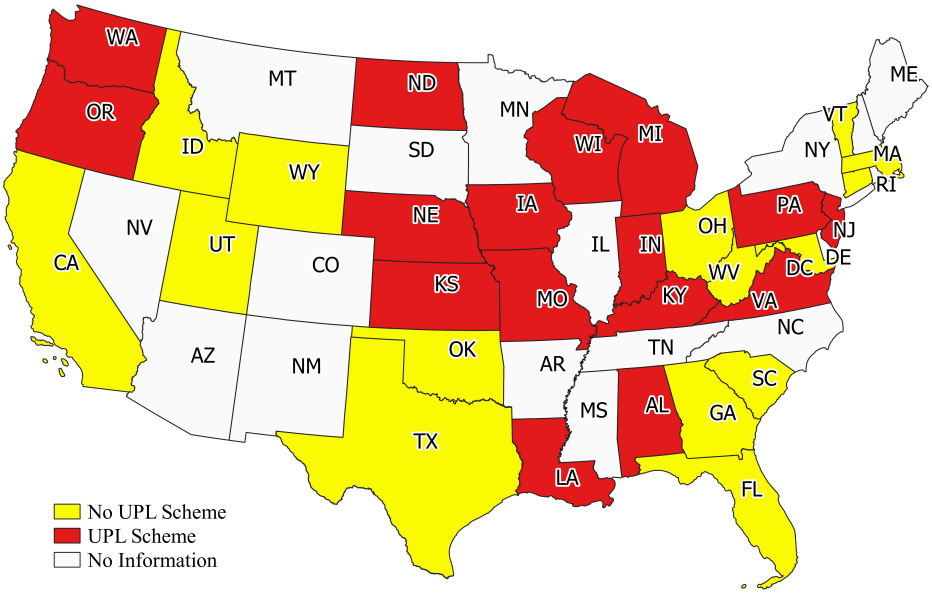
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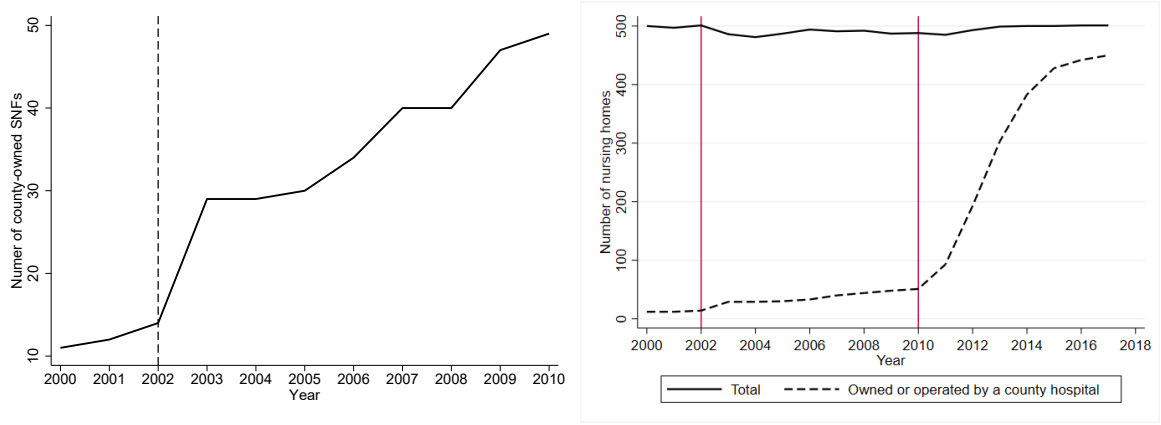
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Figure 1: States Use of UPL-SPs in Nursing Homes in FY 2002



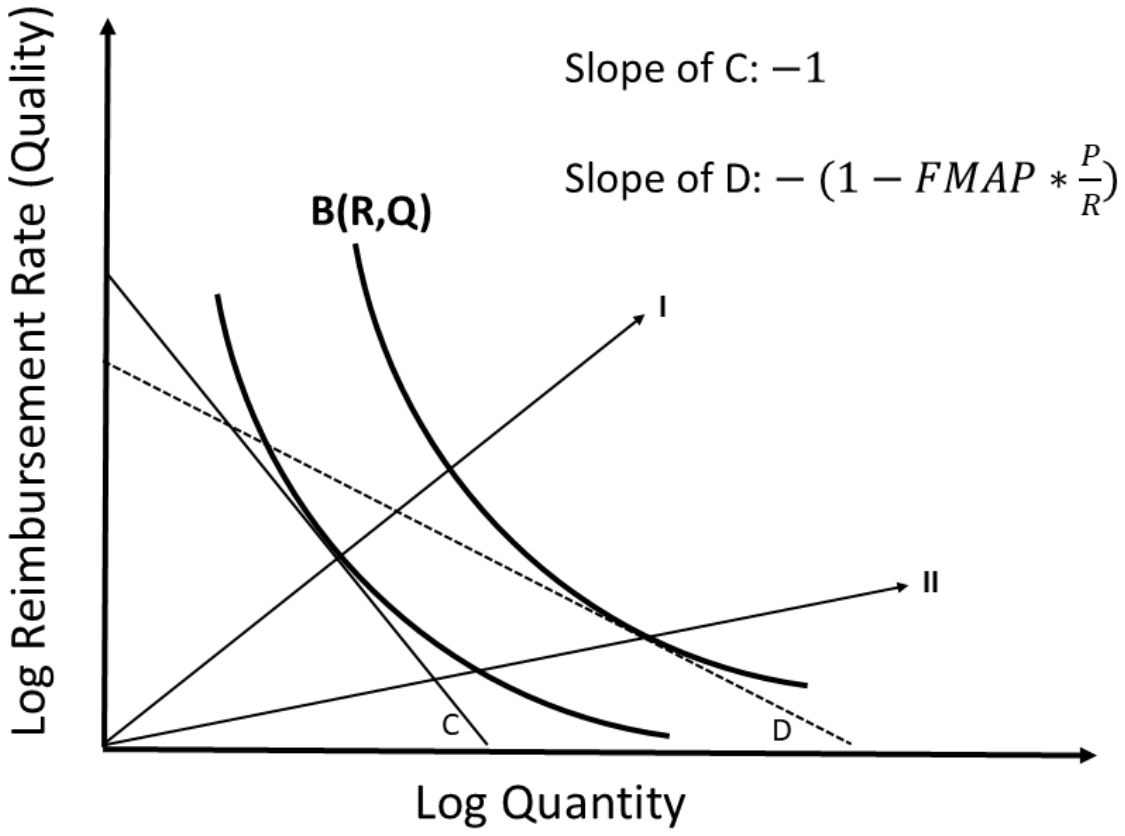
Notes: This map illustrates which states used creative financing in form of an upper payment limit supplemental payment (UPL-SP) scheme in FY 2002 based on the survey from Coughlin, Bruen, and King (2004). Pennsylvania is marked as using a UPL-SP scheme based on Coughlin and Zuckerman (2003b).

Figure 2: Development of County-Owned Nursing Homes in Indiana



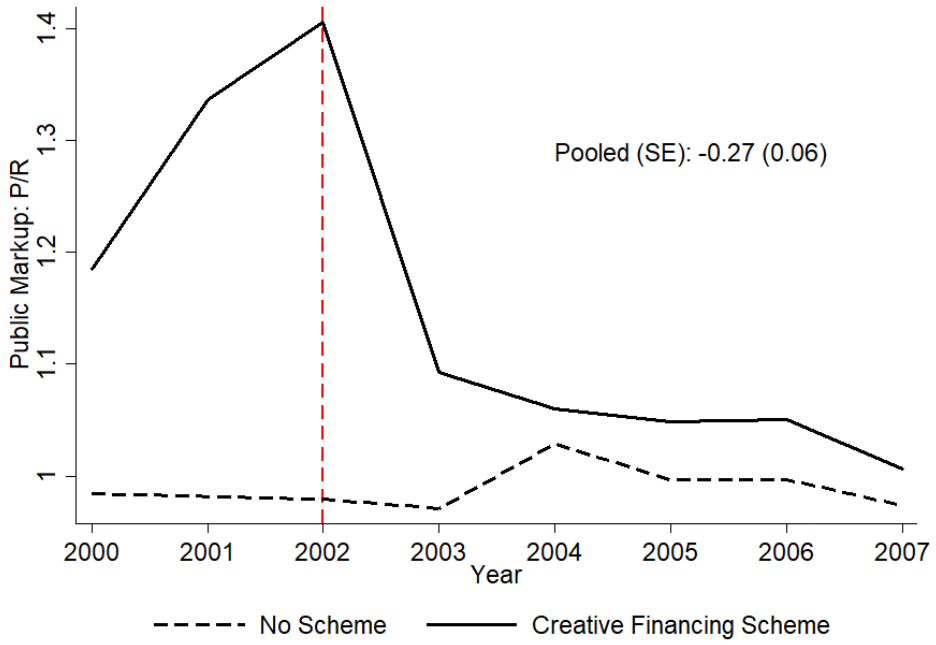
Source: Source: Centers for Medicare & Medicaid Services (2020b) and Indiana Department of Health (2020).

Figure 3: Quality and Quantity Tradeoff—Creative Financing



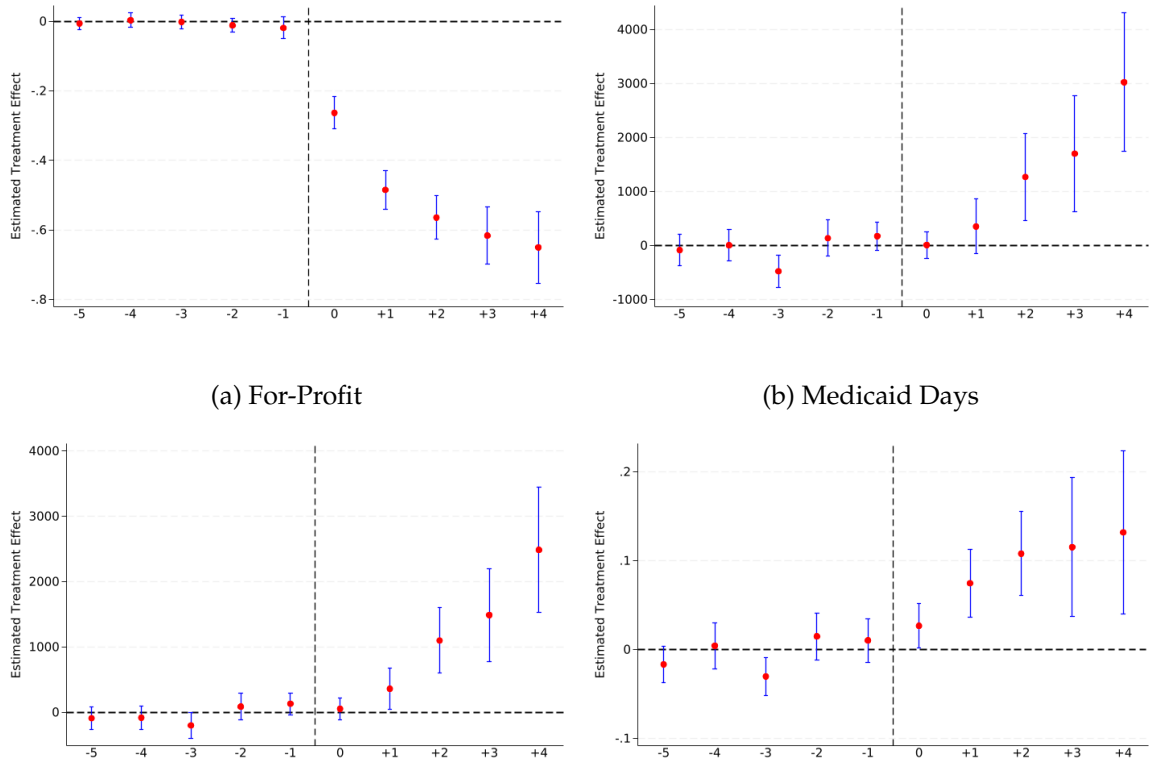
Notes: This figure illustrates the policy tradeoffs between the states' reimbursement rates and quantity settings under joint financing, with and without creative financing (CF). The convex curves denote indifference curves for different benefit levels. Line 'C' denotes the budget constraint for the state without creative financing. 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 creative financing and line 'II' denotes the corresponding expansion path.

Figure 4: 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 markdown, $\frac{P}{R}$ (equation (11)), which indicates the wedge between the nominal Medicaid rate, P, and the effective rate, R. The vertical line denotes the time of the 2003 reform, see main text for details. The categorization of treatment and control states is depicted in Figure 1 and described in Coughlin and Zuckerman (2003a); Coughlin, Bruen, and King (2004).

Figure 5: Municipalizing SNFs: Creative Financing and Public Moral Hazard



(a) For-Profit

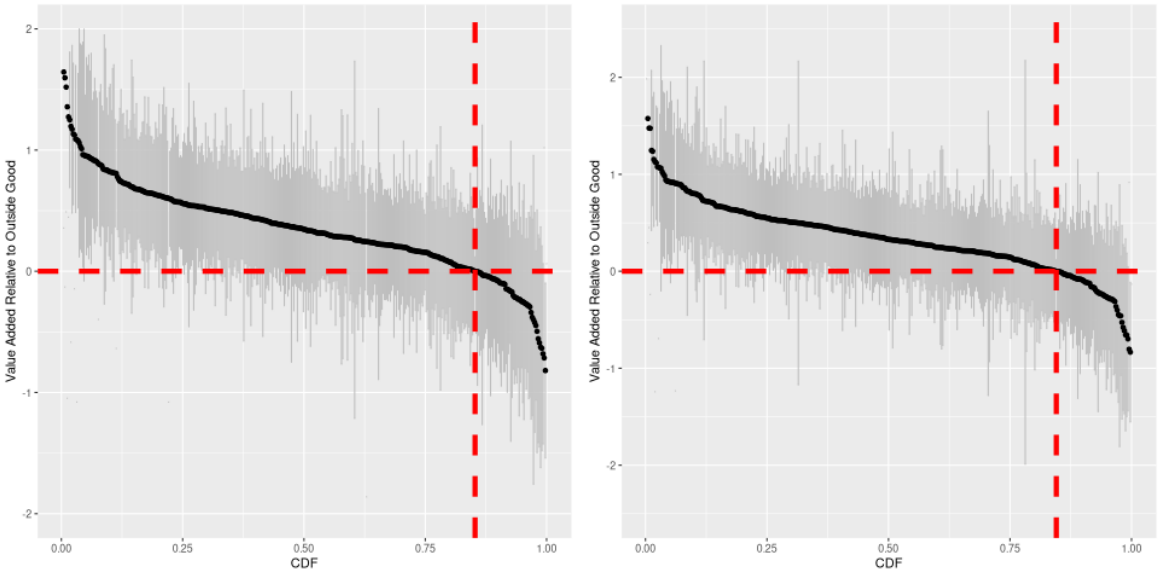
(b) Medicaid Days

(c) SNF w/ Alzheimer Unit

(d) SNF w/ Alzheimer Unit

Source: Centers for Medicare & Medicaid Services (2020b) and Indiana Department of Health (2020). The four subgraphs show Callaway Sant'Anna event studies as in equation (14), where event time 0 indicates the municipalization. The CS DD pooled estimates, over the entire post-reform period, are in Table tab:pubmoral. All event studies show 90% confidence intervals. See main text.

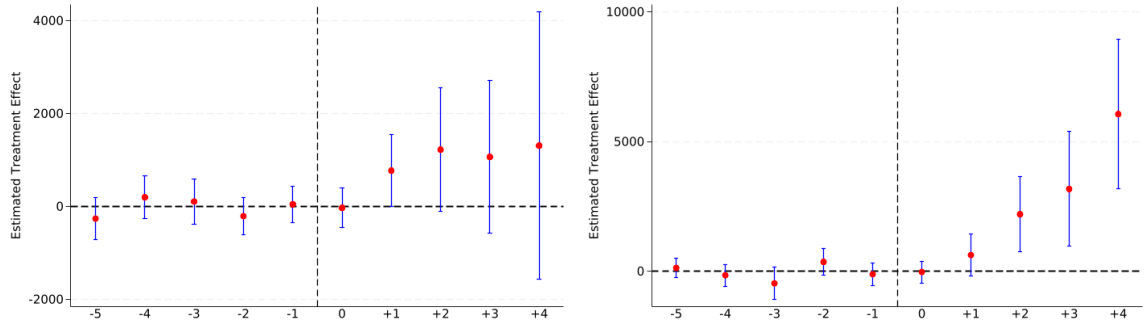
Figure 6: Value Added Estimates (I): One-Year Mortality



(a) Mortality

(b) Mortality: Shrinkage Adjusted

Figure 7: Medicaid Expansion by Quality of SNF Care

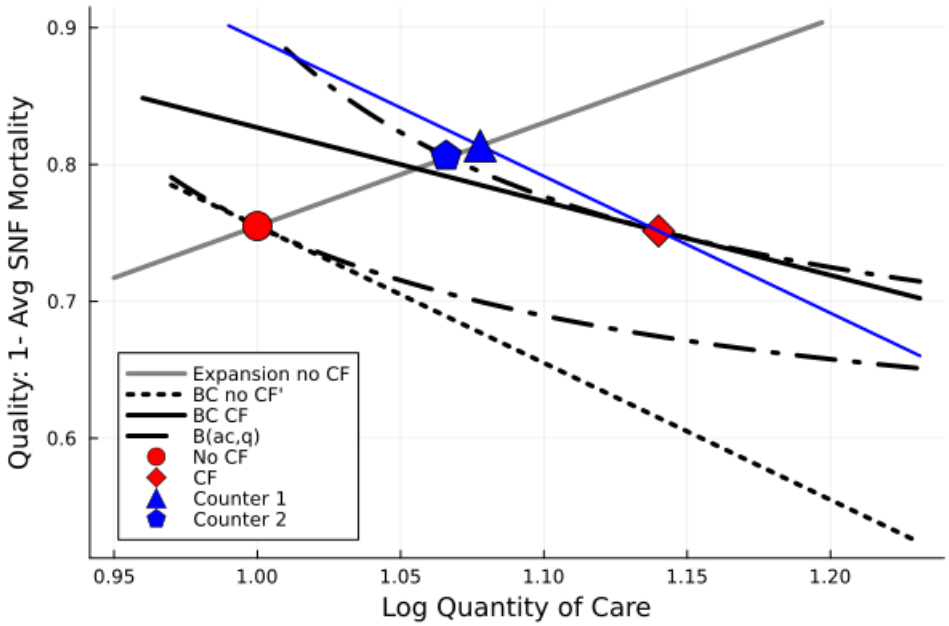


(a) Higher Quality SNFs

(b) Lower Quality SNFs

Source: The figure presents results for cumulative Medicaid days among dementia patients at the SNF year level using Callaway and Sant'Anna (2021). Figure a focuses on higher quality SNFs, which are defined as SNFs whose value added estimate for one-year survival is in the top quintile. Figure b focuses on lower quality SNFs, which are defined as SNFs whose value added estimate is in the bottom quintile.

Figure 8: Quality and Quantity Tradeoffs—Evidence from Indiana



Source: The figure provides an empirical illustration of the theoretical framework in Figure 3 using the empirical evidence from Indiana. The horizontal axis displays log quantity of SNF days, and the vertical axis denotes log average costs per patient day, which is further averaged across SNFs. The grey upward sloping line denotes the expansion path without creative financing (CF) and the red circle 'no CF' denotes the allocation before SNFs are municipalized. 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 social objective but at lower costs.

Table 1: Public Moral Hazard

Panel A	**For-Profit**	**Total Medicaid Days**	**Dementia Medicaid Days**	**Alz Unit**
	(1)	(2)	(3)	(4)
	-0.54	1360	1178	0.09
	(0.03)	(449)	(255)	(0.03)
Panel B		**Dementia Medicaid Days**		
	Low Quality	High Quality	Low Occu	High Occu
	(1)	(2)	(3)	(4)
	1952	1106	1389	300
	(687)	(556)	(299)	(449)
Year FE	X	X	X	X
SNF FE	X	X	X	X

Notes: This table presents ATT estimates based on Callaway and Sant'Anna (2021), Figure 14 shows the equivalent event studies for the four outcomes in Panel A where the column headers indicate the dependent variable, also see main text and Appendix Table D.1 for the sample at the SNF-year level. The total number of observations is XXX. In Panel A, column (1) presents CS DD results using for-profit ownership as dependent variable. Column (2) uses the cumulative number of Medicaid days, and column (3) Medicaid days for patients diagnosed with dementia. The last column presents results for an indicator that denotes whether the SNF 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 6. Columns (3) and (4) of Panel B condition on SNFs with occupancy rates of less and more than 90% in the year 2000, respectively.

Table 2: Nursing Home vs. Home Health Structural Estimates

Panel A: Mixed Logit Demand	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: Mixed Logit Health			
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

Notes: Outcome is the one-year mortality rate. All coefficients are multiplied by -1 to reflect effects on positive health. Columns two and three show the 95% confidence interval (CI). Panel A estimates equation (15) and Panel B equation (18). Estimates are based on sample in Appendix X, Table D.3.

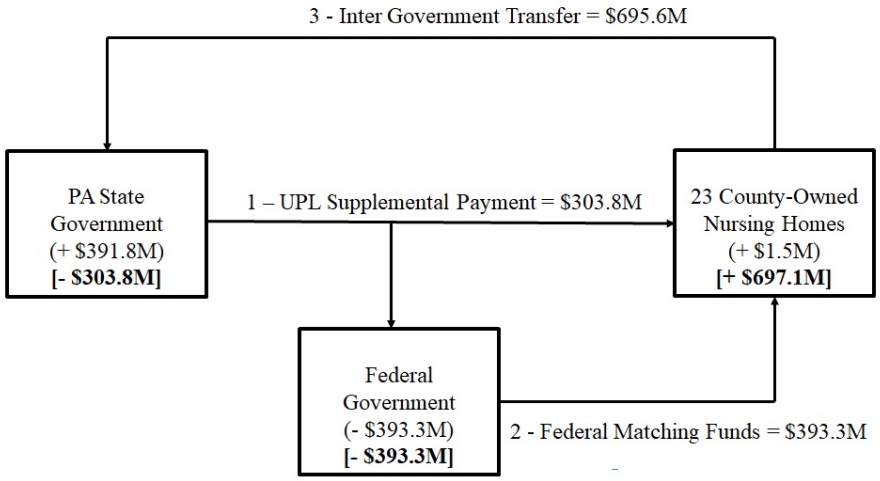
Table 3: Valiation—One-Year Survival Rate vs. Alternative Quality Markers

	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			
One Year Mortality*	$\leq$ 16%	$\geq$ 33%	
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)

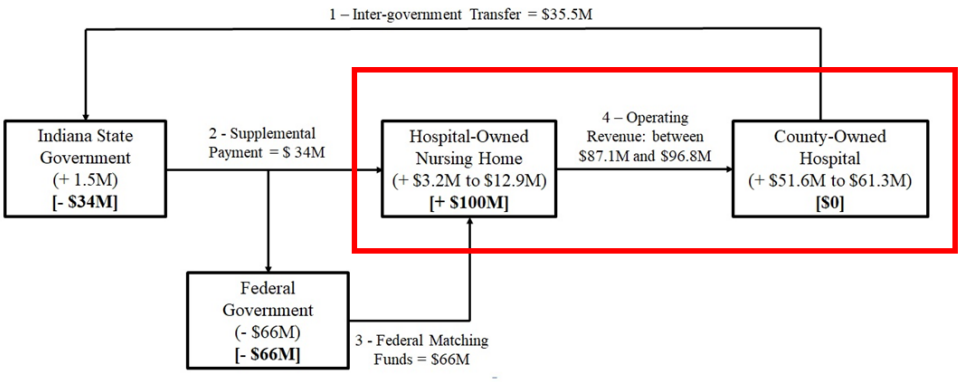
Table shows descriptions based on sample in Appendix X, Table D.3. One-year mortality rate in Panel B is for an 85-year-old, white female with 6 6-day index hospital stay. The quintiles of the nursing home value added estimates that determine the samples in the three columns are in Figure 6.

Appendix

Figure A.1: 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 final net position of payments. Figures in bold and square brackets reflect what was reported as 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)

B Theoretical Framework

B1 Principal-Agent Basic Model: Asymmetric Information & Misallocation

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 verify actual effort e_j, and takes reported effort $\hat{e}_j$ for $j \in \{1, 2\}$ as given. The principal compensates the agent conditional 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:

$$W = U^p + U^a = \Pi(e_1, e_2) - C(e_1, e_2) \tag{B.1}$$

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

$$e^{*,opt} = \underset{e_1, e_2 \in [\underline{e_1}, \overline{e_1}] \times \mathbf{R}^+}{\arg\max} \; \Pi(e_1, e_2) - C(e_1, e_2) \; . \tag{B.2}$$

Imperfect monitoring: Under the empirically relevant case of 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:[25]

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 the effort of type 1, reporting the maximum effort but factually only providing the minimum effort possible. This, in turn, induces additional (ex-

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

cessive) actual effort of type 2, when higher reported effort of type 1 increased the marginal returns on effort of 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 effort of type 2).[26]

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

B2 Alternative 2-2 Stage Game Framework

In this alternative framework, we model the market for Medicaid SNF patients as a two-two stage game. In the first stage, the state bargains with providers over Medicaid reimbursement rates. In the second stage, providers take Medicaid rates as given and compete in service qualities over patients in a differentiated products market.

B2.1 Second Stage: Product Market

Demand: We start with the second stage. Patient preferences over SNF care are described by the indirect utility function:

$$u_{ijt} = \begin{cases} \delta_j + \eta_{ij} & \text{for SNFs} \\ \eta_{io} & \text{otherwise} \end{cases} \tag{B.3}$$

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

$$s_j(\delta) = \frac{\exp\{\delta_j\}}{1 + \sum_k \exp\{\delta_k\}} \tag{B.4}$$

$$Q_j^D(\delta) = s_j(\delta) \times N, \tag{B.5}$$

where N denotes the population size.

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

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

$$Q_j^S = A_j \times h(Q_j, \delta_j) \times I_j \,. \tag{B.6}$$

Here, I_j denotes a variable input factor that can be employed at factor w, for example a wage, whereas $h(\cdot)$ captures the costs of producing higher quality allowing for potential scale economies. A captures total factor productivity. This implies the following cost function:

$$C(Q_j, \delta_j) = \frac{Q_j}{A_j \times h(Q_j, \delta_j)} \times w \tag{B.7}$$

We assume that SNFs take the regulated reimbursement rate, R, as given and choose the profit maximizing quality level:

$$\delta_j^* = \arg\max_{\delta_j} \Pi_j = \arg\max_{\delta_j} \left(R Q_j^D(\delta) - C(Q_j^D(\delta), \delta_j) \right) . \tag{B.8}$$

Analysis: We impose the following simplifying assumption:

$$\frac{w}{A \times h(Q, \delta)} = c_\delta \times \delta + c_m + c_q \times Q^\gamma, \;\; \gamma \geq 0 \,. \tag{B.9}$$

$$\leftrightarrow \qquad C(Q, \delta) = Q \times \left(c_\delta \times \delta + c_m + c_q \times Q^\gamma \right) \tag{B.10}$$

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

Solving the first order condition we get:

$$\delta_j^* = \underbrace{\frac{1}{c_\delta} \left(R - c_m - (1+\gamma) \times c_q \times Q_j^\gamma \right)}_{\text{Perfect Competition}} - \underbrace{\frac{Q_j}{\partial Q_j / \partial \delta_j}}_{\text{Quality Markdown}} \,. \tag{B.11}$$

The first term denotes quality that would arise under perfect competition, whereas the second term denotes a "quality markdown" stemming from SNF market power.

The first order condition suggests a positive direct relationship between quality δ_j and the regulated reimbursement rate, R. As qualities are strategic complements in this set-

ting, provider competition will reinforce the positive relationship. As a result, increases in reimbursement rates will result in higher quality and in higher quantities consumed. Specifically, we expect:

$$\frac{\partial Q_j^*}{\partial R} \geq 0\,. \tag{B.12}$$

B2.2 First Stage: Rate Setting

In the first stage, states negotiate with SNFs over R, considering the quantity and quality effects in the second stage. The regulator trades off the incremental benefits from increased access to SNF care against the costs of funding. States value the quality and quantity of care, which are both affected by R.

Netting out spending, the state's payoff is given by

$$V(R) = \sum_j \tau B_j(R,Q) - \sum_j R \times Q_j^*(R) \times [1 - FMAP]\,. \tag{B.13}$$

Note that the state pays only a fraction $(1 - FMAP)$ of total Medicaid spending; the federal government pays the remaining share, $FMAP$.

Then, states and SNFs engage in Nash Bargaining to determine R, specifically:

$$R^* = \underset{R \leq UPL}{\arg\max}\, V(R)^{\alpha} \times \Big(\sum_j \Pi_j(R)\Big)^{1-\alpha}, \tag{B.14}$$

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

To illustrate the outcome of the bargaining game, it is instructive to consider the case of a single monopoly SNF. Abstracting from a binding upper payment limit and taking logs, the first order condition yields:

$$\begin{aligned} &\frac{\alpha}{V(R)} \times \Big((\tau B_Q(R,Q) - R \times [1 - FMAP]) \times \frac{\partial Q^*}{\partial R} + (\tau B_R(R,Q) - [1 - FMAP]) \times Q^*\Big) \\ + \quad &\frac{(1-\alpha)}{\Pi(R)} \times Q^* = 0, \end{aligned} \tag{B.15}$$

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

$$R^* \times [1 - FMAP] = \underbrace{\tau B_Q(Q,R)}_{\text{Quantity Motive}} + \underbrace{\frac{(\tau B_R(Q,R) - [1 - FMAP]) \times Q^*}{\frac{\partial Q^*}{\partial R}}}_{\text{Quality Motive}} + \underbrace{\frac{(1-\alpha)}{\alpha} \times \frac{V(R)}{\Pi(R)} \times \frac{Q^*}{\frac{\partial Q^*}{\partial R}}}_{\text{SNF Bargaining Power}} = 0. \tag{B.16}$$

The first term represents quantities, capturing the state's interest in expanding access to care and to save on substitute care. The second term represents quality, capturing that higher rembursement rates produce a higher quality of care. Both motives are implicitly subsidized by the FMAP rate. The last term represents the bargaining power of SNFs, which is only relevant for $\alpha < 1$. A larger bargaining power of SNFs will result in higher reimbursement rates.

B2.3 Creative Financing Step 1: Introducing Transfers

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

$$\left(T^{*,T}, R^{*,T}\right) = \underset{T, R \leq UPL}{\arg\max} \left(V(R) + T\right)^{\alpha} \times \left(\Pi(R) - T\right)^{1-\alpha}. \tag{B.17}$$

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

$$R^{*,T} = \underset{R \leq UPL}{\arg\max}\, V(R) + \Pi(R)\,. \tag{B.18}$$

After reorganizing the first order condition, we have:

$$R^{*,T} \times [1 - FMAP] = \tau B_Q(Q,R) - \frac{(\tau B_R(Q,R) - [1 - FMAP]) \times Q^*}{\frac{\partial Q^*}{\partial R}} + \frac{Q^*}{\frac{\partial Q^*}{\partial R}} = 0. \tag{B.19}$$

This optimality condition is closely related to equation (B.16) 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 (B.16) and (B.19) 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, $\alpha > \underline{\alpha}$, (nominal) reimbursement rates and volume increase as states adopt creative financing mechanisms.

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

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

We believe that the case where states do not hold all bargaining power is the empirically relevant one. However, to better understand the intuition behind the changes in incentives, we now assume that the states hold all the bargaining power, $\alpha = 1$. It allows us to simplify the first-order conditions with and without transfers as follows:

$$\Big[\tau B_Q(Q,R) - R \quad + R \times FMAP\Big]\frac{\partial Q}{\partial R} + \Big[\tau B_R(Q,R) - Q \qquad + FMAP \times Q\Big] \quad = \quad 0 \tag{B.20}$$

$$\underbrace{\Big[\tau B_Q(Q,R) - \frac{\partial C}{\partial Q} + R \times FMAP\Big]\frac{\partial Q}{\partial R}}_{\text{Quantity Incentive}} + \underbrace{\Big[\tau B_R(Q,R) - \frac{\partial C}{\partial \delta}\frac{\partial \delta}{\partial R} + FMAP \times Q\Big]}_{\text{Quality Incentive}} \quad = \quad 0 \tag{B.21}$$

where equation (B.20) denotes the case without transfers discussed in Appendix Section B2.2 and equation (B.21) denotes the case with transfers discussed in Appendix Section B2.3. The first term in each equation captures the incentives to increase quantities, and the second term captures the incentives regarding quality of care.

The middle components highlight how the introduction of transfers alters the incentives for setting rates and quantities: The ability of SNFs to extract monies increases the cost of raising the quality. The regulator pays the reimbursement rate R, but only a fraction is passed on to patients, and SNFs extract the rest. When states can extract the surplus through transfers, it reduces the cost of higher volume from R to $\frac{\partial C}{\partial Q}$ and the cost of better quality (through rate increases) from Q to $\frac{\partial C}{\partial \delta}\frac{\partial \delta}{\partial R}$.

As a result, with transfers, states choose a higher reimbursement rate than without (as long as $\alpha > \underline{\alpha}$) which results in a higher quantity of care.

B2.4 Creative Financing Step 2: Introducing Nominal and Effective Prices

We now allow states to inflate spending on nursing homes. Following the notation, we introduce a nominal payment rate P that differs from the effective reimbursement rate R that governs provider incentives. Specifically, we allow for the possibility that providers receive a marginal reimbursement rate R and a lump sum payment $(P - R) \times \bar{Q}$, for a fixed level of $\bar{Q}$. The incremental payments may be entirely diverted back to the state budget through a transfer. Nevertheless, the payments do qualify for federal matching funds. Provider profits before transfers are now given by

$$\Pi(R, P, \bar{Q}) = R * Q - C(\delta, Q) + (P - R) \times \bar{Q} \tag{B.22}$$

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

$$\left(T^{*,CF}, R^{*,CF}, P^{*,CF}, \bar{Q}^{*,CF}\right) = \underset{T, R \leq UPL, P \leq UPL, \bar{Q} \leq Q^{*,CF}}{\arg\max} \left(V(P) + T\right)^{\alpha} \times \left(\Pi(R, P, \bar{Q}) - T\right)^{1-\alpha}. \tag{B.23}$$

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 B2.3, states will choose the effective reimbursement rate R that maximizes the sum of surplus'

$$R^{*,CT} = \underset{R \leq UPL}{\arg\max}\, V(\bar{P}) + \Pi(R, \bar{P}, Q^{*,CF}) = \tau B(Q, R) - C(Q, \delta) + \bar{P} \times FMAP \times Q^{*}\,. \tag{B.24}$$

Taking the first order condition and rearranging yields:

$$\underbrace{\left[\tau B_Q(Q, R) - \frac{\partial C}{\partial Q} + \bar{P} \times FMAP\right] \frac{\partial Q}{\partial R}}_{\text{Quantity Incentive}} + \underbrace{\left[\tau B_R(Q, R) - \frac{\partial C}{\partial \delta} \frac{\partial \delta}{\partial R}\right]}_{\text{Quality Incentive}} = 0\,. \tag{B.25}$$

Thus, allowing states to inflate nominal spending beyond effective rates changes the quality and quantity incentives. Compared to the case with just transfers, see equation (B.21), states have now stronger incentives to increase care quantities $\bar{P} > R$ and engage in public moral hazard. Conversely, states have less incentive to raise quality through higher

R because they do not trigger additional matching funds tied to the nominal rate P. As a result, the quality incentive term in equation (B.25) misses $FMAP \times Q$ from equation (B.21).

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

Specifically, after subtracting equation (B.21) from equation (B.25), 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:

$$\frac{\bar{P} - R}{R} \geq \frac{1}{\epsilon_{Q,R}} \tag{B.26}$$

where $\epsilon_{Q,R}$ denotes the elasticity of volume of care w.r.t. R. In words, states are willing to raise Medicaid reimbursement rates, and hence program costs, when the markup exceeds $\frac{1}{\epsilon_{Q,R}}$, where $\epsilon_{Q,R}$ denotes the elasticity of Q concerning R. Intuitively, when increases in Medicaid rates only have a small effect on volume, e.g. because firms with market power only pass a small share of rate increases onto patients, then the cost saving motive dominates: With creative financing, states prefer to lower Medicaid rates. Conversely, when increases in Medicaid rates have a large effect on volume, or when the public markup is large, states prefer to increase Medicaid rates.

The broader insight from this analysis is that states will prioritize instruments that increase volume at relatively low costs. Such measures may include capacity expansions or targeted investment subsidies that can be divided over many new marginal patient days. Alternatively, it may include advertising efforts or increased patient referrals.

C Data Appendix to Provide Evidence on H1

In the following, we describe the primary data sources to generate a panel at the state-year level from 2000-2007 with 257 observations. The panel only contains data from 15 states with pre-2003 creative financing schemes (treatment group) and 16 states without pre-2003 creative financing schemes (control group), see Figure 1 and Coughlin and Zuckerman (2003a); Coughlin, Bruen, and King (2004). We use this panel to produce simple Difference-in-Differences (DD) estimates in Section 4.1 of the main text.

After that, we will provide evidence on 24 digitized audit reports from 18 states, which we use for complementary evidence.

C1 State-Year CMS Data

First, we use public data from the Medicaid Budget and Expenditure System (MBES) by the Centers for Medicare and Medicaid Services (CMS) (Centers for Medicare & Medicaid Services, 2020a). These data contain Medicaid expenditures at the state and federal level 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, 2025). We merge those data with the CMS data above at the state-year level.

Third, we use public data from Long-Term Care: Facts on Care in the U.S. (2025) (LTC Focus) data at the state-year level covering all U.S. Medicaid and Medicare-certified nursing homes (98% of all nursing homes). The data includes patient demographics and facility characteristics such as staffing levels, the number of beds, and occupancy as well as special care units. As the data also provider average Medicaid per diem rates and the number of Medicaid days provided in nursing homes, we use the product of these to measure effective spending (R) on nursing home Medicaid care by state and year.

Table C.1: Summary Statistics State-Year CMS Data

Variable	Mean	Std. Dev.	N
incidenceIII	1.074	0.243	256
treat	0.485	0.501	264
cms_expenditure	1.182	1.106	264
medicaid_expenditure	1.124	0.961	256
federal_exp1	405388749.322	541363848.531	264
state_exp1	287091621.519	478038960.218	264
paymcaid_sta	64.846	6.8	264
rn2nrs_sta	0.326	0.113	264
rnhrppd_sta	0.508	0.201	264
lpnhrppd_sta	0.830	0.175	264
cnahrppd_sta	2.313	0.259	264
dchrppd_sta	3.537	0.374	264

Source: Centers for Medicare & Medicaid Services (2020a); Kaiser Family Foundation (2025); Long-Term Care: Facts on Care in the U.S. (2025), data are from 2000-2007 at the state-year level.

C2 Audit Reports by the Office of Inspector General (OIG)

To provide additional information on how creating financing may drive a wedge between nominal and effective SNF reimbursement rates. Specifically, we digitized and analyzed 24 audit reports from 18 states in the pre-reform era from 1997 to 2003.

All reports were requested by CMS and carried out by the Office of Audit Services (OAS) of the Office of Inspector General (OIG). OIG has the mandate to protect the integrity of the Department of Health and Human Services (HHS) programs and the well-being of their 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 (IGT).

We combine the IGT transfer 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, see above. We then construct the markdown as

$$\mu = \frac{P - R}{P} = \frac{Transfers}{TotalMHEX} \tag{C.1}$$

Table C.2: Effects of 2003 Reform on SNF State-Level Outcomes

	Markup	**Effective FMAP**	**Federal Expenditure**	**State Expenditure**
$CF \times Post$	-0.27***	-15.7243***	-149.80***	-111.50***
	(0.06)	(3.6935)	(46.76)	(34.25)
	RN Ratio	**LPN Ratio**	**CNA Ratio**	**Lg MA Days**
$CF \times Post$	-0.0106	-0.0021	-0.0084	-0.0293**
	(0.0289)	(0.0260)	(0.0423)	(0.0124)
Year Fixed Effects	X	X	X	X
SNF Fixed Effects	X	X	X	X

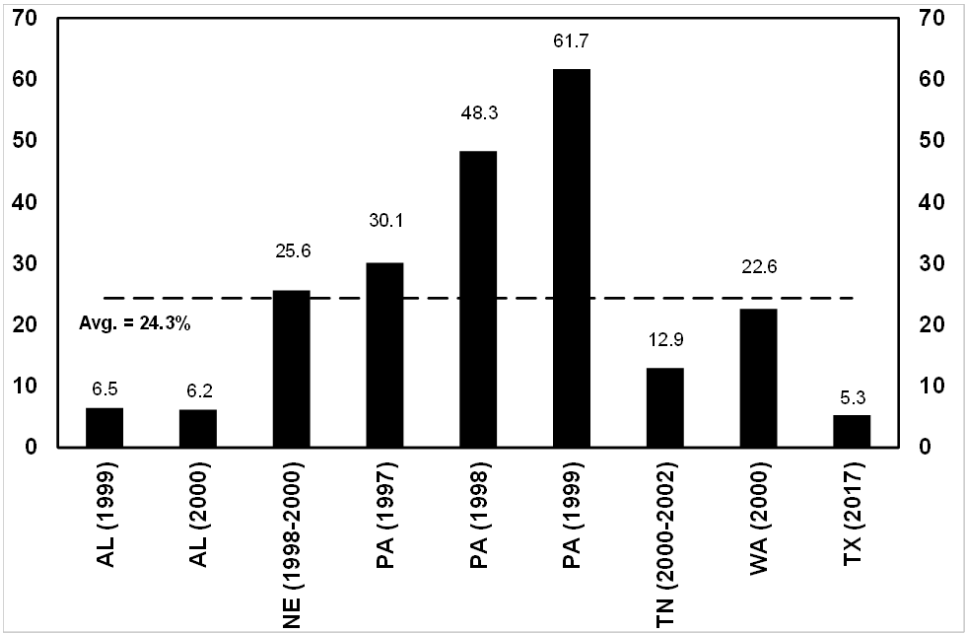
Source: ?Centers for Medicare & Medicaid Services (2020a), authors' calculation. Each column in each panel stands for one standard DD model with CF flagging states with a pre-reform creative financing scheme in place, and $Post$ taking the value 1 for years after 2002. The markup is defined in equation 11. The effective FMAP is given by $FMAP \times (1 + markup)$. Federal and state expenditures are measured in million $. The second panel shows results for the registered nurse (RN), licensed practical nurse (LPN), a certified nurse assistant (CNA) to patient ratios. The last column presents results for the log number of annual Medicaid days (Lg MA Days). ***, **, and * = statistically different from zero at the 1%, 5%, and 10% level. Standard errors are clustered at the state level and reported in parentheses. All models have 256 state-year observations from 31 states. See main text for more details.

C3 Financial Statements by Health and Hospital Corporation (HHC)

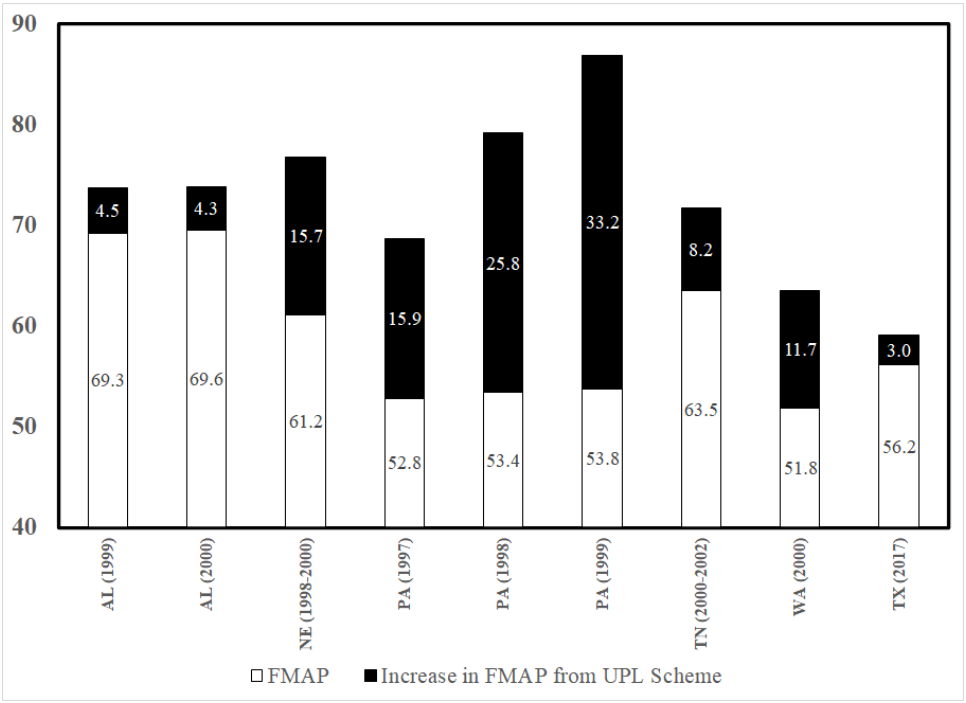
To estimate the markdown from the sophisticated and aggressive creative financing schemes in Indiana, this subsection zooms into Marion County's comprehensive annual financial reports from 2008 to 2019. As discussed in Section 2.4, starting in 2003, HHC became the pioneer of SNF acquisitions in Indiana. By 2009, HHC owned the licenses of 40 nursing homes and received more than 80% of UPL-SPs paid to nursing homes in the state. 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 receiving UPL-SPs did not disclose the size of intergovernmental transfers (IGT) in their financial statements, nor how much of it was used for nursing home patients.

The HHC financial statements provide this information, which allows us to estimate the markdown of their Medicaid revenues. We approximate the regular Medicaid payments on their nursing home patients (*Reg MHEX*) from the revenue that HHC received from their long-term care division and the share of Medicaid patients. HHC disclosed the size of UPL-SPs under "Medicaid Special Revenue" for their long-term division (*Sup MHEX*),

Figure C.1: Public Markups and the Effective FMAP—Evidence from Audit Reports



(a) Public Markups



(b) Effective vs. Nominal FMAP

Notes: Figure C.1a presents the public markup, $\frac{P}{R}$, indicatiung the wedge between the nominal Medicaid reimbursement rate, P, and the effective Medicaid reimbursement rate, R. Figure C.1b presents the nominal FMAP and the effective FMAP. We assembled the information from several audit reports: Department for Health and Human Services: Office of Inspector General (2001a,b,d,c, 2004b,a, 2005e,a,b,d,c, 2014); Centers for Medicare & Medicaid Services (2020a) using equations (C.1).

Table C.3: Creative Financing at HHC—Financial Reports 2008-19

Year	Revenue for SNF Services	Medicaid Percentage of Revenue for Services	Medicaid Revenue for SNF Services	FMAP	Federal Contribution of Medicaid Revenue for SNF Services	Medicaid SNF Supplemental Payments	Federal Contribution of SNF Supplemental Payments	Transfers from SNF to HHC General Fund	Real FMAP	Increase in FMAP from UPL Scheme	Average Real FMAP	Number of SNF Owned by the HHC
2008	$ 236,436,768.00	31%	$ 73,295,398.08	62.69%	$ 45,948,885.06	$ 51,423,940.00	$ 32,237,667.99	$ 30,300,000.00	82.81%	20.12%	101.79%	29
2009	$ 305,802,111.00	34%	$ 103,972,717.74	74.21%	$ 77,158,153.83	$ 74,421,268.00	$ 55,228,022.98	$ 55,000,000.00	107.29%	33.08%	101.79%	40
2010	$ 357,093,417.00	41%	$ 146,408,300.97	75.69%	$ 110,816,443.00	$ 71,102,472.00	$ 53,817,461.06	$ 37,000,000.00	91.20%	15.51%	101.79%	44
2011	$ 416,740,969.00	42%	$ 175,031,206.98	71.57%	$ 125,269,834.84	$ 155,821,249.00	$ 111,521,267.91	$ 108,597,652.00	106.54%	34.97%	101.79%	52
2012	$ 534,791,819.00	55%	$ 294,135,500.45	66.96%	$ 196,953,131.10	$ 153,550,441.00	$ 102,817,375.29	$ 106,700,000.00	87.91%	20.95%	101.79%	59
2013	$ 563,194,830.00	50%	$ 281,597,415.00	67.16%	$ 189,120,823.91	$ 198,664,337.00	$ 133,422,968.73	$ 179,392,756.00	107.20%	40.04%	101.79%	59
2014	$ 587,952,918.00	51%	$ 299,855,988.18	66.92%	$ 200,663,627.29	$ 217,764,223.00	$ 145,727,818.03	$ 150,000,000.00	94.23%	27.31%	101.79%	61
2015	$ 702,924,830.00	49%	$ 344,433,166.70	66.52%	$ 229,116,942.49	$ 239,393,167.00	$ 159,244,334.69	$ 245,000,000.00	114.62%	48.10%	101.79%	78
2016	$ 678,266,000.00	49%	$ 332,350,340.00	66.60%	$ 221,345,326.44	$ 309,998,000.00	$ 206,458,668.00	$ 301,100,000.00	125.36%	58.76%	101.79%	78
2017	$ 677,031,000.00	54%	$ 365,596,740.00	66.74%	$ 243,999,264.28	$ 279,213,000.00	$ 186,346,756.20	$ 240,329,000.00	106.39%	39.65%	101.79%	78
2018	$ 674,642,000.00	55%	$ 371,053,100.00	65.59%	$ 243,373,728.29	$ 292,579,000.00	$ 191,902,566.10	$ 236,700,000.00	101.95%	36.36%	101.79%	78
2019	$ 695,716,000.00	54%	$ 375,686,640.00	65.96%	$ 247,802,907.74	$ 251,916,000.00	$ 166,163,793.60	$ 196,359,000.00	95.99%	30.03%	101.79%	78
	$ 6,430,592,662.00	47%	$ 3,163,416,514.10	0.6805083	$ 2,131,569,068.28	$ 2,295,847,097.00	$ 1,544,888,700.58	$ 1,886,478,408.00	102%	34%	102%	61

Notes

[1] **Revenue for SNF Services** is the total revenue that the Health and Hospital Corporation (HHC) of Marion County for SNF services paid from all sources (i.e., Medicare, Medicaid, Others) as reported in their income statement. SNF are under LT Care in the HHC Financial Statements). This excludes Medicaid supplemental payments.

[2] **Medicaid Percentage of Revenue for Services** is the percentage of revenue for all services by the HHC of Marion County that are paid by Medicaid. This includes only regular services, and thus excludes supplemental payments from UPL and DSH payments.

[3] **Medicaid Revenue for SNF Services** is an estimate of the revenue that the HHC of Marion County receives for SNF services paid by Medicaid. This is not reported as a separate line item in the income statement, but the financial statement includes a note of the total revenue that is paid by Medicaid. Since this percentage is based on the total revenue that also includes hospital and other services, applying this percentage assumes that Medicaid share of revenue for SNF services is similar to that of other services. This will likely underestimate the Medicaid revenue from SNF as these services tend to be covered by Medicaid more than in-hospital services for the general population.

[4] **Medicaid SNF Supplemental Payments** corresponds to the UPL Supplemental Payments. This is reported in the HHC Financial Statements as Medicaid Special Revenue.

[5] **Transfers from SNF to HHC General Fund** are the transfers from the SNF division (LT Care) to the HHC General Fund, which is the chief operating fund for the HHC. We use this as an approximation of UPL payments diverted from SNF use to other uses within the HHC system.

while they disclose IGT transfers as "Returns to the General Fund." Between 2008 and 2019, none of the funds allocated to the General Fund were transferred back for use by the LTC division of HHC. The largest recipient of these funds (approximately 65%) was the in-patient hospital division under *Wishard Health Services* (before 2013) and *Eskenazi Health Services* (starting in 2013). The remainder of the IGT was allocated to *Capital Projects and Debt Service Funds*.

We calculate the markdown and effective FMAP using:

$$\mu = \frac{P}{R} = \frac{RegMHEX + SupMHEX}{RegMHEX} \tag{C.2}$$

$$Effective\ FMAP = FMAP \times \frac{RegMHEX + SupMHEX}{RegMHEX} = FMAP \times \mu \tag{C.3}$$

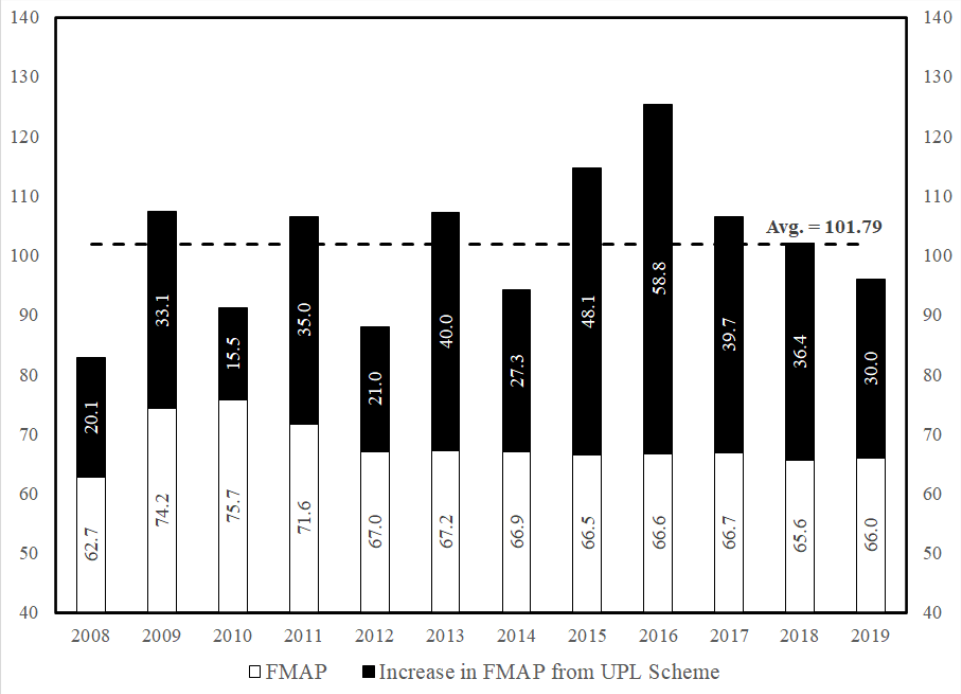
Estimates of equation (C.3) are in Figure C.2.

Table C.4: Creative Financing at HHC—Financial Reports 2008-19

Year	State Base Medicaid SNF Payments to HHC	Nominal FMAP in %	Matching Funds from Federal Government	State Medicaid SP	Federal Matching Funds SP	IGT SNF 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

Source: Financial Reports of Health and Hospital Corporation (HHC) of Marion County, see Section 2.4. SNF stands for "Skilled Nursing Facility." SP stands for "Supplemental Payments." See main text for details. The last row indicates the sum of the annual dollar amounts or the average of the FMAP over all years displayed.

Figure C.2: Effective FMAP—Evidence from the HHC of Marion County



Notes: This figure presents the nominal FMAP and the effective quantity FMAP: $FMAP * \frac{P}{R}$. The estimates refer to SNFs operated by HHC of Marion County and build on the HHC's financial reports as well as equation (C.3).

D Data Appendix to Provide Evidence on H2

In the following, we describe the primary data sources to generate a panel at the SNF-year level focusing on Indiana from 1999 to 2015. The panel uses administrative data, merged into data from Long-Term Care: Facts on Care in the U.S. (2025) and as well as hand-collected data as described above in Section C. The administrative data containing all Medicaid and Medicare-certified nursing homes in Indiana from 1999 to 2015 is from the Long-Term Care Minimum Data Set (MDS) by CMS. As discussed in the main text, we use this panel data to study the impact of creative financing on care volume and the underlying mechanisms. Specifically, we exploit the municipalization of nursing homes in a staggered DD setting to estimate the impact of creative financing activities on a range of patient and provider outcomes.

D1 SNF-Year Data from LTC Focus and MDS

To create the final panel dataset at the SNF-year level we draw on information from various sources, the README file contains more details.

Ownership Data. The ownership data, including nursing home identifiers and exact dates when nursing homes were acquired, come from three data sources: (a) CMS Skilled Nursing Facility Provider Information. The archived data snapshot was downloaded on Oct 28, 2024 from https://data.cms.gov/provider-data/archived-data/nursing-homes using the December 2017 file. (b) Manual searches of Indiana Consumer Reports. Consumer Reports that were available in July 2019 for all nursing facilities were used to assign acquisition dates. When the consumer report showed an acquisition by a publicly owned hospital that preceded what was reported in CMS, the date of the Consumer Report was used. A sample of Consumer Report is available at https://secure.in.gov/health/reports/reports/QAMIS/cr000016.htm. (c) Evans, Hopkins, and Cook (2020b) when the data came from the May 09, 2010 article from the Indianapolis Star titled "Money Flowed, Care Lagged. The article was downloaded in August 29, 2019 in https://www.newspapers.com/image/126265325.

CMS Compare. Legacy data from CMS Compare from 2000 to 2017 as downloaded in July 2018. Note that SNFs that a county hospital owned before the sample's start will have the acquisition year set to 2000. In general, most of these SNFs will be dropped from the balanced samples that we use for the analyses.[27]

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

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

Long Term Care Minimum Data Set (MDS) 2.0. Finally, to produce the working dataset, we merge administrative micro data from (MDS, 2020), aggregated at the SNF-year level, into the datasets above. The Centers for Medicare and Medicaid Services (CMS) provide these data, which cannot be made publicly available. However, we provide the codes in the Supplementary Materials. The file describes in more detail how we generate our main dataset at the SNF-year level. The MDS measures the health of all nursing home residents in all U.S. Medicaid or Medicare-certified nursing homes in a standardized manner. This includes about 98% of all U.S. nursing homes.

[27] We only use this assumption when all of the sources above are unavailable, and it is only used for 18 SNFs (13 of which are dropped in the balanced samples we use for the analyses)

Table D.1: LTCFocus Summary Statistics

Variable	Mean	Std. Dev.	N
County-owned SNF	0.389	0.488	2203
Panel A: Main outcomes			
For-profit	0.586	0.493	2203
Occupancy rate	76.363	14.268	2203
Number Medicaid days	18590.507	10416.805	2203
Alzheimer's Special Care Unit (SCU)	0.383	0.486	2203
Has Nurse practitioner or physician's assistant	0.385	0.487	2203
Panel B: Controls			
Total county population	218,869	281,418	2203
County population above 65	26,962	31,511	2203
Share restrained	2.808	5.051	2203
Share w/ hypertension	62.666	17.047	2055
RN/Nurses Ratio	11.48	1.427	2203
Average Acuity Index	0.274	0.156	2203
Direct-care staff hours per resident day	3.518	1.471	2203
Registered Nurses hours per resident day	0.447	0.704	2203
Licensed Practical Nurse hours per resident day	0.976	0.426	2203
Certified Nursing Assistant hours per resident day	2.095	0.798	2203
SNF is hospital-based	0.037	0.189	2203

Source: Long-Term Care: Facts on Care in the U.S. (2025), CMS Compare, Indiana Consumer Reports, CMS Skilled Nursing Facility Provider Information, State of Indiana (2025), authors' own calculation. See Section 4.2 and Appendix D for a description of the sample construction and selection.

Table D.2: Sample Cuts: Dementia Patients

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

Source: Medicare claims data, MDS data, authors' own calculation.

Table D.3: Summary Statistics: Dementia Patient Population

Variable	Mean	(Std. Dev.)	N
Age/100	0.8258	(0.072)	206833
White	0.8994	(0.3007)	206833
Black	0.0872	(0.2822)	206833
Female	0.6207	(0.4852)	206833
Index Hospital Stay in Days	5.5642	(4.5465)	206833
1-Year Mortality Rate	0.3293	(0.47)	206833
30-Day Readmission Rate	0.1743	(0.3794)	206833
90-Day Readmission Rate	0.3111	(0.4629)	206833
Discharged Home	0.3257	(0.4686)	206833
Discharged to SNF	0.3685	(0.4824)	206833
Discharged to ICF	0.0332	(0.1793)	206833
Discharged to Hospice	0.0215	(0.145)	206833
SNF Matches: MDS Claims			
Discharged to SNF	0.3761	(0.4844)	206833
Distance to SNF in Miles	5.8902	(7.0849)	77794
Medicaid Days	185.8092	(469.9024)	76272
Any Medicaid Days	0.1238	(0.3293)	77794

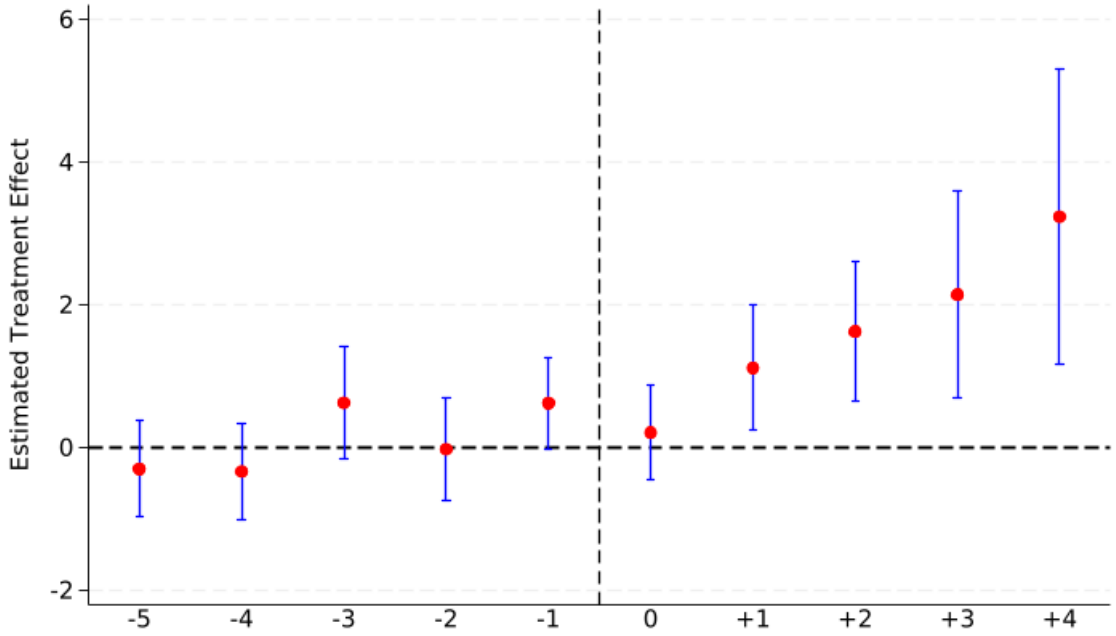
Source: Long-Term Care: Facts on Care in the U.S. (2025), CMS Compare, Indiana Consumer Reports, CMS Skilled Nursing Facility Provider Information, State of Indiana (2025). The sample conditions on XX patients who are observed at XXX with an AD/ADRD diagnoses during the initial nursing home admission assessment. We flag patients as AD/ADRD patients when diagnosed with the Section I diagnosis indicators I1q or I1u active, as per MDS 2.0 definitions. See Section 4.2 and Table D.2 for details on the sample construction and selection.

Table D.4: Characteristics of Early (<2011) vs. Late SNF Acquisitions (>=2011)

Variable Names	Early (mean)	Early (sd)	Late (mean)	Late (sd)	tstat	Norm Diff
Panel A: Main outcomes						
For-profit	0.889	0.316	0.854	0.353	0.953	0.073
Occupancy rate	69.572	14.236	78.523	12.587	-5.655	0.471
Medicaid days	21,563	9,685	20,066	8,912	1.384	0.114
Alzheimer's disease Special Care Unit (SCU)	0.422	0.497	0.394	0.489	0.512	0.041
Has Nurse practitioner or physician's assistant	0.244	0.432	0.312	0.464	-1.373	0.107
Panel B: Controls						
Total county population	247,939	295,987	189,492	266,149	1.773	0.147
County population above 65	27,709	31,413	22,700	28,720	1.429	0.118
Average Acuity Index	11.115	1.147	11.112	1.344	0.019	0.001
RN/Nurses Ratio	0.175	0.071	0.207	0.109	-3.721	0.248
Direct-care staff hours per resident day	3.063	1.049	3.171	0.682	-0.946	0.086
Registered Nurses hours per resident day	0.224	0.210	0.250	0.146	-1.112	0.100
Licensed Practical Nurse hours per resident day	0.972	0.431	0.949	0.250	0.494	0.046
Certified Nursing Assistant hours per resident day	1.866	0.553	1.971	0.585	-1.677	0.131
Share restrained	6.638	7.129	3.485	4.556	4.078	0.373

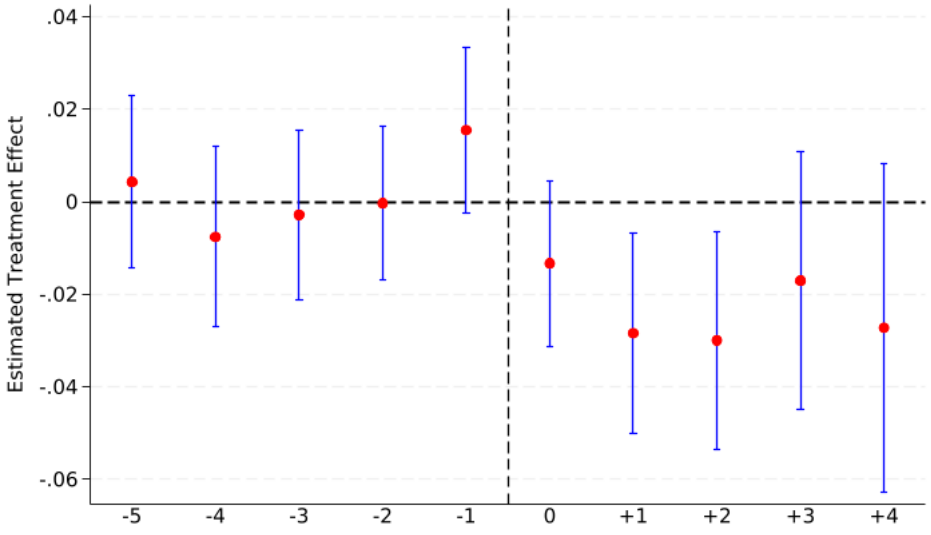
Source: Long-Term Care: Facts on Care in the U.S. (2025), CMS Compare, Indiana Consumer Reports, CMS Skilled Nursing Facility Provider Information, State of Indiana (2025). The sample is balanced in event time. It includes SNFs with observations for all relevant variables between 2000 and 2017 and that were acquired by a county hospital between 2005 and 2012. See main text for more details.

Figure D.1: Long Dementia SNF Stays (100+ Days)

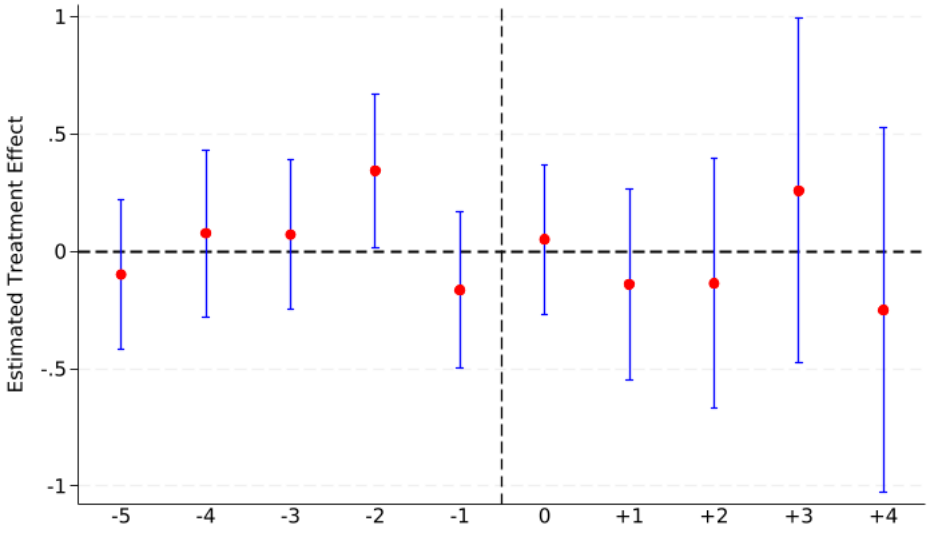


Source: Centers for Medicare & Medicaid Services (2020b) and Indiana Department of Health (2020). The graph shows Callaway Sant'Anna event studies as in equation (14), where event time 0 indicates the municipalization. All event studies show 90% confidence intervals. See Section 4.2 and Table D.2 for details on the sample construction and selection.

Figure D.2: Mortality Results



(a) One Year Morality



(b) 100 Day Mortality

Source: Centers for Medicare & Medicaid Services (2020b) and Indiana Department of Health (2020). The graph shows Callaway Sant'Anna event studies as in equation (14), where event time 0 indicates the municipalization. All event studies show 90% confidence intervals. See Section 4.2 and Table D.2 for details on the sample construction and selection.

E Choice Model: Estimation Details

A key challenge to the estimation of equation (18) is that the researcher only observes outcomes at (endogenously) chosen nursing homes. To account for selection on unobservables, we follow Dubin and McFadden (1984) and adopt a control function approach. We assume that 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:

$$E[m_{ijt}|x_{ijt}, \eta_i, \pi_i, c_i = j] = \alpha_j + \alpha_t + x'_{ijt}\alpha^x + \Big[\sum_{k\in J_i} \phi_k(\eta_{ik} - \mu_\eta) + \psi(\eta_{ij} - \mu_\eta)\Big] + \rho\pi_i + \rho_\psi\pi_i. \quad \text{(E.1)}$$

Following Einav, Finkelstein, and Mahoney (2022), the terms in squared brackets control follow 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 only turns on if the patient chooses the outside good.

As shown by Dubin and McFadden (1984) and Einav, Finkelstein, and Mahoney (2022), integrating out the η's yields:

$$E[m_{ijt}|x_{ijt}, \pi_i, c_i = j] = \alpha_j + \alpha_t + x'_{ijt}\alpha^x + \Big[\sum_{k\in J_i} \phi_k\gamma_{ik}(j) + \psi\gamma_{ij}(j)\Big] + \rho\pi_i + \rho_\psi\pi_i\,, \quad \text{(E.2)}$$

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

$$\gamma_{ij}(j) = \begin{cases} -log\ \hat{p}_{ik} & k = j \\ \frac{\hat{p}_{ik}}{1-\hat{p}_{ik}} log\ \hat{p}_{ik} & otherwise \end{cases} \quad \text{(E.3)}$$

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

$$\hat{p}_{ij} = \frac{\exp(\delta_j + x'_{jt(i)}\beta^x + z'_{ij}\beta^z)}{\exp(\pi_i + \gamma_{t(i)}) + \sum_{k/o}\exp(\delta_k + x'_{kt(i)}\beta^x + z'_{ik}\beta^z)} \,. \tag{E.4}$$

Importantly, and as stated above, $\hat{p}_{ik}$ is conditional on random coefficient shock π_i.

The parameters on the control terms in equation (E.2) have an economic interpretation. As discussed in Einav, Finkelstein, and Mahoney (2022), ϕ_k stands for the control function coefficients correcting for unobservable correlation between demand shocks for SNF k and the value added at SNF k. These terms would correct, for example, for the bias that would arise if patients who are (unobservably) in bad health would systematically chose high-quality SNFs. The $\psi\gamma_{ij}(j)$ term would correct for any remaining potential correlation between demand shocks for SNF j and the value added at SNF 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 random coefficient: Finally, we integrate out the random coefficient π_i to arrive at:

$$E[m_{ijt}|x_{ijt}, c_i] = \int \left(\alpha_j + \alpha_t + x'_{ijt}\alpha^x + \sum_{k\in J_i}\phi_k\gamma_{ik}(\pi) + \psi\gamma_{ij}(\pi) + \rho\pi + \rho_\psi\pi\right) dF_{\pi|x_{ijt},c_i} \,, \tag{E.5}$$

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

$$f_{\pi|x_{ijt},c_i} = \frac{f_{\pi,c_i|x_{ijt}}}{f_{c_i|x_{ijt}}} = f_{c_i|\pi,x_{ijt}} \times \frac{f_{\pi|x_{ijt}}}{f_{c_i|x_{ijt}}} = \hat{p}_{ik}(\pi) \times \frac{\phi(\frac{\pi}{\sigma_\pi})}{\int \hat{p}_{ik}(\pi)\phi(\frac{\pi}{\sigma_\pi})d\pi} \,, \tag{E.6}$$

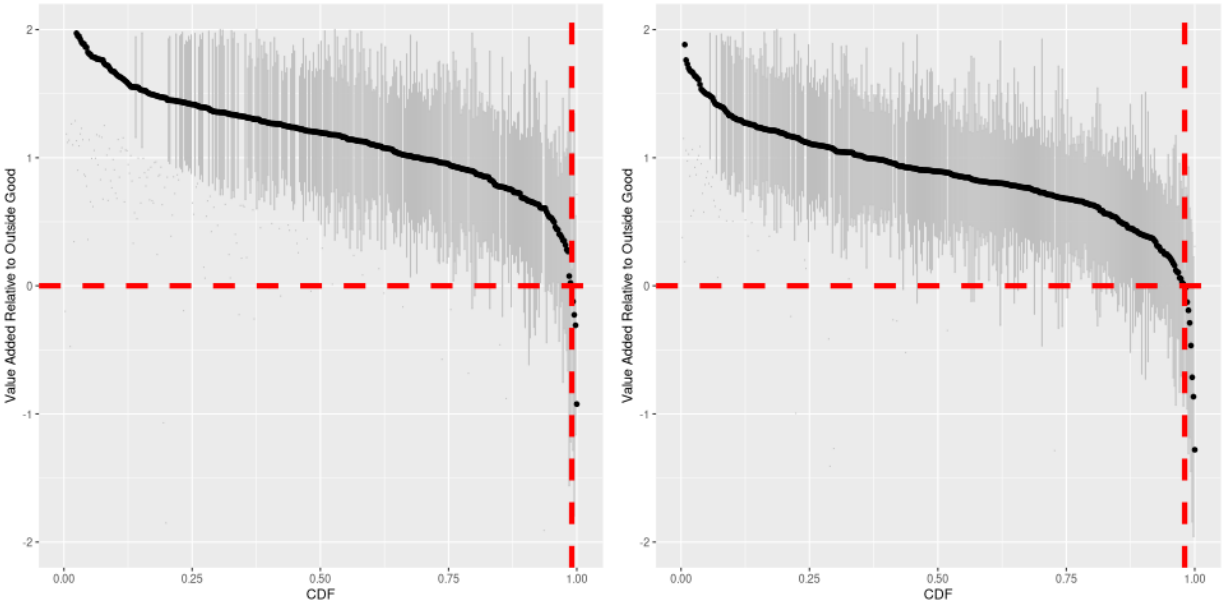
where $\phi(\cdot)$ denotes the standard normal density. Hence, and building on the demand model, we construct the weights

$$w_\pi = \hat{p}_{ik}(\pi) \times \frac{\phi(\frac{\pi}{\sigma_\pi})}{\int \hat{p}_{ik}(\pi)\phi(\frac{\pi}{\sigma_\pi})d\pi} \tag{E.7}$$

such that

$$E[m_i|x_{jt(i)}, c_i] = \int \left(\alpha_j + \alpha_t + x'_{ijt}\alpha^x + \sum_{k\in J_i}\phi_k\gamma_{ik}(\pi) + \psi\gamma_{ij}(\pi) + \rho\pi + \rho_\psi\pi\right) w_\pi \, d\pi \,, \tag{E.8}$$

Figure E.1: Value Added Estimates—Hospital Readmission Rates



(a) 30-Day Readmission Rate

(b) 90-Day Readmission Rate

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

Asymmetric Information: A natural question is whether consumer demand can discipline the expansion of low-quality providers. To explore this possibility, we now analyze the relationship between consumer preferences and our health value-added estimates. Figure E.4 provides a binned scatter plot with value-added on the y-axis and (binned) mean utility on the x-axis. As seen, we find no systematic relationship between the two variables and a correlation of almost 0. This implies that consumers do not consider that SNFs produce different health outcomes in their decision making; for example, because of asymmetric information or because of 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. Furthermore, we note that rationing alone can not explain why patients choose low-quality providers over the outside good. We therefore interpret Figure E.4 as evidence for asymmetric information over the quality of SNFs.

Table E.1: Health Outcome Estimates Using Readmission Rates

	30-Day			90-Day		
	Coefficient	95% CI Lower	95% CI Upper	Estimate	95% CI Lower	95% CI Upper
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
Municipalized SNF	0.01	-0.05	0.06	0.03	-0.02	0.07
Hospital length of stay	0.01	0.01	0.01	-0.00	-0.00	-0.00
Psi_eta	0.03	0.01	0.05	0.02	0.00	0.04
rho_beta	0.43	0.27	0.58	0.11	-0.04	0.25
rho_psi_beta	-0.98	-1.07	-0.90	-0.62	-0.70	-0.54

Source: Medicare claims data, MDS data. Equation (E.2) 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.

Table E.2: Correlation with Other Markers

Variable	Mean Utility	VA: Mort	VA: Read 30	VA: Read 90
Nurse Practioner	.098	-.038	-.076	-.072
Alzheimer's Unit	.179	-.042	-.025	-.03
RN Staffing Ratio	.207	.071	.049	.043
LPN Staffing Ratio	.268	.049	.015	.006
Occupancy Rate	-.025	.008	-.053	-.024
Total Beds	.106	-.123	-.052	-.019
Hospital Based	.242	.065	.043	.023
Overall Rating	.172	.112	.109	.162
Survey Rating	.193	.119	.081	.118
Quality Rating	-.024	.011	-.021	.025
Staffing Rating	.118	.015	.079	.109
RN Staffing Rating	.053	.054	.137	.146

Figure E.2: Selection and Valued Added

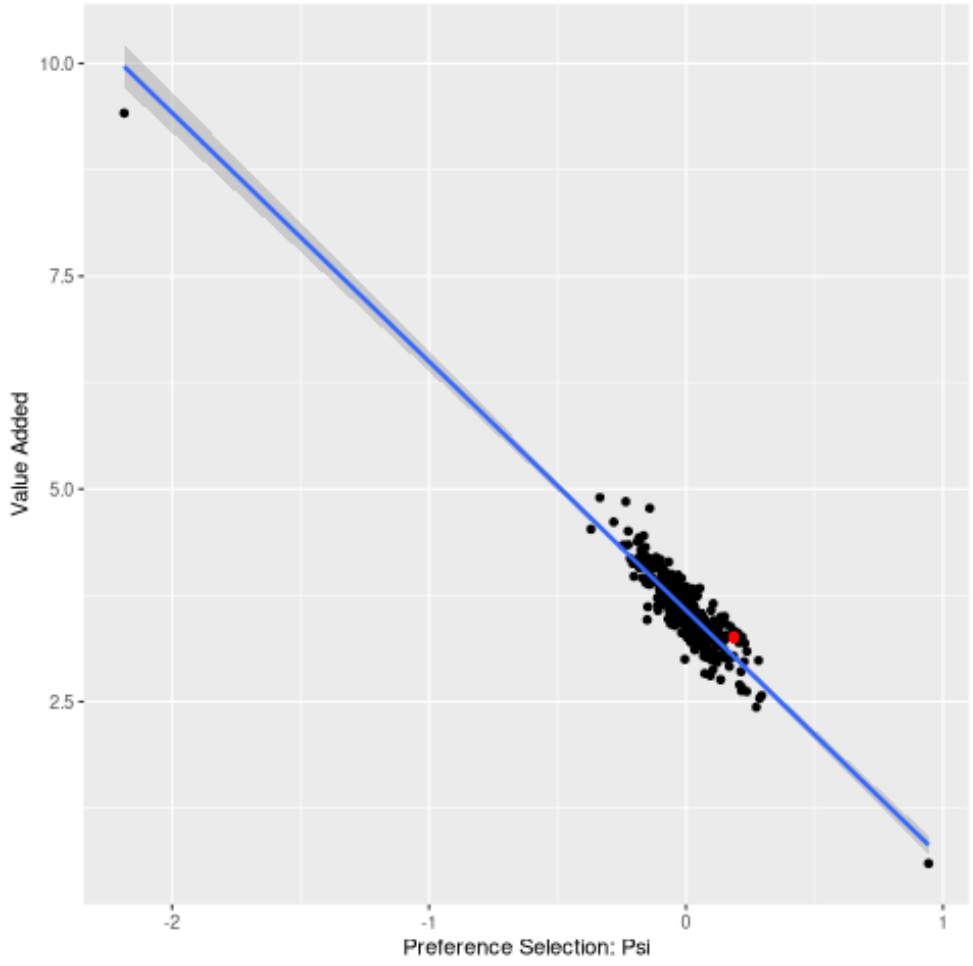
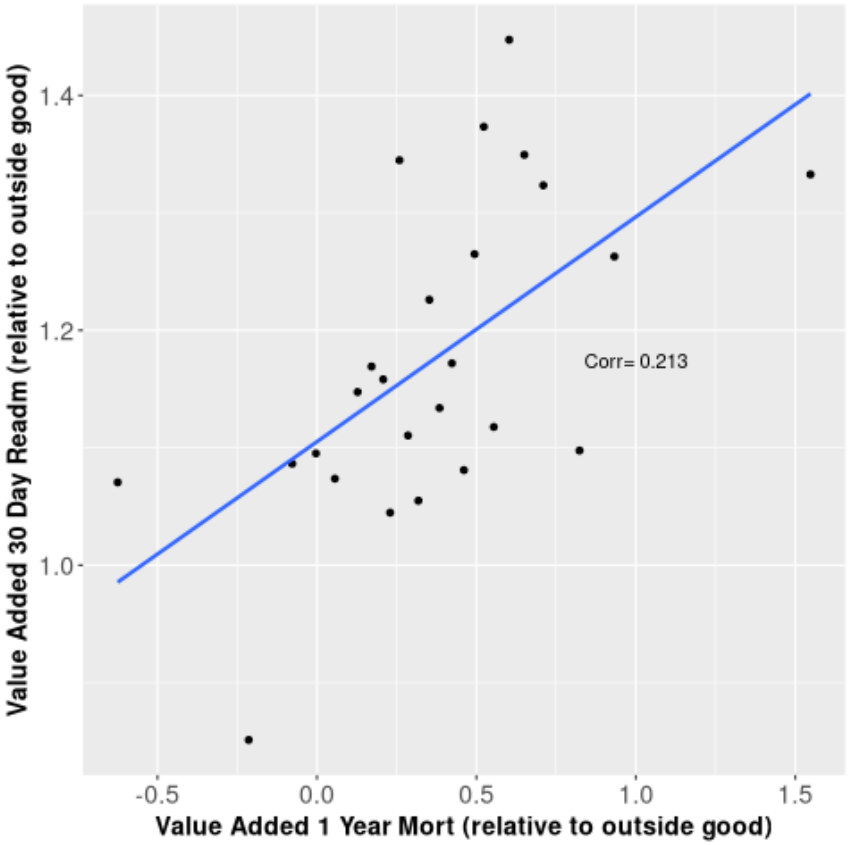
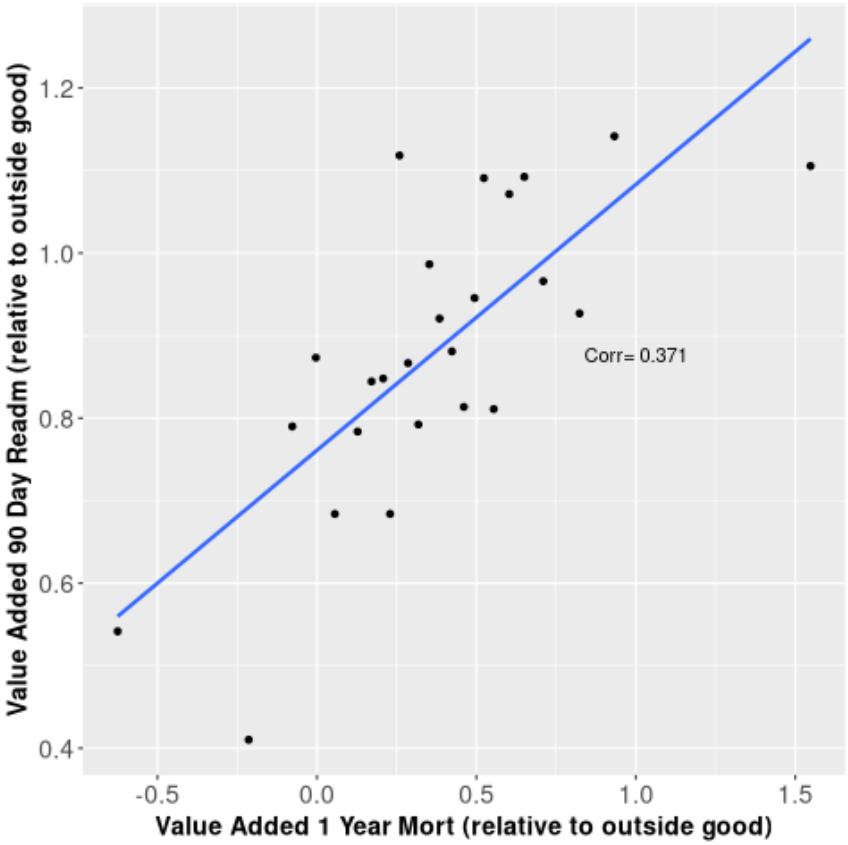


Figure E.3: Valued Added—Mortality vs Readmissions

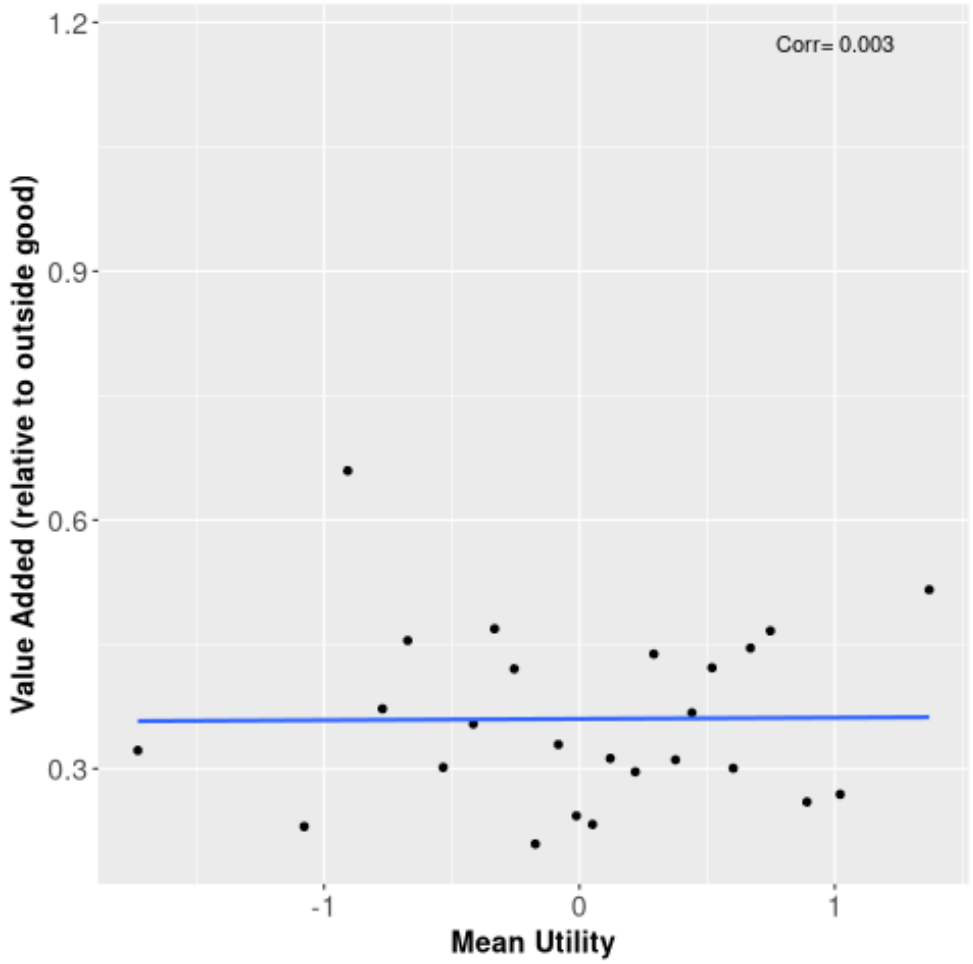


(a) Mortality Against 30-Day readmission



(b) Mortality Against 90-Day readmission

Figure E.4: Utility and Valued-Added—Do Consumers Choose High-Quality SNFs?



F Details on Calibration

The marginal rate of substitution is then:

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

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

$$MRS = 1 \quad \Leftrightarrow \quad \frac{(1-\gamma)\times\beta}{\gamma} = \Big(\frac{\beta \times \overline{log(AC_j)}}{log(\sum_j q_j)}\Big)^{1-\rho}\Big|_{no\ CF} \tag{F.2}$$

$$MRS = 1 - FMAP \times \frac{P}{R} \quad \Leftrightarrow \quad \frac{(1-\gamma)\times\beta}{\gamma} \times (1 - FMAP \times \frac{P-R}{AC}) = \Big(\frac{\beta \times \overline{log(AC_j)}}{log(\sum_j q_j)}\Big)^{1-\rho}\Big|_{with\ CF} \tag{F.3}$$

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. Put differently, with estimates of average costs, mortality, volume and the effective FMAP under creative financing, we can back out the parameters β, γ, and ρ.