NBER WORKING PAPER SERIES

CREATIVE FINANCING AND PUBLIC MORAL HAZARD: EVIDENCE FROM MEDICAID AND THE NURSING HOME INDUSTRY

Martin B. Hackmann
Juan S. Rojas
Nicolas R. Ziebarth

Working Paper 34118
http://www.nber.org/papers/w34118

NATIONAL BUREAU OF ECONOMIC RESEARCH
1050 Massachusetts Avenue
Cambridge, MA 02138
August 2025

We thank Alden Cheng, Sherry Glied, Jörg Schiller, Laura Lasio, and Corina Mommaerts for outstanding discussions of this paper. Further, we would like to thank Neale Mahoney and Matt Notowidigdo for their constructive comments and suggestions on earlier drafts of this paper. We also thank seminar participants at Yale, the University of Washington, and Wharton as well as participants at the 2024 NBER Summer Institute, 2024 Health Care from Early Life to Old Age, 2024 dggö, 2024 EGRIE, 2024 ZEW Public Finance, 2024 APPAM Fall Conference, 2023 VfS, 2023 GEA, 2021 ASHEcon, 2021 iHEA, and the Conference on Aging and Alzheimer's for constructive comments and suggestions. Funding from the National Institute on Aging grant #P01 AG005842-29 is gratefully acknowledged. Neither we nor our employers have relevant or material financial interests related to the research in this paper. We take responsibility for all remaining errors and shortcomings of the paper. The views expressed herein are those of the authors and do not necessarily reflect the views of the National Bureau of Economic Research.

Creative Financing and Public Moral Hazard: Evidence from Medicaid and the Nursing Home Industry
Martin B. Hackmann, Juan S. Rojas, and Nicolas R. Ziebarth
NBER Working Paper No. 34118
August 2025
JEL No. H51, H75, I11, I13, I18, J14

ABSTRACT

This paper studies the misallocation of Medicaid funds, its consequences for reimbursement rates, the quantity, and the quality of care provided. 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, to increase federal matching funds, such schemes distort the quality-quantity tradeoff. In Indiana, exploiting plausibly exogenous variation in the rollout of a creative financing scheme, we find a disproportionate expansion of Medicaid-funded care for dementia patients in the lowest-quality nursing facilities.

Martin B. Hackmann
University of California, Los Angeles
Department of Economics
and NBER
mbhackmann@gmail.com

Juan S. Rojas
Charles River Associates
rojasbjs@gmail.com

Nicolas R. Ziebarth
ZEW Mannheim
nicolas.ziebarth@zew.de

1 Introduction

Joint funding of public programs has been a cornerstone of U.S. federalism. In 2023, the federal government provided states and local governments $1.1 trillion—more than one-third of state budgets— in federal grants to fund a wide range of public policies, including health care, education, transportation, and environmental protection (Congressional Research Service, 2025). Joint funding often includes federal matching grants that subsidize lower-level government spending. Federal matching grants help lower-level governments internalize externalities and provide them with insurance against economic shocks (Oates, 1999). However, they also create a principal-agent problem. Local jurisdictions may misallocate resources when the federal government cannot perfectly monitor effective program spending.

In this paper, we study the misallocation of federal matching funds and their implications for patients and providers within 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 use. We present some of the first evidence that these schemes distort the states' quality-quantity tradeoff, incentivizing the expansion of potentially lower-quality programs to boost federal matching grant revenues. We do so in a crucial empirical setting: the U.S. nursing home industry. In 2023, it contributed $211 billion (or 4.3%) to U.S. health care spending and heavily relies on Medicaid financing (Centers for Medicare & Medicaid Services, 2023). At the same time, the industry has been plagued with quality concerns for decades (Grabowski, 2001; Rau, 2018; Hackmann, 2019). Combining two decades of administrative, audit, and survey data with quasi-experimental variation in the rollout of a creative financing scheme in Indiana, we show that creative financing leads to disproportionate increases in Medicaid-funded care in the lowest-quality nursing facilities, with potentially harmful consequences for patients.

We begin by formalizing how fund diversion distorts the quality-quantity tradeoff in a multitask principal-agent framework, with the federal government and states as the respective actors. Central to this model is the federal government's inability to perfectly monitor state spending of federal funds. Given the widespread use of creative financing practices across states and federal regulators' documented inability to contain them, we argue that this is a reasonable assumption. Despite a 2003 reform to contain such practices, creative financing activities persist (Department for Health and Human Services: Office of Inspector General, 2014; MACPAC, 2021). Further, we document that comprehensive federal audits struggled to track complex financial flows at the state level in the late 1990s. The Department for Health and Human Services (2025) concluded that it was "nearly impossible" to identify and follow these financial streams. Specifically, we assume that the federal government can monitor care quantities and nominal reimbursement rates paid to providers but not the effective rates paid after fund diversion.

In our model, incomplete monitoring allows states to inflate nominal rates that qualify for federal subsidies while reducing *effective* provider rates, "kept" by the provider—potentially degrading care quality. We refer to the gap between nominal and effective rates as a "public markup," which states divert towards other uses. Conversely, higher nominal rates incentivize an increase in the quantity of care, which we call "public moral hazard." States increase quantities to maximize the amount of matching funds that can be diverted toward other uses.

We then test these theoretical predictions regarding Medicaid payments to U.S. nursing homes. First, we present new evidence on the diversion of Medicaid funds in this vital industry and quantify the public markup. Combining audit reports with survey data, we document that between 2000 and 2002, 16 states used creative financing schemes to divert at least $17 billion in Medicaid funds away from nursing homes. We estimate that states inflated nominal reimbursement rates by 30% over the effective rate. 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, much more 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 these schemes. Effective 2003, states could no longer redirect funds from *private* nursing homes via so-called "intergovernmental transfers" (IGTs), restricting the scope of the scheme to patient care delivered in the 7% *public* nursing homes. In response to the 2003 reform, to continue and even expand their creative financing scheme, the state of Indiana systematically encouraged county hospitals to acquire and municipalize private nursing homes. As a result, in Indiana, the share of publicly owned nursing homes surged from 5% in 2000 to 95% by 2017. We exploit this scheme in Indiana to study its causal effects on the quantity and quality of care.

Specifically, 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 care volume. Our findings confirm the existence of public moral hazard: 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 12% and accompanied by an increase in Alzheimer's special care units. AD/ADRD patients are an ideal target population as they have relatively long lengths of stay, accounting for 35% of all Medicaid days in our sample, and require specialized treatment (Mitchell et al., 2009).

Central to the welfare implications of public moral hazard is how Indiana's scheme affects patient health (Baicker, Mullainathan, and Schwartzstein, 2015). On one hand, increased utilization may improve access to care for Medicaid patients (Hackmann, Pohl, and Ziebarth, 2024; Gandhi, 2020). On the other hand, care quality for AD/ADRD patients is positively correlated with experience in treating these patients (Mukamel et al., 2023), suggesting that nursing homes with limited experience, especially in economically disadvantaged areas or those serving minority populations, may deliver lower-quality care (Travers et al., 2024; Estrada et al., 2024). As a result, greater utilization may harm patients if demand shifts toward lower-quality providers. Moreover, the conversion of nursing homes may affect care quality, potentially by introducing Alzheimer's special care units (Joyce et al., 2018).

To assess overall patient health, we examine two mechanisms: (1) changes in nursing home care quality following municipalization, potentially driven by the addition of Alzheimer's special care units, and (2) patient relocation between nursing homes and other care settings. To this end, building on Dubin and McFadden (1984); Abdulkadiroğlu et al. (2020) and Einav, Finkelstein, and Mahoney (2025), 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 choice. We focus this exercise on AD/ADRD patients using one-year survival rates and hospital readmission rates as health care quality measures. The analysis yields three main findings. First, holding the patient composition fixed, we find no statistically 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 43% to 12%, on average. Further, we find that nursing homes in the bottom quintile provide lower-quality care than long-term care provided at home. Third, we find quantity increases throughout the quality distribution. Still, the largest increase for nursing homes is in the bottom quintile, suggesting that dementia patients spend an additional 176 thousand days per year in lower-quality nursing homes. We estimate a one percentage point (ppt) increase in one-year mortality among marginal patients because of the relocation to lower-quality nursing homes.

In the last section of the paper, we connect our findings to our conceptual framework to assess the implications for allocative efficiency. Indiana's scheme distorts the quality-quantity tradeoff, favoring the expansion of lower-quality nursing home care. In contrast, the optimal expansion path would allocate some incremental Medicaid spending towards improving the quality of care (e.g., increased nurse-to-patient staffing ratios) or expanding higher-quality nursing homes. Our calculations suggest that Medicaid spending on dementia patient stays could be reduced by about 1.7% without compromising the quality-adjusted quantity of care, with cost savings up to $310 million over ten years just in Indiana. Our findings raise new doubts about creative financing instruments in the nursing home industry. In Indiana, these instruments serve as funding tools for other programs (such as hospital care) and distort the nursing home industry towards an overprovision of lower-quality care.

Our findings contribute to three main academic areas of literature. First, we add to research on strategic interactions in fiscal federalism (Gordon, 1983; Dahlby, 1996; Knight, 2002; 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; Sharma and Xu, 2023), 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 active debate on Medicaid financing reform, including reducing the scope of creative financing instruments (Kaiser Family Foundation, 2025a), cost-sharing changes (Rudowitz, 2017; Clemens and Ippolito, 2018; Committee for a Responsible Federal Budget, 2024; LoSasso, 2025), and increased surveillance (Federal Register, 2019).

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; Alexander and Schnell, 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, when public stakeholders are not subject to a soft budget constraint (Duggan, 2000). Our analysis shows that public ownership of providers can undermine joint program financing, as local jurisdictions can manipulate their effective contributions using creative financing instruments that are difficult to monitor.

Third, we contribute to the literature on designing reimbursement schemes and the quality of 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 critics argue that policy biases toward institutional nursing home care continue to exist (Chidambaram and Burns, 2023) even though nursing home care is highly unpopular and the elderly prefer to age at home (AP-NORC, 2021). We find that creative financing schemes lower the state's cost share of inpatient long-term care, potentially contributing to the adoption of policies that favor institutional care (Grabowski and Gruber, 2007; Mommaerts, 2018) over other potentially cost-saving forms of care (Hackmann, Pohl, and Ziebarth, 2024; Gruber et al., 2025). We combine recent advances in the estimation of nursing home value added Einav, Finkelstein, and Mahoney (2025); Olenski and Sacher (2024); Cheng (2023) with plausibly exogenous variation in the timing of nursing home acquisitions (Gupta et al., 2023; 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

Medicaid, a cornerstone of the U.S. healthcare system, provides public health insurance to 79 million low-income individuals, with total annual spending of about $800 billion (Kaiser Family Foundation, 2025c; Centers for Medicare & Medicaid Services, 2025). It provides access to critical inpatient and outpatient health care services and protects beneficiaries from catastrophic costs. Beyond individual coverage, it also supports broader public health by stabilizing providers and funding community initiatives.

The Medicaid program operates under a federal-state partnership: states administer the program with significant discretion while sharing costs with the federal government (Kaiser Family Foundation, 2024b, 2025d). 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), see Kaiser Family Foundation (2025b).

However, states often employ creative financing schemes, such as provider taxes or intergovernmental transfers (detailed below), to divert funding. All states but Alaska adopt provider taxes on primary care physicians, insurance plans, hospitals, and nursing homes; provider taxes are now one of the largest funding sources for states' Medicaid costs.[1] As detailed below, states use creative financing to extract federal matching funds, thereby effectively shifting costs to the federal government. The Committee for a Responsible Federal Budget (2023) estimates that the federal government covers 5% more in Medicaid costs than it would without creative financing. It is not obvious whether these sophisticated schemes are legal, which has resulted in heated debates among (legal) scholars, lawsuits, audits, and legislative initiatives, as discussed throughout this paper.

[1] Provider taxes function similarly to IGT schemes (Miller and Wang, 2009). 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.

The Centers for Medicare and Medicaid Services' (CMS) limited oversight and monitoring capacities help explain the scale and persistence of creating financing. For example, a former senior official from the Department of Health and Human Services writes:[2]

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

2.2 Creative Financing in Nursing Homes: Pre-2003

Our analysis focuses on the nursing home industry. The nursing home industry heavily relies on Medicaid spending, with two-thirds of all 1.5 million nursing home patients covered by Medicaid, totaling $59 billion 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 lower quality of care (Grabowski, 2001; Hackmann, 2019). Thus, 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" (UPL) (Mitchell, 2018).[3] In 2019, SPs accounted for seven percent of total Medicaid fee-for-service nursing facility payments (MACPAC, 2019b).

However, states use creative financing to divert nursing home payments. 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 intergovernmental 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

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

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

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.[4] 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 Department of Health and Human Services 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 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 the diversion of Medicaid reimbursements.

2.4 Creative Financing 2.0: Evidence from Indiana

After the 2003 reform, states explored alternative creative financing schemes to continue redirecting federal matching funds. Indiana implemented a scheme that mirrored, and

[4] The federal government covers 56% of total spending, as dictated by the FMAP, which amounts to 56% $\times$ \$700 million $\approx$ \$400 million in this case.

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

Specifically, to bypass the 2003 reform, Indiana induced county-owned hospitals to acquire private nursing homes. 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 SP top-up payments 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 the scheme in Indiana: Under a contractual agreement, county hospitals repaid the state's share of supplemental payments while retaining the federal match, which was divided between hospitals and nursing homes. Because federal matching funds were proportional to Medicaid service days, the integrated hospital-nursing home system had strong incentives to increase patient volume. Pioneering the model was the Health and Hospital Corporation (HHC) of Marion County—a government entity. In 2003, it acquired and municipalized 17 nursing homes. By 2009, HHC owned 40 nursing homes, see Figure 2a.

[Insert Figure 2 about here]

Indiana allowed HHC to use a "lease structure" instead of directly acquiring nursing homes 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 Medicaid 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."* (Gillers et al., 2010). 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 nursing homes in the state were county-owned; see Figure 2b. 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.

This scheme was highly effective in maximizing federal Medicaid revenue. In FY 2020, Indiana received $996 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).

3 Conceptual Framework

The previous discussion highlights that, even after reforms to contain such practices, states continue to develop sophisticated, creative financing schemes. These schemes make it difficult for the federal government to monitor effective program spending, allowing states (or county-owned healthcare systems) 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. Building on Holmstrom and Milgrom (1991), we study a multitask Principal-Agent problem with monitoring frictions. The framework considers two types of Agent effort, but the Principal can only perfectly monitor one of them. The main finding is that when payments to the Agent are complementary in both efforts, actual efforts will be distorted in opposing directions: the Agent shirks in the "non-monitored" effort but inflates the "monitored" effort. The details are in Appendix B.

Next, we apply the general insights to our institutional setting, where the Principal is the federal government and the Agent could be the state or, as in our main empirical application, a county-owned health care system. We restrict our analysis to care provided exclusively to Medicaid patients. Under incomplete monitoring, we treat patient volume as monitored effort and effective spending as non-monitored effort. We develop our predictions in the presence of intergovernmental transfers and discuss the relationship to provider taxes in Appendix Section B4.

3.1 Payoffs

State ("The Agent"): The state values the quality, θ, and quantity,Q, of nursing home care, provided through the benefit function $B(\theta, Q)$, denoted in dollars. However, states internalize only a fraction $\tau \leq 1$ of the benefits because of free-riding on neighboring states.[5]

The federal government ("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 (which is the sum of the base per diem and the supplemental rate per patient day). In contrast, the state (Agent) pays nursing homes *effective* reimbursement rates, net of diversion of funds, worth $R \times Q$, where R is the effective Medicaid reimbursement rate retained by the provider. We assume a positive relationship between the effective rate and the quality of care, $\partial\theta(R)/\partial R > 0$. In addition, we assume that the Agent chooses effort, in our case R and Q, as well as P, under incomplete monitoring; see below. The Agent'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—resources that the Agent could have invested in other programs.

Federal Government ("The Principal"): The federal government internalizes the externalities across states, net of the federal reimbursement cost:[6]

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

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

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

3.2 Social Welfare and Efficiency

We define social welfare as the sum of the two payoffs:[7]

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

Maximizing welfare with respect to R and Q yields two optimality conditions:[8]

$$\begin{aligned} B_R(\theta(R), Q)/Q &= 1 && (4) \\ B_Q(\theta(R), Q)/R &= 1\,. && (5) \end{aligned}$$

Intuitively, the marginal benefit of increasing effective spending should be proportional to increases in rates and quantities. 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 of the state's maximization problem concerning R and Q, we have:

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

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.[9]

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

[7] 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's 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.

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

[9] 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.

inability of the federal government to monitor effective spending $R \times Q$, allowing states to divert $P \times Q - R \times Q$.

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:

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

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

$$\begin{aligned} P &= \bar{P} && (9)\\ \tau \times B_R(R,Q)/Q &= 1 && (10)\\ \tau \times B_Q(R,Q)/R &= 1 - FMAP \cdot \frac{\bar{P}}{R} = 1 - FMAP \times \mu\,. && (11) \end{aligned}$$

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, increasing the program's cost to the federal government. In our case, the state will optimally increase the nominal rate up to the cap, $P = \bar{P} = UPL$. In contrast, the effective rate, R, no longer qualifies for matching funds (equation (10)). Thus, the state internalizes effective rate changes in full—not just $(1 - FMAP)$—and has stronger incentives to reduce R, thereby lowering the quality of care. In other words, the "effective *price* FMAP" is zero. We denote the ratio between nominal and effective reimbursement rates as the "public markup", defined as $\mu = \frac{P}{R}$.

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* $\mu = \frac{P}{R}$*, allowing 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 $\frac{P}{R} = \mu$, see equation (11). 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 the quantity of care, Q. We denote the volume of care and effective reimbursement rates 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, under perfect monitoring, the downward-sloping line 'C' denotes the state's budget constraint without creative financing. The slope does not depend on the 'FMAP', and incentives are aligned between states and the federal government. The expansion path 'I' illustrates the optimal rate and quantity mix for that case. As τ increases, states will choose higher rates and volumes along this path. Allocations along this path minimize the state costs and the social cost of achieving a given benefit level.

[Insert Figure 3 about here]

Second, under imperfect monitoring, the downward-sloping line 'D' denotes the state's budget constraint with creative financing. The budget constraint is now rotated outward.[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 schemes and face incentives to increase care volume, reflecting public moral hazard. As indicated by the

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

[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 $\partial log(Q) / \partial log(R) = -\frac{1}{1-FMAP\times\frac{P}{R}}$.

allocations along the new expansion path 'II', they have relatively weaker incentives to increase rates and thus quality. These allocations minimize state costs but not federal costs, and hence, not the social cost of care.

3.5 Optimal Contracting under Imperfect Monitoring $(P \neq R)$

We next turn to the optimal (linear) contract between the federal government and the states under incomplete monitoring. To this end, we maximize social welfare, see equation (3), subject to the Agent's incentive compatibility constraints:

$$\max_{\bar{P}, FMAP} B(\theta(R), Q) - R \times Q \tag{12}$$

$$s.t. \quad \tau \times B_R(R, Q)/Q = 1 \tag{13}$$

$$\tau \times B_Q(R, Q)/R = 1 - FMAP \cdot \frac{\bar{P}}{R} \tag{14}$$

.

Equation (12) considers that states will maximize nominal rates, $P = \bar{P}$. $\bar{P}$ and $FMAP$ enter the formula multiplicatively. We, therefore, focus on $\tilde{P} = \bar{P} \times FMAP$ as the relevant policy instrument. It can be interpreted as a fixed federal subsidy per unit of volume. Since the Principal cannot monitor R, the federal subsidy will not depend on it.

The first order condition with respect to $\tilde{P}$, see Appendix Section B2, implies:

$$(1-\tau) \cdot \underbrace{\frac{d(R \times Q)}{d\tilde{P}}}_{\text{Positive Externality}} - \underbrace{\tilde{P} \cdot \frac{dQ}{d\tilde{P}}}_{\text{Public Moral Hazard}} = 0\,. \tag{15}$$

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

An interesting case is $dQ/d\tilde{P} > 0, dR/d\tilde{P} = 0$, namely when federal contributions only affect effective spending through quantities and public moral hazard, and the pass-through rate from the nominal rate to the effective rate (and hence quality) is zero. This might be an extreme case, but our empirical evidence for Indiana aligns with it. In that case, we have:

$$\tilde{P}^* = FMAP^* \times \bar{P}^* = (1-\tau) \times R. \tag{16}$$

Setting $FMAP^* = (1-\tau)$ implies $\bar{P}^* = R$. In other words, unless federal matching funds translate into higher effective rates (and thus quality), the upper payment limit should align with R, casting renewed doubt on creative financing practices.

By contrast, without public moral hazard, $dQ/d\tilde{P} = 0$ and $dR/d\tilde{P} = 0$, diverted funds represent a non-distortionary transfer from the federal government to states. Yet, our empirical evidence below clearly demonstrates the presence of public moral hazard.

3.6 Discussion

Our theoretical analysis shows that when the Principal (the federal government) cannot monitor effective program spending, Agents (the states) have incentives to divert funds using creative financing instruments. These instruments distort the state's quality-quantity tradeoff, encouraging volume expansions at relatively low cost. States can influence care volume through capacity regulations, Medicaid eligibility, benefit design, and Home- and Community-Based Services (HCBS) waivers. A key concern is that creative financing in the nursing home industry may reinforce an institutional bias in states' long-term care policy.

Our empirical application focuses on a public hospital–nursing home system, which may respond to these incentives by attracting new patients, increasing advertising, or changing admissions when capacity constraints bind. We test for changes in Medicaid volume following the adoption of a creative financing instrument. While our predictions apply to "public" agents, for example, states or public providers (as implied by public moral hazard), we discuss the case when care is provided by private nursing homes in Appendix Section B3, which may not benefit directly from creative financing.[12] Nonetheless, the broader insight extends to regulatory policy more generally: in the presence of creative financing, states have incentives to adopt instruments that expand care volume at

[12] In this discussion, we abstract from the instruments discussed above and assume that Medicaid reimbursement rates are the primary lever for influencing Medicaid volume in private nursing homes. In this setting, states face a tradeoff: lower rates to contain costs or raise them to expand access. Appendix Section B3.4 derives conditions under which the access (quantity) motive dominates. We find that states are willing to raise Medicaid reimbursement rates to stimulate access to care, when the public markup, precisely $\mu - 1$, exceeds $\frac{1}{\epsilon_{Q,R}}$, where $\epsilon_{Q,R}$ denotes the elasticity of volume of care concerning the effective reimbursement rate R.

relatively low cost, particularly when these instruments help align provider behavior with state objectives under limited oversight.

In conclusion, creative financing in the nursing home sector may lead to two types of distortions. First, a within-industry bias exists as public providers, particularly lower-quality ones that may be able to expand care at lower costs, are incentivized to expand Medicaid volume. Second, a between-industry bias that favors institutional care over home- and community-based alternatives in state long-term care policy. These distortions raise concerns about creative financing practices and may motivate stricter upper payment limits.

4 Data, Empirical Approaches, and Results

The following three subsections 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 the 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.

Data & Empirical Approach: First, we use nursing home information from the On-Line Survey, Certification, and Reporting system (OSCAR), accessed through LTC Focus data at the state-year level from 2000-2007 (Long-Term Care: Facts on Care in the U.S., 2025). 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 (also at the state-year level). We interpret the product of the two as a measure of effective nursing home spending, $R_{st} \times Q_{st}$, for state s in year t, an assumption 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:

$$\mu_{st} = \frac{P_{st} \cdot Q_{st}}{R_{st} \cdot Q_{st}} = \frac{P_{st}}{R_{st}} \,. \tag{17}$$

To test hypothesis **H1**, 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:

$$Y_{st} = \gamma_s + \gamma_t + \beta \times CF_s \times Post_t + \epsilon_{st} \tag{18}$$

for outcome Y_{st} of state s in year t, where γ_s and γ_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.

Our primary outcome of interest is the public markup, but we also use the simple DD design to test for changes in additional outcome measures included in LTC Focus.Specifically, we use our markup measure to calculate the "effective FMAP" rate along with measures of federal and state Medicaid nursing home expenditures, 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 in nursing homes also provides an outlook for our hypothesis on public moral hazard, **H2**.

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 time trends in the post-2003 years, showing only minor differences in our calculated markup in post-reform years. This first observation suggests that the 2003 reform successfully produced an era where states with and without pre-reform creative financing schemes look alike. After 2003, we observe a substantially reduced markup of less than 1.1 between effective and nominal Medicaid nursing home spending, suggesting that the reform worked nationally as intended.

[Insert Figure 4 about here]

Importantly, 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, no wedge exists 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 \$58 billion 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×\$58bn=\$17bn. 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 \$167 and \$118 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 significant changes in staffing levels. This finding implicitly reinforces the idea that nominal pre-2003 nursing spending was artificially inflated and differed substantially from actual spending due to creative financing.

The last column in Panel B of Appendix Table C.2 previews a more refined test of the public moral hazard channel (hypothesis **H**2) in Section 3. We find evidence that the overall number of Medicaid days 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.[13] Likewise, Indiana introduced a new creative financing scheme, see Section 4.2 below.

Evidence from ODI Audit Reports. Next, we use 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 (IGTs). They provide independent estimates and hard evidence on the diversion of funds, allowing us to calculate the public markup for a subset of states based on this alternative source. 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 column (1) of Appendix Table C.2. Further, Appendix Figure C.1b suggests that the "effective FMAP" was up to 33 percentage points higher than the nominal one, for example, in Pennsylvania, where the effective FMAP was 87% 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 financial reports show that HHC received a total of \$3.2 billion in base Medicaid revenues for nursing home services, see column (2) of Table C.3, jointly funded between the federal government and the state at an average nominal FMAP of 68%, see column (3): \$2.1 billion paid by the federal government (column (4)), and \$1.1 billion paid by the state. In addition, the state initiated \$750 million in supplemental payments for nursing home services, generating an extra \$1.5 billion in federal payments (column (6)), for a total of \$2.3 billion in supplemental payments; see column (5). Total nominal Medicaid payments for nursing home services thus amounted to \$3.2bn+\$2.3bn=\$5.5bn. HHC then redirected

[13] 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.*"

\$1.9 billion from the nursing homes via IGTs to its "general fund" (column (7)) to finance its hospital operations.

While we cannot quantify the amount transferred back to the state, independent sources suggest that it recovered its share in supplemental payments. We conservatively assume that the state recovered at least \$400m of the full \$750m via IGTs.[14] This implies that only the Medicaid base payments of \$3.2 billion remained at the nursing homes. Interpreted through the lenses of our conceptual framework, this corresponds to a public markup of:

$$\mu_{HHC} = \frac{P_{HHC} \times Q_{HHC}}{R_{HHC} \times Q_{HHC}} = \frac{\$5.5bn}{\$3.2bn} = 1.72 \tag{19}$$

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 jointly generate a net surplus from providing Medicaid-funded nursing home care.

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

This subsection quantifies the causal effects of creative financing on the care volume ("public moral hazard"). To do so, we zoom into Indiana's scheme. To circumvent the 2003 reform, Indiana encouraged county hospitals to acquire private nursing homes. HHC pioneered the model. It began acquiring nursing homes in 2003, see Section 2.4 and Figure 2b. The introduction of creative financing created significant financial incentives for the integrated hospital-nursing home systems to increase care volume, see Hypothesis 2. For HHC, overall Medicaid revenues increased from \$3.2 billion in base payments to \$5.5bn-\$0.4bn=\$5.1bn, after netting out the diversions to the state, a 55% increase.

Data & Empirical Strategy: We combine three data sources to estimate the impact of municipalization, proxying for creative financing, on several outcomes. First, to exploit the timing of the nursing home acquisitions in an event study framework, we extract information on municipalizations from (i) Nursing Home Compare, (ii) Indiana Department of

[14] This estimate is below the state's supplemental payments but ensures that the nursing home is no worse off than without supplemental payments when the hospital diverts \$1.9 billion.

Health (2020) data and (iii) reports by the IndyStar newspaper (Centers for Medicare & Medicaid Services, 2020b; Gillers et al., 2010). Second, we use LTC Focus data as in Section 4.1, but now at the nursing home-year level from 2000 to 2015. These data include nursing home characteristics, including staffing levels and whether the nursing home has a special care unit. 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 Indiana Medicaid and Medicare-certified nursing homes from 1999 to 2015. Further details are in the Data Appendix C.

Our baseline sample is balanced in calendar time at the nursing home-year level to avoid changes in the sample composition that could confound the analysis. As the acquisitions targeted Medicaid-certified nursing homes, we focus on nursing homes with at least one Medicaid patient in 2000. We arrive at a sample of 368 nursing homes. We track those over 16 years in the LTC Focus data and over 17 years in the MDS data.

To quantify the causal effects of Indiana's creative financing scheme, we exploit the timing of nursing home acquisitions in an event study design. Specifically, to avoid the pitfalls of two-way fixed effects estimators in staggered DD setups, we use the estimator from Callaway and Sant'Anna (2021); see Appendix Section E1 for details. Our empirical approach compares municipalized nursing homes to those that have not yet been municipalized.

Results: Figure 5a shows the event study effects of Callaway and Sant'Anna (2021) for the impact of municipalization on for-profit status. As seen, we find no evidence for a pre-trend in the years leading up to municipalization, but tight estimates are around zero. Then, we observe a sharp decline in the for-profit status starting in year 0, the year of the municipalization. The effect size is around -0.6 three years post-acquisition, in line with expectations considering that about 59% of all nursing homes are for-profit over the entire sample (see Table D.1). The average treatment effect on the treated (ATT) is -0.54 (se=0.03), see column (1) of Panel A in Table 1.

[Insert Figure 5 about here]

Figure 5b shows the event study estimates for 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 **H2**. Four years after the acquisition, the average nursing home provided about 3,000 additional Medicaid days, corresponding to 8.2 full-year residents. The effect size is relatively large, considering that nursing homes serve 28,040 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 4.9% increase.

Investigating the underlying mechanisms, we find that the increase 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.[15] Then, we use the total number of Medicaid days spent by AD/ADRD patients in nursing homes as an outcome in Figure 5c. Figure 5c mirrors the pattern in Figure 5b for all patients. We calculate an ATT of 1178 Medicaid days (se=255), a 12% increase for this group, see column (3) of Panel A in Table 1.[16] This finding is not unexpected given that 38% of all Medicaid days in our sample are accounted for by dementia patients. Additionally, Medicaid reimbursements are risk-adjusted and thus higher for patients with cognitive impairments. Consequently, the roughly 55% increase in nominal rates translates into even greater increases in levels for patients with cognitive impairments, providing strong incentives to expand care volumes. We also find that the increase in dementia days is accompanied by an expansion in Alzheimer's special care units, see 5d. Here, we find an ATT of 9pp (se=3pp) throughout the post-acquisition period, see column (4) of Panel A in Table 1.

4.3 How Does Creative Financing Affect Quality of Care?

Central to patient welfare is how Indiana's creative financing operations affected patient health. This subsection investigates this question. We consider two key mechanisms. First, holding the patient composition fixed, care quality may change following municipalization, for instance, through Alzheimer's special care units. Second, the public moral channel

[15] 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.

[16] In robustness tests, we find 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—which is the maximum number of days covered by Medicare for patients admitted from acute hospital stays and demarks the difference between short and long stays, see Appendix Figure D.2—suggesting that the prolonged stays are not due to enhanced survival.

suggests patient relocation between (i) nursing homes of different qualities and (ii) 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 (2025). Below and in 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 AD/ADRD patients discharged from hospitals after acute care stays. 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.[17] 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 they select inpatient long-term care and, if so, which nursing home they chose. Thus, we can model care choices and subsequent health outcomes. Our primary health outcome measure is patient mortality; we consider hospital readmissions in an additional robustness exercise. Both outcomes are measured for all patients.

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 (hospital)-stay* level and flag hospital stays with Clinical Classification Software (CCS) diagnosis code 653 "Delirium, dementia, and amnestic and other cognitive disorders"(CCS, 2017), drop patients from out-of-state or missing zip codes, and only keep patients 65 and older, see Appendix Table D.3 .[18]

Sample: We arrive at a sample of 206,833 hospital index stays; see Table D.4 for summary statistics. The final dataset includes patient demographics such as age (82.6 years), race

[17] 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).

[18] 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.

(90% white), one-year mortality (33%), and discharge destinations after the acute care stay (37% to a nursing home) as well as hospital readmission rates (31% within 90 days).

We merge these index hospital stays with MDS data to identify subsequent nursing home stays.[19] We find successful nursing home matches for 37.6% of all index stays––nearly identical to the 36.9% of patients reported as discharged to any nursing home in the hospital claims. We assume that patients not matched to a nursing home choose an outside good. In what follows, we interpret the outside good as outpatient care provided in the community—specifically, home care—as it is the most common alternative discharge destination (see Table D.4).

Patients discharged to nursing homes (from an acute care hospital) are typically covered by Medicare initially, but many transition to Medicaid coverage after the 100-day Medicare limit. On average, 12% of all AD/ADRD patients discharged to a nursing home have *any* nursing home Medicaid days, where the average number of Medicaid days is 186 (Table D.4).

Choice sets: To ensure sufficient 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. In addition to the outside good, the patients' choice sets comprise all nursing homes within 50 miles of the patient's former address. The average discharge patient has 74 nursing homes, and the outside good, in her choice set.

4.3.1 Model of Care Choice and Health Outcomes:

To isolate quality changes from patient composition changes, we develop and estimate a nursing home production model that considers the patient composition.

Mixed Logit Model of Care Choices: We start with a mixed logit nursing home choice model. It allows for an outside good corresponding to home care for most patients. We index patients by i and providers by j, and denote by t the year of the hospital discharge. Patients maximize the following indirect conditional utility function:

[19] For a successful merge, the hospital stay precedes the nursing home stay by at most two weeks, ending before the nursing home stay. Further, the ID of the merged nursing home allows the identification of the destination nursing home.

$$
\begin{aligned}
u_{ijt} &= \begin{cases} \delta_j + x'_{ijt}\beta^x + z'_{ij}\beta^z + \eta_{ij} & \text{for nursing home } j \text{ in } i\text{'s choice set} \\ \pi_i + \gamma_t + \eta_{io} & \text{if outside good} \end{cases} \qquad (20) \\
\eta_{ij} &\sim \text{i.i.d. extreme value} \\
\pi_i &\sim N(0, \sigma^2)
\end{aligned}
$$

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

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

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

$$m_{ijt} = \alpha_j + \alpha_t + x'_{ijt}\alpha^x + \epsilon_{it}, \qquad (21)$$

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.

Selection Correction: A key challenge to estimating equation (21) is that we only observe outcomes at (endogenously) chosen nursing homes. We exploit exogenous variation via an excluded instrument to correct for such selection. Put differently, we require variation in preferences that only affect health through provider choice. Following the literature, 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 nursing homes 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. Geographic distance is also likely orthogonal to latent patient health. For a detailed discussion on distance as a valid instrument, see Einav, Finkelstein, and Mahoney (2025). Following Dubin and McFadden (1984), see Appendix Section E2. In the first step, we estimate the mixed logit choice model. In the second step, we construct the control functions and estimate the parameters of equation (21) via simulated maximum likelihood.

4.3.2 Results

Mixed Logit Results: Panel A of Table 2 presents select parameter estimates from equation (20), 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 nursing homes are municipalized. The point estimate suggests that municipalization increases the number of acute care hospital admissions by about 5%.[20]

[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 nursing home 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 coef-

[20]Technically, we have $\frac{\frac{\partial s_{ij}}{\partial Post}}{s_{ij}} = 0.05 \times (1 - s_{ij})$, using the point estimate from Table 2. About 63% choose the outside good, and the remaining inside good market share is divided across 74 nursing homes in the choices set on average, suggesting $s_{ij} \approx (1 - 63\%)/74 = 0.5\%$. This suggests an average effect size from municipalization on admissions from acute care hospitals of $5\% \times (1 - 0.005) \approx 5\%$.

ficient is essential 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 (21). 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 index 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 increase survival significantly. Applying 95% statistical confidence intervals, we can exclude that municipalizations increase survival rates by more than 2.5pp (3.7%) or decrease them by more than 1pp (1.6%) for an average patient in our sample.

Valued-Added Results: To investigate whether changes in nursing home composition (because of "public moral hazard") affect aggregate mortality or readmission rates, we turn to the estimated value-added coefficients, α_j, again redirected to denote positive effects. Figure 6a shows value-added estimates based on one-year survival rates in nursing homes, along with the 95% confidence intervals. The point estimates are shown net of the outside option (e.g., home care), and are ordered from highest to lowest net value-added. The dashed horizontal line corresponds to the value-added of the outside option (normalized to zero for the graph).

[Insert Figure 6 about here]

Figure 6a provides several insights. First, 80% of nursing homes are situated in the upper half. On average, they have a higher value-added than community-based home care (the outside good). Conversely, 20% have a lower value-added than home care.[21] Second, we find substantial heterogeneity in value-added between nursing homes, consistent with the recent literature (Einav, Finkelstein, and Mahoney, 2025). The value-added drops from 0.5 to about -0.5 when moving from the 10th to the 90th percentile, which corresponds to

[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). Shrinkage 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.

comparing the one-year survival rate of a 65-year-old to a 100-year-old resident in a given nursing home (0.35*3.09≈1.).[22]

Robustness: Naturally, the nursing home-specific value-added estimates carry noise. To mitigate this and to validate our value-added measures, we first group nursing homes into higher and lower-quality nursing homes and then compare the results to other quality outcome markers. Motivated by Figure 6, we flag the bottom quintile of nursing homes—those whose mortality impact falls short of the outside option—and label them "lower-quality." Conversely, we label the top quintile "higher-quality." The first row of Table 4 shows the average (standardized) one-year survival rate across these two groups of nursing homes. Survival is 1.16 (1.12) standard deviations higher (lower) among higher (lower) quality nursing homes compared to quintiles two to four.

To put these estimates into perspective, we calculate the average one-year mortality rate for a representative patient across quality quintiles.[23] For the highest quality nursing homes, we estimate an average one-year mortality rate of 11.5%, and for the lowest quality nursing homes, a one-year mortality rate of 42.5%. For the outside good, we estimate a mortality rate of 35.9%, see Panel B of Table 4. In robustness exercises, we use 30 and 90-day hospital readmissions as health outcomes, yielding qualitatively similar results. Nursing homes with the highest estimated survival rates also have lower 30 and 90-day readmission rates, validating our categorization (see second and third row of Table 4).

[Insert Table 4 about here]

Panel B of Table 2 shows nursing home characteristics and the CMS star rating. These provide alternative quality of care measures. As seen, nursing homes with high value-added estimates also have higher registered nurse (RN)-to-patient staffing ratios and a higher RN-to-nurse ratio, which are key determinants of nursing home quality (Friedrich and Hackmann, 2021). Further, they have higher CMS star ratings. These comparisons confirm that our proposed method and categorization capture actual and meaningful differences in the quality of care.

[22] Figure E.1 (Appendix) shows a scatterplot between the valued-added estimates and the control function coefficients ϕ_k of equation (E.3). We find a strong negative relationship similar to Einav, Finkelstein, and Mahoney (2025). The negative preference selection ($\phi < 0$) for higher valued-added 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.

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

Patient Relocation and Mortality: We also probe the mortality effects of patient relocation between care choices due to public moral hazard. To this end, we use our model estimates to quantify ”diversion ratios”, and then relate them to the mortality effects of different care choices. Let s_j denote the share of patients choosing nursing homes j. Diversion ratios then measure substitution between care choices:

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

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

$$D_{gg'} = -\frac{1}{\#g} \sum_{j \in g} \left[\sum_{k \in g', k \neq j} \frac{\partial s_k}{\partial \delta_j} / \frac{\partial s_j}{\partial \delta_j} \right]. \tag{22}$$

The first panel of Table 3 presents diversion ratio estimates. The columns show the destination nursing homes by groups, and the rows present the corresponding origins. The first column considers new residents in higher-quality nursing homes following municipalization. 16.7% would have chosen the outside good, 15.0% a different nursing home of higher quality, and 50.3% a nursing home of ’average’ quality. Lastly, 17.9% would have chosen a nursing home of much lower quality in the lowest quality group. Put differently, the estimates suggest that 83.3% of patients who choose a focal nursing home after municipalization would have chosen a different nursing home.

[Insert Table 3 about here]

The second panel of Table 3 considers implications for mortality. The first row, denoted ”Post”, presents the average one-year mortality rate at the destination nursing home (borrowed from Table 4). The second row, denoted ”Pre”, presents the average one-year mortality rate over the origin care choices among marginal patients. Intuitively, it presents the average mortality had the patients not chosen the destination facility.[24] As seen, the pre-post difference for high-quality nursing homes is $27.4 - 11.5\% = 15.9\%$. Thus, expand-

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

ing higher-quality nursing homes reduces the one-year mortality rate by 15.9 percentage points among marginal residents. In contrast, expansions of lower-quality nursing homes increase mortality by 16.1 percentage points among marginal residents.

4.4 Quantity Expansions and Quality of Care

Building on Table 4, we now investigate whether lower- or higher-quality nursing homes drive the public moral hazard channel. Figure 7 presents changes in Medicaid days for dementia patients in higher-quality (Figure 7a) and lower-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.

Panel B of Table 1 shows an increase of 1952 dementia-related Medicaid days per year in lower-quality nursing homes, a 19% increase (column (1)). In higher-quality nursing homes, the increase is just 11% (column (2)), and in average-quality nursing homes it is 9%. One contributing factor is excess capacity. The third and fourth columns of Table 1 show that the volume increase is concentrated in nursing homes with less than 90% occupancy in 2000 (before municipalization).

We now connect the differential volume expansions with the one-year mortality estimates in Table 3. There are two effects: First, a (i) ”market expansion effect” that reduces aggregate mortality as average nursing home mortality is lower than for the outside good.[25] Second, a (ii) ”relocation effect” towards lower-quality nursing homes increases aggregate mortality.

To quantify the net effect, we cross-multiply the mortality differences with the changes in volume in Medicaid days. Specifically, we estimate a $11\% \times -15.9pp + 9\% \times -3.2pp + 19\% \times 16.1pp = 1pp$ net increase in aggregate mortality among all marginal patients who change their modes of care in response to municipalization. Thus, the relocation of patients across care choices may have *increased* aggregate patient mortality. It suggests a reduction in allocative efficiency as a result of creative financing.

[25] Consider a universal 10% volume increase across all nursing homes. As only 15.5 to 16.9% of the volume expansion is due to patients who would have otherwise chosen the outside good (Table 3), we expect a 1.66% (16.6% average increase, multiplied by 10%) increase in aggregate dementia-related Medicaid days. Using the weighted average over the estimates in the third row of the bottom panel in Table 3, the average effect for all marginal patients is -1.9pp when taking a weighted average over mortality from the last row of the second Panel in Table 3: $0.2 * (-15.9pp) + 0.6 * (-3.2pp) + 0.2 * (+16.1pp) \approx -1.9pp$.

4.5 Misallocation

In a very final step, we connect these empirical findings to the conceptual framework in Figure 3. The objective is to assess the implications for allocative health care efficiency. In the following analysis, we treat the public hospital-nursing home system as "the Agent", playing a game against the federal government, "the Principal."

Agent's Benefits: We approximate the benefit function of a representative hospital-nursing home system via a translog function:[26]

$$
\begin{aligned}
B(\theta, Q) &= v(\theta, Q) + \pi(\theta, Q) && (23)\\
&\approx \gamma \left[\alpha_0 log(Q) + \alpha_0 log(\theta) + \alpha_1 log(Q)^2 + \alpha_2 log(\theta)^2 + \alpha_3 log(Q) log(\theta) \right] && (24)
\end{aligned}
$$

Equation (23) includes non-pecuniary benefits, $v(\theta, Q)$, and nursing home revenues, $\pi(\theta, Q)$. Benefits again depend on care volume, Q, and care quality, θ, where quality is measured by the one-year nursing home survival rate, $log(\theta) = 1 - m_{NH}$. To tie this subsection closely to the theoretical framework, we model the funds diverted via creative financing in the Agent's costs.

Agent's Costs: Without creative financing, total costs are the product of average (variable) costs, AC, and overall volume of care, Q, see the first row of:

$$
log(Costs) = \begin{cases} log(Q) + log(AC) & \text{No CF} \\ log(Q) + log(AC - FMAP \times (P - R)) & \text{CF .} \end{cases} \qquad (25)
$$

With creative financing, the public healthcare system diverts the difference between nominal and effective Medicaid rates, $P - R$. As discussed, the state of Indiana redirected a significant fraction of its supplemental payment contributions $(1 - FMAP) \times (P - R) \times Q$. We, therefore, assume that only the federal share of supplemental payments, $FMAP \times (P - R) \times Q$, can be diverted by the healthcare system; see the second row of equation (25).

[26]In a robustness exercise, we use CES preferences; see Appendix Section F1. While CES preferences explain the ratio of quality over average costs with CES preferences, we cannot match levels.

Health Production: Producing higher 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:

$$log(\theta) = 1 - m_{NH} = \beta \times log(AC) \,. \tag{26}$$

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

Calibration: We focus on Medicaid dementia patients using the estimated overall 12% increase in Medicaid volume (see Section 4.2), and calculate survival, pre- and post-municipalization, as follows[27]. First, we construct the average one-year survival rate over the three quintile groups in Table 4, based on their quintile shares (20%, 20%, and 60%). Pre-municipalization, we calculate an average one-year survival rate of 74.8%.[28] Second, and following municipalization, we estimate a 19% volume increase in lower-quality nursing homes, and 9 and 11% increases in middle and higher-quality nursing homes, respectively (see Table 1). Combined with the diversion ratios from Table 3, these compositional changes reduce the average one-year survival rate to 74.5%.[29] While the 0.3 percentage points decrease in one-year survival rates may appear small, applying it to the estimated 16 thousand AD/ADRD patients in Indiana nursing homes (Kaiser Family Foundation, 2025d; for Disease Control and Prevention, 2025) would suggest that, every year, about 50 patients die earlier because of allocative inefficiencies triggered by creative financing. Moreover, mortality is an extreme outcome but clearly objective, whereas quality-of-life year measures are unavailable. However, rich investigative reporting has documented severe quality shortfalls in Indiana's nursing home industry, which only ranks 33 among all U.S. states (Gillers et al., 2010; Evans, Hopkins, and Cook, 2020c; US News & World Report, 2025). Given the estimated increase of 1952 Medicaid days per year for *each* of the roughly 90 (20% of 450, see Fig-

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

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

[29] Here, we consider the nursing home type's own expansion effect and then net out the substitution effects as given by the diversion ratios. Let $g \in \{low, middle, high\}$ denote the type and $\Delta\%_g$ be the direct expansion effect as in Table 1. Finally, let $D_{gg'}$ denote the diversion ratios denoted in the top panel of Table 3. The relative market shares among nursing homes (ignoring the outside good) with creative financing are then given by $s_g^{CF} = (1 + \Delta\%_g) \times s_g^{NoCF} - \left[\sum_k \Delta\%_k \times s_k^{NoCF} \times \frac{D_{gk}}{\sum_m D_{mk}}\right]$, where s_g^{NoCF} denotes the baseline market shares for nursing home groups.

ure 2) lower-quality nursing homes in Indiana, AD/ADRD patients spend 176 thousand additional days per year in lower-quality nursing homes in Indiana because of economic misallocations.

Next, we solve for the first-order conditions and combine them with the estimated changes in volume and mortality to calibrate the unknown model parameters. With creative financing, the slope of the cost curve flattens from -1 to $-(1 - FMAP \times \frac{P-R}{AC})$.[30] We fix $\gamma = 20$ and set $\beta = 0.64$, ensuring that average costs equal the effective reimbursement rate, R. We then calibrate the four remaining α parameters to match model predictions to the observed coordinates (quality and average cost, with and without creative financing), yielding $\alpha_0 = 1.57, \alpha_1 = -0.8, \alpha_2 = -1.02$ and $\alpha_3 = 0.68$.

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 solid gray upward-sloping line denotes the expansion path, again without creative financing. The red diamond denotes the allocation with creative financing, which is situated below the optimal expansion path.

Connecting the figure to the theoretical discussion in Section 3.5, in blue, we have added the allocations following a gradual increase in the nominal reimbursement rate from R (starting at the red circle) to P (arriving at the red diamond). In this case, quality is gradually decreasing, resulting in a misallocation of resources. Quantitatively, we could achieve the same benefit level at 1.7% lower costs when choosing a quality-quantity bundle on the expansion path without creative financing, see the black pentagon-shaped point. Scaled by Indiana's $1.8 billion[31] annual Medicaid spending on dementia stays, this amounts to $310 million of wasteful spending over a decade.

[30] 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 $-(1 - 0.68 \times \frac{5.5-3.2}{3.2}) = -0.51$.

[31] Nursing homes in Indiana are reimbursed at a $297.4 base rate plus a $108.3 supplemental rate per resident and day (Stulick, 2025). At least 90% of the state's 500 nursing homes participate in the creative financing scheme, each providing 10,000 Medicaid-covered dementia days annually on average. This implies a total annual spending of $90\% \times 500 \times 10,000 \times (\$297.4 + \$108.3) \approx 1.8$ billion.

5 Discussion and Conclusion

This paper studies the misallocation of Medicaid funds and its implications for patients and providers in the context of the nursing home industry. Combining comprehensive audit reports with survey data on nursing homes, we first document that many states use creative financing schemes. The schemes inflated nominal spending by about 30% while diverting at least $17 billion in Medicaid funds between 2000 and 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. To circumvent a federal reform from 2003 that aimed to restrict the scope of creative financing, county hospitals in Indiana municipalized private nursing homes. Following the municipalizations, and in line with our theoretical predictions, the care volume—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).

We then evaluate how the Indiana scheme affected patients' health. We estimate a nursing home value-added model using administrative microdata, focusing on dementia patients and their one-year survival rates. First, we find no notable change in nursing home quality after municipalization, holding the patient composition fixed. Second, quality disparities are significant; shifting patients from the lowest to the highest-quality quintile could boost their survival rate by 31 percentage points. Third, while Medicaid volume increased across the entire quality distribution of nursing homes, the largest increase occurred among the worst 20% of nursing homes.

Finally, we study the implications of our findings for allocative health care efficiency. Our findings show that Indiana's creative financing schemes skew the quality-quantity balance by promoting the expansion of lower-quality nursing home care. Reallocating Medicaid funds to enhance care quality, or usage at higher-quality facilities, could cut costs on dementia care by up to 1.7% without compromising quality-adjusted quantity of care.

The central insight from our analysis is that creative financing schemes can distort state incentives—discouraging increases in effective reimbursement rates retained by the providers, while encouraging expanded access to inpatient care. These schemes can thus contribute to the persistently low effective Medicaid reimbursement rates that contribute to the systematic quality shortfalls in the nursing home industry (Grabowski, 2001; Hackmann, 2019). At the same time, the schemes incentivize higher inpatient care volume, which we call "public moral hazard", despite widespread preferences among older adults to age at home (AP-NORC, 2021). In our setting, we document a causal increase in Medicaid nursing home days. 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 to identify creative financing as a driver of institutional bias, an explanation that both complements and helps account for the existence of other policy factors contributing to this bias, including 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).

References

State of Indiana. 2025. *Indiana's Public Data Utility*. https://www.stats.indiana.edu/stats_dpage/dpage.asp?id=71&view_number=2&menu_level=&panel_number=., retrieved March 9, 2025.

Abdulkadiroğlu, Atila, Parag A Pathak, Jonathan Schellenberg, and Christopher R Walters. 2020. "Do Parents Value School Effectiveness?" *American Economic Review* 110 (5):1502–39.

Agrawal, David R. 2015. "The Tax Gradient: Spatial Aspects of Fiscal Competition." *American Economic Journal: Economic Policy* 7 (2):1–29.

Alexander, Diane and Molly Schnell. 2024. "The impacts of physician payments on patient access, use, and health." *American Economic Journal: Applied Economics* 16 (3):142–177.

AP-NORC. 2021. "Long-Term Care in America: Americans Want to Age at Home." Tech. rep. https://apnorc.org/wp-content/uploads/2021/04/LTC_Report_AgingatHome_final.pdf, retrieved February 28, 2025.

Averch, Harvey and Leland L Johnson. 1962. "Behavior of the Firm Under Regulatory Constraint." *The American Economic Review* 52 (5):1052–1069.

Baicker, Katherine, Sendhil Mullainathan, and Joshua Schwartzstein. 2015. "Behavioral Hazard in Health Insurance." *The Quarterly Journal of Economics* 130 (4):1623–1667.

Baicker, Katherine and Douglas Staiger. 2005. "Fiscal Shenanigans, Targeted Federal Health Care Funds, and Patient Mortality." *The Quarterly Journal of Economics* 120 (1):345–386.

Baker, Andrew, Brantly Callaway, Scott Cunningham, Andrew Goodman-Bacon, and Pedro H. C. Sant'Anna. 2025. "Difference-in-Differences Designs: A Practitioner's Guide." mimeo. =https://arxiv.org/abs/2503.13323, retrieved March 28, 2025.

Callaway, Brantly and Pedro HC Sant'Anna. 2021. "Difference-in-Differences with Multiple Time Periods." *Journal of Econometrics* 225 (2):200–230.

CCS, HCUP. 2017. *Healthcare Cost and Utilization Project (HCUP)*. Agency for Healthcare Research and Quality, Rockville, MD. www.hcup-us.ahrq.gov/toolssoftware/ccs/ccs.jsp, retrieved November 13, 2023.

Centers for Medicare & Medicaid Services. 2020a. *Expenditure Reports From MBES/CBES*. https://www.medicaid.gov/medicaid/financial-management/state-expenditure-reporting-for-medicaid-chip/expenditure-reports-mbescbes/index.html, retrieved January 4, 2021.

———. 2020b. *Nursing Home Compare*. https://www.medicare.gov/care-compare/, retrieved January 4, 2021.

———. 2023. "National Health Expenditures by Type of Service and Source of Funds: Calendar Years 1960 to 2023." https://www.cms.gov/files/zip/national-health-expenditures-type-service-and-source-funds-cy-1960-2023.zip.

———. 2025. *November 2024 Medicaid & CHIP Enrollment Data Highlights*. https://www.medicaid.gov/medicaid/program-information/medicaid-and-chip-enrollment-data/report-highlights, retrieved April 29, 2025.

Chandra, Amitabh, Amy Finkelstein, Adam Sacarny, and Chad Syverson. 2016. "Health Care Exceptionalism? Performance and Allocation in the US Health Care Sector." *American Economic Review* 106 (8):2110–2144.

Cheng, Alden. 2023. "Demand for Quality in the Presence of Information Frictions: Evidence from the Nursing Home Market." Mimeo.

Chidambaram, P and Alice Burns. 2023. *How Many People Use Medicaid Long-Term Services and Supports and How Much Does Medicaid Spend on Those People?* https://www.kff.org/medicaid/issue-brief/how-many-people-use-medicaid-long-term-services-and-supports-and-how-much-does-medicaid-spend-on-those-people/, retrieved February 28, 2025.

Clemens, Jeffrey and Joshua D Gottlieb. 2014. "Do Physicians' Financial Incentives Affect Medical Treatment and Patient Health?" *American Economic Review* 104 (4):1320–49.

Clemens, Jeffrey and Benedic Ippolito. 2018. "Implications of Medicaid Financing Reform for State Government Budgets." *Tax Policy and the Economy* 32 (1):135–172.

Clemens, Jeffrey and Stan Veuger. 2023. "Intergovernmental Grants and Policy Competition: Concepts, Institutions, and Evidence." Tech. rep., National Bureau of Economic Research Working Paper 31251.

Committee for a Responsible Federal Budget. 2023. *Medicaid Provider Taxes Inflate Federal Matching Funds*. https://www.crfb.org/papers/medicaid-provider-taxes-inflate-federal-matching-funds, retrieved November 24, 2023.

———. 2024. "Medicaid Savings Options." Tech. rep. https://www.crfb.org/blogs/medicaid-savings-options, retrieved March 28, 2025.

Commonwealth of Pennsylvania. 2005. “Nursing Facility Assessment Program.” *Pennsylvania Bulletin* 35 (13):1959–1926. https://www.pacodeandbulletin.gov/secure/pabulletin/data/vol35/35-13/35-13.pdf, retrieved March 5, 2025.

Congressional Budget Office. 2023. *Federal Subsidies for Health Insurance: 2023 to 2033*. https://www.cbo.gov/publication/59273, retrieved November 25, 2023.

Congressional Research Service. 2024. “Medicaid Provider Taxes.” By Alison Mitchell, https://www.congress.gov/crs-product/RS22843, retrieved April 27, 2025.

———. 2025. “Impacts of Federal Grants and Other Funds on State and Local Budgets.” Tech. rep. https://www.congress.gov/crs-product/IN12506, retrieved April 24, 2025.

Coughlin, T. A. and S. Zuckerman. 2003a. “States’ Strategies for Tapping Federal Revenues: Implications and Consequences of Medicaid Maximization.” In *Federalism and Health Policy*, edited by J. Holahan, A. Weil, and J. M. Wiener, chap. 5. 145–178.

Coughlin, Teresa A., Brian K. Bruen, and Jennifer King. 2004. “States’ Use Of Medicaid UPL and DSH Financing Mechanisms.” *Health Affairs* 23 (2):245–257.

Coughlin, Teresa A. and Stephen Zuckerman. 2003b. “States’ Strategies for Tapping Federal Revenues: Implications and Consequence of Medicaid Maximization.” In *Federalism and Health Policy*, edited by John Holahan, Alan Weil, and Joshua M. Wiener, chap. 5. The Urban Institute Press, ”145–178”.

Dahlby, Bev. 1996. “Fiscal Externalities and the Design of Intergovernmental Grants.” *International Tax and Public Finance* 3:397–412.

Department for Health and Human Services. 2025. *Office of Inspector General*. https://oig.hhs.gov/., retrieved December 9, 2025.

Department for Health and Human Services: Office of Inspector General. 2001a. *Review of Medicaid Enhanced Payments to Public Providers and the Use of Intergovernmental Transfers by the Alabama State Medicaid Agency (A-04-00-02165)*.

———. 2001b. *Review of Medicaid Enhanced Payments to Public Providers and the Use of Intergovernmental Transfers by the State of Nebraska (A-07-00-02076)*.

———. 2001c. *Review of Medicaid Supplemental Payments to Public Hospital District Nursing Facilities and the Use of Intergovernmental Transfers by Washington State (A-10-00-0001 1)*.

———. 2001d. *Review of the Commonwealth of Pennsylvania’s Use of Intergovernmental Transfers to Finance Medicaid Supplementation Payments to County Nursing Facilities (A-03-00-00203)*.

———. 2004a. *Review of State Fiscal 2002 Medicare Upper Payment Calculations and Payments: Kentucky Medicaid Agency (A-04-03-02029)*.

———. 2004b. *Review of Tennessee’s Intergovernmental Transfers (A-04-02-02018)*.

———. 2005a. *Audit of New York State’s Medicaid Upper Payment Limits for Non-State Government Inpatient Hospitals and Nursing Homes (A-02-03-01021)*.

———. 2005b. *Review of Alabama’s Medicaid Upper-Payment-Limit Calculations for Hospitals and Nursing Facilities (A-04-03-02027)*.

———. 2005c. *Review of Indiana's Medicaid Upper Payment Limits for State Fiscal Years 2001 and 2002 (A-05-03-00068)*.

———. 2005d. *Review of Medicaid Upper-Payment-Limit Requirements for Kansas Nursing Facility Reimbursement (A-07-03-02672)* .

———. 2005e. *Review of Mississippi's Medicaid Upper-Payment-Limit Calculations for Hospitals and Nursing Facilities (A-04-03-02025)*.

———. 2014. *Colorado Claimed Unallowable Medicaid Nursing Facility Supplemental Payments (A-07-14-04215)* .

Dubin, Jeffrey A. and Daniel L McFadden. 1984. "An Econometric Analysis of Residential Electric Appliance Holdings and Consumption." *Econometrica* 52 (2):345–362.

Duggan, Mark G. 2000. "Hospital Ownership and Public Medical Spending." *The Quarterly Journal of Economics* 115 (4):1343–1373.

Einav, Liran, Amy Finkelstein, and Neale Mahoney. 2018. "Provider Incentives and Healthcare Costs: Evidence from Long-Term Care Hospitals." *Econometrica* 86 (6):2161–2219.

———. 2025. "Producing Health: Measuring Value Added of Nursing Homes." *Econometrica* forthcoming.

Eliason, Paul J., Paul L. E. Grieco, Ryan C. McDevitt, and James W. Roberts. 2018. "Strategic Patient Discharge: The Case of Long-Term Care Hospitals." *American Economic Review* 108 (1):3232–3265.

Estrada, Leah V., Veronica Barcelona, Lara Dhingra, Jose A. Luchsinger, Andrew W. Dick, Laurent G. Glance, and Patricia W. Stone. 2024. "Potentially Avoidable Hospitalizations Among Historically Marginalized Nursing Home Residents." *JAMA Network Open* 7 (5):e249312–e249312.

Evans, T, E Hopkins, and T Cook. 2020a. "Nursing Home Residents Suffer as County Hospitals Rake in Millions." *Indianapolis Star: March* 9:2020.

Evans, Tim, Emily Hopkins, and Tony Cook. 2020b. "Careless." *Indianapolis Star* https://eu.indystar.com/in-depth/news/investigations/2020/03/11/indiana-nursing-home-patients-suffer-medicaid-money-diverted-hospitals/2517834001/, retrieved May 24, 2021.

———. 2020c. "Nursing Home Residents Suffer as County Hospitals Rake in Millions." *Indianapolis Star: March 9, 2020* URL https://www.indystar.com/in-depth/news/investigations/2020/03/11/indiana-nursing-home-patients-suffer-medicaid-money-diverted-hospitals/2517834001/,retrievedDecember4,2023.

———. 2021. "Lawsuit: Johnson County Hospital Paid $6M a Year in Illegal Nursing Home Kickbacks." *Indianapolis Star* www.indystar.com/in-depth/news/investigations/2020/10/22/nursing-home-fraud-whistleblower-johnson-county-indianapolis-indiana/5678049002/.

Federal Register. 2001. "Part III: Department of Health and Human Services, 42 CFR Part 447." *Federal Register* 66 (9):"3148–3177". https://www.govinfo.gov/link/fr/66/3147, retrieved April 29, 2021.

———. 2019. "Medicaid Program; Medicaid Fiscal Accountability Regulation, 42 CFR." *Federal Register* https://www.federalregister.gov/documents/2019/11/18/2019-24763/medicaid-program-medicaid-fiscal-accountability-regulation, retrieved May 24, 2021.

Finkelstein, Amy, Sarah Taubman, Bill Wright, Mira Bernstein, Jonathan Gruber, Joseph P Newhouse, Heidi Allen, Katherine Baicker, and Oregon Health Study Group. 2012. "The Oregon Health Insurance Experiment: Evidence from the First Year." *The Quarterly Journal of Economics* 127 (3):1057–1106.

for Disease Control, Centers and Prevention. 2025. "Alzheimer Disease." Tech. rep. https://www.cdc.gov/nchs/fastats/alzheimers.htm?utm_source=chatgpt.com, retrieved March 24, 2024.

Fosdick, D. 2007. "A Summary of Quality Assurance Assessment Programs. July/ August." *Lansing, MI: State Fiscal Agency, Michigan Senate. www.senate.michigan .gov* .

Friedrich, Benjamin U and Martin B Hackmann. 2021. "The returns to nursing: Evidence from a parental-leave program." *The Review of Economic Studies* 88 (5):2308–2343.

Gabrel, Celia S. 2000. "An Overview of Nursing Home Facilities: Data from the 1997 National Nursing Home Survey." *Advance Data* 1 (311):1–12.

Gandhi, Ashvin. 2020. "Picking Your Patients: Selective Admissions in the Nursing Home Industry." *Working Paper* .

Gandhi, Ashvin, YoungJun Song, and Prabhava Upadrashta. 2023. "Private Equity, Consumers, and Competition." mimeo. http://selective_admissions.ashvingandhi.com/, last retrieved December 4, 2023.

Gillers, Heather, Tim Evans, Mark Nichols, and Mark Alesia. 2010. "Cash Flowed In, Care Lagged." *Indianapolis Star: May 9, 2010* :1; A11–A13https://www.newspapers.com/image/126265325, last retrieved May 5, 2025.

Gordon, Roger H. 1983. "An Optimal Taxation Approach to Fiscal Federalism." *The Quarterly Journal of Economics* 98 (4):567–586.

Grabowski, David C. 2001. "Medicaid Reimbursement and the Quality of Nursing Home Care." *Journal of Health Economics* 20 (4):549–569.

Grabowski, David C and Jonathan Gruber. 2007. "Moral Hazard in Nursing Home Use." *Journal of Health Economics* 26 (3):560–577.

Gruber, Jonathan, David H Howard, Jetson Leder-Luis, and Theodore L Caputi. 2025. "Dying or Lying? For-Profit Hospices and End-of-Life Care." *American Economic Review* 115 (1):263–294.

Guo, Jing, R Tamara Konetzka, and Willard G Manning. 2015. "The Causal Effects of Home Care Use on Institutional Long-Term Care Utilization and Expenditures." *Health Economics* 24:4–17.

Gupta, Atul, Sabrina T Howell, Constantine Yannelis, and Abhinav Gupta. 2023. "Does Private Equity Investment in Healthcare Benefit Patients? Evidence from Nursing Homes." National Bureau of Economic Research Working Paper 28474.

Hackmann, Martin B. 2019. "Incentivizing Better Quality of Care: The Role of Medicaid and Competition in the Nursing Home Industry." *American Economic Review* 109 (5).

Hackmann, Martin B, R Vincent Pohl, and Nicolas Ziebarth. 2024. "Patient Versus Provider Incentives in Long-Term Care." *American Economic Journal: Applied Economics* 16 (3):178–218.

Hatcher, Daniel L. 2017. "Medicaid Maximization and Diversion: Illusory State Practices that Convert Federal Aid into General State Revenue." *Seattle University Law Review* 39 (1225):1225–1261.

Holmstrom, Bengt and Paul Milgrom. 1991. "Multitask Principal–Agent Analyses: Incentive Contracts, Asset Ownership, and Job Design." *The Journal of Law, Economics, and Organization* 7 (special_issue):24–52.

Indiana Department of Health. 2020. *Health Facilities Consumer Reports*. https://www.in.gov/isdh/28260.htm, retrieved January 4, 2021.

Joyce, Nina R, Thomas G McGuire, Stephen J Bartels, Susan L Mitchell, and David C Grabowski. 2018. "The Impact of Dementia Special Care Units on Quality of Care: An Instrumental Variables Analysis." *Health Services Research* 53 (5):3657–3679.

Kaiser Family Foundation. 2024a. *10 Things about Long-Term Services and Supports (LTSS)*. https://www.kff.org/medicaid/issue-brief/10-things-about-long-term-services-and-supports-ltss/, retrieved March 3, 2025.

———. 2024b. *Medicaid Enrollment & Spending Growth: FY 2024 & 2025*. https://www.kff.org/medicaid/issue-brief/medicaid-enrollment-spending-growth-fy-2024-2025/, retrieved April 27, 2025.

———. 2025a. *5 Key Facts About Medicaid and Provider Taxes*. https://www.kff.org/medicaid/issue-brief/5-key-facts-about-medicaid-and-provider-taxes/, retrieved April 15, 2025.

———. 2025b. *Federal Medical Assistance Percentage (FMAP) for Medicaid and Multiplier*. https://www.kff.org/medicaid/state-indicator/federal-matching-rate-and-multiplier/, retrieved March 3, 2025.

———. 2025c. *Total Medicaid Spending*. https://www.kff.org/medicaid/state-indicator/total-medicaid-spending/, retrieved March 3, 2025.

———. 2025d. *Total Number of Residents in Certified Nursing Facilities*. https://www.kff.org/other/state-indicator/number-of-nursing-facility-residents/, retrieved April 7, 2025.

Knight, Brian. 2002. "Endogenous federal grants and crowd-out of state government spending: Theory and evidence from the federal highway aid program." *American Economic Review* 92 (1):71–92.

Ku, Leighton and Edwin Park. 2001. *Administration's Regulation to Reduce Medicaid "Upper Payment Limit" Would Further Worsen State Budget Crises*. https://www.cbpp.org/sites/default/files/archive/12-11-01health.htm retrieved April 25, 2021.

Lin, Haizhen. 2015. "Quality Choice and Market Structure: A Dynamic Analysis of Nursing Home Oligopolies." *International Economic Review* 56 (4):1261–1290.

Long-Term Care: Facts on Care in the U.S. 2025. *Online Survey Certification And Reporting (OSCAR)/Certification and Survey Provider Enhanced Reporting (CASPER)*. http://ltcfocus.org/1/about-us, retrieved April 9, 2025.

LoSasso, Tony. 2025. *It's Time to Block-Grant Medicaid*. https://www.statnews.com/2025/03/27/block-grant-medicaid-entitlement-reform-health-care-fmap/, retrieved March 28, 2025.

MACPAC. 2019a. "Nursing Facility Fee-for-Service Payment Policy." *Advising Congress on Medicaid and CHIP Policy* https://www.macpac.gov/wp-content/uploads/2019/12/Nursing-Facility-Fee-for-Service-Payment-Policy.pdf, retrieved May 24, 2021.

———. 2019b. "Upper Payment Limit Supplemental Payments." *Advising Congress on Medicaid and CHIP Policy* https://www.macpac.gov/wp-content/uploads/2021/11/Upper-Payment-Limit-Supplemental-Payments.pdf, retrieved December 7, 2021.

———. 2021. "The Effect of State Approaches to Medicaid Financing on Federal Medicaid Spending." Issue Brief, Advising Congress on Medicaid and CHIP Policy. https://www.macpac.gov/publication/the-effect-of-state-approaches-to-medicaid-financing-on-federal-medicaid-spending/, retrieved December 7, 2023.

Mangano, Michael F. 2001. "Review of the Commonwealth of Pennsylvania's Use of Intergovernmental Transfers to Finance Medicaid Supplementation Payments to County Nursing Facilities." Memo from Acting Inspector General to Acting Principal Deputy Administrator of the Health Care Financing Administration.

McClellan, Mark and Douglas Staiger. 2000. "Comparing the Quality of Health Care Providers." In *Forum for Health Economics & Policy*, vol. 3.

McGuire, Thomas G. 2000. "Physician Agency." In *Handbook of Health Economics*, vol. 1 Part A, edited by Anthony J. Culyer and Joseph P. Newhouse, chap. 9. 461–536.

MDS. 2020. *Long-Term Care Minimum Data Set*. https://www.cms.gov/Medicare/Quality-Initiatives-Patient-Assessment-Instruments/NursingHomeQualityInits/NHQIMDS30, retrieved April 9, 2020.

Medicaid and CHIP Payment and Access Commission. 2021. "Exhibit 25: Medicaid Supplemental Payments to Non-Hospital Providers by State, FY 2020 (millions)." *MACStats: Medicaid and CHIP Data Book* Available at https://www.macpac.gov/wp-content/uploads/2015/11/EXHIBIT-25.-Medicaid-Supplemental-Payments-to-Non-Hospital-Providers-by-State-FY-2020-millions.pdf.

Miller, Edward Alan and Lili Wang. 2009. "Maximizing Federal Medicaid Dollars: Nursing Home Provider Tax Adoption, 2000–2004." *Journal of Health Politics, Policy and Law* 34 (6):899–930.

Miller, Sarah, Norman Johnson, and Laura R Wherry. 2021. "Medicaid and Mortality: New Evidence From Linked Survey and Administrative Data." *The Quarterly Journal of Economics* 136 (3):1783–1829.

Mitchell, Alison. 2018. "Medicaid Supplemental Payments." Congressional Research Service Report, https://crsreports.congress.gov/product/pdf/R/R45432, retrieved April 27, 2025.

Mitchell, Susan L., Joan M. Teno, Dan K. Kiely, Michele L. Shaffer, Richard N. Jones, Holly G. Prigerson, Ladislav Volicer, Jane L. Givens, and Mary Beth Hamel. 2009. "The Clinical Course of Advanced Dementia." *New England Journal of Medicine* 361 (16):1529–1538.

Mommaerts, Corina. 2018. "Are Coresidence and Nursing Homes Substitutes? Evidence from Medicaid Spend-Down Provisions." *Journal of Health Economics* 59:125–138.

Morris, Carl N. 1983. "Parametric Empirical Bayes Inference: Theory and Applications." *Journal of the American Statistical Association* 78 (381):47–55.

Mukamel, Dana B., Debra Saliba, Heather Ladd, and R. Tamara Konetzka. 2023. "Dementia Care Is Widespread In US Nursing Homes; Facilities With The Most Dementia Patients May Offer Better Care." *Health Affairs* 42 (6):795–803.

Muramatsu, Naoko, Hongjun Yin, Richard T Campbell, Ruby L Hoyem, Martha A Jacob, and Christopher O Ross. 2007. "Risk of Nursing Home Admission among Older Americans: Does States' Spending on Home-and Community-Based Services Matter?" *The Journals of Gerontology Series B: Psychological Sciences and Social Sciences* 62 (3):S169–S178.

Oates, Wallace E. 1999. "An Essay on Fiscal Federalism." *Journal of Economic Literature* 37 (3):1120–1149.

Olenski, Andrew and Szymon Sacher. 2024. "Estimating Nursing Home Quality with Selection." *Review of Economics and Statistics* :1–31.

Pahud, Kevid and Mark Myers. 2016. *Webinar on Skilled Nursing Supplemental Payment Programs: Architecture for Expansion & Utilization*. URL https://www.bkd.com/webinar/2016/08/skilled-nursing-supplemental-payment-programs-architecture-expansion-utilization.

Rau, Jordan. 2018. "'It's Almost Like a Ghost Town': Most Nursing Homes Overstated Staffing for Years." URL https://www.nytimes.com/2018/07/07/health/nursing-homes-staffing-medicare.html. Accessed April 2025.

Roth, Jonathan, Pedro H.C. Sant'Anna, Alyssa Bilinski, and John Poe. 2023. "What's trending in difference-in-differences? A synthesis of the recent econometrics literature." *Journal of Econometrics* 235 (2):2218–2244.

Rudowitz, Robin. 2017. *Key Questions: Medicaid Block Grants & Per Capita Caps*. https://www.kff.org/medicaid/issue-brief/5-key-questions-medicaid-block-grants-per-capita-caps/, retrieved May 5, 2025.

Sharma, Hari and Lili Xu. 2023. "Use of Intergovernmental Transfers–based Medicaid Supplemental Payments to Boost Nursing Home Finances: Evidence From Indiana Nursing Homes." *Medical Care* 61 (8):546–553.

Spanko, Alex. 2019. "Medicare Advantage Eats Into Margin Gains for Skilled Nursing Facilities." *Skilled Nursing News* https://skillednursingnews.com/2019/03/medicare-advantage-eats-into-margin-gains-for-skilled-nursing-facilities/, retrieved May 24, 2021.

Stulick, Amy. 2025. *At Least $2.6B Diverted from County-Owned Nursing Homes in Indiana*. https://skillednursingnews.com/2025/03/at-least-2-6b-diverted-from-county-owned-nursing-homes-in-indiana//, retrieved March 30, 2025.

Travers, Jasmine L., Erinn M. Hade, Steven Friedman, Aasha Raval, Kimberly Hadson, and Jason R. Falvey. 2024. "Staffing and Antipsychotic Medication Use in Nursing Homes and Neighborhood Deprivation." *JAMA Network Open* 7 (4):e248322–e248322.

U.S. Department of Health and Human Services. 2001. "Medicaid Program; Revision to Medicaid Upper Payment Limit Requirements to Hospital Services, Nursing Facility Services, Intermediate Care Facility Services for the Mentally Retarded, and Clinic Services." *Federal Register* 66 (9):3148.

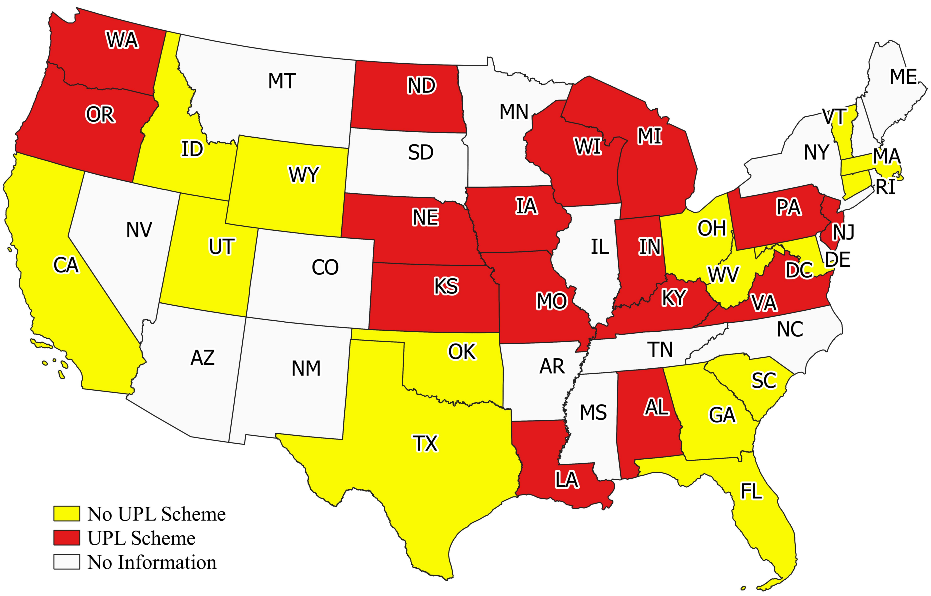
US News & World Report. 2025. *States With High-Quality Nursing Homes*. https://www.usnews.com/news/best-states/rankings/health-care/healthcare-quality/nursing-home-quality, retrieved April 7, 2025.

Wang, Sijiu, Di Yan, Helena Temkin-Greener, and Shubing Cai. 2020. "Does Medicaid Hcbs Generosity Influence Nursing Home Placement for Dually Eligible Adrd Patients?" *Health Services Research* 55:23–24.

Werner, Rachel M, R Tamara Konetzka, and Daniel Polsky. 2013. "The Effect of Pay-For-Performance in Nursing Homes: Evidence from State Medicaid Programs." *Health Services Research* 48 (4):1393–1414.

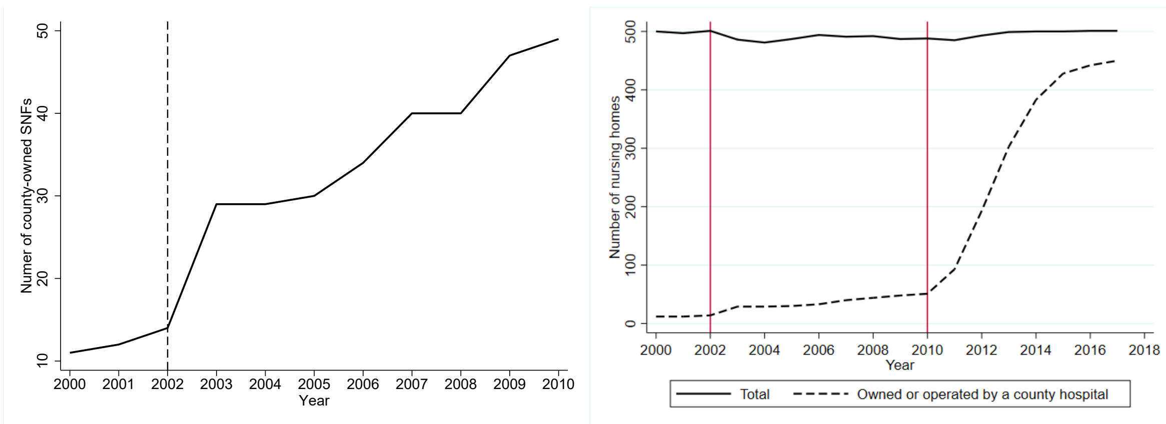
Young, Samantha. 2023. *Feds Say Hospitals That Redistribute Medicaid Money Violate Law*. https://www.bkd.com/webinar/2016/08/skilled-nursing-supplemental-payment-programs-architecture-expansion-utilization, retrieved May 9, 2025.

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



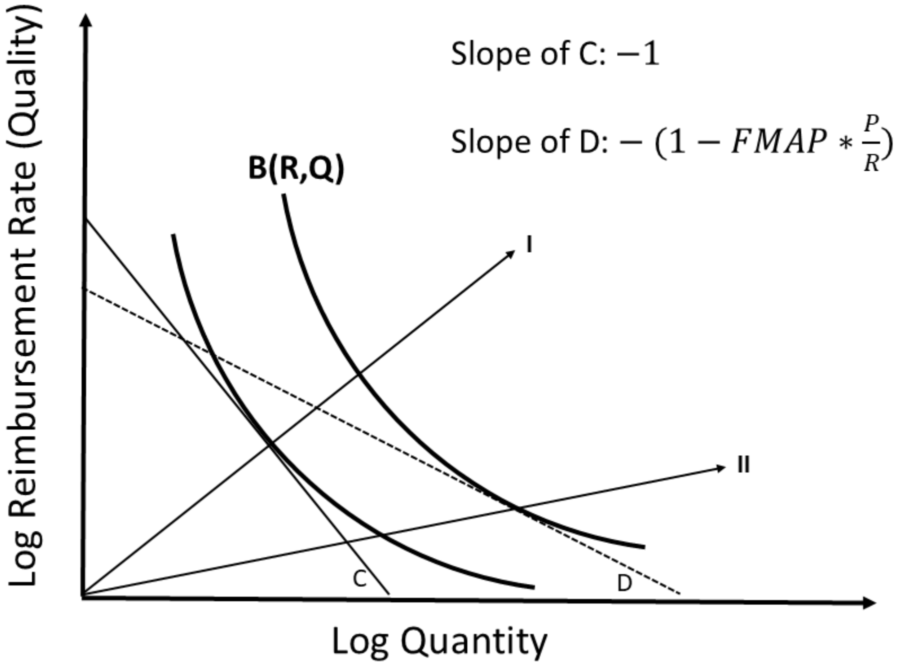
Notes: This map illustrates states that used creative financing in the form of an upper payment limit supplemental payment (UPL-SP) scheme in FY 2002 based on the survey from Coughlin, Bruen, and King (2004). Pennsylvania is marked as using a UPL-SP scheme based on Coughlin and Zuckerman (2003b).

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



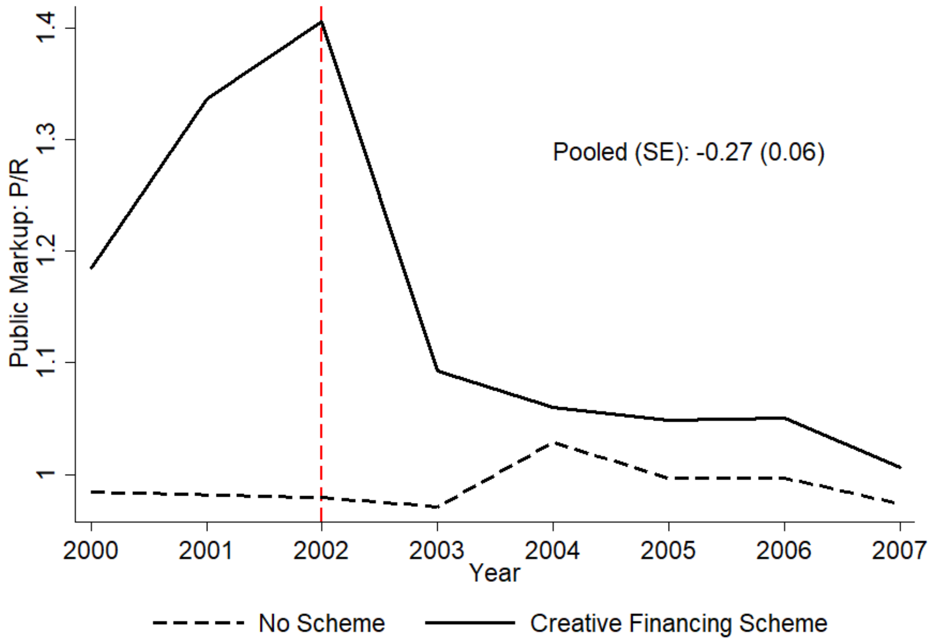
Source: Centers for Medicare & Medicaid Services (2020b) and Indiana Department of Health (2020).

Figure 3: Quality and Quantity Tradeoff—Creative Financing



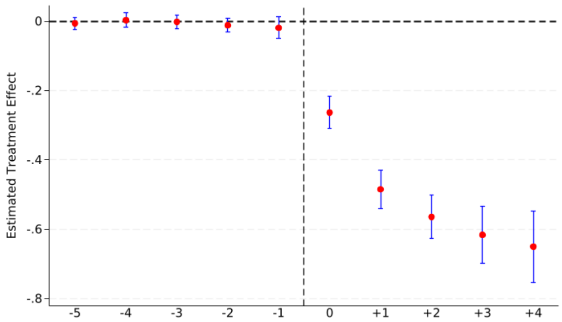
Notes: This figure illustrates policy tradeoffs between states' reimbursement rates and quantity settings under joint financing, with and without creative financing (CF). The convex curves denote indifference curves for different benefit levels. Line 'C' denotes the budget constraint for the state without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

Figure 4: 2003 Reform and Public Markups

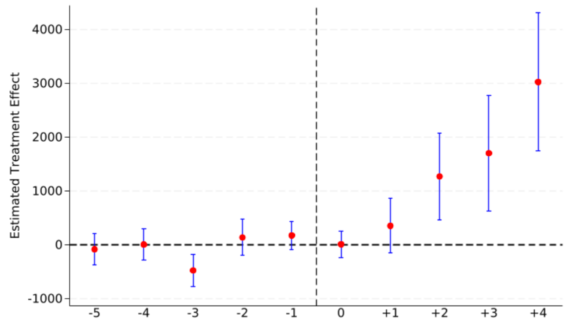


Source: Long-Term Care: Facts on Care in the U.S. (2025); Centers for Medicare & Medicaid Services (2020a). This figure presents the public markdown, $\frac{P}{R}$ (equation (17)), which indicates the wedge between the nominal Medicaid rate, P, and the effective rate, R. The vertical line denotes the time of the 2003 reform; see the 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).

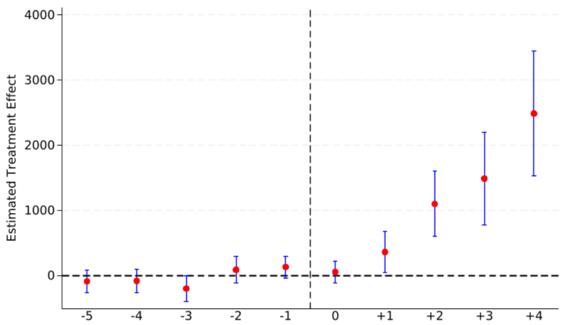
Figure 5: Municipalizing SNFs: Creative Financing and Public Moral Hazard



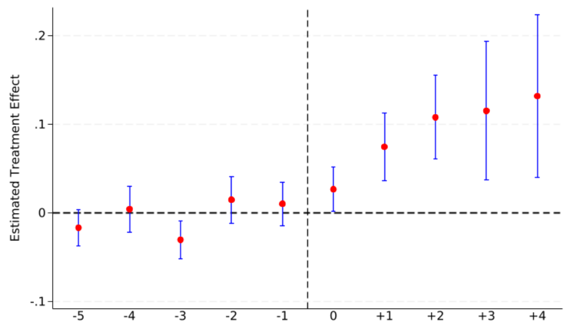
(a) For-Profit



(b) Medicaid Days



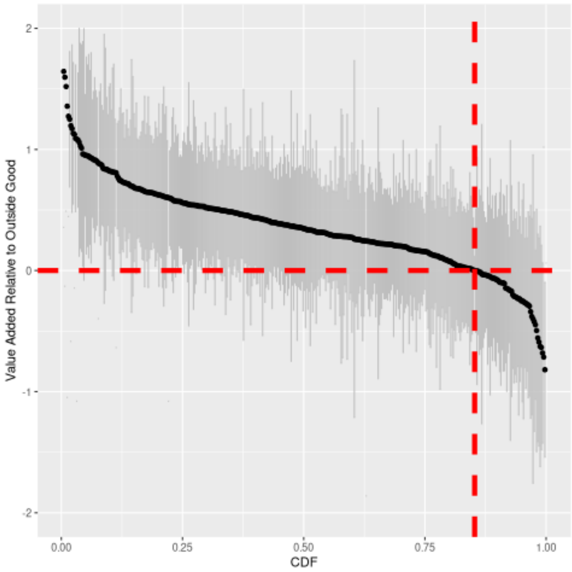
(c) Dementia-Related Medicaid Days



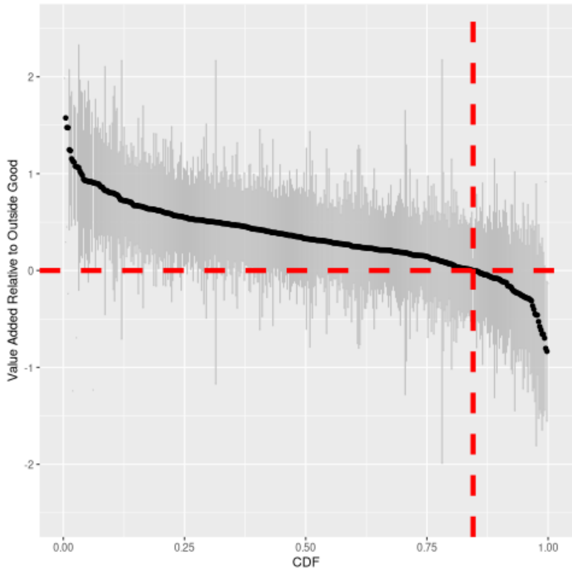
(d) SNF w/ Alzheimer Unit

Source: Long-Term Care: Facts on Care in the U.S. (2025); Centers for Medicare & Medicaid Services (2020b) and Indiana Department of Health (2020). The four subgraphs show Callaway Sant'Anna event study estimates, where event time 0 indicates the municipalization of nursing homes. Subgraph captions indicate the outcome variable of a Callaway Sant'Anna event study. The CS DD pooled estimates over the entire post-reform period are in Table 1. All event studies show 90% confidence intervals. See main text.

Figure 6: Value Added Estimates: One-Year Mortality



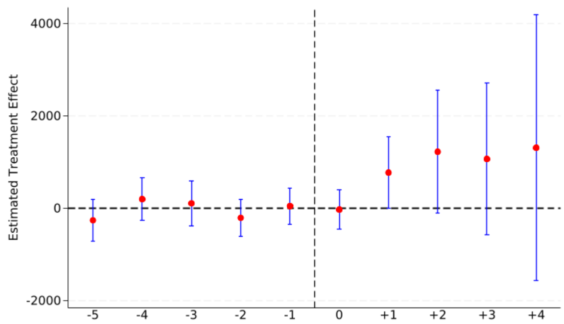
(a) Mortality



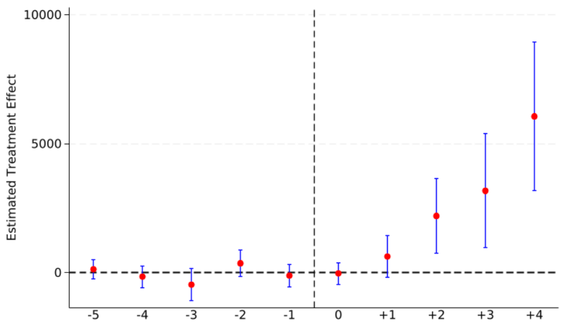
(b) Mortality: Shrinkage Adjusted

Source: Long-Term Care: Facts on Care in the U.S. (2025); Centers for Medicare & Medicaid Services (2020b) and Indiana Department of Health (2020). The figure shows the redirected value-added estimates α_j, see equation (21) for one-year survival on the vertical axis. Estimates are presented relative to the outside good $\alpha_j - \alpha_0$, in descending order along with the 95% confidence interval (grey bars). The horizontal axis denotes the cumulative density, and the vertical line divides the mass of nursing homes into those whose value-added exceeds and falls short of the value added of the outside good, mostly home-based care. The right graph applies a shrinkage technique from the empirical Bayes literature, following Chandra et al. (2016).

Figure 7: Medicaid Expansion by Quality of Care



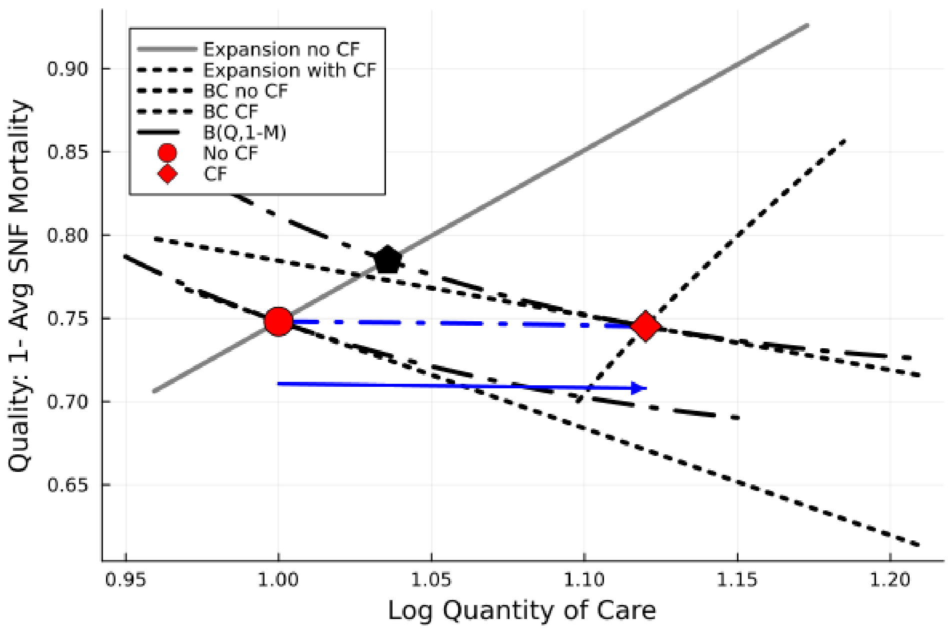
(a) Higher Quality SNFs



(b) Lower Quality SNFs

Source: Long-Term Care: Facts on Care in the U.S. (2025); Centers for Medicare & Medicaid Services (2020b) and Indiana Department of Health (2020). The figures show Callaway Sant'Anna event studies (Callaway and Sant'Anna, 2021). They present results for cumulative Medicaid days among dementia patients at the nursing home-year level. Figure a focuses on higher-quality nursing homes, whose value-added estimate for one-year survival is in the top quintile. Figure b focuses on lower-quality nursing homes, whose value-added estimate is in the bottom quintile.

Figure 8: Quality and Quantity Tradeoffs—Evidence from Indiana



Notes: Using the empirical evidence from Indiana, the figure illustrates the theoretical framework in Figure 3. The horizontal axis displays log quantity of nursing home days, and the vertical axis denotes log average costs per patient day, which is further averaged across nursing homes. The grey upward sloping line denotes the expansion path without creative financing (CF), and the red circle 'no CF' denotes the allocation before municipalization. The red diamond 'CF' denotes the allocation with CF. The intersection between the indifference curve and the expansion path, the black pentagon point, denotes the allocation that achieves the same hospital-nursing home objective at lower costs.

Table 1: Public Moral Hazard

Panel A	**For-Profit**	**Total Medicaid Days**	**Dementia Medicaid Days**	**Alzheimer Unit**
	(1)	(2)	(3)	(4)
	-0.54	1,360	1,178	0.09
	(0.03)	(449)	(255)	(0.03)
Mean	0.67	28,040	9,720	0.37
N	5,888	6,256	6,256	5,888
Panel B		**Dementia Medicaid Days**		
	Low Quality	High Quality	Occu<90% (2000)	High Occu >90% (2000)
	(1)	(2)	(3)	(4)
	1952	1106	1389	300
	(687)	(556)	(299)	(449)
Sample Mean	10,150	10,020	9,620	10,070
Observations	1,037	986	4,828	1,428
Year FE	X	X	X	X
SNF FE	X	X	X	X

Sources: See Appendix D and Appendix Table D.1 for details on data sources and the sample at the SNF-year level. This table presents ATT estimates based on Callaway and Sant'Anna (2021), Figure 5 shows the equivalent event studies for the four outcomes in Panel A where the column headers indicate the dependent variables, also see main text. In Panel A, column (1) presents CS DD results using for-profit ownership as the dependent variable. Column (2) uses the cumulative number of Medicaid days, and column (3) uses Medicaid days for patients diagnosed with dementia. The last column presents results for an indicator that denotes whether the 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: 1-Year Survival			
Municipalized	0.02	-0.03	0.07
Age	-0.04	-0.04	-0.03
Female	0.29	0.27	0.30
White	-0.05	-0.07	-0.03
Hospital LOS	-0.02	-0.02	-0.02
$Corr(\pi, \epsilon)$	0.40	0.27	0.53
Roy Selection SNFs	0.02	-0.00	0.04
Roy Selection Outside good	-0.25	-0.34	-0.16

Sources: See Appendix C and Appendix Tables D.3 and D.4 for details on data sources and the sample at the SNF-year level. The outcome is the one-year mortality rate, but 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 (20) and Panel B equation (21). Estimates are based on the same of dementia related index hospital stays described in Appendix Table D.4.

Table 3: Patient Relocation and One-Year Mortality

	By Value Added Estimates		
	High	Middle	Low
Diversion Ratios			
From Outside	16.7%	16.9%	15.5%
From High VA	15.0%	12.7%	16.2%
From Middle VA	50.3%	55.5%	54.3%
From Low VA	17.9%	14.9%	14.1%
Mortality			
Post	11.5%	24.0%	42.5%
Pre	27.4%	27.2%	26.4%
Difference	-15.9ppt	-3.2ppt	16.1ppt

The top panel shows the estimated diversion ratios based on equation (22) using the estimates in Table 2. The columns present the destination nursing homes, grouped by value added into top quintile ("High"), bottom quintile ("Low") and three middle quintiles ("Middle"). The rows present the origin nursing homes as well as the outside good. The bottom panel shows the one-year mortality rate for an 85-year-old white female with a 6-day index hospital stay. The first row presents the average mortality rate in the destination nursing home. The second row presents the counterfactual mortality rate for marginal residents had they not chosen the destination nursing home. The last row presents the difference.

Table 4: Validation—One-Year Survival Rate vs. Alternative Quality Markers

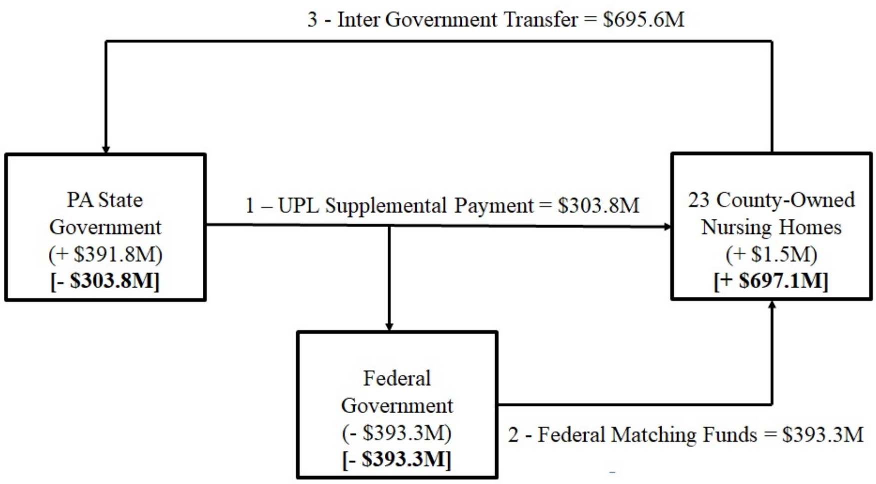
	NH Value Added 1-Year Survival		
	High (top 20%)	Low (bottom 20%)	Medium
Standard. Value-Added			
One Year Survival	1.163 (1.288)	-1.117 (0.709)	-0.015 (0.298)
1- (30-Day Readmission)	0.247 (1.198)	-0.359 (0.938)	0.037 (0.917)
1-(90-Day Readmission)	0.429 (1.071)	-0.537 (1.194)	0.036 (0.813)
Other: Quality of Care			
Avg One Year Mortality*	11.5%	42.5%	24.0%
RN to Nurse Ratio	0.265 (0.129)	0.213 (0.065)	0.244 (0.132)
RN hours per Patient-Day	0.680 (1.075)	0.325 (0.383)	0.522 (0.731)
CMS Star Rating	2.870 (1.334)	2.486 (1.096)	2.544 (1.263)

Table shows descriptive statistics based on the sample of dementia related index hospital stays described in Appendix Table D.4. The first column presents results for nursing homes whose value-added estimates fall in the top quintile of the value added distribution shown in Figure 6. The second column pools nursing homes in the bottom quintile of the distribution and the third column pools the remaining nursing homes situated in the second-fourth quintile of the distribution.

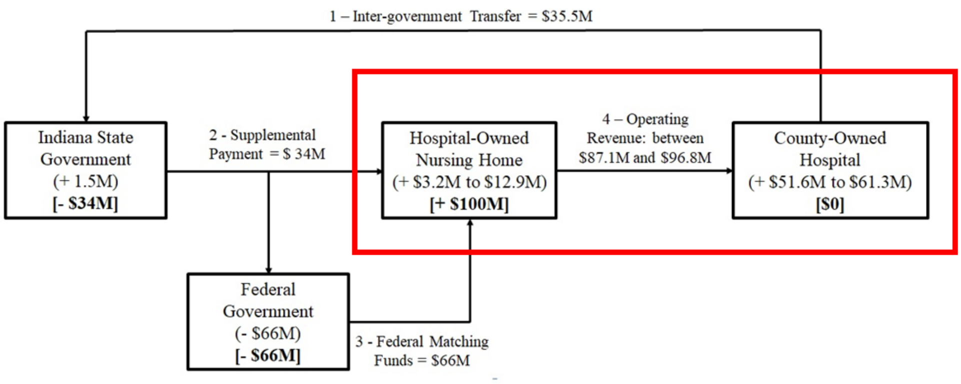
* The one-year mortality rate in Panel B is for an 85-year-old white female with a 6-day index hospital stay. For comparison, the corresponding one-year mortality rate for individuals choosing the outside good is 35.9%.

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 based on reported effort: $w(\hat{e}_1, \hat{e}_2)$.

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

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

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

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 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:[32]

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 only providing the minimum effort. This, in turn, induces additional (excessive) actual

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

effort of type 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).[33]

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

B2 Details on Optimal Contract under Incomplete Monitoring

As discussed in the main text, we aim to solve the following problem

$$\max_{\tilde{P}} V(\tilde{P}) = B(R(\tilde{P}), Q(\tilde{\tilde{P}})) - R(\tilde{P})Q(\tilde{P}) \tag{B.3}$$

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

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

Note that $\tilde{P} = FMAP \times P$ is defined as the federal contribution to the nominal rate P. Taking the first order condition of equation (B.3), we have:

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

Using the constraints

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

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

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

$$\begin{aligned}
\frac{dV}{d\tilde{P}} &= \left(\frac{Q}{\tau} - Q\right) \cdot \frac{dR}{d\tilde{P}} + \left(\frac{R - \tilde{P}}{\tau} - R\right) \cdot \frac{dQ}{dP} \\
&= \left(\frac{1-\tau}{\tau}\right) Q \cdot \frac{dR}{d\tilde{P}} + \left(\frac{-\tilde{P} + (1-\tau)R}{\tau}\right) \cdot \frac{dQ}{d\tilde{P}} \qquad \text{(B.4)} \\
&= \left(\frac{1-\tau}{\tau}\right) \cdot \frac{d(R * Q)}{d\tilde{P}} - \frac{\tilde{P}}{\tau} \cdot \frac{dQ}{d\tilde{P}} \,. \qquad \text{(B.5)}
\end{aligned}$$

Multiplying equation (B.5) by τ yields the expression in the main text.

B3 Alternative 2-Stage Game Framework

In this section, we abstract from the instruments discussed in the main text through which states can directly influence care volume. Instead, the care volume is determined in equilibrium by demand and supply. In this model, states can only influence care provision through Medicaid reimbursement rates. This setup presents states with a tradeoff: (a) lower reimbursement rates to contain costs vs. (b) higher reimbursement rates to expand access.

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

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

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

B3.1 Second Stage

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

$$u_{ijt} = \begin{cases} \delta_j + \eta_{ij} & \text{for nursing homes} \\ \eta_{io} & \text{otherwise} \end{cases} \tag{B.6}$$

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

$$s_j(\delta) = \frac{\exp\{\delta_j\}}{1 + \sum_k \exp\{\delta_k\}} \tag{B.7}$$

$$Q_j^D(\delta) = s_j(\delta) \times N, \tag{B.8}$$

where N denotes the population size.

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

$$Q_j^S = A_j \times h(Q_j, \delta_j) \times I_j \,. \tag{B.9}$$

Here, I_j denotes a variable input factor with an input price 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:

$$C(Q_j, \delta_j) = \frac{Q_j}{A_j \times h(Q_j, \delta_j)} \times w \tag{B.10}$$

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

$$\delta_j^* = \arg\max_{\delta_j} \Pi_j = \arg\max_{\delta_j} \left(RQ_j^D(\delta) - C(Q_j^D(\delta), \delta_j) \right) . \tag{B.11}$$

Analysis: We impose the following simplifying assumption:

$$\frac{w}{A \times h(Q,\delta)} = c_\delta \times \delta + c_m + c_q \times Q^\gamma, \ \ \gamma \geq 0 . \tag{B.12}$$

$$\leftrightarrow \qquad C(Q,\delta) = Q \times \left(c_\delta \times \delta + c_m + c_q \times Q^\gamma \right) \tag{B.13}$$

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

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

$$\delta_j^* = \underbrace{\frac{1}{c_\delta}\left(R - c_m - (1+\gamma) \times c_q \times Q_j^\gamma \right)}_{\text{Perfect Competition}} - \underbrace{\frac{Q_j}{\partial Q_j / \partial \delta_j}}_{\text{Quality Markdown}} . \tag{B.14}$$

The first term denotes quality under perfect competition, whereas the second term denotes a ″quality markdown″ stemming from nursing home market power.

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

$$\frac{\partial Q_j^*}{\partial R} \geq 0 . \tag{B.15}$$

B3.2 First Stage: Rate Setting (w/o Creative Financing)

In the first stage, states negotiate with nursing homes over the (effective) reimbursement rate R, considering the quantity and quality effects in the second stage. (We introduce creative financing in the next subsection.) The state trades off the incremental benefits from increased access to nursing home care against the funding costs. States value the quality and quantity of care, which are both affected by R.

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

$$V(R) = \sum_j \tau B_j(R,Q) - \sum_j R \times Q_j^*(R) \times [1 - FMAP]\,. \tag{B.16}$$

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 nursing homes engage in Nash Bargaining to determine R, specifically:

$$R^* = \underset{R \leq UPL}{\arg\max}\, V(R)^\alpha \times \Big(\sum_j \Pi_j(R)\Big)^{1-\alpha}, \tag{B.17}$$

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

FOC and Optimality Condition: To illustrate the outcome of the bargaining game, consider the case of a single monopoly nursing home. Abstracting from a binding upper payment limit and taking logs, the first order condition yields:

$$\begin{aligned} &\frac{\alpha}{V(R)} \times \Big((\tau B_Q(R,Q) - R \times [1 - FMAP]) \times \frac{\partial Q^*}{\partial R} + (\tau B_R(R,Q) - [1 - FMAP]) \times Q^* \Big) \\ + \quad &\frac{(1-\alpha)}{\Pi(R)} \times Q^* = 0, \end{aligned} \tag{B.18}$$

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

$$\begin{aligned} R^* \times [1 - FMAP] \quad = \quad & \underbrace{\tau B_Q(Q,R)}_{\text{Quantity Motive}} + \underbrace{\frac{(\tau B_R(Q,R) - [1 - FMAP]) \times Q^*}{\frac{\partial Q^*}{\partial R}}}_{\text{Quality Motive}} \\ + \quad & \underbrace{\frac{(1-\alpha)}{\alpha} \times \frac{V(R)}{\Pi(R)} \times \frac{Q^*}{\frac{\partial Q^*}{\partial R}}}_{\text{NH Bargaining Power}} = 0. \end{aligned} \tag{B.19}$$

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

B3.3 Creative Financing Step 1: Introducing Transfers

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

$$\left(T^{*,T}, R^{*,T}\right) = \underset{T, R \leq UPL}{\arg\max} \left(V(R) + T\right)^{\alpha} \times \left(\Pi(R) - T\right)^{1-\alpha}. \tag{B.20}$$

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

$$R^{*,T} = \underset{R \leq UPL}{\arg\max}\, V(R) + \Pi(R)\,. \tag{B.21}$$

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

$$R^{*,T} \times [1 - FMAP] = \tau B_Q(Q,R) - \frac{(\tau B_R(Q,R) - [1 - FMAP]) \times Q^*}{\frac{\partial Q^*}{\partial R}} + \frac{Q^*}{\frac{\partial Q^*}{\partial R}} = 0. \tag{B.22}$$

This optimality condition is closely related to equation (B.19) 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.19) and (B.22) equal for $\alpha = \underline{\alpha}$. Provided that the support for $V(R)$ and $\Pi(R)$ is compact and convex, we have the following two cases:

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

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

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

Plausibly, the case where states do not hold all bargaining power is the empirically relevant case. However, to understand the changes in incentives, we now assume that the states hold all the bargaining power.

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

$$\begin{aligned}
\left[\tau B_Q(Q,R) - R \quad + R \times FMAP\right]\frac{\partial Q}{\partial R} + \left[\tau B_R(Q,R) - Q \qquad + FMAP \times Q\right] &= 0 \quad \text{(B.23)}\\
\underbrace{\left[\tau B_Q(Q,R) - \frac{\partial C}{\partial Q} + R \times FMAP\right]\frac{\partial Q}{\partial R}}_{\text{Quantity Incentive}} + \underbrace{\left[\tau B_R(Q,R) - \frac{\partial C}{\partial \delta}\frac{\partial \delta}{\partial R} + FMAP \times Q\right]}_{\text{Quality Incentive}} &= 0 \quad \text{(B.24)}
\end{aligned}$$

where equation (B.23) denotes the case without transfers, discussed in Appendix Section B3.2, and equation (B.24) denotes the case with transfers. The first term in each equation captures the incentives to increase quantities, and the second term captures the incentives regarding the quality of care.

The middle summand highlights how transfers alter incentives for setting rates and quantities: The ability of nursing homes to extract monies increases the cost of better quality. The regulator pays the rate R, but only a fraction is passed on, and the rest is extracted. When states redirect funding, it reduces the cost of a higher volume from R to $\frac{\partial C}{\partial Q}$ and the cost of a better quality (through rate increases) from Q to $\frac{\partial C}{\partial \delta}\frac{\partial \delta}{\partial R}$, see equations B.23 vs. B.24.

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

B3.4 Creative Financing Step 2: Introducing Nominal and Effective Rates

We now introduce a nominal reimbursement rate P, in addition to the effective rate R. Specifically, providers receive a marginal reimbursement rate R and a lump sum payment $(P - R) \times \bar{Q}$. These payments may be entirely diverted back to the state budget through a transfer. Importantly, P qualifies for federal matching funds. Provider profits before transfers are now:

$$\Pi(R, P, \bar{Q}) = R * Q - C(\delta, Q) + (P - R) \times \bar{Q} \tag{B.25}$$

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

$$\left(T^{*,T}, R^{*,T}, P^{*,T}, \bar{Q}^{*,T}\right) = \underset{T, R \leq UPL, P \leq UPL, \bar{Q} \leq Q^{*,CF}}{\arg\max} \left(V(P) + T\right)^{\alpha} \times \left(\Pi(R, P, \bar{Q}) - T\right)^{1-\alpha}. \tag{B.26}$$

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 B3.3, states will choose rate R that maximizes the sum of surplus:

$$R^{*,T} = \underset{R \leq UPL}{\arg\max}\, V(\bar{P}) + \Pi(R, \bar{P}, Q^{*,T}) = \tau B(Q, R) - C(Q, \delta) + \bar{P} \times FMAP \times Q^* . \tag{B.27}$$

Optimality Condition: Taking the first order condition and rearranging yields, similar to equation (B.24):

$$\underbrace{\left[\tau B_Q(Q, R) - \frac{\partial C}{\partial Q} + \bar{P} \times FMAP\right] \frac{\partial Q}{\partial R}}_{\text{Quantity Incentive}} + \underbrace{\left[\tau B_R(Q, R) - \frac{\partial C}{\partial \delta} \frac{\partial \delta}{\partial R}\right]}_{\text{Quality Incentive}} = 0 . \tag{B.28}$$

Thus, introducing nominal rates beyond effective rates changes the quality and quantity incentives. Compared to the case with just transfers, equation (B.24), states have now more incentives to increase quantities as $\bar{P} > R$, and engage in public moral hazard. Conversely, states have less incentive to raise quality through higher R because it does not trigger additional matching funds tied to P. As a result, the quality incentive term in equation (B.28) misses $FMAP \times Q$ from equation (B.24).

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

To see this, after subtracting equation (B.24) from equation (B.28), 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:

$$\frac{\bar{P} - R}{R} \geq \frac{1}{\epsilon_{Q,R}} \tag{B.29}$$

where $\epsilon_{Q,R}$ denotes the elasticity of volume of care with respect to R. In words: states are willing to raise Medicaid reimbursement rates, and hence program costs, when the public markup (-1), $\mu - 1 = \frac{\bar{P}}{R} - 1 = \frac{\bar{P}-R}{R}$ exceeds $\frac{1}{\epsilon_{Q,R}}$. Intuitively, when rate increases have a small effect on volume, e.g., because firms with market power only pass through a small share of rate increases to patients, the cost-saving motive dominates and states lower Medicaid rates. Conversely, states prefer to increase Medicaid rates when rate increases have a relatively large effect on volume, or when the public markup is large.

B4 Provider Taxes

An alternative creative financing instrument is provider taxes. States also use them to reduce their Medicaid cost share (MACPAC, 2021). Provider taxes must satisfy the following legal requirements.

Federal rules require that provider taxes must be (a) broad-based, (b) uniform, and (c) not hold providers harmless (Congressional Research Service, 2024). An (a) broad-based tax must apply to all providers within a defined class—states, meaning it cannot single out providers serving primarily Medicaid patients. The tax must also be (b) uniform, meaning it must be applied at the same rate to all providers within the class, without imposing higher rates on Medicaid-related revenue.[34] Lastly, states are (c) prohibited from holding providers "harmless"—they cannot directly or indirectly guarantee that providers will be reimbursed for their taxes, ensuring that provider taxes reflect real contributions rather than redirected funds. Under current rules, the "Hold Harmless Test" is waived if tax revenue accounts for 6% or less of net patient revenue, a threshold known as the "safe harbor" (42 CFR § 433.68).

However, states have been creative in finding arrangements between providers to sidestep the Hold Harmless Test, e.g., via "pooling agreements." Pooling agreements mean that

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

providers contribute taxes to a shared pool, which then pays out funds to providers in some relation to their tax burden. Like IGTs, pooling agreements are a legal grey area and thus currently contested; federal regulators have had difficulties tracking and monitoring these schemes (Young, 2023). In California, for instance, hospitals have effectively neutralized provider taxes through a redistribution mechanism, holding them harmless. Hospitals serving a high share of low-income patients receive more in Medicaid payments than they contribute in taxes. They then donate a portion of this surplus to a charity affiliated with the California Hospital Association. That charity, in turn, distributes grants to hospitals with fewer low-income patients to offset their net losses under the tax scheme.

Incentives: Provider taxes vary across states and provider classes, particularly in their tax base. This affects provider incentives. Sometimes, taxes are a percentage of revenues, incentivizing higher volume and Medicaid rates. Or they are a flat tax on the number of facility beds, incentivizing higher capacity, but not directly higher utilization. Most closely related to our model, some states impose a flat tax on the number of inpatient days or enrollment (Kaiser Family Foundation, 2025a), providing incentives to expand volume, see below. For example, California's provider tax on nursing homes is a flat tax per resident day. And its tax on Managed Care Organizations is a flat tax per enrollee and month.[35]

Discussion: Provider taxes aim to reduce the state's cost share. They incentivize capacity expansions in programs that are more exposed to provider taxes. For instance, the most common provider taxes are levied on nursing facilities (46 states) and hospitals (45 states), biasing—all else equal—Medicaid care towards institutional care. Specifically, while 46 states have a provider tax on nursing homes, only three states have a tax on home health long-term care providers (Kaiser Family Foundation, 2025a).[36] That means provider taxes disproportionately subsidize the state's cost share for inpatient long-term care, incentivizing an institutional bias in Medicaid long-term care policies.

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

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

B4.1 Quality-Quantity Tradeoff Under Volume-Based Provider Taxes

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

$$\max_{R,Q} \tau \times B(\theta(R), Q) - (1 - FMAP) \times (R + t) \times Q + t \times Q\,. \tag{B.30}$$

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

$$\tau \times B_R(R, Q)/Q = 1 - FMAP \tag{B.31}$$

$$\tau \times B_Q(R, Q)/R = 1 - FMAP \cdot \frac{R+t}{R} = 1 - FMAP \cdot \frac{P}{R}\,. \tag{B.32}$$

A few differences exist between the incentives created by intergovernmental transfer and provider taxes. First, the size of the tax is capped by the Hold Harmless Test. Most states calibrate the tax to follow the "Below 6% of Revenues" rule, such that nominal rates are linearly related to effective rates via $P = R + t$. As a result, increases in effective rates still qualify for matching funds on the margin, leaving the incentives for rate setting unaffected (compared to the case with perfect monitoring).

The cap on provider taxes also reduces the public markup to $\mu = \frac{R+t}{R}$.[37] Nevertheless, consistent with hypothesis **H2**, the provider tax increases the effective quantity FMAP and incentivizes states to increase the volume eligible for joint funding, thereby distorting the quality-quantity tradeoff.

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

C Data Appendix to Provide Evidence on H1

Here, we describe the primary data sources to generate a panel at the state-year level from 2000 to 2007 with 264 observations for most outcomes. The panel only contains data from 17 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 Centers for Medicare & Medicaid Services (2020a). These data contain Medicaid expenditures at the state and federal levels by service categories based on Form CMS-64. We use these data to measure total nominal spending (P) on nursing home care by state and year.

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

Third, we use public data from LTC Focus at the state-year level (Long-Term Care: Facts on Care in the U.S., 2025). It covers all U.S. Medicaid and Medicare-certified nursing homes, which are 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 provides average Medicaid per diem rates and the number of Medicaid days 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
Treatment states	0.4848	(0.5007)	264
Markup	1.0738	(0.2431)	256
Effective FMAP	66.24	(17.77)	256
Federal Expenditures	688.81	(603.55)	264
State Expenditures	492.86	(514.17)	264
RN Ratio	0.5078	(0.2013)	264
LPN Ratio	0.8295	(0.1749)	264
CNA Ratio	2.3133	(0.2591)	264
Medicaid days	7,562,009	(6,302,317)	264
log Medicaid days	15.4319	(1.0002)	264

Source: Centers for Medicare & Medicaid Services (2020a); Kaiser Family Foundation (2025d); Long-Term Care: Facts on Care in the U.S. (2025), data are from 2000-2007 at the state-year level. The markup is defined in equation 17. The effective FMAP is given by $FMAP \times (1 + markup)$. Federal and state expenditures are measured in millions \$. Registered nurse (RN), licensed practical nurse (LPN), and certified nurse assistant (CNA) to patient ratios are displayed. Medicaid days are calculated by multiplying the total number of beds by the occupancy rate and the share of Medicaid patients for each nursing home and year. The ”incidence” and ”effective FMAP” variables have only 256 observations because Hawaii does not have an LTC Focus estimate of the average Medicaid rate, so we cannot compare CMS expenditures with the estimated LTC Focus.

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 nursing home reimbursement rates, we digitized and analyzed 24 audit reports from 18 states from 1997 to 2003, during the pre-reform era.

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

We combine the IGT amounts with information on total nominal Medicaid spending (*Total MHEX*) separately for states (*State MHEX*) and the federal government (*Total MHEX - State MHEX*), from CMS-64 forms, see above. We then construct the markdown as

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

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

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

Source: Long-Term Care: Facts on Care in the U.S. (2025); 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 17. The effective FMAP is given by $FMAP \times (1 + markup)$. Federal and state expenditures are measured in millions $. The second panel shows results for the registered nurse (RN), licensed practical nurse (LPN), and certified nurse assistant (CNA) to patient ratios. "NH" abbreviates nursing home. The last column presents results for the log number of annual Medicaid days (Lg MA Days). ***, **, 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 (except those for Federal and State Expenditures, which have 256) have 264 state-year observations from 17 treated and 16 nontreated states. See the main text for more details.

C3 Financial Statements by Health and Hospital Corporation (HHC)

To estimate the markdown from the 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 nursing home acquisitions in Indiana. By 2009, HHC owned the licenses of 40 nursing homes and received more than 80% of supplemental payments provided 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 did not disclose the size of IGTs in their financial statements, nor how much of it was used for nursing home patients.

The HHC financial statements provide this information, allowing us to estimate their Medicaid revenues' markdown. We approximate the regular Medicaid payments on their nursing home patients (*Reg MHEX*) from the revenue HHC received from their long-term care division and the share of Medicaid patients. HHC disclosed the size of supplemental payments under "Medicaid Special Revenue" for their long-term division (*Sup MHEX*), while they disclose IGTs 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 inpatient 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*.

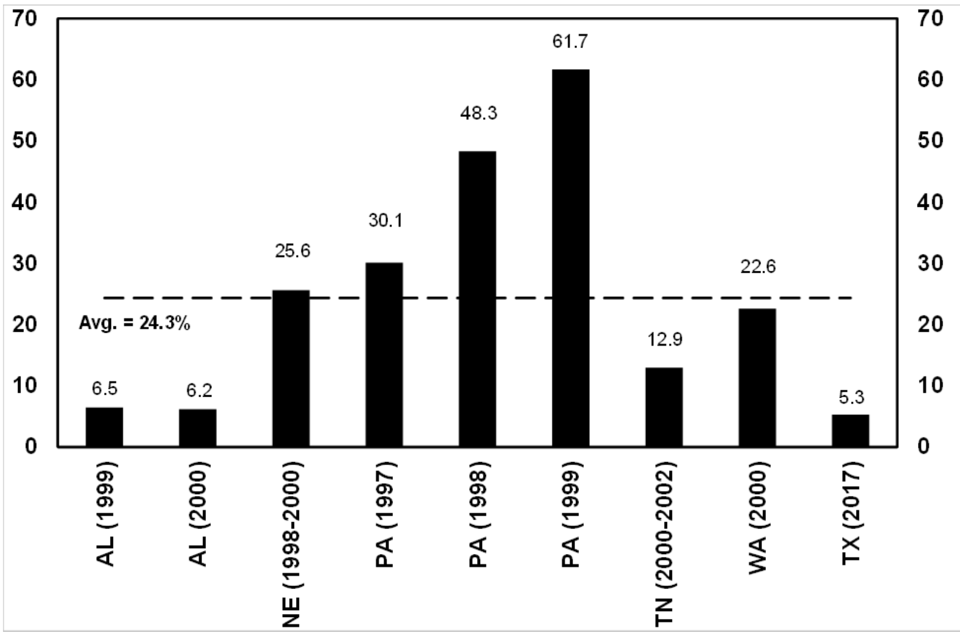
We calculate the markdown and effective FMAP using:

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

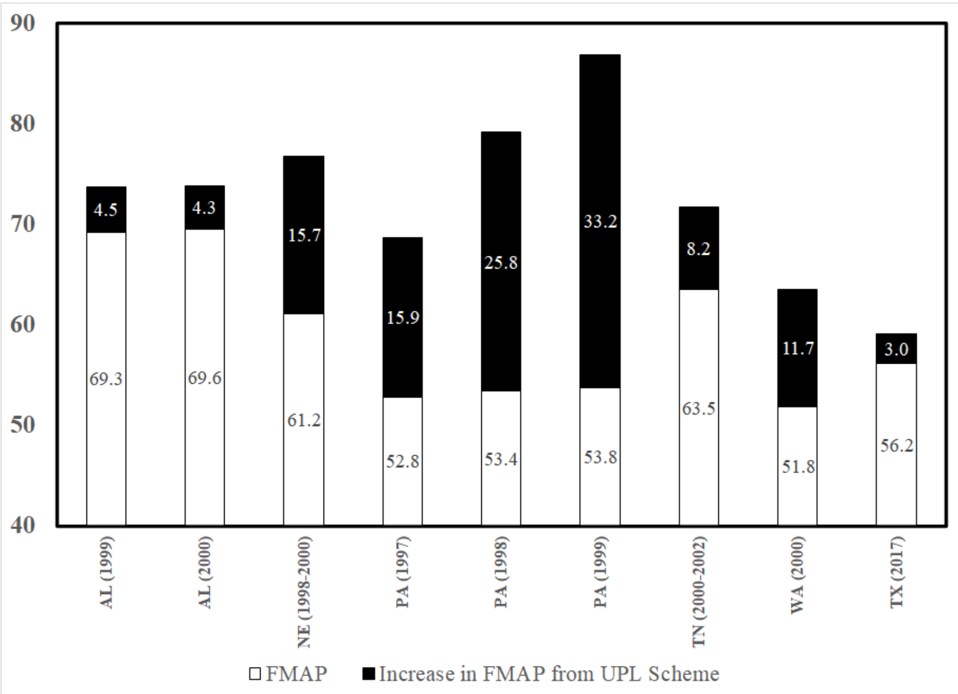
$$Effective\ FMAP \quad = \quad FMAP \times \frac{RegMHEX + SupMHEX}{RegMHEX} = FMAP \times \mu \tag{C.3}$$

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

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



(a) Public Markups



(b) Effective vs. Nominal FMAP

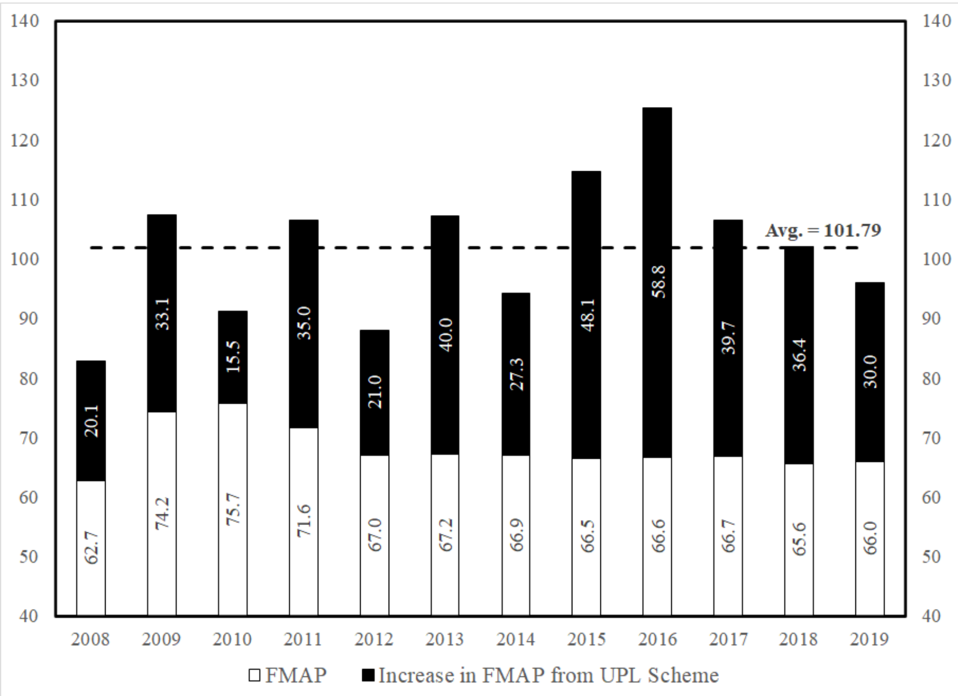
Notes: Figure C.1a presents the public markup, $\frac{P}{R}$, indicating the wedge between the nominal Medicaid reimbursement rate, P, and the effective Medicaid reimbursement rate, R. Figure C.1b presents the nominal FMAP and the effective FMAP. We assembled the information from several audit reports: 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 (1)	Total Base Medicaid NH Payments to HHC (2)	Nominal FMAP in % (3)	Matching Funds from Federal Government (4)	Total Medicaid SP (5)	Federal Matching Funds SP (6)	IGT NH to HHC (7)	Effective FMAP in % (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. NH stands for "Nursing Home." 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 nursing homes 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

Here, we describe the primary data sources to generate a panel at the nursing home-year level in Indiana from 1999 to 2015. The panel uses administrative data, merged with data from Long-Term Care: Facts on Care in the U.S. (2025) and hand-collected data as described in Section C. The administrative data, MDS by CMS, contains all Medicaid and Medicare-certified nursing homes in Indiana from 1999 to 2015. As discussed in the main text, we use this panel to study the impact of creative financing on care volume—moral hazard—and its underlying mechanisms. Specifically, we exploit the municipalization of nursing homes in a staggered DD setting to estimate the impact of creative financing activities on patient and provider outcomes.

D1 Nursing Home-Year Data from LTC Focus and MDS

We used information from various sources to create the panel dataset at the nursing home-year level; Section 4.2 and the README file contain 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.[38] (b) Manual searches of Indiana Consumer Reports. We used consumer reports from July 2019 for all nursing facilities 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.[39] (c) Reporting from Indystar in an article titled ”Money Flowed, Care Lagged (Evans, Hopkins, and Cook, 2020b).

CMS Compare. Legacy data from CMS Compare from 2000 to 2017 as downloaded in July 2018. Note that nursing homes that a county hospital owned before the sample's start will have the acquisition year set to 2000. In general, most of these nursing homes will be dropped from the balanced samples that we use for the analyses.[40]

[38] 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.

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

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

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 nursing home-year level, into the datasets above. The CMS provide these data, which cannot be made publicly available. However, we provide the codes in the Supplementary Materials. The file describes how we generate our primary dataset at the nursing home-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.

Table D.1: Summary Statistics

Variable	Mean	Std. Dev.	N
Panel A: Main outcomes			
For-profit	0.67	0.22	5888
Total Medicaid days in 1k	28.04	12.56	6256
Alzheimer's Medicaid days in 1k	9.72	6.52	6256
Alzheimer's Special Care Unit (SCU)	0.37	0.48	5888
Panel B: Supplemental Outcomes			
Occupancy rate in %	80.36	12.85	5886
Total Beds	108.2	45.94	5888
RN Hours PPD	0.30	0.29	5888
LPN Hours PPD	0.88	0.27	5887

Source: Long-Term Care: Facts on Care in the U.S. (2025), MDS (2020), CMS Compare, Indiana Consumer Reports, CMS Skilled Nursing Facility Provider Information, State of Indiana (2025), authors' calculation. See Section 4.2 and Appendix D for a description of the sample construction and selection.

Table D.2: Characteristics of Early (<2011) vs. Late Nursing Home 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 nursing homes with observations for all relevant variables between 2000 and 2017, and that were acquired by a county hospital between 2005 and 2012. See the main text for more details.

D2 Patient-Stay Data

We used information from various sources as in Section D1 to create a dataset at the patient-stay level primarily using MDS data in Indiana from 2000-2012; Section 4.3 and the README file contain more details.

Table D.3: Sample Cuts: Dementia Patients

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

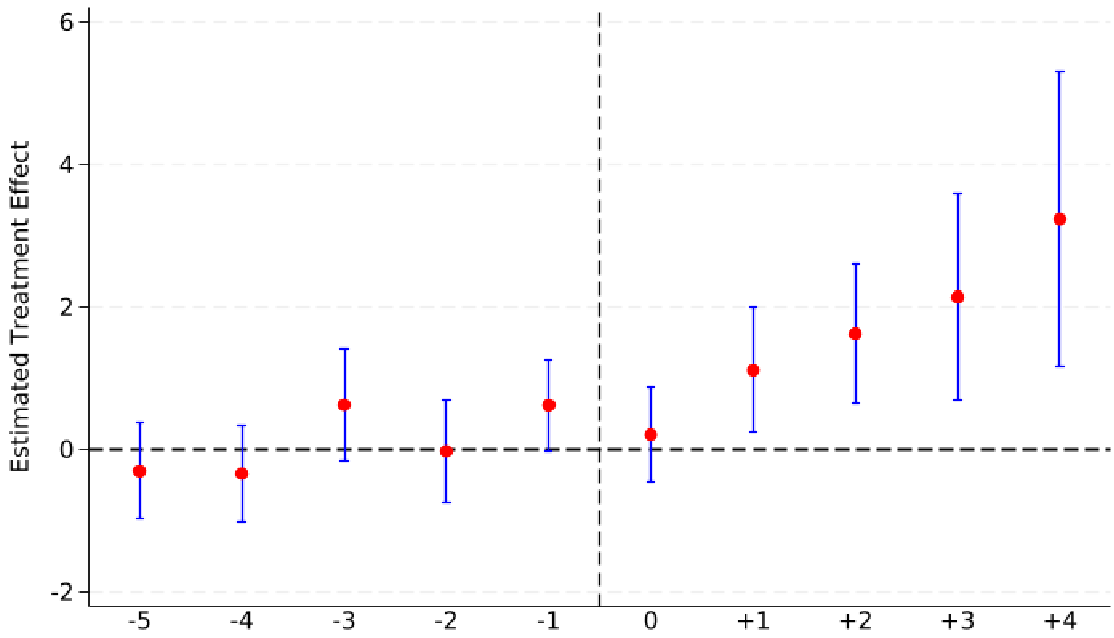
Source: Long-Term Care: Facts on Care in the U.S. (2025), MDS (2020), CMS Compare, Indiana Consumer Reports, CMS Skilled Nursing Facility Provider Information, State of Indiana (2025), authors' calculation. The sample is based on AD/ADRD patients in acute care hospitals and at the patient-stay level in Indiana from 2000-2012.

Table D.4: 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 Nursing Home	0.3685	(0.4824)	206833
Discharged to ICF	0.0332	(0.1793)	206833
Discharged to Hospice	0.0215	(0.145)	206833
Nursing Home Matches: MDS Claims			
Discharged to Nursing Home	0.3761	(0.4844)	206833
Distance to Nursing Home in Miles	5.8902	(7.0849)	77794
Medicaid Days	185.8092	(469.9024)	76272
Any Medicaid Days	0.1238	(0.3293)	77794

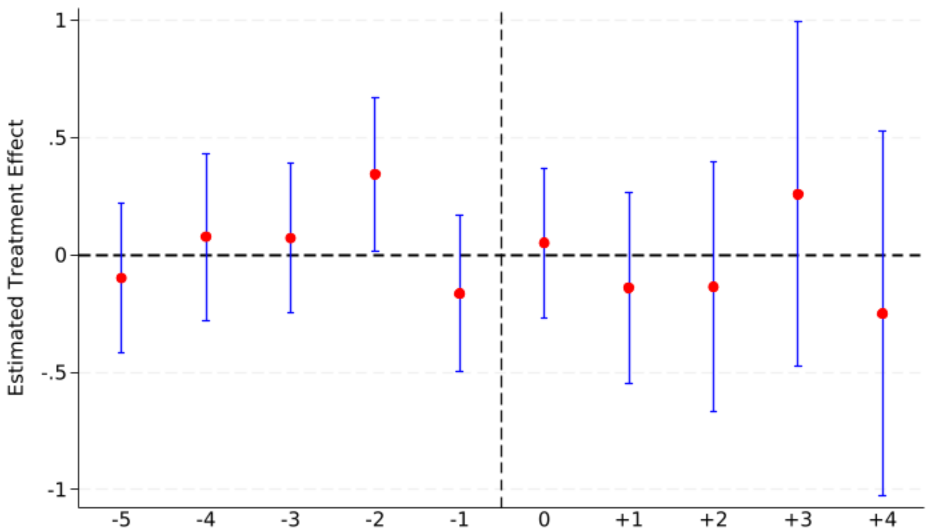
Source: Long-Term Care: Facts on Care in the U.S. (2025), MDS (2020), CMS Compare, Indiana Consumer Reports, CMS Skilled Nursing Facility Provider Information, State of Indiana (2025), authors' calculation. The sample is based on AD/ADRD patients in acute care hospitals and at the patient-stay level in Indiana from 2000-2012, see Table D.3 for the sample selection. 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 Appendix D for details on the sample construction. Discharged 'Home' comprises community discharges, where patients may seek care at their "homes". 'ICF' denotes intermediate care facilities.

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



Source: Centers for Medicare & Medicaid Services (2020b) and Indiana Department of Health (2020). The graph shows Callaway Sant'Anna event studies, where event time 0 indicates the municipalization. All event studies show 90% confidence intervals. See Section 4.2 and Table D.3 for details on the sample construction and selection.

Figure D.2: Mortality Results



(a) 100 Day Mortality

Source: Centers for Medicare & Medicaid Services (2020b) and Indiana Department of Health (2020). The graph shows Callaway Sant'Anna event study estimates, where event time 0 indicates the municipalization. All event studies show 90% confidence intervals. See Section 4.2 and Table D.3 for details on the sample construction and selection.

E Difference-in-Differences and Mixed Logit Estimation

E1 Details on Callaway and Sant'Anna (2021) Estimator

To avoid the pitfalls with two-way fixed effects estimators in staggered difference-in-differences setups, we implement the estimator from Callaway and Sant'Anna (2021). Specifically, while the simple 2x2 DD design in equation (18) has solely one target parameter, in the staggered Callaway Sant'Anna (CS) DD, each treatment group (here municipalized nursing homes) is defined by its year of conversion g and produces T-1 event study parameters.

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

ATT(g, t) can be identified by comparing the expected outcome change for g between periods $g-1$ and t to that for the not-yet-treated at period t (Roth et al., 2023).[41]

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

which is estimated via the sample analogues:

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

E2 Details on Choice Model

A key challenge to estimating equation (21) in the main text is that we only observe 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 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:

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

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

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

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

$$E[m_{ijt}|x_{ijt}, \pi_i, c_i = j] = \alpha_j + \alpha_t + x'_{ijt}\alpha^x + \Big[\sum_{k \in J_i} \phi_k\gamma_{ik}(j) + \psi\gamma_{ij}(j)\Big] + \rho\pi_i + \rho_\psi\pi_i\,, \quad \text{(E.3)}$$

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

$$\gamma_{ij}(j) = \begin{cases} -log\ \hat{p}_{ik} & k = j \\ \frac{\hat{p}_{ik}}{1-\hat{p}_{ik}} log\ \hat{p}_{ik} & otherwise \end{cases} \quad \text{(E.4)}$$

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

$$\hat{p}_{ij} = \frac{\exp(\delta_j + x'_{jt(i)}\beta^x + z'_{ij}\beta^z)}{\exp(\pi_i + \gamma_{t(i)}) + \sum_{k/o}\exp(\delta_k + x'_{kt(i)}\beta^x + z'_{ik}\beta^z)}\,. \quad \text{(E.5)}$$

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

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

$$E[m_{ijt}|x_{ijt},c_i] = \int \left(\alpha_j + \alpha_t + x'_{ijt}\alpha^x + \sum_{k\in J_i} \phi_k\gamma_{ik}(\pi) + \psi\gamma_{ij}(\pi) + \rho\pi + \rho_\psi\pi\right) dF_{\pi|x_{ijt},c_i}\ , \tag{E.6}$$

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

$$f_{\pi|x_{ijt},c_i} = \frac{f_{\pi,c_i|x_{ijt}}}{f_{c_i|x_{ijt}}} = f_{c_i|\pi,x_{ijt}} \times \frac{f_{\pi|x_{ijt}}}{f_{c_i|x_{ijt}}} = \hat{p}_{ik}(\pi) \times \frac{\phi(\frac{\pi}{\sigma_\pi})}{\int \hat{p}_{ik}(\pi)\phi(\frac{\pi}{\sigma_\pi})d\pi}\ , \tag{E.7}$$

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

$$w_\pi = \hat{p}_{ik}(\pi) \times \frac{\phi(\frac{\pi}{\sigma_\pi})}{\int \hat{p}_{ik}(\pi)\phi(\frac{\pi}{\sigma_\pi})d\pi} \tag{E.8}$$

such that

$$E[m_i|x_{jt(i)},c_i] = \int \left(\alpha_j + \alpha_t + x'_{ijt}\alpha^x + \sum_{k\in J_i} \phi_k\gamma_{ik}(\pi) + \psi\gamma_{ij}(\pi) + \rho\pi + \rho_\psi\pi\right) w_\pi\ d\pi\ , \tag{E.9}$$

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

Figure E.1: Selection and Value Added

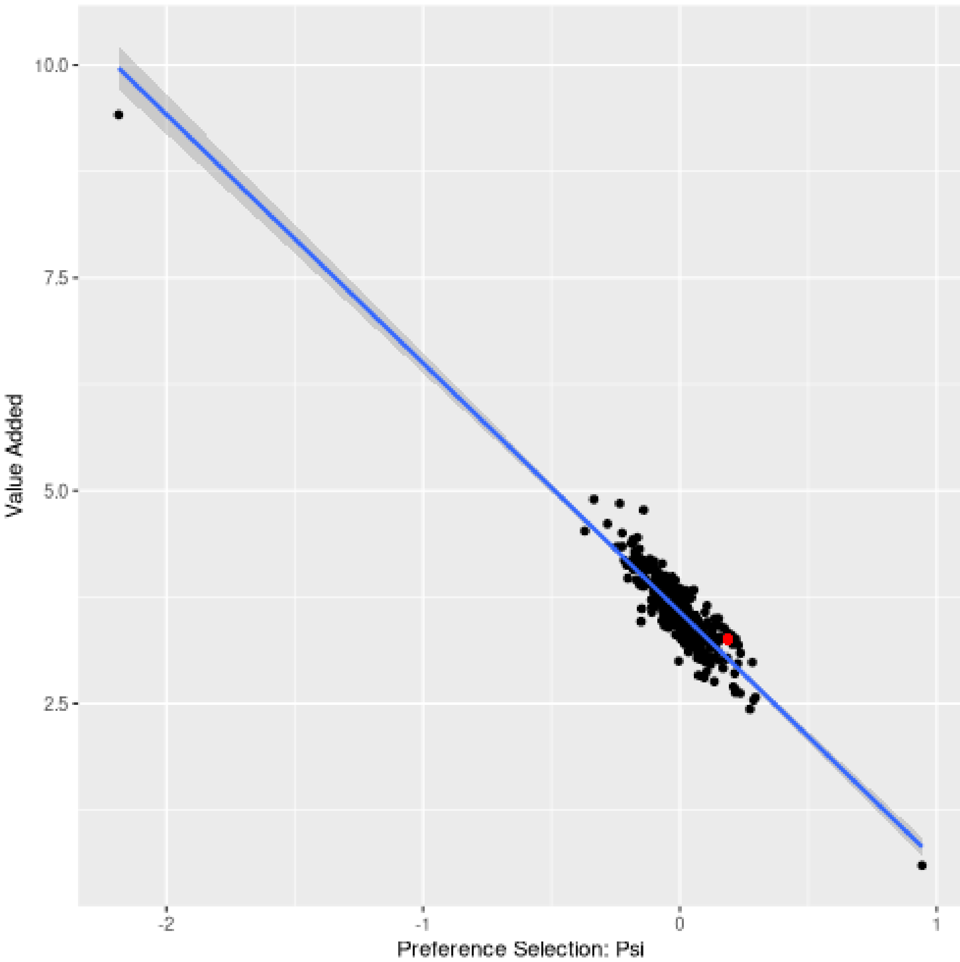
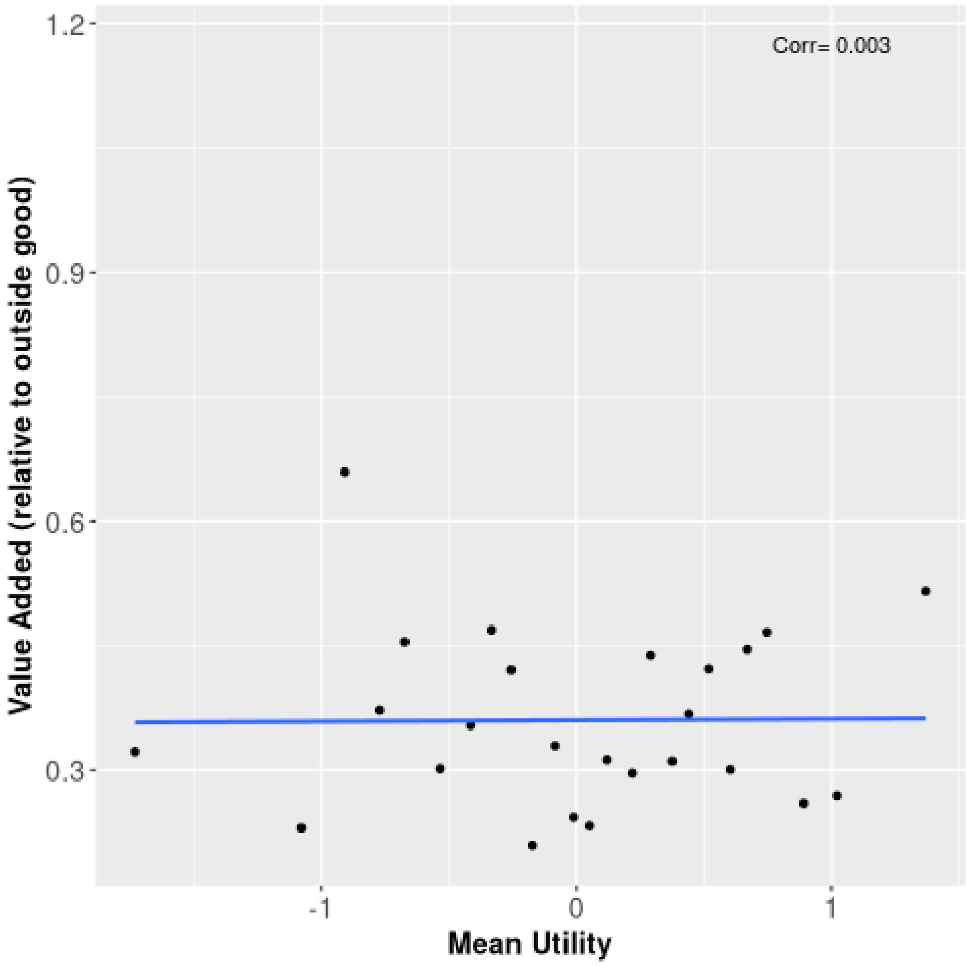


Figure E.2: Utility and Valued-Added—Do Consumers Choose High-Quality Nursing Homes?

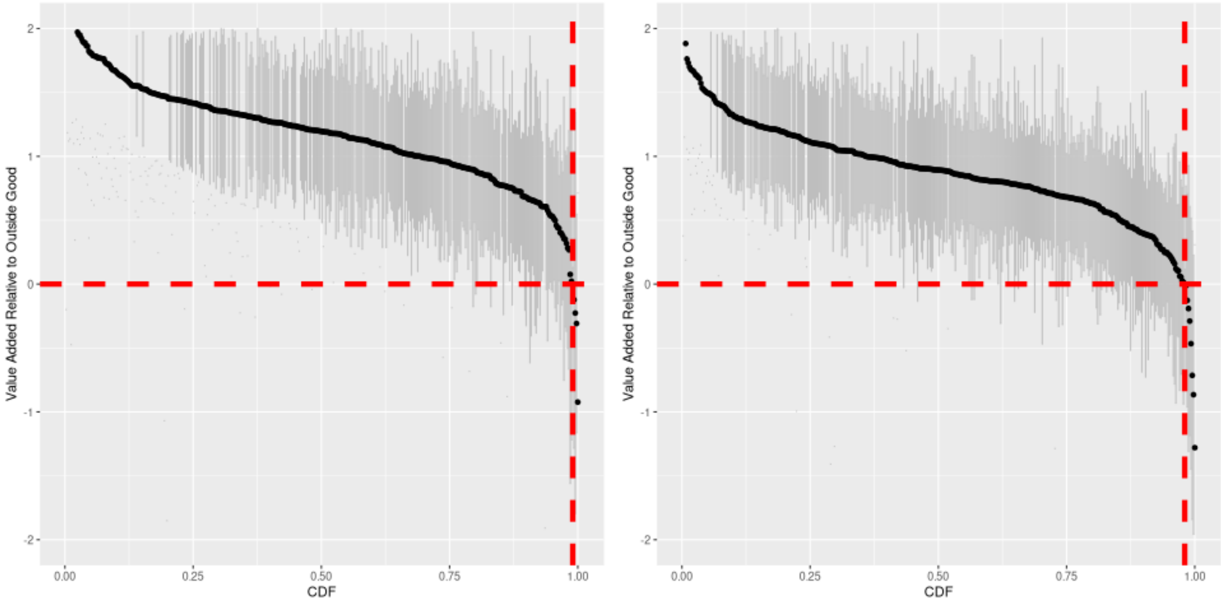


Asymmetric Information: Can consumer demand discipline the expansion of low-quality providers? To explore this possibility, we now analyze the relationship between consumer preferences and our health value-added estimates.

First, Figure E.1 shows clear evidence for selection into nursing homes via the strong correlation between our value-added estimates and the preference selection coefficient Ψ

Figure E.2 provides a binned scatter plot with value-added on the y-axis and (binned) mean utility on the x-axis. We find no systematic relationship between the two variables and a correlation of almost 0. Apparently, consumers (or their surrogates) do not consider that nursing homes produce different health outcomes, for example, because of asymmetric information or capacity constraints. Below, we find no link between occupancy and our value-added estimates, suggesting that rationing alone is unlikely to reconcile the lack of a statistical link. Further, rationing alone cannot explain why patients choose low-quality providers over the outside good.

Figure E.3: Value Added Estimates—Hospital Readmission Rates



(a) 30-Day Readmission Rate

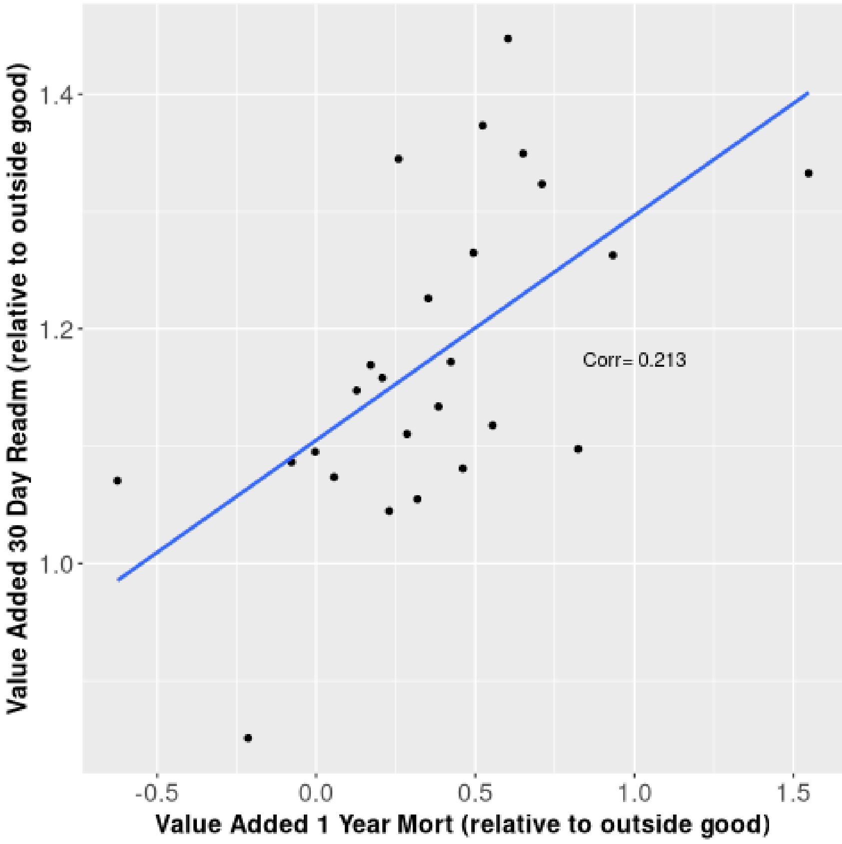
(b) 90-Day Readmission Rate

We, therefore, interpret Figure E.2 as evidence for asymmetric information over the quality of nursing homes.

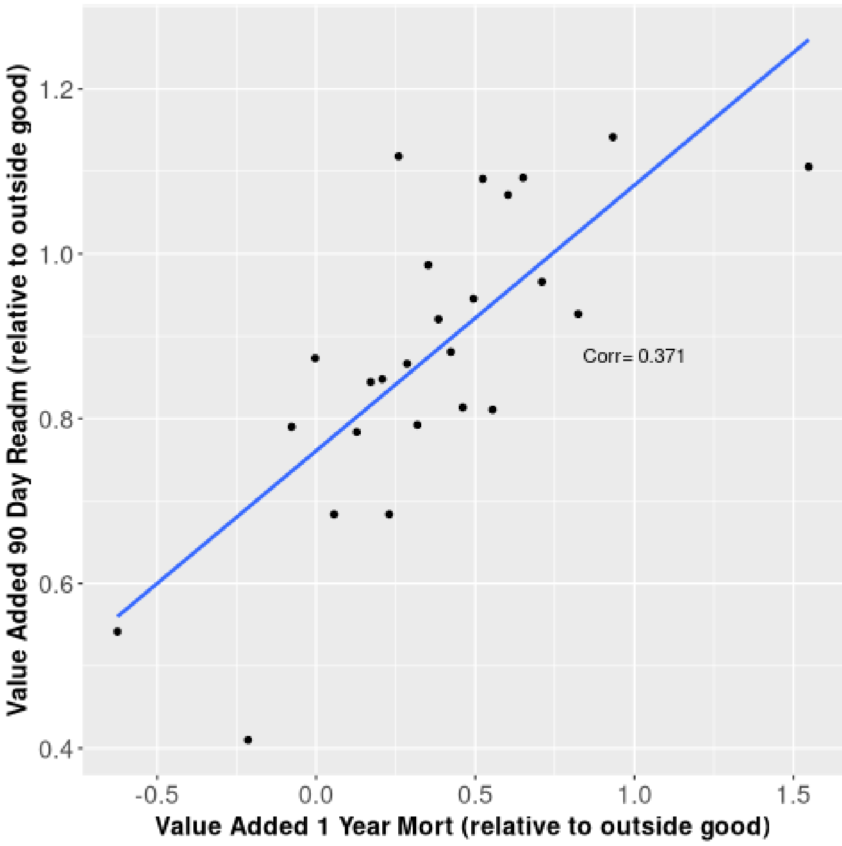
Validation of Nursing Home Quality Measures: Next, we validate our quality measures by correlating the value-added estimates generated by the one-year mortality vs. 30-day (Figure E.3a) and 90-day (Figure E.3b) hospital readmission rates in Figure E.4.

Moreover, Table E.1 shows the correlation between our three quality measures and nursing home characteristics, such as staffing ratios or star ratings. Finally, following Panel B of Table 2, Table E.2 shows estimates for the health outcome equation using readmission rates instead of mortality.

Figure E.4: Valued Added—Mortality vs Readmission Rate



(a) Mortality Against 30-Day readmission



(b) Mortality Against 90-Day readmission

Table E.1: Correlation with Other Markers

Variable	Mean Utility	VA: Mort	VA: Read 30	VA: Read 90
Nurse Practitioner	0.098	-0.038	-0.076	-0.072
Alzheimer's Unit	0.179	-0.042	-0.025	-0.03
RN Staffing Ratio	0.207	0.071	0.049	0.043
LPN Staffing Ratio	0.268	0.049	0.015	0.006
Occupancy Rate	-0.025	0.008	-0.053	-0.024
Total Beds	0.106	-0.123	-0.052	-0.019
Hospital Based	0.242	0.065	0.043	0.023
Overall Rating	0.172	0.112	0.109	0.162
Survey Rating	0.193	0.119	0.081	0.118
Quality Rating	-0.024	0.011	-0.021	0.025
Staffing Rating	0.118	0.015	0.079	0.109
RN Staffing Rating	0.053	0.054	0.137	0.146

Table shows correlations based on the sample of dementia related index hospital stays described in Appendix Table D.4.

Table E.2: Health Outcome Estimates Using Readmission Rates

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

Sources: See Appendix C and Appendix Tables D.3 and D.4 for details on data sources and the sample at the nursing home-year level. Equation (E.3) is estimated. The outcome is the 30-day and the 90-day readmission rate. All coefficients are multiplied by -1 to reflect effects on positive health. Estimates are based on the same of dementia related index hospital stays described in Appendix Table D.4.

F Details on Calibration

F1 CES Approximation

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

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

but maintain the same specifications for costs and health production. Note that, here, the parameter γ captures the relative importance of care volume.[42]

Calibration: We focus on Medicaid dementia patients using the estimated overall 12% increase in Medicaid volume (see Section 4.2).[43] We then calculate survival, pre- and post-municipalization, as follows: First, we take one-year mortality in each of the three groups in Table 4. Pre-municipalization, survival is the weighted average over the three estimates and implies a one-year survival rate of 74.8%.[44] We find a 19% increase in volume in lower-quality nursing homes and a 9 and 11% increase in middle and higher-quality nursing homes, respectively (see Table 1). Using the diversion ratios from Table 3, we estimate that the compositional changes reduce the average one-year survival rate to 74.5%.[45]

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

$$MRS = MB_q / MB_m = \frac{\gamma}{(1-\gamma) \times \beta} \times \left(\frac{\beta \times log(AC)}{log(\sum_j q_j)}\right)^{1-\rho} \tag{F.2}$$

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

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

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

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

[45] For this calculation, we consider the nursing home type's own expansion effect and then net out the substitution effects as given by the diversion ratios. Let $g \in \{low, middle, high\}$ denote the type and $\Delta\%_g$ be the direct expansion effect as indicated in Table 1. Finally, let $D_{gg'}$ denote the diversion ratios denoted in the top panel of Table 3. The relative market shares among nursing homes (ignoring the outside good) with creative and then given by $s_g^{CF} = (1+\Delta\%_g) \times s_g^{NoCF} - \left[\sum_k \Delta\%_k \times s_k^{NoCF} \times \frac{D_{gk}}{\sum_m D_{mk}}\right]$, where s_g^{NoCF} denotes the baseline market shares for nursing home groups.

$$MRS = 1 \quad \Leftrightarrow \quad \frac{(1-\gamma)\times\beta}{\gamma} = \Big(\frac{\beta \times \overline{log(AC_j)}}{log(\sum_j q_j)}\Big)^{1-\rho}\Big|_{no\ CF} \tag{F.3}$$

$$MRS = 1 - FMAP \times \frac{P-R}{AC} \quad \Leftrightarrow \quad \frac{(1-\gamma)\times\beta}{\gamma} \times (1 - FMAP \times \frac{P-R}{AC}) = \Big(\frac{\beta \times \overline{log(AC_j)}}{log(\sum_j q_j)}\Big)^{1-\rho}\Big|_{with\ CF} \tag{F.4}$$

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

With creative financing, the slope of the cost curve flattens from -1 to $-(1 - FMAP \times \frac{P-R}{AC})$ (Figure 3).[46] With two conditions and three unknown parameters (β, γ, ρ), we need to impose one additional normalization and set $\beta = 1$. We then set $\gamma = 0.84$ and $\rho = -4.73$ to match the first order conditions pre and post-creative financing.

Results: Figure F.1 illustrates the quality-quantity tradeoff based on the empirical evidence from Indiana. The horizontal axis denotes log Medicaid dementia patient days per nursing home and year. The vertical axis denotes one-year survival rates. The red circle represents the allocation without creative financing, and the gray upward sloping line denotes the expansion path. The red diamond indicates the allocation with creative financing, which is below the optimal expansion path.

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

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

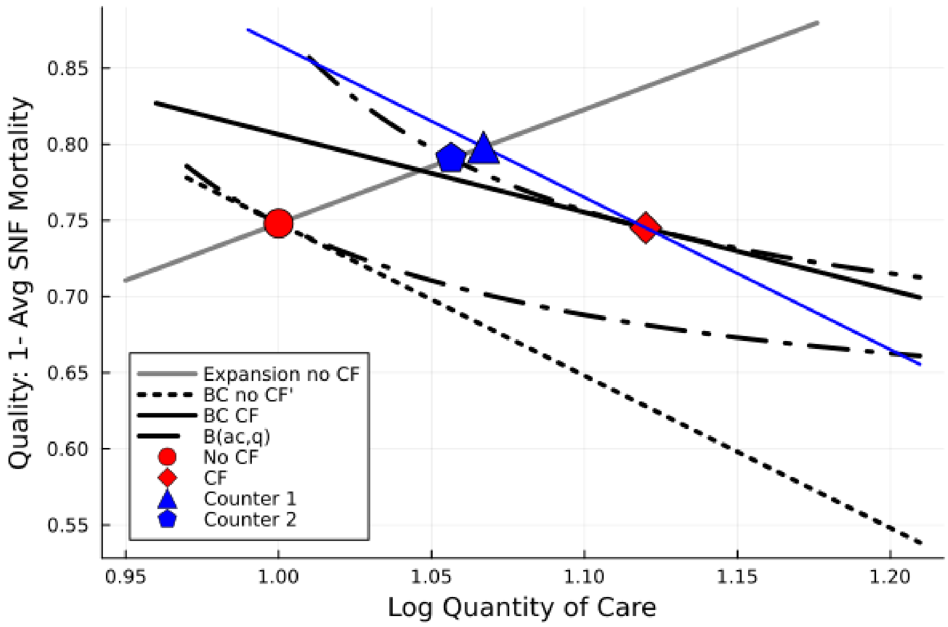
According to our estimates from Table 3, only 16.6% of new residents would otherwise choose outpatient care. That means that the aggregate quantity effects are accordingly smaller. While it is unclear whether nursing homes internalize the effects of business stealing from other nursing homes, the federal government would. We, therefore, also consider a specification with a smaller quantity expansion of only 16.6%×12%=2%[47]. The results are qualitatively similar, but the cost savings are proportionally smaller and equal 0.3% (without holding benefits fixed). We note, however, that it is unlikely that the entire increase in patient days can be attributed to increases in admissions from acute care hospitals. To the extent that nursing homes also prolong stays and delay discharges to the community following increases in Medicaid rates (Hackmann, Pohl, and Ziebarth, 2024), increases in total nursing home days will be larger. Hence, we view this second estimate as a lower bound.

Taking stock, we estimate that Medicaid days among dementia patients increase by between 2 and 12% because of public moral hazard. In Indiana, at least 90% of the state's 500 nursing homes participate in the creative financing scheme, each providing 10,000 Medicaid-covered dementia days annually on average. Indiana nursing homes are reimbursed at a $297.4 base rate plus a $108.3 supplemental rate per resident and day (Stulick, 2025). This translates to an additional Medicaid spending of $42-$255 million per year.[48] Hence, between 0.3 and 3.3% of overall ADRD spending can be considered wasteful; in Indiana alone, this amounts to between $55 and $600 million over 10 years. To put it further into context, the amount corresponds to roughly 20% of the increased spending. It is attributable to lower-quality nursing homes that held a 20% market share before the scheme's introduction.

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

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

Figure F.1: 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 nursing home days, and the vertical axis denotes log average costs per patient day, which is further averaged across nursing homes. The grey upward sloping line denotes the expansion path without creative financing (CF), and the red circle 'no CF' denotes the allocation before municipalizing nursing homes. The red diamond point 'CF' denotes the allocation with CF. The social budget constraint has a slope of -1, denoted by the blue line. The intersection between this budget constraint and the expansion path, the triangular blue point, denotes the optimal bundle, holding total costs under creative financing fixed. The intersection between the indifference curve and the expansion path, the blue pentagon point, denotes the allocation that achieves the same hospital-nursing home objective but at lower costs.