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ADMINISTERED PRICES AND SUBOPTIMAL PREVENTION: EVIDENCE FROM THE MEDICARE DIALYSIS PROGRAM

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ABSTRACT

Pricing methodologies in Medicare vary from one component of the system to another, often leading to conflicting incentives. The dialysis program represents a particularly interesting case, whereby outpatient payments are much more rigid than payments for related hospital care. Failure to recognize the preventive nature of outpatient services may result in inefficient allocation of medical care and higher overall costs. To motivate the analysis, a simple extension of basic prevention and insurance theory to fit a welfare-maximizing regulator is offered. I show that while optimal inpatient payments are standard Ramsey prices, optimal outpatient payments must incorporate net loss due to unnecessary hospitalizations, as well as supply elasticities. A myopic regulator will tend to ignore this, leading to underprovision of preventive services. With constant prices, empirical analysis examines the effect of dialysis intensity on various measures of hospital use, for a local sample of patients, using count data models. Results indicate that greater dialysis intensity (measured by a state-of -the-art clinical index) indeed reduces hospital use. Moreover, this is found even at moderate or high levels of intensity, where dialysis is viewed ex ante as being adequate. A simple cost-benefit calculation suggests that for every dollar of additional spending on outpatient intensity, nearly $2 in hospital expenditures can be saved. The research confirms that the current pricing structure within aspects of the Medicare program is inefficient.

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Administered Prices and Suboptimal Prevention:
The Case of Outpatient-Inpatient Substitution in the Medicare Dialysis Program

I. Introduction

While the familiar adage "an ounce of prevention is better than a pound of cure" enjoys popular appeal, it has not escaped the attention of economic theorists, who have recognized the importance of providing preventive services on grounds of efficiency. With optimal allocation of preventive care, unnecessary levels of curative services can be averted with no adverse effects on health outcomes. A number of different perspectives have been considered in the theoretical literature. Early models have focused on individual demand for self-protection and preventive medical services in the presence of insurance (Ehrlich and Becker, 1972; Nordquist and Wu, 1976). Subsequently, Schlesinger and Venezian (1986) considered this problem from the perspective of profit-maximizing insurers. Using a single period model, they showed that when insurance and prevention are bundled together, both a competitive insurer and a monopolistic insurer will select the optimal amount of loss-prevention investment. However, health services are often provided in the context large government programs where incentives may not be the same as those facing an individual consumer or profit-maximizing firm. Although the problem of overprovision of insurance in the public sector is by now well-known (Pauly, 1974), the issue of incentives for provision of preventive services specifically, as opposed to curative services, has not received significant attention. In the face of an increasingly complex medical product no one expects government to successfully make decisions regarding the appropriate levels of care. Rather, the pertinent issue is how to design incentives so as to ensure that appropriate tradeoffs are made independently by agents in health care markets. The problem is especially relevant for large government programs such as Medicare, seeks to provide high quality of care to large segments of the population, often under severe budgetary constraints.

Ostensibly prevention of disease in younger populations, and prevention of complication from pre-existing conditions in older populations are goal shared by all government agencies (U.S

Department of Health and Human Services, 1989). In recent years, however, greater emphasis has been placed on controlling expenditures rather than promoting health. In the Medicare program, efforts to reduce costs take the form of fixed payment mechanisms such as capitation or prospective payments. At the same time, it does not appear that a concerted effort is being made in favor of designing a cohesive pricing strategy, one that recognizes the link between the different modes of patient care. In particular, cost-containment measures that are imposed too stringently on preventive services may lead to underuse of these services, and to overuse of costlier curative services. At least two explanations for the existence of the myriad of pricing rules within Medicare can be offered: First, organizational or bureaucratic reasons, whereby different components of an agency may be administered separately, resulting in failure to coordinate regulatory policies and prices (Rizzo and Sindelar, 1996). Second, information problems related to the underlying clinical practice issues as viewed by administrators. In particular, administrators may not fully recognize the relationship between different types of services that are provided to the same patients at different stages. Indeed, identifying such linkages is becoming more difficult as medicine grows more complex, and as treatment paths evolve beyond a simple preventive-curative dichotomy

Whatever the reason, failure to account for spillover effects may lead to inefficient regulatory pricing policies, with unintended consequences on allocation of resources devoted to medical care. The example of dialysis services is especially poignant, because it represents a well-defined case where a particular diagnosis is subject to multiple pricing regimes. In particular, dialyzed patients are subject to one set of rules when they are outpatients, and another set of rules when they enter the hospital as inpatients. As will be described below, payment rules corresponding to these modes of care initially appear to be consistent, in the sense of providing incentives to reduce costs across the board. However, when spillover effects between different modes of care are taken account, this may no longer be true. In particular, the preventive nature of outpatient dialysis services vis-a-vis hospital care, these pricing policies no longer appear to be consistent. Since it is unlikely that the regulator is actually misinformed about the clinical connection between outpatient and inpatient care, it would appear that bureaucratic impediments are to blame. Whatever the reason may be, lack of coordination of pricing policies may lead to unintended consequences from the perspective of the regulator.

Remarkably little research has focused on the implications of reallocating resources from one mode of care to another or on the actual dollar tradeoff involved. This study attempts to fill the gap, using the case of end stage renal failure and dialysis as an example. The rest of the paper is divided as follows. Section II discusses the Medicare dialysis program, especially the current payment issues, as well as medical practice issues that are of relevance to policy. Section III presents a simple theoretical model of optimal pricing for a welfare-maximizing regulator. In particular it demonstrates that the optimal price for preventive services reflects supply elasticities and net costs of curative services. Conversely, the magnitudes of these effects determine the degree to which a myopic regulator will deviate from the optimal price. Section IV describes the data used in the empirical analysis. Methods and results are presented in section V. The letter section also summarizes preliminary cost-benefit estimates, drawn from the empirical analysis. Finally, conclusions and policy implications are discussed in section VI.

II. Medicare and the Renal Dialysis Program

Medicare is the federal program that provides health care coverage for the elderly, as well as persons with end stage renal disease and certain individuals with disabilities. It is the single largest payer of health care in the United States, accounting for 20 percent of total national health expenditures. In addition, within Medicare there is a specialized program that provides coverage for all individuals with kidney failure, regardless of age. This is known as the End Stage Renal Disease (ESRD) program. In 1997, more than 300,000 patients were treated in the ESRD program, representing approximately 200,000 adjusted life years. Total Medicare spending for ESRD amounted to $14.5 billion or 5 percent of total Medicare expenditures (National Institutes of Health, 1999;

MedPAC 1999). Of this amount $3.5 billion were devoted to direct inpatient hospital care, excluding capital pass-through reimbursements, costs of kidney transplants, and other administrative costs.

Prices in the Medicare system are administratively determined, and pricing rules vary substantially from one component of the system to another. For instance, under 'Part A' hospitals are reimbursed prospectively for every episode of care by setting fixed payments for every diagnostic group, using a payment methodology known as the *prospective payment system* (PPS). On the other hand, under 'Part B' Medicare reimburses physicians using a hybrid cost-based payment method known as the relative value scale, which provides relatively more generous reimbursements to general practitioners than to specialists, but allows for flexible compensation based on the number of services rendered. Clearly, different parts of the system that are administered separately may provide conflicting incentives to suppliers of medical services. From the point of view of the regulator, inconsistencies between the various components of the system may result in inefficient allocation of resources. Within the limits of an administered program, the challenge is to come up with the most efficient regulatory pricing policy.

The ESRD program presents an especially poignant case in which treatment of a patient with a given medical condition may be the object of multiple pricing regimes. Dialysis services, which are provided on an outpatient basis, fall under a capitated payment method known as the *composite rate*. Once a patient is hospitalized for any reason other than kidney transplantation, he or she remain within the ESRD program administratively, but payments for inpatient services rendered at this stage are paid for using the standard hospital payment rules, namely PPS.

Although both the composite rate and PPS can be regarded as variants of fixed pricing rules, important differences exist. Under the composite rate, dialysis centers receive a payment of $125 per session of hemodialysis per patient at a fixed protocol of three sessions per week.[1] In practice, this

[1] Hemodialysis is the main technology for delivering a dialyzer into the patient's blood stream, accounting for 95 percent of outpatient expenditures in the Medicare program. In this technology, a patient is connected to a dialysis machine at the facility. The remainder of Medicare outpatient spending is devoted to patients receiving on an on-going basis, while being connected to a portable devise. For payment purposes a week such treatment

represents a capitation rate since the dialysis facility cannot be reimbursed for additional sessions (Iglehart, 1993). Under PPS, payments to hospitals are fixed for a given episode of hospital care, rather than for the individual patient. Unlike cost-based reimbursement, which enables suppliers of medical services to simply pass on costs to the payer, fixed payment rules provide incentives to sellers to reduce costs by becoming more efficient. On the other hand, prospective payments also provide incentives for sellers to "skimp" on care for patients already admitted (Ellis, 1998), by reducing the intensity of services provided. Furthermore, it has been shown that for many patients, PPS resulted in higher readmission rates and multiple hospital stays, thereby allowing hospitals to leverage their revenue stream (Cutler, 1995). Thus, opportunities for gaming the system in order to maximize payments to providers are greater under prospective payments than under strict capitation.

It is important to note that the composite rate has become more stringent over time. In an effort to curb program costs, Medicare has kept the composite rate frozen for the past two decades, resulting in a real decline of nearly 50 percent during that period. Clearly, dialysis facilities are faced with greater incentives to skimp on care than ever before. Given the potential spillover effects on continuing hospital care, this may lead to a paradoxical situation where skimping on dialysis care results in greater use of resources overall and with higher program costs as the unintended consequence.

To better understand the relationship between outpatient dialysis and the need for hospital care, it may be useful to summarize the underlying clinical practice issues. This also provides important background to empirical specifications discussed in the next section. The state-of-the-art clinical literature offers a widely accepted index of intensity of outpatient dialysis, known as Kt/V (Daugirdas, 1996). Specifically, this index measures the amount of urea removed during treatment relative to body mass (v). A higher Kt/V can be achieved by increasing treatment time (t), increasing

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is equivalent the three weekly hemodialysis treatments, hence the term 'composite rate'. For more details about the medical technologies used see Dor, Held, and Pauly (1992).

blood or dialysate flow rates (K) or using larger dialyzers (Held et al., 1996). The amount of dialysis patients receive is an important determinant of survival (Own et al., 1993, Collins et al., 1994. It has been estimated that each increase of 0.1 in the Kt/V index is estimated to decrease the relative risk of death by 5-7 percent (Held et al., 1996). Similarly, it has been shown that inadequate dialysis contributes to declines in related medical conditions, i.e comorbidities, in addition to loss of renal function (Hakim et al., 1994; Maiorca et al., 1995).[2] While medically optimal levels remain to be established, doses of dialysis represented by Kt/V less than 1.2 are generally considered inadequate. Using this standard, approximately one fourth of American patients currently receive inadequate amounts of dialysis (HCFA 1998).

Since facilities are not free to reduce the number of treatments under the Medicare guidelines, the only option for "skimping" in this context is to reduce the intensity or dose of dialysis delivered per session (Hull, 1992). It appears that this reimbursement method creates a financial disincentive to provide longer treatments and thus contributes to inadequate intensity of dialysis (HCFA, 1998). Since inadequate dialysis is so clearly a determinant in deteriorating health, by conjecture, it should also increase the need for hospital care. This spillover effect is compounded by the fact that once a person is hospitalized, there are further opportunities for costs to rise given that payments for hospital services are not fully capitated. If this is the case, it may be advisable for Medicare to increase payments and provide incentives for more "intense" dialysis in order to avert much higher costs in the future. In section V we explore the issue by empirically examining the effect of intensity of dialysis treatment on a variety of measures of hospital resource use, within a well-defined Medicare population. Prices of both outpatient care and inpatient care are essentially constant given a patient's diagnosis; therefore prices are omitted from the regressions. To gain some insights on the role of prices in this setting, I also provide some simple theoretical background. The optimal pricing rule below shows more generally that failure to take account of the link between outpatient an inpatient

[2] Major comorbidities include heart failure, gastrointestinal and other infections, diabetes, and peripheral vascular disease.

care leads to overshooting in administrative pricing and therefore to suboptimal provision of outpatient services.

III. Theoretical Motivation

To motivate the model we use the following stylized fact: Patient care is provided sequentially, in two distinct stages. In the first stage, patients receive dialysis treatments on an outpatient basis. A fraction π of people who need outpatient care will eventually need inpatient care ($\pi < 1$), which will be provided in the second stage. Next we assume that the government (Medicare) maximizes social welfare, subject to a balanced budget constraint, and acts on behalf of patients. We initially write the regulator's maximization problem as

$$\begin{aligned} max \quad & NB^o + N\pi B^i + \lambda(I - Np_o x_o - N\pi p_i x_i) \\ & = N[B^o + \pi B^i + \lambda(I/N - p_o x_o - \pi p_i x_i)] \end{aligned}$$

where N is the number of patients entering the program, all of whom require outpatient care at the very least. The regulator derives benefits B^o from outpatient care, and B^i from inpatient care. The flow of services (intensity) is given by x_o for outpatient care, and x_i for inpatient care; p_o and p_i are the corresponding prices. The Medicare budget is denoted as I, and λ is the Lagrangian multiplier for the balanced budget constraint.

As written above, the objective function resembles the basic model of optimal insurance with prevention in private insurance settings (Pauly, 1974; Herring, 1999). However, without additional structure this model does not adequately describe the problem at hand. In the basic model, prices are exogenous, and consumers choose how to allocate their consumption of preventive and curative services. In the case of Medicare, however, prices are administratively determined and are thus endogenous. In this framework the utility maximizing regulator chooses prices, and in return providers choose the flow of services for patients given the announced price. Moreover, at times the optimal insurance literature has proceeded with the assumption that while prevention affects the probability of requiring curative care, health care expenditures in both the preventive and curative case are exogenous (Herring, 1999). In reality, preventive care should affect both the state of health and the probability of illness.

Rewriting the objective function to take account of both issues, we can specify the regulator's problem explicitly as:

$$max\ B_o(x_o\,(p_o)) + \pi(x_o\,(p_o\,))\ B_i\,(x_i\,(p_i\,)) + \lambda\ [I/N - p_o\,x_0\,(p_o) - p_i\,x_i\,(p_i\,)\ ]$$

Solving the first order conditions and rearranging, yields the optimal prices:

$$p_o = (dB_o / dx_o) / \ \ (\lambda\ [1 + \frac{1}{\varepsilon_o}] + \frac{\pi\ \varepsilon_\pi}{p_o\, x_o}\ [\lambda\ p_i\, x_i - B_i])$$

$$p_i = (dB_i / dx_i) / (\lambda\ [1 + \frac{1}{\varepsilon_i}]).$$

where

$$\varepsilon_o = \frac{dx_o}{dp_o}\frac{p_o}{x_o}, \varepsilon_i = \frac{dx_i}{dp_i}\frac{p_i}{x_i}, \varepsilon_\pi = \frac{d\pi}{dx_o}\frac{x_o}{\pi}$$

Here ε_o and ε_i represent supply (provider) elasticities and ε_π represents the elasticity of the fraction of patients needing inpatient care with respect to the level of outpatient care. Note that $\varepsilon_o > 0$, $\varepsilon_i > 0$, and $\varepsilon_\pi < 0$.

Beginning first with the simpler price rule, that for inpatient services, it is immediately noticeable that p_i is analogous to the familiar Ramsey price, with supply elasticities replacing elasticities of demand. The current rule states that the bigger the price elasticity of supply, the higher the p_i needs to be in order to induce suppliers to provide more care. The condition also states that the optimal price of inpatient price is equal to the marginal benefit of inpatient care divided by its implicit cost. Further note that in the optimum, price cannot exceed marginal benefit.

The optimal condition for p_0 is somewhat more complex. In addition to the own-price elasticity of supply this pricing rule also takes ε_π and the regulator's net loss from inpatient care [$\lambda p_i x_i - B_i$] into account. It states that the greater the efficacy of outpatient care in terms of reducing the incidence of illness, the lower the optimal price of outpatient care should be. Similarly the bigger the net loss from inpatient care, the higher the optimal price of outpatient care. In the case of a myopic regulator, the relationship between outpatient care and inpatient care is ignored and all relevant terms disappear. Letting $p_0^{'}$ denote this case, this will result in $p_0^{'} < p_0$, thus leading to underprovision of outpatient care.

From the objective function the regulator's conditional supply function for inpatient care is given by

$$x_i = x_i \langle I / N, p_o, p_i \, | \pi(x_o) \rangle$$

Without altering the optimal payment rule, we may also note that at the level of the individual patient (l) the probability of requiring inpatient care also depends on his or her severity of illness (S_l), so that $\pi_l = \pi_l\ (x_1\ ,\ \ S_l)$. Further taking into account that suppliers of outpatient services and suppliers of inpatient services both receive fixed prices for a given group of medical conditions and diagnoses that are comprise the vector S, and substituting into the into the expression for the probability yields the following patient-level equation:

$$x_{il} = x_{il}(S_l, x_{ol})$$

The last equation is of empirical interest. In particular, we expect to find that and $\partial \pi_l / \partial x_{ol} < 0$, and $\partial x_l / \partial x_{ol} < 0$.

IV. Data

The analysis file was created under the Health Care Financing Administration (HCFA) and National Institute of Diabetes and Digestive and Kidney Diseases (NIDDK) Hemodialysis Adequacy Project. As part of the study, data at all 22 hemodialysis units in Northeast Ohio were collected from

September 1995 to April 1996. At each facility, a random number generator was used to select one third of patients who met the inclusion criteria of being aged 18 years or older and on chronic dialysis for at least six months. Data included information on patient characteristics, health status and comorbidities. Under the project, the analysis file was further augmented with hospitalization data for a six month period following the 90 day dialysis dose assessment, originally drawn from (HCFA) Medicare Provider Analysis and Review (MEDPAR) claims data. Specifically, this provided the number and cause of any hospitalizations, lengths of stay, and Medicare reimbursements for the estimating sample for a follow up period of 180 days. The analysis file contains 711 patients, of which 671 were officially enrolled in Medicare, thus having complete information. Patients who did not survive to the end of the period where excluded from the analysis, resulting in a final sample of 616 observations. A more detailed description of the data, particularly the method of computing dialysis intensity levels can be found in Sehgal et al., 1998.

Sample statistics are presented in Table 1. The upper panel reports measures of hospital resource use. The dummy variable for hospital admission is coded as 1 if the individual was hospitalized at least once during the six-month risk period, and zero otherwise. The variable labeled as total hospital days (length of stay) is equal to the sum of days in the hospital across all hospital admissions for the individual during the risk period. If no hospital admissions occurred, this variable is coded as zero. Total Medicare reimbursement for each individual is equal to the sum of Medicare payments for each hospital admissions associated with a given individual. Again, if no hospital admission, the reimbursement amount is set to zero. The econometric specifications are further discussed in the next section, along with a description of the limited dependent variables techniques used.

Independent variables include information on patient demographics and medical characteristics, as well as measures of the intensity of outpatient dialysis. The patient's age is expressed in continuous years, since stratifying by age group did not contribute to robustness of the estimates. Binary indicators are used to describe gender (female), minority status, time since dialysis started (>1 year), diabetes as a cause of renal failure versus all other causes, and number of associated medical conditions or 'comorbidities'. It should be noted that diabetes as a cause accounted for 38 percent of all cases, followed by hypertension, namely high blood pressure (27 percent), and glomerulonephritis, a condition resulting from inflation of the kidney (16 percent). However, in earlier runs detailed specification of non-diabetic causes did not improve the estimates, compared with current models with all such causes lumped together. Similarly, only 14 patients were characterized as Asian or Hispanic; separating out all of the minority groups did not improve any of the models. Therefore, the 'minority' designation in the tables pertains mostly to African-Americans.

Intensity of dialysis is divided into three categories, namely 'low', 'medium', and 'high' intensities. These categories are defined according to clinically accepted guidelines, using the clinically-based Kt/v index previously defined. The low group corresponds to index values below 1.2, the medium group falls between 1.2 and 1.4, and the high group has index values above 1.4. Note that the intensity index was recorded at a point in time three months prior to the beginning of the 180 day follow-up period. As noted earlier an index value below 1.2 is generally regarded as being inadequate. Figure 1 shows that Kt/v in the sample is approximates normal distribution with both the mean and median at 1.3, i.e., not much a higher than the adequate level.

V. Empirical Analysis

Estimation Strategy

Three types of models are used to estimate the impact of dialysis intensity and other variables on hospital resource use at the level of the individual patient, corresponding to each of the dependent variables previously defined. Table 2 presents results from a logistic regression on the binary indicator of hospital use; Table 3 presents results from negative binomial regressions on number of stays. Table 4 presents results from a negative binomial regression on total length of stay. Although data were available on hospital expenditures (those attributed to Medicare) during the risk period, this variable proved too skewed for estimation purposes (skewness = 3.3, full sample; skewness = 2.7, censored sample).[3] Nevertheless, knowledge of this variable is rather useful, as it allows one to assign monetary values to changes in hospital admissions, at least around the sample means. This aids in stating the benefits that would be accrued to the Medicare program from increased outpatient intensity.

Most of the independent variables we use are binary indicators, so that elasticities could not be calculated using the standard formula. However, logistic and count data models of the kind estimated here provide similar information in the form of risk ratios. For binary variables, these ratios indicate the excess risk associated with being in a particular category relative to the reference group. Risk ratios can also be calculated for continuous variables. In this case they reflect the excess risk associated with a unit increase in the value of an independent variable. This provides a convenient way to express the effect of a change in index values such as the outpatient intensity variable used in this study. Therefore risk ratios are presented along with the coefficients in Tables 2-4.

Note that the probability model was estimated using a probit model as well as a logit and, as expected, both models yielded similar marginal effects. For expositional convenience, only logit models are presented in table 1. The risk ratios specific to these models are odds-ratios, namely the percentage increase of the probability of hospitalization in a given group. The relative odds-ratio for the reference group is normalized to 1.00. It is easy to show that $q/1\text{-}q = e^{b'x}$, where q is the probability of an event.

The poisson model and negative binomial model resemble non-linear least square models of the form: $\lambda = e^{bx}$, where λ represents the expected count of events, namely number of hospital admissions or number of days, with added restrictions on the error terms (Long 1997). Both the poisson model and the negative binomial model yield consistent estimates for count data, unlike least

[3] Results for a tobit model are available from the author upon request. Although outpatient intensity had the expected negative sign, he results were hypersensitive to log-linear transformation of the tobit. The sample size precluded estimation of a two-part model.

squares regressions. The only difference between the two count data models is that the negative binomial model allows for overdispersion in the underlying count data, thereby relaxing the restrictive assumption of equality between the mean and the variance of the distribution contained in the poisson. A likelihood ratio test of overdispersion led us to reject the negative binomial in the *stays* model, as well as in the *days* model (Greene, 1997, p. 938).[4]

As in the logit results, the coefficients of count models in Table 3 and Table 4 are presented along with corresponding risk ratios, called incidence rate ratios (IRRs). In the poisson, the IRR presents the percent difference in the number of hospitalizations experienced by a group relative to the reference group. Similarly, the incidence rate ratio in the negative binomial represents a percent difference for hospital days. For any unit change in an explanatory variable x_i, the IRR is given by e^{bi}. For every type of model included in Tables 2-4, I present three different versions of the regression, labeled as Model I, Model II, and Model III. Each represents the same specification of the independent variables, with the important exception of the dialysis intensity variables. Model I includes binary indicators for the medium intensity and high intensity groups, with the low intensity group as the omitted category. Model II includes continuous values of the intensity index, conditional on being in a group. This is essentially the same as interacting group dummies with the index. This specification is used to determine whether the slope of index changes as intensity levels are increased. Equivalently, it allows us to test whether increasing dialysis intensity has affect the use of hospital resources not only at "low" preventive levels, as defined by the clinical literature, but at higher levels as well. A combined model with binary indicators and interaction terms yielded a poor fit and is not reported. Model III includes continuous values of the intensity index for all groups combined.

[4] Note that the negative binomial allows for a variance of $\lambda+\alpha(N-\lambda)^2$, which reduces to poisson variance if the dispersion parameter α is equal to zero. Large values of α indicate that the negative binomial is the appropriate model. The likelihood ratio test yielded an extremely large chi-square of about 300 in all versions related to Table 3, leading us to comfortably reject the zero-value hypothesis for the number of hospital stays days. The corresponding chi-squared values for specifications in Table 4 were all about 700, similarly leading us to reject the zero-value hypothesis for the number of hospital days.

The dialysis intensity measure in the data pertains to levels measured three months prior to the hospitalization risk period. This sequential relationship between outpatient treatments and inpatient care mitigated concerns about endogeneity. Nevertheless, it is possible that when patients are anticipated to have greater hospitalization needs, higher dialysis rates are prescribed. Failure to account for simultaneity bias may lead us to overestimate the intensity coefficients, and underestimate the impact of prevention in averting excess hospital care. To address this I implemented an exogeneity test for limited dependent variable models due to Smith and Blundell (1986) and Blundell and Smith (1989) that could be applied to all of the models tested here.[5] Identification of the model was feasible thanks to a number of variables in the data set that pertain to the underlying medical technology used in dialysis, which are also orthogonal to inpatient hospital care.[6] In all models the test parameter was statistically insignificant, indicating that exogeneity could not be rejected. Goodness of fit measures are presented at the bottom of each table. In particular, chi-square tests indicate that models perform well, with underlying coefficients jointly being significantly different from zero. Z-scores for the coefficients are reported in brackets.

Results

Coefficients in Tables 2-4 are reported along with their corresponding risk ratios, providing a convenient way of interpreting the results. In order to have risk ratios of all variables appear along the same scale, age variable was divided by 10. Thus, a unit increase in the transformed age variables

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[5] The Blundell-Smith specification test applies to the following system of equations

$Y_1 = f(x_1, \theta) + v$

$Y_2 = g(Y_1, x_2, \theta) + u$

Where g denotes the particular functional form for probit, tobit or other truncated and limited dependent variables models. The specification test is obtained by retaining the observed value for Y_1 but including the residual from the regression on Y_1 in the model for Y_2. Thus we estimate:

$Y_2 = g(Y_1, x_1, \theta, v) + e$

The Blundell-Smith test for exogeneity specifies the null hypothesis H_0: $\alpha=0$, where α is the coefficient of v in the above. In all of our models alphas were always close to zero in value (<0.1) and not statistically significant.

[6] The predictive model for delivered dialysis intensity included variables such as treatment time missed, type of catheter, manufacturer recommended dose given patient anthropometrics, dialyzer use, and patient demographics. Further details are available in Sehgal et al. (1998).

corresponds to an added risk from 10 additional years. Because of similarities in specifications, it will be convenient to summarize the results in all tables jointly, by order of covariates.

All versions of the logit in Table 2 indicate that each age group, measured in decades, was about 20 percent more likely to be admitted to the hospital compared with the next youngest cohort. Similarly, older cohorts required 12 percent more hospitalizations, and 15 to 16 percent more hospital days than younger cohorts, based on the poisson model in Table 4 and the negative binomial model in table 5. All of these results were statistically significant. Females had higher risk of any admission or total number of admissions compared with males, but had slightly lower risk in terms of number of hospital days. Relative to whites, minority patients had a higher chance of being hospitalized, but were at a lower risk of in terms of number of admissions or days; however, minority status was not statistically insignificant in any of the analyses.

Turning to health status variables, diabetes as a cause of renal failure entailed higher rates of hospital utilization compared with all other causes, but these results were not statistically significant in any of the models. Being a dialysis patient for a relatively longer period of time (over year), implied lower odds of being admitted to the hospital, fewer hospitalizations, and lower expenditures. Only one statistically significant result was associated with this variable, which indicated that such patients required 56 percent more hospital days compared with patients who went on dialysis closer to the beginning of the follow-up period. The number of comorbidities that accompany renal failure is a much stronger predictor of hospital resource use. An increase in the number lead to progressively higher utilization rates, with statistically significant coefficients in most cases. For instance, at the high end of the scale, patients with four or more conditions were almost twice as likely to be admitted to the hospital than individuals in the default category, i.e., those having only the base condition of renal failure. Patients with four or more comorbidities also required more than twice as many hospitalizations or hospital days compared with patients in the default category. For the middle group having two or three comorbidities the added risk relative to the reference group was in the range of 60 to 70 percent. These results underscore importance of baseline health status in determining future use of medical resources.

The various measures of dialysis intensity are the most relevant to the policy questions posed in this study. The related results are in general agreement in all variants of the model, indicating that greater intensity of dialysis is associated with lower risk for hospital resource use. Using the model specification denoted as version I (binary indicators) it can be seen that patients in the medium group were 23 percent more likely to be admitted to a hospital compared with patients in the omitted low intensity group. Patients in the high intensity group were 33 percent less likely to be admitted to a hospital compared with the low intensity group. Similarly, patients in the medium group required 28 percent fewer hospitalizations, and patients in the high intensity group required 40 percent fewer hospitalizations than the reference group. The analysis of hospital days mirrored these results, albeit at lower significance levels.

In all of the models that were estimated, a second specification (version II) included interaction terms for the outpatient intensity levels in each group, rather than group dummies. None of the corresponding coefficients were significant. On the other hand, in version III the continuous variable for all groups combined was highly significant. Overall, the results suggest that there are no significant differences in the slope of the intensity index across the groups. Thus, version III is of greater interest.[7]

Averted hospital costs represent the benefits from preventive intervention, and for policy purposes one would like to get a sense of the dollar tradeoff involved between prevention and inpatient costs. Due to the data limitations noted earlier, is was not possible to estimate the impact of prevention on inpatient expenditures directly. However, noting that average Medicare hospitalization cost per patient was $5,931 (Table 1), it is possible to gauge this effect indirectly using the model for admissions. The relevant risk ratio states that a unit increase in the mean value of the (continuous)

[7] Adding a quadratic term for intensity did not yield significant results.

outpatient intensity index results in a 60 percent reduction in hospitalizations, which is equivalent to an elasticity of 0.82, at the sample means.

Of course, providing greater intensity of dialysis is not without cost itself, and this must be taken into account in any cost-benefit calculation. While the current data do not provide information on the price of dialysis, independent estimates from the related literature can be found. Thus, Hirth et al. (1999) calculate that a 10% increase in the intensity of hemodialysis leads to an increase of $3.5 in the cost of a single hemodialysis treatment. In the current analysis this translates into $273 during the relevant period (26 weeks with a requisite three treatments per week). From the above, a 10 percent increase in dialysis intensity implies a reduction of $491 in Medicare expenditures per patient, or $1.8 in averted inpatient costs for every one dollar increase in outpatient dialysis delivered.

Although the estimated coefficients suggest that a linear relationship between outpatient prevention and inpatient expenditures dominate our data, clinical consensus in favor of increasing dialysis dosage exists mainly for the low intensity group. Thus, from a policy perspective it may be more relevant to consider the impact of targeting intervention to this group alone rather than increasing dosage across the board. Raising intensity to the requisite 1.2 level for every individual in this group implies an increase of 11 percent in outpatient intensity (see Figure 1), and a 9 percent decline in hospital admissions for the low-intensity group as a whole. On a national basis this would be roughly the equivalent of $45 million in net savings for the Medicare program annually, assuming a similar distribution of patients nationally as in our data, and simply prorating the 6 month follow-up period to match a full year.[8] While these assumptions can be further tinkered with, in the absence of more accurate information from the Medicare program currently available, they provide a reasonable

[8] Admittedly, the conditional nature of the available sample requires making somewhat crude assumptions to get at the full population estimates. Since there is no basis to determine the rate of increase of hospital expenditures in the second half of the year, I assumed a simple 2:1 ratio to annualize costs. In addition, for 20 percent of patients who die in the middle of the year, I assumed that the elasticity of admissions with respect to outpatient dialysis is the same as that of patients who survive a full year. National inpatient dialysis expenditures are $3.5 billion, or about $840 million for the low intensity group. Based on the elasticity, raising kt/v for this group to required levels would lower inpatient costs by about $76 million, or about $46 million in net savings after costs of additional dialysis are taken into account.

basis for assessing the order of magnitude of potential savings from better prevention. Moreover, the net savings figure of $45 million as calculated above serve as a lower bound, given that increasing dialysis intensity appeared to be beneficial for a greater number of patients, including those already receiving doses deemed as adequate.

VI. Discussion

The Medicare end stage renal disease program is of broad interest because of the debate over the appropriate use of medical technology, as well as its relatively complex structure of financial incentives aimed at suppliers of this technology. Moreover, dialysis treatments serve as a point of entry to continued medical care within the program, making the outpatient-inpatient substitution in this special case analogous to the tradeoff between prevention and curative care in other settings. The analogy is especially appropriate for chronic care populations, where preventive intervention is provided on an on-going basis.

Focusing on the case of end-stage renal disease, empirical analysis in this study examined the tradeoffs between outpatient services and inpatient care in a sample of dialysis patients. The principal finding was that of a strong negative effect of outpatient care on inpatient utilization. This effect extends to all patients, regardless of the initial level of preventive intervention. Thus, the beneficial effect of prevention does not appear to be limited to the subset of patients for whom outpatient intensity is deemed to be inadequate according to conventional medical standards. At present, however, policy discussion is guided by such standards, making the subset of patients who fall into the lowest intensity category especially relevant. Based on our results, targeting this group alone would yield net savings of about $45 million to the Medicare dialysis program. While this amount may appear to be small, representing 1.5 percent of the program's inpatient outlays, it should be viewed merely as a lower bound estimate. Net savings would be substantially higher if preventive doses were to be administered across the board.

Implications of the results for payment policies are of greatest interest here. It is generally believed that the current method of capitated payments for outpatient dialysis, coupled with a decline in inflation-adjusted payments in recent years has contributed to the low levels of preventive intensity presently observed. Indeed, this is consistent with profit-maximizing behavior for providers of dialysis. The indirect effect of this pricing strategy leads to higher spending on inpatient services. Due to constant prices, price effects could not be estimated directly. Nevertheless, it is possible to draw lessons for payment policies from the results of this analysis.

Three options for pricing preventive services merit consideration. First, non-linear pricing, namely allowing for differentially higher payments aimed at low-intensity suppliers. Second, linear pricing, i.e., unit-cost reimbursement that rewards higher preventive intensity at all levels. Third, keeping the current principle of fixed prices (capitation) in tact, but increasing the payment rate to optimal levels.

Each one of these payment schemes raises its own difficulties that must be put in the balance. Beginning with non-linear pricing schemes, the regulator would be required to posses ex-ante knowledge of who the low-intensity providers might be, or be able to add monitoring functions to administer prices. In turn, additional monitoring costs would offset some of the pecuniary benefits accrued from greater prevention. Moreover, empirical analysis suggests that targeting only the low intensity group may yield full benefits.

Empirical evidence in favor of increased prevention across-the-board suggests that linear pricing of preventive services may be more efficient. However, in recent years policy makers have become increasingly prone to reject cost-based reimbursements due to the problem of overprovision of medical care. For instance, prospective payments which have replaced cost-based hospital payments in the broader Medicare program nearly two decades ago, are now being expanded to the outpatient setting as well (Medical Prospective Payment Commission, 2000, Ch. 2). While linear pricing may be easier to implement in a technical sense, given the prevailing political consensus, a return to reimbursement systems of the past is unlikely to take place any time soon, even if accommodating additional prevention is the issue. Indeed, this corresponds to the myopic case described in the theoretical section of this paper.

A third option that sidesteps the political constraint is to increase the administered prices of outpatient dialysis while keeping the principle of capitation in tact. Determining the increment by which to increase administrative prices for prevention is a yet unresolved question. The pricing rule developed in the theoretical section of this paper provides some insights, but it also highlights the need for additional information. It was shown that the optimal price of prevention should take both the preventive and curative stages of medical care into account. Thus the greater the potential benefits of prevention in terms of averting net inpatient costs, the higher the price of prevention needs to be. However, the degree to which preventive prices should be increased in order to accommodate these benefits also depends on the elasticity of supply for preventive care. Stated differently, the less sensitive suppliers of preventive services are to prices, the less effective an increase in payment for prevention will be.

It should be noted that forecasting optimal prices based on the above rule requires information that may not be fully observable to the regulator. This calls for yet another class of payment policies that require only a minimal amount of information. An alternative policy proscription that has been considered, but not yet implemented, entails bundled payments covering outpatient treatments and related inpatient services jointly. Here, it would be up to the suppliers to decide how a global payment should be split. This has been proposed specifically for the case of dialysis patients (Farley et al., 1996), for treatments around heart bypass surgery (Cromwell, Dayhoff, and Thoumaian, 1997) as well for hospital care in general (Miller and Welsh, 1992). Although price bundling may help to ameliorate incentive for ‘skimping’ (Ellis, 1998), particularly in the preventive stage, this payment system also introduces new complications. Dor and Watson (1996) have shown that the bargaining process that would ensue from global payments yields non-optimal outcomes from the perspective of the players. Whether global payments can move suppliers closer to the social optimum is an open question. Until the incentives within such payment systems become better understood, increasing payment levels for preventive services remains a viable policy option, especially in cases involving populations with chronic illnesses.

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Table 1—Summary Statistics

Variable	Mean	Std D.	Min	Max
Dependent variables:				
Any hospital admission	0.42	0.49	0.0	1.0
Number of hospital admissions	1.02	1.62	0.0	10.00
Total hospital days	5.58	11.44	0.0	89.00
Hospital reimbursements	5930.82	11984.76	0.0	125885.70
Regressors:				
Age	62.16	15.29	19.80	89.40
Female (binary indicator)	0.48	0.50	0.0	1.0
Minority (binary indicator)	0.50	0.50	0.0	1.0
Diabetes (binary indicator if cause of renal failure)	0.38	0.48	0.0	1.0
Time (binary indicator for dialysis dialysis time > 1 year)	0.79	0.41	0.0	1.0
2 comorbidities	0.21	0.43	0.0	1.0
3 comorbidities	0.42	0.49	0.0	1.0
4+ comorbidities	0.18	0.38	0.0	1.0
Dialysis Intensity Index				
Low (Binary: Kt/V < 1.2)	0.24	0.43	0.0	1.0
Medium (Binary: 1.2 ≤ Kt/V < 1.4)	0.37	0.48	0.0	1.0
High (Binary: Kt/V >= 1.4	0.38	0.49	0.0	1.0
Low: = (Kt/V x binary indicator)	1.06	0.12	0.59	1.19
Medium: = (Kt/V x binary indicator)	1.29	0.05	1.20	1.39
High: = (Kt/V x binary indicator)	1.56	0.13	1.40	1.97
All groups (continuous)	1.34	0.23	0.46	1.97

N = 616
Days at Risk = 180

Table 2—Regression analyses for probability of any hospitalization

	Any Hospitalization (Logistic Regressions)					
	Model I		Model II		Model III	
	ß	OR	ß	OR	ß	OR
Age/10	0.175	1.192***	0.178	1.195***	0.176	1.201***
	[2.979]		[3.014]		[2.987]	
Female	0.084	1.088	0.108	1.114	0.103	1.346*
	[0.481]		[0.612]		[0.586]	
Minority	-0.066	0.936	-0.081	0.922	-0.086	0.787
	[-0.375]		[-0.461]		[-0.490]	
Cause of renal failure: Diabetes	0.164	1.177	0.155	1.167	0.160	1.140
	[0.874]		[0.824]		[0.850]	
Time since dialysis started: > 1 year	-0.080	0.923	-0.066	0.936	-0.074	0.941
	[-0.386]		[-0.319]		[-0.357]	
Number of comorbidities						
None						
1	0.335	1.398	0.345	1.412	0.350	1.544
	[1.182]		[1.215]		[1.234]	
2-3	0.505	1.656*	0.505	1.656*	0.503	1.733*
	[1.845]		[1.844]		[1.842]	
> 4	0.597	1.816*	0.609	1.839*	0.616	1.901*
	[1.829]		[1.862]		[1.886]	
Dialysis Intensity - indicators						
Low						
Medium	-0.261	0.770				
	[-1.169]					
High	-0.401	0.670*				
	[-1.742]					
Dialysis Intensity – interaction terms						
Low			-0.607	0.545		
			[-0.608]			
Medium			-0.720	0.487		
			[-0.867]			
High			-0.698	0.498		
			[-1.018]			
All groups (continuous)					-0.818	0.441
					[-2.018]	
Constant	-1.570		-0.926		-0.742	
	[-3.441]		[-0.823]		[-1.116]	
Log likelihood	-406.101		-405.445		-405.567	
χ^2-statistic	26.73		28.04		27.80	
p-value of χ^2-statistic	0.003		0.003		0.001	

*, **, and *** indicate statistical significance at the 0.10, 0.05, and 0.01 levels, respectively

Table 3—Regression analysis for number of hospital admissions

	Total Hospital Admissions (Negative Binomial Regressions)					
	Model I		Model II		Model III	
	ß	IRR	ß	IRR	ß	IRR
Age/10	0.123	1.131***	0.126	1.135***	0.125	1.133***
	[2.578]		[2.642]		[2.616]	
Female	0.046	1.047	0.063	1.066	0.065	1.067
	[0.340]		[0.464]		[0.470]	
Minority	-0.018	0.983	-0.027	0.973	-0.038	0.963
	[-0.128]		[-0.199]		[-0.276]	
Cause of renal failure: Diabetes	0.243	1.275*	0.242	1.273***	0.248*	1.282*
	[1.644]		[1.635]		[1.677]	
Time since dialysis started: > 1 year	0.010	1.010	0.025	1.026	0.021	1.021
	[0.062]		[0.154]		[0.127]	
Number of comorbidities						
None						
1	0.291	1.338	0.289	1.335	0.294	1.341
	[1.219]		[1.212]		[1.231]	
2-3	0.473	1.605**	0.471	1.601**	0.469	1.599**
	[2.088]		[2.079]		[2.069]	
> 4	0.800	2.226***	0.815	2.259***	0.829	2.290***
	[3.068]		[3.123]		[3.176]	
Dialysis Intensity - indicators						
Low						
Medium	-0.330	0.719*				
	[-1.937]					
High	-0.520	0.595***				
	[-2.940]					
Dialysis Intensity – interaction terms						
Low			-0.424	0.654		
			[-0.540]			
Medium			-0.606	0.546		
			[-0.933]			
High			-0.628	0.534		
			[-1.176]			
Dialysis Intensity: continuous					-0.918	0.399***
					[-3.019]	
Constant term	-6.220		-5.798		-5.332	
	[-16.900]		[-6.646]		[-10.481]	
Log likelihood	-827.784		-827.176		-827.595	
χ^2-statistic	41.730		42.940		42.100	
p-value of χ^2-statistic	0.000		0.000		0.000	

*, **, and *** indicate statistical significance at the 0.10, 0.05, and 0.01 levels, respectively

Table 4—Regression analysis for total hospital days

	Total Hospital Days (Negative Binomial Regressions)					
	Model I		Model II		Model III	
	ß	**IRR**	**ß**	**IRR**	**ß**	**IRR**
Age/10	0.140	1.150*	0.146	1.157**	0.144	1.155**
	[1.943]		[2.022]		[1.998]	
Female	-0.063	0.939	-0.037	0.964	-0.040	0.961
	[0.762]		[-0.177]		[-0.188]	
Minority	0.112	1.118	0.088	1.092	0.056	1.058
	[0.541]		[0.415]		[0.272]	
Cause of renal failure: Diabetes	0.298	1.348	0.288	1.333	0.269	1.309
	[1.295]		[1.251]		[1.172]	
Time since dialysis started: > 1 year	0.419	1.520	0.444	1.558*	0.412	1.511
	[1.596]		[1.674]		[1.579]	
Number of comorbidities						
None						
1	0.459	1.583	0.443	1.558	0.457	1.580
	[1.374]		[1.326]		[1.366]	
2-3	0.551	1.735*	0.546	1.727*	0.571	1.770*
	[1.739]		[1.727]		[1.804]	
> 4	0.937	2.551**	0.953	2.594**	0.982	2.671***
	[2.418]		[2.466]		[2.556]	
Dialysis Intensity – binary						
Medium	-0.431	0.650				
	[-1.610]					
High	-0.508	0.601*				
	[-1.908]					
Dialysis intensity - interaction terms						
Low			-0.481	0.618		
			[-0.361]			
Medium			-0.748	0.473		
			[-0.676]			
High			-0.682	0.506		
			[-0.744]			
Dialysis intensity - continuous					-0.912	0.403**
					[-2.001]	
Constant	-5.046		-4.562		-4.181	
	[-8.902]		[-3.169]		[-5.295]	
Log likelihood	-1343.512		-1343.086		-1343.606	
χ^2-statistic	21.70		22.55		21.51	
p-value of χ^2-statistic	0.017		0.020		0.011	

*, **, and *** indicate statistical significance at the 0.10, 0.05, and 0.01 levels, respectively.

Figure 1

Sample Distribution, by Kt/V Parameter