# Supplement to “Physician incentives and treatment choices in heart attack management”

(*Quantitative Economics*, Vol. 6, No. 3, November 2015, 703–748)

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## SA. Semiparametric identification

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

$$U_{i,j} = X_i'\beta_j^X + \big(X_i'\alpha_j^X + Z_i'\alpha_j^Z\big)\beta^p + e_{i,j} \tag{SA.1}$$

and payments

$$\ln p_{i,j} = X_i'\alpha_j^X + Z_i'\alpha_j^Z + u_{i,j} \tag{SA.2}$$

for $j = 1, \dots, J$. Define $V_{i,j} = X_i'\beta_j^X + (X_i'\alpha_j^X + Z_i'\alpha_j^Z)\beta^p$, so that $U_{i,j} = V_{i,j} + e_{i,j}$. Define $V_i^{(j)} = (V_{i,j} - V_{i,1}, \dots, V_{i,j} - V_{i,J})$ with the $V_{i,j} - V_{i,j}$ term omitted, and define $e_i^{(j)} = (e_{i,1} - e_{i,j}, \dots, e_{i,J} - e_{i,j})$ with the $e_{i,j} - e_{i,j}$ term omitted. Denote the distribution of the $k$ random variables $(X_i, Z_i)$ by $F_{X,Z}$. Define $\overline{\beta}^X = (\beta_2^X - \beta_1^X, \dots, \beta_J^X - \beta_1^X)$, $\alpha^X = (\alpha_1^X, \dots, \alpha_J^X)$, and $\alpha^Z = (\alpha_1^Z, \dots, \alpha_J^Z)$. Make the following assumptions:

- $\mathcal{A}1$. The set $(e_{i,1}, \dots, e_{i,J})$ is absolutely continuous and $\operatorname{supp}(e_{i,1}, \dots, e_{i,J}) = \mathbb{R}^J$.
- $\mathcal{A}2$. The set $(e_{i,1}, \dots, e_{i,J}, u_{i,1}, \dots, u_{i,J})$ is mean zero and independent of $(X_i, Z_i)$.
- $\mathcal{A}3$. We have $\beta^p \neq 0$.
- $\mathcal{A}4$. For almost every $X_i$, $\operatorname{supp}(X_i'\alpha_1^X + Z_i'\alpha_1^Z, \dots, X_i'\alpha_J^X + Z_i'\alpha_J^Z) = \mathbb{R}^J$.
- $\mathcal{A}5$. The random variables $(X_i, Z_i)$ are linearly independent.
- $\mathcal{A}6$. We have $\operatorname{Var}(e_{i,2} - e_{i,1}) = 1$.

Proposition. *Under $\mathcal{A}1$–$\mathcal{A}6$, in the generalized Roy model defined by equations (SA.1) and (SA.2), $\overline{\beta}^X$, $\beta^p$, $\alpha^X$, $\alpha^Z$, and the joint distribution of $(u_{i,j}, e_i^{(j)})$ for each $j$ are identified.*

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This work was submitted while at Stanford University and does not represent the views of my current employer, Facebook, Core Data Science.


DOI: 10.3982/QE365

Proof. Treatment $j$ is chosen for $i$ if and only if $e_i^{(j)} \leq V_i^{(j)}$ (we ignore ties; under $\mathcal{A}1$ and $\mathcal{A}2$, they occur with probability 0). By $\mathcal{A}1$–$\mathcal{A}4$, for each $j$ there is a sequence $\{X_i(n), Z_i(n)\}_n$ such that $V_i^{(j)} \to \infty$ and $\mathbb{P}(j \text{ chosen for } i) \to 1$ as $n \to \infty$. The payment coefficients $\alpha_j^X$, $\alpha_j^Z$ are identified in this limit: $\mathbb{E}(\ln p_{i,j} \mid X_i(n), Z_i(n), j \text{ is chosen for } i) = X_i(n)'\alpha_j^X + Z_i(n)'\alpha_j^Z + \mathbb{E}(u_{i,j} \mid X_i(n), Z_i(n), e_i^{(j)} \leq V_i^{(j)})$, and by $\mathcal{A}2$, $\lim_{n\to\infty} \mathbb{E}(u_{i,j} \mid X_i(n), Z_i(n), e_i^{(j)} \leq V_i^{(j)}) = 0$.

By $\mathcal{A}3$ and $\mathcal{A}4$ there is also a sequence of covariates such that for each $j$, either 1 or $j$ is chosen with positive probability, and in the limit, either 1 or $j$ is chosen for sure. In this limit, the model reduces to a binary choice model between 1 and $j$, which given $\mathcal{A}1$–$\mathcal{A}5$ is semiparametrically identified up to scale (Manski (1985)). Thus $(\beta_j^X - \beta_1^X)\operatorname{Var}(e_{i,j} - e_{i,1})^{-1/2}$ and $\beta^p \operatorname{Var}(e_{i,j} - e_{i,1})^{-1/2}$ are identified for each $j$. By $\mathcal{A}6$, $\beta^p$ is identified, and so $\operatorname{Var}(e_{i,j} - e_{i,1})^{-1/2}$ and $\beta_j^X - \beta_1^X$ are also identified.

Finally, for each $j$, the probabilities $\mathbb{P}(u_{i,j} < c, e_i^{(j)} \leq V_i^{(j)})$ 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, Heckman, and Mullen (2004) and Heckman and Vytlacil (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, Heckman, and Mullen (2004), we use 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 $\mathcal{A}4$ 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.

## SB. Insurance plan types and physician payments

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 S1 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 data are consistent with HMOs using their bargaining power to choose service prices in a way that induces physicians to treat more conservatively.

Table S1. Physician prices of selected services by plan type.

| | $N$ | HMO | POS | PPO | Comp. |
|---|---|---|---|---|---|
| Initial hospital care | 963,085 | 185 | 188 | 191 | 179 |
| | | (84) | (66) | (62) | (54) |
| Chest X-ray | 818,381 | 16 | 17 | 16 | 15 |
| | | (10) | (9) | (9) | (9) |
| Electrocardiogram | 736,577 | 16 | 17 | 16 | 14 |
| | | (11) | (12) | (10) | (9) |
| Angiography contrast injection | 174,899 | 51 | 56 | 63 | 49 |
| | | (54) | (61) | (59) | (51) |
| Stent placement | 90,595 | 1195 | 1248 | 1346 | 1244 |
| | | (683) | (592) | (685) | (705) |
| Single bypass | 28,706 | 2042 | 2252 | 2301 | 2194 |
| | | (1185) | (1221) | (1284) | (1301) |

*Note*: The 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 S2 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). 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.

## SC. Physician treatment propensities and plan types

Do some plan types tend to affiliate with hospitals with particular treatment propensities? If this selection occurs and it is not captured by our included covariates, it could bias our estimates of physicians' price responses.

To obtain measures of hospitals' treatment propensities (or, more precisely, the physicians associated with those hospitals), we estimate linear probability models of the form

$$T_{i,j} = H_i' \eta_j^H + X_i' \eta_j^X + \text{Ins}_i' \eta_j^{\text{Ins}} + \varepsilon_{i,j}, \tag{SC.1}$$

where $T_{i,j}$ is 100 if patient $i$ receives treatment $j$ and is 0 otherwise; $H_i$ is a set of hospital fixed effects; and $X_i$ and $\text{Ins}_i$ are as described in Section 4. We use $H_i' \hat{\eta}_j^H$, the estimated

Table S2. Total physician payments by plan type and treatments for other diagnoses.

(A) Prostate Cancer

| $N = 114{,}628$ | No Surgery | Surgery |
|---|---|---|
| HMO | 4807 | 10,846 |
| | (15,318) | (15,199) |
| POS | 6881 | 13,524 |
| | (19,088) | (17,181) |
| PPO | 5863 | 14,781 |
| | (18,412) | (18,674) |
| Comprehensive | 4706 | 15,769 |
| | (15,992) | (19,562) |

(B) Breast Cancer

| $N = 232{,}733$ | No Mastectomy | Mastectomy |
|---|---|---|
| HMO | 9197 | 35,104 |
| | (29,032) | (45,866) |
| POS | 13,369 | 47,798 |
| | (34,817) | (54,302) |
| PPO | 12,114 | 48,268 |
| | (33,529) | (55,426) |
| Comprehensive | 12,169 | 42,281 |
| | (34,411) | (54,032) |

(C) Inguinal Hernia

| $N = 197{,}763$ | No Surgery | Surgery |
|---|---|---|
| HMO | 867 | 4311 |
| | (2551) | (4345) |
| POS | 740 | 4731 |
| | (3761) | (5994) |
| PPO | 691 | 5369 |
| | (3347) | (4378) |
| Comprehensive | 667 | 4581 |
| | (2102) | (3207) |

(D) Spinal Disc Herniation

| $N = 908{,}596$ | No Surgery | Surgery |
|---|---|---|
| HMO | 1210 | 10,193 |
| | (2328) | (8536) |
| POS | 1717 | 13,584 |
| | (3361) | (11,403) |
| PPO | 1597 | 13,660 |
| | (3216) | (11,848) |
| Comprehensive | 1601 | 12,307 |
| | (3091) | (10,502) |

*Note*: The 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, and 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 and 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 S3. Hospital treatment propensities by insurance plan types: regression results.

| $N = 25{,}155$ | MM | A'graphy | A'plasty | Bypass | Other Surgery |
|---|---|---|---|---|---|
| HMO | −0.52 | −0.40 | 0.17 | 0.88 | −0.12 |
| | (0.44) | (0.44) | (0.52) | (0.28) | (0.29) |
| POS | −0.49 | −0.13 | −0.28 | 0.82 | 0.09 |
| | (0.36) | (0.43) | (0.44) | (0.38) | (0.29) |
| Comprehensive | −0.33 | 0.19 | 0.17 | 0.24 | −0.26 |
| | (0.31) | (0.32) | (0.39) | (0.22) | (0.20) |

*Note*: Each treatment column corresponds to a regression of the corresponding proxy for hospital treatment propensity, $H_i' \hat{\eta}_j^H$, on $X_i$ and plan type. The table presents only the plan type coefficients. PPOs are the omitted plan type category. We omit patients for whom hospital identifiers are not available. We also omit patients who are treated in hospitals that treat under 10 patients in the data, to reduce measurement error in $H_i' \hat{\eta}_j^H$. Standard errors are calculated from 50 bootstrap repetitions, resampling at the hospital level.

value of $H_i' \eta_j^H$, as a proxy for the propensity of the hospital in which patient $i$ is treated to do procedure $j$. To see if hospital treatment propensities vary by plan type, we regress these proxies on $X_i$ and plan type. Table S3 presents the coefficient estimates, along with bootstrapped standard errors.

There is no evidence that PPOs tend to affiliate with hospitals with greater propensities to treat aggressively, as would be expected if hospital selection explained the differences in treatment choices across plan types. On the contrary, there is slight evidence that hospitals in this sample serving HMOs and POSs tend to perform bypasses at higher rates.

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Submitted May, 2013. Final version accepted November, 2014.