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**Physician Incentives and Treatment Choices in Heart Attack Management**

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Physician Incentives and Treatment Choices in Heart Attack Management*

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Abstract

We estimate how physicians’ financial incentives affect their treatment choices in heart attack management, using a large dataset of private health insurance claims. Different insurance plans pay physicians different amounts for the same services, generating the required variation in financial incentives. We begin by presenting evidence that, unconditionally, plans that pay physicians more for more invasive treatments are associated with a considerably larger fraction of such treatments. To interpret this correlation as causal, we continue by showing that it survives conditioning on a rich set of diagnosis and provider-specific variables. We perform a host of additional checks verifying that differences in unobservable patient or provider characteristics across plans are unlikely to be driving our results. We find that physicians’ treatment choices respond positively to the payments they receive, and that the response is quite large. If physicians received bundled payments instead of fee-for-service incentives, for example, heart attack management would become considerably more conservative. Our estimates imply that 20 percent of patients would receive different treatments, physician costs would decrease by 27 percent, and social welfare would increase.

JEL Classifications: I14, I31

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1 Introduction

The United States performs 96% more MRI exams, 81% more knee replacements, 25% more cesarean sections and 101% more coronary angioplasties than the OECD average (OECD (2011))\(^1\). While this is partially due to differences in health, income, and tastes, many believe that physicians’ financial incentives also play a role (Orszag and Ellis (2007); Emanuel and Fuchs (2008); Garber and Skinner (2008)). Physicians may be responding to a fee-for-service payment system that rewards them for performing costly, sophisticated treatments. In the gray area of medicine where it is not clear what treatment is in the patient’s best interest, financial incentives might prove decisive (Chandra et al. (2011)).

Our goal in this paper is to estimate these payment responses in the context of heart attack management, using a large administrative dataset of private health insurance claims paid by insurers and self-insured firms. With a discrete choice model of physician behavior, we quantify how heart attack treatment decisions depend on the payments physicians expect to earn from each potential treatment, and how treatments would change in response to different financial incentives such as bundled payments.\(^2\) The model also allows us to evaluate the likely effect of counterfactual payment regimes on the cost of care and social welfare. Our results suggest that fee-for-service incentives induce a substantial and social-welfare decreasing shift towards more expensive treatments.

Our empirical strategy is motivated by two key patterns of correlation in the data. First, different health insurance plan types, like Health Maintenance Organizations and Preferred Provider Organizations, pay different amounts for the same treatments. Second, treatment choices vary with this variation in payments. Some plan types tend to pay relatively more for aggressive treatments, and patients in those plan types tend to receive aggressive treatments more often.

\(^1\)Cesarean sections are per live births, other statistics are per capita.
\(^2\)Bundled payments are a fixed payment for the entire episode of care, irrespective of which services the patient receives.
Any attempt to interpret these simple correlations as causal has to confront the obvious concern that patients and providers are not assigned to insurance plan types at random. Plan types that pay more for aggressive treatments may be more likely to attract patients with severe heart attacks, or may tend to contract with physicians who prefer to treat aggressively. Fortunately, our data contain a rich set of control variables about the patient, the heart attack episode, and the physician, mitigating much of the selection concern. These variables include the kind of heart attack and where in the heart it occurs; comorbidities such as hypertension, diabetes and obesity; previous diagnoses, treatments performed, and health care expenditures; and the provider’s average resource use, as measured by inpatient expenditures and length of hospital stays. The main identifying assumption is that conditional on our observables, heart attack treatment choices are related to insurance plan type only to the extent that plan type changes the prices paid for physicians’ services.

Following Cutler et al. (2000), who make a related identifying assumption, we note that this is considerably weaker than ruling out adverse selection. Because we condition on comprehensive health status data, there may be selection across plan types on diagnoses recorded in our data. The assumption does however place some restrictions on selection across plan types. A series of checks investigate whether our estimates might reflect selection, rather than the causal effect of prices on treatment choice. We analyze hospital admission rates across plan types for heart attacks and other serious conditions and find that selection on unobservable sickness is unlikely to explain our results. We show that differences in cost-sharing across plan types are mostly irrelevant for heart attack treatment choice, as on the margin the patient will generally not be contributing towards his health care bills. We examine the possibility that physicians with different practice styles are attracted to different plan types, beyond what our controls can capture, and find that our results do not support such selection.

We also explore physicians’ response to financial incentives under a different exogeneity

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3Cutler et al. rule out patient selection on unobservables across plan types, as in our analysis, but make no assumption about the mechanism by which plan type affects treatments.
assumption, using variation in insurance plan type across employers rather than across individuals. The assumption is that patients’ choice of employer is unrelated to employers’ plan type enrollment at the time of the patients’ heart attack. This seems reasonable, especially because people often choose their employers long before they know they have heart disease, and the changing health insurance industry makes it difficult to predict what plans an employer would offer years in the future. We still reject the hypothesis that physicians are uninfluenced by financial incentives.

Inference in this setting is complicated by missing payment data. Health care providers do not submit claims for treatments that are not performed. We do not observe how much physicians would get paid for performing angioplasty on patients who actually receive medical management, yet the angioplasty payments may affect treatment choice. To measure the effect of payment on treatment choice, we need to estimate the “first stage”, or how plan types affect payments. But if plan types affect payments, and payments affect choices, missingness of payments is correlated with plan type. Changing plan type has a causal effect on payments, but it also changes the patient mix receiving a given treatment. Regressing observed payments on plan types is thus subject to selection bias. While we study the privately insured, this problem would also be present with Medicare or Medicaid data.

Each treatment is a collection of services. “Angioplasty” may involve ECGs, X-rays, and physician consultations, as well as the angioplasty itself. Our data have detailed information on the quantities used and unit prices of these underlying services. This disaggregated information plays a crucial role in dealing with the missing payments problem. We first estimate the effect of plan type on service prices. Together with data on how much of each service is typically used in each treatment, we show how these estimates allow us to infer the effect of plan type

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5The difficulty in estimating price responses when the prices of unchosen goods are missing arises in other contexts. Erdem et al. (1999) study the case of scanner panel data on household purchasing behavior.
on overall treatment payments. With estimates of the first stage parameters, we can recover the effect of changing payments on treatment choices.

Physicians’ treatment choice is represented by a multinomial probit model. We estimate the choice model and the payment equations simultaneously by Bayesian methods, using the Gibbs sampler. The results, which are robust in size across widely different specifications, indicate that increasing the price paid for a treatment increases the frequency with which it is performed. The own-price elasticities in the main specification vary from 0.3 to 0.9, depending on the treatment. Physicians’ price responsiveness appears to decrease when they treat sicker patients.

Our model predicts that if physicians received bundled payments instead of facing fee-for-service incentives, heart attack management would be considerably more conservative. 18 percent fewer patients would receive angioplasty or bypass surgery. This is roughly equal to the difference in the incidence of these treatments between the United States and France, and half the difference between the United States and Israel, found in an international clinical trial (Gupta et al. (2003)). The cost of care would decline by about 27 percent. Extrapolating to the United States as a whole, this corresponds to a $5 billion reduction in health care expenditure each year. Our estimates account for the cost differences between the average and marginal treatment recipients.

Despite limited information on quality of life post-treatment, our model still permits welfare analysis. 20 percent of patients would receive different treatments under bundled payments and fee-for-service. We show how these patients’ change in welfare from bundled payments depends on physicians’ disutility of labor and thus their desire to shirk. A back-of-the-envelope calculation suggests that any welfare losses patients might experience from bundled payments are likely to be smaller than the cost savings from more conservative treatment choices.

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6The estimates can be understood as summarizing the posterior parameter distribution, but also have the usual frequentist interpretation. Other applications of Bayesian methods in health economics include Munkin and Trivedi (2003); Deb et al. (2006a); and Deb et al. (2006b), who study the effect of insurance on health care utilization, and Geweke et al. (2003) who analyze hospital quality.
Much evidence exists on physicians’ response to financial incentives generally.\footnote{A related literature treats hospitals’ response to incentives (Hodgkin and McGuire (1994); Finkelstein (2007); Acemoglu and Finkelstein (2008); Dafny (2008); Kim (2011)). Ho and Pakes (2012) and Swanson (2012) examine how physician incentives affect the hospital referral decision. Ho and Pakes’ study is of particular interest here, as they also use variation in financial incentives generated by health insurance.} Rice (1983); Escarce (1993); Yip (1998) and Clemens and Gottlieb (2012) estimate how changes in Medicare’s reimbursement rates affect aggregate quantities of health care services. Helmchen and LoSasso (2009) and Melichar (2009) analyze the effect of fee-for-service payments on the number of patient encounters office-based physicians schedule, and the time they spend per encounter. But possibly because of the challenge posed by missing payment data, very few studies explicitly quantify physicians’ substitution between different treatments when their payments change, and develop a framework which can measure the overall effect of fee-for-service incentives on the distribution of treatments. Perhaps closest to this paper are Gruber et al. (1999), who find that cesarean deliveries are more common if they are highly reimbursed relative to normal deliveries, and Dickstein (2012), who finds that capitated physicians tend to choose drugs that require fewer follow-up visits when treating depression. Cutler et al. (2000) examine heart attack treatment choices across plan types, but do not estimate physicians’ payment response.

2 Heart Attack Management

Figure 1 (adapted from (Cutler et al., 2000)) presents the main treatment and diagnosis options for a heart attack, or acute myocardial infarction (AMI). An AMI is caused by an arterial blockage interrupting blood flow to the heart. Treatments aim to restore the heart’s blood supply. Medical management involves administering drugs, often including aspirin, beta-blockers and thrombolytics. Angiography, or diagnostic catheterization, is an imaging technique in which a catheter is guided to the coronary arteries to inject an X-ray dye, allowing X-rays to show blood flow around the heart and reveal arterial occlusions. Depending on the severity of disease this reveals, physicians may choose no further intervention, angioplasty, or bypass surgery. In an
angioplasty, or interventional catheterization, the cardiologist inflates a balloon at the site of the blockage to widen the interior of the artery, and typically also leaves a stent to keep the vessel open. A coronary artery bypass surgery involves grafting a vein or artery taken from elsewhere in the body to the coronary artery, bypassing the blockage. Some patients have another form of major surgery because the other alternatives are unsuitable, or because they also suffer from another heart condition.

The American College of Cardiology and the American Heart Association produce joint guidelines on AMI management (Antman (2004); Anderson (2007)). Delays in coordinating personnel for catheterization or inexperienced interventional cardiologists make medical management more attractive, for example, while hypotension favors an initial angiography. If the angiography reveals minimal coronary artery disease no further intervention may be necessary. Angioplasty is otherwise a common choice, but three vessel disease and diabetes increase the benefit from bypass surgery relative to angioplasty.

Even with such recommendations, it is not always clear what is in the patient’s best interest. The guidelines themselves state as much: “Despite the wealth of reports on reperfusion for STEMI [ST Elevation Myocardial Infarction], it is not possible to produce a simple algorithm, given the heterogeneity of patient profiles and availability of resources in various clinical settings at various times of day.” (Antman (2004)). Doctors may not often recommend entirely inappropriate treatments purely for their own personal benefit.8 But physicians with patients on the margin between treatments might be influenced by the payments attached to the options.9,10

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8Although counterexamples exist (Devi (2011)). Chan et al. (2011) review over half a million angioplasties, and judge 12 percent of procedures for non-acute patients to be inappropriate, with a further 38 percent of uncertain value.

9Lucas et al. (2010) survey cardiologists and find that they almost uniformly deny being influenced by money. Others are skeptical that physicians are unaffected: “The US is just about the only developed country where health care is delivered on a fee-per-service basis and we very liberally incentivize physicians for doing invasive procedures. The economic incentives are just too strong.” (Steven Nissen, chief of cardiovascular medicine in the Cleveland Clinic, quoted in Devi (2011).)

10In other cases there is a clear consensus but it is not followed. Many patients, for example, fail to receive aspirin and beta-blockers post-AMI (Jencks et al. (2000); Baicker and Chandra (2004); Chandra and Staiger (2007)).
3 Data and Summary Statistics

3.1 Data Sources

Our primary data source is the Thomson Reuters MarketScan database, a large administrative collection of claims paid by private health insurance companies and self-insured firms. We select inpatient admission records from 2002 to 2007 where the primary diagnosis is AMI. Each record has information on patient demographics and insurance plan type, the type and quantity of services used and the corresponding payments to the hospital and physicians, and the physicians’ diagnoses. Patients can be identified over time, so medical history is available for each patient from when they enter the sample. The payment variables are actual adjudicated and paid amounts, not list prices. Appendix A describes in detail how the sample is constructed and the diagnosis and service codes used to identify AMI and its treatments. The final sample contains 66,014 AMI. We use the Health Resources and Services Administration’s Area Resource File for additional county-level information on demographics, ischemic heart disease mortality, hospital and physician characteristics and per capita surgery rates.

3.2 Insurance Plan Types and Physician Payments

There are 4 major insurance plan types in these data. In order of increasing restrictiveness of the provider network and decreasing patient choice, they are Comprehensive, Preferred Provider Organizations (PPOs), Point of Service (POSs) and Health Maintenance Organizations (HMOs). They vary depending on whether patients are incentivized to use a particular network of providers, whether the insurer makes any contribution to out-of-network services, and whether a primary care physician controls referrals to specialists. Table 1 summarizes these differences.
Fee-For-Service Billing  Insurers in the MarketScan data pay physicians and hospitals by fee-for-service or by capitation. In 2007, over 95 percent of AMI patients in our data are covered by insurance which paid entirely by fee-for-service. Capitation is more common for primary care physicians than specialists like cardiologists and cardiac surgeons (Kongstvedt (2007)). We drop the few patients who are recorded as having insurance which pays by capitation.

The provider group contracting with the insurer may be paid by fee-for-service, while individual physicians are paid in some other way. Most evidence suggests, however, that the fee-for-service incentives filter through to the physicians themselves. A 2007 survey found that 73% of cardiology practices were physician-owned (American College of Cardiology (2007)). For 84 percent of surgical specialists, reimbursements depend on the quantity of services they personally supply.

Physicians submit claims to private health insurers by listing the services performed. Under the Health Insurance Portability and Accountability Act of 1996, these claims must use a standardized coding system called the Current Procedural Terminology (CPT). Medicare reimburses physicians by associating “relative value units” to the CPT codes and multiplying these units by a conversion factor to find the dollar payment amount. Private insurers’ reimbursement schemes are generally modeled on this system (Ginsburg (2010)), but may differ in some respects. A large survey of private plans found that most use more than a single conversion factor (MedPAC (2003)), so their payments need not be proportional to Medicare’s. Using multiple conversion factors allows plans to control how they reimburse each category of service (e.g. evaluation and management versus surgery).

11Capitation is a fixed payment from the insurer to the provider for each enrollee-month, irrespective of services used.

12MarketScan started recording whether services are paid by fee-for-service or capitation in 2007. For previous years there may remain a small fraction of patients in our sample whose insurance pays by capitation. This appears to be unimportant for our results: when we allow the price responsiveness coefficient \( \beta^p \) defined in Section 4 to vary by year, the estimate for 2007 is close to other years’ estimates.

13Author’s calculations from the Center for Studying Health System Change’s Physician Survey, 2004-2005. See also Reschovsky and Hadley (2007).
Physician-Insurer Negotiations and Physician Payments  Insurers negotiate with in-network physicians over the prices for each service (defined by the CPT codes). For physicians with limited market power these “negotiations” take a simple form: the insurer makes a take-it-or-leave-it offer of a fee schedule, and the physician decides whether to join the network on those terms. Physicians sometimes combine into large groups to give themselves more bargaining power, and may succeed in extracting higher payments from the insurer (Kongstvedt (2007); Ginsburg (2012)). Relatedly, Ho (2009) examines the formation of hospital-insurer networks.

Insurer bargaining power is likely to vary by plan type. The restrictiveness of the insurer’s network is one determinant of the concessions it can extract from physicians. The ability to better control costs may be a major reason why restrictive networks exist at all (Dranove et al. (1993); Gal Or (1997); Town and Vistnes (2001)). HMOs have tighter networks than PPOs, so all else equal exclusion from a HMO network is likely to lead to a greater fall in revenue for a physician than exclusion from a PPO network. More restrictive plan types should therefore be able to obtain more favorable contracts from physicians. Other factors like insurer market share and number of enrollees may also affect payments.

Using data on services billed we assign each admission to one of the five treatment groups. Table 2 is a cross-tabulation of the sample by plan type and treatment. Table 3 displays the mean and standard deviation of total physician and total facility payments, overall and by plan type and treatment. Physician payments are all payments the insurer makes to physicians involved in the treatment of that patient, which may include cardiologists, emergency physicians and cardiac surgeons. Facility payments are largely hospital payments. The total payments the insurer makes are the sum of physician and facility payments.

Averaging over patients, total physician payments for an AMI are around $3,400. They are lower in the more restrictive HMO and POS plans than the less restrictive PPOs. The least restrictive Comprehensive plans have the lowest payments. This is partly due to selection on

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14Sorensen (2003); Dor et al. (2004) and Wu (2009) make this point in the context of insurer negotiations with hospitals, and show considerable price variation within a hospital across insurers.
observables across plan types, but also reaffirms the importance of factors other than network structure in determining bargaining power.

For angioplasty, HMOs and PPOs both pay physicians slightly under $3,000. But average payments for medical management are considerably higher in HMOs, at about $1,800, than in PPOs, at $1,200. And bypass payments are larger in PPOs, at $9,100, than HMOs, at $8,500. These patterns suggest that physicians’ financial incentives to treat intensively vary by plan type. In particular, PPOs seem to pay relatively large amounts, and HMOs relatively small amounts, for aggressive interventions compared to other plan types. Insurers may use their bargaining power not just to reduce the level of payments, but also to induce physicians to treat more conservatively.\footnote{\text{Relatedly, Town et al. (2011) find that physician groups in stronger bargaining positions are more likely to be paid by fee-for-service than capitation. Dafny et al. (2012) find that insurers may use their bargaining power to affect how care is provided, by substituting nurses for physicians.}} Table 3b shows that HMOs, POSs, and PPOs pay comparable amounts to facilities for medical management, but PPOs pay more for the other treatments.\footnote{As a point of comparison, the Medicare payments for these patients would be about 23 percent lower overall but only 12 percent lower for medical management, suggesting they tend to incentivize conservative treatment somewhat more than the average private insurer.}

Each treatment is a collection of services. Differences in treatment payments by plan type could be because of differences in the service quantities that go into a given treatment, rather than differences in the services’ unit prices. Our service level data allow us to disentangle the role of service prices and quantities. Table 4 gives a sense of the difference in per unit service prices underlying the differences in treatment payments. It presents the mean and standard deviations of physician prices by plan type for some common services. Initial hospital care, chest x-rays, and electrocardiograms are standard services for all AMI patients. Their mean payments do not vary substantially by plan type. Angiography contract injections, stent placements and single bypass surgeries are only used for those receiving more intensive treatments. Larger price differences by plan type emerge for these services: HMOs tend to reimburse at lower rates than PPOs, for example. These differences by plan type do not seem to be determined by the level of payments, as hospital care is more expensive than contrast injections.
These data are instead consistent with HMOs using their bargaining power to choose service prices in a way that induces physicians to treat more conservatively.

Table 5 presents evidence that similar payment patterns exist for four other common conditions: prostate cancer, breast cancer, inguinal hernia, and spinal disc herniation. We choose these conditions because like AMI, physicians can choose between a more intensive treatment (prostate surgery, mastectomy, inguinal hernia repair, spinal surgery) and less intensive alternatives (active surveillance, lumpectomy, hernia trusses, anti-inflammatory drugs). HMOs and POSs tend to reimburse relatively less than PPOs for the intensive treatment option than the less intensive alternative. For all conditions, the ratio of mean payments for the intensive treatment option to mean payments for the less intensive alternative is at least as great in PPOs as in HMOs and POSs. Compared to these other conditions, studying AMI has the advantage that detection rates are unlikely to vary much by plan type.

4 Empirical Strategy

4.1 Overview

Just as payments vary by plan type, so does the distribution of AMI treatments. Table 2 shows, for example, that 17 percent of patients receive medical management in a HMO, but only 11 percent of patients in a PPO do.\footnote{Langa and Sussman (1993); Every et al. (1995); Sada et al. (1998) and Canto et al. (2000) also find that invasive treatments for AMI patients are less common in HMOs than other plan types. Cutler et al. (2000) do not, attributing lower expenditures in HMOs to lower unit prices rather than treatment differences.} This kind of pattern suggests that payments affect treatment choice. For PPO patients, the expensive, invasive procedures are relatively more remunerative to physicians than cheaper, simpler alternatives. Physicians seem correspondingly more likely to treat PPO patients aggressively.

While these correlations might be suggestive, our empirical strategy allows us to see if these patterns hold up on average comparing all treatments across all plan types, after dealing with
the problem of missing payments, and after controlling for demographic, clinical and provider variables. It also allows us understand how counterfactual reimbursement structures are likely to influence choices, welfare and costs. The empirical strategy has two steps. First, we estimate how treatment payments vary by plan type. Simple OLS would yield inconsistent estimates because payments are systematically missing. We account for the missing payments by using the detailed price and quantity data we have on the services that compose a treatment. Intuitively, our strategy is similar to fixing the bundle of services that make up the typical angioplasty, for example, and evaluating the total payments for this bundle at the service price schedules of different plan types. This isolates the effect of service prices from service quantities. Second, we estimate physicians’ responses to the across-plan type variation in treatment payments found in the first step.

4.2 Model and Assumptions

Service Prices and Treatment Payments  Let \( p_{i,j} \) denote the total payments physicians would receive if they were to treat patient \( i \) with treatment \( j \), for \( j = 1, \ldots, 5 \) corresponding to medical management, angiography, angioplasty, bypass surgery and other surgery. Let \( \pi_{i,s} \) denote the service price patient \( i \)’s insurance pays for service \( s \) and let \( q_{i,s,j} \) denote the number of units \( i \) would receive of service \( s \), if treated with \( j \). The total payment \( p_{i,j} \) is the sum of all service revenues: \( p_{i,j} = \sum_s \pi_{i,s} q_{i,s,j} \). For each service \( s = 1, \ldots, S \), log service prices are given by

\[
\ln \pi_{i,s} = W_i Y_s^W + \text{Ins}_i Y_s^{\text{Ins}} + v_{i,s}.
\]  (4.1)

The variables in \( \text{Ins}_i \) are insurance plan type indicators interacted by region (Northeast, North Central, South, and West), so that the effect of plan type is allowed to vary geographically.\(^{18}\)

\(^{18}\)There is considerable geographic variation in plan type market shares (Baker (1999); Shen et al. (2010)), suggesting that the effect of plan type on payments within a region varies by region. We include state fixed effects in all estimated equations, however, so we do not rely on across region variation in prices.
PPO is the omitted category in each region. $W_i$ collects other variables that might affect service prices, like state and year fixed effects, described in full in the next subsection. The $v_{i,s}$ term is determined by the particular insurance plan patient $i$ has, as opposed to his general plan type. Reflecting actual reimbursement practices, $\pi_{i,s}$ is not indexed by $j$, as the amount a plan type pays for a service does not depend on the treatment of which it is part.

For each treatment $j$, we approximate log total payments by

$$\ln p_{i,j} = X'_i a_j^X + \text{Ins}_i a_j^\text{Ins} + u_{i,j}. \quad (4.2)$$

Demographic, clinical and provider covariates are collected in $X_i$. They include $W_i$ from the service price equation, but also include other variables such as patient comorbidities which do not affect service prices but may affect service quantities.

**Treatment Choices and Treatment Payments** Over financial outcomes, physicians are risk-averse expected utility maximizers with log Bernoulli utility. They know $X_i, \text{Ins}_i$, the payment equations (4.2), and have a signal $s_{i,j}$ of the payment error $u_{i,j}$. Utility from financial incentives from patient $i$ and treatment $j$ is

$$\mathbb{E}(\ln p_{i,j} | X_i, \text{Ins}_i, s_{i,j}) = X'_i a_j^X + \text{Ins}_i a_j^\text{Ins} + \mathbb{E}(u_{i,j} | s_{i,j}). \quad (4.3)$$

Utility from non-financial factors is $X'_i \beta_j^X + \epsilon_{i,j}^0$. Demographic, clinical and provider covariates may affect how much a patient is likely to benefit from a treatment, and how much effort physicians must exert in providing that treatment. Both are captured by the term $X'_i \beta_j^X$. Overall physician utility is the sum of financial and non-financial components:

$$U_{i,j} = \mathbb{E}(\ln p_{i,j} | X_i, \text{Ins}_i, s_{i,j})\beta^p + X'_i \beta_j^X + \epsilon_{i,j}^0 \quad (4.4)$$

$$= X'_i \beta_j^X + (X'_i a_j^X + \text{Ins}_i a_j^\text{Ins})\beta^p + \epsilon_{i,j}, \quad (4.5)$$
where $\beta^p$ is the weight physicians place on financial incentives, and $e_{i,j} = e_{i,j}^0 + E(u_{i,j} \mid s_{i,j})\beta^p$. Treatment $j$ is chosen for $i$ if and only if $U_{i,j} \geq U_{i,k}, \forall k$.19 The plan type variables $Ins_i$ only affect utility indirectly, through payments. The aim is to estimate $\beta^p$ and the effect of changing payments on the distribution of treatments performed.20

The principal decision-maker in AMI treatment, whose utility is modeled by (4.5), is generally the cardiologist. But the cardiologist may not receive all physician fees associated with the treatment choice. Bypass surgery, for example, is performed by cardiac surgeons rather than cardiologists. Since the payment of others seems less likely to influence one’s decision than one’s own payment, the effect of a physician’s own payments on his choices may be larger than our results will suggest. Our estimates are suited to the counterfactuals we explore, where changes in total payment for a treatment need not go solely to the principal decision-maker.

We allow payment and utility errors to be correlated. This is important for two reasons, corresponding to the two terms in the utility error $e_{i,j} = e_{i,j}^0 + E(u_{i,j} \mid s_{i,j})\beta^p$. First, payments may be endogenous in the sense that they may be correlated with the benefits the treatment confers to the patient (correlation between $u_{i,j}$ and $e_{i,j}^0$). Second, payments may directly affect utility (correlation between $u_{i,j}$ and $E(u_{i,j} \mid s_{i,j})\beta^p$).

We observe $\ln p_{i,j}$ if and only if $j$ is chosen for $i$. This is a multinomial generalized Roy model (Heckman and Vytlacil (2007)). There is a multinomial choice equation determining which payment is observed, and unlike the basic Roy model payment is not the only determinant of choice. Observed payments are a selected sample of all payments, which makes OLS estimation of the payment equation (4.2) inconsistent. Changing plan types has a causal effect

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19 In our model physician payments affect treatment choice, but hospital payments do not. This is informed by the classical view of physician–hospital relations in the United States, according to which the hospital is the physician’s workshop and can exert relatively little control over the physician, who has ultimate responsibility for treatment choices (Pauly and Redisch (1973); Starr (1982); Burns and Muller (2008); Reinhard (2008)). There are legal reasons for this: tort law and hospital bylaws often restrict hospitals’ ability to interfere with physicians’ decisions (Elhauge (2010)).

20 The parameter $\beta^p$ is constant across $j$. This is consistent with the data: we also estimate the model in which $\beta^p_j$ may vary by $j$, and fail to reject the hypothesis that $\beta^p_j$ is constant across $j$ ($p$-value of 0.75).
on service prices \( \pi_{i,s} \) and thus treatment payments \( p_{i,j} \), but it also changes the treatment cutoffs in the utility model, and so changes the mean of the payment errors \( u_{i,j} \).

As mentioned above, our empirical strategy proceeds in two steps. First, we estimate the effect of plan type on treatment payments, allowing for missing payments. We show how to obtain these estimates from estimates of the service price equations, that is, we use the \( \mathcal{V}_{i}^{\text{Ins}} \) in (4.1) to infer the \( \mathcal{a}_{j}^{\text{Ins}} \) in (4.2). Second, we use the first step results to find physicians’ payment response. Utilities can be written as \( U_{i,j} = X_{i}'(\beta^{X} + \alpha^{X}p) + \text{Ins}_{i}\mathcal{a}_{j}^{\text{Ins}}p + e_{i,j} \). Estimating this model with the \( \mathcal{a}_{j}^{\text{Ins}} \) fixed at the values found in the first step gives an estimate of \( \beta^{p} \). We now turn to the assumptions underpinning this empirical strategy.

**Assumptions** Define \( u_{i} = (u_{i,1}, \ldots, u_{i,5}) \), \( e_{i} = (e_{i,1}, \ldots, e_{i,5}) \), and \( v_{i} = (v_{i,1}, \ldots, v_{i,5}) \). Let

\[
    w_{i,s,j,0} = \frac{\exp(W_{i}'\mathcal{V}_{s}^{W} + v_{i,s})q_{i,s,j}}{\sum_{k}\exp(W_{i}'\mathcal{V}_{k}^{W} + v_{i,k})q_{i,k,j}} \tag{4.6}
\]

denote the share of total payment that would go to service \( s \), for patient \( i \) receiving treatment \( j \) if \( i \) were in the “base” plan type (so that \( \text{Ins}_{i}'\mathcal{V}_{s}^{\text{Ins}} = 0 \)), where the choice of the base is arbitrary. We make the following assumptions throughout.

A1. \( (u_{i}, e_{i}, v_{i}) \) is independent across \( i \).

A2. \( (u_{i}, e_{i}) \sim N(0, \Sigma) \).

A3. \( (u_{i}, e_{i}) \perp (X_{i}, \text{Ins}_{i}) \).

A4. \( v_{i,s} \perp (W_{i}, \text{Ins}_{i}, \text{i receives service s}), \text{for all s.} \)

A5. \( w_{i,s,j,0} \perp e_{i} \mid X_{i}, \text{Ins}_{i} \), for all \( j \) and \( s \).

A1 is a standard assumption of independent sampling. A2 imposes normality of errors, but Appendix B gives a set of sufficient conditions for semiparametric identification. A3 implies
independence of the utility errors and regressors. This ensures that the discrete choice model (4.5) can be estimated. In particular the effect of payments on utility, $\beta^p$, can be estimated once the payment regression parameters $\alpha^\text{Ins}_j$ have been recovered. A3 requires, for example, that patients in different plan types who are identical on observables are not differently suited to the potential treatments. It also implies that plan type does not directly affect the service quantities in a particular treatment. If a patient would receive different kinds of angioplasties depending on whether he is in a PPO or a HMO, the angioplasty utility error would vary by plan type. Section 5 assesses this assumption.

As is common with missing data problems, we make some assumptions about how what we observe relates to what we do not. We avoid the strong assumption that payments are missing at random conditional on the observables, instead requiring A4 and A5. A4 implies that there is no selection on the individual-specific service price errors $v_{i,s}$, so we can estimate the coefficients of the service price equations in (4.1) by simply running these regressions on the observed service data. The utilities $U_{i,j}$ depend on Ins$_i$, so treatment choice, and therefore service choice, may depend on plan type. A4, however, rules out physicians’ service choice being influenced by the specific prices a patient’s plan pays, which would introduce correlation between $v_{i,s}$ and the event that $i$ receives service $s$. This seems plausible, as a physician may perform dozens of different services for dozens of different plans. Keeping track of each service price for each plan would be a rather formidable task, and certainly much more difficult than learning how overall treatment payments vary by plan type.

A5 rules out selection on the service composition of treatments. The utility error $e_{i,j}$ may be correlated with the total payment $p_{i,j}$, but conditional on observables it must be independent of the service composition of $p_{i,j}$, or the fraction of $p_{i,j}$ spent on any particular service. Physicians’ decisions may be affected by the overall amount they stand to gain from the possible treatments, but not by the treatments’ compositions. This means we can estimate the share of the total angioplasty payment that would go to chest X-rays on average across all patients, using only
data on those patients who did in fact receive angioplasties. A5 greatly simplifies the analysis of physician choice. Instead of having to jointly model service quantity choice for almost two hundred services, we can aggregate the services into treatments and focus only on the choice between treatments.

A4 means we can infer the effect of plan type on service prices, and A5 means we can infer the average service compositions of each treatment. With this information we can approximate the effect of plan type on total treatment payments, \( \alpha^\text{Ins}_j \). Appendix C presents the argument in detail, but the intuition is as follows: if we know the percentage change in each service price caused by plan types, and we know how important each service is on average in determining the overall treatment payment, we can infer the percentage change in the treatment payment caused by plan types.\(^{21}\) Put otherwise, the service price regression parameters \( \psi^\text{Ins}_s \) determine the percentage change in each of the terms in the sum \( p_{i,j} = \sum_s \pi_{i,s} q_{i,s,j} \). With the average of the service composition terms \( w_{i,s,j,0} \), we can find the average percentage change in the \( p_{i,j} \). By A3, once these estimates of \( \alpha^\text{Ins}_j \) are available we can estimate the discrete choice model and the effect of payments on utility, \( \beta^p \).

### 4.3 Demographic, Clinical and Provider Covariates

The covariates \( W_i \) are the service quantities (insurers may charge different unit prices for different quantities), state and year fixed effects, and where available, CPT modifier codes.\(^{22}\) In all specifications, \( X_i \) includes a set of controls for the patient’s age group (< 40, 40 - 44, 45 - 49, 50 - 54, 55 - 59, > 60), year of admission, state of residence, sex, and urban place of residence. The Health Resources and Services Administration’s Area Resource File provides additional county-level information. All specifications control at the county-level for the fraction of physi-

---

\(^{21}\) Another approach to estimating the first stage would rely on instruments for treatment selection in addition to instruments for payments (Heckman and Vytlacil (2007)).

\(^{22}\) Physicians sometimes use CPT modifier codes to convey more information about how the procedure was performed. These codes may affect service prices.
cians reporting a medical (rather than a surgical) speciality, median age, median household income, ischemic heart disease mortality rates, the number of hospitals with adult interventional cardiac catheterization facilities per capita, the number of hospitals with adult cardiac surgery facilities per capita, the number of hospital beds for cardiac intensive care per capita, and the number of inpatient surgeries per capita.

Our clinical covariates contain information on the type of AMI (e.g. ST elevation myocardial infarction of anterolateral wall), all 29 Elixhauser comorbidities (Elixhauser et al. (1998)), cardiac dysrhythmia, cardiomyopathy, whether the patient is a smoker, and whether the record corresponds to the initial episode of care for the AMI. Importantly for our purposes, many of the Elixhauser comorbidities have been linked in the medical literature with AMI severity, including congestive heart failure (Krumholz et al. (1999)), hypertension (Pedrinelli et al. (2012)), diabetes (Rytter et al. (1985)), chronic obstructive pulmonary disease (Kjøller et al. (2004)), peripheral vascular disease (Guerrero et al. (2005)), and renal failure (Beattie et al. (2001)).

Our covariates also contain information on medical and insurance history for the patients who are in-sample for at least six months prior to their AMI. We include an indicator variable for being in-sample during this period. For those who are, we include a continuous variable measuring inpatient expenditure, and indicator variables for incurring no inpatient expenditure, being admitted for any form of ischemic heart disease (not necessarily AMI) and the kind of treatment received, and changing insurance plan type.

Plan types may contract with different kinds of physicians or hospitals. HMOs might prefer to contract with those who tend to treat conservatively. Including provider fixed effects

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23 The Elixhauser comorbidities are congestive heart failure, valvular disease, pulmonary circulation disorders, peripheral vascular disease, hypertension, paralysis, other neurological disorders, chronic pulmonary disease, diabetes without chronic complications, diabetes with chronic complications, hypothyroidism, renal failure, liver disease, chronic peptic ulcer disease, HIV and AIDS, lymphoma, metastatic cancer, solid tumor without metastasis, rheumatoid arthritis/collagen vascular diseases, coagulation deficiency, obesity, weight loss, fluid and electrolyte disorders, blood loss anemia, deficiency anemias, alcohol abuse, drug abuse, psychoses, and depression.

24 Because patients of a given sickness might receive different treatments and incur different inpatient expenditures in different plan types, the continuous variable measuring inpatient expenditure is the patient’s percentile among others in the same plan type who also incur positive expenditure, rather than the dollar amount.

25 The ICD-9 diagnosis codes used to identify any form of ischemic heart disease are 410, 411, 413, 414 and 786.
to account for this selection is problematic. There are about 9,000 different providers in the sample, so including fixed effects for each of the four normalized utility and five payment equations would involve estimating a nonlinear model with over 80,000 parameters. Because our sample size is around 66,000, we instead choose to control for provider characteristics parsimoniously, but in a way which is informed by the concerns about provider selection across plan types. We find each provider’s percentile in the distribution of treatment intensity, for two measures of treatment intensity: mean inpatient expenditures and mean inpatient length of hospital stay. These two variables serve as our proxies for provider practice style.

Tables 6a and 6b display summary statistics of some variables contemporaneous with the AMI, including selected Elixhauser comorbidities. Because these patients are pre-Medicare they are younger than the average AMI sufferer. “ST elevation” and “Some Emergency Department Expenditure” are of particular interest. Section 7 presents evidence that physicians’ payment responses are smaller for more severe AMI, where these variables proxy for severity.

Table 6c describes patients’ histories prior to the AMI. 76 percent of patients are in-sample for the six months preceding their AMI. “Total inpatient expenditure” is all payments from the insurer to hospitals and physicians for admissions during those six months. About 15 percent of the sample were admitted for some form of ischemic heart disease. Insurance plan type changes in the period before the AMI are rare.

5 Assessing the Identification Strategy

A3 requires that insurance plan type does not directly affect treatment utilities. We consider whether this assumption is reasonable.

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26 By “provider”, we refer to the hospital when hospital identifiers are available (45% of the sample), the principal physician when physician identifiers are available and hospital identifiers missing (31% of the sample), and the principal physician’s practice zipcode when both hospital and physician identifiers are missing (24% of the sample).
**Selection on Patients' Unobservables**  
People may select into plan types on the basis of variables not observed in these data. HMO patients might be unobservably healthier than PPO patients, for example, making them relatively suited to medical management. This would lead to correlation between the unobservable benefits from treatments and plan types, violating the restriction $e_i \perp \text{Ins}_i$.

The clinical covariates, described in the previous subsection, are fairly rich. We observe the kind of AMI and where in the heart it occurs, as well as the full set of Elixhauser comorbidities, including hypertension, diabetes and obesity. MarketScan is a panel dataset, so we can also track medical history. Since all this is observable, it is less evident how selection on patients' unobservables might operate. At the time of choosing a plan type, people would have to know something about their health status which affects the kind of AMI they are likely to suffer from, but which does not show up in their observed medical history (including the diagnostic, procedural and expenditure data from previous inpatient visits and outpatient admissions) or recorded clinical information from the AMI itself. It is somewhat unclear what such factors might be, as Cutler et al. (2000) note in their study of AMI treatment and managed care.

Adverse selection typically refers to selection on variables on which the insurer does not price. The observables include many such variables, so the assumption of no selection on unobservables is much weaker than ruling out adverse selection. We condition on medical diagnoses. Insurers do not freely price on diagnoses almost by definition, since their purpose is to shield consumers from the full cost of medical bills. There may be any degree of selection on the likelihood of suffering a health event that would be recorded in the data.

One way to get a sense of how problematic selection on unobservable sickness is likely to be is to estimate how the probability of being admitted for various conditions, including AMI, varies by plan type. We estimate linear probability models of the form

$$
\text{Adm}_i = \delta_{\text{V}} + \delta_{\text{Comp}} \text{Comp}_i + \delta_{\text{HMO}} \text{HMO}_i + \delta_{\text{POS}} \text{POS}_i + r_i.
$$

(5.1)
An observation is a person-year in the MarketScan data enrolled in a Comprehensive, HMO, POS or PPO plan. Adm is 1000 if that person-year is admitted as an inpatient with a particular primary diagnosis and 0 otherwise. Different primary diagnoses correspond to different regressions. \( V_i \) includes controls for age, year, state, sex, and urban place of residence, and the county-level data from the Area Resources File. Clinical data like hypertension and obesity are not available for all enrollees, as they are only recorded during a visit to a physician. PPO is the omitted plan type.

The conditions we choose are among the leading causes of death in the United States.\(^{27}\) Table 7 displays the estimates of the plan type coefficients from these regressions. The patterns are fairly consistent across diagnoses. Comprehensive and HMO enrollees are somewhat more likely to be admitted for these conditions, and POS enrollees somewhat less likely, than PPO enrollees. There is no evidence that on average restrictive plan types attract healthier people. In particular, there is no evidence that the relatively high rate of conservative AMI treatment in HMOs is because HMO patients tend to suffer from less severe AMIs. HMO patients suffer from AMIs at a somewhat higher rate than PPO patients. It is hard to determine what might cause more, but less severe AMIs.\(^ {28}\) It appears that HMO patients in this sample are if anything more likely to suffer from severe AMI. These regressions control for demographics, but in the choice model we include a much richer set of controls, including comorbidities and medical history. This would likely narrow unexplained health differences across plan types further.

As a further check, we test the hypothesis that payments have no effect on treatment choice under a different exogeneity assumption, using variation in insurance plan type across employers rather than across individuals. The test is based on the individual’s employer choices being unrelated to employers’ future plan type enrollment at the time of his AMI. This seems

\(^{27}\) See [http://www.cdc.gov/nchs/fastats/leod.htm](http://www.cdc.gov/nchs/fastats/leod.htm), accessed on 14 September 2012. Our chosen conditions cover seven of the ten leading causes of death. The other three are accidents, Alzheimer’s disease and suicide. These are less relevant as indicators of physical health for our sample of mostly under 65 year olds.

\(^{28}\) The Framingham risk points, for example, draw no distinction between risk factors for less and more severe AMI (A. Pearson et al. (2000)).
plausible, especially in view of the potentially long lag between employer choice and AMI, and the unpredictability of future plan type offerings. The results, in section 7.2, easily reject the hypothesis that physicians do not respond to payments.

Finally, it is unclear even in principle why more restrictive plan types should attract healthier enrollees. Bundorf et al. (2012) argue that risk-based selection may not be a major characteristic of modern health insurance markets, and find evidence supporting the “horizontal” differentiation of plan types. Relative to the healthy, the sick might dislike having their choice of provider curtailed, but they might also prefer the lower rates of cost sharing that restrictive plan types typically impose. Breyer et al. (2012) survey the literature starting from the 1990s and come to a similar conclusion: there is no pattern of restrictive plan types systematically attracting healthier enrollees.

Utilization Management The exclusion restriction $e_i \perp \text{Ins}_i$ might fail because of differences in utilization management across plan types. Some plan types may encourage conservative treatments by reimbursing them at relatively high rates. If they also use non-financial means to encourage physicians to treat conservatively, we would attribute the combined effect of non-financial and financial incentives solely to financial incentives, and thus incorrectly estimate the extent to which physicians respond to payments.²⁹

Insurers’ attempts to influence treatments face legal obstacles. Some states require insurers to pay for any care a physician judges to be medically necessary, in covered categories (Elhauge (2010)). Nevertheless insurers may attempt some form of utilization management, and the comprehensiveness of these programs may differ by plan type. These differences seem unlikely to be pronounced for AMI treatment, however. Utilization management primarily targets condi-

²⁹A related concern is that even controlling for providers’ mean inpatient expenditures and length of stays, plan type might be correlated with being treated in a hospital which does not have the facilities to perform some treatments. To test this we construct indicators for whether a provider is ever recorded as treating an ischemic heart disease patient with angioplasty, bypass or other surgery, and regress these indicators on the $X_i$ and plan type variables. There is no evidence that HMO or POS patients are less likely to be treated in hospitals where angioplasty, bypass or other surgery are available, using this measure.
tions which are chronic (e.g. “disease management” for diabetes, asthma, and stable angina) or unusually expensive (e.g. “catastrophic case management” for transplants, spinal cord injuries, and some cancers) (Kongstvedt (2007)). AMI treatments are well established and understood, not experimental or extremely expensive. In addition, quick treatment is crucial for AMI patients (Cannon et al. (2000); De Luca et al. (2004)), so there is limited scope for the insurer to require the physician’s proposed treatment to be preauthorized. For these reasons it is less plausible that plan types in our data directly influence AMI treatment choice.\footnote{Even looking at medical care more generally, utilization management programs may be of somewhat limited effectiveness in constraining physician behavior. In a randomized controlled trial, Rosenberg et al. (1995) found that utilization management had no discernible effect on inpatient care. Remler et al. (1997) survey physicians and find the overall denial rate for cardiac catheterization to be under 1 percent, and for surgical procedures under 2 percent. Again, these effects are likely to be smaller still for AMI.}

**Patients’ Influence on Treatment Choice** If patients influence the treatment they receive in a way that varies by plan type, this would also introduce correlation between $e_i$ and $\text{Ins}_i$. This might occur because of cost sharing. If enrollees of one plan type pay more for more expensive procedures, they might push their doctor to treat conservatively.

In practice it is improbable that this accounts for the variation in treatments by plan type. For some patients the MarketScan data include information on deductibles, coinsurance rates and individual out of pocket maximums. These variables determine the spending level beyond which the insurer completely covers the bill.\footnote{This is conservative, since spending by other family members may mean that the family out of pocket maximum is met sooner.} Table 8 presents this information, overall and by plan type. The mean spending threshold is $9,689, and the mean total payment for medical management is $11,891 (the median is $8,326). Patients will often be paying zero on the margin, in which case they have no financial reason to prefer one treatment over another.

Some patients will not reach the threshold if they only receive medical management. Since they are still contributing to their medical bills, they might prefer less expensive treatments. Table 8 shows that the spending thresholds are much lower for HMO enrollees. This is because
HMO enrollees are much less likely to face coinsurance (11 percent versus 98 percent in other plan types). But despite the lack of cost sharing they face, the HMO patients are treated relatively conservatively. This suggests that if patient cost sharing affects treatment, it would tend to offset—and so lead us to underestimate—the physician payment response.\footnote{MarketScan has no data on cost sharing provisions for most of the sample, but other evidence suggests that the basic picture is unchanged. Plans with looser networks tend to rely more on cost sharing to keep costs low. \textit{Kaiser Family Foundation and HRET} (2007) find in a representative survey of firms’ health plans that 65 percent of PPOs and 30 percent of POSs have coinsurance for hospital admissions, and only 18 percent of HMOs do. Of those plans that do have coinsurance, patients pay about the same percentage in HMOs as on average (15 percent versus 17 percent).}

Patient influence over treatment choice could potentially violate the exclusion restriction for other reasons. Patients who are risk-averse over money outcomes might prefer HMOs’ low cost sharing, and might also be disinclined to choose riskier procedures. In reality it seems improbable that an AMI patient would be both willing and able to second-guess his physician’s recommendation. Most angioplasties are for instance performed on an “ad-hoc” basis, directly following the angiography, and without an intervening opportunity to discuss treatment options with the patient (\textit{Hannan et al.} (2009); \textit{Nallamothu and Krumholz} (2010)).

**Physicians and Plan Types** The assumption $e_i \perp \text{Ins}_i$ also restricts how a particular treatment varies by $\text{Ins}_i$. If a given patient would receive different kinds of angioplasties depending on whether he is in a PPO or a HMO, his angioplasty utility would vary by plan type. While plan type may change service prices, $e_i \perp \text{Ins}_i$ implies it does not affect the service quantities a patient would receive from a treatment. If these services can vary by plan type, this undermines our approach of aggregating services into treatments. An alternative would be to conduct the analysis at the service level. This would require modeling not only the level of each of the 195 services in the data, but also the covariances between them. Given that interpreting the estimation results would likely involve aggregating up to the treatment level anyway, the advantages of such an exercise seem limited. We choose instead to greatly reduce the dimension of the estimation problem by aggregating services into treatments.
A related concern is that different plan types may attract physicians with different practice styles, in a way which is not fully captured by our provider controls. Section 7.2 explores this possibility, noting that physician selection should lead to particularly large differences in treatments between providers dominated by a single plan type. We find no evidence of such differences.

6 Estimation

The utility equations in (4.5) are not normalized for location or scale. Fixing the location of utility by subtracting $U_{i,1}$ from each $U_{i,j}$ gives

$$
\bar{U}_{i,j} = X_i \bar{B}_j^X + (X_i (\alpha_j^X - \alpha_j^X) + \text{Ins}_i (\alpha_j^\text{Ins} - \alpha_j^\text{Ins})) \beta^p + \bar{e}_{i,j},
$$

(6.1)

for $j = 1, \ldots, 5$, where we define $\bar{U}_{i,j} = U_{i,j} - U_{i,1}$, $\bar{B}_j^X = \beta_j^X - \beta_1^X$, and $\bar{e}_{i,j} = e_{i,j} - e_{i,1}$. We write the variance of the payment and utility errors $(u_{i,1}, \ldots, u_{i,5}, \bar{e}_{i,2}, \ldots, \bar{e}_{i,5})$ as

$$
\Sigma = \begin{bmatrix}
\Sigma_{uu} & \Sigma_{ue} \\
\Sigma_{eu} & \Sigma_{ee}
\end{bmatrix}.
$$

Dividing $\bar{B}_j^X$ and $\beta^p$ by $\text{tr}(\Sigma_{ee})^{0.5}$ sets the scale of utility. We estimate the model in two steps. The first step uses the service price data to recover an estimate of the effect of plan type in the total payment equations. The second step takes this estimate as given and finds the remaining payment and utility parameters.

Recovering the Effect of Plan Type on Payments Under A4, insurance plan type may affect service choice but insurance plan for a given plan type does not. Conditional on a service being received, the distribution of $v_{i,s}$ does not change with $W_i$ or $\text{Ins}_i$. The service price regressions in (4.1) can therefore be estimated by OLS. Knowing in addition the average share of total treatment payments that each service makes up allows us to determine how total treatment payments vary by plan type. Appendix C shows that we can estimate the effect of plan type on
treatment payments up to an approximation error which is second-order in the effect of plan type on service prices. The estimator $\hat{a}_{t}^{\text{Ins}}$ is a weighted sum of the estimators $\hat{\gamma}_{s}^{\text{Ins}}$: it is the sample average in each region of $\sum_{s} \hat{\gamma}_{s}^{\text{Ins}} w_{i,s,j,0}$ over those i that receive treatment j.

Physician compensation is determined by services rather than diagnoses. The payment for a chest X-ray does not depend on whether the patient suffers from AMI or angina. An advantage of using the services data is that we are not restricted to using data on AMI patients to estimate the first stage. Our procedure allows data from all diagnoses to be used in estimating the service price regressions, which gives more precise estimates of the effect of plan type on payments.\(^{33}\)

**Estimating the Remaining Payment and Utility Parameters** We implement the second step by Gibbs sampling.\(^{34}\) Let $Y_{i}$ denote the treatment that i receives; $Z_{i} = (Y_{i}, X_{i}, p_{i,y})$ treatment and total payment data for the ith patient; $Z = \{Z_{i}\}$ all treatment and total payment data; $p_{-} = \{p_{i,-y}\}$ all unobserved payments and $\bar{U} = \{\bar{U}_{i}\}$ all utilities. Define $\alpha^{X} = (\alpha_{1}^{X}, \ldots, \alpha_{5}^{X})$, $\alpha^{\text{Ins}} = (\alpha_{1}^{\text{Ins}}, \ldots, \alpha_{5}^{\text{Ins}})$ and $\bar{\alpha} = (\bar{\alpha}^{X}_{2}, \ldots, \bar{\alpha}^{X}_{5}, \beta^{p})$.

The Gibbs sampler draws parameters in four main steps: first, $p_{-}, \bar{U} | \alpha^{X}, \bar{\alpha}, \Sigma, \alpha^{\text{Ins}}, Z$; second, $\alpha^{X} | p_{-}, \bar{U}, \bar{\alpha}, \Sigma, \alpha^{\text{Ins}}, Z$; third, $\bar{\alpha} | p_{-}, \bar{U}, \alpha^{X}, \Sigma, \alpha^{\text{Ins}}, Z$; and finally $\Sigma | p_{-}, \bar{U}, \alpha^{X}, \bar{\alpha}, \alpha^{\text{Ins}}, Z$.

Appendix D describes these steps in detail. Unlike the Bayesian analysis of the standard multinomial probit model (e.g. Train (2009)), here the data augmentation is not only of unobserved utilities but also of unobserved payments ($p_{-}$ as well as $\bar{U}$). The estimate $\hat{\alpha}^{\text{Ins}}$ comes from the service data, as previously described. The scale of utility is not fixed in this Gibbs sampler. We report results on the identified parameters by dividing draws of the utility conditional mean parameters by $\text{tr}(\Sigma_{\text{err}})^{0.5}$ and of the utility error variance matrix by $\text{tr}(\Sigma_{\text{err}})$.

Let $L(\alpha^{X}, \alpha^{\text{Ins}}, \bar{\alpha}, \Sigma)$ be the likelihood of the payment and treatment data given by the pay-

\(^{33}\)This is somewhat analogous to two-sample instrumental variables.

\(^{34}\)An advantage of Bayesian methods like Gibbs sampling relative to maximum simulated likelihood is that consistency and efficiency can be guaranteed under weaker conditions on the number of simulation draws (Train (2009)). Geweke et al. (1994) find that Gibbs sampling slightly outperforms classical simulation methods in two Monte Carlo experiments. Gibbs sampling with data augmentation is due to Albert and Chib (1993); see also McCulloch and Rossi (1994) and Chib and Hamilton (2000).
ment equations (4.2) and the utility equations (6.1), under the distributional assumptions A1 - A3. Our estimator is asymptotically equivalent to a two step parametric M-estimator, in which first step obtains $\hat{\alpha}^{\text{Ins}}$ and the second step maximizes $L(\alpha^X, \hat{\alpha}^{\text{Ins}}, \hat{\beta}, \hat{\Sigma})$ with respect to $(\alpha^X, \hat{\beta}, \hat{\Sigma})$, subject to tr($\Sigma_{\alpha^{\text{Ins}}}$) = 1. Showing consistency and asymptotic normality is standard (e.g. Wooldridge (2004), section 14.2).\(^{35}\)

7 Results

7.1 Payments and Plan Types

Figure 2 shows the percentage effect of plan type on payment, as estimated from the service data. These estimates are driven entirely by variation in service prices, not service quantities. Standard errors are computed by the nonparametric bootstrap, resampling at the inpatient-episode level. The effects in each region are relative to PPOs. The summary statistics in Table 3 suggested that physicians’ treatment choice incentives vary by plan type. Figure 2 further supports this view, showing that these differences persist after controlling for the $W_i$ and accounting for missing payment data. The amount PPOs pay in excess of HMOs or POSs, for example, tends to be smaller for medical management than angioplasty. The differences are large enough to plausibly affect physician behavior: a reimbursement differential of 9 percent for angioplasty, as with PPOs versus POSs in the Midwest, is about $250. Payment patterns in the West appear rather different from those in other regions. In our model we allow the effect of plan type on payments to vary by region, to reflect this variation in the data.\(^{36}\)

\(^{35}\)An alternative to using the service data to estimate $\alpha^{\text{Ins}}$ and Gibbs sampling the remaining parameters is estimating all parameters by Gibbs sampling. The disadvantage of this procedure is that a missing data problem would reemerge, since patients do not receive all services. The missing service price data would need to be augmented for each patient, which would increase by several hundred the number of latent variables in the model. The two step procedure avoids this issue, and in particular avoids having to estimate the large dimensional variance matrix of service price errors.

\(^{36}\)When we also allow the price responsiveness parameter $\beta^p$ to vary region, we find positive and significant price responses in each region, although slightly smaller in the West than elsewhere.
7.2 Treatments and Payments

Magnitude of Payment Responses As we are using the variation in total payments generated by differences in per-unit service prices, we use “payment responses” and “price responses” interchangeably. Table 9 shows the average partial effects for the main specification. Increasing the payment to medical management by 1 percent increases the fraction of medical management cases by 8.62/100 percentage points, and reduces the fraction of angioplasties by 5.44/100 percentage points. Specification 1 of Table 10 displays the corresponding own-price elasticities. 12.1 percent of cases are treated by medical management, so the own-price elasticity is 8.62/12.1 ≈ 0.71. Increasing the payment to angioplasty by 1 percent results in a larger absolute increase in the number of angioplasties, but a smaller elasticity (18.75/55 ≈ 0.34). Elasticities range from 0.34 (angioplasty) to 0.87 (bypass).

Across all specifications in Table 10, there is a positive physician price response. Comparing 1 with 2 and 3 shows just how robust is the finding of a positive price response: not only does it remain after controlling for clinical and provider covariates, it does not even appear to decrease by much. Specification 4 mimics a “naive” procedure which ignores the selection bias in the first stage equations (4.2). It estimates αIns by OLS and imposes zero covariance between payment errors $u_i$ and utility errors $e_i$. The direction of the bias from ignoring selection is ambiguous in theory. We find the price responses to be somewhat underestimated and their precision overstated.

Payment Responses by AMI Severity The physician may not always know the patient’s plan type. This is more likely for more severe AMI, because there may be less time to obtain the patient’s insurance information. Physicians might also be less concerned with maximizing their income when treating severe AMI. Physicians’ payment response may consequently be smaller for more severe AMI. We use two proxies for AMI severity to examine this effect in our data.

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37 Symmetry of the average partial effects matrix is a consequence of constant β’s across treatments.
The first is ST elevation. ST elevation AMI are more severe and have higher mortality rates than non-ST elevation AMI (Swanton (2003); Fox et al. (2007)). The second is whether the patient has some recorded emergency department expenditure. Specifications 5 and 6 of Table 10 show the corresponding own-price elasticities. As expected, physicians appear to be more price responsive when treating less severe AMIs. The bypass price elasticity, for instance, is almost 50 percent higher for non-ST elevation AMI, and over 25 percent higher for patients with no emergency department expenditures.

**Payment Responses by Provider’s Plan Type Concentration** Specification 7 of Table 10 is informative about physician selection across plan types. If physician selection is an issue, there ought to be particularly large differences in treatments between providers dominated by a single plan type. Take for instance a comparison between a hospital which treats almost all HMO patients and one which treats almost all PPO patients. If physicians respond to prices patients will receive more conservative treatments in the HMO-dominated hospital. If in addition the HMO hospital’s physicians have more conservative practice styles, the treatment distributions in the HMO and the PPO hospital will be more different still. There is no evidence of this in the data. We calculate the Herfindahl index of plan type concentration for each provider in the data, and allow the price response parameter $\beta^p$ to vary by the tertiles of the index. Price elasticities appear mildly smaller when comparing providers with high plan type concentration.

**Testing for Payment Responses Under a Different Exogeneity Assumption** We form the fitted values $\mathbf{h}_s$ from the regression of $\text{Ins}_s$ on employer plan type shares and $X_i$. Utilities are

$$U_{i,j} = X_i (\beta^X_j + \alpha^X_j \beta^p) + \mathbf{h}_s \alpha^{\text{Ins}_s \beta^p} + r_{i,j}, \quad (7.1)$$
where \( r_{i,j} = e_{i,j} + (\text{Ins}_i - \text{Hs}_i)a^\text{Ins}_j \beta^p \). Testing the null of \( \beta^p = 0 \) under the assumption that \( e_i \perp \text{Hs}_i \) is straightforward, as the standard errors of \( \beta^p \) from the Gibbs sampler are valid.\(^{38}\) As discussed in Section 5, this allows people to select into plan types on their idiosyncratic unobservable characteristics, but requires that their choice of employer is unrelated to their employer’s plan type offerings. The test rejects at any conventional significance level, with a t-statistic of 4.6.

### 7.3 Counterfactuals and Welfare

**Treatments and Payments under Counterfactual Financial Incentives** We model bundled payments by setting to zero the part of the conditional mean of utility corresponding to financial incentives, so that utilities are \( U_{i,j} = X_i^\text{B} \beta^X_j + e_{i,j} \). We keep the utility error variances fixed in this counterfactual. It is not possible to identify how much of the utility error corresponds to physician financial incentives \( (\mathbb{E}(u_{i,j} | s_{i,j}) \beta^p) \) and how much to other factors \( (e^0_{i,j}) \), since the data are only informative about the sum of the two. This benchmark corresponds to the case where physicians’ signal \( s_i \) of the payment error is constant, so that financial incentives do not enter into the utility errors. The predicted outcomes under this counterfactual are in Table 11. The first four rows indicate that the in-sample model fit is reasonable. Our model predicts mean physician payments to within 1 percent of the actual value. The final rows suggests that bundling payments would greatly increase the fraction of AMI treated conservatively. 50 percent more patients would receive medical management or angiography. 18 percent fewer would receive either angioplasty or bypass, and 61 percent fewer would receive bypass alone.\(^{39}\)

These numbers are fairly substantial relative to international treatment differences. In an international clinical trial Gupta et al. (2003) find that in France and Israel 18 and 34 percent fewer

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\(^{38}\)Estimation is another matter, as if \( \beta^p = 0 \) the utility errors \( r_{i,j} \) in this model are heteroskedastic and non-normal. This precludes using the conjugate distributions which greatly simplify the Gibbs sampler. Computing a test statistic under the null \( \beta^p = 0 \) presents no such difficulties.

\(^{39}\)Hospitals’ investment responses to bundled payments are unmodeled here, but may further incline physicians to treat conservatively.
AMI patients receive angioplasty or bypass. Moise and Jacobzone (2003) find that Finland and Sweden perform about 60 to 70 percent fewer bypass surgeries than the United States.

Conservative treatments are cheaper than aggressive ones, so the distribution of treatments under the bundled payments counterfactual should be cheaper than the distribution of treatments under the current payment regime. We quantify this difference in cost, using current prices. In performing this exercise, our model captures the difference in treatment cost between the average and marginal patients. A patient who was just sick enough to receive angiography under fee-for-service may only receive medical management if payments are bundled. Because we have estimated the covariance matrix $\Sigma$, when we simulate counterfactual outcomes we can incorporate the utility and payment error correlation. The physician cost savings from bundled payments evaluated at current prices are 27 percent. If the savings on facility payments were of the same order, the average reduction in total costs would be around $7,600 per patient. Extrapolating to the entire United States, this corresponds to a reduction in expenditure of approximately $5 billion per year.\footnote{There are around 935,000 AMI in the United States each year (Roger and Turner (2012)). About 25% result in sudden death; the vast majority of the remainder (around 700,000) are treated in hospital (Wennberg and Birkmeyer (1999)).}

Our model also enables us to project how treatment patterns and physician payments would change if the payment schedule for a given plan type applied for all patients. Table 12 shows these results by region. They reflect the first stage estimates of Figure 2. For example, relative to all patients in the Northeast being in PPOs, if all were in POSs there would be 6 percent more medical management cases and total physician payments would be 4 percent lower.

\textbf{Welfare Consequences of Financial Incentives} The estimates from the main specification imply that 20 percent of patients (with a 6 percent standard error) are marginal: they would receive different treatments under fee-for-service and bundled payments. Even without post-treatment quality of life data, under some assumptions the model allows us to use physicians’ revealed
preference to quantify these patients’ change in welfare. Whereas randomized controlled trials from the medical literature are informative about average effects, assessing a payment reform requires understanding how the marginal patient is affected. Our model-based analysis has the advantage that we can study the effects on the marginal patients’ welfare.

Our welfare analysis captures the idea that physicians’ disutility of labor is an important determinant of whether bundled payments are better for patients than fee-for-service. In our analysis, if physicians’ payments always exactly cancel out their disutility of labor, they have no self-interested reason to choose one treatment over another, and their utility is aligned with their patients’. Bundled payments, for instance, maximize patient welfare in the case where the physician’s effort costs are constant across treatments. If costs are not constant, bundled payments may induce physicians to shirk, and fee-for-service incentives may be better for patients (Ellis and McGuire (1986)).

We assume utility can be decomposed as

\[ U_{i,j} = X_i^j \beta_j^X + (X_i^j \alpha_j^X + \text{Ins}_i^j \alpha_j^\text{Ins}) \beta_p + e_{i,j} \]

\[ = X_i^j \beta_j^X + e_{i,j} + \rho X_i^j \alpha_j^X \beta_p + (X_i^j \alpha_j^X + \text{Ins}_i^j \alpha_j^\text{Ins}) \beta_p - \rho X_i^j \alpha_j^X \beta_p \]

for some scalar \( \rho \). The implicit assumptions here are that the utility error belongs to the patient and that physician disutility of labor is proportional to physician utility from PPO revenue (the omitted plan type). The case of \( \rho = 0 \) corresponds to physician disutility of labor which is constant across treatments, and can be normalized to 0. Given \( \rho \), we can calculate the average value of the patient welfare term under bundled payments and fee-for-service. Because we have estimated how physician revenue translates into utility, we can express the welfare difference in dollar terms, as evaluated by the physicians in terms of their own revenue.

\[^{41}\] We focus on disutility of labor rather than the financial costs of treatment (e.g. for medical supplies), which are typically borne by the hospital rather than the physicians.
Figure 3 shows patients’ average welfare gain from bundled payments relative to fee-for-service as a function of \( \rho \), assuming that physicians value a dollar of patient welfare at one-tenth or one-fiftieth of the value they place on their own revenue. If \( \rho < 0.57 \), bundled payments are better for patients than fee-for-service. A simple back-of-the-envelope calculation suggests that bundled payments increase social surplus because of cost savings. If physicians value $50 of patient welfare at $1, and even if \( \rho = 1 \), the loss of patient welfare from bundled payments of slightly over $5,000 is outweighed by the reduction in total treatment costs of around $7,600.

8 Conclusion

Financial incentives do appear to influence how physicians manage AMI. The effects are particularly pronounced for less severely ill patients. Our estimates imply that it is not uncommon for patients to receive different treatments than they would if physicians received bundled payments. The costs of providing the more intensive treatments associated with fee-for-service payments are quite substantial, and suggest that bundled payments may increase social surplus.

Cardiology is one of the more evidence-based branches of medicine, and compared to other conditions AMI has fairly standardized treatment protocols. Moreover it is an acute condition, and supply is probably more likely to affect decisions when physicians are treating chronic illnesses, like congestive heart failure and cancer, or for elective procedures (Clemens and Gottlieb (2012); Wennberg (2010)). If payments influence physicians even for AMI management, for other conditions they are likely to have more substantial effects still.
References


Baicker, Katherine and Amitabha Chandra. “Medicare Spending, The Physician Workforce, And Beneficiaries’ Quality Of Care,” Health Affairs, April 2004.


Clemens, Jeffrey and Joshua D. Gottlieb, “Do Physicians’ Financial Incentives Affect Medical Treatment and Patient Health?,” February 2012, pp. 1–90.


___ and Ariel Pakes, “Hospital Choices, Hospital Prices and Financial Incentives to Physicians,” June 2012, pp. 1–50.


Kim, Daeho, “Medicare Payment Reform and Hospital Costs: Evidence from the Prospective Payment System and the Treatment of Cardiac Disease,” December 2011.


### Table 1: Plan Type Characteristics

“Network” means insurers incentivise patients to use certain providers. “Out-of-Network Coverage” means plan types make some contribution to out-of-network expenses. “Primary Care Physician” means plan types require referrals to specialists to be made through primary care physicians.

<table>
<thead>
<tr>
<th>Plan Type</th>
<th>Network</th>
<th>Out-of-Network Coverage</th>
<th>Primary Care Physician</th>
</tr>
</thead>
<tbody>
<tr>
<td>HMO</td>
<td></td>
<td>x</td>
<td></td>
</tr>
<tr>
<td>POS</td>
<td></td>
<td></td>
<td>x</td>
</tr>
<tr>
<td>PPO</td>
<td>x</td>
<td>n/a</td>
<td>x</td>
</tr>
<tr>
<td>Comprehensive</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

### Table 2: Insurance Plan Types and Treatments

The “%” rows display the percentage of AMI patients in the corresponding plan type who received the corresponding treatment. The “N” rows display the number of AMI patients with the corresponding plan type and treatment. Appendix A describes the codes used for categorizing diagnoses and treatments.
<table>
<thead>
<tr>
<th></th>
<th>MM</th>
<th>A'graphy</th>
<th>A'plasty</th>
<th>Bypass</th>
<th>Other</th>
<th>All Treatments</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>HMO</strong></td>
<td>1,836</td>
<td>1,782</td>
<td>2,888</td>
<td>8,497</td>
<td>7,104</td>
<td>3,291</td>
</tr>
<tr>
<td></td>
<td>(2,525)</td>
<td>(1,980)</td>
<td>(2,421)</td>
<td>(4,182)</td>
<td>(4,950)</td>
<td>(3,463)</td>
</tr>
<tr>
<td><strong>POS</strong></td>
<td>1,115</td>
<td>1,687</td>
<td>2,841</td>
<td>8,787</td>
<td>7,919</td>
<td>3,432</td>
</tr>
<tr>
<td></td>
<td>(1,355)</td>
<td>(1,345)</td>
<td>(1,886)</td>
<td>(3,841)</td>
<td>(4,871)</td>
<td>(3,388)</td>
</tr>
<tr>
<td><strong>PPO</strong></td>
<td>1,152</td>
<td>1,670</td>
<td>2,958</td>
<td>9,087</td>
<td>7,852</td>
<td>3,537</td>
</tr>
<tr>
<td></td>
<td>(1,405)</td>
<td>(1,344)</td>
<td>(2,153)</td>
<td>(4,164)</td>
<td>(4,956)</td>
<td>(3,530)</td>
</tr>
<tr>
<td><strong>Comprehensive</strong></td>
<td>1,048</td>
<td>1,600</td>
<td>2,506</td>
<td>8,188</td>
<td>6,670</td>
<td>3,066</td>
</tr>
<tr>
<td></td>
<td>(1,367)</td>
<td>(1,407)</td>
<td>(1,812)</td>
<td>(3,774)</td>
<td>(4,771)</td>
<td>(3,231)</td>
</tr>
<tr>
<td><strong>All Plan Types</strong></td>
<td>1,264</td>
<td>1,678</td>
<td>2,878</td>
<td>8,839</td>
<td>7,604</td>
<td>3,426</td>
</tr>
<tr>
<td></td>
<td>(1,697)</td>
<td>(1,459)</td>
<td>(2,128)</td>
<td>(4,085)</td>
<td>(4,941)</td>
<td>(3,470)</td>
</tr>
</tbody>
</table>

**Table A**: Total Physician Payments, by Insurance Plan Type and Treatment

<table>
<thead>
<tr>
<th></th>
<th>MM</th>
<th>A'graphy</th>
<th>A'plasty</th>
<th>Bypass</th>
<th>Other</th>
<th>All Treatments</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>HMO</strong></td>
<td>10,319</td>
<td>10,209</td>
<td>20,643</td>
<td>41,633</td>
<td>48,824</td>
<td>21,107</td>
</tr>
<tr>
<td></td>
<td>(12,496)</td>
<td>(10,447)</td>
<td>(17,001)</td>
<td>(29,476)</td>
<td>(37,369)</td>
<td>(22,467)</td>
</tr>
<tr>
<td><strong>POS</strong></td>
<td>11,040</td>
<td>10,863</td>
<td>23,759</td>
<td>43,412</td>
<td>51,136</td>
<td>24,478</td>
</tr>
<tr>
<td></td>
<td>(12,849)</td>
<td>(9,582)</td>
<td>(15,935)</td>
<td>(25,485)</td>
<td>(35,048)</td>
<td>(22,084)</td>
</tr>
<tr>
<td><strong>PPO</strong></td>
<td>11,004</td>
<td>12,652</td>
<td>25,075</td>
<td>49,448</td>
<td>53,154</td>
<td>26,366</td>
</tr>
<tr>
<td></td>
<td>(13,665)</td>
<td>(11,487)</td>
<td>(16,943)</td>
<td>(30,023)</td>
<td>(35,390)</td>
<td>(23,702)</td>
</tr>
<tr>
<td><strong>Comprehensive</strong></td>
<td>9,516</td>
<td>11,491</td>
<td>21,150</td>
<td>42,696</td>
<td>46,165</td>
<td>22,257</td>
</tr>
<tr>
<td></td>
<td>(11,030)</td>
<td>(10,956)</td>
<td>(15,130)</td>
<td>(26,542)</td>
<td>(35,527)</td>
<td>(21,692)</td>
</tr>
<tr>
<td><strong>All Plan Types</strong></td>
<td>10,627</td>
<td>11,955</td>
<td>23,850</td>
<td>46,754</td>
<td>51,447</td>
<td>24,866</td>
</tr>
<tr>
<td></td>
<td>(12,958)</td>
<td>(11,121)</td>
<td>(16,718)</td>
<td>(29,143)</td>
<td>(35,706)</td>
<td>(23,186)</td>
</tr>
</tbody>
</table>

**Table B**: Total Facility Payments, by Insurance Plan Type and Treatment

**Table 3**: Payments, by Insurance Plan Type and Treatment

Total physician payments are the sum in dollars of all payments made to all physicians involved in treating the AMI, from the patient and the insurer. Total facility payments are the sum in dollars of all payments made to all facilities, including hospitals, involved in treating the AMI, from the patient and the insurer. Each cell contains the mean and standard deviation of total payments for that plan type and treatment.
<table>
<thead>
<tr>
<th>Service</th>
<th>N</th>
<th>HMO</th>
<th>POS</th>
<th>PPO</th>
<th>Comp.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Initial Hospital Care</td>
<td>963,085</td>
<td>185</td>
<td>188</td>
<td>191</td>
<td>179</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(84)</td>
<td>(66)</td>
<td>(62)</td>
<td>(54)</td>
</tr>
<tr>
<td>Chest X-ray</td>
<td>818,381</td>
<td>16</td>
<td>17</td>
<td>16</td>
<td>15</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(10)</td>
<td>(9)</td>
<td>(9)</td>
<td>(9)</td>
</tr>
<tr>
<td>Electrocardiogram</td>
<td>736,577</td>
<td>16</td>
<td>17</td>
<td>16</td>
<td>14</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(11)</td>
<td>(12)</td>
<td>(10)</td>
<td>(9)</td>
</tr>
<tr>
<td>Angiography Contrast Injection</td>
<td>174,899</td>
<td>51</td>
<td>56</td>
<td>63</td>
<td>49</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(54)</td>
<td>(61)</td>
<td>(59)</td>
<td>(51)</td>
</tr>
<tr>
<td>Stent Placement</td>
<td>90,595</td>
<td>1195</td>
<td>1248</td>
<td>1346</td>
<td>1244</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(683)</td>
<td>(592)</td>
<td>(685)</td>
<td>(705)</td>
</tr>
<tr>
<td>Single Bypass</td>
<td>28,706</td>
<td>2042</td>
<td>(1221)</td>
<td>(1284)</td>
<td>(1301)</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

**Table 4: Physician Prices of Selected Services by Plan Type**

Table shows average and standard deviation of unit prices paid to physicians in dollars for selected services. “Initial Hospital Care” is CPT code 99223: “Initial Hospital Care, per day, for the evaluation and management of a patient, which requires these three components: a comprehensive history; a comprehensive examination; and medical decision making of high complexity.” “Chest X-ray” is CPT code 71010: “Radiologic examination, chest; single view, frontal.” “Electrocardiogram” is CPT code 93010: “Electrocardiogram, routine ECG with at least 12 leads; with interpretation and report only.” “Angiography Contrast Injection” is CPT code 93545: “Injection procedure during cardiac catheterization; for selective opacification of arterial conduits, whether native or used for bypass, for selective coronary angiography.” “Stent Placement” is CPT code 92980: “Transcatheter placement of an intracoronary stent(s), percutaneous, with or without other therapeutic intervention, any method; single vessel.” “Single Bypass” is CPT code 33533: “Coronary artery bypass, using arterial graft(s); single arterial graft.”
<table>
<thead>
<tr>
<th>N</th>
<th>No Surgery</th>
<th>Surgery</th>
</tr>
</thead>
<tbody>
<tr>
<td>HMO</td>
<td>4,807 (15,318)</td>
<td>10,846 (15,199)</td>
</tr>
<tr>
<td>POS</td>
<td>6,881 (19,088)</td>
<td>13,524 (17,181)</td>
</tr>
<tr>
<td>PPO</td>
<td>5,863 (18,412)</td>
<td>14,781 (18,674)</td>
</tr>
<tr>
<td>Comprehensive</td>
<td>4,706 (15,992)</td>
<td>15,769 (19,562)</td>
</tr>
</tbody>
</table>

**A** Prostate Cancer

<table>
<thead>
<tr>
<th>N</th>
<th>No Surgery</th>
<th>Surgery</th>
</tr>
</thead>
<tbody>
<tr>
<td>HMO</td>
<td>867 (2,551)</td>
<td>4,311 (4,345)</td>
</tr>
<tr>
<td>POS</td>
<td>740 (3,761)</td>
<td>4,731 (5,994)</td>
</tr>
<tr>
<td>PPO</td>
<td>691 (3,347)</td>
<td>5,369 (4,378)</td>
</tr>
<tr>
<td>Comprehensive</td>
<td>667 (2,102)</td>
<td>4,581 (3,207)</td>
</tr>
</tbody>
</table>

**C** Inguinal Hernia

<table>
<thead>
<tr>
<th>N</th>
<th>No Surgery</th>
<th>Surgery</th>
</tr>
</thead>
<tbody>
<tr>
<td>HMO</td>
<td>1,210 (2,328)</td>
<td>10,193 (8,536)</td>
</tr>
<tr>
<td>POS</td>
<td>1,717 (3,361)</td>
<td>13,584 (11,403)</td>
</tr>
<tr>
<td>PPO</td>
<td>1,597 (3,216)</td>
<td>13,660 (11,848)</td>
</tr>
<tr>
<td>Comprehensive</td>
<td>1,601 (3,091)</td>
<td>12,307 (10,502)</td>
</tr>
</tbody>
</table>

**D** Spinal Disc Herniation

**TABLE 5**: Total Physician Payments by Plan Type and Treatment for Other Diagnoses

Table includes everyone with a diagnosis of the corresponding condition in inpatient or outpatient records between 2002 and 2007. Prostate cancer includes ICD-9 diagnosis codes 185.X; prostate surgery includes CPT codes 55801 - 55866, 52601 - 52640, 53850 - 53852 and ICD-9 procedure codes 60.2X - 60.6X. Breast cancer includes ICD-9 diagnosis codes 174.X; mastectomy includes CPT codes 19180 - 19240, 19303 - 19307 and ICD-9 procedure codes 85.4X and 85.7X. Inguinal hernia includes ICD-9 diagnosis codes 550.X; inguinal hernia repair surgery includes CPT codes 49491 - 49525 and 49650 - 49659 and ICD-9 procedure codes 53.XX. Spinal disc herniation includes ICD-9 diagnosis codes 722.0 - 722.2; spinal surgery includes CPT codes 22100 - 22899 and ICD-9 procedure codes 80.XX, 81.XX and 03.XX.
<table>
<thead>
<tr>
<th>Variable</th>
<th>Value</th>
<th>Description</th>
<th>Reference</th>
</tr>
</thead>
<tbody>
<tr>
<td>Age</td>
<td>54.45</td>
<td>Diabetes with Chronic Complications</td>
<td>0.02</td>
</tr>
<tr>
<td>Male</td>
<td>0.73</td>
<td>Obesity</td>
<td>0.05</td>
</tr>
<tr>
<td>Urban Place of Residence</td>
<td>0.75</td>
<td>Smoker</td>
<td>0.14</td>
</tr>
<tr>
<td>Congestive Heart Failure</td>
<td>0.13</td>
<td>Cardiac Dysfunction</td>
<td>0.20</td>
</tr>
<tr>
<td>Valvular Disease</td>
<td>0.10</td>
<td>Cardiomyopathy</td>
<td>0.03</td>
</tr>
<tr>
<td>Hypertension</td>
<td>0.31</td>
<td>Initial Episode of Care</td>
<td>0.99</td>
</tr>
<tr>
<td>Chronic Pulmonary Disease</td>
<td>0.08</td>
<td>ST Elevation</td>
<td>0.51</td>
</tr>
<tr>
<td>Diabetes without Chronic Complications</td>
<td>0.15</td>
<td>Some Emergency Dept. Expenditure</td>
<td>0.72</td>
</tr>
</tbody>
</table>

(A) Contemporaneous Patient-Level Variables, N = 66,014

<table>
<thead>
<tr>
<th>Variable</th>
<th>Value</th>
<th>Description</th>
<th>Reference</th>
</tr>
</thead>
<tbody>
<tr>
<td>Fraction of Physicians with Medical Specialty</td>
<td>0.61</td>
<td>No. Hospitals with Adult Cardiac Cath. Facilities Per Million</td>
<td>7.45</td>
</tr>
<tr>
<td>Median Age</td>
<td>35.73</td>
<td>No. Hospitals with Adult Cardiac Surgery Facilities Per Million</td>
<td>6.22</td>
</tr>
<tr>
<td>Median Household Income (Thousands)</td>
<td>45.89</td>
<td>No. Hospital Beds for Cardiac Intensive Care Per Million</td>
<td>93.64</td>
</tr>
<tr>
<td>Ischemic Heart Disease Mortality Per Thousand</td>
<td>1.54</td>
<td>No. Inpatient Surgeries Per Thousand</td>
<td>53.04</td>
</tr>
</tbody>
</table>

(B) Contemporaneous County-Level Variables, N = 66,014

<table>
<thead>
<tr>
<th>Variable</th>
<th>Value</th>
<th>Description</th>
<th>Reference</th>
</tr>
</thead>
<tbody>
<tr>
<td>No Inpatient Expenditure</td>
<td>0.79</td>
<td>Admitted for IHD and Received Angioplasty</td>
<td>0.04</td>
</tr>
<tr>
<td>Total Inpatient Expenditure (Thousands)</td>
<td>4.38</td>
<td>Admitted for IHD and Received Bypass Surgery</td>
<td>0.01</td>
</tr>
<tr>
<td>Admitted for IHD and Received Medical Management</td>
<td>0.06</td>
<td>Admitted for IHD and Received Bypass Surgery</td>
<td>0.01</td>
</tr>
<tr>
<td>Admitted for IHD and Received Angiography</td>
<td>0.03</td>
<td>Plan Type Change</td>
<td>0.01</td>
</tr>
</tbody>
</table>

(C) Medical and Insurance History Over 6 Months Prior to AMI, N = 50,454

**TABLE 6: Summary Statistics, Selected Variables**

All variables are binary unless standard deviations are displayed. We use the Healthcare Cost and Utilization Project’s description of Elixhauser comorbidity ICD-9 codes to identify Elixhauser comorbidities, some of which are displayed in Table 6a. Contemporaneous county-level variables are obtained from the Area Resources File. “IHD” stands for ischemic heart disease, which corresponds to the ICD-9 codes 410, 411, 413, 414 and 786.

45
<table>
<thead>
<tr>
<th></th>
<th>AMI</th>
<th>Other Acute &amp; Subacute Ischemic Heart Disease</th>
<th>Angina Pectoris</th>
<th>Other Chronic Ischemic Heart Disease</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>N = 60,321,748</strong></td>
<td>0.092 (0.010)</td>
<td>0.009 (0.004)</td>
<td>0.006 (0.003)</td>
<td>0.130 (0.016)</td>
</tr>
<tr>
<td>HMO</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>POS</td>
<td>-0.056 (0.013)</td>
<td>-0.025 (0.004)</td>
<td>-0.009 (0.003)</td>
<td>-0.125 (0.019)</td>
</tr>
<tr>
<td>Comprehensive</td>
<td>0.052 (0.020)</td>
<td>0.034 (0.008)</td>
<td>0.007 (0.005)</td>
<td>0.126 (0.032)</td>
</tr>
<tr>
<td><strong>Mean of Dependent Variable</strong></td>
<td>0.893</td>
<td>0.116</td>
<td>0.054</td>
<td>1.800</td>
</tr>
</tbody>
</table>

(A) Heart Disease Related Conditions

<table>
<thead>
<tr>
<th></th>
<th>Cancer</th>
<th>Chronic Obstructive Pulmonary Disease</th>
<th>Cerebrovascular Disease</th>
<th>Diabetes</th>
<th>Flu and Pneumonia</th>
<th>Kidney Disease</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>N = 60,375,372</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>HMO</td>
<td>-0.023 (0.016)</td>
<td>0.132 (0.012)</td>
<td>0.068 (0.011)</td>
<td>0.051 (0.010)</td>
<td>0.041 (0.013)</td>
<td>0.033 (0.06)</td>
</tr>
<tr>
<td>POS</td>
<td>-0.020 (0.019)</td>
<td>-0.049 (0.015)</td>
<td>-0.046 (0.013)</td>
<td>-0.017 (0.011)</td>
<td>-0.084 (0.016)</td>
<td>-0.001 (0.007)</td>
</tr>
<tr>
<td>Comprehensive</td>
<td>0.017 (0.029)</td>
<td>0.302 (0.023)</td>
<td>0.137 (0.021)</td>
<td>0.170 (0.017)</td>
<td>0.245 (0.023)</td>
<td>0.093 (0.011)</td>
</tr>
<tr>
<td><strong>Mean of Dependent Variable</strong></td>
<td>1.884</td>
<td>0.983</td>
<td>0.862</td>
<td>0.620</td>
<td>1.241</td>
<td>0.258</td>
</tr>
</tbody>
</table>

(B) Other Conditions

**Table 7:** Admission Probabilities by Plan Type

An observation is a person-year and standard errors are clustered at the person-level. The sample is restricted to those in the data for the full year. The dependent variable is 1000 if that person-year is admitted for the corresponding condition. PPO is the omitted plan type. Not shown are controls for year, age, state, urban place of residence, sex, and all variables in Table 6b. AMI is ICD-9 diagnosis code 410, other acute and subacute forms of ischemic heart disease is 411, angina pectoris is 413, other forms of chronic ischemic heart disease is 414, cancer is 140 - 208, chronic obstructive pulmonary disease (and allied conditions) is 490 - 496, cerebrovascular disease is 430 - 438, diabetes is 250, influenza and pneumonia is 480 - 487, and kidney disease (nephritis, nephrotic syndrome and nephrosis) is 580 - 589.
\[
\begin{array}{|c|c|c|}
\hline
\text{Plan Types} & \text{Mean} & \text{Std. Dev.} \\
\hline
\text{HMO} & 554 & (1,278) \\
\text{POS} & 11,728 & (4,438) \\
\text{PPO} & 10,616 & (5,074) \\
\text{Comprehensive} & 9,399 & (2,944) \\
\text{All Plan Types} & 9,689 & (5,548) \\
\hline
\end{array}
\]

**Table 8:** Spending Thresholds

For patients for whom detailed coinsurance and copayment data is available, the table presents the dollar amount of total medical expenses (facility and physician) beyond which the patient is not financially liable.

<table>
<thead>
<tr>
<th></th>
<th>MM</th>
<th>A’graphy</th>
<th>A’plasty</th>
<th>Bypass</th>
<th>Other</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>MM</strong></td>
<td>8.62</td>
<td>-1.06</td>
<td>-5.44</td>
<td>-1.16</td>
<td>-0.95</td>
</tr>
<tr>
<td></td>
<td>(2.89)</td>
<td>(0.37)</td>
<td>(1.83)</td>
<td>(0.44)</td>
<td>(0.32)</td>
</tr>
<tr>
<td><strong>A’graphy</strong></td>
<td>-1.06</td>
<td>8.52</td>
<td>-5.25</td>
<td>-1.45</td>
<td>-0.76</td>
</tr>
<tr>
<td></td>
<td>(0.37)</td>
<td>(2.89)</td>
<td>(1.84)</td>
<td>(0.82)</td>
<td>(0.27)</td>
</tr>
<tr>
<td><strong>A’plasty</strong></td>
<td>-5.44</td>
<td>-5.25</td>
<td>18.75</td>
<td>-3.61</td>
<td>-4.45</td>
</tr>
<tr>
<td></td>
<td>(1.83)</td>
<td>(1.84)</td>
<td>(6.34)</td>
<td>(1.23)</td>
<td>(1.56)</td>
</tr>
<tr>
<td><strong>Bypass</strong></td>
<td>-1.16</td>
<td>-1.45</td>
<td>-3.61</td>
<td>7.12</td>
<td>-0.90</td>
</tr>
<tr>
<td></td>
<td>(0.44)</td>
<td>(0.82)</td>
<td>(1.23)</td>
<td>(2.46)</td>
<td>(0.43)</td>
</tr>
<tr>
<td><strong>Other</strong></td>
<td>-0.95</td>
<td>0.76</td>
<td>4.45</td>
<td>-0.90</td>
<td>7.06</td>
</tr>
<tr>
<td></td>
<td>(0.32)</td>
<td>(0.27)</td>
<td>(1.56)</td>
<td>(0.43)</td>
<td>(2.42)</td>
</tr>
</tbody>
</table>

**Table 9:** Average Partial Effects of Prices on Treatments, Main Specification

The \((j, k)\)th entry is 100 times the percentage point increase in the share of treatment \(j\) resulting from a 1 percent increase in the price paid for treatment \(k\), averaged over patients. Choice probabilities are calculated by GHK simulation. The included regressors are the demographic, clinical and provider covariates described in Section 4.3.
<table>
<thead>
<tr>
<th>(1) Main Specification</th>
<th>MM</th>
<th>A’graphy</th>
<th>A’plasty</th>
<th>Bypass</th>
<th>Other</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>0.71</td>
<td>0.55</td>
<td>0.34</td>
<td>0.87</td>
<td>0.75</td>
</tr>
<tr>
<td></td>
<td>(0.24)</td>
<td>(0.19)</td>
<td>(0.12)</td>
<td>(0.30)</td>
<td>(0.26)</td>
</tr>
<tr>
<td>(2) No Provider Covariates</td>
<td>0.74</td>
<td>0.45</td>
<td>0.18</td>
<td>0.67</td>
<td>0.38</td>
</tr>
<tr>
<td></td>
<td>(0.36)</td>
<td>(0.21)</td>
<td>(0.09)</td>
<td>(0.32)</td>
<td>(0.18)</td>
</tr>
<tr>
<td>(3) No Clinical Covariates</td>
<td>1.19</td>
<td>0.36</td>
<td>0.24</td>
<td>1.10</td>
<td>1.08</td>
</tr>
<tr>
<td></td>
<td>(0.45)</td>
<td>(0.14)</td>
<td>(0.09)</td>
<td>(0.42)</td>
<td>(0.41)</td>
</tr>
<tr>
<td>(4) No Selection Correction</td>
<td>0.62</td>
<td>0.37</td>
<td>0.20</td>
<td>0.70</td>
<td>0.58</td>
</tr>
<tr>
<td></td>
<td>(0.14)</td>
<td>(0.08)</td>
<td>(0.06)</td>
<td>(0.14)</td>
<td>(0.12)</td>
</tr>
<tr>
<td>(5) ST Elevation</td>
<td>0.45</td>
<td>0.18</td>
<td>0.10</td>
<td>0.35</td>
<td>0.29</td>
</tr>
<tr>
<td>Non-ST Elevation</td>
<td>(0.23)</td>
<td>(0.10)</td>
<td>(0.35)</td>
<td>(0.29)</td>
<td></td>
</tr>
<tr>
<td></td>
<td>0.74</td>
<td>0.69</td>
<td>0.23</td>
<td>1.04</td>
<td>0.53</td>
</tr>
<tr>
<td></td>
<td>(0.32)</td>
<td>(0.30)</td>
<td>(0.10)</td>
<td>(0.45)</td>
<td>(0.23)</td>
</tr>
<tr>
<td>(6) Some Emergency Spending</td>
<td>0.61</td>
<td>0.55</td>
<td>0.23</td>
<td>0.89</td>
<td>0.61</td>
</tr>
<tr>
<td>Non-Emergency Spending</td>
<td>(0.27)</td>
<td>(0.24)</td>
<td>(0.10)</td>
<td>(0.38)</td>
<td>(0.26)</td>
</tr>
<tr>
<td></td>
<td>0.72</td>
<td>0.60</td>
<td>0.24</td>
<td>1.13</td>
<td>0.62</td>
</tr>
<tr>
<td></td>
<td>(0.29)</td>
<td>(0.24)</td>
<td>(0.10)</td>
<td>(0.45)</td>
<td>(0.25)</td>
</tr>
<tr>
<td>(7) High Provider Concentration</td>
<td>0.54</td>
<td>0.42</td>
<td>0.16</td>
<td>0.67</td>
<td>0.40</td>
</tr>
<tr>
<td></td>
<td>(0.38)</td>
<td>(0.30)</td>
<td>(0.12)</td>
<td>(0.47)</td>
<td>(0.29)</td>
</tr>
<tr>
<td>Medium Provider Concentration</td>
<td>0.56</td>
<td>0.46</td>
<td>0.19</td>
<td>0.82</td>
<td>0.51</td>
</tr>
<tr>
<td></td>
<td>(0.35)</td>
<td>(0.30)</td>
<td>(0.13)</td>
<td>(0.52)</td>
<td>(0.33)</td>
</tr>
<tr>
<td>Low Provider Concentration</td>
<td>0.59</td>
<td>0.47</td>
<td>0.20</td>
<td>0.86</td>
<td>0.55</td>
</tr>
<tr>
<td></td>
<td>(0.35)</td>
<td>(0.29)</td>
<td>(0.13)</td>
<td>(0.51)</td>
<td>(0.34)</td>
</tr>
</tbody>
</table>

**Table 10**: Own-Price Elasticities, Various Specifications

Double lines separate specifications. All specifications include as regressors the demographic covariates described in Section 4.3. Unless stated otherwise, all specifications also include the clinical and provider covariates, correct for selection by estimating $\alpha_{ins}$ using the service data, and allow for correlation between payment and utility errors. “No Selection Correction” estimates $\alpha_{ins}$ by running OLS on the first stage equations (4.2), and imposes independence of payment and utility errors. Specifications (5), (6), and (7) allow $\beta_p$ to vary by patient group, for the named groups.
<table>
<thead>
<tr>
<th></th>
<th>MM</th>
<th>A’graphy</th>
<th>A’plasty</th>
<th>Bypass</th>
<th>Other</th>
<th>All Treatments</th>
</tr>
</thead>
<tbody>
<tr>
<td>Actual Payments</td>
<td>1,264</td>
<td>1,678</td>
<td>2,878</td>
<td>8,839</td>
<td>7,604</td>
<td>3,426</td>
</tr>
<tr>
<td>Actual Shares</td>
<td>12.1</td>
<td>15.4</td>
<td>54.9</td>
<td>8.2</td>
<td>9.4</td>
<td>100.0</td>
</tr>
<tr>
<td>Predicted Payments</td>
<td>1,333</td>
<td>1,744</td>
<td>2,885</td>
<td>9,242</td>
<td>7,726</td>
<td>3,462</td>
</tr>
<tr>
<td></td>
<td>(27)</td>
<td>(36)</td>
<td>(34)</td>
<td>(331)</td>
<td>(140)</td>
<td>(53)</td>
</tr>
<tr>
<td>Predicted Shares</td>
<td>12.1</td>
<td>17.4</td>
<td>53.2</td>
<td>8.2</td>
<td>9.1</td>
<td>100.0</td>
</tr>
<tr>
<td></td>
<td>(0.2)</td>
<td>(0.3)</td>
<td>(0.4)</td>
<td>(0.4)</td>
<td>(0.2)</td>
<td></td>
</tr>
<tr>
<td>Bundled Payments, Costs</td>
<td>1,524</td>
<td>1,796</td>
<td>2,540</td>
<td>7,815</td>
<td>6,851</td>
<td>2,530</td>
</tr>
<tr>
<td></td>
<td>(86)</td>
<td>(53)</td>
<td>(114)</td>
<td>(1050)</td>
<td>(409)</td>
<td>(226)</td>
</tr>
<tr>
<td>Bundled Payments, Shares</td>
<td>18.9</td>
<td>26.3</td>
<td>46.9</td>
<td>3.2</td>
<td>4.8</td>
<td>100.0</td>
</tr>
<tr>
<td></td>
<td>(2.2)</td>
<td>(3.1)</td>
<td>(2.9)</td>
<td>(1.1)</td>
<td>(1.2)</td>
<td></td>
</tr>
</tbody>
</table>

**TABLE 11:** Treatments and Physician Payments, Actual and Predicted

Table shows actual average physician payments and treatment shares, model predicted payments and shares from the main specification with $\beta^p$ equal to its estimated value, and model predicted payments and shares from the main specification with $\beta^p = 0$ (the bundled payments counterfactual). We evaluate the costs of treatments provided under bundled payments using the predicted payments under the current fee-for-service system.
<table>
<thead>
<tr>
<th>Region</th>
<th>Plan Type</th>
<th>N</th>
<th>MM</th>
<th>A’graphy</th>
<th>A’plasty</th>
<th>Bypass</th>
<th>Other</th>
<th>Payments</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Northeast</td>
<td>HMO</td>
<td>969</td>
<td>16.7</td>
<td>16.0</td>
<td>52.0</td>
<td>6.8</td>
<td>8.5</td>
<td>3,097</td>
</tr>
<tr>
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<td>POS</td>
<td>1,023</td>
<td>17.0</td>
<td>16.0</td>
<td>51.5</td>
<td>7.0</td>
<td>8.4</td>
<td>3,179</td>
</tr>
<tr>
<td></td>
<td>PPO</td>
<td>2,833</td>
<td>16.1</td>
<td>16.1</td>
<td>52.5</td>
<td>6.9</td>
<td>8.4</td>
<td>3,320</td>
</tr>
<tr>
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<td>Comp</td>
<td>943</td>
<td>16.2</td>
<td>16.6</td>
<td>55.4</td>
<td>8.1</td>
<td>9.9</td>
<td>3,261</td>
</tr>
<tr>
<td>Midwest</td>
<td>HMO</td>
<td>1,738</td>
<td>10.0</td>
<td>16.7</td>
<td>54.7</td>
<td>8.3</td>
<td>10.1</td>
<td>3,359</td>
</tr>
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<td>POS</td>
<td>1,446</td>
<td>10.2</td>
<td>16.6</td>
<td>55.8</td>
<td>8.1</td>
<td>9.9</td>
<td>3,570</td>
</tr>
<tr>
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<td>PPO</td>
<td>11,782</td>
<td>9.6</td>
<td>16.6</td>
<td>55.7</td>
<td>8.2</td>
<td>9.9</td>
<td>3,399</td>
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<tr>
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<td>5,375</td>
<td>9.6</td>
<td>18.7</td>
<td>51.8</td>
<td>8.8</td>
<td>9.1</td>
<td>3,341</td>
</tr>
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<td>South</td>
<td>HMO</td>
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<td>18.9</td>
<td>51.6</td>
<td>8.8</td>
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<td>PPO</td>
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<td>9.0</td>
<td>9.1</td>
<td>3,423</td>
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<tr>
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<td>Comp</td>
<td>2,304</td>
<td>11.2</td>
<td>15.1</td>
<td>52.0</td>
<td>7.4</td>
<td>7.9</td>
<td>3,605</td>
</tr>
<tr>
<td>West</td>
<td>HMO</td>
<td>2,910</td>
<td>17.7</td>
<td>14.8</td>
<td>52.5</td>
<td>7.3</td>
<td>7.9</td>
<td>3,613</td>
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<td>POS</td>
<td>485</td>
<td>18.4</td>
<td>14.8</td>
<td>51.8</td>
<td>7.4</td>
<td>7.9</td>
<td>3,367</td>
</tr>
<tr>
<td></td>
<td>PPO</td>
<td>4,115</td>
<td>17.5</td>
<td>14.8</td>
<td>51.8</td>
<td>7.4</td>
<td>7.9</td>
<td>3,367</td>
</tr>
<tr>
<td></td>
<td>Comp</td>
<td>521</td>
<td>18.0</td>
<td>15.1</td>
<td>52.0</td>
<td>7.4</td>
<td>7.9</td>
<td>3,605</td>
</tr>
</tbody>
</table>
Table 12: Treatment Shares and Payments for Different Payment Schedules
Rows show the estimated treatment shares and total physician payments that would result from all patients in the corresponding region having insurance which pays like the corresponding plan type. The “N” column displays the number of patients in the corresponding region and plan type.
**Figure 1**: Acute Myocardial Infarction Treatments
Adapted from Cutler et al. (2000). Some patients may receive another treatment, if the above are unsuitable or inadequate.
**Figure 2: Effect of Plan Type on Payments**

Figure depicts estimates and 95 percent confidence intervals of the parameters in $\alpha^{\text{Ins}}$ from (4.2), as obtained from the service data. There are 22,078,493 service data observations. The regressors in the service price regressions are the plan type by region interactions $\text{Ins}_i$, the service quantities $q_{i,s,j}$, state and year fixed effects, and where available, CPT modifier codes. PPO is the omitted category against which changes are measured in each region. Standard errors are computed from 50 bootstrap draws, where services are resampled at the inpatient-episode level.
**Figure 3:** Patient Welfare Gain from Bundled Payments vs. Cost-Payment Ratio

Welfare losses from patient utility level $P_1$ to $P_2$ calculated as the certainty equivalent of physician payments for the chosen treatment $j$, multiplied by the percent change in payments corresponding to the welfare loss, and a factor representing the rate at which physicians trade off their patients’ welfare for their own income: $d \exp(X'_j \sigma_j^x + \text{Ins}'_j \sigma_j^{\text{ins}}) [\exp((P_1 - P_2)/\beta) - 1]$, for $d = 10$ or 50.
APPENDICES

A Data

AMI Patients  This sample is used to estimate the payment equations (4.2) and the discrete choice model (6.1) given the estimate of $\alpha^{\text{Ins}}$ from the first stage. It includes only those patients with AMI as their primary diagnosis (ICD-9 diagnosis code 410). Patients are categorized as receiving medical management if their admission has a non-surgical DRG assigned and there is no record of their receiving angiography, angioplasty or bypass surgery, and as receiving other surgery if they have a surgical DRG assigned but their principal procedure is not angiography, angioplasty or bypass surgery. For angiography, angioplasty and bypass surgery the codes are:

**Coronary Angiography**

ICD-9 Procedure Codes:  8850  8851  8852  8853  8854  8855  8856  8857  8858  3721  3722  3723.

CPT Codes:  93501  93503  93508  93510  93511  93514  93524  93526  93527  93528  93529  93539  93540  93541  93542  93543  93544  93545  93555  93556  93561  93562  93571  93572.

**Coronary Angioplasty**

ICD-9 Procedure Codes:  0066  3601  3602  3605  3606  3607  3609.

CPT Codes:  92980  92981  92982  92984.

**Coronary Bypass Surgery**

ICD-9 Procedure Codes:  3610  3611  3612  3613  3614  3615  3616  3617  3619.

CPT Codes:  33510  33511  33512  33513  33514  33516  33517  33518  33519  33521  33522  33523  33530  33533  33534  33535  33536.
Patients who receive multiple treatments are assigned to the most invasive of their treatments (where the order of "invasiveness" from least to most is medical management, angiography, angioplasty, bypass surgery, other surgery).

We keep the patients belonging to the largest four plan types, HMO, PPO, POS and Comprehensive, and drop the less than 4 percent of observations from exclusive provider organizations, capitated and partially capitated point of service plans, and consumer driven health plans. We also drop the few observations which are recorded as including capitated payments in 2007 (the first year MarketScan records capitation), and those which appear to have unreliable or missing data: those with zero or negative total inpatient expenditures, or missing geographical region data. Physician payments are winsorized at the 1st and 99th percentiles.

**Services Prices** This sample is used to estimate the service price regressions (4.1). We focus on the most common services which make up the large majority of all services, dropping the 3 percent of services which appear less than 500 times for our AMI patients. 195 kinds of service remain. We keep services from all diagnoses, not just AMI, as the prices paid for a service typically depend on the service itself and not on the patient’s diagnosis. We only keep services received by patients in HMO, PPO, POS and Comprehensive plans, and drop the claims recorded as capitated. We omit the outliers, defined as those over ten times larger or smaller than the median service price, which are more likely to reflect measurement error than true prices.

**B Semiparametric Identification**

This section presents a semiparametric identification result for the generalized Roy model with utility

\[ U_{i,j} = X_{i,j}'\beta^X + (X_{i,j}'\alpha^X + Z_{i,j}'\alpha^Z)\beta^p + e_{i,j} \]  \hspace{1cm} (B.1)
and payments
\[ \ln p_{i,j} = X_i'\alpha^X + Z_i'\alpha^Z + u_{i,j} \]  
(B.2)

for \( j = 1, \ldots, J \). Define \( V_{i,j} = X_i'\beta^X_j + (X_i'\alpha^X_j + Z_i'\alpha^Z_j)\beta^p \), so that \( U_{i,j} = V_{i,j} + e_{i,j} \). Define \( V^{(j)}_i = (V_{i,j} - V_{i,1}, \ldots, V_{i,j} - V_{i,J}) \), with the \( V_{i,j} - V_{i,j} \) term omitted, and \( e^{(j)}_i = (e_{i,1} - e_{i,j}, \ldots, e_{i,J} - e_{i,j}) \), with the \( e_{i,j} - e_{i,j} \) term omitted. Denote the distribution of the \( k \) random variables \( (X_i, Z_i) \) by \( F_{X,Z} \). Assume:

A1. \((e_{i,1}, \ldots, e_{i,j})\) is absolutely continuous and \( \text{supp}(e_{i,1}, \ldots, e_{i,J}) = \mathbb{R}^J \).

A2. \((e_{i,1}, \ldots, e_{i,J}, U_{i,1}, \ldots, U_{i,J})\) is mean zero and independent of \((X_i, Z_i)\).

A3. \( \beta^p = 0 \).

A4. For almost every \( X_i \), \( \text{supp} \left\{ X_i'\alpha^X_1 + Z_i'\alpha^Z_1, \ldots, X_i'\alpha^X_J + Z_i'\alpha^Z_J \right\} = \mathbb{R}^J \).

A5. The random variables \((X_i, Z_i)\) are linearly independent.

A6. \( \text{Var}(e_{i,2} - e_{i,1}) = 1 \).

**Proposition.** Under A1-A6, in the generalized Roy model defined by equations (B.1) and (B.2), \( \beta^X, \beta^p, \alpha^X, \alpha^Z \) and the joint distribution of \((U_{i,j}, e^{(j)}_i)\) for each \( j \) are identified.

Proof. Treatment \( j \) is chosen for \( i \) if and only if \( e^{(j)}_i \leq V^{(j)}_i \) (we ignore ties; under A1 and A2 they occur with probability 0). By A1 - A4, for each \( j \) there is a sequence \( \{X_i(n), Z_i(n)\}_n \) such that \( V^{(j)}_i \to \infty \) and \( P(\text{j chosen for i}) \to 1 \) as \( n \to \infty \). The payment coefficients \( \alpha^X_j, \alpha^Z_j \) are identified in this limit: \( E(\ln p_{i,j} | X_i(n), Z_i(n), j \text{ chosen for } i) = X_i(n)'\alpha^X_j + Z_i(n)'\alpha^Z_j + E(u_{i,j} | X_i(n), Z_i(n), e^{(j)}_i \leq V^{(j)}_i) \), and by A2, \( \lim_{n \to \infty} E(u_{i,j} | X_i(n), Z_i(n), e^{(j)}_i \leq V^{(j)}_i) = 0 \).

By A3 - A4 there is also a sequence of covariates such that for each \( j \) in the limit either 1 or \( j \) is chosen for sure, and each is chosen with positive probability. In this limit the model reduces to a binary choice model between 1 and \( j \), which given A1 - A5 is semiparametrically identified up to scale (Manski (1985)). Thus \( \beta^X_j \text{Var}(e_{i,j} - e_{i,1})^{-1/2} \) and \( \beta^p \text{Var}(e_{i,j} - e_{i,1})^{-1/2} \) are identified for each \( j \). By A6 \( \beta^p \) is identified, and so \( \text{Var}(e_{i,j} - e_{i,1})^{-1/2} \) and \( \beta^X_j \) are also identified.
Finally, for each $j$ the probabilities $P(u_{i,j} < c, e_i^{(j)} \leq V_i^{(j)})$ are identified for all $(c, V_i^{(j)})$ in the support of $(u_{i,j}, e_i^{(j)})$, so the joint distribution of $(u_{i,j}, e_i^{(j)})$ is identified.

Hansen et al. (2004) and Heckman and Vytacil (2007) contain similar arguments identifying related semiparametric and nonparametric generalized Roy models. Instead of using exclusion restrictions in the utility equations to identify the ratio of variances as in Hansen et al. (2004), we use the the fact that $\beta^p$ is constant across equations.

The proof does not rely on knowledge of $\alpha^Z$ from the service data. In practice such knowledge is useful, as identification-at-infinity arguments are no longer necessary to identify $\alpha^Z$. Assumption A4 is not satisfied if the instruments $Z_i$ are discrete, as the plan type variables are. Imposing stronger distributional assumptions on the error terms (e.g. normality) helps achieve identification with discrete instruments.

C Estimating the Effect of Plan Type on Total Payments Using the Services Data

We obtain a first-order approximation of the effect of plan type on total payments, given the effect of plan type on service prices. To reduce notational burden we treat the case where there are just two plan types so $\text{Ins}_i$ is a binary variable; the extension to multiple plan types is straightforward. Service prices, treatment payments and treatment utilities are given by equations (4.1), (4.2) and (4.5).

Let $q_{i,j}^{\text{Ins}}$ denote the percent change in $i$’s total payment for treatment $j$ when $i$ switches from $\text{Ins}_i = 0$ to $\text{Ins}_i = 1$, and let $w_{i,s,j,0} = \exp(W_i W_s + v_{i,s})q_{i,s,j}(\sum_k \exp(W_i W_k + v_{i,k})q_{i,k,j})^{-1}$ denote the share of $i$’s physician bill that would be spent on service $s$, were he to receive treatment $j$ when in plan type $\text{Ins}_i = 0$. We write $x(y^{1 \text{ns}}) \approx y(y^{1 \text{ns}})$ if $x(y^{1 \text{ns}})$ and $y(y^{1 \text{ns}})$ are equal up to first-order in $y^{1 \text{ns}}$, i.e. if $\lim_{y^{1 \text{ns}} \to 0} \parallel x(y^{1 \text{ns}}) - y(y^{1 \text{ns}}) \parallel / \parallel y^{1 \text{ns}} \parallel = 0$. The following
proposition allows us to approximate the average effect of plan type on payments, given the observed, selected sample.

**Proposition.** Given the service price, treatment payment and treatment utility equations (4.1), (4.2) and (4.5), and under assumptions A3 and A5,

\[
E(\alpha_{i,j}^{\text{Ins}} | X_i, \text{Ins}_i, i \text{ receives } j) \approx E(\alpha_{i,j}^{\text{Ins}} | X_i, \text{Ins}_i). \tag{C.1}
\]

Proof. We first note that the response of total payments to plan type can be written as a weighted sum of the responses of service prices to plan type:

\[
\alpha_{i,j}^{\text{Ins}} = \frac{\sum_s \exp(W_i^{\prime}Y_s^{W} + \gamma_s^{\text{Ins}} + v_{i,s})q_{i,s,j} - \sum_s \exp(W_i^{\prime}Y_s^{X} + v_{i,s})q_{i,s,j}}{\sum_s \exp(X_i^{\prime}Y_s^{X} + v_{i,s})q_{i,s,j}}
\]

\[
= \sum_s \frac{\exp(W_i^{\prime}Y_s^{W} + \gamma_s^{\text{Ins}} + v_{i,s})q_{i,s,j} - \exp(W_i^{\prime}Y_s^{W} + v_{i,s})q_{i,s,j}}{\sum_s \exp(W_i^{\prime}Y_s^{W} + v_{i,s})q_{i,s,j}} \exp(W_i^{\prime}Y_k^{W} + v_{i,k})q_{i,k,j}
\]

\[
\approx \sum_s \gamma_s^{\text{Ins}} \frac{\exp(W_i^{\prime}Y_k^{W} + v_{i,s})q_{i,s,j}}{\sum_k \exp(W_i^{\prime}Y_k^{W} + v_{i,k})q_{i,k,j}}
\]

\[
= \sum_s \gamma_s^{\text{Ins}} w_{i,s,j,0}. \tag{C.2}
\]

The first equality is true because by A3 changing plan type changes service prices only, not service quantities (see section 5, “Physicians’ Response to Plan Type” for discussion of this assumption). The second step is simple algebra, the third is a first-order approximation, and the fourth is true by definition. The proposition follows:

\[
E(\alpha_{i,j}^{\text{Ins}} | X_i, \text{Ins}_i, i \text{ receives } j) = E\{E(\alpha_{i,j}^{\text{Ins}} | X_i, \text{Ins}_i, e_i) | X_i, \text{Ins}_i, i \text{ receives } j\}
\]

\[
\approx E\{E(\sum_s \gamma_s^{\text{Ins}} w_{i,s,j,0} | X_i, \text{Ins}_i, e_i) | X_i, \text{Ins}_i, i \text{ receives } j\}
\]

\[
= E\{E(\sum_s \gamma_s^{\text{Ins}} w_{i,s,j,0} | X_i, \text{Ins}_i) | X_i, \text{Ins}_i, i \text{ receives } j\}
\]

\[
\approx E\{E(\alpha_{i,j}^{\text{Ins}} | X_i, \text{Ins}_i) | X_i, \text{Ins}_i, i \text{ receives } j\}
\]

\[
= E(\alpha_{i,j}^{\text{Ins}} | X_i, \text{Ins}_i).
\]

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The first step follows from the law of iterated expectations because the event \{i receives treatment j\} can be expressed in terms of \((X_i, \text{Ins}_i, e_i)\), the second is true by C.2, the third is implied by A5, the fourth is true by C.2, and the final equality is elementary.

The effect of plan type is patient-specific: the coefficient \(a_{i,j}^{\text{Ins}}\) depends on the particular bundle of services that patient i consumes. By A4, the \(y_{s}^{\text{Ins}}\) can be estimated by ordinary least squares. If bundles of services for counterfactual treatments were observed then \(a_{i,j}^{\text{Ins}}\) could be estimated for every patient i and treatment j, and the model could be estimated with total payment regressions of the form \(\ln p_{i,j} = X_i'\alpha_j + \text{Ins}_i'a_{i,j}^{\text{Ins}} + u_{i,j}^0\). Counterfactual bundles are not observed, so we instead form total payment regressions featuring the average coefficients over patients: \(\ln p_{i,j} = X_i'\alpha_j + \text{Ins}_i'E(a_{i,j}^{\text{Ins}} | X_i, \text{Ins}_i) + u_{i,j}\), where \(u_{i,j} = \text{Ins}_i'(a_{i,j}^{\text{Ins}} - E(a_{i,j}^{\text{Ins}} | X_i, \text{Ins}_i)) + u_{i,j}^0\). The proposition implies that a feasible, consistent estimator of \(E(a_{i,j}^{\text{Ins}} | X_i, \text{Ins}_i)\) is the sample average of \(\sum_s y_{s}^{\text{Ins}}w_{s,i,j,0}\) conditional on \(X_i, \text{Ins}_i,\) and i receiving j. Thus the service data allow the effect of plan type on total payments to be recovered. In practice there is not enough data for each \((X_i, \text{Ins}_i)\) combination to give precise estimates of \(E(a_{i,j}^{\text{Ins}} | X_i, \text{Ins}_i)\). We estimate the mean of \(a_{i,j}^{\text{Ins}}\) by region only. Standard errors are calculated from 50 bootstrap draws, resampling the service data at the inpatient-episode level.

\[D\] The Likelihood and the Gibbs Sampler

Patient i receives treatment j if and only if \(X_i'((\beta_j^X + \beta^p(\alpha_j^X - \alpha_j^X)) + \text{Ins}_i'\beta^p(a_{i,j}^{\text{Ins}} - a_{i}^{\text{Ins}}) + \bar{e}_{i,j} \geq \max_k X_i'((\beta_k^X + \beta^p(\alpha_k^X - \alpha_k^X)) + \text{Ins}_i'\beta^p(a_{k,i}^{\text{Ins}} - a_{i}^{\text{Ins}}) + \bar{e}_{i,k})\). Define \(E_{i,j}\) to be the set of \(\bar{e}_i = (\bar{e}_{i,2}, \ldots, \bar{e}_{i,5})\) where this inequality holds. Write the variance of the payment errors \(u_i\) and utility errors \(\bar{e}_i\) as

\[
\Sigma = \begin{bmatrix}
\Sigma_{uu} & \Sigma_{u\bar{e}} \\
\Sigma_{u\bar{e}} & \Sigma_{\bar{e}\bar{e}}
\end{bmatrix}
\]

and let \(Y_i\) be the treatment that i receives. Abusing notation slightly by
writing \( u_i = (u_{i,Y_i}, u_{i,\neg Y_i}) \), the likelihood contribution for \( i \) is:

\[
1(\bar{e}_i \in E_{i,Y_i})\varphi(\ln p_{i,Y_i} - X_i'\alpha_{Y_i} - \text{Ins}_i'\alpha_{\text{Ins},i}, u_{i,\neg Y_i}, \bar{e}_i \mid \Sigma)d(u_{i,\neg Y_i}, \bar{e}_i)
\]

where \( \varphi(u_i, \bar{e}_i \mid \Sigma) \) is the multivariate normal density with mean 0 and variance \( \Sigma \). The likelihood \( L(\alpha^X, \alpha^\text{Ins}, \beta, \Sigma) \) is the product of these terms over all \( i \). We have not yet set the scale of utility so this model is not point identified.\(^{42}\) This is the likelihood for the total payment and treatment choice data only. The service data are only used to obtain \( \hat{\alpha}^\text{Ins} \), and do not feature directly in the likelihood.

Recalling some notation, \( Z_i = (Y_i, X_i, p_{i,Y_i}) \) denotes the treatment and total payment data for the \( i \)th patient, \( Z = \{Z_i\} \) all treatment and total payment data, \( p_- = \{p_{i,\neg Y_i}\} \) all unobserved payments and \( \bar{U} = \{\bar{U}_i\} \) all utilities. Define \( \alpha^X = (\alpha^X_1, \ldots, \alpha^X_5), \alpha^\text{Ins} = (\alpha^\text{Ins}_1, \ldots, \alpha^\text{Ins}_5) \) and \( \beta = (\beta^X_2 \ldots \beta^X_5, \beta^p) \). The Gibbs sampler draws parameters sequentially: first, \( p_-, \bar{U} \mid \alpha^X, \beta, \Sigma, \alpha^\text{Ins}, Z \); second, \( \alpha^X \mid p_-, \bar{U}, \beta, \Sigma, \alpha^\text{Ins}, Z \); third, \( \beta \mid p_-, \bar{U}, \alpha^X, \Sigma, \alpha^\text{Ins}, Z \); and finally \( \Sigma \mid p_-, \bar{U}, \alpha^X, \beta, \alpha^\text{Ins}, Z \). Iterative draws from these conditional distributions form a Markov chain with a strictly positive transition kernel (the kernel here is the product of truncated normal, untruncated normal and inverse Wishart distributions). Standard results on Markov chains imply it converges to the posterior parameter distribution (Geweke and Keane (2001)).

We specify independent priors on \( \alpha^X, \beta, \Sigma^{-1} \) as follows: \( \alpha^X \sim N(0, \psi_{\alpha^X}I) \), \( \beta \sim N(0, \psi_{\beta}I) \), and \( \Sigma^{-1} \sim \text{Wishart}(\zeta, \psi_{\Sigma}I) \) (McCulloch and Rossi (1994)).\(^{43}\) Large \( \psi_{\alpha^X}, \psi_{\beta} \) and small \( \zeta \) correspond to a diffuse prior. We choose \( \psi_{\alpha^X} = \psi_{\beta} = 100, \zeta = 10 \) and \( \psi_{\Sigma} = 1 \). The norm of the utility error variance matrix \( \Sigma_{ee} \) is unrestricted so the model is unidentified. The Gibbs sampler takes values in the unidentified parameter space but we report results on the identified parameters, by dividing the utility conditional mean parameter draws by \( \text{tr}(\Sigma_{ee})^{0.5} \) and the utility error

\(\footnotesize{\text{\(^{42}\)Regardless of whether utilities are normalized the cross-payment correlations are unidentified, because only one payment is observed at a time. None of the results we report rely on estimates of these parameters.}}\)

\(\footnotesize{\text{\(^{43}\)In this parameterization \( \zeta \) is the degrees of freedom and \( \psi_{\Sigma}I \) is the scale matrix, so that the Wishart density \( f(A) \) is proportional to \( |A|^{\frac{\zeta + p + 1}{2}} \exp -\frac{1}{2}\text{tr} \psi_{\Sigma}^{-1}A \), where \( p \) is the dimension of \( A \).}}\)
variance by \( \text{tr}(\Sigma_{\text{Cor}}) \) (Geweke et al. (1994); McCulloch and Rossi (1994)).

We draw from the conditional distributions as follows:

1. \( p_{-}, U | \alpha^{X}, \beta, \Sigma, \hat{\alpha}_{\text{Ins}}, Z \)

This is the data-augmentation part of the algorithm. It comprises 8 substeps, one for each of the four missing utilities (one utility is normalized to zero) and four missing payments (one payment is observed). For each patient, we draw each latent variable, or equivalently, its corresponding error term, conditional on the values of all other error terms for that patient, and on the observed choice. This is Gibbs sampling from a truncated multivariate normal distribution, as described by Geweke (1991).

2. \( \alpha^{X} | p_{-}, U, \beta, \Sigma, \hat{\alpha}_{\text{Ins}}, Z \)

This is a Bayesian seemingly-unrelated regression system. Collecting the 5 payment equations in (4.2) across \( j \) gives

\[
\ln p_{i} = (I_{5} \otimes X_{j})\alpha^{X} + \left(I_{5} \otimes Ins_{i}\right)\hat{\alpha}_{\text{Ins}} + u_{i}, \quad u_{i} \sim N(\Sigma_{\text{uu}}\Sigma_{\text{ee}}^{-1}\bar{\varepsilon}_{i}, \Sigma_{\text{uu}} - \Sigma_{\text{ue}}\Sigma_{\text{ee}}^{-1}\Sigma_{\text{eu}}). \tag{D.2}
\]

Because \( \bar{\varepsilon}_{i} \) is a function of \( \bar{U}_{i} \) and \( \beta \), the distribution of \( u_{i} \) is conditional on \( \bar{\varepsilon}_{i} \). Write the Cholesky decomposition of the inverse of the conditional variance as \( (\Sigma_{\text{uu}} - \Sigma_{\text{ue}}\Sigma_{\text{ee}}^{-1}\Sigma_{\text{eu}})^{-1} = C_{u}C_{u}' \). Define \( \ln \tilde{p}_{i} = C_{u}'(\ln p_{i} - (I_{5} \otimes Ins_{i})\hat{\alpha}_{\text{Ins}} - \Sigma_{\text{ue}}\Sigma_{\text{ee}}^{-1}\bar{\varepsilon}_{i}), \quad \tilde{\alpha}_{i} = C_{u}'(I_{5} \otimes X_{j}) \) and 
\( \tilde{u}_{i} = C_{u}(u_{i} - \Sigma_{\text{ue}}\Sigma_{\text{ee}}^{-1}\bar{\varepsilon}_{i}) \), so that

\[
\ln \tilde{p}_{i} = \tilde{\alpha}_{i}\tilde{\alpha}^{X} + \tilde{u}_{i}, \quad \tilde{u}_{i} \sim N(0, I_{5}), \tag{D.3}
\]

or stacking over \( i \)

\[
\ln \tilde{p} = \tilde{\alpha}\tilde{\alpha}^{X} + \tilde{\alpha}, \quad \tilde{\alpha} \sim N(0, I_{5n}). \tag{D.4}
\]

Given the prior over \( \alpha^{X} \), the posterior \( \alpha^{X} | p_{-}, U, \beta, \Sigma, \hat{\alpha}_{\text{Ins}}, Z \) is normal with mean \((\tilde{\alpha}'\tilde{\alpha} + \)
\( \psi_{\alpha x}^{-1} I \)^{-1} \bar{A}' \ln \mathbf{p} \) and variance \( \bar{A}' \bar{A} + \psi_{\alpha x}^{-1} I \)^{-1}.

3. \( \bar{\beta} \mid \mathbf{p}_-, \bar{U}, \alpha_X, \Sigma, \hat{\alpha}_{\text{ins}}, Z \)

This is a Bayesian regression system. Define

\[
X_i' (\hat{\alpha}_2^X - \alpha_i^X) + \text{Ins}_i' (\hat{\alpha}_2^{\text{ins}} - \hat{\alpha}_1^{\text{ins}})
\]

\[
B_i = I_4 \otimes X_i
\]

and \( \bar{\beta} = (\bar{\beta}_1^{X'}, ..., \bar{\beta}_4^{X'}, \beta^0)' \). Collecting

\[
X_i' (\hat{\alpha}_3^X - \alpha_i^X) + \text{Ins}_i' (\hat{\alpha}_3^{\text{ins}} - \hat{\alpha}_1^{\text{ins}})
\]

the 4 utility equations in (6.1) across \( j \) gives

\[
\bar{U}_i = B_i \bar{\beta} + \bar{e}_i, \quad \bar{e}_i \sim N(\Sigma_{cc} \Sigma_{uu}^{-1} \mathbf{u}_i, \Sigma_{ee} - \Sigma_{eu} \Sigma_{uu}^{-1} \Sigma_{ue}). \tag{D.5}
\]

Write the Cholesky decomposition of the inverse of the conditional variance as \( (\Sigma_{ee} - \Sigma_{eu} \Sigma_{uu}^{-1} \Sigma_{ue})^{-1} = C \tilde{C}' \). Define \( \tilde{U}_i = C_{c'} (U_i - \Sigma_{eu} \Sigma_{uu}^{-1} \mathbf{u}_i) \), \( \tilde{B}_i = C_{c'} B_i \) and \( \tilde{e}_i = C_{e'} (\tilde{e}_i - \Sigma_{eu} \Sigma_{uu}^{-1} \mathbf{u}_i) \), so that

\[
\tilde{U}_i = \tilde{B}_i \tilde{\beta} + \tilde{e}_i, \quad \tilde{e}_i \sim N(0, I_4). \tag{D.6}
\]

or stacking over \( i \),

\[
\bar{U} = \tilde{B} \tilde{\beta} + \tilde{e}, \quad \tilde{e} \sim N(0, I_{4n}). \tag{D.7}
\]

Given the prior over \( \tilde{\beta} \), the posterior \( \tilde{\beta} \mid \mathbf{p}_-, \bar{U}, \alpha^X, \Sigma, \hat{\alpha}^{\text{ins}}, Z \) is normal with mean \( (\tilde{B}' \tilde{B} + \psi_{\tilde{\beta}}^{-1} I)^{-1} \tilde{B}' \tilde{U} \) and variance \( (\tilde{B}' \tilde{B} + \psi_{\tilde{\beta}}^{-1} I)^{-1} \).

4. \( \Sigma \mid \mathbf{p}_-, \bar{U}, \alpha^X, \tilde{\beta}, \hat{\alpha}^{\text{ins}}, Z \)

This step is conditional on both \( \mathbf{u}_i \) and \( \bar{e}_i \). The conjugate prior on \( \Sigma^{-1} \) is Wishart(\( \zeta, \psi_{\Sigma} I \)), so the posterior is Wishart(\( \zeta + n, (\psi_{\Sigma}^{-1} + \Sigma_{i=1}^n (u_i' \bar{e}_i')(u_i' \bar{e}_i'))^{-1} \)) (Gelman et al. (2003)).

For \( \alpha^{\text{ins}} \) fixed at its true value, the Bernstein-von Mises theorem implies that the difference between the posterior mean and the maximum likelihood estimator is \( o_p(n^{-1/2}) \), and that the asymptotic distribution of the MLE is the same as the asymptotic posterior (van der Vaart
(1998); Train (2009)). By the first part of the theorem, the mean of the posterior is asymptotically equivalent to the MLE. By the second part, the posterior variance can be used as an estimate of the sampling variance of the MLE. Moments of the posterior are all that is required for inference. The transition kernel is strictly positive and therefore ergodic, so the mean and variance of the posterior can be estimated by finding the sample mean and variance of the draws from each iteration of steps 2-4 (Geweke and Keane (2001) section 2.4 collects the relevant results). We run the Gibbs sampler for 5000 draws and allow for “burn-in” by discarding the first half of the draws, following Gelman et al. (2003). Because \( \sigma^{\text{Ins}} \) is not known but instead estimated in a first stage, standard errors need to be adjusted to account for the sampling variation in \( \hat{\sigma}^{\text{Ins}} \). We use the posterior variance from the Gibbs sampler together with the bootstrapped standard errors of \( \hat{\sigma}^{\text{Ins}} \) to calculate the overall standard errors.