Should Physicians Choose Their Reimbursement Rate? Menu Design for Physician Payment Contracts*

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Abstract

Experts can leverage asymmetric information to induce demand for their services, complicating the design of payment contracts. In healthcare, physicians are widely believed to induce excessive treatment under a piece rate contract ("fee-for-service") and inadequate treatment under a flat-fee contract ("capitation"). A single contract that mixes fee-for-service and capitation payments may balance these forces for an average physician, but heterogeneous physicians plausibly have different socially optimal contracts. I study whether offering physicians a menu of contracts can improve welfare relative to a single contract. I first develop a model of treatment decisions, showing that welfare impacts are theoretically ambiguous and depend on the correlation between physicians' altruism, cost of effort, and patient needs. I then estimate the model using administrative data on Norwegian primary care physicians and their patients. In this population, the status quo single contract is inefficient. Physicians prefer a menu and respond by spending more time treating patients without increasing aggregate expenditure. The increase in patient health is equivalent to 5 percent of expenditure, with the largest gains for older, chronically ill, and rural patients.

Keywords: physician agency, self-selection

JEL Codes: D04, D47, H51, I11, J33

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1 Introduction

A central challenge in healthcare is that physicians almost invariably have private information about the appropriate amount of treatment to provide to a patient. Compared to physicians, patients lack medical expertise, and medical records do not fully convey a physician's information to third-party payers. As a result, common reimbursement arrangements may not fully align physicians' incentives. Most often, payers reimburse physicians for each unit of treatment ("fee-for-service"). This arrangement can incentivize wasteful spending because a physician may only be willing to accept a marginal payment that exceeds the effective marginal cost. An alternative is to pay physicians an upfront flat fee based on a patient's expected costs. Removing the financial incentive to spend more time with patients may result in inadequate treatment. Moreover, insurance programs typically use a uniform fee schedule, which sets the same incentives for all physicians.[1] However, a physician's socially efficient incentive structure may vary with unobserved characteristics like an idiosyncratic cost of effort.

I present the first empirical evidence that replacing a single fee schedule with a shared menu of contracts can improve patient health without increasing spending. A menu allows each physician to choose a combination of a fee-for-service rate and a flat fee. I show how, for some distributions of unobserved physician heterogeneity, a menu can efficiently separate physicians across multiple fee-for-service rates. I estimate one such distribution in the context of Norwegian primary care, evaluate the social cost of information asymmetry, and derive a budget-neutral and voluntary menu of linear contracts that maximizes patient health. The welfare increase from offering multiple contracts is equivalent to 5 percent of initial expenditure.

I present a model of physician decision-making to quantify the expenditure and health impacts of counterfactual reimbursement schemes. In the model, physicians choose a reimbursement contract and then treatment hours.[2] For each patient on a fixed list, a physician chooses treatment hours to maximize a weighted sum of private net income and patient health production (e.g., as in Ellis and McGuire, 1986).[3] Drawing on novel evidence from plausibly causal reduced-form research designs, I supplement

[1]Fixed administrative fee-for-service rate schedules are employed by public insurers in Australia, Canada, China, Denmark, France, Germany, Japan, Norway, Singapore, Sweden, Switzerland, and Taiwan. These schedules generally cover primary care and sometimes also cover specialist and hospital services. In the United States, 44 percent of healthcare spending is paid by public insurance programs according to a fee schedule and private insurers increasingly negotiate physician reimbursement rates as a multiple of Medicare or Medicaid rates (Gottlieb et al., 2020).

[2]Each contract consists of a base payment per patient-month and a reimbursement rate per unit of treatment, e.g., an hour of patient interactions. In the United States, Medicare reimburses physicians based on the relative time and difficulty associated with furnishing a Medicare physician fee schedule service, measured as "relative value units."

[3]In the model, physicians do not exclude some patients to spend more time with others.

this model with three types of physician heterogeneity: altruism is the weight on patient health relative to private profit, cost of effort represents the difficulty of spending time with patients, and productivity makes treatment more effective in improving health. Compared to a regulator, physicians have private information about both their characteristics and patients' initial illness severity. Patients' health returns to treatment are decreasing in effort and increasing in illness severity.

This model provides intuition for why a budget-neutral menu of contracts can sometimes increase patient health relative to a default uniform contract. A menu can increase the effort of physicians who spend relatively little time with patients. To see this, consider a simplified example with two physicians and a two-contract menu, which consists of a low-rate contract ($45 per hour and $b per patient) and a high-rate contract ($50 per hour and $0 per patient). For each physician, there is a social gain and a private gain from increasing the fee-for-service rate from $45 to $50. A menu outperforms a uniform contract when the social gain and private gain are larger for the same physician. In that case, only the physician with the larger private gain (which exceeds $b) will choose $50. The social gain – the health benefit of increased physician effort – is larger for the physician who works fewer hours at $45 per hour, because the patients of these physicians have similar needs.[4]

Depending on the correlation structure of physician heterogeneity, private and social gains may be aligned so that a menu of contracts can strictly increase welfare. Continuing the example, suppose that the two physicians vary in cost of effort and altruism. First, an older physician might work fewer hours at $45 due to trouble hearing patients (high cost), which implies a larger social gain of switching to $50. Second, a rural physician might have long-term relationships with patients (high altruism), leading to a larger private gain from switching to $50, because he especially values the incremental health. Combining these two forces, a menu can efficiently allocate an older rural physician to a high fee-for-service rate and a younger urban physician to the low rate. On the other hand, a menu is unlikely to be efficient if one physician has relatively high cost and low altruism, e.g., from being older and urban. High cost and low altruism both lower treatment hours, so in this case, the private gain is small while the social gain is large. For the same reason, a menu is unlikely to be efficient if physicians only vary along one dimension.

For a menu to improve a uniform contract, physicians must be sufficiently differentiated. I find novel reduced-form evidence that Norwegian primary care physicians vary along multiple dimensions. Consistent with heterogeneity in cost of effort, treatment hours vary widely across observably similar patients,

[4]This simplified example also assumes that locally, patient health increases in treatment hours, but the benefits may not outweigh costs of effort.

and persistent physician heterogeneity explains a large share of this variation.[5] Consistent with heterogeneity in productivity, some physicians cause worse health outcomes among quasi-randomly assigned patients.[6] Consistent with heterogeneity in altruism, treatment hours change heterogeneously across physicians in response to increased reimbursement rates.[7] With this multi-dimensional heterogeneity, physicians' efficient reimbursement rates may be dispersed enough that a menu of contracts can meaningfully increase efficiency. Still, to simulate the effects of counterfactual reimbursement schemes, I need to estimate the joint distribution of physician heterogeneity including its correlation structure.

Norway's institutional setting and data are particularly well-suited for estimating each physician's cost of effort, altruism, and productivity. I exploit a large and sudden increase in the reimbursement rate to identify altruism. Local regulations rule out several sources of potentially confounding variation. For example, payment rates are otherwise uniform across physicians and physicians do not choose their patients. Moreover, the restricted administrative data reflect the public healthcare utilization of nearly all Norwegian residents. I observe individual procedures, detailed demographics, medical histories, and adverse outcomes like avoidable hospitalizations and mortality. To estimate parameters of the structural model, I construct a balanced sample of registered patients and maximize the likelihood of observed treatment hours.[8] With patient records outside of the estimation sample, I can relax and test assumptions that may be necessary in other settings.[9]

I estimate considerable heterogeneity in physicians' marginal cost, altruism, and patients' treatment needs, implying large social costs of information asymmetry. Parameter estimates accurately predict treatment hours across physicians and across time for each physician, even for physicians outside of the estimation sample. With perfect information, the regulator would offer a different contract to each physician. Physician heterogeneity corresponds to widely dispersed full-information fee-for-service rates which incentivize greater treatment hours, increasing welfare by \$8.39 per patient-month or approximately 70 percent of baseline spending.[10] Welfare reflects patients' benefits from incremental treatment hours, as

[5]Figure A.6 illustrates the identification intuition. On average, a physician with a high cost of effort treats all types of patients less than an otherwise similar physician with a low cost of effort.

[6]Productivity augments treatment hours in health production, so treatment hours are less dispersed among patients of a high-productivity physician than among patients of an otherwise identical low-productivity physician.

[7]Relatively altruistic physicians are less responsive to a reimbursement rate increase because they have less scope to vary treatment hours. At any reimbursement rate, these physicians sacrifice profit to further improve patient health.

[8]I focus on total treatment hours rather than subsets of care like procedures or diagnostics, which represent a small share of reimbursement and time. In Norway, primary care physicians screen for illness, manage chronic conditions, approve paid sick leave, and refer patients to specialist and non-emergency hospital services.

[9]For example, I test whether physicians' hours bunch at capacity constraints, whether patients systematically sort toward physicians with high health production, whether physicians with reimbursement rate increases are selected on unobserved characteristics, and whether in-sample patients and physicians are nationally representative.

[10]All welfare comparisons are measured relative to the status quo before observed reimbursement rates increase.

perceived by physicians. The underlying assumption is that physicians all perceive the same production function that maps treatment hours and patient need to a socially relevant measure of patient health. Alternative measures have limitations: for example, inadequate primary care may not have measurable effects on adverse health outcomes until several years later, in part because outcomes like mortality are rare and highly random. Likewise, due to asymmetric information, patient satisfaction may have a weak relationship with objective treatment quality.

With imperfect information about physician heterogeneity, the optimal menu of contracts still meaningfully increases welfare over the status quo. The difference amounts to \$33 million per year across the Norwegian population. For comparison, the best uniform contract improves welfare by \$22 million. The menu consists of seven traded contracts that mostly exchange higher fee-for-service rates for lower base payments. Higher rates imply greater perceived health for all patients. Gains are largest among patients with high need and low initial treatment, and these patients tend to have physicians with high cost of effort and low altruism. All else equal, these physicians have low private gains from high fee-for-service rates, but an efficient separation of physicians across contracts is possible because of variation in productivity and patient characteristics that shift severity.

Relative to the status quo, the gains from a menu of linear contracts are striking because menus are rarely featured in physician contract design.[11] Relative to full-information contracts, the menu's impact is somewhat modest, highlighting the significance of information asymmetry and the potential for further flexibility in contracting. For example, I find evidence for large regional health disparities because rural communities tend to have both high-severity patients and low-treatment physicians. A national menu of linear contracts helps narrow these disparities, but there is room for further improvement from complementary policies. For example, the regulator could incentivize high-treatment physicians to establish practices in high-need communities.

Several robustness analyses suggest that welfare improvements are not driven by an idiosyncrasy of the empirical approach or setting. For example, counterfactual outcomes are similar when I incorporate more flexible specifications like preferences for leisure or large perturbations to the estimated joint distribution of physicians' cost, altruism, and productivity. Shifting from a uniform contract to a menu of contracts might therefore improve outcomes in settings other than Norwegian primary care.

In this paper I synthesize a large theoretical literature on physician contracting into an empirical

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[11] I study a budget-neutral menu that maximizes patient health. Historically, menu initiatives prioritized lower spending but had limited impact, e.g., Quebec's 1999 reform studied in Fortin, Jacquemet and Shearer (2021) and Medicare's Comprehensive Primary Care model.

framework for menu design. In both this paper and the stylized settings featured in prior work, the distribution of physician heterogeneity determines which types of contracts are efficient (Jack, 2005; Choné and Ma, 2011; Naegelen and Mougeot, 2011; Allard, Jelovac and Léger, 2014; Barham and Milliken, 2014; Wu, Chen and Li, 2017; Wu, 2020; Ji, 2021). I characterize the optimal menu of contracts in terms of parameters that can be estimated with panel variation in reimbursement. I derive the menu for Norwegian primary care physicians to provide the first empirical evidence that any uniform contract is strictly less efficient. I also extend the empirical literature on socially optimal menu design with multi-dimensional consumer heterogeneity from insurance to a new selection market (physician labor supply) while incorporating unique dimensions of heterogeneity (Fang and Wu, 2018; Marone and Sabety, 2022; Ho and Lee, 2023). Similar to the study of health insurance menus in Marone and Sabety (2022), I estimate a joint distribution of agent types and characterize the relative efficiency of a uniform contract. In a parallel exercise, I use the graphical framework from Einav, Finkelstein and Cullen (2010) to provide intuition for how a two-contract menu can increase efficiency for only some distributions of physicians. Outside of healthcare, there are few studies that empirically evaluate menus of contracts in selection markets, where multi-dimensional heterogeneity is first-order (Bellemare and Shearer, 2013; D'Haultfœuille and Février, 2020; Taburet, Polo and Vo, 2024).

I simultaneously estimate three key correlated dimensions of heterogeneity, which extends the literature that separately documents variation in physicians' altruism (Hennig-Schmidt, Selten and Wiesen, 2011; Godager and Wiesen, 2013; Douven, Remmerswaal and Zoutenbier, 2017; Galizzi et al., 2015) and practice style (Epstein and Nicholson, 2009; Chan and Chen, 2022; Doyle, Ewer and Wagner, 2010; Gowrisankaran, Joiner and Léger, 2017). Policies that assume physicians vary along only one dimension may have unintended consequences.[12] Consistent with prior work, I show that physician treatment decisions respond to financial incentives (Brekke et al., 2017; Einav, Finkelstein and Mahoney, 2018; Eliason et al., 2018; Clemens and Gottlieb, 2014; Cabral, Carey and Miller, 2021; Xiang, 2021). I find heterogeneity in this response, and decompose physician heterogeneity into structural physician types and variation in patient treatment need. This decomposition enables welfare analysis in contexts where selection affects both expenditure and healthcare quality.[13]

My framework emphasizes unobserved patient severity and a menu of linear contracts rather than a non-linear uniform contract. In primary care, dermatology, and dentistry – but also non-healthcare

[12]For example, if an insurer believed that physicians only vary in productivity, they might end contracts for physicians with low treatment. However, reimbursing these physicians at higher rates might be more cost-effective.

[13]In a setting with no effects on healthcare quality, Einav et al. (2021) study hospitals' selection into bundled contracts and subsequent changes in spending.

settings like indigent criminal defense – the regulator cannot observe the socially efficient level of effort and instead must rely on altruistic agents to exercise discretion in allocating effort across clients. In such settings, aligning incentives through differentiated contracts can improve welfare relative to targeting a fixed level of effort for each combination of patient and physician. In related work, Gaynor, Mehta and Richards-Shubik (2023) estimate distributions of cost and altruism of dialysis clinics and derive the optimal non-linear uniform contract for an anti-anemia drug. I extend the framework from that paper to include unobserved patient severity and heterogeneity in productivity. Although a nonlinear uniform contract can achieve greater patient health than a menu of linear contracts, the uniform contract is not cost-effective without making many physicians worse off.

In Section 2 I present the theoretical model and provide intuition about the importance of correlated physician heterogeneity. In Section 3 I describe the empirical setting and present novel reduced-form evidence consistent with multi-dimensional physician heterogeneity. In Section 4 I discuss the parameterization and identification to recover the estimates, which are summarized in Section 5. In Section 6 I demonstrate the efficiency of a counterfactual menu of contracts, evaluate robustness, and discuss extensions.

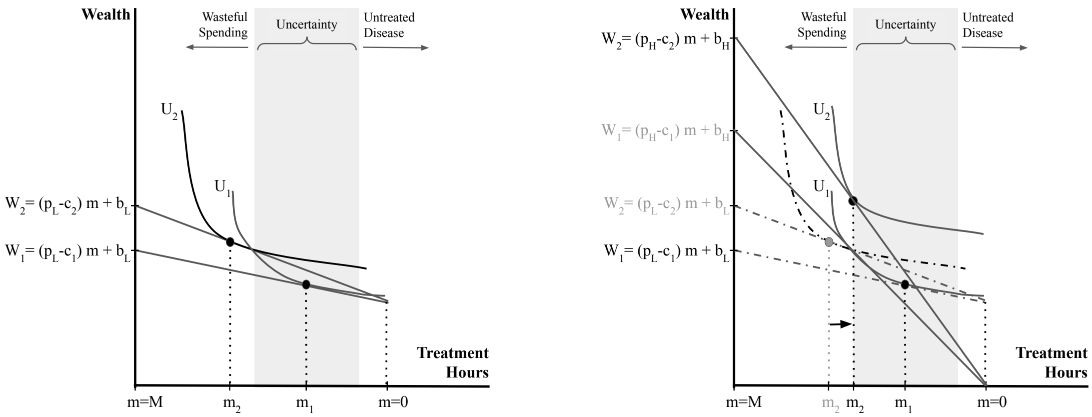
2 Theoretical Framework

2.1 Graphical Intuition for a Menu of Contracts

A uniform contract may be inefficient when physicians are heterogeneous. I first show this using a stylized graphical example. Consider the canonical model in which a worker chooses the number of hours to work $m \in [0, M]$ given a wage contract (p, b), where p is the reimbursement rate and b is the base payment. With this contract and private marginal cost of effort c, the worker earns wealth $W(m) = (p - c)\, m + b$. Privately optimal labor supply is where the indifference curve is tangent to the contract budget constraint. The budget constraint is steeper for smaller values of marginal cost.

Figure 1 plots wealth W against treatment hours m for two physicians, each with their own marginal cost and indifference curve. Typically, a competitive labor market implies that the reimbursement rate p should be the marginal product of labor. In many healthcare markets, the regulator does not observe the underlying treatment need, so the efficient level of labor supply is also unobserved. Labor supply that is too high may correspond to wasteful spending. Labor supply that is too low may lead to untreated disease. The shaded region reflects the regulator's uncertainty about patient severity and, consequently,

Figure 1: Two Contracts May Be More Efficient Than One



(a) Initial Uniform Contract

(b) Menu of Contracts

Notes: This figure shows a stylized example with two physicians, in which a two-contract menu is more efficient than a uniform contract. The x-axis plots treatment hours $m \in [0, M]$ from right to left. Each panel shows the indifference curves of these physicians and the budget constraint(s) implied by simple reimbursement contract(s) with a base payment b and an hourly wage p. The shaded region includes the efficient level of labor supply which is unobserved to the regulator. In the left panel, the single status quo contract is efficient only for Physician 1. In the right panel, the regulator optimally offers a menu with two contracts to lower the labor supply of Physician 2.

the efficient level of labor supply. The figure is drawn in Panel A so that the initial uniform contract (p_L, b_L) is likely efficient for Physician 1, but the labor supply of Physician 2 is inefficiently high. Panel B introduces a second contract with a higher reimbursement rate p_H and a lower base payment b_H. Physician 2 chooses the new contract and lowers labor supply while increasing wealth. Labor supply is unchanged for Physician 1, who is indifferent between the two contracts.

The introduction of a second contract increased expenditure and moved labor supply closer to the efficient level. Whether this is efficient depends on the costs and preferences of physicians, as well as the social tradeoff between expenditure and patient health. Figure A.1 shows a counterexample where a uniform contract is efficient. If the physicians are nearly identical, then the differences between their choices of labor supply under a uniform contract may be negligible. Likewise, a uniform contract with a sufficiently large reimbursement rate p and small base payment b can induce any two physicians with quasi-concave preferences into the shaded region, but improvements in patient health may not justify the corresponding increase in expenditure. Below, with multi-dimensional heterogeneity for a continuum of physicians, the relative efficiency of a uniform contract still depends on the distribution of physician types and the social tradeoff between health and expenditure.

2.2 Model

I develop a model of physician decision-making to quantify expenditure and health outcomes under counterfactual menus. In the model, each physician has private information about her multi-dimensional type and patients' illness severity. A regulator designs a menu from which each physician chooses a contract. Next, each patient's severity of illness is drawn from a known distribution. Based on the severity and contract, the physician chooses the treatment intensity for each ill patient. Treatment intensity, physician productivity, and illness severity jointly determine a patient's health benefits.

Reimbursement Contracts. A contract maps treatment intensity m into a physician's revenue $x(m)$. Motivated by the empirical setting, I focus on contracts with a linear form, also called a two-part tariff: $x(m) = p\,m + b$. For example, the average physician in my sample receives $p = \$43$ per hour of patient interactions and $b = \$4$ per registered patient per month.[14]

The Physician. A physician determines treatment intensity m for each registered patient on a panel. Ex-ante, patients are characterized by a distribution of illness severity, $F(\lambda)$. Ex-post, realizations of severity λ are only observed by the physician. The physician also has private information about her type $\theta = \{c, \alpha, \gamma\}$, which is distributed in the population according to $G(\theta)$. Private cost of effort c is an opportunity cost of providing treatment. Altruism α is the weight on utility derived from patient health production relative to utility derived from net income. Both intrinsic and extrinsic forces may motivate physicians to value patient health, e.g., prosociality and reputation. Productivity γ^{-1} measures physician skill in terms of how efficiently treatment intensity translates into patient health benefits. A high-productivity physician needs relatively low effort to produce a certain amount of patient health. This notion of productivity is distinct from heterogeneous diagnostic skill (e.g., Abaluck et al., 2016). Here, a low-skill physician always requires more time to fully treat patients, rather than sometimes under-diagnosing them.

Before observing realized patient severity, the physician chooses the contract with the highest expected indirect utility: $p^*_\theta = \arg\max E\left[V(p;\lambda,\theta) \mid \lambda \sim F\right]$. Following the literature on physician-induced demand, e.g., Ellis and McGuire (1986), indirect utility V is a weighted average of private net income $(p - c)\,m + b(p)$ and patient health production $h(m, \gamma\lambda)$:

$$V(p;\lambda,\theta) \equiv \max_{m\geq 0}\,(p-c)\,m + b(p) + \alpha h(m,\gamma\lambda)\,. \tag{1}$$

[14] Sections 3.2 and B.2 describe how I calculate reimbursement per hour using data on higher-resolution services, e.g., visits, procedures, and diagnostics.

After selecting a contract, the physician observes each patient's severity and chooses a corresponding quantity of treatment: $m^*(p) = \arg\max V(p; \lambda, \theta)$. Incremental treatment will earn additional revenue and influence patient health, but the value does not necessarily outweigh the additional cost of effort.[15]

The Regulator. The regulator observes the distributions of physician types θ and patient severity λ but not the realizations. The regulator chooses the menu of contracts $b(p)$ to maximize expected patient health production subject to a global budget constraint and each physician's participation constraint.[16] Expenditure, i.e., total payments to physicians, cannot exceed the budget threshold, which incorporates the government's opportunity cost of healthcare spending. Non-health goods and services are also valued and taxation may distort behavior. Participation in the public system is optional, so the expected indirect utility of the physician must stay above a threshold. In the long run, physicians may choose an alternative medical specialty, practice location, or non-healthcare occupation. Physician exit is undesirable because a small number of physicians cannot realistically treat all patients.

The regulator's objective is:

$$\begin{aligned} \max_{b(p)} \quad & \int_\theta E[h(m^*(p^*_\theta;\theta), \gamma\lambda; \theta) \mid \lambda \sim F]\, dG(\theta) && (2) \\ \text{s.t.} \quad & \int_\theta E[p^*_\theta m^*(p^*_\theta;\theta) + b(p^*_\theta) \mid \lambda \sim F]\, dG(\theta) \leq \bar{B} && [\mu_B, \text{ Budget}] \\ & E[V(p^*_\theta;\theta) \mid \lambda \sim F] \geq \bar{v}(\theta), \ \forall\theta && [\mu_{P,\theta}, \text{ Participation}] \end{aligned}$$

where μ_B and $\mu_{P,\theta}$ are the shadow costs of expenditure and participation.[17] The social objective partially coincides with the physician objective because of altruism and the participation constraints, but otherwise differs because the regulator is budget-constrained, limiting physician payments. The optimal menu of contracts ("second best") satisfies the constraints as well as the first-order condition: in expectation, marginal health production equals marginal reimbursement minus marginal indirect utility, weighted by shadow costs:

$$\int_\theta E\left[h_m(m^*(p^*_\theta;\theta), \gamma\lambda) - \mu_B p^*_\theta m^* + \mu_{P,\theta} V_m(p^*_\theta, \theta) \mid \lambda \sim F\right] dG(\theta) = 0\,.$$

[15] Appendix A.3 relaxes and tests the assumption of linear cost of effort with a taste for leisure and a constraint on aggregate treatment intensity.

[16] Equivalently, the regulator maximizes a weighted sum of expectations over health production, expenditure, and physician indirect utility. In reality, it may be politically difficult to increase healthcare budgets even with a positive aggregate net impact, so I focus on strict constraints for exposition and counterfactual analysis.

[17] Privately optimal treatment intensity also depends on patient severity λ which is omitted for readability.

The first-order condition provides intuition about how physician quality is context-dependent, so physicians are not necessarily vertically differentiated. The degree to which a physician contributes to the social objective depends on both the type θ and menu $b(p)$: $h(m^*(x;\theta), \gamma\lambda) - \mu_B p_\theta^* m^* + \mu_{P,\theta} V(x,\theta)$. Likewise, persistent variation in treatment intensity across physicians does not necessarily convey quality.

To benchmark social efficiency, consider the regulator's problem without information asymmetry about physician types θ. In this case, the regulator sets a personalized contract for each physician. The base payment b_θ^{FB} is just high enough for each participation constraint to bind, and the reimbursement rate p_θ^{FB} induces the efficient level of treatment intensity, $m^*(p_\theta^{FB};\theta)$ ("first-best"). Now, a stricter condition can hold for every physician:

$$E\left[h_m(m^*(p_\theta^{FB};\theta), \gamma\lambda) - \mu_B p_\theta^{FB} m^* + \mu_P V_m(p_\theta^{FB}, \theta) \mid \lambda \sim F\right] = 0\,.$$

This first-order condition implies that the efficient reimbursement rate increases with physicians' marginal cost and decreases with altruism (See Appendix C.1). As the budget constraint relaxes, this level converges to private marginal cost.

2.3 Conditions for Efficient Self-Selection

The principal question of this paper is whether introducing a choice among contracts ("self-selection") is socially efficient. With the stylized example in Figure 1, a menu of two contracts may be more efficient than a uniform contract, but this depends on the distribution of types and the social tradeoff between health production and expenditure. This subsection extends that intuition to the full model: when starting from a reference contract, under what conditions will introducing a second contract strictly increase social welfare? I present a sufficiency condition and illustrate how efficient self-selection is facilitated by a dispersed and correlated distribution of cost, altruism, and productivity. From comparative statics, physicians who choose the high reimbursement rate will have relatively low cost, high altruism, and high productivity because they have the largest private benefit, all else equal. Increases in the reimbursement rate also lead to relatively large increases in public expenditure among these physicians, potentially outweighing the gains in health production.

Suppose that the regulator starts with a reference contract (p_L) and adds a higher fee-for-service contract to the menu (p_H). This two-contract menu increases efficiency if expected health production increases among the set of physicians who prefer the higher reimbursement rate, without increasing average expenditure. Let $\Delta z(p) \equiv z(p_H) - z(p_L)$, then

$$E[\Delta h(m(p), \gamma\lambda) \mid \Delta E\,V(p) \geq 0, \Delta E[pm(p) + b(p)] \leq 0] \geq 0\,. \tag{3}$$

All physicians who choose p_H will increase treatment intensity relative to p_L. If h is locally monotonic and concave in m, then an increase in treatment intensity necessarily increases health production. As a result, the problem simplifies to a question of feasibility: are any physicians willing to choose the high contract when the reduction in base payments offsets expected increases in fee-for-service reimbursement? Necessarily, physicians choosing the high fee-for-service contract must value incremental health production more than incremental costs on average. Importantly, physician contract choice is a selection market – expenditure on the high-fee-for-service contract depends on the set of physicians who choose it. A decrease in expenditure on base payments must offset both the mechanical ($m(p_L)\Delta p$) and behavioral ($p_H \Delta m(p)$) increases in fee-for-service expenditure among physicians who choose the high-fee-for-service contract:

$$E\left[\Delta\left(pm(p,\lambda) + b\right) \mid \Delta E[V(p,b,\lambda)] \geq 0\right] \leq 0 \tag{4}$$

Comparing the partial derivatives of indirect utility and expenditure highlights the roles of correlation and dispersion.[18] Physicians are more likely to choose the high-fee-for-service contract if they have low cost, high altruism, high productivity, or high patient severity $E\lambda$.[19] If physicians only vary along one of these four dimensions, self-selection leads to more positive incremental expenditure, potentially violating the budget constraint. In direct contrast, physicians are most likely to decrease expected fee-for-service expenditure if they have high cost, low altruism, low productivity, or low patient severity, all else equal. With correlation among physician types, partial derivatives do not necessarily imply that physicians who most prefer higher rates will most increase expenditure, e.g., those with both high cost and high altruism.

The sufficiency condition for efficiently adding a high-fee-for-service contract requires additional assumptions to generalize to the broader question of menu design with any number of contracts. For example, if the fee-for-service rate of the reference contract is lower than the optimal uniform contract, it may be efficient to add a higher fee-for-service contract that attracts all physicians. A separating

[18] See Appendix C.1 for derivations and a similar discussion with weaker assumptions.

[19] As an aside, these statics may also be informative about the characteristics of physicians who choose to accept long-term positions with fee-for-service rather than salary reimbursement, e.g., private practice vs. HMO employment in the United States.

equilibrium in which more than one contract is traded also requires that some physician types prefer the low-fee-for-service contract: $\exists\theta : \Delta V(p, \theta) < 0$. With menus of three or more contracts, it may be efficient to offer a contract that decreases health production among some physicians if that lowers expenditure enough to efficiently subsidize higher fee-for-service rates and health production for other physicians. As a starting point, the intuition from the sufficiency condition is helpful for re-framing the problem as a sequence of two-contract menus that span a large set of reimbursement rates.[20]

3 Empirical Setting

The theoretical framework establishes that for some distributions of physician types, a menu of contracts can increase welfare relative to a uniform contract. Here I extend the framework to estimate such a distribution, derive the optimal menu, and measure its impacts. I first explore several necessary assumptions in the setting of Norwegian primary care. I present institutional details in Section 3.1 which support the assumption that the focal variation in treatment intensity is driven by physician heterogeneity and contracts rather than patient composition. In Section 3.2 I detail the construction of a balanced estimation sample of patients that further removes potentially confounding variation. In Section 3.3 I introduce reduced-form evidence consistent with physician heterogeneity in cost, altruism, and productivity, which suggests that the status-quo uniform contract may be inefficient.

3.1 Institutional Setting

In Norway, each practicing primary care physician can increase their reimbursement by becoming certified as a general practitioner. In 2023, physicians without the certificate received \$33 for a basic consultation and certified physicians received \$44. As a result, with no changes to treatment intensity, a newly certified physician would suddenly earn 24 percent more fee-for-service revenue.[21] Crucially for causal inference, certification does not formally change a physician's patient pool, treatment options, or responsibilities. Physicians become eligible for the certificate by completing two years of additional part-time training and also having four years of full-time practice experience. Training includes both coursework and small-

[20] In the closely related context of health insurance contracts, Chade et al. (2022) "decouple" a similar menu design problem. This requires quasiconcave household utility with respect to insurance coverage level. In the empirical application, I find that the optimal menu meets a related condition: each physician's expected indirect utility is quasiconcave with respect to reimbursement rate among traded contracts.

[21] 24 percent reflects an average within the estimation sample, including reimbursement for other services provided during consultations.

group meetings with other physicians, guided by national learning objectives.[22] Once the training is completed, physicians can apply for the certificate, which they typically receive after several months. Supplementary payments begin around that time and continue for five years. Before 2017, 80 percent of physicians received this certificate during their careers.[23]

Apart from certification, physicians face nationally uniform reimbursement incentives. On average, physicians receive 70 percent of their revenue from fee-for-service payments, at rates listed in a national administrative schedule.[24] For example, in 2021, physicians received $17 for an E-consultation, made up of $16 from national health insurance and $1 from a patient copay (Legeforening, 2022).[25] In 2023, the schedule included 189 reimbursement codes, covering broad categories of physician services. The most commonly billed codes cover unspecified time spent with patients, rather than a specific procedure or diagnostic, highlighting the importance of physicians' discretion in choosing treatment intensity (See Table A.1).[26] The other 30 percent of revenue comes from base payments of approximately $4 per registered patient per month. Both fee-for-service rates and base payments are negotiated annually between the regulator and the physicians' union. If prices were instead negotiated individually between physicians and payers, as is common in the United States, it would be difficult to attribute variation in treatment intensity to reimbursement rates rather than physician skill or patient composition.

Within the scope of these national reimbursement agreements, physicians contract directly with municipalities. Among other details, these contracts stipulate the maximum number of registered patients and opening hours. Each physician agrees to meet the primary care treatment needs of between 500 and 2500 registered patients. National guidance states that physicians must be accessible to registered patients within contracted opening hours and that patients should not wait more than five days for a consultation in most circumstances (Lovdata, 2017). If physicians are unavailable, registered patients may seek treatment from stand-alone urgent care centers. Physicians provide consultations about symptoms, diagnostic tests, and general medical procedures to registered patients. They also sign off on sick leave and refer patients to all specialist and non-emergency hospital services.

Patients often choose to remain with their registered physician for years at a time. One contributing

[22] In 2019, physicians needed to meet 88 learning objectives. For example, Objective #18 is to understand challenges with over- and under-treatment.

[23] In March 2017, it became mandatory for most primary care physicians to start training toward certification. In March 2019, municipalities became responsible for facilitating supervised hours requirements and subsidizing part of the costs.

[24] As of 2016, over 95 percent of physicians face this mixed contract. The remainder are fixed-salary employees of municipalities with no fee-for-service reimbursement.

[25] Once a patient reaches an annual individual cap on copayments, the public insurer funds the entire $17.

[26] In the United States, most claims for primary care consultations also include one of a small number of procedure codes.

factor is the centralized registration system, which allows patients to request a new physician twice per year. Patients can choose any physician who has fewer patients than the contracted maximum. The choice set changes infrequently due to the national licensing system, which fixes the total number of local physicians in the short term. I am able to construct a representative balanced panel for the estimation sample because physicians and patients tend to have long-term relationships.

3.2 Data

The estimation sample is a balanced panel of patients who are registered to certified physicians in the six months before and after certification (a "spell").[27] I focus on short-term variation and fix the composition of patients to attribute any sudden change in treatment intensity to the sudden change in marginal reimbursement. I construct the sample using restricted administrative records on registration, individual demographics, and healthcare reimbursement, which are maintained by Statistics Norway and the Directorate of Health.[28] These records nearly span the universe of Norway's residents and primary care physicians from 2008 to 2017.

The estimation sample excludes potentially confounding variation. First, each physician must only practice in one location during the entire period and each patient must be registered for the entire period. Second, both the physician and patient must have identification numbers to attribute treatment intensity to a particular physician of interest, which excludes recent migrants. I separately consider primary care from urgent care centers or second opinions. Third, each physician must provide some treatment during every month of the spell to exclude irregular variation that arises from the physician's absence, e.g., an anticipatory effect or temporary replacement physician. Table A.2 provides more detail on sample selection. In robustness analyses, I compare the estimation sample to a similarly defined control sample that includes patients whose physicians do not experience sudden changes in reimbursement.[29]

I construct measures of treatment intensity and marginal reimbursement rates that aggregate over the particular types of services provided. Treatment intensity m equals patient-month fee-for-service revenue divided by marginal reimbursement. This measure of intensity roughly corresponds to hours of treatment per patient-month ("simulated hours"). Marginal reimbursement p_{kt} is a "simulated wage"

[27] I classify the first month a physician is certified based on when they first receive a supplementary payment, including reimbursement codes 2dd, 2dk, 6ad, 11dd, 11min, and 14d, which is generally consistent with the certification date.

[28] See Appendix B.1 for additional details on data sources.

[29] To accommodate computer memory constraints, I use a 10-percent random subsample of physicians who never receive the certification supplement during the study period. I randomly select a 13-month spell that meets the same conditions as the main estimation sample, except for certification. Spells prior to certification are also safe comparisons, but I exclude these from the control sample to be conservative when analyzing selection into certification.

Table 1: Registered Patient Summary Statistics

	Control Sample	Estimation Sample					
	Mean	Mean	Std. Dev.	% > 0	10th	50th	90th
Patient Characteristics							
Reimbursement	8.59	8.33	25.49	20.74	0.00	0.00	30.92
Simulated Hourly Rate	43.82	43.76	6.86	100.00	32.38	45.49	50.95
Simulated Hours	0.19	0.18	0.56	20.74	0.00	0.00	0.68
Base Payment	4.03	4.01	0.11	100.00	3.84	4.02	4.13
Age	40.54	37.57	22.78	100.00	6.67	36.58	69.00
Chronic Illness	0.23	0.21	0.41	21.03	0.00	0.00	1.00
Months Registered	43.89	40.93	32.32	98.99	6.00	36.00	84.00
Physician Characteristics							
Max Enrollment	1268.60	1273.48	293.21	100.00	900.00	1220.00	1600.00
Physician Hours/Week	28.36	26.56	9.44	100.00	13.13	27.33	37.27
Physician Age	42.87	40.23	5.92	100.00	34.08	38.83	48.67
Patients Age 60+	0.23	0.19	0.10	100.00	0.07	0.18	0.32
Patients with Chronic Illness	0.23	0.21	0.06	100.00	0.14	0.20	0.29
Patients	131800	643363					
Physicians	136	619					

Notes: Summary statistics reflect registered patients' monthly totals six months before certification (or a randomly selected month for patients in the control sample). % > 0 indicates the share of patients with a strictly positive measure (row). Other columns reflect the mean, standard deviation, and 10$^{\text{th}}$, 50$^{\text{th}}$, and 90$^{\text{th}}$ percentiles. Monetary measures are in USD. Physician Characteristics are also averaged across patients. The last two Physician Characteristics reflect shares of registered patients.

equal to the reimbursement per hour a physician would receive for providing the average bundle of services to a patient of type k in month t. I group patients with similar characteristics into ten types, and for each type, I use all Norwegian patients to calculate the average bundle of services received and the average hours required to provide that bundle.[30] I inflate all money-metric variables by Norway's monthly all-goods-and-services CPI to January 2023 USD.

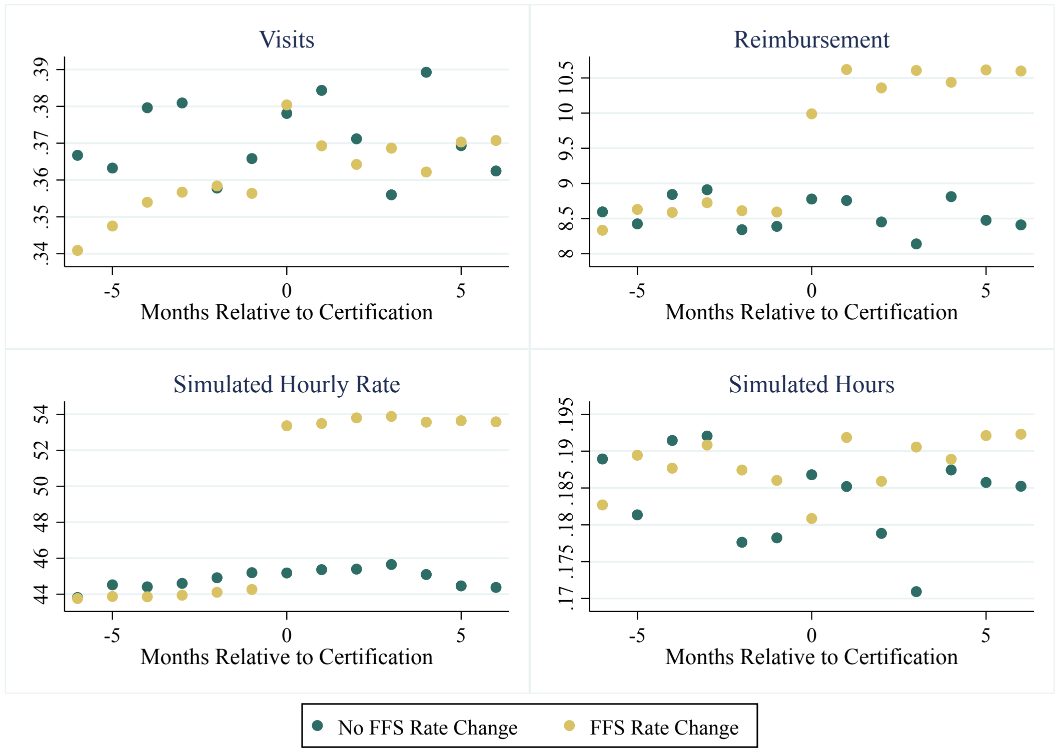
The final estimation sample is approximately representative, and it includes 619 unique physicians and 643,363 patient-spells (13 months each).[31] Table 1 describes the distribution of selected characteristics and outcomes six months before certification, and three facts stand out.[32] First, most patients do not visit their physician during a typical month. Second, the average physician spends 28 hours per week with registered patients (90$^{\text{th}}$ percentile = 37) suggesting that with sufficient reimbursement, physicians can increase treatment intensity. Third, there is meaningful heterogeneity across physicians for proxies

[30] See Appendix B.2 for additional details on constructing measures. For example, hours reflect time spent in encounters with registered patients and not work like administrative tasks. Table A.3 shows average characteristics and sample share separately for each patient type, including the simulated wage.

[31] When estimating the structural model, I split this sample into three parts and use the best-fitting set of estimates.

[32] See Table A.4 for the distributions of additional variables. See Table A.5 for comparisons to the Norwegian population: patients have similar characteristics, and certifying physicians are more often young and female.

Figure 2: Raw Means of Treatment Intensity Relative to Certification



Notes: These plots show averages of treatment intensity outcomes across patient-months in the estimation and control samples in each month relative to certification. Each sample is a balanced panel of patients, and in the estimation sample, Month 0 is the first month in which the registered physician received a certification supplement. I include registered patients' Visits and fee-for-service Reimbursement for the focal certified physician. Simulated hours equals monthly reimbursement divided by the Simulated Hourly Rate, an aggregation of service-level reimbursement rates that varies with patient characteristics, described in Appendix B.2.

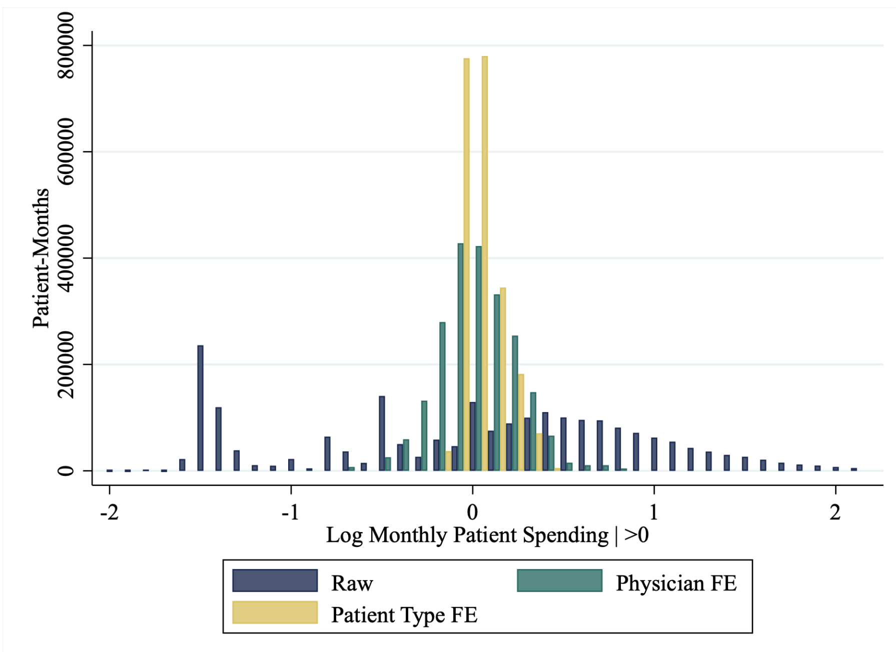
of mean patient severity like average age and chronic illness.

Trends suggest that treatment intensity varies systematically with marginal reimbursement and short-run changes are persistent. Figure 2 plots the trend in raw means, showing that visits, total reimbursement, and simulated hours all increase suddenly after certification in the estimation sample but not the control sample. Unlike treatment intensity, trends in the number and composition of registered patients do not change with certification (See Figure A.2). These plots and most subsequent analyses reflect short-run variation around the sudden change in incentives which usually occurs months after physicians complete the prerequisite training. Short-run variation might obscure differences in long-run trends between certified and non-certified physicians that limit validity. For example, physicians who pursue certification might also make cost-reducing investments, or training might have delayed effects. Mitigating these concerns, Figure A.3 shows that even over five years, certification corresponds to a sudden and persistent increase in related measures of treatment intensity. Raw means suggest that the effects of certification might be overstated if using a longer time horizon, because treatment intensity dips during the middle of training.

3.3 Stylized Facts

A necessary condition for physician self-selection is variation in physician types. I show novel reduced-form evidence consistent with heterogeneity in physicians' cost, altruism, and productivity. First, I show descriptively that observably similar patient receive more treatment at some physicians than at others, driving a large share of variation in treatment intensity. Second, I exploit quasi-random patient assignment to estimate the heterogeneous causal effects of physicians on treatment and adverse outcomes, consistent with variation in cost and productivity. Third, with a stacked difference-in-differences model, I show that treatment intensity increases in marginal reimbursement across a range of measures, highlighting the role of altruism. Fourth, I show heterogeneity in this effect, which suggests dispersion in altruism.

Figure 3: Decomposition of Treatment Intensity



Notes: This histogram shows the plot of log reimbursement for patient-months in the estimation sample with any utilization (Raw), as well as fixed effects from a regression of that outcome on an indicator for post-certification, physician fixed effects, high-resolution fixed effects for patients with similar observed characteristics (combinations of age bins, primary diagnosis, gender, and an indicator for lagged hospitalization), and a quadratic function of patient age.

Cost and Productivity. Figure 3 shows the persistent variation across physicians in how intensively they treat observably similar patients. To make this comparison, I regress log reimbursement on fixed effects for each physician and 108 bins of patients with similar observed characteristics, as well as other controls.[33] Reimbursement per patient-month is approximately log-normally distributed with significant dispersion, while variation across patients with different observed characteristics (e.g., age, gender, chronic diagnoses) is relatively small. The limited dispersion across patients' observed characteristics implies that the regulator can only weakly predict patients' underlying treatment need and must generally defer to physicians' judgment about the appropriate level of treatment intensity. Physician fixed effects are more dispersed, highlighting the large role of physicians in treatment intensity, similar to recent work such as that of Badinski et al. (2023).

These physician fixed effects should not be interpreted causally if, for example, patients with high unobserved severity systematically register with certain physicians. Fortunately, conditionally random patient assignment in Norway allows me to recover plausibly causal estimates of assignment to each physician ("assignment effects") on subsequent log treatment intensity, following the approach in Ginja et al. (2022).[34] As shown in Figure A.5, there is substantial dispersion in these physician effects even after shrinking effects to account for estimation error, reinforcing the importance of persistent physician heterogeneity. Limited patient selection is consistent with evidence from Norway that a patient's choice of physician is uncorrelated with the physician's effect on mortality (Ginja et al., 2022). In Norway and other settings, patients tend to respond to public measures of quality like star ratings (Bensnes and Huitfeldt, 2021; Vatter, 2022; Brown et al., 2023; Chartock, 2023). By contrast, treatment intensity does not appear to drive patient switching (Iversen and Lurås, 2011).

Continuing to use random patient assignment, I estimate effects of individual physicians on related outcomes to distinguish cost and productivity as drivers of persistent physician heterogeneity. In the model, low-productivity physicians treat patients multiplicatively more – leading to variation in assignment effects on log reimbursement – while low-cost physicians treat patients additively more – leading to variation in levels of reimbursement. Figure A.5 shows significant variation among both sets of assignment effects. For example, moving from the 10^{th} to 90^{th} percentile of physician treatment intensity

[33]I regress log reimbursement on an indicator for post-utilization, physician fixed effects, high-resolution patient observed-type fixed effects (combinations of age bins, primary diagnosis, gender, and an indicator for lagged hospitalization), a time trend, and a quadratic function of patient age, among patient-months with positive reimbursement.

[34]When one physician exits, the municipality reassigns remaining patients to nearby available physicians, and the assignment is conditionally random. This variation exists for a subset of physicians. The research design compares patients of the same exiting physician who are assigned to different nearby physicians to recover those nearby physicians' assignment effects, controlling for the exiting physician, year, and nearby physician's municipality and availability. I shrink all physician assignment effects using Empirical Bayes.

corresponds to 1.19 additional visits each month over a patient mean of 0.34. I also estimate dispersion in assignment effects on avoidable hospitalization, which is largely uncorrelated with assignment effects for treatment intensity. This pattern suggests that due to physicians, health can vary even among patients with identical treatment hours and illness severity. Other natural experiments show dispersion across physicians in measures of productivity like resource use and skill, e.g., avoiding hospital readmissions (Doyle, Ewer and Wagner, 2010; Gowrisankaran, Joiner and Léger, 2017; Chan, Gentzkow and Yu, 2022; Chan and Chen, 2022; Kwon, 2023).

Altruism. Altruism is identified by how physicians' choice of treatment intensity responds to the reimbursement rate. Intuitively, relatively altruistic physicians have less scope to change treatment intensity when the reimbursement rate changes. At any reimbursement rate, these physicians sacrifice profit to provide greater health production.[35] To evaluate the effect of higher reimbursement from certification on treatment intensity, I estimate the following stacked difference-in-differences regression:

$$Y_{ijt} = \beta_1 Post_{jt} \times Certified_j + \boldsymbol{\beta}_x \boldsymbol{X}_{jt} + \gamma_i + \gamma_{y(t)} + \gamma_{m(t)} + \epsilon_{ijt} \tag{5}$$

where Y_{ijt} is the outcome of interest for patient i of physician j in month t. $Post_{jt}$ is an indicator for months in which physicians receive certification supplements, $Certified_j$ indicates the main estimation sample of certified physicians rather than randomly selected non-certified physicians. β_1 is the coefficient of interest, X_{jt} is a vector of practice characteristics following Brekke et al. (2017), and $\gamma_i, \gamma_{y(t)}, \gamma_{m(t)}$ are fixed effects for patient, year, and calendar month.

A threat to identification would require that patients of certified physicians systematically need more treatment in the six months after certification than in the six months before for reasons other than certification, beyond the variation captured by time-invariant differences between patients and shared time shocks. Such variation is unlikely. First, physicians are not suddenly eligible to provide more expensive services. Second, as shown in Figure 3, future treatment need is difficult to anticipate, so physicians likely have little scope or incentive to strategically time their application for certification after completing the training. Alternative explanations are generally incompatible with Figure 2, which shows that average reimbursement does not trend differently for certified versus non-certified physicians in the months before certification.[36]

[35] For any health production function with fixed concavity, the responsiveness of treatment intensity to marginal reimbursement, $\frac{dm}{dp}$, is proportional to inverse altruism, $\frac{1}{\alpha}$, among patients with positive treatment intensity.

[36] See Section 3.2 for discussion of the long-run variation shown in Figures A.3 and A.13.

Table 2: Main Effects of Certification on Treatment Intensity

	Post × Certified		Mean (Pre)	R^2	Obs.
Visits	0.015***	(0.001)	0.355	0.401	9,301,956
Reimbursement	2.093***	(0.106)	8.581	0.213	9,301,956
Simulated Hours	0.006**	(0.002)	0.187	0.186	9,301,956
Procedures	−0.001	(0.001)	0.071	0.237	9,301,956
Diagnostics	0.009***	(0.002)	0.229	0.266	9,301,956
Extra Time Codes	0.002***	(0.001)	0.086	0.230	9,301,956
Other Reimbursement	−0.303***	(0.076)	2.486	0.099	9,301,956
Specialist Reimbursement	0.245	(0.310)	19.702	0.190	9,301,956
Acute Hospitalizations	−0.000	(0.000)	0.019	0.153	9,301,956

Notes: This table estimates equation 5 using the pooled estimation and control samples, showing the coefficient on the interaction of indicators for the main (certified) estimation sample and post-certification. The unit of analysis is a patient-month and the sample includes the six months before and after a physician becomes certified for registered patients, among complete spells. Unless otherwise indicated, all outcomes are specific to a physician-patient pair with registration numbers, and zeroes are included. Visits includes any in-person encounter. Reimbursement indicates fee-for-service revenue. Simulated Hours is reimbursement divided by a price index as described in Section 3.2. Procedures, Diagnostics, and Extra Time Codes are counts of reimbursement codes grouped by the chapter of the reimbursement code. These categories are mutually exclusive but not exhaustive. Other Reimbursement includes treatment by any primary care physician other than the registered one, e.g., at community health clinics. Specialist Reimbursement includes all non-primary physician care eligible for public reimbursement. Acute Hospitalizations are unscheduled with admission within six hours. Mean (Pre) is an average of patient-months in the six months before certification, excluding the control sample. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level.

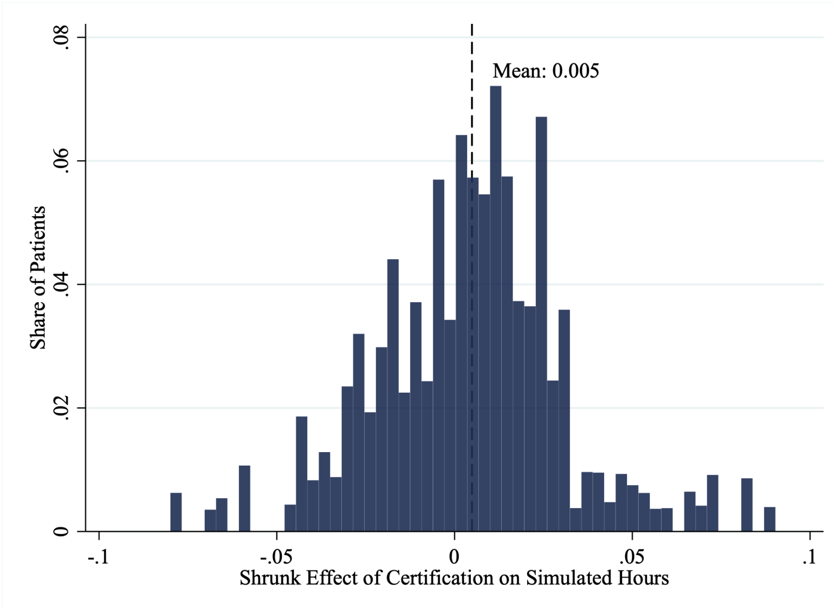
Table 2 shows that higher reimbursement rates result in greater treatment intensity. I observe precise increases both in visits, which are directly incentivized, and other measures of treatment intensity, which suggests complementarity between visits and in-visit services.[37] Simulated hours, which combines all categories of treatment, increase by approximately 3 percent of the pre-certification mean. Relative increases are similar for sub-categories of reimbursement codes like diagnostics and extra time per visit. Notably, increased treatment intensity provided by the registered physician coincides with small decreases in primary care from other physicians. The counterfactuals below focus on the treatment intensity of registered physicians and might overstate incremental expenditure from higher marginal reimbursement rates relative to this substitution effect.[38] I do not find evidence that certification immediately affects specialist treatment or acute hospitalizations.

Consistent with dispersion in physicians' altruism, I find heterogeneity in the effect of certification on treatment intensity. I extend the difference-in-differences analysis to include a post-certification indi-

[37] Brekke et al. (2017) perform a similar analysis, finding a comparable effect on visits but no evidence of effects on treatment intensity per visit. The difference might be due to lower power from the narrower sample, confounding effects of changing patient composition from the underlying unbalanced patient panel, or confounding time-specific shocks from the lack of a comparison group like non-certified physicians.

[38] Changes to health production might be understated if registered physicians do not fully internalize substitution with other providers.

Figure 4: Distribution of Physician-Level Effect of Certification on Simulated Hours

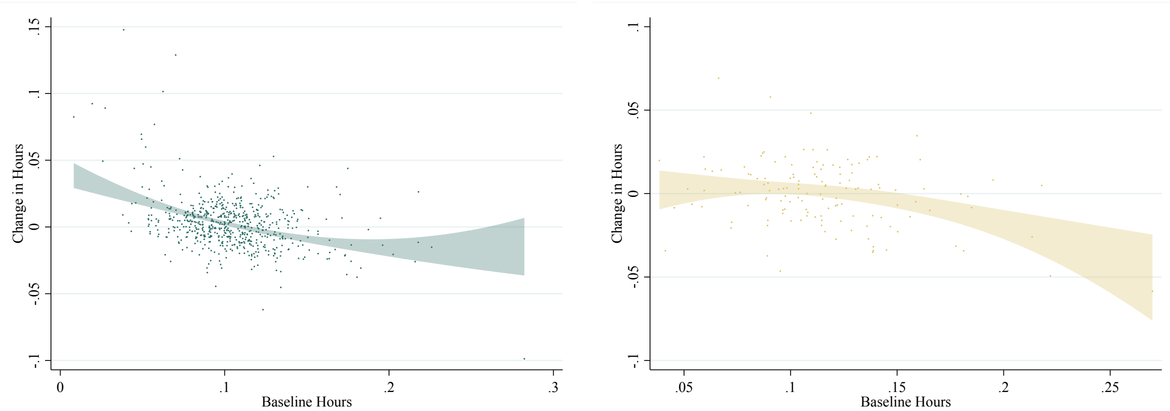


Notes: This histogram shows estimates of β_{1j} from equation 5 where the effect of certification is allowed to vary by certified physician. I shrink estimates to the mean using Empirical Bayes. Frequencies are weighted by the number of patients. Estimates are based on a subsample of spells starting 2010-2012.

cator for each physician. Figure 4 is a plot of the physician-specific estimates after adjusting for error. Although the average physician increases treatment intensity post-certification, there is meaningful heterogeneity including precise negative estimates, motivating the test for income effects in Section 6.2. Estimates do not correlate precisely with physicians' observed characteristics like employment history or the maximum number of patients. Dispersion in altruism is consistent with experimental evidence of heterogeneity (Godager and Wiesen, 2013; Hennig-Schmidt, Selten and Wiesen, 2011). To interpret estimated elasticities exclusively as altruism, physicians must not vary in their ability to increase treatment intensity. In Section 6.2 I discuss several tests of this assumption. For example, in Figure A.14 I present descriptive evidence that capacity constraints do not bind in this setting and in Figure A.15 I show that high-altruism and low-altruism physicians respond similarly after observed shocks to patient health.

Correlation. Dispersion in physicians' cost of effort, productivity, and altruism satisfy a necessary condition for physician self-selection. However, to separate physicians across contracts, these dimensions of heterogeneity should also be correlated. In Section 2.3, I illustrate how physicians with high efficient reimbursement rates must have relatively high willingness-to-pay for higher rates. Before estimating the correlation structure for physician types in the next section, I check for a consistent pattern in the raw data. Figure 5 shows that when the reimbursement rate increases, physicians with large increases in treatment hours (e.g., from low altruism) tend to initially provide low treatment intensity (e.g., from high cost). This pattern is likely not only regression to the mean because it does not clearly hold among physicians without reimbursement rate variation.

Figure 5: Raw Data Consistent with Correlated Cost and Altruism



(a) Certified Physicians

(b) Non-Certified Physicians

Notes: These plots shows the correlation between pre-certification treatment intensity and the change in treatment intensity (post-certification relative to pre). Each point is a physician. I calculate the average hours of treatment per registered patient in the six months before certification and the six months after certification. The placebo certification date is randomly selected for the control sample of non-certified physicians. The shaded region indicates a 95 percent confidence interval for a quadratic prediction.

4 Empirical Model

I estimate the joint distribution of physician heterogeneity to predict behavior under counterfactual menus and determine whether introducing a menu would increase efficiency relative to a uniform contract. In this section I review additional assumptions to support estimation as well as the intuition for which patterns in the data help to recover each parameter.

4.1 Parameterization

I estimate the distributions of physician heterogeneity and patient illness severity by maximizing the likelihood of observed treatment intensity. Privately optimal treatment intensity sets marginal net income equal to marginal health production scaled by altruism. The key assumption supporting empirical analysis is that conditional on observed characteristics, patient severity λ is independent of the reimbursement rate p and physician type θ.[39] To generate a likelihood, I make two parametric assumptions

[39]In Sections 3.3 and 6.2 I discuss evidence supporting this assumption.

that I later relax in Section 6.2. First, since economies of scale are unlikely in this setting, I continue to assume that costs increase linearly in treatment intensity: $c(m) = c\,m$.[40] Second, health production is quadratic in the distance between treatment intensity and patient severity scaled by productivity: $h(m, \lambda; \gamma) = H - \frac{1}{2}(m - \gamma\lambda)^2$. Quadratic functional forms are common in the insurance literature to model households' valuation of treatment intensity, e.g., Cardon and Hendel (2001), Einav et al. (2013), and Marone and Sabety (2022). Given these assumptions, privately optimal treatment intensity takes the form:

$$m^*(p, \lambda, F) = \max\{0, \frac{p - c}{\alpha} + \gamma\lambda\}\,. \tag{6}$$

Gaynor, Mehta and Richards-Shubik (2023) use a special case of this parameterization where γ is constant across physicians and λ is a deterministic function of patient characteristics.

The final step is to solve for the model residual, the unobserved component of patient severity. I parameterize the distribution of severity as a two-stage process. Conditional on being positive, severity is distributed log-normal, where the mean varies with observed characteristics: $(\ln \lambda \mid \lambda > 0) \sim N(\beta_\lambda X_\lambda, \sigma_\lambda)$.[41] I parameterize the probability that severity is positive as $Pr(\lambda > 0) = \frac{\exp d_0 + d_1 \beta_\lambda X_\lambda}{1 + \exp d_0 + d_1 \beta_\lambda X_\lambda}$. This step helps rationalize why patients often have zero treatment intensity, similar to Ho and Lee (2023). Appendix C.2 presents the full expression of the conditional likelihood.

4.2 Identification Intuition

An altruistic physician places high weight on patient health production relative to private net income. When reimbursement rates increase the altruistic physician's treatment intensity is relatively unresponsive, despite the incentive of higher marginal revenue. For any concave health production function, responsiveness $\frac{dm}{dp}$ is proportional to inverse altruism $\frac{1}{\alpha}$. Next, consider the distribution of treatment intensity across patients of one physician at a time. If two physicians and their patients are otherwise identical – the same altruism, productivity, and mean patient severity – then a high-cost physician will have the entire distribution of treatment intensity shifted to the left of a low-cost physician. Likewise, all

[40] For example, the regulator dissuades a large number of patients per physician by approving the entry of each new practice. Similarly, the maximum number of patients per physician can be up to 2500 but most physicians choose a much lower maximum. I exclude the small number of physicians who share a workload with other physicians.

[41] These characteristics include fixed effects for each of the 10 observed patient types, fixed effects for calendar months, normalized lagged treatment intensity, an indicator for zero lagged treatment intensity, indicators for cancer, diabetes, COPD, Asthma, and CVD, indicators for 1 or 2+ of these chronic illnesses, indicators for female and disability receipt, percentile of income as of 2016, indicators for 1 or 2+ acute hospital visit in the last 6 months, and indicator for registering with the current physician in the last 6 months and a scaled time trend.

else equal, a low-productivity physician will have a more dispersed distribution than a high-productivity physician. In figure A.6, I show stylized visual examples of these patterns. Conditioning on physician heterogeneity, the remaining correlation between treatment intensity and patients' observed characteristics identifies the conditional means of the distribution of patient severity. Variance in residual treatment intensity reflects the variance of unobserved patient severity.

The key assumption supporting identification is that the data include within-physician variation which separately shifts marginal utility from net income (in this case, $p - c$) and marginal health production ($h_m(m, \gamma\lambda)$). Increased marginal revenue p shifts marginal net income, and patient characteristics X shift marginal health production via expected severity $E[\lambda|X]$. For example, older patients likely need more care on average so there are different returns to health from treatment. Besides the additive separability of net income and health production, an implicit assumption is that these terms have different second derivatives with respect to treatment intensity.

4.3 Estimation

To recover parameters of the model, I maximize the likelihood of observed treatment intensity for patients of certified physicians in the six months before and after a change in marginal reimbursement from certification: $l(m \mid \theta_i, p, F)$.[42] Parameters include the conditional means and variance of patient severity $F(\lambda)$, and each certified physician's marginal cost c, altruism α, and productivity γ^{-1}. Estimated parameters are sometimes simple transformations of model parameters.[43] The full distributions of productivity and patient severity are not separately identified, so I fix the intercept of log severity $\beta_{\lambda,0}$ at zero.[44] To accommodate computer resource constraints, I separately estimate parameters for three subsamples: 2008-2010, 2011-2013, and 2014-2016. I use the 2011-2013 subsample for counterfactuals because parameter estimates best predict treatment hours.

[42] I use L-BFGS-B with the Python module JAX to calculate the analytic gradients of the log-likelihood objective. The box constraints are that cost, altruism and productivity are strictly positive and that marginal cost is no more than ten times as large as marginal revenue.

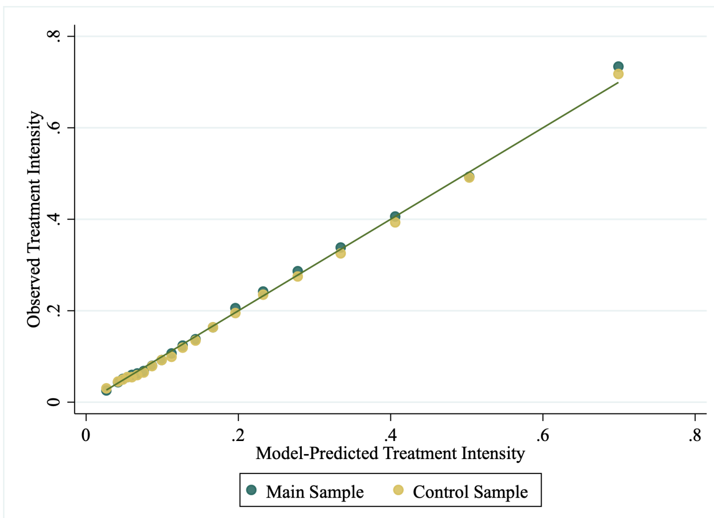
[43] c is a multiple of the fee-for-service rate six months before certification, α is scaled by 1000, and σ_λ is exponentiated. The transformation of c implies that marginal cost varies across patients of the same physician.

[44] With this normalization, I assume that a young long-term low-income male patient with no major diagnoses or lagged utilization in the first month of the sample has diminishing returns to treatment after 1 hour per month.

5 Estimates

Parameter estimates are sensible and fit the data, accurately predicting treatment intensity both in- and out-of-sample. To assess the model fit, I first plot observed treatment intensity against predicted values. Figure 6 shows a correlation of nearly 1 for both the estimation sample and a control sample of never-certified physicians.[45] Estimates predict treatment intensity well both across physicians and over time for particular physicians. Table A.11 shows corresponding regressions: the coefficient on predicted treatment intensity is approximately 1, even when including physician fixed effects in columns (3) and (5). Column (5) shows that, conditional on estimates, patient covariates explain little remaining variation in treatment intensity.[46] In counterfactual analysis, estimates also rationalize the choice of physicians to become certified even though that choice is not used to estimate the model. All physicians in the estimation sample have higher expected indirect utility EV after certification, with an average of \$1.80 per patient-month. Figure A.8 shows the distribution of this change in EV across physicians.

Figure 6: Model Fit: Ventiles of Predicted Treatment Intensity



Notes: This plot shows ventiles of predicted patient-month treatment intensity on the x-axis against means of actual treatment intensity on the y-axis. The 45-degree line is also plotted.

The correlation between estimated cost, altruism, and productivity reinforces the potential for efficient self-selection. Figure A.7 shows the joint density of physician heterogeneity. High-cost physicians tend to have low altruism, productivity, an mean patient illness severity. The upper panel of Table 3 shows that

[45] The control sample is a nearly identical balanced panel of patients for randomly selected spells of other physicians with no reimbursement variation from certification (See Section 3.2).

[46] Adding patient covariates does not increase in R^2 and slightly increases the coefficient on predicted intensity.

Table 3: Correlates of Physician Heterogeneity

	$\ln c$	$\ln \alpha$	$\ln \gamma$
Constant	0.902^{***}	8.418^{***}	-0.348^{***}
	(0.168)	(0.280)	(0.011)
Age	0.031	0.024	0.035^{***}
	(0.028)	(0.048)	(0.002)
Max Enrollment	-0.011	0.019	-0.015^{***}
	(0.032)	(0.052)	(0.002)
Pr(Diagnostic)	-0.057^{*}	0.023	-0.085^{***}
	(0.030)	(0.049)	(0.002)
Ever Fixed-Salary	0.113	-0.050	0.113^{***}
	(0.184)	(0.297)	(0.010)
Female	0.018	-0.049	-0.003
	(0.060)	(0.101)	(0.004)
Migrant	-0.104^{*}	-0.022	-0.021^{***}
	(0.063)	(0.110)	(0.004)
Rural Municipality	0.099	-0.091	0.003
	(0.077)	(0.127)	(0.004)
Trend	0.121	-0.639	-0.138^{***}
	(0.304)	(0.517)	(0.018)
S.D. Residual	0.227^{***}	0.318^{***}	0.145^{***}
	(0.031)	(0.029)	(0.002)
$\rho(\ln c, \ln \alpha)$	-0.269^{*}		
	(0.139)		
$\rho(\ln c, \ln \gamma)$	0.561^{***}		
	(0.101)		
$\rho(\ln \alpha, \ln \gamma)$	-0.295^{**}		
	(0.137)		

Notes: This table regresses log physician-level estimates of cost c, altruism α, and inverse productivity γ on observable characteristics. Standard errors come from the delta method using the approximate Hessian of parameter estimates. Continuous covariates are normalized by mean and standard deviation relative to the full population of physicians. Max Enrollment is the largest number of patients a physician agrees to have on their registered list. Pr(Diagnostic) is the share of reimbursement lines that are diagnostic relative to procedures. Ever Fixed-Salary is an indicator for physicians ever working as employees, rather than contractors, of municipalities with no marginal reimbursement. S.D. Residual is the standard deviation of the residual of log estimates after regressing on covariates. ρ indicates the correlation between residuals.

*, **, and *** denote statistical significance at the 10%, 5%, and 1% level.

observed characteristics explain some of this variation.[47] For example, productive physicians tend to be younger and born outside of Norway. They hold larger lists of patients, make greater use of diagnostics relative to procedures, and historically worked under fee-for-service contracts. The bottom panel shows residual variation in physician types is also widely dispersed and correlated.[48]

Patient observable characteristics explain a moderate share of the variation in treatment intensity by shifting illness severity (See Table A.6). Seasonality and particular chronic illnesses are major determinants of patients' treatment needs. For example, utilization is much lower in August than in January, and diabetes patients are more likely to visit a primary care physician than cancer patients. Other coefficients are precise but unexpectedly low in magnitude relative to raw correlations with treatment intensity, e.g., lagged treatment intensity and gender. Increasing lagged treatment by one standard deviation would only increase the health shock about as much as the average difference between January and April. This small coefficient reinforces the assumption that the distribution of health shocks is conditionally independent across months within each patient. Finally, conditioning on the full set of patient covariates, patient severity is highly dispersed and difficult to predict.

6 Counterfactual Menus of Contracts

6.1 Baseline Counterfactuals

Using estimates, I simulate physicians' choices under counterfactual menus to illustrate the welfare effects of self-selection. First, I quantify the cost of information asymmetry by solving for the personalized contracts offered by the regulator with perfect information. Second, I benchmark to the status quo and find that the existing reimbursement supplement is nearly optimal if the regulator can only offer a single (uniform) contract. Third, I demonstrate that even an arbitrary two-contract menu can increase welfare relative to a uniform contract because the distribution of physician heterogeneity satisfies key properties of dispersion and correlation. Fourth, I derive the menu of linear contracts that maximizes welfare given imperfect information. I conclude by assessing the equity implications of the optimal menu.

To scale health production into dollars, I assume that the regulator values incremental health production from certification as much as incremental expenditure. This assumption implies that the regulator is

[47] All standard errors are adjusted for noise in parameter estimates.

[48] Rather than introduce a menu, a regulator could condition the reimbursement rate on observed physician characteristics. The substantial unobserved heterogeneity suggests that targeting observed characteristics may be ineffective. Likewise, targeting may be infeasible given, e.g., legal protections for age and physicians' collective bargaining.

3.1 times as altruistic as the median certified physician.[49] Table 4 compares aggregate health production across counterfactual menus, relative to the pre-certification status quo. Columns for expenditure and physician indirect utility reflect the budget and participation constraints. To focus on the role of reimbursement in treatment intensity, I fix other sources of variation at values six months before certification: enrollment, the share of patient types for each physician, and pre-certification fee-for-service rates. I provide additional detail on how I measure counterfactual outcomes and search for counterfactual menus in Appendix B.3.

Table 4: Annual Counterfactual Outcomes for Norwegian Population ($M)

	Health Production	Share of Max	Expenditure	$E[V]$
Pre-Certification	0.0	0.000	0.0	0.0
Post-Certification	139.0	0.264	138.9	113.6
	(0.4)	(0.001)	(0.4)	(0.4)
Efficient Contracts	525.8	1.000	137.2	0.0
	(3.0)	(0.000)	(0.6)	(0.0)
Optimal Uniform Contract	153.7	0.292	132.5	103.6
	(2.1)	(0.003)	(0.5)	(0.5)
Optimal Menu of Contracts	176.5	0.336	144.9	109.1
	(1.9)	(0.003)	(0.4)	(0.6)

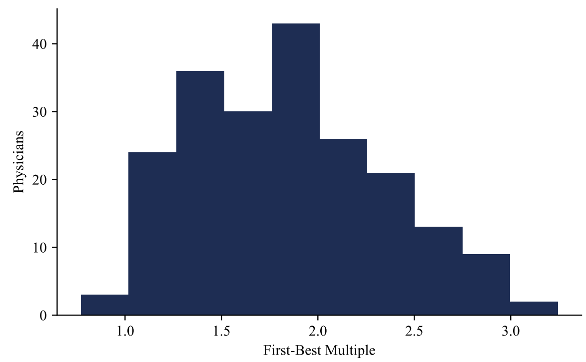
Notes: This table shows key outcomes from realized and counterfactual contract menus, scaled annually to the Norwegian population (5.24M). All outcomes are based on ex-ante expectations over patient-months using estimated distributions of G and F, weighted across physicians by enrollment. Enrollment, the share of patient-types, pre-certification fee-for-service rates, and base payments are fixed at values six months before certification. Post-certification fee-for-service rates are fixed at values in the month after certification. Counterfactuals vary fee-for-service rates and base payments, enforcing participation and budget constraints. Health production is scaled such that the regulator is indifferent between incremental expenditure and incremental expenditure from certification. Share of Max divides the first column by its maximum from efficient contracts. Expenditure includes both fee-for-service and base payments. $E[V]$ is the expected indirect utility per patient-month of private physicians. Standard errors, shown in parentheses, are calculated across 25 bootstrap estimation samples, with randomly selected patient-months within physician and re-solved counterfactual menus. Figures A.11 and A.12 further illustrate the distribution of counterfactual contracts across bootstrap samples.

With perfect information about physician heterogeneity, personalized contracts would increase expected health production by $525 million per year nationally. In this first-best allocation, efficient contracts achieve nearly four times the gain in health production of the observed reimbursement rate increase at a lower cost while satisfying strict participation and budget constraints. I identify efficient contracts by selecting the fee-for-service rate for each physician from a grid that maximizes $E[\alpha_R h(m^*, \lambda) - p\, m^*]$. I set base payments so that in expectation, each physician is indifferent between the efficient contract and the status quo. Figure 7 shows substantial heterogeneity in the efficient reimbursement rates.[50] On

[49]For comparison, Gaynor, Mehta and Richards-Shubik (2023) calibrate a comparable parameter at 52.6 times the median altruism among providers based on the value of a statistical life-year. My approach does not internalize the regulator's valuation of certification training beyond immediate changes to health production.

[50]Throughout this section, I discuss multiples of counterfactual reimbursement rates. For example, 1.2 indicates 120 percent

Figure 7: Dispersion in Efficient Reimbursement Rates



Notes: The y-axis is the count of physicians in each bin. The x-axis is a multiple of pre-certification fee-for-service that maximizes scaled health production subject to strict physician-level participation constraints and a global budget constraint (average expenditure must be less than status quo post-certification). The grid of fee-for-service multiples includes 200 points between 0 and 2.5. The base payment is the lowest level for each physician to satisfy the participation constraint for each physician.

average, efficient rates are 84 percent above the initial status quo rate with substantial variation (SD = 49 percent). Efficient rates are far above the status quo because a large share of physicians have high cost of effort or low altruism. In the status quo, these physicians spend relatively little time with patients, so the health benefits of incremental treatment are large.

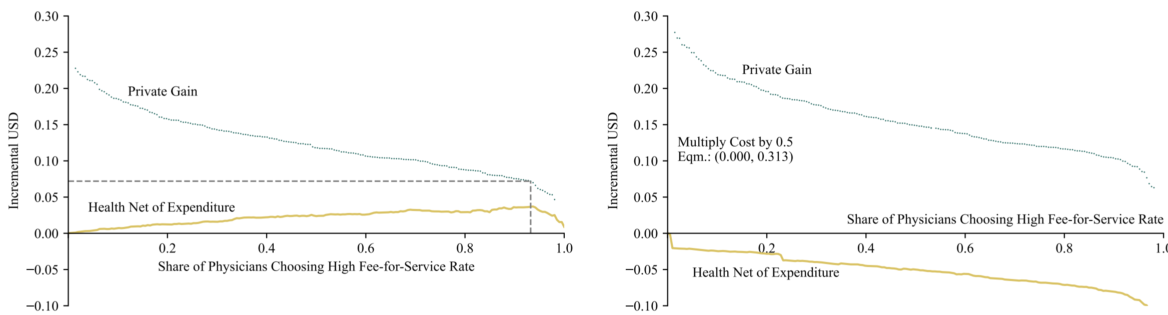
In the status quo, the reimbursement rate increases by 24 percent which improves health production by approximately one-fourth as much as efficient rates. Part of the difference is because the new status quo rate is too high for some physicians. For example, the most altruistic physicians do not change treatment intensity enough to justify the mechanical increase in expenditure. Since most physicians have even higher efficient rates, the regulator could still improve health production at lower cost with an ever higher uniform reimbursement rate and lower base payments. On average, physician surplus would be lower, but all physicians weakly prefer this contract to the initial status quo.

Even a two-contract menu achieves meaningful efficiency gains relative to the best uniform contract. Reinforcing the intuition from Section 2.3, this intermediate exercise shows how the self-selection may not increase welfare for some distributions of physicians. I adapt the graphical framework for selection markets introduced in Einav, Finkelstein and Cullen (2010) and extended by Marone and Sabety (2022). I start with the optimal uniform contract (p_L) and add a contract (p_H) to the menu with a marginally higher reimbursement rate. If p_H requires accepting a relatively low base payment, then only a fraction of physicians with large private benefits ($EV(p_H, 0) - EV(p_L, 0)$) will choose it. Physicians with large

of the initial fee-for-service rate. This approach preserves variation in fee-for-service rates across patients while allowing simple graphical comparisons across counterfactuals. In a robustness check below, I consider a unique reimbursement rate for each type of patient with similar observed characteristics.

private benefits have relatively low cost, high altruism, and high productivity (See Appendix C.1). However, these characteristics also predict relatively large increases in expenditure which might outweigh the corresponding increase in health production, especially if cost is low relative to altruism.

Figure 8: Two-Contract Menus: Setting Incremental Base Payments



(a) Estimated Distribution

(b) Counterfactual Distribution: $\frac{1}{2} \times c$

Notes: This figure shows outcomes under a menu that includes the best uniform fee-for-service rate and a fee-for-service rate that is incrementally higher while varying the difference in the base payment between these contracts. The x-axis orders a continuum of physicians according to their decreasing private gains from an increased reimbursement rate. The green line is incremental social surplus for each percentile of private gain: expected (scaled) health production minus expenditure among all patients (and all physicians). Grey dashed lines indicate the optimal share of physicians choosing the high-fee-for-service contract and the corresponding difference in base payments between the two contracts. Panel A shows the estimated distribution of physician heterogeneity. Panel B multiplies estimated marginal cost by 0.5.

Figure 8a shows the tradeoff between increased health production and increased expenditure across physicians, ordering physicians in decreasing order by their private benefit from an increased fee-for-service rate ("WTP"). The WTP curve is like a demand curve, indicating participation in the high-fee-for-service contract for various prices Δb, i.e., lower base payments. I also summarize welfare as incremental social surplus: expected health production minus expected expenditure, relative to the low-fee-for-service contract, where expenditure reflects both fee-for-service and base payment changes in equilibrium.[51] For each share of physicians choosing high-fee-for-service, I show the average incremental surplus across all patients. The regulator sets incremental base payments to maximize expected social surplus: 93 percent of physicians choose the high-fee-for-service contract with a \$0.07 lower base payment. With smaller differences in the base payment, more physicians would choose the high-fee-for-service contract and expenditure would outweigh incremental health production. Figure A.10 shows that variation in social surplus is best explained by cost. Variation in WTP is best explained by mean patient severity rather than cost, altruism, or productivity.

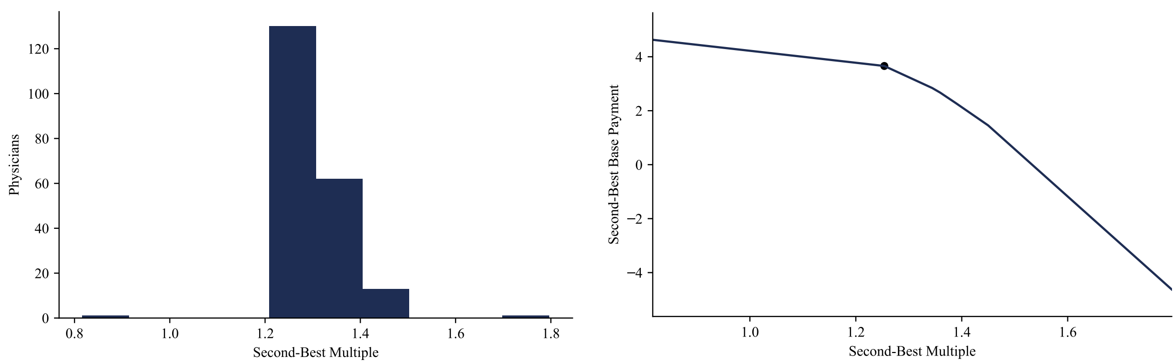
Figure 8b illustrates a counterexample where the two-contract menu is not more efficient than the

[51] At virtually any quantile of WTP, some physicians will be inefficiently selected into the high-fee-for-service contract and some will be inefficiently selected into the low-fee-for-service contract, relative to full information with the same restricted menu.

uniform contract. This panel repeats the previous exercise with a counterfactual distribution of physician heterogeneity. When marginal costs are half as large, WTP is greater and efficient rates are lower. WTP and social surplus are not sufficiently correlated for both contracts to be traded. Incremental expenditure would always exceed incremental health production. The regulator sets the incremental base payment high enough for a corner solution where all physicians choose the low-fee-for-service contract. Lower cost of effort makes efficient rates more affordable and more similar, so efficient rates are all relatively close to a feasible uniform contract.

The optimal 7-contract menu achieves large efficiency gains by separating some physicians into high-fee-for-service contracts: \$33 million per year more than the status quo or 34 percent of first-best. To search for this menu, I adapt the line-search algorithm from Marone and Sabety (2022) and Azevedo and Gottlieb (2017). Most physicians choose just one of three contracts (Figure 9a) and the optimal base payment decreases concavely in the fee-for-service rate (Figure 9b).[52] Perhaps a smaller menu would involve lower implementation costs: Figure A.9 shows that while increasing the number of contracts per menu generally improves welfare, most efficiency gains can be achieved with a small number of contracts.

Figure 9: Optimal Menu of Contracts



(a) Physicians' Reimbursement Rates

(b) Base Payment Schedule

Notes: In Panel A, the y-axis is the count of physicians in each bin. The x-axis is a multiple of pre-certification fee-for-service that maximizes scaled health production subject to strict physician-level participation constraints and a global budget constraint (average expenditure must be less than status quo post-certification). Panel B plots base payments versus multiples of status-quo fee-for-service rates for the optimal menu. The point indicates the optimal uniform contract.

Redistribution across patients drives some of the gains in average welfare from efficient contracts and the optimal menu. To explore redistribution, I disaggregate counterfactual outcomes across physician types. In Table 5 I categorize physicians into 16 groups based on whether each of cost, altruism, productivity, and expected patient severity are above or below the median. For both efficient contracts and

[52]Moreover, Figure A.12 shows that across bootstrap samples, the optimal menu consistently lies on approximately the same curve of Base Payment versus fee-for-service Multiple.

the optimal menu, health production increases most among the 40 percent of physicians with high cost and low altruism. Changes in expenditure are relatively small. All else equal, these physicians tend to have low private gain from increased rates. The menu can separate some of these physicians into high fee-for-service rates because productivity and average patient severity are highly dispersed.

Table 5: Counterfactual Outcomes by Physician Type

Physicians		Efficient Contracts		Menu of Contracts		
Type	Share	$\Delta E[h(m)]$	$\Delta E[p\,m+b]$	$\Delta E[h(m)]$	$\Delta E[p\,m+b]$	$\Delta E[V(p)]$
$c_L, \alpha_H, \gamma_L, F_L$	0.171	1.311	0.554	0.855	1.505	1.177
$c_H, \alpha_L, \gamma_H, F_L$	0.160	14.165	3.420	2.984	1.545	1.161
$c_H, \alpha_L, \gamma_H, F_H$	0.155	20.003	4.486	5.793	3.140	2.303
$c_L, \alpha_H, \gamma_L, F_H$	0.154	1.441	0.622	1.155	2.549	2.012
$c_L, \alpha_L, \gamma_H, F_L$	0.049	3.860	1.367	1.749	1.963	1.527
$c_H, \alpha_L, \gamma_L, F_H$	0.047	21.554	4.820	4.905	2.010	1.412
$c_L, \alpha_H, \gamma_H, F_H$	0.045	3.201	1.251	2.336	4.003	3.155
$c_H, \alpha_H, \gamma_L, F_L$	0.037	5.670	1.977	1.722	1.567	1.206
$c_L, \alpha_H, \gamma_H, F_L$	0.033	2.172	0.847	1.218	2.031	1.630
$c_H, \alpha_H, \gamma_L, F_H$	0.031	6.620	2.372	2.468	2.529	1.953
$c_H, \alpha_H, \gamma_H, F_L$	0.025	5.997	2.052	1.942	2.064	1.654
$c_H, \alpha_L, \gamma_L, F_L$	0.022	7.306	2.315	2.157	1.366	0.977
$c_H, \alpha_H, \gamma_H, F_H$	0.019	6.240	2.288	3.405	3.974	3.067
$c_L, \alpha_L, \gamma_L, F_L$	0.017	5.755	1.285	6.489	2.202	1.129
$c_L, \alpha_L, \gamma_L, F_H$	0.017	6.694	1.690	10.557	4.990	2.875
$c_L, \alpha_L, \gamma_H, F_H$	0.017	4.359	1.639	3.106	3.880	2.872

Notes: This table shows average outcomes for efficient (personalized) contracts and the optimal menu of contracts, disaggregated across groups of physicians (rows). For physician types, the subscript "H" indicates above-median, and "L" indicates below median. Physician type is a combination of physicians' cost c, altruism α, productivity γ^{-1}, and expected patient severity F. $\Delta E[h(m)]$ represents the change in health production relative to the status quo, for efficient contracts and the optimal menu of contracts. Likewise, $\Delta E[p\,m+b]$ represents incremental expected expenditure and ΔEV represents incremental expected indirect utility. Outcomes are averages across patients within each group, measured in USD.

6.2 Robustness

Relaxing restrictions on model assumptions and sample construction suggests that the efficiency of self-selection does not rely on an idiosyncrasy of the empirical approach or setting. First, I find evidence for external validity within Norway: including out-of-sample physicians in counterfactuals does not change the main finding. The model predicts that physicians would select into the certification sample based on observed and unobserved characteristics. Table 1 shows that non-certified physicians have slightly higher treatment intensity which may be explained by relatively old and chronically ill patients. Non-certified physicians are also more likely to be old, born outside of Norway, and use diagnostics. To explore unobserved differences for non-certified physicians, I estimate the distribution of unobserved heterogeneity based on the relatively weak assumption that non-certified physicians have the average log altruism among certified physicians with identical observed characteristics. This assumption is necessary because the identification of altruism requires observing the same physician with different fee-for-service rates. Physicians in the main estimation sample can still be selected on observed heterogeneity in altruism and both observed and unobserved heterogeneity in cost and productivity. Reinforcing this assumption, unobserved heterogeneity in altruism is precise and small relative to the mean (Table 3). Likewise, Table A.11 shows that estimates fit observed treatment intensity well for both samples. If non-certified physicians were meaningfully selected on unobserved heterogeneity in altruism, predicted treatment intensity would be a weak predictor of observed treatment intensity. Finally, repeating the counterfactual analysis for the combined population of certified and non-certified physicians results in similar outcomes.[53]

Second, I find evidence for external validity outside of Norway: even large perturbations of estimates rarely change the main finding. In Table A.9, I first perturb cost c, altruism α, and productivity γ^{-1}. A menu increases efficiency when halving or doubling estimates, removing unobserved heterogeneity by replacing estimates with the sample mean for one or two dimensions at a time, or limiting dispersion in estimates by halving variance or dropping outliers. When doubling the variance of cost or altruism, I cannot find efficiency gains from a menu. Although this perturbation increases the variance of efficient rates, it weakens the correlation between incremental health and physicians' private gain from increased rates and makes efficient rates relatively unaffordable. The variance of severity σ_λ and regulator altruism α_R have large impacts on the levels of counterfactual outcomes. With sufficiently low regulator altruism, a uniform contract is optimal.

Robustness to scaling variance and dropping outliers of physician heterogeneity also suggests that estimation error does not drive the main findings. With overestimated heterogeneity in cost, altruism, and productivity, the gains from self-selection might appear artificially large. Likewise, bootstrapped standard errors are small across aggregate counterfactuals outcomes (Table 4), physician-specific contracts (Figure A.11), and the relationship between the reimbursement rate and base payment in the optimal menu (Figure A.12).

Third, descriptive evidence reinforces the exclusion assumption that high-severity patients do not

[53]See Table A.9. This specification should be interpreted with caution because estimates are pooled across subsamples. Results are also similar when excluding rural physicians. Anecdotally, rural physicians may face unusual circumstances.

systematically choose particular physicians. The assumption simplifies the analysis by avoiding dynamic considerations. In practice, patients can freely switch between physicians whose enrollment is below the contracted maximum, up to twice per year. As a result, physicians might perceive a link between current treatment intensity decisions and future enrollment, e.g., through reputation effects, which would increase future revenue. Likewise, patients with higher unobserved severity might systematically sort towards physicians with higher expected health production (low cost, high altruism, high productivity). Descriptive evidence suggests that these are not first-order concerns. Figure A.2 shows that enrollment and the share of enrolled patients that are over 60 or chronically ill do not systematically vary with certification, unlike treatment intensity and health production.[54] Enrollment and the share of patients with higher treatment need should increase if patients are sorting towards physicians with greater health production after certification due to increased treatment intensity. Likewise, as shown in Section 3.3, physicians' fixed effects in treatment intensity are highly dispersed whether estimated among all patients or only quasi-randomly assigned patients. To test for medium-run sorting, I regress an indicator for switching physicians in the next six months on model-predicted health production, patient covariates, and fixed effects for year and calendar month.[55] Column (2) of Table A.10 shows that the correlation between health and switching to a new physician is imprecise, with point estimates that are small in magnitude. By contrast, expected health production is predictive of (lower) future avoidable hospitalizations and mortality. In Figure A.13, raw means also suggest a decline in avoidable hospitalization after three years. Likewise, cumulative mortality is 36 percent lower than among patients of non-certified physicians.

Fourth, motivated by Ellis and McGuire (1986) and McGuire and Pauly (1991), I test for income effects – nonlinear cost of effort – with a likelihood ratio and cannot reject the baseline model. Income effects can also rationalize why some physicians reduce treatment intensity by a small amount in response to newly registered patients (Barash, 2024) or an increase in reimbursement rates (Figure 4). To estimate physicians' marginal disutility of expected workload, I extend the theoretical framework and estimation strategy with additional assumptions, detailed in Appendix A.3. If income effects do exist, they seem too small relative to unobserved variation in patient severity to be economically meaningful. Figure A.14 tests the related assumption that physicians do not face binding capacity constraints. Over ten years, the distribution of physicians' monthly treatment intensity varies smoothly near each physician's maximum. Monthly treatment intensity should bunch at high values if some physicians occasionally reach

[54] Figure A.3 shows that certified and non-certified physicians experience similar trends in enrollment for at least two years after certification.

[55] I use model estimates to calculate expected health production for each patient in the main estimation sample during the six months post-certification. I measure switching 7-12 months after certification.

capacity, e.g., due to idiosyncratic variation over time in the number of patients or realized severity. Next, Figure A.15 shows that the treatment intensity of high-altruism and low-altruism physicians is similarly responsive to the shock of a first avoidable hospitalization. This suggests that estimates of high altruism are not biased by an unobserved constraint. Likewise, the across-time variance of pre-certification workload is similar for low- and high-altruism physicians.[56] I do not find evidence that patients of high-altruism physicians are more likely to seek treatment elsewhere.[57] Finally, as shown in Table A.9, the optimal menu of contracts leads to similar welfare gains over a uniform contract when I impose a capacity constraint and repeat counterfactuals.[58] The constraint limits large expenditure increases on high-severity patients when the health production curve is relatively flat, while high rates still permit large gains for less severe patients. As a caveat, physicians might respond to counterfactual contracts by spending less time on other work, e.g., at nursing homes or universities, that is socially valuable but unmeasured.[59]

Finally, counterfactual outcomes are nearly identical with an alternate health production parameterization from the insurance literature (Cardon and Hendel, 2001; Einav et al., 2013; Marone and Sabety, 2022). Those papers use a quadratic function with a linear term which results in a convenient expression for treatment intensity: $h_0 + h_1(m - \gamma\lambda) - \frac{h_2}{2}(m - \gamma\lambda)^2$. In the baseline approach, I assume $h_1 = 0$ because it is not separately identified from the mean of private marginal cost apart from functional form.[60] To test the alternate parameterization, I re-estimate the model with $h_1 \geq 0$. I focus on non-negative values because previous studies estimate a parameter close to 1, and health production should initially increase in treatment. I estimate $h_1 = 0.073$.

6.3 Extensions

Even when considering more flexible contract structures, a menu of linear contracts tends to dominate a uniform contract, and the gap between a menu and personalized contracts under full information remains

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[56] I aggregate hours for each physician in each month before certification and then calculate the across-month variance. This physician-specific variance does not correlate precisely with estimated altruism. If some physicians are less responsive to certification because of capacity, then low altruism should correlate with low variance. Such physicians would work a similar amount each month (at capacity).

[57] Patients registered with high-altruism physicians receive relatively little primary care from secondary opinions and urgent care centers. If the registered physician was capacity-constrained, patients might seek more treatment from other physicians.

[58] In this case, I bound workload (total simulated hours per physician-month) below the 99th percentile reached after certification.

[59] Table A.9 shows similar gains to a menu when excluding physicians that initially work part-time, i.e., those who spend fewer than 25 hours per week with registered patients.

[60] h_0 is also not identified but does not affect choices. h_2 is absorbed in altruism.

large. First, instead of requiring all physicians to choose from a single menu of contracts ("Baseline"), I derive multiple menus of contracts that incorporate observed heterogeneity. Table A.8 shows that offering ten menus – one for each bin of patients with similar characteristics – does not lead to larger welfare gains.[61] One explanation is that in the baseline counterfactual, each contract includes a multiple of the status quo fee-for-service rate. This approach preserves variation in fee-for-service rates across types of patients who on average consume different bundles of services. Further expanding variation in fee-for-service rates across patients for a given physician may have limited benefits.

Second, Table A.9 shows that counterfactual outcomes are similar to Baseline when separating the analysis between urban and rural patients.[62] The limited benefit of regional contracts is surprising because in the status quo, regional variation is one of the few exceptions to nationally uniform reimbursement.[63] Baseline (national) contracts might perform relatively well because within-region physician heterogeneity is larger than across-region heterogeneity. Consistent with prior literature, Table A.7 shows that health disparities among rural patients remain a pressing concern. Relative to the status quo, eliminating information asymmetry about physicians improves patient health by \$13 for the most rural patients and \$6 for most urban patients. A national menu of contracts helps narrow the gap in health, but only by a fraction. Similarly, regional menus achieve less than one-third of first-best welfare gains.

Third, relaxing the linear structure of contracts does not increase the welfare achievable with a uniform contract. Although such contracts are rare in healthcare settings and perhaps difficult to implement, larger welfare gains may be possible when revenue is a flexible function of treatment intensity. For example, after a large amount of treatment, the marginal return to health may be small, and low marginal reimbursement would limit relatively inefficient spending. I find that the optimal nonlinear uniform contract substantially improves patient health relative to a menu of contracts. The gain is around half as large as from efficient linear contracts. However, the participation constraint requires large increases in expenditure on base payments, so the net gains to welfare are small: 23 percent of first-best. Without base payments, 56 percent of physicians are worse off, and these losses represent up to 5 percent of status quo revenue. Appendix A.5 provides details on deriving the nonlinear contract (extending Gaynor, Mehta and Richards-Shubik, 2023), and compares distributional outcomes across

[61] I use the same procedure as before, except that each counterfactual fee-for-service rate is a level rather than a multiple of the status quo.

[62] I use the same procedure as Baseline, but separately for rural and urban physicians. Approximately one-fourth of physicians are classified as rural because they practice in a low-centrality municipality.

[63] For example, in Norway, physicians in very small municipalities receive additional payments per registered patient. In the United States, Medicare reimbursement adjusts for rural status, the share of low-income patients, and a local wage index.

counterfactuals. For each segment along a grid of treatment intensity, the optimal marginal payment maximizes incremental health production net of incremental private costs, among patients with marginal treatment intensity. I find that the optimal nonlinear contract is approximately linear beyond low levels of treatment intensity (Figure A.16), redistributing away from patients with low severity to most other patients with relatively high severity (Figure A.17).

Institutional differences may explain the different impacts of a non-linear uniform contract in this setting relative to Gaynor, Mehta and Richards-Shubik (2023). With primary care and the large estimated dispersion in unobserved patient severity, there does not seem to be a narrow range of medically appropriate treatment intensity for a non-linear contract to target. Moreover, my estimates imply that marginal health production is nearly universally positive, so decreasing treatment intensity is not generally efficient. In Gaynor, Mehta and Richards-Shubik (2023), more than half of observed treatment intensity was high enough to damage health because medication dosage exceeded a known cutoff.[64]

In addition to contract flexibility, the regulator might further improve patient health through policies that complement contracts by shifting the allocation of patients across physicians. For example, in Table 5, the decomposition across physician and patient types suggests that perhaps high-severity patients should not be registered with high-cost low-altruism physicians. The combination of relatively high severity, high cost, and low altruism partly explains the larger impacts of counterfactual contracts in rural areas (see Table A.7). In reality, physicians decide where to establish a practice and most will move at least once during their career. At these times, contract heterogeneity could incentivize different location choices. For example, it might induce better match quality to increase the base payment for a high-fee-for-service contract in areas where nearby patients have relatively high observed severity. Alternatively, the regulator could incentivize patients to switch to under-subscribed high-quality physicians. While this question is beyond the scope of the current work, it may be a fruitful path for future research: combining efficient reimbursement rates with optimal patient switches can increase incremental social surplus by 17 percent relative to efficient reimbursement rates alone.[65]

So far, while fixing the distribution of physicians, information asymmetry remains costly even after adding contract flexibility – perhaps the regulator could further improve patient health through complementary long-run investments that alter the distribution of physician heterogeneity. At reasonable

[64] These characterizations mostly refer to Figure 3 in that paper, which is based on a patient with median observed severity.

[65] This exercise involves a stylized example of two vertically differentiated physicians at the 10^{th} and 90^{th} percentile of (initial) efficient fee-for-service rates. I begin by counterfactually assigning both physicians the average patient distribution, corresponding fee-for-service rates, and average enrollment. I alternate between searching for first-best contracts and looping through the maximally profitable patient switch for a given set of contracts. This method maintains the initial number of patients per physician and converges after 53 percent of patients have switched.

reimbursement rates, the regulator prefers a physician with low cost of effort, high altruism, and high productivity. Public subsidies for support staff or telehealth might lower cost of effort; performance benchmarks might increase altruism, and promoting long-term patient-physician relationships might increase productivity via soft knowledge. For example, performance benchmarks can increase information and facilitate learning, particularly about past patients that have since left the list. Physicians currently do not observe all the long-term impacts of treatment, like utilization and avoidable hospitalizations.

7 Conclusion

In this paper I present a framework for deriving the optimal menu of physician reimbursement contracts. The framework incorporates unobserved patient illness severity and physicians' endogenous choices of contract and treatment intensity. I characterize the conditions on multidimensional physician heterogeneity under which self-selection among a menu of contracts is more efficient than a uniform reimbursement contract. These conditions are met in the empirical example of Norwegian primary care physicians. I estimate the distributions of physician and patient heterogeneity, exploiting the sudden large variation in marginal reimbursement when physicians become certified as general practitioners. I find large efficiency gains from introducing self-selection, and that finding is robust to several model enrichments, estimate perturbations, and alternative samples.

The most direct policy implication is that the Norwegian National Insurance Scheme could cost-effectively improve access to primary care by offering a menu of 2-7 linear contracts. These contracts are easy to understand because they have the same linear structure as status quo reimbursement. The difference is that each contract exchanges a higher multiple on service-level reimbursement for lower revenue per registered patient-month. The regulator could use its existing data and infrastructure to administrate the policy counterfactual as an occasional settlement payment. Moreover, the menu of contracts is efficient even as a voluntary reform: physicians can still choose the status quo contract, which might make it acceptable to the association that negotiates reimbursement on behalf of physicians. I also find evidence that is consistent with reductions in hospitalization and mortality. By contrast, economic theory and empirical evidence alike predict that Norway's recent initiative to increase base payments for relatively ill patients will not immediately affect treatment intensity, because marginal incentives are unchanged.[66]

[66] On the other hand, such a reform may effectively deter exit in the long term. With sufficient exit, capacity constraints may bind and reduce treatment intensity.

Beyond Norway, my framework for evaluating the efficiency of self-selection is broadly applicable to settings featuring heterogeneous altruistic agents that experience panel variation in marginal reimbursement. In healthcare, this includes systems in which many physicians derive most revenue from contracts with a single payer, e.g., several countries' health agencies or Kaiser Permanente in the United States. External validity might be limited in settings where prices are negotiated or patients frequently switch physicians based on reputations for treatment intensity. Outside of healthcare, menu design may be an effective tool in the markets for indigent defense attorneys, K-12 educators, and social workers. These agents are likely altruistic – sacrificing some profit to improve outcomes for their clients and students – and also heterogeneous in marginal cost and productivity. The frequent lack of compensation for incremental effort may also contribute to capacity constraints and disparities in outcomes. My framework uses reimbursement variation, which often exists in these settings, but even cross-sectional data can be sufficient with additional assumptions.[67]

Why are uniform contracts ubiquitous if the potential gains from self-selection are large? First, variation in incentives across physicians may conflict with norms concerning uniformity. Moreover, before considering multidimensional unobserved physician heterogeneity, policymakers may not find it intuitive that increasing dispersion in patients' treatment could be efficient. Second, there may be fixed costs of introducing counterfactual menus, e.g., costly experiments in reimbursement variation to derive the optimal menu or incremental costs of negotiation with a physicians' union.

I also explore related applications of the model that may be productive directions for future research. First, several studies decompose dispersion in healthcare utilization between broadly supply-side or demand-side factors. I begin to further decompose supply-side factors by simulating dispersion in treatment intensity with counterfactual distributions and characteristics. Consistent with existing evidence that patients imperfectly perceive physician quality, I find evidence that patients may not be optimally allocated across physicians to maximize cost-effective health production. Future work might consider self-selection in the context of physician entry, incorporating reimbursement contracts as well as the number and composition of nearby patients. I also do not find evidence of income effects or capacity constraints in Norway, but these features may add nuance to contracting in related settings.

[67] For example, a simulation-based estimator could recover a parametric distribution of altruism with cross-section variation in reimbursement under a stronger exclusion assumption. Client severity must be conditionally independent of agent type and reimbursement, which is unlikely if, e.g., high-quality agents receive higher reimbursement. See Lee (2021), Biasi (2021), or Hanushek et al. (2023) for reimbursement variation among attorneys and teachers.

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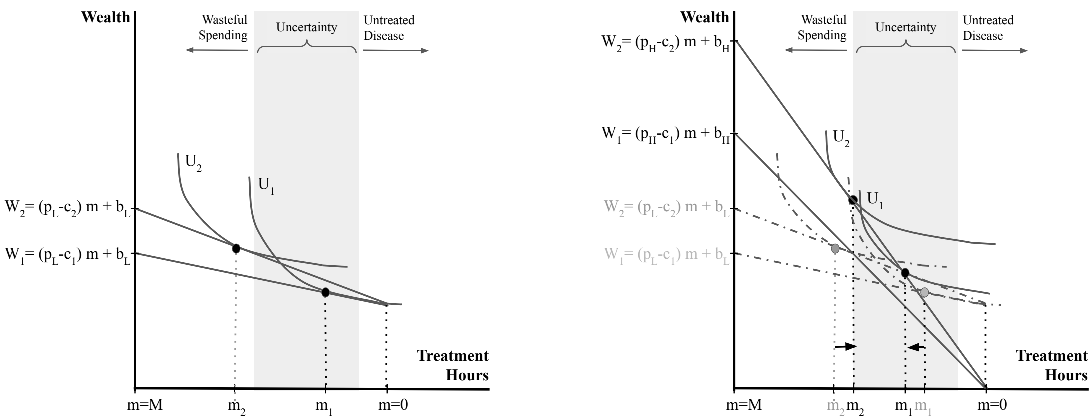
A Additional Analysis

A.1 Additional Figures

Figure A.1: A Uniform Contract May Be Efficient

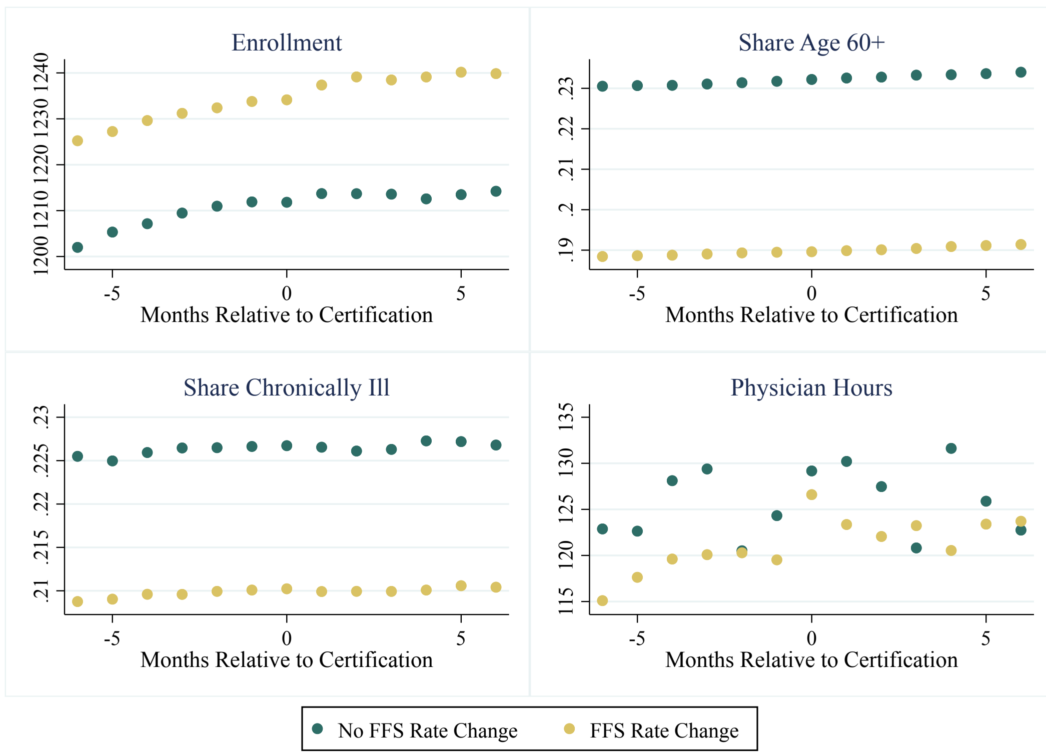


(a) Initial Uniform Contract

(b) Better Uniform Contract

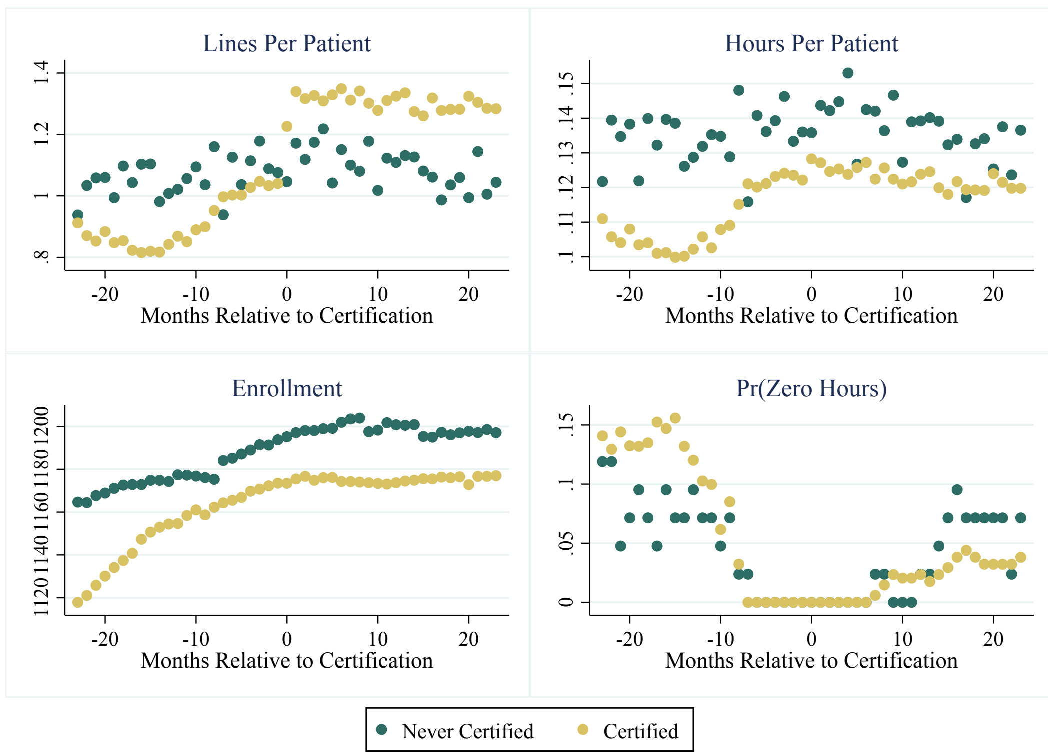
Notes: This figure shows a stylized example with two physicians, in which a a uniform contract is efficient. The x-axis plots treatment intensity $m \in [0, M]$ from right to left. Each panel shows the indifference curves of these physicians and the budget constraint(s) implied by simple reimbursement contract(s) with a base payment and an hourly wage. The shaded region includes the efficient level of labor supply which is unobserved to the regulator. In the left panel, the single status quo contract is efficient only for Physician 1. In the right panel, the new uniform contract has high marginal reimbursement p and is efficient for both physicians.

Figure A.2: Raw Means of Characteristics Relative to Certification



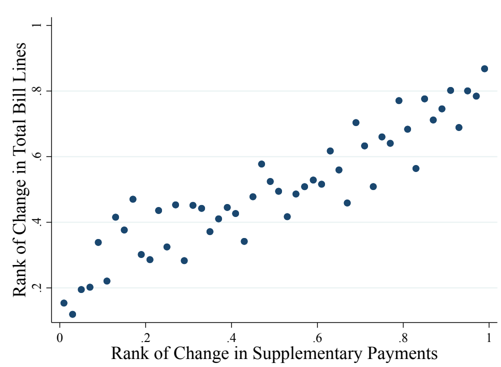
Notes: These plots show averages of treatment intensity outcomes across patient-months in the estimation and control samples in each month relative to certification. Each sample is a balanced panel of patients, and in the estimation sample, Month 0 is the first month in which the registered physician received a certification supplement.

Figure A.3: Long-Run Means Relative to Certification

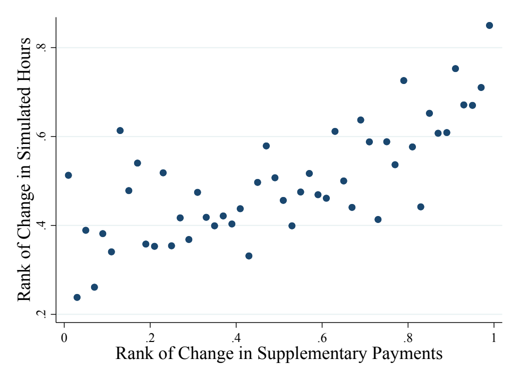


Notes: These plots show average across physicians in the estimation and control samples in each month relative to certification. Each sample is a panel of physicians, and in the estimation sample, Month 0 is the first month in which the registered physician received a certification supplement. Unlike in other analyses like Figures 2 and A.2, each observation used to generate plots reflects aggregate labor supply of physicians, rather than the subset of treatment in a balanced sample of registered patients. Physicians must be registered to at least one list in each of the 49 months, but that list may change and labor supply may be zero in a given month. Bill lines include the certification supplement. Per Patient indicates that the aggregate is divided by the total number of registered patients.

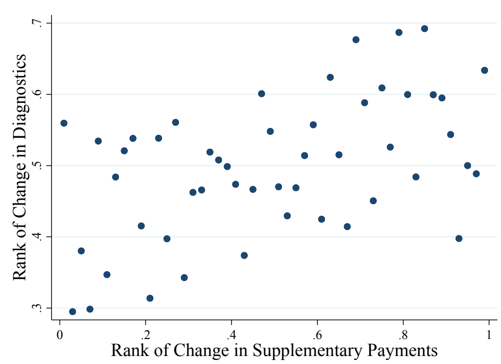
Figure A.4: Similarity of Physician-Specific Responses to Certification Across Treatment Types



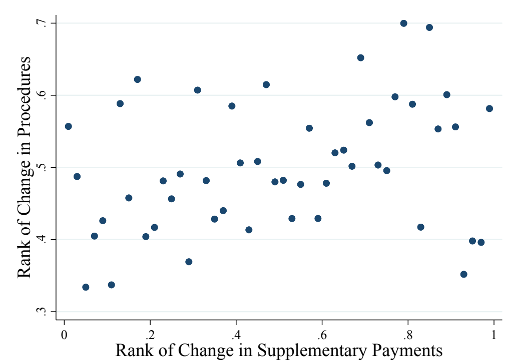
(a) Total Bill Lines



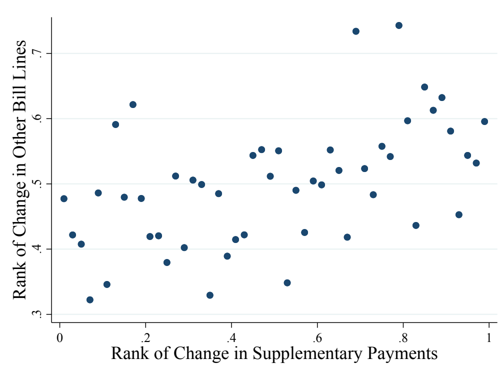
(b) Simulated Hours



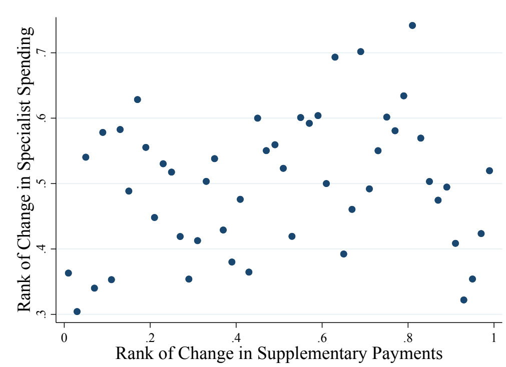
(c) Diagnostics



(d) Procedures



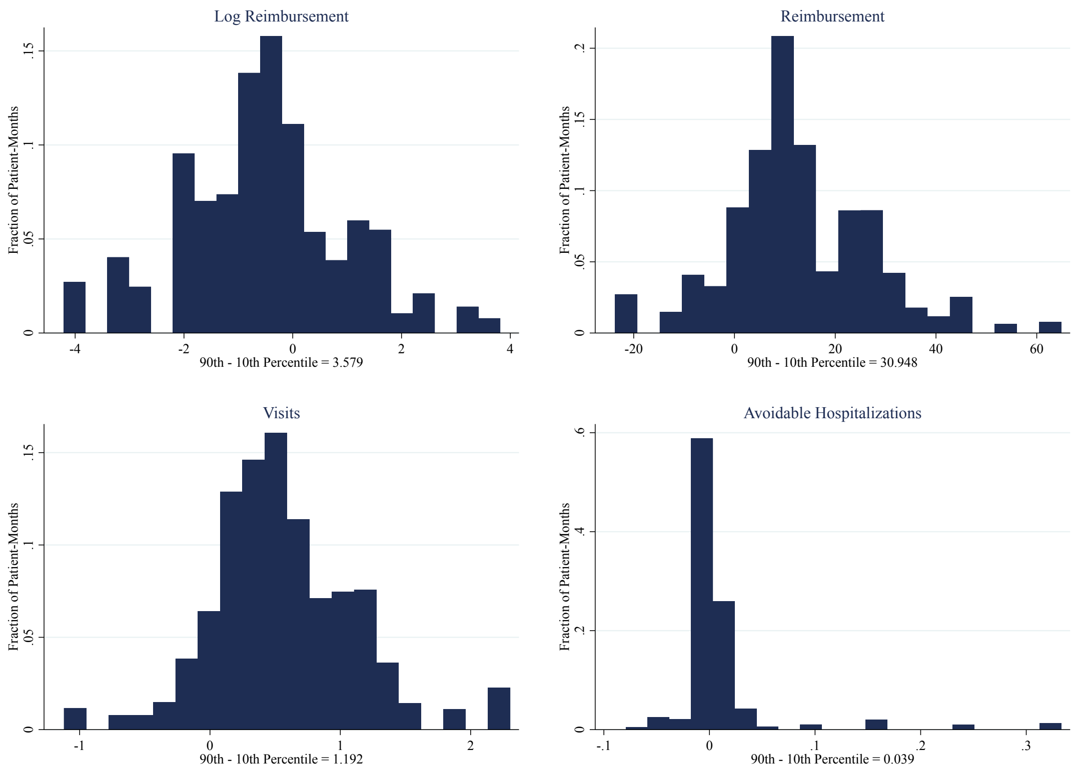
(e) Other Bill Lines



(f) Specialist Spending

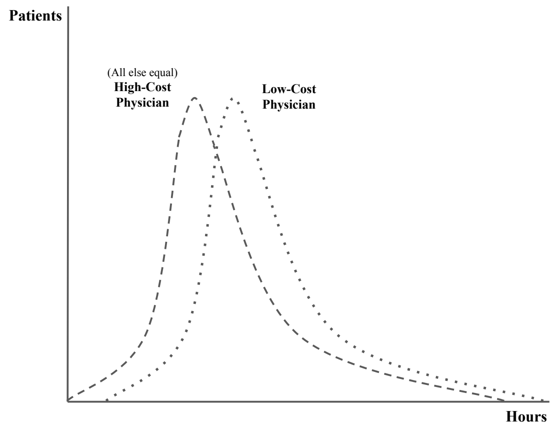
Notes: These plots show that physicians with relatively large increases in supplementary payments post-certification also have relatively large post-certification increases in other measures of treatment intensity. I first take means across patient-months in the six months pre-certification and the six months post-certification, for each physician. Next, I calculate the percentile rank across physicians of $Post - Pre$. Each panel use a different treatment measure to construct the y-axis. Each point is a mean for one of 50 quantiles along the x-axis. The sample includes certified physicians.

Figure A.5: Shrunk Assignment Effects for Certified Physicians

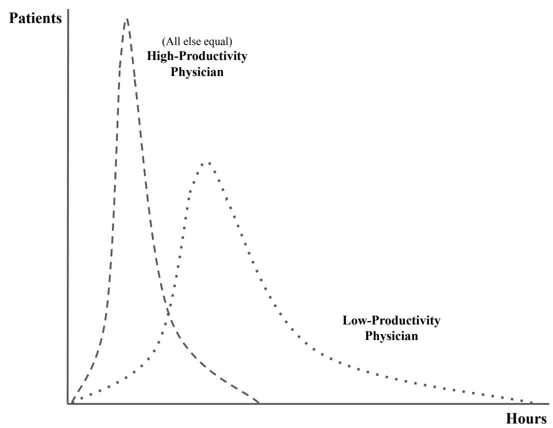


Notes: These histograms show the distribution assignment effects among physicians in the main estimation sample. Following Ginja et al. (2022), I estimate assignment effects by comparing patients from the same exiting physician who are conditionally randomly assigned to various focal physicians. Assignment effects are focal physician fixed effects from a regression including fixed effects for the exiting physician and calendar year. To reflect conditional randomness, I add controls for focal physician availability and an indicator for the same municipality. All estimates are shrunk to the mean using Empirical Bayes, where within- and across-physician variance are estimated using the full list of patients. All dependent variables are per-patient monthly averages during the (up to) six months after assignment.

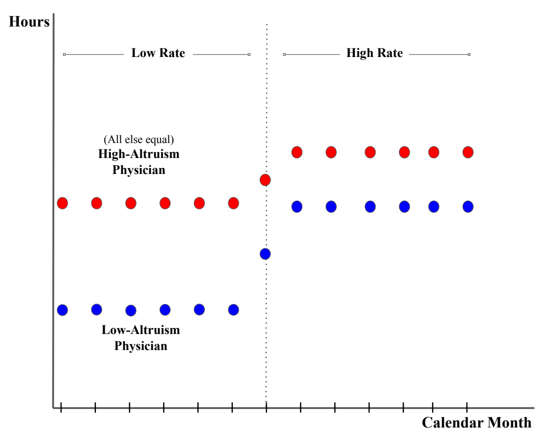
Figure A.6: Stylized Example of Identification Intuition



(a) Cost



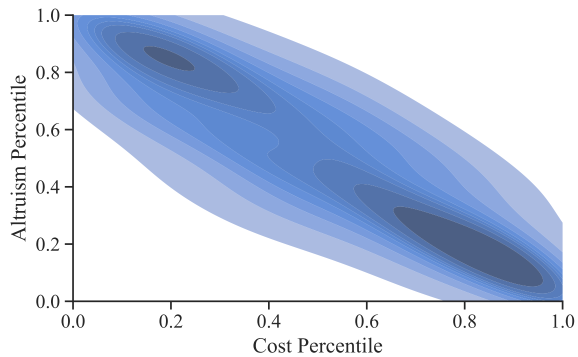
(b) Productivity



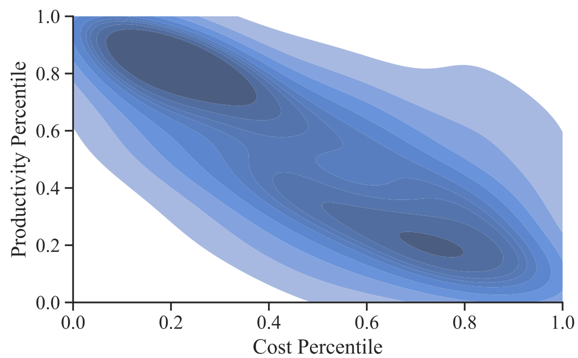
(c) Altruism

Notes: These plots illustrate the identification intuition of physician heterogeneity for the main specification ($\sigma = 0$). All else equal, cost represents a level shift in the distribution of treatment intensity, productivity increases the dispersion of that distribution, and altruism lowers responsiveness to fee-for-service rates.

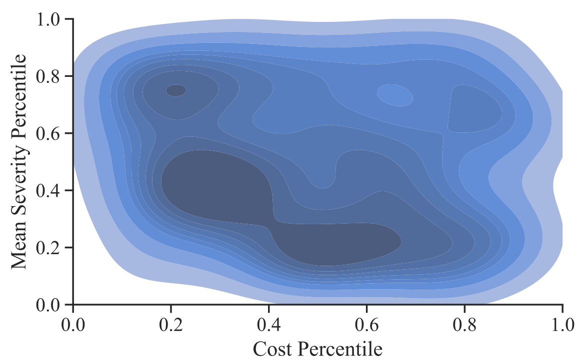
Figure A.7: Distribution of Physician Heterogeneity



(a) Cost and Altruism



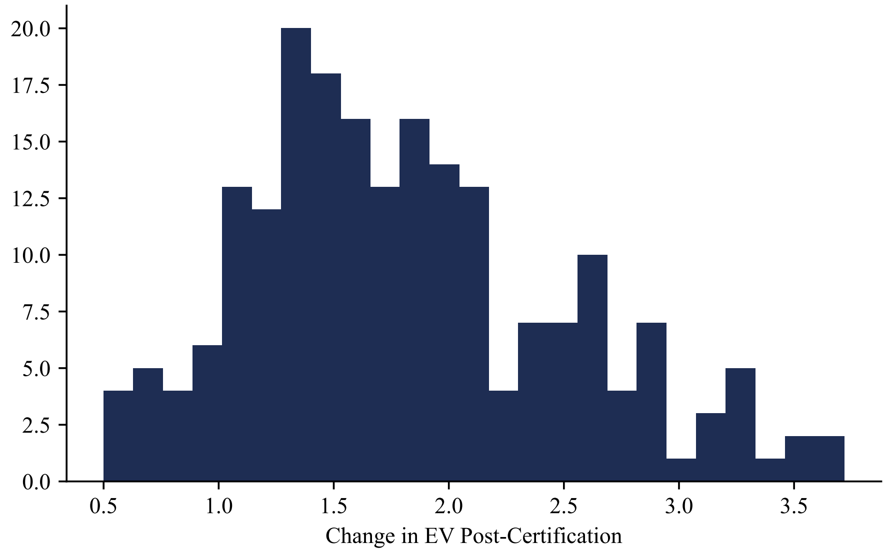
(b) Cost and Productivity



(c) Cost and Severity

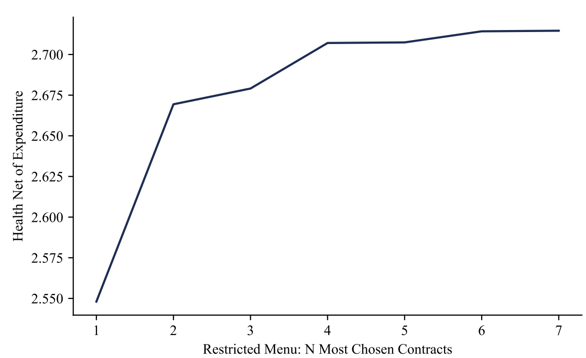
Notes: These plots summarize the joint distribution of estimated cost, altruism, and productivity across the estimation sample. Darker regions indicate higher density.

Figure A.8: Change in Expected Indirect Utility from Certification



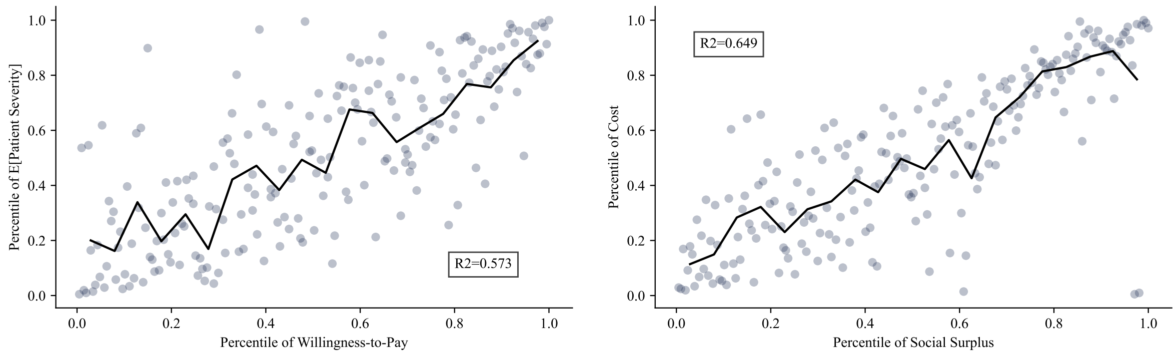
Notes: The y-axis is the count of physicians in each bin. The x-axis is the difference in average expected indirect utility (per patient-month) after certification minus before certification. Integration uses 6 quadrature nodes.

Figure A.9: Restricted Menus Achieve Less Welfare



Notes: The y-axis is expected scaled health production net of expenditure. The x-axis is the number of contracts per menu. For each menu, I re-solve for optimal base payments. I focus the search on the optimal menu's N most chosen contracts. I restrict this function to be non-decreasing when setting the base payment for the marginal contract.

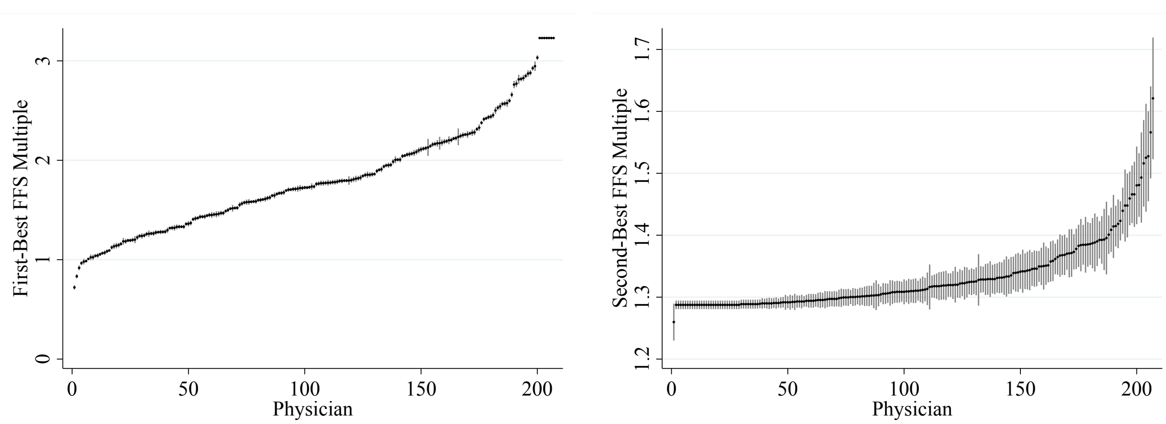
Figure A.10: Two-Contract Menus: Correlations with Physician Type



(a) Private Gain and Mean Patient Severity (b) Social Surplus and Cost

Notes: This figure plots, across physicians, the correlation between each incremental outcome from the two-contract menu in Figure 8a and its strongest predictor by bivariate R^2. I separately regress the outcomes (private gain and social surplus) on percentiles of each dimension (cost, altruism, production). The R^2 statistics for private gain are 0.038 for c, 0.010 for α, and 0.041 for γ. The R^2 statistics for social surplus are 0.588 for α, 0.097 for λ, and 0.096 for mean patient severity. Private gain is the difference in expected indirect utility between the high- and low-fee-for-service contracts. Social surplus is the difference between contracts in expected (scaled) health production minus expenditure.

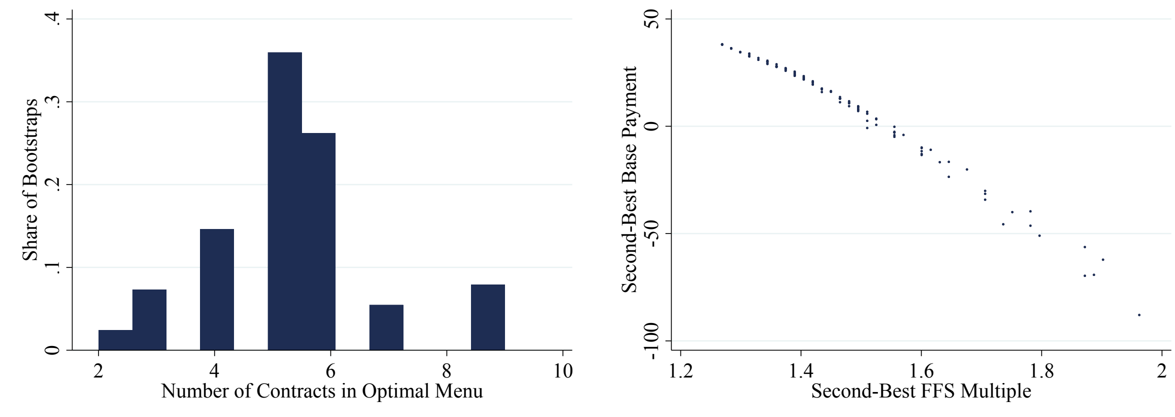
Figure A.11: Physician-Specific Contracts Across Bootstrap Samples



(a) First-Best Fee-For-Service Multiple By Physician (b) Second-Best Fee-For-Service Multiple By Physician

Notes: This figure plots the distribution of fee-for-service multiples across bootstrap samples for each physician. The x-axis is sorted separately for each panel, by mean Fee-For-Service Multiple. Error bars represent the bootstrapped 95 percent confidence interval. In each bootstrap sample, patient-months are randomly selected to maintain the original sample size per physician. In First-Best, the regulator has perfect information about physician types and offers each physician her efficient rate. In Second-Best, given imperfect information, the regulator designs the optimal menu of contracts and each physician self-selects a contract.

Figure A.12: Optimal Menu Across Bootstrap Samples

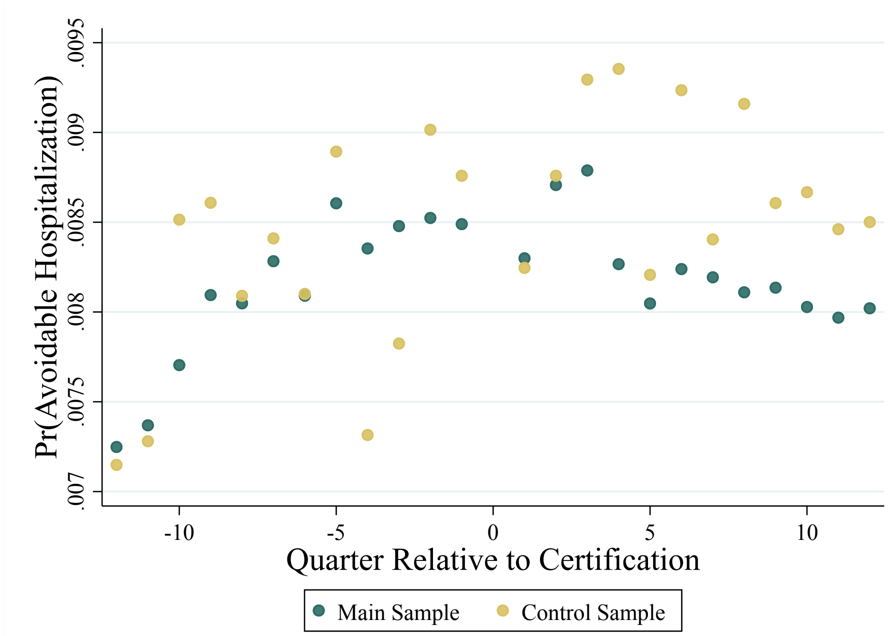


(a) Number of Contracts

(b) Base Payment Schedule

Notes: The left panel plots the distribution of the number of contracts in the optimal menu across bootstrap samples. Only contracts selected by two or more physicians are included. The right panel plots every optimal menu contract selected by two or more physicians, pooled across bootstrap samples. A contract is a pair of the reimbursement rate multiple and base payment. In each bootstrap sample, patient-months are randomly selected to maintain the original sample size per physician. In Second-Best, given imperfect information, the regulator designs the optimal menu of contracts and each physician self-selects a contract.

Figure A.13: Certification and Avoidable Hospitalization



Notes: The plot shows the share of patients with an avoidable hospitalization in each quarter over six years. Each point is a mean across physicians. The underlying data includes patients who were consistently registered in the six months surrounding certification. The denominator of the physician-quarter patient share is the number of patients who are alive. Outside of Quarters -2 to 2, patients are not necessarily registered to the focal physician. The Main Sample includes certified physicians and the Control Sample includes non-certified physicians with randomly selected focal months. Both samples are restricted to physicians with certification dates in 2011-2014 so that utilization data exists in across all 72 months.

A.2 Additional Tables

Table A.1: Types of Reimbursement Codes

	Volume	Count	Examples
Time/Talking	48%	10	Consultation with GP; Supplement for 20+ min visit; Remote patient contact
Testing	22%	8	Taking lab samples; Immunological CRP test; Glucose dry chemical analysis; Thrombotest/INR test
Materials	4%	4	Local anesthetic; Equipment for Category 2 (e.g., ECG)
Procedures	1%	1	Major surgical procedures; Minor surgical procedures
Other	18%	3	Continuing educ. supplement
Infrequently Used	8%	163	Surcharge for biopsy; Finger; Wrist region; Travel Supplement

Notes: This table classifies the top 26 reimbursement codes by volume into categories. All other codes representing 8 percent of volume are included in the final row. Volume is the share of reimbursement lines and Count is the number of unique codes in each category. Examples include a selection of translated descriptions for reimbursement codes.

Table A.2: Sample Selection

	Physicians	Patients
Total Personnel	12,677	
Registered to Patient List	8,928	
Linkable to Utilization	7,956	
Overlapping Certification	1,288	
Fixed and Present Physician	1,269	
Balanced 13-Month Spell	714	799,083
Balanced Patient Panel	619	643,363

Notes: This table shows the number of remaining physicians after each sample selection criterion which are applied cumulatively. The utilization for a particular physician-patient pair is available if both the physician and patient are citizens or permanent residents with tax identifiers. Not all certified physicians receive their certification during the sample period. "Fixed and Present" indicates that each physician is linked to exactly one patient-list with every month at a single location throughout the spell, so the list has no change in the associated list; moreover, neither the physician nor the list exits within or immediately after the spell. Spells are balanced when all prior conditions are met for the six months before and after certification, rather than in at least one month.

Table A.3: Means by Patient Type

	Patients	Share	Age	Chronic	Spend	FFS Rate	Hours
1	147,775	0.115	10.484	0.000	2.646	32.973	0.081
2	96,503	0.075	32.094	0.099	5.080	47.685	0.107
3	83,275	0.065	40.384	0.122	5.765	45.822	0.126
4	54,410	0.042	37.941	0.055	8.752	45.807	0.192
5	65,015	0.051	41.193	0.001	9.331	46.662	0.201
6	51,919	0.040	43.938	0.041	10.248	46.466	0.222
7	50,825	0.039	59.143	0.501	11.671	47.772	0.246
8	35,968	0.028	66.521	0.760	15.302	45.837	0.336
9	33,473	0.026	59.451	1.000	18.823	48.723	0.388
10	24,200	0.019	72.333	1.000	25.271	50.351	0.504

Notes: Summary statistics reflect patients' monthly totals six months before certification in the estimation sample. Monetary measures are in USD. Hours are total reimbursement divided by a wage index.

Table A.4: Registered Patient Summary Statistics

	Control Sample	Estimation Sample					
	Mean	Mean	Std. Dev.	% > 0	10th	50th	90th
Patient Characteristics							
Reimbursement	8.59	8.33	25.49	20.74	0.00	0.00	30.92
Simulated Hourly Rate	43.82	43.76	6.86	100.00	32.38	45.49	50.95
Simulated Hours	0.19	0.18	0.56	20.74	0.00	0.00	0.68
Base Payment	4.03	4.01	0.11	100.00	3.84	4.02	4.13
Visits	0.37	0.34	0.84	20.76	0.00	0.00	1.00
Hours	0.11	0.10	0.29	20.78	0.00	0.00	0.33
Reimbursement Lines	0.90	0.87	2.59	20.79	0.00	0.00	3.00
Procedures	0.06	0.07	0.57	3.55	0.00	0.00	0.00
Diagnostics	0.24	0.22	0.99	8.04	0.00	0.00	0.00
Extra Time	0.10	0.08	0.45	5.03	0.00	0.00	0.00
Clinic Reimbursement	2.49	2.84	101.22	7.43	0.00	0.00	0.00
Specialist Reimbursement	19.84	19.24	86.66	22.88	0.00	0.00	59.67
Acute Hospitalizations	0.02	0.02	0.22	1.38	0.00	0.00	0.00
Age	40.54	37.57	22.78	100.00	6.67	36.58	69.00
Female	0.48	0.50	0.50	50.42	0.00	1.00	1.00
Chronic Illness	0.23	0.21	0.41	21.03	0.00	0.00	1.00
New Patient	0.20	0.10	0.29	9.59	0.00	0.00	0.00
Disability	0.07	0.06	0.25	6.42	0.00	0.00	0.00
Physician Characteristics							
Enrollment	1201.99	1225.23	299.93	100.00	867.00	1197.00	1589.00
Max Enrollment	1268.60	1273.48	293.21	100.00	900.00	1220.00	1600.00
Physician Hours/Week	28.36	26.56	9.44	100.00	13.13	27.33	37.27
Female Physician	0.45	0.43	0.49	42.94	0.00	0.00	1.00
Physician Age	42.87	40.23	5.92	100.00	34.08	38.83	48.67
Migrant Physician	0.27	0.28	0.45	27.82	0.00	0.00	1.00
Pr(Diagnostic)	0.81	0.76	0.10	100.00	0.63	0.77	0.87
Ever Fixed-Salary	0.01	0.03	0.17	2.82	0.00	0.00	0.00
Patients Age 60+	0.23	0.19	0.10	100.00	0.07	0.18	0.32
Patients with Chronic Illness	0.23	0.21	0.06	100.00	0.14	0.20	0.29
Patients	131800	643363					
Physicians	136	619					

Notes: Summary statistics reflect patients' monthly totals six months before certification (or the control month 0 for the control sample). % > 0 indicates the share of patients with a strictly positive measure (row). Other columns reflect the mean, standard deviation, and 10^{th} , 50^{th} , and 90^{th} percentiles. Monetary measures are in USD. Physician Characteristics are also averaged across patients. The last two Physician Characteristics reflect shares of registered patients.

Table A.5: Registered Patient Summary Statistics versus Population

	Population	Estimation Sample					
	Mean	Mean	Std. Dev.	% > 0	10th	50th	90th
Patient Characteristics							
Age	38.436	37.225	22.684	1.000	6.417	36.250	68.417
Female	0.495	0.505	0.500	0.505	0.000	1.000	1.000
Chronic Illness	0.200	0.210	0.407	0.210	0.000	0.000	1.000
Disability	0.060	0.064	0.244	0.064	0.000	0.000	0.000
Physician Characteristics							
Enrollment	1297.232	1235.749	314.715	1.000	880.000	1197.000	1592.000
Female Physician	0.356	0.438	0.496	0.438	0.000	0.000	1.000
Physician Age	49.000	39.777	6.123	1.000	33.500	38.083	49.500
Migrant Physician	0.215	0.226	0.418	0.226	0.000	0.000	1.000
Patients	5525876	215529					
Physicians	4769	207					

Notes: Summary statistics reflect patients' monthly totals. The Population column reflects all Norwegian patients in 2012. All other columns reflect patients in the estimation sample six months before certification (or the control month 0 for the control sample). % > 0 indicates the share of patients with a strictly positive measure (row). Other columns reflect the mean, standard deviation, and 10^{th} , 50^{th} , and 90^{th} percentiles. Physician Characteristics are also averaged across patients.

Table A.6: Distribution of Patient Severity

	Estimate	Std. Err.
Patient Type 2	0.039	(0.001)
Patient Type 3	0.053	(0.001)
Patient Type 4	0.083	(0.001)
Patient Type 5	0.091	(0.001)
Patient Type 6	0.092	(0.001)
Patient Type 7	0.091	(0.001)
Patient Type 8	0.109	(0.001)
Patient Type 9	0.111	(0.001)
Patient Type 10	0.129	(0.002)
February	0.030	(0.001)
March	0.011	(0.001)
April	0.020	(0.001)
May	0.010	(0.001)
June	0.018	(0.001)
July	0.014	(0.001)
August	−0.059	(0.001)
September	0.013	(0.001)
October	0.017	(0.001)
November	0.017	(0.001)
December	0.018	(0.001)
$\log(1+m_{t-1})$	0.024	(0.000)
$m_{t-1}=0$	0.050	(0.001)
Cancer	0.010	(0.002)
Diabetes	0.028	(0.002)
COPD	0.031	(0.002)
Asthma	0.018	(0.002)
CVD	0.035	(0.002)
1+ Chronic Illness	0.014	(0.002)
2+ Chronic Illnesses	−0.005	(0.002)
Female	0.001	(0.000)
Disability Receipt	0.055	(0.001)
Income Percentile	−0.013	(0.001)
Recent Acute ER Visit	0.022	(0.001)
Recent Acute ER Visit 2+	0.032	(0.001)
Time Trend	0.009	(0.002)
New Patient	0.006	(0.001)
$\log\sigma_\lambda$	−0.389	(0.003)
$P(\lambda>0):d_0$	−3.389	(0.019)
$P(\lambda>0):d_1$	11.462	(0.132)

Notes: This table shows model estimates with asymptotic standard errors calculated using the approximate Hessian. Unobserved patient severity is distributed $\ln\lambda \sim N(\beta_\lambda X_\lambda, \sigma_\lambda) \mid \lambda > 0$ and $Pr(\lambda>0) = f(d_0 + d_1\beta_\lambda X_\lambda)$, where $f(z) = \frac{\exp z}{1+\exp z}$. The first set of estimates corresponds to β_λ.

Table A.7: Counterfactual Outcomes by Physician Location

Physicians		Efficient Contracts		Menu of Contracts		
Type	Share	$\Delta E[h(m)]$	$\Delta E[p\,m+b]$	$\Delta E[h(m)]$	$\Delta E[p\,m+b]$	$\Delta E[V(p)]$
Most Urban: 1	0.11	6.09	1.72	2.10	2.18	1.68
2	0.31	8.90	2.30	3.08	2.42	1.80
3	0.34	7.32	1.99	2.65	2.23	1.68
4	0.16	9.22	2.46	2.57	2.15	1.65
5	0.04	11.11	2.58	3.43	2.51	1.88
Most Rural: 6	0.04	13.50	2.69	4.36	2.84	2.07

Notes: This table shows average outcomes for efficient (personalized) contracts and the optimal menu of contracts, disaggregated across groups of physicians (rows). Physicians are grouped by the centrality index of their municipality. $\Delta E[h(m)]$ represents the change in health production relative to the status quo, for efficient contracts and the optimal menu of contracts. Likewise, $\Delta E[p\,m+b]$ represents incremental expected expenditure and ΔEV represents incremental expected indirect utility. Outcomes are averages across patients within each group, measured in USD. I assume that the less than 1 percent of physicians who do not have a linked municipality are in the most urban category.

Table A.8: Counterfactual Outcomes: Menu for each Patient Type

	$\Delta SS_{Efficient}$	$\Delta SS_{Uniform}$		ΔSS_{Menu}		Menu $\succ$ Uniform
	Level	Level	Share of Eff.	Level	Share of Eff.	
Baseline	8.396	2.548	0.303	2.714	0.323	✓
Patient Type 1	3.190	0.877	0.275	0.977	0.306	✓
Patient Type 2	4.560	1.264	0.277	1.332	0.292	✓
Patient Type 3	6.343	1.928	0.304	1.990	0.314	✓
Patient Type 4	7.810	2.447	0.313	2.520	0.323	✓
Patient Type 5	9.802	2.701	0.276	2.892	0.295	✓
Patient Type 6	11.868	3.389	0.286	3.554	0.299	✓
Patient Type 7	11.844	3.321	0.280	3.505	0.296	✓
Patient Type 8	15.291	4.328	0.283	4.511	0.295	✓
Patient Type 9	19.851	5.593	0.282	5.975	0.301	✓
Patient Type 10	25.702	6.842	0.266	7.185	0.280	✓
All Patient Types	8.586	2.433	0.283	2.569	0.299	✓

Notes: This table compares key outcomes between counterfactual contract menus. All outcomes are based on ex-ante expectations over patient-months using estimated distributions of G and F, weighted across physicians by enrollment. Outcomes are summarized by the change in social surplus, defined as the change in health production versus pre-certification minus the change in expenditure versus post-certification. Share of Eff. divides the change in levels of social surplus for the optimal menu by the change in levels for efficient contracts. Relative to Table 4 (included as "Baseline"), each row after the first summarizes a separate analysis for each observed patient type. Analyses are separate in the sense of unique benchmarks, menus, and weighting across physicians. All Patient Types weights the type-specific counterfactual outcomes by share of the main estimation sample.

Table A.9: Counterfactual Outcomes with Perturbations

	$\Delta SS_{Efficient}$	$\Delta SS_{Uniform}$		ΔSS_{Menu}		Menu $\succ$ Uniform
	Level	Level	Share of Eff.	Level	Share of Eff.	
Baseline	8.396	2.548	0.303	2.714	0.323	✓
$0 \times Var(c)$	7.885	2.122	0.269	2.464	0.313	✓
$\frac{1}{2} \times c$	3.423	2.183	0.638	2.184	0.638	✓
$2 \times c$	5.560	1.194	0.215	1.332	0.240	✓
$2 \times Var(c)$	15.123	2.361	0.156	2.361	0.156	
$0 \times Var(\alpha)$	8.664	2.606	0.301	2.921	0.337	✓
$\frac{1}{2} \times \alpha$	5.838	2.005	0.343	2.040	0.349	✓
$2 \times \alpha$	11.188	2.791	0.249	3.178	0.284	✓
$2 \times Var(\alpha)$	9.978	2.327	0.233	2.327	0.233	
$0 \times Var(\gamma)$	8.645	2.564	0.297	2.652	0.307	✓
$\frac{1}{2} \times \gamma$	2.892	0.881	0.305	0.933	0.322	✓
$2 \times \gamma$	22.371	5.519	0.247	6.030	0.270	✓
$2 \times Var(\gamma)$	8.733	2.542	0.291	2.733	0.313	✓
Uncorrelated c, α, γ	10.215	2.117	0.207	2.176	0.213	✓
Drop Outliers of c, α, γ	8.993	2.576	0.286	2.802	0.312	✓
$\frac{1}{2} \times Var(\theta_k), \theta_k \in c, \alpha, \gamma$	8.416	2.721	0.323	2.998	0.356	✓
$0 \times Var(\gamma), 0 \times Var(\alpha)$	8.680	2.763	0.318	2.991	0.345	✓
$0 \times Var(c), 0 \times Var(\alpha)$	7.622	2.466	0.324	2.819	0.370	✓
$0 \times Var(c), 0 \times Var(\gamma)$	8.318	2.124	0.255	2.421	0.291	✓
$\frac{1}{2} \times \sigma_\lambda$	6.446	1.732	0.269	1.803	0.280	✓
$2 \times \sigma_\lambda$	23.791	5.530	0.232	6.456	0.271	✓
$\frac{1}{2} \times \alpha_G$	4.449	1.324	0.298	1.310	0.294	
$2 \times \alpha_G$	16.599	4.991	0.301	5.667	0.341	✓
Add Control Sample	9.681	4.010	0.414	4.161	0.430	✓
Constrain Capacity	17.524	2.063	0.118	4.376	0.250	✓
Exclude Part-Time Physicians	8.781	2.559	0.291	2.730	0.311	✓
Only Urban Physicians	8.374	2.561	0.306	2.737	0.327	✓
Only Rural Physicians	9.360	2.644	0.282	2.788	0.298	✓
Alt. Health Parameterization	8.426	2.561	0.304	2.737	0.325	✓

Notes: This table compares key outcomes between counterfactual contract menus. All outcomes are based on ex-ante expectations over patient-months using estimated distributions of G and F, weighted across physicians by enrollment. Outcomes are summarized by the change in social surplus, defined as the change in health production versus pre-certification minus the change in expenditure versus post-certification. Share of Eff. divides the change in levels of social surplus for the optimal menu by the change in levels for efficient contracts. Relative to Table 4 (included as "Baseline"), each row perturbs one or more parameters before repeating counterfactual analyses. The parameters are marginal cost c, altruism α, productivity γ^{-1}, standard deviation of the log patient severity σ_λ, and altruism of the regulator α_R. $0 \times Var(c)$ fixes c at the sample mean. $\frac{1}{2} \times c$ multiplies c by 0.5 for all physicians. $2 \times Var(c)$ uses the following function: $f(c) = \bar{c} + \sqrt{2} \times (c - \bar{c})$. Outliers are below the 1st percentile or above the 99th of c, α, or γ. In one perturbation, I impose a capacity constraint on simulated hours per physician-month and approximate the shadow cost of capacity (see Appendix A.3 for details). Rural physicians are in municipalities with low centrality indexes. Part-Time physicians spend less than 25 hours per week with patients in the six months before certification.

Table A.10: Test for Patient Sorting

	Predicted Health (SDs) (1)	Switch (2)	Hospitalization (3)	Mortality (4)
Post-Certification	0.133***			
	(0.044)			
Predicted Health (SDs)		−0.001	−0.003***	−0.001*
		(0.004)	(0.001)	(0.001)
Age	−0.014***	−0.001***	−0.000***	−0.045***
	(0.002)	(0.000)	(0.000)	(0.002)
Asthma	−0.200***	−0.005	0.052***	0.016
	(0.075)	(0.009)	(0.014)	(0.015)
Age^2	0.000***	0.000***	0.000***	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)
Cancer	−0.183***	0.006	−0.025*	0.072***
	(0.070)	(0.008)	(0.014)	(0.015)
COPD	−0.291***	0.033***	0.181***	0.108***
	(0.087)	(0.009)	(0.015)	(0.016)
CVD	−0.341***	0.007	−0.034**	0.025*
	(0.089)	(0.008)	(0.014)	(0.015)
Diabetes	−0.400***	−0.004	−0.036***	0.035**
	(0.113)	(0.008)	(0.014)	(0.015)
Female	−0.164***	0.009**	−0.001	−0.001
	(0.033)	(0.004)	(0.001)	(0.002)
Income Percentile	0.099***	0.022***	−0.010***	0.085***
	(0.034)	(0.005)	(0.001)	(0.006)
1+ Chronic Illness	−0.111	−0.009	0.038***	−0.037**
	(0.086)	(0.008)	(0.014)	(0.015)
2+ Chronic Illnesses	−0.046	−0.000	0.040***	−0.032*
	(0.069)	(0.009)	(0.014)	(0.017)
Observations	2583264	215272	215272	54192
R^2	0.102	0.022	0.043	0.133
Outcome mean	-0.013	0.060	0.021	0.042

Notes: This table shows estimates of the correlation between patients' model-predicted health production and outcomes of interest measured after the estimation sample. Health production is normalized to standard-deviation units within the estimation sample. All specifications include year and calendar month fixed effects and cluster at the physician level. Column (1) includes the entire spell and regresses expected health production given parameter estimates on an indicator for months after specialization and patient covariates. Columns (2)-(4) are cross-sectional regressions using expected health production as the treatment variable of interest. The dependent variables are an indicator for switching to a new physician within 6 months, an indicator for an avoidable hospitalizations in the next 12 months, and an indicator for mortality within the next 24 months. Column (4) includes patients over 45 years old. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level.

A.3 Income Effects and Capacity Constraints

This section extends the main model to cases with decreasing returns to treatment intensity from higher reimbursement rates. The first case is lower marginal utility of marginal reimbursement for high-workload physicians: income effects. High workload is driven by differences between physicians in the number of patients ("enrollment") and those patients' expected severity ("composition"). Moreover, income effects introduce complementary between the treatment intensity decisions of various patients. For example, increasing the treatment intensity for patient 1 may increase the marginal utility of leisure, lowering treatment intensity for patient 2. To tractably model this dynamic, I assume that patients arrive sequentially and only short-term future treatment intensity affects the marginal utility of leisure.[68] Equivalently, a physician will treat a patient slightly less intensively if that physician expects to work many hours over the next month treating other patients. As before, for each patient $i \in 1, ..., N$, the health shock is realized only when that patient arrives. The private objective becomes:

$$EV(x; \lambda_i, F, \theta) = \max_{m_i \geq 0} \; x(m_i) - c(m_i) + \sigma E\left[l\left(\sum_{i'=1}^{N} m^*_{i'} \right) \mid F(\lambda_{i'}) \right] + \alpha h(m_i, \lambda_i)\,, \tag{7}$$

The additional term ($\sigma E\left[l\left(\sum_{i'=1}^{N} m^*_{i'} \right)\right]$) represents the money-metric distaste for expected workload. The expectation enters because, before arrival, each future patient i' has uncertain severity.

The key assumption is that the expected (but not realized) treatment of one patient may affect the privately optimal choice for another patient of the same physician: $\frac{dm'}{dm} = 0$. Physicians anticipate the effect of making similar choices on the marginal utility of leisure. With this assumption, each patient's likelihood depends on an independent draw of their own severity, along with the contract and the number and composition of other patients. In estimation, I assume quadratic preferences, $l(x) = -\frac{(x)^2}{2}$, so the marginal utility of leisure is strictly positive and increases exponentially in the expected number of hours worked, and I substitute observed average treatment intensity for expected treatment intensity since the two should coincide at true parameters. The privately optimal level of treatment intensity becomes:

$$m^*(p, \lambda, (N-1)\bar{m}) = \max\{0, \frac{p - c - \sigma(N-1)\bar{m} + \alpha\gamma\lambda}{\alpha + \sigma}\} \tag{8}$$

and the likelihood is constructed as before by inverting for ϵ_λ.

[68] Alternatively or additionally, I could relax the assumption that the marginal utility of net income equals 1 by introducing curvature, but that approach unnecessarily complicates the expression for physicians' private gain from switching contracts.

For identification intuition, it is helpful to first discuss two reduced-form parameters. Given *any* distribution of patient severity and additive quadratic health production, the first-order condition can be simplified to $m = \max\{0, \beta_0 + \beta_1\lambda\}$ where the level β_0 and slope β_1 are specific to a combination of physician and time period. It could also be specific to patient observables. Generally, to identify β_0 and β_1, these quantities need to be independent of (the random component of) λ. To separably identify β_1 from parameters governing $F(\lambda)$, a physician needs to be observed for at least two periods with the same distribution of patients and no model-predicted change to β_1. In that case, repeated draws of λ drive variation in m, so conditional moments of m match the corresponding moments $F(\lambda)$. Linear separability between utility from net income and health production implies that β_0 and β_1 are constant for a physician if the reimbursement rate and the set of patients are constant. Given β_1 and the distribution of λ, β_0 is identified by the responsiveness of a physician's average treatment intensity (over patients), relative to other physicians or time periods.

The marginal rate of substitution between leisure and net income σ is identified by the responsiveness of β_0 to the number (N) and composition $(\bar{m})$ of patients within physician over time. Given σ and practice characteristics, the responsiveness of β_0 and β_1 to fee-for-service over time within-physician identifies altruism. Critically, this requires observing treatment intensity choices for the same physicians at different fee-for-service rates, which only occurs in the certification sample. Persistent residual variation in β_1 identifies productivity and persistent residual variation in β_0 identifies cost. Only altruism must be time-invariant; all other parameters can be both physician-specific and time-varying, including curvature of preferences over leisure. However, for estimation, I assume time-invariance and symmetric σ because implied β_0 and β_1 may be noisy even with large data leading to overestimation of across-time variance in physician heterogeneity.

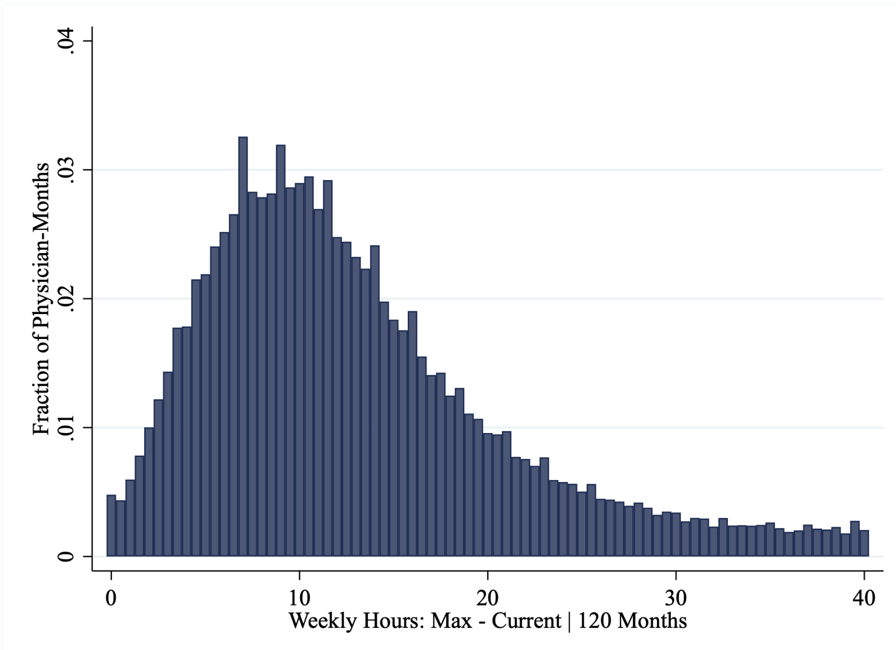
Consistent with prior studies that find treatment intensity increases in marginal reimbursement, likelihood ratio tests fail to find evidence of income effects.[69] Although simulated hours of treatment do not increase with fee-for-service rates for some physicians, high altruism and large variance in patient health shocks better explain this pattern than income effects – marginal utility of leisure increasing in the expected workload.

In addition to income effects, capacity constraints may limit counterfactual treatment intensity from greater fee-for-service rates. For example, physicians may only be able to treat patients up until a threshold number of hours each month ($\sum_{i=1}^{N} m_i \leq \bar{M}$). If capacity constraints sometimes bind, then

[69]In estimation, I search over positive scaled values of σ.

over a long period (120 months) with idiosyncratic variation in enrollment, composition, and realized severity, some physicians' monthly total treatment intensity should bunch near the maximum. I instead find that the distribution of treatment intensity relative to a physician-specific maximum is relatively smooth near the maximum.

Figure A.14: Capacity Constraints: Hours Do Not Bunch Near Each Physician's Maximum

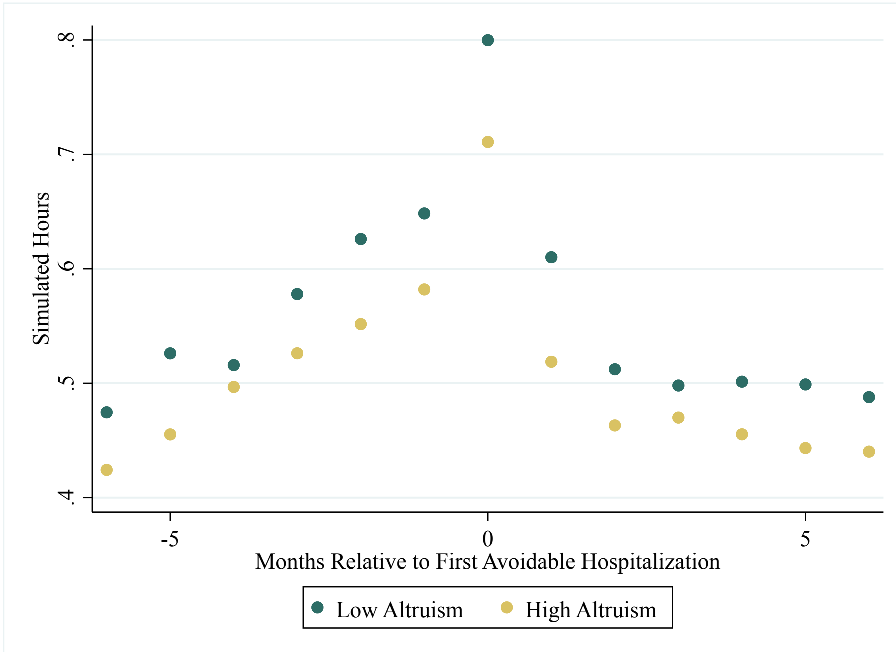


Notes: This figure shows the distribution of transformed hours per week ($\tilde{M}_{jt}$) across physician-months ($j-t$). The transformation is $\max_t M_{jt} - M_{jt}$. The x-axis is truncated at 40 and I exclude the first month when a physician works the maximum number of hours. According to the theoretical framework, $M_{jt} = \sum_i^{N_{jt}} \operatorname{argmax} u(x(m_{ijt}) - c(m_{ijt})) + \alpha h(m_{ijt}, \gamma\lambda_{ijt})$, s.t. $\sum_i^{N_{jt}} m_{ijt} \leq \bar{M}_j$, where λ_{ijt} is stochastic. If capacity binds and $F(\lambda)$ is continuous, then $Pr(M_{jt} = \bar{M}_j \equiv \max_t M_{jt}) >> Pr(M_{jt} = \bar{M}_j - \epsilon)$ for small $\epsilon > 0$.

The main findings are also robust to imposing capacity constraints (See Table A.9). Intuitively, adding a capacity constraint means reducing each treated patient's treatment intensity by a fixed amount per physician-month – excess total hours per treated patient – where excess total hours is the difference between unconstrained total hours and capacity. The more general first-order condition is $m^*(p) = \max\{0, \frac{p-c-\mu_c}{\alpha} + \gamma\lambda\}$. Substituting this condition into the capacity constraint pins down the shadow cost of capacity, $\mu_c = \alpha(\frac{\sum_i \max\{0, \frac{p-c-\mu_c}{\alpha} + \gamma\lambda\} - \bar{M}_j}{N_{jt} Pr(m^*(p) > 0)})$. An exact μ_c is a fixed point of this equation which varies for each physician-month pair. This fixed point may not converge with quadrature, so for the robustness check, I approximate it as $\hat{\mu}_c = \alpha(E[m^0_{ijt} \mid m^0_{ijt} > 0] - \frac{\bar{M}}{N_{jt} Pr(m^0_{ijt} > 0)})$ where $m^0_{ijt} = \max\{0, \frac{p-c}{\alpha} + \gamma\lambda\})$ is the unconstrained treatment intensity.[70]

[70]Two further adjustments help limit approximation error. First, I bound the denominator below by 1. Second, I use 0.5

Figure A.15: Treatment Intensity Responds to Health Shocks



Notes: This figure shows average simulated hours across patient months in the six months before and after each patient's first avoidable hospitalization. The sample includes pre-certification patient-months for a balanced panel of consistently registered patients and is subset by whether the registered physician's estimated altruism is above or below the sample median.

Finally, I conclude that altruism estimates are not biased because high-altruism physicians are not contained from increasing treatment intensity when a patient has an avoidable hospitalization. Estimates of high altruism reflect that some physicians are less responsive to increased reimbursement rates. These estimates may be biased if the low response reflects some unobserved constraint rather than altruism. A.15 shows that the mean treatment intensity of high-altruism and low-altruism physicians is similarly responsive to the shock of a first avoidable hospitalization.

A.4 Selection into Certification

To empirically estimate the model outlined above, I rely on plausibly exogenous within-physician variation in reimbursement rates generated by receiving certification as a general practitioner. 80 percent of physicians receive this certification at some point in their career, and the estimation sample includes a fraction of these. If certified physicians in the estimation sample are selected on unobserved heterogeneity, then counterfactuals lack external validity for the full population of physicians. This section extends the

as a threshold for m^0_{ijt} in the denominator to avoid over-correcting based on mass near zero treatment intensity. This threshold represents approximately the 90^{th} percentile of status quo treatment intensity.

model to account for potential selection and test its implications. Although this extended model could be fully estimated, I find that estimates using the subset of physicians are similarly predictive of treatment intensity in a control sample of never-certified physicians, and conclude that selection is not a first-order concern for the main research question.

Physicians choose to become certified if the increase in indirect expected utility outweighs the cost of certification and difference in iid taste shocks:

$$\max_{S,NS} \left\{ E_\lambda V(p + p_S; \theta, F(\lambda)) - C_s + \epsilon_S, E_\lambda V(p; \theta, F(\lambda)) + \epsilon_{NS} \right\} .$$

I include taste shocks for certification choice but not counterfactual contract choice because certification requires additional training with idiosyncratic benefits and costs, rather than a purely financial change with impacts fully characterized by physician type. The key assumptions here are the constant cost of certification and independence between taste shocks, physician type, and patient severity. These might be violated if, e.g., only some physicians have binding time constraints outside of work with registered patients. Another assumption is that certification (with required training) does not impact health production, but this can be relaxed. Consistent with empirical findings, this model of certification assumes that certification does not change the distribution of registered patients F or the number of patients. If the cost of certification is large relative to taste shocks, then the distribution of types who become certified will differ from the unconditional distribution.

This model helps guide intuition about how physicians in the estimation sample might be selected on unobserved heterogeneity. Larger draws of taste shocks might drive certification, which would not impact external validity. However, if the costs of certification are relatively large, then certified physicians have greater private gain from switching to the certified fee-for-service rate. Section C.1 shows that such physicians have relatively low cost, high altruism, and high productivity. As a result, estimates should be less predictive of treatment intensity out-of-sample. To test this, I follow a similar estimation procedure to recover all parameters besides the set of α in the control sample. I use the correlation between $\ln \alpha$ and observed physician characteristics to predict α in the control sample and then hold those values fixed. Table A.11 shows regression of actual treatment intensity m on predicted $E[m]$. Although the differences between the samples are precise, they are small. The coefficient on $E[m]$ is just as far from 1 in both samples but in opposite directions, and disappears with fixed effects, suggesting that selection on unobserved heterogeneity is minimal.

Table A.11: Test for Selection on Unobserved Physician Heterogeneity

	Certified	Non-Certified	Certified and Non-Certified		
	(1)	(2)	(3)	(4)	(5)
$E[m]$	1.041***	1.025***	1.032***	1.041***	1.087***
	(0.002)	(0.005)	(0.002)	(0.002)	(0.003)
$E[m]$ × Control				−0.016***	−0.018***
				(0.005)	(0.005)
Control				−0.001	
				(0.001)	
Female					−0.013***
					(0.001)
Age					−0.000***
					(0.000)
Chronic Illnesses					−0.021***
					(0.001)
Intercept	−0.007***	−0.008***		−0.007***	
	(0.001)	(0.001)		(0.001)	
Physician FEs			✓		✓
Observations	2013672	385416	2399088	2399088	2399088
R^2	0.113	0.108	0.114	0.112	0.114

Notes: All regressions use observed treatment intensity as the dependent variable. The control (Non-Certified) sample is constructed identically to the main estimation (Certified) sample, except that the starting pool of physicians is a random subset of those that never become certified. The last three columns pool both samples. $E[m]$ is calculated based on parameter estimates given observable characteristics. Control is an indicator for the control sample.

Estimates are consistent with physicians rationally choosing to become certified. All physicians experience an increase in expected indirect utility (EV). A.8 shows the distribution of this change in EV across physicians. The large average increase in EV and a symmetric (rather than left-skewed) distribution suggest minimal selection on unobserved heterogeneity.[71]

A.5 Optimal Nonlinear Uniform Contract

This paper primarily investigates contracts in which revenue is a linear function of treatment intensity. This structure nests the ways healthcare providers are typically reimbursed in most settings. Linear contracts may be common because they are relatively easy to implement and understand.[72] However, larger welfare gains may be possible when revenue is a flexible function of treatment intensity. For example, after a large amount of treatment, the marginal return to health may be small, so low marginal reimbursement can limit relatively inefficient spending.

[71] Since most physicians in the sample waited several years to become certified despite large potential increases in EV, taste shocks of certification must be large relative to costs.

[72] For example, Norway uses a survey of physicians' costs to inform service-level uniform reimbursement rates.

The optimal nonlinear uniform contract performs about half as well as efficient linear contracts in terms of improving patient health, but the participation constraint requires large increases in expenditure, so the gains to social surplus are small. Figure A.16 shows that relative to the best linear uniform contract, the nonlinear contract lowers the marginal rates of low levels of treatment intensity and increases the marginal rates of high levels of treatment intensity. Figure A.17 shows that this means redistributing away from patients with relatively low severity to most other patients with relatively high severity. The distribution of treatment intensity more closely resembles efficient linear contracts with the nonlinear uniform contract that with menu of linear contracts. Figure A.18 shows corresponding distribution of health production and expenditure. However, without a base payment, the nonlinear uniform contract is not directly comparable to other counterfactuals because the nonlinear contract redistributes from physicians towards patients. Figure A.19 illustrates this tradeoff: although physicians are on average equally well off under the nonlinear contract relative to the status quo, 56 percent are individually worse off, and these losses represent up to 5 percent of status quo revenue. Physicians with losses tend to have high productivity and low patient severity, i.e., less initial under-treatment. If these physicians eventually exit the system, the risk of under-treatment for unmatched patients grows. For all physicians to be weakly better off, as required in other counterfactuals, the nonlinear contract needs \$3.32 in base payments, which is slightly higher than average base payments under the menu. After this adjustment, the gain in social surplus is only 23 percent of first best while the menu of linear contracts achieves 32 percent.[73]

Institutional differences also help explain the different impacts of a non-linear uniform contract in this setting relative to Gaynor, Mehta and Richards-Shubik (2023). With primary care and the large estimated dispersion in unobserved patient severity, there does not seem to be a narrow range of medically appropriate treatment intensity for a non-linear contract to target. Moreover, my estimates imply that marginal health production is nearly universally positive, so decreasing treatment intensity is not generally efficient. In Gaynor, Mehta and Richards-Shubik (2023), more than half of observed treatment intensity was high enough to damage health based on a known cutoff.[74]

I use a demand profile approach to derive the nonlinear contract, similar to Gaynor, Mehta and Richards-Shubik (2023), while also drawing on intuition from Chade et al. (2022). The demand profiling

[73] Alternatively, one could moderate the participation constraint by incorporating physician exit: if indirect utility is lower than the threshold, then the corresponding patients have zero treatment intensity and zero public expenditure. However, this form of the constraint would only negligibly change counterfactual outcomes. Across counterfactuals, health production net of expenditure exceeds health production with zero treatment intensity by more than the base payment for either all physicians or all but one.

[74] These characterizations mostly refer to Figure 3 in that paper, which is based on a patient with median observed severity.

approach approximates the global design problem – avoiding the need to simultaneously optimize the social objective for a continuum of marginal reimbursement. I approximate the continuum with finitely many reimbursement rates and independently optimize one rate at a time. Each rate applies to a fixed segment of treatment intensity. An increase in one rate corresponds to incremental treatment intensity, and in turn, incremental health production, private costs, and public expenditure. These changes only occur among the patients with marginal treatment intensity.

I discretize the support of treatment intensity into T intervals.[75] For each interval $[m_t, m_{t+1})$, I find the corresponding reimbursement rate p_t that maximizes scaled incremental health production net of incremental private costs:

$$E_{\theta,\lambda}\left[(\alpha_G + \alpha)(h(m^*, \gamma\lambda) - h(m_t, \gamma\lambda)) - c\,(m^* - m_t) \mid m^* \geq m_t\right]$$

The interior of the expectation is a transformation of the social objective. Recall that the regulator maximizes expected health production subject to budget and participation constraints as well as privately optimal treatment intensity m^* which depends on the contract x, type θ, and patient severity. Based on equivalence of the first-order conditions after fixing shadow costs, I maximize a weighted sum of health production, private indirect utility, and public expenditure.[76]

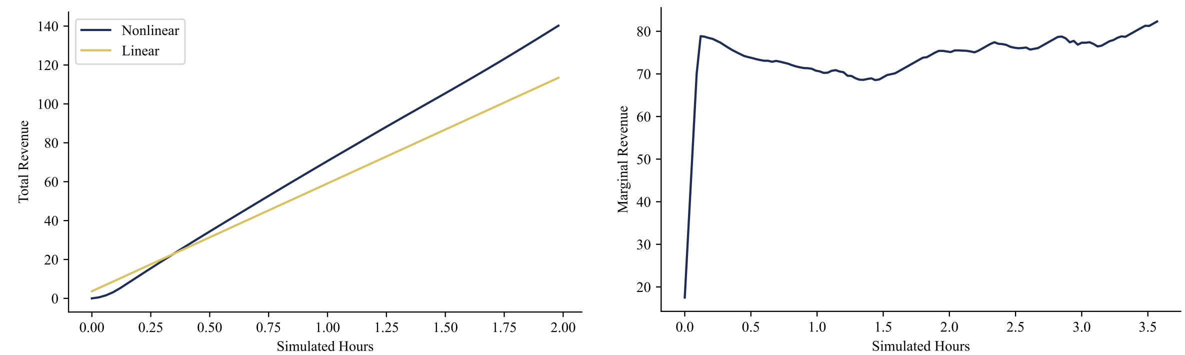
In the objective's conditional expectation, I focus on patients and physicians who contribute to incremental social surplus, i.e., those whose treatment intensity varies with p_t. I also restrict the space of contracts so that marginal reimbursement $p(m)$ only crosses effective marginal cost $c - \alpha h_m(m, \gamma\lambda)$ for a unique value of treatment intensity $m^*(x = \{p_t\}_t)$.[77] If marginal reimbursement p_t exceeds effective marginal cost at m_t (or equivalently, $m^*(p_t) \geq m_t$), then the same is true at all lower levels of treatment.

[75] Each interval spans approximately 2 simulated minutes of treatment intensity between 0 and 2 simulated hours.

[76] I fix the shadow costs of expenditure (μ_B) and participation ($\mu_{P,\theta}$ at $\frac{1}{\alpha_G}$ before rescaling the objective by α_G. Equivalently, α_G is the regulator's altruism and the regulator is willing to sacrifice \$1 of expenditure to either increase scaled health production or private indirect utility by \$1, so public expenditure and private revenue add to zero.

[77] Equivalently, the physician objective is concave and single-peaked for all physicians and patients. Marginal revenue cannot increase at a greater rate than marginal health production: $p_t - p_{t-1} < \alpha\,\forall t, \alpha$. I also focus on contracts where revenue is weakly increasing in treatment intensity. Neither of these constraints binds at the solution.

Figure A.16: Optimal Nonlinear Uniform Contract

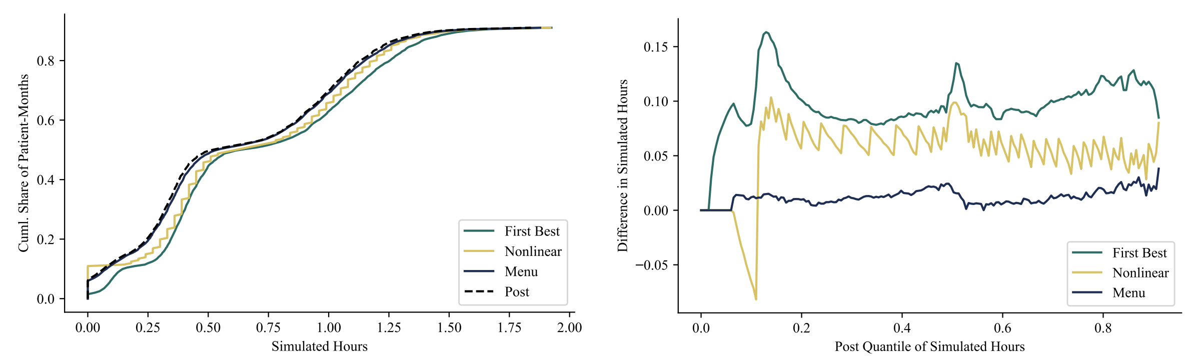


(a) Total Revenue

(b) Marginal Revenue

Notes: These plots illustrate the optimal nonlinear uniform contract which provides revenue as a flexible function of treatment intensity (along the x-axis). Linear indicates the optimal linear uniform contract including the base payment. In this figure, the nonlinear contract does not include the base payment.

Figure A.17: Distribution of Treatment Intensity Across Contract Types

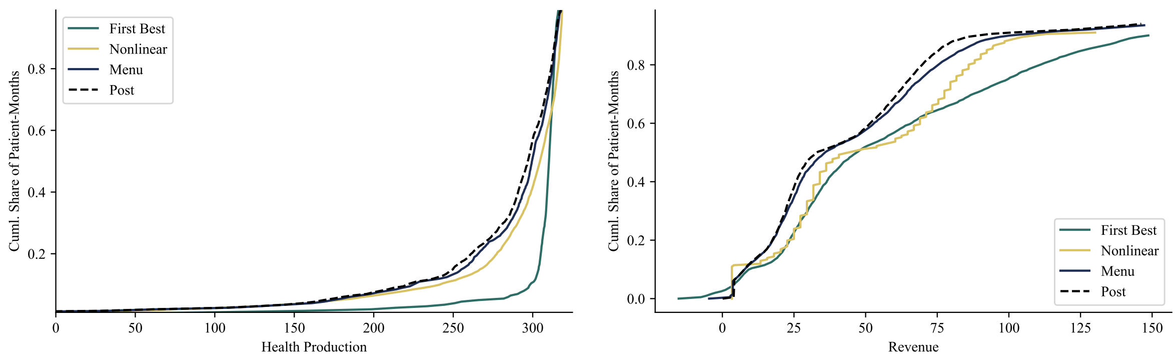


(a) Cumulative Distribution

(b) Difference in Cumulative Distributions

Notes: These plots compare the optimal nonlinear uniform contract to a menu of linear contracts and first-best (full information) linear contracts. The right panel illustrates how treatment intensity compares to the status quo, under the higher reimbursement rate of certified physicians, by subtracting corresponding quantiles, e.g., the 5th percentile of treatment intensity under first-best contracts minus the 5th percentile of treatment intensity under the status quo. Post-Cert. indicates the status quo with a high reimbursement rates from certification. First Best indicates efficient linear contracts under full information. These plots condition on a positive health shock.

Figure A.18: Distribution of Health Production and Expenditure Across Contract Types

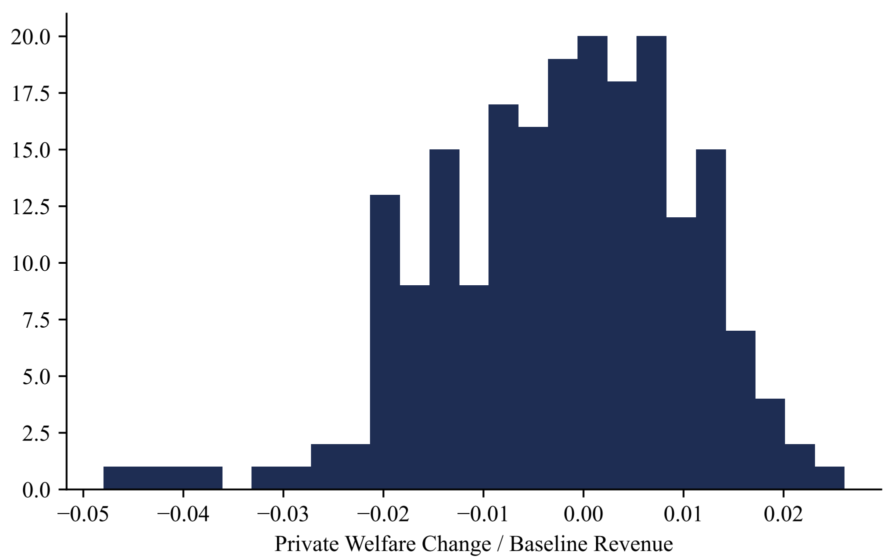


(a) Cumulative Distribution of Health Production

(b) Cumulative Distribution of Expenditure

Notes: These plots compare the optimal nonlinear uniform contract to a menu of linear contracts and first-best (full information) linear contracts. Post-Cert. indicates the status quo with a high reimbursement rates from certification. First Best indicates efficient linear contracts under full information. These plots condition on a positive health shock.

Figure A.19: Some Physicians Worse Off with the Optimal Nonlinear Uniform Contract



Notes: This plot shows that many physicians experience moderate losses in private indirect utility under the optimal nonlinear uniform contract, as a share of status quo revenue. The reference point is each physician's pre-certification status quo. The y-axis is a count of physicians. The underlying data is an expectation over patients the distribution of severity.

B Data and Estimation Details

B.1 Data Sources

I use several data sources to construct the estimation sample. The Norwegian Control and Payment of Health Reimbursements Database (KUHR) tracks reimbursement for outpatient claims organized at the level of bill line, i.e., reimbursement code, and identifies most patients and physicians. The Norwegian Patient Registry (NPR) is a database of reimbursement for inpatient claims organized at the level of encounter. I use ICD-10 and ICPC-2 codes from both sources to classify chronic illness. I identify avoidable hospitalizations following Table A1 from Page et al. (2007). base payments come from a basic subsidy rate dataset. Various datasets from the Norwegian GP Registry identify periods when patients are registered to patient lists and when physician are contracted to provide care to those patient lists. The physician-list dataset also identifies contract details: the maximum number of registered patients and indicators for shared lists and fixed-salary reimbursement. I use anonymous identifiers for physicians, lists, and patients to link datasets and convert periods into monthly panels. Physicians' birth date, gender, and birth country come from a personnel file. Patients' birth date, gender, disability payment receipt, and income come from tax records.

B.2 Construction of Treatment Intensity

I classify each patient into an observed type based on the combination of gender, 5-year age bins, and indicators for first and second prior chronic diagnosis, including cancer, diabetes, COPD, CVD, or asthma. I sort these 108 initial groups based on average reimbursement and further aggregate them into 10 types. Each aggregated type represents approximately 10 percent of aggregate spending in the estimation sample because treatment intensity is distributed approximately log-normally. The lowest type includes 23 percent of patient-months and the highest type represents 4 percent of patient-months.

For each patient type, I use all Norwegian patients to calculate the average bundle of services received and the average hours required to provide that bundle. I attribute time to encounters and reimbursement codes based on the share of reimbursement within an hour in the utilization data, e.g., 1-2 pm on January 1, 2010. I multiply each non-certification reimbursement code by the current administrative reimbursement rate. I average across codes, weighting where the number of lines per patient type per month. After certification, this numerator also includes current certification supplementary payments for an average number of visits per patient type. Finally, I divide by average hours per patient-type to calculate the simulated wage p_{kt}, i.e., the reimbursement per hour a physician would receive for providing the average bundle of services to a patient of type k in month t. Treatment intensity m_{ijt} equals patient-month fee-for-service revenue divided by marginal reimbursement and roughly corresponds to hours of treatment per patient-month ("simulated hours").

B.3 Counterfactual Analysis

This section reviews the technical assumptions underlying counterfactual analysis. I first describe the process for quantifying counterfactual outcomes given contracts. Then, I detail the algorithms that identify each set of contracts: efficient contracts, the optimal uniform contract, the optimal two-contract menu, and the optimal menu of contracts.

I measure all counterfactual outcomes as ex-ante expectations over registered patients of certified PCPs. I simulate patient severity for 60 patient simulants for each physician in the sample: 10 patient observed types multiplied by 6 quadrature nodes. For each of the 10 patient types per physician, I use averages of β_λ and $Pr(\lambda > 0)$, which aggregate over in-sample patients' observed characteristics like chronic illnesses and age. From the physician's first-order condition, treatment intensity is a function of simulated severity, estimated physician type, and contract. Likewise, indirect utility is a function of predicted treatment intensity, simulated severity, and the contract. Within a given menu, each physician's privately optimal contract maximizes average indirect utility. Ex-ante expectations reflect three levels of aggregation.[78] First, I average across quadrature nodes using quadrature weights to approximate the integral of normally distributed log patient severity. Second, I average across patient types, weighting by the observed number of patients in the estimation sample per physician. Third, I average across physicians, weighting by total registered patients six months before certification.

Scaled health production per simulated patient equals $H - \frac{1}{2}\alpha_R(m^* - \gamma\lambda))^2$. α_R can be thought of as the regulator's altruism or the inverse of the shadow cost of expenditure. I calibrate it with a revealed preference assumption. When setting supplementary reimbursement for certification, the regulator values incremental health production exactly as much as incremental expenditure. Expenditure equals $pm^*(p; \lambda, \theta) + b$, i.e., privately optimal treatment intensity multiplied by fee-for-service rates plus the base payment. I generally report incremental expected health production which subtracts the pre-certification expected value.

[78]When calculating expected indirect utility per physician per contract, I only aggregate over quadrature nodes and patient types.

To focus on the role of reimbursement in treatment intensity, I fix total registered patients, the share of patient types for each physician, pre-certification fee-for-service rates, and status quo base payments at values six months before certification. For example, this removes variation in patient severity from seasonality and the time trend, so counterfactual treatment intensity at post-certification fee-for-service rates will typically be higher than observed in the data. To be consistent, I simulate all post-certification outcomes following the same process as counterfactuals, using the immediate change in the fee-for-service rate.

I enforce budget and participant constraints in counterfactuals when possible. I assume post-certification expected expenditure is the budget. Likewise, for participation constraints, I use expected indirect utility during the sample period to construct physician-specific participation thresholds. Physicians continue to work throughout the sample period at those levels of indirect utility, so they might reasonably be expected to continue in counterfactuals. All physicians prefer their post-certification contract, so I aggregate participation constraints by requiring that the same share of physicians weakly prefer counterfactual contracts over the lesser of their pre- or post-certification contract.

I solve the regulator's objective numerically for the set of physicians in my sample. All counterfactuals use a grid of 200 equally spaced points between 0.5 and 3.5. Each point reflects a multiple of pre-certification fee-for-service rates, which vary across physicians and patient types. The optimal uniform contract maximizes overall expected health production while satisfying global constraints. The other counterfactuals involve a large number of control variables and constraints. The global budget constraint also creates complementarity across physicians. Constrained maximization algorithms do not work well in this context. Instead, I enforce the participation constraints directly and search for contracts that maximize social surplus, i.e., incremental expected scaled health production minus incremental expected expenditure.

Efficient contracts are personalized to each physician with counterfactual perfect information about physician types. I identify efficient contracts by solving physician-specific problems. I select the fee-for-service rate that maximizes a physician's social surplus conditional on also satisfying her participation constraint. I minimize base payments so that participation constraints bind given the efficient contract and privately optimal treatment intensity. This solution is approximate because physicians have different numbers of patients and the weighted average of differences does not equal the difference of weighted averages. In some robustness checks, I take an additional step to enforce the global budget constraint. I lower the fee-for-service rate multiple by one grid point for one physician at a time to produce the smallest reduction in social surplus while lowering expenditure until the budget is slack.

For the optimal menu of contracts, I use a line-search algorithm. The algorithm finds the optimal base payment for each fee-for-service multiple on the grid, one at a time, while holding base payments for other fee-for-service multiples fixed. For stability, I search over discrete values of base payments rather than use an optimization routine. I also run the line-search algorithm twice. The first iteration uses a broad grid of base payments specific to each contract that covers a wide range of potential participation in that contract: $dEV > 0$ for each of $1, 2, ..., I$ physicians in a uniform contract. The second iteration searches locally for improvements using a grid of quadrature nodes. I enforce the participation constraint by always including the uniform contract in the menu, but the global budget constraint is difficult to strictly enforce with this method, so I maximize health production net of expenditure and penalize increased expenditure over the budget. In particular, the objective is $\Delta E[h(m^*)|b(p)] - \min\{0, \Delta R\} + \max\{0, \Delta R\}^2$ where $R \equiv E[pm^* + b(p)|b(p)]$ and Δ subtracts the reference values from counterfactual outcomes.

C Derivations

C.1 Comparative Statics

This section characterizes how multi-dimensional heterogeneity contributes to the feasibility and efficiency of a menu of contracts relative to a uniform contract. Building on the exposition in Section 2.2, it is convenient to substitute the regulator's constraints into the objective. I assume that the shadow cost of the budget constraint $\mu_B \equiv \frac{1}{\alpha_R}$ is constant and that base payment $b(p)$ is large enough to satisfy all participation constraints.[79] Then, a realization of money-metric social surplus has the following expression:

$$SS(p, b, \lambda) = \alpha_R h\left(m^*, \gamma\lambda\right) - \left(pm^* + b(p)\right) .$$

I also assume that health production is twice continuously differentiable: returns to treatment are sometimes positive, strictly decreasing in treatment, and weakly decreasing in weighted patient severity $\gamma\lambda$.

With perfect information, base payment b_{FB} is set so that the participation constraint binds: $V(p, b, \lambda) = \underline{\mathrm{V}}$. This results in a special case of social surplus:

$$\begin{aligned} SS^{FB}(p, b, \lambda) &= \alpha_R h\left(m^*, \gamma\lambda\right) - pm^* + V(p, \lambda) - \underline{\mathrm{V}} \\ &= (\alpha_R + \alpha) h\left(m^*, \gamma\lambda\right) - cm^* - \underline{\mathrm{V}} \, . \end{aligned}$$

In this case, the first-best reimbursement rate p^{FB} satisfies the first-order condition:

$$\frac{d}{dp} SS(p, b, \lambda) = \left((\alpha_R + \alpha) h_m\left(m^*, \gamma\lambda\right) - c\right) m_p^* = 0 \, .$$

Equivalently, private cost equals marginal health production, scaled by both social and private altruism, at the privately optimal level of treatment intensity. Substituting the parameterization for health production, the efficient rate is proportional to private cost, and decreasing in private altruism: $p^{FB} = \frac{\alpha_R}{\alpha + \alpha_R} c$. As the regulator relaxes the budget constraint by increasing the weight on health production relative to expenditure ($\alpha_R \to \infty$), $p_{FB} \to c$.[80]

Next, consider the second-best framing from Section 2.3. Starting from a uniform contract, when is

[79] α_R can be interpreted as the regulator's altruism.

[80] Conversely, with altruistic physicians and an extreme budget constraint ($\alpha_R = 0$), the efficient rate approaches 0.

it efficient to add a second contract with greater fee-for-service to the menu? This requires a comparison of incremental indirect utility ("private benefits" or "WTP") and incremental surplus, so let $\Delta f(p) \equiv f(p_H) - f(p_L)$ and focus on realizations of patient severity λ large enough for positive treatment intensity. How does WTP vary with physician type, all else equal? Since $\frac{d\Delta \int V(p) dF(\lambda)}{d\theta_k} = \Delta \int \frac{dV(p)}{d\theta_k} dF(\lambda)$, I first derive $\frac{dV(p)}{d\theta_k}$ using the envelope theorem:

$$
\begin{aligned}
\frac{dV(p)}{dc} &= \frac{d}{dc}\left((p-c)m(p) + \alpha h(m(p), \gamma\lambda)\right) = -m(p) \\
\frac{dV(p)}{d\alpha} &= h(m(p), \gamma\lambda) \\
\frac{dV(p)}{d\gamma} &= \alpha h_{(\gamma\lambda)}(m(p), \gamma\lambda)\lambda \\
\frac{dV(p)}{d\lambda} &= \alpha h_{(\gamma\lambda)}(m(p), \gamma\lambda)\gamma
\end{aligned}
$$

From $h_{mm} < 0$, the physician's first-order condition implies that $m(p)$ is strictly increasing, so $\Delta \frac{d}{dc} V(p) < 0$. Next, $\Delta \frac{d}{d\alpha} V(p) > 0$ when health production increases in treatment intensity. Finally, from $h_{(\lambda\gamma)m} \geq 0$, $\Delta \frac{d}{d\gamma} V(p) \geq 0$ and $\Delta \frac{d}{d\lambda} V(p) \geq 0$.

Before proceeding, it is useful to derive statics of treatment intensity with respect to physician type by differentiating the physician's first-order condition:

$$
\begin{aligned}
\frac{dV}{dm} &= \frac{d}{dm}\left((p-c)m + \alpha h(m, \gamma\lambda)\right) & \\
&= p - c + \alpha h_m(m, \gamma\lambda) & = 0 \\
\frac{d^2V}{dpdm} &= 1 + \alpha h_{mm}(m, \gamma\lambda)\frac{dm}{dp} & = 0 \\
\frac{d^2V}{dcdm} &= -1 + \alpha h_{mm}(m, \gamma\lambda)\frac{dm}{dc} & = 0 \\
\frac{d^2V}{d\alpha dm} &= \alpha h_{mm}(m, \gamma\lambda)\frac{dm}{d\alpha} + h_m(m, \gamma\lambda) & = 0 \\
\frac{d^2V}{d\gamma dm} &= \alpha h_{mm}(m, \gamma\lambda)\frac{dm}{d\gamma} + \alpha h_{m(\gamma\lambda)}(m, \gamma\lambda)\lambda & = 0 \\
\frac{d^2V}{d\lambda dm} &= \alpha h_{mm}(m, \gamma\lambda)\frac{dm}{d\lambda} + \alpha h_{m(\gamma\lambda)}(m, \gamma\lambda)\gamma & = 0
\end{aligned}
$$

Then,

$$\begin{aligned}
\frac{dm}{dp} &= \frac{-1}{\alpha h_{mm}(m(p),\gamma\lambda)} \\
\frac{dm}{dc} &= \frac{1}{\alpha h_{mm}(m(p),\gamma\lambda)} \\
\frac{dm}{d\alpha} &= \frac{-h_m(m(p),\gamma\lambda)}{\alpha h_{mm}(m(p),\gamma\lambda)} \\
\frac{dm}{d\gamma} &= \frac{-\lambda h_{m(\gamma\lambda)}(m(p),\gamma\lambda)}{h_{mm}(m(p),\gamma\lambda)} \\
\frac{dm}{d\lambda} &= \frac{-\gamma h_{m(\gamma\lambda)}(m(p),\gamma\lambda)}{h_{mm}(m(p),\gamma\lambda)}
\end{aligned}$$

For $\frac{d}{d\theta_k}SS(p)$:

$$\begin{aligned}
\frac{dSS(p)}{dc} &= \frac{d}{dc}\left(\alpha_R h\left(m^*,\gamma\lambda\right) - \left(pm^* + b(p)\right)\right) \\
&= (\alpha_R h_m(m(p),\gamma\lambda) - p)\frac{dm(p)}{dc} \\
\frac{dSS(p)}{d\alpha} &= (\alpha_R h_m(m(p),\gamma\lambda) - p)\frac{dm(p)}{d\alpha} \\
\frac{dSS(p)}{d\gamma} &= (\alpha_R h_m(m(p),\gamma\lambda) - p)\frac{dm(p)}{d\gamma} + \alpha_R h_{(\gamma\lambda)}(m(p),\gamma\lambda)\lambda
\end{aligned}$$

Since $\frac{dm(p)}{dc} < 0$ and $h_{mm} < 0$, $\Delta\frac{dSS(p)}{dc} > 0$. If h is increasing over the relevant support, then $\frac{dm(p)}{d\alpha} > 0$ and $(\alpha_R h_m(m(p),\gamma\lambda) - p)$ is decreasing in p, so $\Delta\frac{dSS(p)}{d\alpha} < 0$. From $h_{m(\lambda\gamma)} \leq 0$, $\frac{dm(p)}{d\gamma} < 0$, so $\Delta\frac{dSS(p)}{d\gamma} > 0$ and $\Delta\frac{dSS(p)}{d\lambda} > 0$.

In summary, given assumptions and all else equal, low-cost, high-altruism, high-productivity (low γ), and low-severity (low $E[\lambda]$) physicians are relatively likely to choose a high-fee-for-service contract, but this choice produces relatively small increases in social surplus. The feasibility and efficiency of a separating equilibrium sometimes require correlation in cost, altruism, and productivity.

C.2 Likelihood

The likelihood is based on the random component of patient severity. Treatment intensity m may equal zero either because the underlying severity is zero or because it is too low for a privately optimal choice of $m > 0$. Since $\frac{dm}{d\lambda} > 0$, I can split cases based on $\tilde{\lambda}$, the minimum λ such that $m \geq 0$.

$$\begin{aligned} l(m \mid \theta, x, X_\lambda) &= l(m \mid \lambda \leq \tilde{\lambda})Pr(\lambda \leq \tilde{\lambda}) + l(m \mid \lambda > \tilde{\lambda})Pr(\lambda > \tilde{\lambda}) \\ &= 1[m = 0]Pr(\lambda \leq \tilde{\lambda}) + 1[m > 0]Pr(\lambda = \lambda^{-1}(m) \mid \lambda > \tilde{\lambda})Pr(\lambda > \tilde{\lambda}) \left| \frac{d\epsilon}{d\lambda} \frac{d\lambda}{dm} \right| . \end{aligned}$$

For $\tilde{\lambda} > 0$,[81] denoting the CDF of $\lambda \mid \lambda > 0$ as F_λ, the two-stage process for λ can be decomposed:

$$\begin{aligned} Pr(\lambda \leq \tilde{\lambda}) &= Pr(\lambda = 0) + Pr(\lambda > 0)F_\lambda(\tilde{\lambda}) \\ Pr(\lambda > \tilde{\lambda}) &= (1 - F_\lambda(\tilde{\lambda}))Pr(\lambda > 0) \, . \end{aligned}$$

Under parametric assumptions,

$$\begin{aligned} \lambda^{-1}(m) &= \frac{m - \beta_0}{\beta_1} && \text{if } m > 0 \\ 0 \leq \lambda^{-1}(m) \leq \tilde{\lambda} &\equiv \max\left\{0, \frac{-\beta_0}{\beta_1}\right\} && \text{if } m = 0 \\ \beta_0 &= \frac{p - c - \sigma(N-1)E[m']}{\alpha + \sigma} \\ \beta_1 &= \frac{\alpha\gamma}{\alpha + \sigma} = \frac{dm}{d\lambda} \\ Pr(\lambda > 0) &= \frac{\exp d_0 + d_1\beta_\lambda X_\lambda}{1 + \exp d_0 + d_1\beta_\lambda X_\lambda} \\ Pr(\lambda = \lambda^{-1}(m) \mid \lambda > \tilde{\lambda}) &= (1 - F_\lambda(\tilde{\lambda}))^{-1}\phi\left(\frac{\log \lambda^{-1}(m) - \beta_\lambda X_\lambda}{\sigma_\lambda}\right) \\ F_\lambda(\tilde{\lambda}) &= 1[\tilde{\lambda} > 0]\Phi\left(\frac{\log \tilde{\lambda} - \beta_\lambda X_\lambda}{\sigma_\lambda}\right) \\ \frac{d\epsilon}{d\lambda} &= \frac{1}{\sigma_\lambda \lambda} \end{aligned}$$

where Φ and ϕ are the CDF and PDF of a standard normal.

[81] If $\tilde{\lambda} = 0$, then $Pr(\lambda > \tilde{\lambda}) = Pr(\lambda > 0)$.