Optimal Contracting with Altruistic Agents: A Structural Model of Medicare Reimbursements for Dialysis Drugs

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PRELIMINARY—PLEASE DO NOT CITE

Abstract

We study physician agency and optimal payment policy in the context of an expensive medication (epoetin alfa) used with dialysis. Using Medicare claims data we estimate a model of treatment decisions, in which physicians are partially altruistic and value both their own compensation and their patients’ health. We then use the recovered parameters of the model in combination with results from contract theory to derive and simulate optimal linear and nonlinear reimbursement schedules. Comparing outcomes under these optimal contracts against those observed under the actual contracts suggests that substantial improvements in payment policy can be achieved within a fee-for-service framework.

1 Introduction

A central problem in health economics, and in health care organizations, is how to compensate physicians for their services. Physicians are typically viewed as imperfect agents for their patients, deriving utility from both their private benefits and costs and from the impact of their services on patient health. A substantial theoretical literature in health economics considers how these partially altruistic agents might behave under various payment systems, and a related empirical literature examines how physicians respond to financial incentives. We extend this work by specifying and estimating a physician utility function that depends on patient health and physician income, thereby quantifying the level of altruism among physicians in our setting. We then use the recovered parameters of this utility function in combination with results from contract theory to derive and simulate optimal payments to physicians for service provision. Comparing the optimal contract with actual contracts suggests tractable improvements in payment policy.
Our empirical analysis is on the provision of an expensive and controversial medication used by dialysis centers to treat anemia in patients with end stage renal disease (ESRD). The medication, epoetin alpha (or “EPO”), was the largest single drug expenditure in Medicare for several years. Medicare is the predominant payer for the treatment of ESRD in the United States (at any age), and we use Medicare claims data from 2008 and 2009 to estimate our model. In the model, physicians choose the quantity of treatment to provide to each patient, based on the predicted health impact, the cost of treatment, and the payment contract. Uniquely in our setting, a quantitative measure of patient need is available in the claims records because providers were required to report a blood measurement in order to be reimbursed for EPO. The revealed weight placed on improvements in patient health relative to the physician’s private marginal benefit is our measure of altruism. This parameter and the other parameters of our model are recovered in a simple manner from the coefficients of a linear fixed effects regression.

We then address the agency problem that arises when physicians are heterogeneous in their cost of providing treatment. Using the estimated physician utility function, we derive both optimal (constrained) linear and unconstrained (potentially nonlinear) payment contracts. These contracts are fairly straightforward to construct from the output of the fixed effects regression. We then compare the reimbursement schedules and induced treatments under these contracts against the observed outcomes. Preliminary results suggest that the historical reimbursement rates for EPO were supra-optimally high, and by a wide margin. This is intuitive, as physician altruism and cost heterogeneity, neither of which may have been accounted for by the government, both reduce the per-unit payment in the optimal linear contract. We derive optimal reimbursement rates in the linear contract that are 30 percent lower than the actual rates used by Medicare in 2008 and 2009. The optimal nonlinear contract improves outcomes further, notably by reducing medically unjustified variation in treatment intensities while also decreasing total expenditures. A simulation for patients with anemia at the median level of severity finds that the standard deviation of dosages falls by 70 percent while the mean payment decreases by 40 percent.

1.1 Related literature

We view our paper as being closely related to two literatures described below.

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1There are substantial differences across providers in the acquisition cost of the drug, as documented in Medicare renal dialysis facility cost reports (see Section 3). We plan on extending our approach to consider both cost and altruism heterogeneity in a future version. The optimal nonlinear contract in the case of multidimensional heterogeneity is more difficult to characterize than that for the case of one-dimensional heterogeneity because physician “types” can no longer be ordered, as they can be in the one-dimensional case (see (Maskin et al., 1987; Wilson, 1993; Deneckere and Severinov, 2015)).
Health economics: There is a rich theoretical literature on physician agency; much of this literature is discussed in McGuire (2000) and Chalkley and Malcomson (2000). Ellis and McGuire (1986) provide a seminal contribution. They model physicians as partially altruistic (imperfect agents) and show that partial cost reimbursement can improve outcomes when physicians are imperfect agents for their patients and inputs are noncontractible.

By contrast, there are relatively few theoretical papers on optimal contracting in health care. Chalkley and Malcomson (1998) characterize optimal contracts when patient demand does not reflect quality, and show that the optimal contract differs depending on the degree of physician altruism. De Fraja (2000) studies optimal contracts when there is heterogeneity in physician costs. Jack (2005) allows for heterogeneity in physician altruism and solves for the optimal contract in an environment where quality is noncontractible. Malcomson (2005) examines optimal contracts when providers are better informed than purchasers, with no provider altruism. Choné and Ma (2011) also study how physician altruism may affect the design of optimal payment schemes.

There is also an empirical literature studying how physicians respond to incentives and other changes in the environment. Gaynor and Pauly (1990) is an early paper showing that physicians respond strongly to financial incentive. Chandra et al. (2012) review the literature studying determinants of physician treatment choices. One determinant they focus on is physician altruism. Gaynor et al. (2004) specify and estimate a structural model of physician treatment choice where physicians are partially altruistic. Godager and Wiesen (2013) use data obtained from a laboratory experiment to document the existence of physician altruism, which they find to be heterogeneous. Clemens and Gottlieb (2014) examine the impact of financial incentives in Medicare payment for physicians and find substantial effects on supply, technology adoption, and patient outcomes.

Our model contains many components of the above literature. The basic model of physician utility is very similar to that in Gaynor et al. (2004), but allows for cost heterogeneity as well as altruism. De Fraja (2000) and Jack (2005), noted above, address heterogeneity across physicians, although there are various distinctions between their models and ours. Like Clemens and Gottlieb (2014), we examine the impact of Medicare payment incentives, although they look at payment incentives broadly, as opposed to our focus on a very specific program and treatment decision. Last, in contrast to the existing empirical literature, we not only estimate a model of physician treatment choices and recover physician altruism, we also empirically characterize the optimal contract and compare it to the actual contracts used in this context.

2For example, Jack (2005) uses a model with unobserved effort while in our setting the most relevant aspect of the treatment is observed (i.e., the dosage of the drug).
Empirical contracts: As Chiappori and Salanié (2003) discuss, there is empirical work testing for the existence of salient features for the design of optimal contracts (e.g., Chiappori et al. (2006) test for asymmetric information), but there is little work specifying and estimating structural models and using them to derive optimal contracts. This matters because the insights from the literature on contracts are most useful when applied in designing optimal policies that could be implemented in reality.

To the best of our knowledge, there is no work that structurally estimates a model of physician treatment choices in a principal-agent, or asymmetric information, framework and uses this to characterize optimal contracts. A handful of papers estimate asymmetric information models in other settings. For example, Einav et al. (2010) discuss the small literature doing this for insurance contracts. Paarsch and Shearer (2000) characterize the optimal linear contract in a hidden action environment. Gayle and Miller (2009) also study hidden action models, quantifying the welfare loss from moral hazard. In contrast, we study a screening, or hidden information, model and flexibly characterize the optimal wage schedule. Screening models, with their focus on unobserved heterogeneity, are clearly policy relevant.

There is a fairly rich literature on optimal regulation, which considers screening models in institutional contexts that differ from ours in important ways. Wolak (1994) develops and estimates a model in which a principal seeks to regulate public utilities of (potentially) hidden types. Data limitations, including a lack of variation in regulatory regime, mean the distribution of types cannot be estimated without imposing optimality of the observed contract. Gagnepain and Ivaldi (2002), study a similar environment, but exploit variation in the regulatory regime to estimate a parametric distribution of types without having to assume optimality of the observed contract. This allows them to test whether the observed contract is optimal. Abito (2017) extends this approach to study optimal pollution regulation. As in the latter two articles, our setting and data allow us to estimate structural parameters, including agent types, without imposing optimality of the observed contract. We allow for a fully flexible type distribution, which is made possible by variation in the observed regime (i.e., reimbursement contract) and a large number of repeated measures of physicians, as each physician chooses a treatment choice for each patient they see, under a variety of observed reimbursement rates.

1.2 Institutional background

ESRD, or kidney failure, is a chronic and life-threatening condition that affects over half a million individuals in the United States at a given point in time. Since 1973, the Medicare
program has provided universal coverage for the treatment of ESRD, regardless of age. In 2009 Medicare spent $28 billion on health care for individuals with ESRD, and of that amount, $1.74 billion went to payments for the drug EPO.\textsuperscript{3} The drug is used to treat anemia, a lack of red blood cells, which often accompanies chronic kidney disease.\textsuperscript{4} It is similarly used to treat anemia in chemotherapy patients. EPO stimulates red blood cell production, and dialysis providers administer it to their patients to try to maintain a certain level of red blood cells. The level is commonly measured as \textit{hematocrit}, which is the volume percentage of red blood cells in the blood.

Medicare’s payment policy for EPO was debated throughout the 1990s and 2000s, largely because of concerns that the reimbursement rates were too generous and encouraged over-provision. While dialysis itself was reimbursed with a prospective payment system (PPS) known as the “composite rate,” EPO was a separately billable drug with its own per-unit reimbursement rate. Prior to 2005, the rate was held fixed at $10.00 per 1000 units. In 2006, Medicare adopted a new policy where the reimbursement rate was based on average sales prices calculated from data reported by the drug manufacturer. This policy, which was in effect through 2010 (including the years we use to estimate provider behavior), set a reimbursement rate each quarter equal to 106 percent of the national average sales price from roughly six months earlier (GAO, 2006). Later, in 2011, Medicare adopted a comprehensive “bundled” PPS for dialysis that included EPO, so the payment policy for the drug effectively switched from fee-for-service to prospective payment.\textsuperscript{5}

Important safety concerns about EPO emerged in the mid 2000s. A major clinical trial found that patients who were given more EPO to achieve a higher target level of hematocrit suffered a higher risk of serious cardiovascular events and death (Singh et al., 2006). This study was published in November 2006, and strong warnings (“black box warnings”) were added to the drug’s labels in 2007. As a result of these findings, the recommended target level for hematocrit remained at a lower range, specifically 30–36%, which was the existing standard at the time (e.g., the range for which the FDA had approved the drug).

In terms of the billing procedures, Medicare claims for dialysis care are typically filed monthly and include separate lines for each administration of EPO. The drug is most commonly administered intravenously during dialysis, which occurs multiple times per week. To be reimbursed for EPO, providers are required to report a hematocrit level taken just prior

\textsuperscript{3}USRDS 2017 Annual Data Report, available at \url{https://www.usrds.org/adr.aspx}. The amount given for EPO includes a related drug darbepoetin alpha. The total social expenditures on ESRD and these drugs were even higher because many beneficiaries also make a 20% copayment.

\textsuperscript{4}EPO is a biological product, or “biologic,” but we will typically refer to it as a drug.

\textsuperscript{5}In future work we will evaluate the decreases in dosages that occurred when the bundled PPS was adopted, and compare these to the simulated dosages under our optimal contracts.
to that monthly billing cycle. This gives a quantitative measure of patient need, in this case the severity of the anemia, which is a key component of our model. Last, a relevant medical point is that the half-life of EPO is under 12 hours (Elliott et al., 2008), so there is no substantial stock effect of the drug from one month to the next. This helps to support our use of a static model that is applied separately to each month of treatment.

2 Model

In our theoretical model there is one time period, one principal, and one agent. The government (the principal) hires a physician (the agent) to treat a patient. The government seeks to maximize patient health, net of the cost of transfers to the physician. Thus the government can be thought of as acting on behalf of patients, who receive benefits from treatment but have to fund public health insurance through taxes. Physician utility depends on patient health, the cost of the treatment provided, and the compensation received.

The patient arrives at the physician with a baseline health status, $e_0$, which in our application is the hematocrit level from the prior month. The physician then chooses an amount of treatment (the action), $a$, which is the total units of EPO administered over the month. As is standard in this literature, we assume the patient passively accepts the treatment prescribed by their physician (e.g., Ellis and McGuire (1986)). Both $e_0$ and $a$ are observed by the government since they are reported in the monthly claims. Given the patient’s baseline health status, the treatment produces health according to the function $h(a, e_0)$. Health is increasing in the amount of treatment when the resulting hematocrit level is below the target, $e_\tau$, is decreasing when the resulting level is above the target, and is concave in treatment (i.e., $\frac{\partial h}{\partial a} > 0$ if $h(a, e_0) < e_\tau$, $\frac{\partial h}{\partial a} < 0$ if $h(a, e_0) > e_\tau$, and $\frac{\partial^2 h}{\partial a^2} < 0$). This reflects the fact that patients with more severe anemia (i.e., lower hematocrit) benefit more from EPO, while there are serious risks from over-provision.

The physician is of a “type,” indexed by $i \in I$, which is unobserved by the government. Here the type represents the physician’s cost of providing treatment. We will refer to physicians by their type $i$ when it is convenient and not confusing to do so. The cost type determines the per-unit cost of treatment and is denoted by $z_i$. We order cost types such that $z_i < z_{i+1}$; i.e., lower indices correspond to lower treatment costs. Treatment cost has support on a closed interval $[\underline{z}, \overline{z}]$ and a distribution $F_z$, which is known to the government, with density $f_z$ and mean $\mu_z$.

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6Section 4 discusses how this model extends naturally to multiple physicians with multiple patients.
7We consider an alternative specification in which types comprise altruism heterogeneity, i.e., variation in the weight on patient health in physician utility, in Appendix A.4.
The government sets a reimbursement policy (the payment contract, or “wage” schedule), \( w(a, e_0) \), that may depend on both the treatment amount and the baseline health. This can be understood as a set of (potentially) nonlinear contracts, one for each possible value of \( e_0 \). The reimbursement policy is established before the physician sees the patient. The timing of the model is summarized below.

**Timing:**

1. Government sets the wage schedule \( (w(a, e_0)) \)
2. Physician’s type is realized \( (z_i) \)
3. Patient’s baseline hematocrit level is realized \( (e_0) \)
4. Physician decides whether to participate
5. Physician chooses an amount of treatment \( (a) \)
6. Outcomes occur: patient health \( (h(a, e_0)) \), government payment to physician \( (w(a, e_0)) \), cost of treatment \( (c(a, z_i)) \)

The utility function for a physician of cost type \( i \) is

\[
u_i(a; e_0, w) \equiv \alpha_p h(a, e_0) - c(a, z_i) + w(a, e_0), \tag{1}\]

where \( c(\cdot) \) is the cost function, which gives the total cost of providing treatment amount \( a \) for a physician with cost factor \( z_i \). As described above, \( h(a, e_0) \) gives the resulting health of the patient, \( w(a, e_0) \) gives the reimbursement amount from the government, and the altruism parameter, \( \alpha_p \), is the weight placed on patient health.

The government values patient health minus the payment to the physician. The weight that the government places on patient health, \( \alpha_g \), may be different than the weight placed by physicians (e.g., this weight may be larger because the government represents the patients). The government’s net value of the outcome, given the amount of treatment provided, is thus

\[
u_g(a, e_0) \equiv \alpha_g h(a, e_0) - w(a, e_0). \tag{2}\]

The government’s expected value of the outcome integrates this over the actions that would be taken by different physician types, given the reimbursement policy.

We use subgame perfect Nash equilibrium to define behavior. The physician chooses a treatment amount to maximize utility function (1) given the wage schedule (and the patient’s baseline health). The government sets the wage schedule knowing how the physician will respond. The government’s problem is therefore to maximize the expected value of (2)
subject to the physician’s incentive compatibility and voluntary participation constraints, which we assume must hold for all physicians.

We next provide an example that yields intuitive, closed-form solutions, and which is the basis of our empirical specification. The functions $c$ and $h$ are, respectively, linear and quadratic, and the government is restricted to offer linear contracts. In addition to providing clear intuition, a linear contract was the actual payment policy during the period we use to estimate the model, creating a tight link between our model, estimation strategy, and the institutional context. In Section 2.2, we summarize the solution for the optimal unrestricted contract (i.e., the “second-best”). Although the solution for the optimal unrestricted contract would, with minor adaptation, work for more general specifications of $c$ and $h$ (see Appendix A.2 for details), we maintain the linear $c$ and quadratic $h$ because they are sufficiently flexible for our empirical work.

### 2.1 Optimal Linear Contract

The specifications for this example, which are also applied in the empirical analysis, are as follows. The health production function is a quadratic loss in the distance from the target level of hematocrit:

$$h(a, e_0) \equiv -\frac{1}{2} [\delta a + e_0 - e_\tau]^2,$$

where $\delta$ is a linear technology that converts the dosage $a$ of EPO to an increase in hematocrit.\(^8\)

The bliss point of the health function is achieved when baseline hematocrit plus this output from the drug equals the target level (i.e., $\delta a + e_0 = e_\tau$). The cost function is $c(a; z_i) = az_i$; in other words, the cost factor $z_i$ is the marginal cost of providing the drug, and there is no fixed cost.\(^9\) Finally, the government offers a linear contract for each $e_0$:

$$w(a, e_0) \equiv w_0(e_0) + w_1(e_0) \cdot a.$$

This means that there is a fixed payment ($w_0$) and a per-unit payment ($w_1$), and these amounts may depend on the baseline hematocrit.\(^10\) For convenience, however, we suppress the dependence of $w(\cdot)$ and other functions on $e_0$ when it is not confusing to do so.

\(^8\)To some extent this equates health with the amount of red blood cells in the blood, which has been questioned in the medical literature (Jacques et al., 2011). Interpreted more broadly as health, this specification with a bliss point represents the tradeoff between the benefits of increasing very low blood counts against the serious risks associated with EPO, and the fact that those risks outweigh the benefits when the blood count is above the target level.

\(^9\)Adding a fixed cost that is constant across types would not affect the results.

\(^10\)In fact, the Medicare payment policy during our analysis period included a reduced reimbursement rate for claims where the prior hematocrit level was above 39%.
We solve by backward induction. Given the patient’s baseline hematocrit and the corresponding linear contract, the physician of cost type \(i\) solves
\[
\max_{a \geq 0} -\alpha_p \frac{1}{2}[\delta a + \epsilon_0 - \epsilon_T]^2 - a z_i + w_0 + w_1 a.
\]
At an interior solution, the optimal treatment amount is
\[
a^*_i = a^*(z_i; \epsilon_0, w) \equiv \frac{\epsilon_T - \epsilon_0}{\delta} + \frac{w_1 - z_i}{\delta^2 \alpha_p}, \tag{3}
\]
which is unique due to the weak concavity of \(c\) and \(w\), which, when added to the strictly concave \(h\), produces a strictly concave physician objective. For this example, we assume the conditions are such that an interior solution always applies. Hence, under the equilibrium contract, a physician of any cost type will provide a positive amount of the drug to a patient with any baseline hematocrit level that the government would like to have treated (i.e., any \(\epsilon_0 < \epsilon_T\)).\(^{11}\)

The physician behavior above implies that the hematocrit level resulting from the chosen treatment amount (i.e., \(\delta a_i^* + \epsilon_0\)) may be less than, equal to, or greater than the target level \(\epsilon_T\), depending on the wage schedule and the physician’s marginal cost of EPO. If the marginal cost is greater than the reimbursement rate (\(z_i > w_1\)) then the resulting hematocrit will be below the target. If the marginal cost of acquiring and administering EPO is less than the reimbursement rate, then the resulting hematocrit will be above the target. This matches concerns that were raised about high reimbursement rates encouraging over-provision of EPO.

The government’s problem is to set a slope \(w_1\) and an intercept \(w_0\) for the payment contract (for each \(\epsilon_0\)) that maximizes the expectation of (2), while ensuring participation and treatment. This problem is expressed as follows:
\[
\max_{(w_0, w_1) \in \mathbb{R}^2} \int_{\mathbb{R}} \left[ \alpha g(h(a, \epsilon_0) - w_0 - w_1 a) f_z(z) dz \right. \tag{4}
\]
\[
\text{s.t.} \quad a = a^*(z_i; \epsilon_0, w), \forall i \in I \quad \text{IC}
\]
\[
u_i(a^*(z_i; \epsilon_0, w); \epsilon_0, w) \geq 0, \forall i \in I \quad \text{VP},
\]
where the functions \(u_i\) and \(a^*\) are defined in equations (1) and (3). The incentive compatibility (IC) constraints recognize that the physician implements her optimal treatment amount

\(^{11}\)We relax the interior solution requirement in Section 2.2.
given the contract, and the voluntary participation constraints (VP) require the government
to offer payments such that action \( a_i^* \) provides nonnegative utility for any cost type.\(^{12}\) Since
lower cost types have strictly greater utility for any actions and payments, this simplifies to
a Lagrangian with one constraint because all VP constraints are slack except the one for the
highest cost type \( z \).

Solving the Lagrangian yields the optimal intercept (i.e., fixed payment) and slope (i.e.,
per-unit rate) given below (details are in Appendix A.1):

\[
\begin{align*}
\omega_0^* &= \left[ 2 + \frac{\alpha_g}{\alpha_p} \right] \tau - \left[ 1 + \frac{\alpha_g}{\alpha_p} \right] \mu_z \left[ \epsilon_T - \epsilon_0 \right] + \frac{\left[ 1 + \frac{\alpha_g}{\alpha_p} \right] \mu_z \left[ 2 + \frac{\alpha_g}{\alpha_p} \right] \tau}{2(\alpha_p + \alpha_g)} \\
\omega_1^* &= \mu_z - \frac{\alpha_p}{\alpha_p + \alpha_g} \tau.
\end{align*}
\]  

(5)

The optimal per-unit rate \( \omega_1^* \) is decreasing in both physician altruism and the upper limit
of the cost type distribution, which is related to the “spread” of this distribution. The
maximum cost type thus affects the strength of the incentives given to physicians of all
types, because the participation constraint for this type is the one that binds. The higher
is \( \tau \), the more expensive it is for the government to induce a positive action: the intercept
\( \omega_0^* \) is higher while the per-unit rate \( \omega_1^* \) is lower (see Appendix A.1.1 for details). Also, we
note that the patient’s baseline hematocrit \( (\epsilon_0) \) only appears in the intercept, which keeps
this contract fairly simple. The fixed payment \( (\omega_0^*) \) would vary with the patient’s measured
severity, but there would be a common per-unit rate \( (\omega_1^*) \) as in traditional fee-for-service
systems.

Substituting the optimal per-unit rate into the physician’s treatment choice function (3)
yields the equilibrium action under the optimal linear contract:

\[
\begin{align*}
a_i^*_{\text{linear}} &= \frac{\epsilon_T - \epsilon_0}{\delta} - \frac{z_i}{\delta^2 \alpha_p} + \frac{\mu_z}{\delta^2 \alpha_p} - \frac{\tau}{\delta^2 [\alpha_g + \alpha_p]}.
\end{align*}
\]  

(6)

This is decreasing in the physician’s own marginal cost \( (z_i) \) but increasing in the average
marginal cost \( (\mu_z) \). These equilibrium treatment amounts can be compared with the first-
best amounts that would occur in a full-information benchmark scenario, where physician
cost types are observable and contractible.\(^{13}\) Using the assumed functional forms, the

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\(^{12}\) The utility of the outside option is normalized to zero.

\(^{13}\) The full-information benchmark chooses a desired treatment for each \( z_i \), which has the interior optimality condition for each \( z_i \) of \( [\alpha_g + \alpha_p] h'(a_i^{\text{full info}}) = z_i \). Payments in the full-information scenario would take the physician’s cost type as an argument and would extract all the surplus from the physician. The payment to a physician of cost type \( z_i \) would be \( w_i^{\text{full info}} = a_i^{\text{full info}} z_i - \alpha_p h(a_i^{\text{full info}}) \).
treatment amounts in the full-information benchmark scenario would be

\[ a_i^\text{full info} = \frac{e_r - e_0}{\delta} - \frac{z_i}{\delta^2[\alpha_g + \alpha_p]} \]  \hspace{1cm} (7)

Unlike the equilibrium amount under the linear contract (6), the full-information benchmark amount for a physician of cost type \( z_i \) does not depend on the other cost types in the economy (i.e., \( \mu_z \) and \( \overline{z} \) do not appear in 7). The mean treatment amount is smaller under the optimal linear contract than in the full information benchmark, but there is a threshold in \( z \) such that cost types below the threshold provide more under the linear contract.\(^{14}\)

Thus, although the full-information benchmark features a higher average treatment level, the optimal linear contract results in over-provision by low-cost types and under-provision by high-cost types, because all types are given the same marginal incentive. The unrestricted (potentially nonlinear) contract we consider next will not result in this kind of pooling, as it will allow the government to separate types by providing variable marginal incentives.

### 2.2 Optimal Unrestricted Contract

This section presents and discusses the optimal unrestricted contract for a given baseline hematocrit level \( e_0 \). (As we did earlier, for convenience we will suppress the dependence of the wage contract and other functions on \( e_0 \) when it is not confusing to do so.) Our solution approach draws on the price discrimination literature (Maskin and Riley, 1984), where we invoke the revelation principle to derive an optimal contract specifying treatments and payments. For details please see Appendix A.2.

Using our functional form assumptions, the optimal (i.e., “second-best”) induced actions are

\[ a_i = \frac{e_r - e_0}{\delta} - \frac{z_i + F_z(z_i)}{\delta^2[\alpha_g + \alpha_p]} \]  \hspace{1cm} (8)

This is distorted away from the full-information benchmark in (7) due to the \( F_z(z_i) \) term, which is positive, hence the treatment amounts under the optimal unrestricted contract are lower than those in the full-information benchmark (except for the lowest-cost type, where \( F_z(z_i) = 0 \)). The treatment amounts are decreasing in cost type if \( \lambda_z \equiv \frac{F_z(z_i)}{f_z(z_i)} \) is decreasing in \( z \), and this allows the optimal contract to be implemented with a single, nonlinear payment schedule (see Appendix A.2). As with the full-information benchmark, the optimal treatment amount is increasing in patient need (i.e., decreasing in \( e_0 \)) and in

\(^{14}\)The mean of (6) is \( \frac{e_r - e_0}{\delta} - \frac{\overline{z}}{\delta^2[\alpha_g + \alpha_p]} \), while the mean of (7) is \( \frac{e_r - e_0}{\delta} - \frac{\mu_z}{\delta^2[\alpha_g + \alpha_p]} \), and \( \overline{z} \geq \mu_z \). Subtracting (7) from (6), we have \( a_i^\text{linear} > a_i^\text{full info} \) iff \( z_i > \mu_z + \frac{\alpha_p}{\alpha_g} [\mu_z - \overline{z}] \).
government and physician valuations of patient health, and is decreasing in the physician’s cost of treatment. Additionally, we note that higher degrees of physician altruism can blunt the distortion away from the first-best that is caused by the unobserved heterogeneity. This highlights the potential importance of allowing for both physician heterogeneity and physician altruism when characterizing optimal payment contracts.

The payments in the unrestricted contract can be derived from the optimal treatment amounts and the specification of physician utility (see Appendix A.2). The result is

\[ w(a_i) = \left[ \int_{z_{i+1}}^{z_i} a_j dj \right] - [\alpha_p h(a_i) - a_i z_i]. \quad (9) \]

This expression involves the integral of actions by higher cost types \((z_{i+1} \text{ to } z_i)\) because the additive separability in our utility specification allows the IC constraints to simplify in a way that yields this integral as the utility of cost type \(z_i\) in equilibrium (see Appendix A.3). Notably, as in Ellis and McGuire (1986), the payments in the optimal unrestricted contract result in partial cost sharing if \(\alpha_p > 0\); i.e., if physicians are partially altruistic.\(^{15}\)

Figure 1 plots outcomes for full-information benchmark (black, solid line), linear contract (red, dotted line), and unrestricted contract (blue, dashed line) scenarios for a specific parameterization of the model, where physician cost types are distributed according to a truncated normal distribution. Figure 1a shows the induced action (treatment amount) for each cost type in each scenario. Under full information (the “first-best”), the treatment amount decreases as the cost factor \(z\) increases. The same is also true in both asymmetric information scenarios. However the linear contract, which offers the same marginal incentive to all types, leads to over-provision for low-cost types and under-provision for high-cost types. In contrast, the unrestricted contract, which separates types by providing variable marginal incentives, leads to under-provision for all but the lowest-cost type, \(z\). The amount of this distortion relative to the full-information benchmark is increasing in cost type.

Figure 1b shows how the payment depends on the treatment amount under the linear and unrestricted contracts; in other words, this figure plots the payment schedules. Both schedules are upward-sloping, meaning that pure prospective payment is not optimal in this example, similar to Ellis and McGuire (1986). Also similar to Ellis and McGuire (1986), neither contract implements full cost sharing. The range of payments under the unrestricted contract is lower than the range under the linear contract, because the nonlinear schedule provides lower marginal rates and induces lower treatment amounts among low-cost physicians, and because it induces substantially lower treatment amounts among high-cost physicians as well. (However, as seen in figure 1a, the unrestricted contract induces higher treatment

\(^{15}\)This is because \(\frac{\partial w(a_i)}{\partial a_i} = z_i - \alpha_p h'(a_i)\), which is strictly less than the marginal cost \(z_i\) for \(e_0 < e_\tau\).
Figure 1: Comparison of Outcomes in Model Simulation

(a) Treatment choice by cost type

(b) Payment as function of treatment choice

(c) Physician objective by cost type

(d) Government objective by cost type
amounts among cost types in the middle of the range.)

The qualitative relationship between payment and treatment amounts depends on the asymmetric information. In a full-information scenario, the government could fully compensate high-cost types to implement the desired action, thereby paying them more than low-cost types and leading to a negative relationship between payment and treatment amounts. However, the asymmetric information would then enable low-cost types to obtain large surpluses by pretending to be high-cost types. Thus, incentive compatibility requires that payment and treatment amounts must both be lower for high-cost types, so that low-cost types enjoy a larger surplus (i.e., are paid more) by providing larger amounts. This results in a payment contract that increases with treatment amounts.

Finally, figures 1c and 1d respectively plot the physician objective \( u_p \) and the government objective \( u_g \) against the cost type, in each scenario. Since the government can extract all the surplus under full information, all cost types receive zero utility in the benchmark scenario. In the optimal contracts under asymmetric information, only the highest cost type receives zero utility (because the VP constraint only binds for this type) while all lower cost types receive positive surpluses. The physician surpluses are in fact quite similar under the linear and nonlinear contracts in this example. The government naturally fares best under full information and second-best with the unrestricted contract.

3 Data

Our data come primarily from Medicare outpatient claims from renal dialysis centers (free-standing or hospital-based) in 2008 and 2009, for the treatment of patients with ESRD. As noted earlier, these facilities provide dialysis treatment to patients multiple times per week, and claims are typically filed monthly. EPO can be administered at each visit, and each injection is individually listed as a separate line on the claim.

The raw 20% sample for 2008 and 2009 contains 1.4 million ESRD claims with 11.1 million claim lines for EPO or related medications. Almost 90% of the claims bill for at least one injection of these drugs (1.25 million claims). All claims with an injection include a baseline hematocrit level from the previous month (or a related hemoglobin level), but the full-information treatment choice solves \[ \alpha_g + \alpha_p h'(a_{\text{full info}}) = z_i \], and \( \alpha_g \geq 0 \).

\[ \frac{\partial u_i^*_{\text{full info}}}{\partial a_{\text{full info}}} = - \left[ z_i - \alpha_p h'(a_{\text{full info}}) \right], \] where we know the term in the brackets is weakly positive because the full-information treatment choice solves \[ \alpha_g + \alpha_p h'(a_{\text{full info}}) = z_i \], and \( \alpha_g \geq 0 \).

\[ \frac{\partial u_i^*_{\text{full info}}}{\partial a_{\text{full info}}} = - \left[ z_i - \alpha_p h'(a_{\text{full info}}) \right], \] where we know the term in the brackets is weakly positive because the full-information treatment choice solves \[ \alpha_g + \alpha_p h'(a_{\text{full info}}) = z_i \], and \( \alpha_g \geq 0 \).

The substantial downward distortion of the treatment amounts from high-cost physicians results in lower values of the government’s objective from these types, but this is in the far upper tail of the distribution.

Epoetin alpha constitutes 97.6% of the claim lines for this class of medication in our sample. The alternative drug was darbepoetin alpha. For the present analysis we restrict to epoetin alpha because dosages and reimbursements differ between the two drugs.
claims without an injection typically do not report a red blood cell level. As a consequence, for the present analysis we exclude claims without any injections of EPO.

The unit of analysis is the (typically) monthly claim, which reports the treatment given by provider \( i \) to patient \( j \) in period \( t \).\(^{19}\) The total amount of EPO injected over the month is the action, \( a_{ijt} \), and the prior hematocrit level reported in the claim is the baseline hematocrit, \( e_{0,jt} \).\(^{20}\) The reimbursement rate, \( w_{1t} \), is the national payment rate per 1,000 units of EPO for the quarter in which the claim was filed. These rates are listed in Medicare Part B Average Sales Price Drug Pricing Files available on the CMS website.\(^{21}\) The claims also list the actual payments for each injection of EPO, so a claim-specific reimbursement rate can be computed. These actual reimbursement rates are highly correlated with the national payment rates.\(^{22}\)

In order to avoid extreme outliers, which often reflect data entry errors, we remove observations where the baseline hematocrit (\( e_{0,jt} \)) is above its 99th percentile or below its 1st percentile or where the amount of EPO (\( a_{ijt} \)) is above its 99th percentile. The final analytic sample has 1.1 million claims for 76,985 unique patients from 5,150 unique providers. The providers are defined as facilities, not individual physicians, because within each facility there are multiple doctors and nurses who jointly treat their patients.\(^{23}\)

Table 1 provides summary statistics on the three main variables in our analytic sample. The average monthly dosage of EPO is 67.0 thousand units, with a relatively large standard deviation of 66.4 thousand units, and the average baseline hematocrit is 34.5 percent (volume percentage of red blood cells in the blood). The national reimbursement rate has a mean of $9.26 per 1,000 units of EPO and ranges from a low of $8.96 in 2008Q1 to a high of $9.62 in 2009Q3. Table 1 also presents information on the distribution of acquisition costs for EPO from a separate source, the Renal Dialysis Facility Cost Reports. The Centers for Medicare and Medicaid Services (CMS) requires dialysis facilities to submit detailed annual cost reports, which include their total expenditures on EPO and the total number of units provided. These data are publicly available on the CMS website.\(^{24}\) From the total expenditures (less any rebates) and total units, we compute the average acquisition cost per 1,000 units for each facility in the cost report data for 2008. The percentiles listed in the

---

\(^{19}\)Note that we now use \( i \) to index providers instead of unobserved types.

\(^{20}\)For claims that report hemoglobin rather than hematocrit, we use the standard rule of thumb of multiplying by three to convert the levels.

\(^{21}\)See https://www.cms.gov/Medicare/Medicare-Fee-for-Service-Part-B-Drugs/McrPartBDrugAvgSalesPrice/index.html.

\(^{22}\)In our analytic sample the correlation is 0.92, net of provider fixed effects.

\(^{23}\)Also, many facilities belong to large, national chains (DaVita and Fresenius), but we treat the individual facilities separately.

Table 1: Summary Statistics

<table>
<thead>
<tr>
<th>Variable</th>
<th>Mean</th>
<th>SD</th>
<th>10th</th>
<th>25th</th>
<th>50th</th>
<th>75th</th>
<th>90th</th>
</tr>
</thead>
<tbody>
<tr>
<td>Monthly EPO dosage (1,000u)</td>
<td>67.0</td>
<td>66.4</td>
<td>8.8</td>
<td>20.0</td>
<td>45.0</td>
<td>90.0</td>
<td>156.2</td>
</tr>
<tr>
<td>Prior hematocrit level (%)</td>
<td>34.5</td>
<td>3.4</td>
<td>30</td>
<td>32.4</td>
<td>34.8</td>
<td>36.9</td>
<td>38.7</td>
</tr>
<tr>
<td>Reimbursement rate ($/1000u)</td>
<td>9.26</td>
<td>0.24</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Addendum 1 – Percentiles of EPO acquisition costs from annual cost reports:

| Acquisition cost ($/1000u) | 7.13 | 7.23 | 7.53 | 8.15 | 9.11 |

Addendum 2 – Medicare reimbursement rate for EPO in each quarter:

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>(2008Q1)</td>
<td>(Q2)</td>
<td>(Q3)</td>
<td>(Q4)</td>
<td>(2009Q1)</td>
<td>(Q2)</td>
<td>(Q3)</td>
<td>(Q4)</td>
<td></td>
</tr>
</tbody>
</table>

Notes: The EPO dosage and hematocrit come from Medicare outpatient claims data. The reimbursement rate comes from quarterly Medicare Part B ASP Drug Pricing Files for 2008 and 2009. This latter variable takes one of eight values depending on the quarter, as listed in Addendum 2, so we do not present its percentiles. The distribution of EPO acquisition costs shown in Addendum 1 is computed from Renal Dialysis Facilities Cost Report Data for 2008. We do not present the mean or standard deviation because extreme outliers in the cost report data make those statistics unreliable, compared to the percentiles.

Table show non-trivial differences across providers in the acquisition cost, even though the drug was produced by a single manufacturer.

To present some preliminary evidence on the relationships between patient need, payment rates, and drug provision, Figure 2 plots average dosages of EPO as a function of baseline hematocrit in the first and last quarters of our analytic sample. In both periods the dosages decline with higher hematocrit levels, as would be expected, and the decline is steeper at lower levels. A notable difference between the two periods is that in 2009Q4, when the reimbursement rate was higher, average dosages are higher for patients with low hematocrit levels, and these dosages decrease more rapidly in relation to hematocrit. Our empirical model, discussed next, will use specifications designed to fit these qualitative features.

### 4 Empirical Implementation

We now describe how we adapt the model from Section 2 to our empirical context. The model naturally extends to an environment with many agents, each treating many patients,
under the assumptions that the providers’ utility functions and the government’s objective function are additive across patients.\textsuperscript{25}

The empirical specification extends the example in Section 2.1 by adding flexibility in relation to the patient’s baseline hematocrit. We add $\delta(e_0)$ to the parameter $\delta$, which allows the productivity of EPO to depend on the baseline level of hematocrit.\textsuperscript{26} Also we add $\alpha(e_0)$ to the altruism parameter, so that the total weight on the patient’s health in the physician’s utility is $\alpha_p + \alpha(e_0)$. This means that physicians may have greater or lesser concern for the health of patients with different baseline levels of hematocrit.\textsuperscript{27} The physician’s utility function is thus

$$- [\alpha_p + \alpha(e_0)] \frac{1}{2} [\delta + \delta(e_0)] a + e_0 - e_T]^2 - a z_i + w_0 + w_1 a.$$  

The parameters $\alpha(e_0)$ and $\delta(e_0)$ are specified take different values over certain intervals of $e_0$, noted below, which makes this a piecewise quadratic function of $a$ and $e_0$.

\textsuperscript{25} The static framework can be applied to to multiple time periods if there are no dynamic effects of EPO (as discussed in Section 1.2), and if the government does not use treatment histories in setting reimbursement rates. This has always been the case when patient hematocrit levels are within the recommended range. However, the Medicare payment policy during our analysis period paid reduced rates for EPO given to patients who had high hematocrit levels for three consecutive months (over 39%).

\textsuperscript{26} This captures diminishing returns in a simple fashion that maintains our closed-form solutions.

\textsuperscript{27} We still refer to physicians when discussing the model, but to be clear, we use facilities as the providers in the empirical analysis.
Given this utility function, the optimal treatment amount (at an interior solution) is

\[ a_i^* = \frac{[e_x - e_0]}{\delta + \delta(e_0)} + \frac{w_1 - z_i}{[\alpha_p + \alpha(e_0)](\delta + \delta(e_0))^2}. \]  

(10)

The treatment policy function is thus piecewise linear, with the segments corresponding to the intervals in \( e_0 \). As we will show, this specification has the advantages of maintaining closed-form solutions from Section 2.1 while having sufficient flexibility to fit the qualitative features seen in Figure 2.

To allow for unexplained variation from the econometrician’s perspective we add an independent, mean-zero shock \( \eta \). We also decompose the individual cost type as \( z_i = \mu z + \zeta_i \).

The observed treatment amount provided by physician \( i \) to patient \( j \) at time \( t \) is then

\[ a_{ijt} = \frac{[e_x - e_{0jt}]}{\delta + \delta(e_{0jt})} + \frac{w_{1t} - [\mu z + \zeta_i]}{[\alpha_p + \alpha(e_{0jt})](\delta + \delta(e_{0jt}))^2} + \eta_{ijt}, \]  

(11)

where \( e_{0jt} \) is patient \( j \’s \) baseline hematocrit in period \( t \) and \( w_{1t} \) is the national reimbursement rate for EPO in period \( t \). Within each interval of baseline hematocrit, in which the parameters \( \alpha(e_0) \) and \( \delta(e_0) \) are constant, (11) is linear in \( e_0 \) and \( w_1 \).

### 4.1 Identification

To derive an optimal contract and simulate provider behavior, we need values for the following structural parameters: \( \alpha_p \) and \( \alpha(e_0) \) (altruism weights), \( \delta \) and \( \delta(e_0) \) (productivity of EPO), and \( e_x \) (target hematocrit level). We also need the distribution of \( z \), because the mean and maximum (\( \mu_z \) and \( \overline{z} \)) appear in the optimal linear contract and the inverse hazard ratio \( (F_z(z)/f_z(z)) \) appears in the optimal unrestricted contract. These parameters and the distribution of \( z \) can be identified from the reduced form (11), except that we require additional data on costs to establish the mean value of \( z \) (described below).

The reduced form can be re-expressed as follows:

\[ a_{ijt} = \sum_k 1\{e_{0jt} \in E^k\} [\beta_0^k + \beta_1^k e_{0jt} + \beta_2^k w_{1t}] + \nu_i + \epsilon_{ijt}, \]  

(12)

where \( 1\{e_{0jt} \in E^k\} \) indicates that the baseline hematocrit is in interval \( E^k \). This is a piecewise linear regression model with provider fixed effects. The parameters \( \delta(E^k) \) and \( \alpha_p + \alpha(E^k) \) are recovered from the coefficients of this regression as follows:

\[ \delta + \delta(E^k) = -\frac{1}{\beta_1^k} \quad \text{and} \quad \alpha_p + \alpha(E^k) = \frac{[\beta_1^k]^2}{\beta_2^k}, \]  

18
with the $\delta(E^k)$ and $\alpha(E^k)$ in one interval normalized to zero.\textsuperscript{28} The result for the altruism parameters has intuitive appeal: it is the ratio of the responsiveness to a measure of patient need (squared) to the responsiveness to remuneration. The intercept in each interval, $\beta_0^k$, identifies a linear combination of $\epsilon_r$ and $\mu_z$, and the distribution of the provider fixed effects identifies the distribution of deviations from the mean cost. We use external data, from the Renal Dialysis Facility Cost Reports, to identify the mean per-unit cost, $\mu_z$. Specifically we take the median value reported in Table 1 as the value of $\mu_z$, which is equal to $7.53$ per 1,000 units.\textsuperscript{29} This then completes the identification of the distribution of $z$ (from the fixed effects) and the target level of hematocrit $e_r$ (from the intercepts).

The identification of the structural parameters also depends on the consistency of the reduced-form coefficient estimates. There are two variables in the reduced form (12): the baseline hematocrit ($e_{0jt}$) and the national payment rate ($w_{1t}$). These must be uncorrelated with the error term ($\epsilon_{ijt}$) net of the provider fixed effects ($\nu_i$). The baseline hematocrit satisfies this so long as any selection of patients to providers did not change over the two years of our estimation period. That makes the within-provider variation in $e_{0jt}$ across patients and over time exogenous.\textsuperscript{30} The national payment rate, as described in Section 1.2, was determined by the national average price of EPO roughly six months earlier. An individual facility could not affect the national average price, but if demand shocks were substantially correlated across facilities and over time, there could be a bias. However we include a year dummy for 2009 and month dummies for each calendar month. These would address both secular and cyclical trends in demand. Also, dialysis facilities were not the only purchasers of EPO because the drug was also widely used in chemotherapy. Thus there are two potential sources of exogenous variation in the lagged prices that determined $w_{1t}$: demand shocks from chemotherapy providers and supply shocks from the drug manufacturer.

\textsuperscript{28}The coefficients of the reduced form are the following combinations of the structural parameters:

$$\beta_0^k = \frac{\epsilon_r}{\delta + \delta(E^k)} - \frac{\mu_z}{[\alpha_p + \alpha(E^k)][\delta + \delta(E^k)]^2}, \quad \beta_1^k = -\frac{1}{\delta + \delta(E^k)}, \quad \beta_2^k = \frac{1}{[\alpha_p + \alpha(E^k)][\delta + \delta(E^k)]^2}.$$

\textsuperscript{29}We use the median rather than the mean because it is less sensitive to extreme outliers in the cost report data. Also to be precise, the cost reports reflect the acquisition cost but not any additional cost of administering the drug. The cost of injecting EPO is nevertheless small relative to the price of purchasing it.

\textsuperscript{30}A more subtle concern is the fact that the hematocrit level from the prior month reflects the treatment given in the prior month. So long as each provider’s treatment protocols are stable during our analysis period, the provider fixed effects would address this as well.
Table 2: Reduced-Form Coefficient Estimates

<table>
<thead>
<tr>
<th>Interval of Baseline Hematocrit</th>
<th>Coefficient</th>
<th>Up to 27,</th>
<th>&gt; 27 to 30,</th>
<th>&gt; 30 to 33,</th>
<th>&gt; 33 to 36,</th>
<th>&gt; 36 to 39,</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\beta^k_0$</td>
<td>352.1</td>
<td>173.7</td>
<td>281.1</td>
<td>229.3</td>
<td>153.8</td>
<td>28.3</td>
</tr>
<tr>
<td>Constant term</td>
<td>(46.0)</td>
<td>(51.3)</td>
<td>(28.2)</td>
<td>(18.7)</td>
<td>(17.9)</td>
<td>(25.1)</td>
</tr>
<tr>
<td>$\beta^k_1$</td>
<td>-6.20</td>
<td>-7.56</td>
<td>-9.48</td>
<td>-6.70</td>
<td>-4.00</td>
<td>-2.06</td>
</tr>
<tr>
<td>Baseline HCT</td>
<td>(0.14)</td>
<td>(0.37)</td>
<td>(0.20)</td>
<td>(0.13)</td>
<td>(0.13)</td>
<td>(0.16)</td>
</tr>
<tr>
<td>$\beta^k_2$</td>
<td>-7.20</td>
<td>17.09</td>
<td>11.45</td>
<td>7.22</td>
<td>4.97</td>
<td>10.40</td>
</tr>
<tr>
<td>Reimb. rate</td>
<td>(5.21)</td>
<td>(5.64)</td>
<td>(3.10)</td>
<td>(2.03)</td>
<td>(1.94)</td>
<td>(2.76)</td>
</tr>
<tr>
<td>Obs. in interval</td>
<td>97,983</td>
<td>82,640</td>
<td>216,391</td>
<td>379,530</td>
<td>267,245</td>
<td>83,344</td>
</tr>
</tbody>
</table>

Notes: Estimates are from a single fixed-effects regression where variables are interacted with indicators for the listed ranges in baseline hematocrit (HCT). Standard errors in parentheses, clustered by provider.

4.2 Estimation

We estimate (12) via standard fixed effects estimation with provider fixed effects. As noted above, the regression also includes separate effects for year and month (not year x month). The year effect(s) capture possible secular changes, while the month effects account for billing behavior that may change throughout the year (e.g., a spike in claims dated December 31).

Table 2 presents the estimates of the main coefficients. These come from a single regression with separate coefficients for each of the listed intervals of baseline hematocrit. For example, in the interval from 30 to 33, a patient with one unit higher hematocrit (say 32 vs. 31) receives 9,480 less units of EPO per month on average. Also for patients in the interval from 30 to 33, a one dollar increase in the reimbursement rate (per 1,000 units) would induce providers to increase dosages by 11,450 units per month on average.

The intervals of baseline hematocrit were chosen to reflect treatment guidelines and policies in place at the time, and to balance the flexibility of the specification with the precision of the estimates for each interval. The FDA approved EPO for use in patients with hematocrit between 30 and 36, and Medicare reduced the reimbursement rate for EPO provided to patients with hematocrit above 39.\footnote{Medicare did not use 36% as the cutoff for payment reductions because of the acknowledged difficulty in maintaining a target level exactly over time.} Using 3-point intervals divides this range from 30 to 39 evenly, and the estimation results indicate that this width allows sufficient power within each interval while maintaining flexibility globally. We consider the estimates in the intervals from 30 up to 39 to be the most reliable, because these are the most common...
Table 3: Structural Parameter Estimates

<table>
<thead>
<tr>
<th>Interval of Baseline Hematocrit</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Parameter</td>
<td>Up to 27,</td>
</tr>
<tr>
<td>$\alpha_p + \alpha(E^K)$</td>
<td>-5.34</td>
</tr>
<tr>
<td></td>
<td>(3.89)</td>
</tr>
<tr>
<td>$\delta + \delta(E^K)$</td>
<td>0.161</td>
</tr>
<tr>
<td></td>
<td>(0.004)</td>
</tr>
<tr>
<td>$e_{\tau}$</td>
<td>48.0</td>
</tr>
<tr>
<td></td>
<td>(1.3)</td>
</tr>
</tbody>
</table>

Notes: Values are recovered from reduced form coefficients, using the value of $\mu_z = $7.53, as described in Section 4.1. Delta method standard errors in parentheses.

...clinically (over 80% of the observations are in these intervals) and because this range has at least implicit approval from the FDA or Medicare policy. Within this range there is decreasing responsiveness to both baseline hematocrit and the reimbursement rate, going from lower to higher intervals. This matches the decreasing magnitude of the slopes seen in Figure 2.

Table 3 presents the structural parameters, recovered as described above. Across the intervals from 30 to 39, the altruism weight decreases while the productivity of EPO increases. The former could be interpreted as a lower concern for the health of patients with less severe anemia. The latter is consistent with diminishing marginal productivity of EPO. The magnitudes of the altruism parameters imply that, for example in the interval from 30 to 33, physicians would require $7.84 to compensate for providing an amount of EPO intended to achieve a hematocrit above or below the target level by 1 percentage point. The estimate of $\delta + \delta(E^K)$ in this interval implies that 1,000 units of EPO raises hematocrit by 0.105 percentage points. This and the other estimates of the average productivity of EPO across the intervals from 30 to 39 are consistent with estimates obtained from clinical trials.

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32 Patients with lower baseline hematocrit are given more EPO on average, and the estimates of $\delta + \delta(E^K)$ reflect the average productivity of EPO for patients with baseline hematocrit in each range.

33 The average dosages and the average increases from initial hemoglobin levels reported in Singh et al. (2006) imply average productivities of 0.143 and 0.167 for the two treatment groups in the study (our calculations). Also, Tonelli et al. (2003) construct a dose-response curve based on results from five other clinical trials, which indicates average marginal productivities ranging from 0.135 to 0.241 for hematocrit levels in this range.
values of the implied hematocrit target are also reasonably close to what would be expected based on clinical and policy guidelines.\textsuperscript{34}

5 Quantitative Results

We now present preliminary results on the optimal linear contract and optimal unconstrained contract. First we compute the optimal per-unit payment rate in the linear contract ($w_1^{\text{lin}}$) and use it to simulate counterfactual EPO dosages for the entire sample. We then construct the optimal unrestricted contract for a particular value of baseline hematocrit, and compare this with the linear contract and the observed contract (i.e., the actual reimbursement rate).

The reimbursement rate in the optimal linear contract depends on mean and maximum costs ($\mu_z$ and $\tau$) and the altruism weights for both the providers and the government ($\alpha_p$ and $\alpha_g$).\textsuperscript{35} However, the altruism weight for the government cannot be recovered without making further assumptions (e.g., that the observed payment policy is optimal, an assumption we do not want to make). Instead we consider two possible values for $\alpha_g$ that span a wide range. Specifically, we use $\alpha_g = \alpha_p$ as the low value and $\alpha_g = 10\alpha_p$ as the high value. Also, because the maximum cost $\tau$ is highly sensitive to outliers, we use the 95th percentile of the recovered distribution of $z$ in place of the maximum. We then use the estimated reduced form to predict a counterfactual dosage for each observation (i.e., for each patient in each month).\textsuperscript{36}

Table 4 shows the results of this exercise. The actual reimbursement rates range from $8.96 to $9.62 (over time), and with these observed rates the average predicted monthly dosages for patients within each interval of baseline hematocrit essentially match the average observed dosages (by construction). The payment rate in optimal linear contract with $\alpha_g = 10\alpha_p$ is $6.44$, and with $\alpha_g = \alpha_p$ is $1.54$.\textsuperscript{37} With the higher counterfactual rate, dosages are reduced by about 30–40% and with the lower rate they are reduced even further. Interestingly, with the $6.44 rate the proportional reductions are largest in the top interval of baseline hematocrit, where Medicare sought to discourage the use of EPO.

Figure 3 presents our results for the optimal unrestricted contract. The contract is computed for the median level of baseline hematocrit ($e_0 = 34.8$) and with the high value for

\textsuperscript{34}These implied targets are slightly higher than one would expect based on the FDA and Medicare policies (e.g., 36 or 39). This indicates a misspecification in the model, for example in the quadratic loss around the target, but the misspecification is mild because the implied targets are rather close to the expected amounts.

\textsuperscript{35}See equation (5).

\textsuperscript{36}Negative predicted dosages are replaced with 0.

\textsuperscript{37}Although $\alpha_p$ varies across the intervals of baseline hematocrit, the reimbursement rate does not vary because we have set $\alpha_g$ to be proportional to $\alpha_p$, which makes these parameters cancel in equation (5).
Notes: Panel (a) shows the payment contract (i.e., total payment as a function of the treatment amount) for the observed contract and the optimal linear and unrestricted contracts derived from the estimated model. Panel (b) shows the treatment amounts chosen under these contracts as a function of the physician cost type. The observed contract uses the sample mean of the payment rate (9.26). The optimal contracts are computed from the estimated parameters and the recovered distribution of cost types, using equations (3) and (5) for the linear contract and equations (8) and (9) for the unrestricted contract. The contracts and outcomes are computed for a patient with the median level of baseline hematocrit (34.8).
Table 4: Simulation of Average Monthly Dosages of EPO under Linear Contracts

<table>
<thead>
<tr>
<th>Scenario</th>
<th>Interval of Baseline Hematocrit</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Up to 27, &gt; 27 to 30, &gt; 30 to 33, &gt; 33 to 36, &gt; 36 to 39, &gt; 39</td>
<td></td>
</tr>
<tr>
<td><strong>Observed reimbursement rates</strong></td>
<td>($8.96–$9.62)</td>
<td>79.6</td>
</tr>
<tr>
<td><strong>Optimal linear contract,</strong></td>
<td>$6.44</td>
<td>99.8</td>
</tr>
<tr>
<td>$α_g = 10α_p$</td>
<td></td>
<td>13.6</td>
</tr>
<tr>
<td><strong>Optimal linear contract,</strong></td>
<td>$1.54</td>
<td>135.0</td>
</tr>
<tr>
<td>$α_g = α_p$</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Notes: Predicted monthly dosages are generated for each observation in the sample using the estimated version of (12), with the payment rate set to the observed amounts, or $6.44, or $1.54, as indicated.

government altruism ($α_g = 10α_p$). The payment and treatment amounts are shown for the observed contract (green, long-dashed line), the optimal linear contract (red, dotted line), and the optimal unrestricted contract (blue, dashed line). Figure 3a plots the contracts; i.e., how the total payment depends on the treatment amount. Figure 3c underneath shows the distribution of treatment amounts provided under each contract (to patients with $e_0 = 34.8$). Consistent with the payment rates presented in Table 4, the observed contract is steeper (i.e., has a higher per-unit rate) than the optimal linear contract, even though the government values patient health ten times as much as do physicians. The optimal unrestricted contract has a roughly similar average payment rate as the optimal linear contract, but the government’s ability to provide different marginal incentives for different dosages results in a much more compressed distribution of treatment amounts under this contract.

Figure 3b shows how treatment amounts are related to physician cost types under each contract. The full-information benchmark is included for comparison (gray, solid line). Consistent with Table 4, treatment amounts under the observed contract are too high, exceeding first-best, full-information dosages and even the implied bliss point (i.e., $e_τ$) for most cost types. The optimal linear contract offers a uniformly lower payment rate, so dosages under this contract lie below those under the observed contract, and the two move in parallel. The optimal unrestricted contract, which better separates physician types, is much closer to the full-information benchmark. In contrast to both the observed and optimal linear contracts, the optimal unrestricted contract leads to mild under-provision for most cost types. This indicates the potential importance of the subtle differences between the optimal linear and

---

38We trim the distribution of cost types at the 5th and 95th percentiles and use this as the $F_z$. For the observed contract we use the sample mean of the actual reimbursement rates, $S9.26$. 

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Table 5: Summary of Outcomes under Optimal Contracts

<table>
<thead>
<tr>
<th>Contract</th>
<th>Mean Pmt</th>
<th>Mean Dosage</th>
<th>SD Dosage</th>
</tr>
</thead>
<tbody>
<tr>
<td>Observed</td>
<td>$582</td>
<td>62.9</td>
<td>12.5</td>
</tr>
<tr>
<td>Linear</td>
<td>$440</td>
<td>42.3</td>
<td>12.5</td>
</tr>
<tr>
<td>Unrestricted</td>
<td>$484</td>
<td>42.4</td>
<td>3.7</td>
</tr>
<tr>
<td>Full Information</td>
<td>$342</td>
<td>45.4</td>
<td>1.1</td>
</tr>
</tbody>
</table>

Note: Table shows summary statistics of outcomes plotted in Figure 3.

unrestricted contracts seen in Figure 3a.

Table 5 summarizes the outcomes under these contracts (again, for patients with the median level of hematocrit). With the observed contract, the predicted mean payment is $582 and the predicted mean dosage is 62,900 units of EPO per month. The optimal linear contract reduces the mean payment by 25% and the mean dosage by 33%.\(^{39}\) The optimal linear contract does not change the variation in dosages, however, because it provides a constant marginal incentive just like the observed contract. The optimal unrestricted contract, by contrast, is nonlinear and induces a substantial reduction in the variation in treatment amounts across physicians. The standard deviation of the dosages falls by 70%, while the mean dosage is essentially the same as with the optimal linear contract. The mean payment is larger under the nonlinear contract compared to the linear contract, but this relatively small additional expenditure yields better patient health because of the reduction in treatment variation. Finally, for comparison, the full information scenario indicates what could be obtained in the absence of asymmetric information about physician costs. The mean dosage is slightly higher than under the optimal contracts, while the mean payment is lower (because all physicians receive zero surplus). Some variation in treatment amounts remains, which reflects the government’s valuation of the physicians’ actual marginal costs.\(^{39}\)

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\(^{39}\)The optimal linear contract also includes a fixed payment, \(w_0\), here equal to $168.
References


A Model Details

A.1 Linear Contract with Cost Heterogeneity

The government’s problem in (4) maximizes patient health, net the cost of transfers, subject to using a linear contract. Note that we can remove all participation constraints except for that for physician cost type \( z \) because \( u_p(a,z) \) is decreasing in \( z \); i.e., the only participation constraint that binds is that of the highest cost type. Using interior physician’s policy functions, government’s problem (4) can be rewritten as

\[
\max_{\{w_0, w_1\} \in \mathbb{R}^2} \int_{\mathbb{R}} \left[ u_g(a) - w_0 - w_1 a(z, w) \right] f(z) dz \tag{13}
\]

s.t.

\[
u_\pi(a^*(\pi, w), w) \geq 0, \quad \text{VP}
\]

\[
a^*(z, w) = \frac{e_\tau - e_0}{\delta} + \frac{w_1 - z}{\delta^2 \alpha_p}, \quad \forall z, \quad \text{IC}.
\]

Setting up the Lagrangian based on this constraint and using interior physician’s policy functions we obtain

\[
\mathcal{L} = \int_{\mathbb{R}} \left[ \alpha_g \left( \frac{-(w_1 - z)^2}{2 \delta^2 \alpha_p^2} \right) - w_0 - w_1 \left( \frac{e_\tau - e_0}{\delta} + \frac{w_1 - z}{\delta^2 \alpha_p} \right) \right] f(z) dz
\]

\[
+ \mu \left[ \frac{(w_1 - \pi)^2}{2 \delta^2 \alpha_p^2} + \frac{(e_\tau - e_0)(w_1 - \pi)}{\delta} + w_0 \right].
\]

First order conditions with respect to \( w_0 \) and \( w_1 \) yield the following system of equations:

\[
\int_{\mathbb{R}} \left[ -f(z) dz \right] + \mu = 0 \Rightarrow \mu = F'(\pi) = 1
\]

\[
\int_{\mathbb{R}} \left[ -\alpha_g \left( \frac{w_1 - z}{\delta^2 \alpha_p^2} \right) - \left( \frac{e_\tau - e_0}{\delta} + \frac{w_1 - z}{\delta^2 \alpha_p} \right) \right] f(z) dz + \mu \left[ \frac{w_1 - \pi}{\delta^2 \alpha_p} + \frac{e_\tau - e_0}{\delta} \right] = 0.
\]

The first part of the second equation has to do with the average of the cost type distribution while the last term of the second equation, following the multiplier \( \mu \), pertains to the binding participation constraint of the highest-cost-type. Using \( \mu = 1 \), from the first equation, the
second equation can be simplified further to

$$-\frac{[\alpha_g + \alpha_p]w_1}{\delta^2 \alpha_p^2} - \frac{z}{\delta^2 \alpha_p} + \int_{\tilde{z}}^{z} \frac{[\alpha_g + \alpha_p]z}{\delta^2 \alpha_p^2} f(z) dz = 0$$

$$\Rightarrow w_1^* = \int_{\tilde{z}}^{z} zf(z) dz - \frac{\alpha_p \tilde{z}}{\alpha_p + \alpha_g} = \mu_z - \frac{\alpha_p}{\alpha_p + \alpha_g} \tilde{z}$$

The next step is to characterize $w_0^*$, which we do using the binding participation constraint of $\tilde{z}$:

$$u_\tilde{z}(a^*(\tilde{z}, w), w) = \frac{(w_1 - \tilde{z})^2}{2 \delta^2 \alpha_p} + \frac{(e_\tau - e_0)(w_1 - \tilde{z})}{\delta} + w_0 = 0$$

$$\Rightarrow w_0^* = -\frac{w_1 - \tilde{z}}{\delta} \left[ (e_\tau - e_0) + \frac{w_1 - \tilde{z}}{2 \delta \alpha_p} \right]$$

Plugging in $w_1^* = \mu_z - \frac{\alpha_p}{\alpha_p + \alpha_g} \tilde{z}$ one can characterize $w_0$ as

$$w_0 = \left[ 2 + \frac{\alpha_g}{\alpha_p} \right] \tilde{z} - \left[ 1 + \frac{\alpha_g}{\alpha_p} \right] \frac{\mu_z}{\delta} \left[ \frac{e_\tau - e_0}{\delta} + \frac{\mu_z}{2 \delta \alpha_p} \left[ 1 + \frac{\alpha_g}{\alpha_p} \right] - \frac{2 + \frac{\alpha_g}{\alpha_p}}{\delta} \tilde{z} \right]$$

### A.1.1 Comparative Statics

**Comparative statics for $w_1^*$** Based on equation (5) it is clear that

$$\frac{\partial w_1^*}{\partial \tilde{z}} < 0$$

$$\frac{\partial w_1^*}{\partial \alpha_g} > 0$$

$$\frac{\partial w_1^*}{\partial \alpha_p} = -\frac{\mu \alpha_g}{(\alpha_p + \alpha_g)^2} < 0.$$

**Comparative statics for $w_0^*$** To do comparative statics for $w_0^*$, we first define the indirect utility function for a physician of type $z$, $V_p(z; w)$, which is obtained by plugging the interior solution of the physician’s action into the utility function. Note that this constraint for the highest cost type is binding under the optimal linear contract, i.e., they get no surplus. Thus,

$$V_p(\tilde{z}; w_0^*, w_1^*) = \frac{(w_1^* - \tilde{z})^2}{2 \delta^2 \alpha_p} + \frac{(e_\tau - e_0)(w_1^* - \tilde{z})}{\delta} + w_0^* = 0.$$
We use the binding constraint on the indirect utility function for the high cost type for the comparative static analysis.

\[
\frac{\partial V_p(z; w_0^*, w_1^*)}{\partial \tau} = 0 \iff \frac{\partial w_0^*}{\partial \tau} - 2 \frac{w_0^* - \tau}{2\delta^2\alpha_p} + 2 \frac{w_1^* - \tau}{2\delta^2\alpha_p} \frac{\partial w_1^*}{\partial \tau} - \frac{(e_\tau - e_0)}{\delta} + \frac{(e_\tau - e_0)}{\delta} \frac{\partial w_1^*}{\partial \tau} = 0
\]

\[
\iff \frac{\partial w_0^*}{\partial \tau} = (1 - \frac{\partial w_1^*}{\partial \tau})(\frac{w_1^* - \tau}{\delta^2\alpha_p} + \frac{(e_\tau - e_0)}{\delta}) = a_{zl}^{linear} (1 - \frac{\partial w_1^*}{\partial \tau}) > 0.
\]

\[
\frac{\partial V_p(z; w_0^*, w_1^*)}{\partial \alpha_g} = 0 \iff \frac{\partial w_0^*}{\partial \alpha_g} + 2 \frac{w_1^* - \tau}{2\delta^2\alpha_p} \frac{\partial w_1^*}{\partial \alpha_g} + \frac{(e_\tau - e_0)}{\delta} \frac{\partial w_1^*}{\partial \alpha_g} = 0
\]

\[
\iff \frac{\partial w_0^*}{\partial \alpha_g} = -\frac{\partial w_1^*}{\partial \alpha_g} (\frac{w_1^* - \tau}{\delta^2\alpha_p} + \frac{(e_\tau - e_0)}{\delta}) = -a_{zl}^{linear} \frac{\partial w_1^*}{\partial \alpha_g} < 0.
\]

\[
\frac{\partial V_p(z; w_0^*, w_1^*)}{\partial \alpha_p} = 0 \iff \frac{\partial w_0^*}{\partial \alpha_p} - \frac{(w_1^* - \tau)^2}{2\delta^2\alpha_p^2} + \frac{w_1^* - \tau}{\delta^2\alpha_p} \frac{\partial w_1^*}{\partial \alpha_p} + \frac{(e_\tau - e_0)}{\delta} \frac{\partial w_1^*}{\partial \alpha_p} = 0
\]

\[
\iff \frac{\partial w_0^*}{\partial \alpha_p} = \frac{(w_1^* - \tau)^2}{2\delta^2\alpha_p^2} - \frac{w_1^* - \tau}{\delta^2\alpha_p} \frac{\partial w_1^*}{\partial \alpha_p} = -a_{zl}^{linear} \frac{\partial w_1^*}{\partial \alpha_p} a_{zl}^{linear} > 0.
\]

### A.2 Unrestricted Contract with Cost Heterogeneity

We now solve for the optimal unrestricted contract for a given baseline hematocrit level \(e_0\).

(As we did earlier, for convenience we will suppress the dependence of the wage schedule and other functions on \(e_0\) when it is not confusing to do so.) This section considers the specification where types represent cost heterogeneity; Section A.4 considers the specification where types represent altruism heterogeneity.

First, we show how two useful properties for the agent’s utility function can be obtained from reasonable assumptions on the primitives. The properties are monotonicity and single-crossing with regard to the unobserved heterogeneity. They arise from the assumptions on health production function described earlier and from monotonicity and complementarity assumptions in the cost function. These assumptions are formally stated below.

**Assumption 1. Technology and Costs**

We assume the technology and cost functions have the following properties:
1. Health production function:

   (i) $\frac{\partial h}{\partial a} > 0$ if $e_0 < e_\tau$ and $\frac{\partial h}{\partial a} < 0$ if $e_0 \geq e_\tau$

   (ii) $\frac{\partial^2 h}{\partial a^2} < 0$

2. Cost function:

   (i) $c(0; z) = 0$ and

   (ii) $\frac{\partial c}{\partial a} > 0$ and $\frac{\partial^2 c}{\partial a^2} \geq 0$

   (iii) $\frac{\partial c}{\partial z} > 0$ and $\frac{\partial^2 c}{\partial z \partial a} > 0$.

A1(1) reflects the aforementioned fact that patients with low hematocrit benefit more from EPO, while there are serious risks from above-target provision. A1(2.ii) is the standard assumption that marginal costs are positive and nondecreasing and A1(2.iii) says that lower cost types also face lower marginal costs of increasing their action; such an assumption is standard in the theoretical literature studying screening models. Note that the assumed quadratic $h$ and linear $c$ satisfy A1. Further note that, although the optimal contracts derived in this section and Section A.4 are for the assumed functional forms of $h$ and $c$, the results characterizing the optimal contract and treatment choices can be adapted without much trouble for other $h$ and $c$ that satisfy A1.

Given these properties in A1, the utility function has the following useful properties.

**Proposition 1.** Given the above assumptions, the agent’s utility function has the following properties:

1. Monotonicity: $z_i < z_j$ implies $u_i(a; e_0, w) \geq u_j(a; e_0, w)$; this inequality is strict if $a > 0$

   **Proof.** Eq. (1) shows that the only difference in utilities comes from $c(a, z)$. A1(2.i,iii) together imply that $c(a; z_i) \leq c(a; z_j)$ (with a strict inequality if $a > 0$).

2. Single crossing: $z_i < z_j$ implies $\frac{\partial u_i(a; e_0, w)}{\partial a} \geq \frac{\partial u_j(a; e_0, w)}{\partial a}$; this inequality is strict if $a > 0$

   **Proof.** This follows directly from eq. (1) and A1(2.iii).

Now we turn to the physician’s problem and the government’s problem, which we restate here for convenience.
Physician’s problem: Given $w$ and $e_0$, physician $i$ chooses a drug treatment level $a_i$ to solve
\[
\max_{a \geq 0} u_i(a; e_0, w).
\]
The solution $a^*(z; e_0, w)$ will satisfy
\[
\alpha_p h'(a^*) + w'(a^*) \leq c'(a^*; z_i).
\]

Government’s problem: The government solves
\[
\max_{w \in \mathbb{W}} \int_{z_i} [\alpha g(a, e_0) - w(a)] f_z(z) dz
\]
\[
\text{s.t.}
\]
\[
a = a^*(z_i; e_0, w),
\]
\[
u_i(a^*(z_i; e_0, w); e_0, w) \geq 0, \forall i \in I
\]
\[
\text{IC}
\]
\[
\text{VP},
\]
where $\mathbb{W}$ is the set of functions containing all possible contracts.

Characterizing the optimal unrestricted wage schedule is complicated, due to the considerable flexibility allowed by $\mathbb{W}$. Therefore, we take the standard approach of considering the equivalent direct revelation mechanism, in which the government offers a menu of pairs $\{(a_i, t_i)\}_{i \in I}$, where each $(a_i, t_i) \in \mathbb{R}^+ \times \mathbb{R}$, to the physician, who truthfully reveals their type $i$. In such a mechanism, the physician tells the government their type, after which the government implements their “prescribed” action $a_i$. We can then determine the optimal $w(a_i)$ by identifying the relevant $t_i$ for action $a_i$.

We show how to arrive at the government’s transformed problem in Appendix A.3, which allows for a direct solution of treatment levels for a physician of each cost type. For convenience, we reproduce the government’s transformed, or “relaxed”, problem here:
\[
\max_{\{a_i\}_{i \in I}} \int_{z_i} [u_g(a_i) + u_p(a_i, z_i)] f_z(z_i) - a_i F(z_i)] dz_i.
\]
Note that the relaxed problem drops the monotonicity constraint required to implement the direct revelation mechanism. As is standard, we proceed by first solving for the set of actions and then verifying that the actions satisfy monotonicity.

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40See the literature on price discrimination, e.g., Maskin and Riley (1984).

41For each baseline hematocrit $e_0$, the resulting $w(a_i)$ could be thought of as either a menu of linear schedules, one for each cost type $i \in I$, or a single, potentially nonlinear, schedule. We treat the optimal contract as the latter, as we find it a more intuitive representation.
Solution: By differentiating (15) with respect to the action of cost-type $i$, we obtain

$$\frac{\partial u_g(a_i)}{\partial a_i} + \frac{\partial u_p(a_i, z_i)}{\partial a_i} = \frac{F_z(z_i)}{f_z(z_i)},$$

where $\frac{F_z(z_i)}{f_z(z_i)}$ is the reciprocal of the reverse hazard function, $\lambda_z(z_i)$; i.e., $\lambda_z(z_i)$ represents the likelihood of being cost type $z_i$ conditional on not being above that cost type. Because the right side is strictly positive, the action of $a_i$ will be distorted for all but the lowest-cost type; i.e., we obtain the standard “no distortion at the top” result (where the “top” is the best type with the lowest cost). If $z$ has the monotone decreasing hazard property, then $\frac{F_z(z_i)}{f_z(z_i)}$ is increasing in $i$, meaning actions become increasingly distorted as we consider higher and higher cost types.\(^{42}\)

To provide more intuition, we show the optimal treatment choice, using our functional form assumptions:

$$a_i = \frac{e_\tau - e_0}{\delta} - \frac{z_i + \frac{F_z(z_i)}{f_z(z_i)}}{\delta^2[\alpha_g + \alpha_p]}.$$  \hspace{1cm} (16)

As discussed above, treatment choice will be decreasing in cost type, i.e., the required monotonicity condition (20) will be satisfied, if $\lambda_z$ is decreasing in $z$. Optimal treatment choice is increasing in need (i.e., decreasing in baseline hematocrit $e_0$) and government and physician valuation of health, and is decreasing in the cost of treatment. Note that the aforementioned distortions mean that actions characterized in (16) are lower than those in the full-information benchmark, (7), for all but the lowest-cost type. However, increases in physician altruism $\alpha_p$ can blunt the distortions induced by unobserved heterogeneity. This highlights the usefulness of allowing for physician heterogeneity and physician altruism when characterizing optimal remuneration for physicians.

Based on the optimal treatment choice the nonlinear transfer, or wage, function can be obtained by substituting for surplus

$$t_i = w(a_i) = u_i - u_p(a_i, z_i) = \left[\int_{z_{i+1}}^{z_i} a_j \, dj\right] + a_i z_i - \alpha_p h(a_i),$$

which, as in Ellis and McGuire (1986), results in partial cost sharing if $\alpha_p > 0$, i.e., physicians are altruistic.\(^{43}\) Using our functional form assumptions to use (16) to substitute for treatment

\(^{42}\)This is analogous to the standard monotone increasing hazard condition, because as we decrease $z$ we encounter “better” cost types.

\(^{43}\)This is because $\frac{\partial w(a_i)}{\partial a_i} = z_i - \alpha_p h'(a_i)$, which is strictly less than the marginal cost $z_i$ for $e_0 < e_\tau$. 
choice results in the following expression for the equilibrium transfer

\[ t_i = \frac{\alpha_p}{2} \left[ z_i + \frac{F_z(z_i)}{f_z(z_i)} \right]^2 + a_i z_i + \int_{z_{i+1}}^z \left[ \frac{e_\tau - e_0}{\delta} - \frac{z_j + \frac{F_z(z_j)}{f_z(z_j)}}{\delta^2[\alpha_g + \alpha_p]} \right] dz_j. \]  

(17)

We now address *indirect* implementation, which is relevant for applying the above solution to the real world using a schedule depending on \(a_i\), instead of *direct* implementation via revelation. Note that \(a_i\) is strictly monotonic in type. If \(t_i\) is also strictly monotonic then we could indirectly implement the direct revelation mechanism via a single nonlinear schedule \(t(a_i)\), or \(w(a_i)\), since each cost type would have a unique treatment choice and each transfer would correspond to a unique action and, hence, cost type. Due to the single-crossing condition, transfer \(t_i\) increasing in action \(a_i\) would be equivalent to \(t_i\) being decreasing in cost type \(z_i\). Differentiating (17), the transfer function will be decreasing in \(z\) when\(^{44}\)

\[ \frac{\partial t_i}{\partial z_i} = \frac{\partial a_i}{\partial z_i} \left[ z_i - \alpha_p \frac{\partial h(a_i)}{\partial a_i} \right] < 0 \]

which occurs if

\[ \left[ z_i - \alpha_p \frac{\partial h(a_i)}{\partial a_i} \right] > 0 \iff \frac{F_z(z_i)}{f_z(z_i)} < \frac{\alpha_g}{\alpha_p} z_i. \]

The left and right sides of the last expression are both increasing in \(z\); therefore, only if \(\alpha_g\) is sufficiently high (relative to \(\alpha_p\)) will the wage increase in action. Intuitively, transfers serve to compensate physicians for treatment costs. If physicians have a high enough valuation of patient health, these transfers become less important. As with the optimal linear contract, to understand how physician altruism affects incentive strength we now examine the slope of the transfer function is affected by an increase in altruism. Differentiating \(\frac{\partial t_i}{\partial z_i}\) with respect to \(\alpha_p\), we find

\[ \frac{\partial^2 t_i}{\partial z_i \partial \alpha_p} = \frac{\partial^2 a_i}{\partial z_i \partial \alpha_p} \left[ z_i - \alpha_p \frac{\partial h(a_i)}{\partial a_i} \right] + \frac{\partial a_i}{\partial z_i} \left[ - \frac{\partial h(a_i)}{\partial a_i} - \alpha_p \frac{\partial^2 h(a_i)}{\partial a_i^2} \frac{\partial a_i}{\partial \alpha_p} \right], \]

which is positive if \(\frac{F_z(z_i)}{f_z(z_i)} < \frac{\alpha_g}{\alpha_p} z_i\), i.e., if the condition guaranteeing a monotonic wage function holds. Since this condition ensures that \(\frac{\partial t_i}{\partial z_i} < 0\), increasing physician altruism dampens the relationship between physician treatment choices and reimbursement. Intuitively, higher altruism reduces the importance of cost heterogeneity, the driving force behind the existence of an increasing wage function.

\(^{44}\)See Appendix A.3.1 for details.
A.3 Further Details for Unrestricted Contract with Cost Heterogeneity

It will be convenient to express the utility of physician of type $i$ at their prescribed action $a_i$ as
\[ u_i \equiv \alpha_p h(a_i) - a_i z_i + t_i, \]  
(18)
i.e., it can be decomposed into a component depending on patient health and cost of treatment and a component representing the transfer from the government to the physician.

The government's problem can then be written as
\[
\begin{align*}
\max_{\{(a_i,t_i)\} \in I} \int \int \left[ u_g(a_i) - t_i \right] f_z(z_i) dz_i \\
s.t. \quad u_i \geq 0, \forall i \quad \text{VP} \\
\quad u_p(a_i, z_i) + t_i \geq u_p(a_j, z_i) + t_j, \forall i,j \quad \text{IC},
\end{align*}
\]  
(19)
i.e., the government maximizes its objective, given the constraints that all physicians must participate (VP) and that no type of physician has an incentive to mimic a physician of another type (IC).

To solve for the optimal set of actions, we first use the definition of $u_i$ (from (18)) eliminate $t_i$. Using the expression for a physician’s utility, the IC constraints imply that $u_i \geq u_{i+1} + a_{i+1} [z_{i+1} - z_i]$ and $u_{i+1} \geq u_i + a_i [z_i - z_{i+1}]$, which can be combined to produce $a_i \geq a_{i+1}$; i.e., treatment choice is monotonic, and, in particular, nonincreasing, in $z$.\footnote{Using $i$’s surplus, the IC constraint in eq. (19) can be re-written as $u_i \geq u_p(a_j, z_i) + t_j$; substituting for $t_j$ and re-arranging, we obtain $u_i \geq u_j + a_j [z_j - z_i]$.}

We next examine which of the constraints in (19) will not bind. First, as was also the case in the linear schedule, we can remove all participation constraints except for that for the physician with cost type $\bar{z}$, because $u_p(a, z)$ is decreasing in $z$. Second, the single-crossing property means that the IC constraints will be “upwards” binding, because “better” (i.e., lower-cost) types could always at least obtain “worse” (i.e., higher-cost) types’ utility by mimicking them (i.e., lower-cost types could take higher actions). Therefore, the IC constraints for all but the physician with the highest-cost type, $\bar{z}$, will bind. We will sometimes abuse notation and refer to types using their cost level as their index, e.g., $a_{\bar{z}} = a(\bar{z})$.

Dropping the slack constraints and imposing monotonicity, the government’s problem
becomes
\[
\max_{\{a_i\}_{i \in I}} \int_{\bar{z}}^{z} \left[ u_g(a_i) + u_p(a_i, z_i) - u_i \right] f_z(z_i) dz_i
\]  
\text{s.t.}
\[
\begin{align*}
u_\bar{z} &= 0 & \text{VP} \\
u_i &= u_{i+1} + a_{i+1} [z_{i+1} - z_i], \text{ for } \{i : z_i < \bar{z}\} & \text{IC} \\
a_i &\geq a_{i+1}, \forall i & \text{M.}
\end{align*}
\]

The remaining VP constraint says the government will extract all the surplus from the highest-cost type, \( \bar{z} \). Because \( a_i \geq 0 \) and \( z_i < z_{i+1}, \forall i \), the IC, or truth-telling, constraint implies that physician surplus weakly increases as we decrease cost types, and strictly increases when the cost type immediately above has a positive action (as is assumed here). Intuitively, a lower-cost type captures surplus because she can pretend to be the higher-cost type, by taking a lower action; this surplus disappears when the higher-cost type does not choose a positive treatment level. Using the binding VP constraint and recursively substituting for \( u_i \) in the binding IC constraints, we obtain the following expression for type \( i \)'s surplus:
\[
u_i = \int_{z_{i+1}}^{\bar{z}} a_j dj.
\]  
\[
\text{(21)}
\]

Therefore, the government chooses treatments to solve
\[
\max_{\{a_i\}_{i \in I}} \int_{\bar{z}}^{z} \left[ u_g(a_i) + u_p(a_i, z_i) - \left[ \int_{z_{i+1}}^{\bar{z}} a_j dj \right] \right] f_z(z_i) dz_i
\]
\[
\Leftrightarrow
\]
\[
\max_{\{a_i\}_{i \in I}} \int_{\bar{z}}^{z} \left[ [u_g(a_i) + u_p(a_i, z_i)] f_z(z_i) - a_i F(z_i) \right] dz_i
\]  
\text{(22)}

Note that we have temporarily dropped the monotonicity constraint. As is standard, we proceed by first solving for the set of actions and then verifying that the actions satisfy monotonicity.
A.3.1 Monotonicity of Nonlinear Schedule with Cost Heterogeneity

It has been shown that based on the optimal treatment choice the nonlinear wage function can be characterized as

\[ w(a_i) = u_i - u_p(a_i, z_i) = \int_{z_{i+1}}^{z_i} a_j dj + a_i z_i - \alpha_p h(a_i), \]

which means the derivative of \( w \) with respect to \( z \) is

\[ \frac{\partial w}{\partial z} = \frac{\partial a}{\partial z} \left[ z - \alpha_p \frac{\partial h}{\partial a} \right] = \frac{\partial a}{\partial z} \left[ z - \alpha_p \delta [e_f - e_0 - \delta a] \right]. \]

Plugging in for the optimal treatment choice \( a = e_f - e_0 - \delta z + F \mu_z f(z) \), we obtain

\[ \frac{\partial w}{\partial z} = \frac{\partial a}{\partial z} \left[ z + \alpha_p \left[ -\frac{z + \frac{F_z(z)}{f_z(z)}}{\alpha_g + \alpha_p} \right] \right] = \frac{\partial a}{\partial z} \left[ \frac{\alpha_g z - \alpha_p \frac{F_z(z)}{f_z(z)}}{\alpha_p + \alpha_g} \right]. \]

Since \( \frac{\partial a}{\partial z} \leq 0 \), the transfer function is decreasing in \( z \) if

\[ \frac{\partial t}{\partial z} \leq 0 \iff \alpha_g z > \alpha_p \frac{F_z(z)}{f_z(z)}. \]

A.4 Altruism Heterogeneity

We now consider the second-best (i.e., optimal nonlinear) contract for a specification where physician types describe heterogeneity in altruism, instead of treatment cost, i.e., \( \alpha_p = \alpha_i \) and \( z = \mu_z \). We introduce a slight change to the technology, where we now define health according to \( h_\alpha(a; e_0) \equiv H + h(a; e_0) \), where \( H \) is such that \( h_\alpha(a; e_0) > 0 \); we show below why this is convenient. We continue to index physicians using \( i \), where \( \alpha_i \) is distributed over \([\alpha, \overline{\alpha}]\) according to \( F_\alpha(\cdot) \), which has density \( f_\alpha(\cdot) \). We order physician types such that \( \alpha_i > \alpha_{i-1} \). In contrast to the specification with cost heterogeneity, higher indices here correspond to “better” types, or higher treatment choices, and adapt \( u_p(a, \cdot) \) to instead take as an argument \( \alpha_i \), resulting in

\[ u_p(a_i, \alpha_i) = \alpha_i [H + h(a; e_0)] - a_i \mu_z. \quad \text{(23)} \]

Proposition 2 shows that the properties of the physician’s problem are similar to those with cost heterogeneity: there is both a level dominance and single-crossing condition with respect to \( \alpha_i \), where physicians with higher \( \alpha_i \) (i.e., lower indices) choose higher treatment
levels, given the same schedule.

**Proposition 2.** Given the above assumptions, the agent’s utility function has the following properties:

1. **Monotonicity:** \( \alpha_i > \alpha_j \) implies \( u_i(a; e_0, w) \geq u_j(a; e_0, w) \)

   \[ \text{Proof.} \] This follows directly from eq. (23) because \( h_\alpha(\cdot) > 0 \).

2. **Single crossing:** \( \alpha_i > \alpha_j \) implies \( \frac{\partial u_i(a; e_0, w)}{\partial a} \geq \frac{\partial u_j(a; e_0, w)}{\partial a} \), when \( e_0 < e_\tau \).

   \[ \text{Proof.} \] This follows directly from eq. (23) and A1(1.i).

We state and solve the government’s problem in the case of altruism heterogeneity in Appendix A.5. Using our functional form assumptions, the optimal treatment choice for a physician of cost type \( z_i \) is (implicitly) defined by the equation

\[
a_i = \frac{e_\tau - e_0}{\delta} - \frac{\mu_z + \delta [e_\tau - e_0 - \delta a_i]^{1-F_\alpha(\alpha_i)}}{\delta^2 [\alpha_z + \alpha_i]}.
\]

(24)

As was the case with cost heterogeneity, there is no distortion at the “top”, i.e., for the altruism type \( \alpha ( \text{because } F_\alpha(\alpha) = 1) \), while types with lower and lower indices (i.e., altruism) have increasingly distorted treatment choices.

### A.5 Unrestricted Contract with Altruism Heterogeneity

The government’s problem adapts (19) to adjust for the change in \( u_p(a_i, \cdot) \):

\[
\max_{\{(a_i, t_i)\}_{i \in I}} \int_\alpha [u_y(a_i) - t_i] f_\alpha(\alpha_i) d\alpha_i
\]

s.t.

\[
u_i \geq 0, \forall i \quad \text{VP}
\]

\[
u_p(a_i, \alpha_i) + t_i \geq u_p(a_j, \alpha_i) + t_j, \forall i, j \quad \text{IC}.
\]

(25)

Proposition 2 allows us to drop the participation constraint for all types except for that with altruism \( \alpha \). As with the cost-heterogeneity specification, we can re-write the IC constraints.

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\( ^{46} \)Recall that the government will never seek to induce positive actions when \( e_0 \geq e_\tau \).
for physician of type $i$ with respect to any physician of type $j$ using

\[ u_p(a_i, \alpha_i) + t_i \geq u_p(a_j, \alpha_i) + t_j \quad \Rightarrow \]
\[ \alpha_i h_\alpha(a_i) - a_i \mu_z + t_i \geq \alpha_i h_\alpha(a_j) - a_j \mu_z + t_j \]
\[ u_i \geq u_j + h_\alpha(a_j) [\alpha_i - \alpha_j], \]

except that, opposite to the specification with cost heterogeneity, only the “downwards” IC constraint for each type (i.e., that preventing physician $i$ from mimicking $i - 1$) will bind.

The resulting “relaxed” government problem with altruism heterogeneity is

\[
\max_{\{a_i\} \in I} \int_\alpha [u_g(a_i) + u_p(a_i, \alpha_i) - u_i] f_\alpha(\alpha_i) d\alpha_i \\
\text{s.t.} \quad u_\alpha = 0 \quad \text{VP} \\
\quad u_i = u_{i-1} + h_\alpha(a_{i-1})[\alpha_i - \alpha_{i+1}], \text{ for } i : \alpha_i > \alpha \quad \text{IC} \\
\quad a_i \geq a_{i-1}, \forall i \quad \text{M.}
\]

The remaining VP constraint says the government will extract all the surplus from the highest-cost type, $\alpha$. Because $h_\alpha(a_i) > 0$ and $\alpha_i > \alpha_{i-1}, \forall i$, the IC, or truth-telling, constraint implies that physician surplus increases as we increase altruism types. Intuitively, as was the case with cost heterogeneity, a “higher” (high-$\alpha_i$ or low-$z_i$) type captures surplus because she can pretend to be a “lower” type by taking a lower action.

Physician surplus can be computed using the same approach used in the case of cost heterogeneity:

\[ u_i = \int_\alpha^{\alpha_i} h_\alpha(a_j) dj. \quad (27) \]

Maximizing the appropriately adjusted (15), we obtain the following characterization of optimal treatment level for altruism-type $i$,

\[
\frac{\partial u_g(a_i)}{\partial a_i} + \frac{\partial u_p(a_i, \alpha_i)}{\partial a_i} = h_\alpha'(a_i) \frac{1 - F_\alpha(\alpha_i)}{f_\alpha(\alpha_i)},
\]

where $\frac{1 - F_\alpha(\alpha_i)}{f_\alpha(\alpha_i)}$ is the reciprocal of the hazard function, $\lambda_\alpha(\alpha_i)$. 

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