Moral Hazard and Adverse Selection in Private Health Insurance

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Discussion
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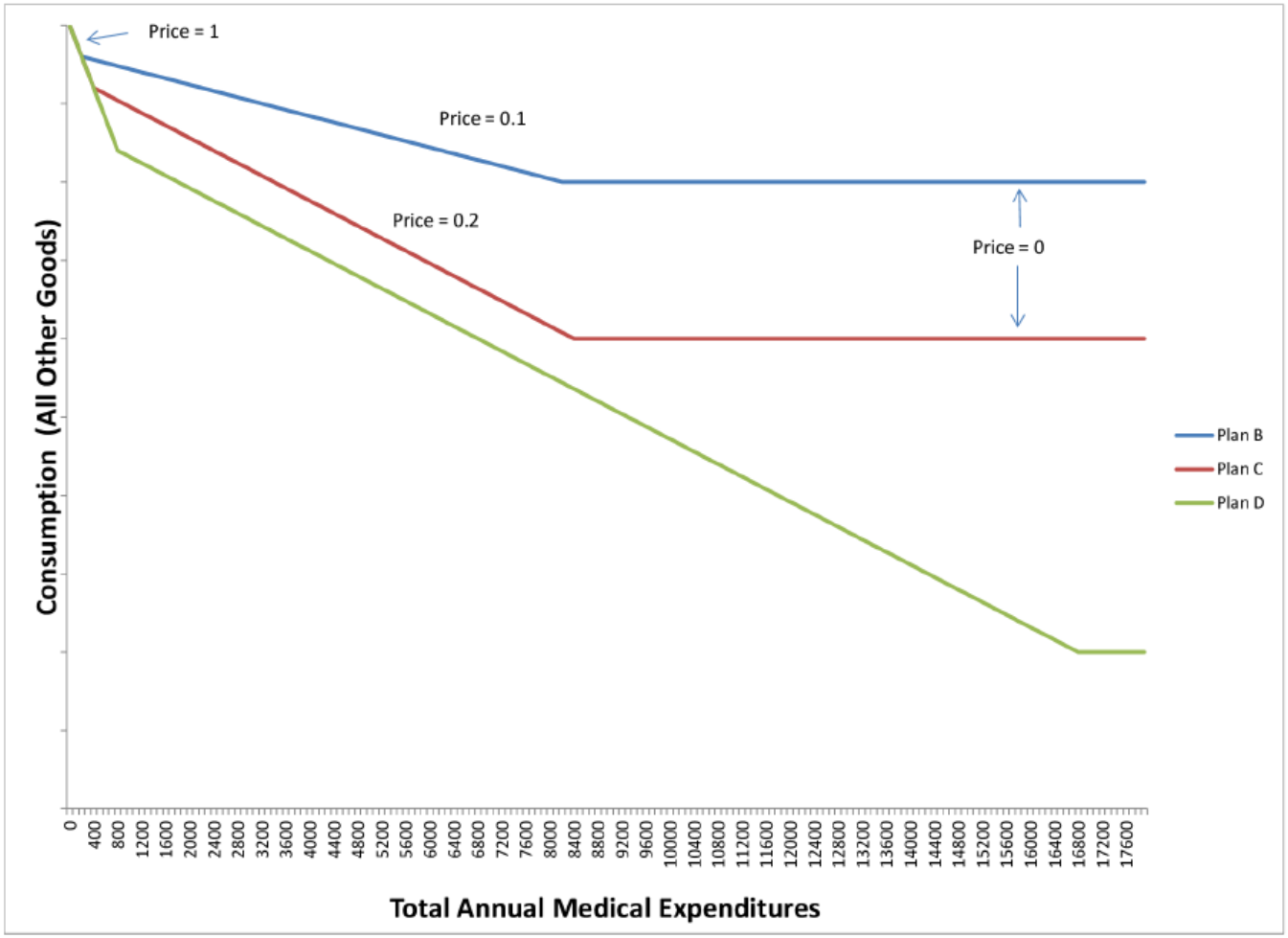
Setting:

Administrative health claims data from a large employer in US in years 2005 and 2006.

In 2005, only one insurance plan was offered, with a simple coinsurance rate of 0.2.

In 2006, three plans were offered that varied in deductables, coinsurance rates and stop lossess.

No details are given on how individuals chose plan or what premiums were paid.


Price = 1
Price = 0.1
Price = 0.2
Price = 0
Consumption (All Other Goods)
Total Annual Medical Expenditures
Plan B
Plan C
Plan D
0
400
800
1200
1600
2000
2400
2800
3200
3600
4000
4400
4800
5200
5600
6000
6400
6800
7200
7600
8000
8400
8800
9200
9600
10000
10400
10800
11200
11600
12000
12400
12800
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14000
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15600
16000
16400
16800
17200
17600

Aim of the paper is to estimate the causal effect of each plan on expenditures.

Using quantile IV methods, the effects are estimated across the distribution of expenditures.

As introduction of the plans in 2006 is random, the paper argues that conditioning on observed characteristics age, gender, family size (1 or 2) and relationship results in causal identification.

Note sample selection.

The quantile treatment effects model for plan elasticities is specified as

$$\ln M_{it} = \phi_t\left(U_{it}^*\right) + \sum_k \beta_k\left(U_{it}^*\right) 1\left[plan_{it} = k\right]$$

With corresponding structural quantile function

$$S_{\ln M} = \phi_t\left(\tau\right) + \sum_k \beta_k\left(\tau\right) 1\left[plan_{it} = k\right]$$

Although the introduction refers to a type of DiD approach, the comparison of expenditures in 2005 and 2006 is unclear from this specification.

The IV-GQR estimator is based on the moment conditions

$$E\left\{Z\left[1\left(Y \le D'\beta\left(\tau\right)\right) - \hat{\tau}_X\right]\right\} = 0$$

$$E\left[1\left(Y \le D'\beta\left(\tau\right)\right) - \tau\right] = 0$$

where $\hat{\tau}_X$ is an estimate for $P\left(Y \le D'\beta\left(\tau\right) | X\right)$. This is to allow for different distributions of expenditures by X, as the probability to be in a certain quantile is lower for older people than for younger people. This results in unconditional quantile estmates.

What is the role of instruments Z? Here Z is specified as the probability of choosing plan k, given cell X. A bit (but not quite) like a propensity score? Normally an instrument affects choice of plan, but not outcomes.

What are the assumptions needed/used for identification of causal effects? How are these satisfied here? Formalise.

The instruments are constant within cell X, as is $\hat{\tau}_X$.
The sample moments are based on

$$g_i(b) = Z_i\left[1(Y_i \le D_i'b) - \hat{\tau}_X(b)\right]$$

But then

$$\frac{1}{n_c}\sum_{i\in c} Z_c\left[1\left(Y_i \le D_i'(\beta)\right) - \hat{\tau}_c\right] = 0$$

As $\frac{1}{n_c}\sum_{i\in c}\left[1\left(Y_i \le D_i'(\beta)\right)\right] = \hat{\tau}_c$,

And so $\frac{1}{n}\sum_{i=1}^{n} g_i(b) = \sum_{c=1}^{C}\frac{n_c}{n}\frac{1}{n_c}\sum_{i\in c} Z_c\left(1\left(Y_i \le D_i'b\right) - \hat{\tau}_c\right) = 0$

Make clearer in the paper what is exactly done, also specifying how the panel data structure has been utilised.

First stage estimates: as Z is only positive when choice is positive, what does this tell us?

Partial F? (Sanderson and Windmeijer, 2014)

Table 4: First Stage Estimates

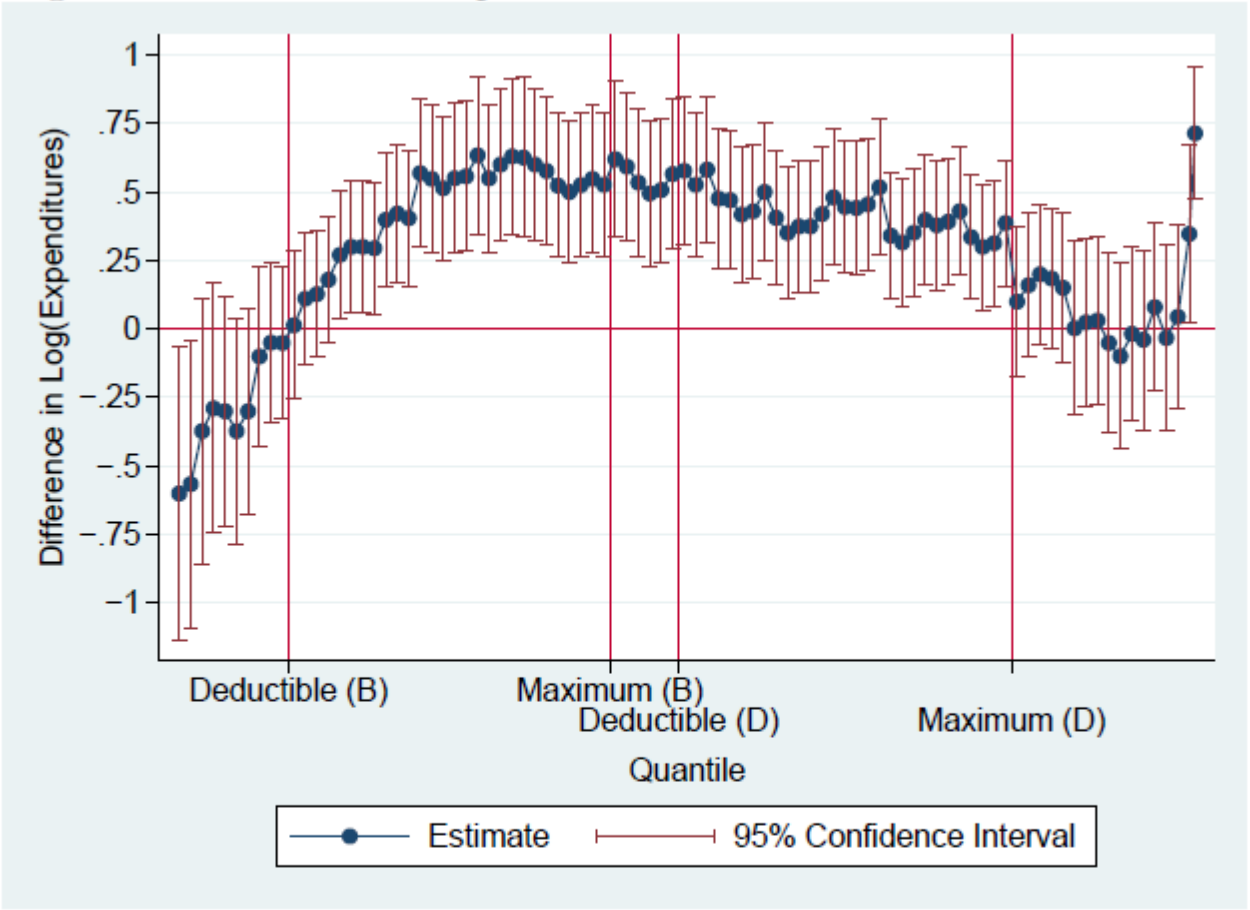
Instruments	Actual Plan Choice	
	Plan B	Plan C
Predicted Pr(Plan B) $\times \mathbf{1}(2006)$	0.937***	0.180***
	(0.044)	(0.070)
Predicted Pr(Plan C) $\times \mathbf{1}(2006)$	-0.035	1.187***
	(0.107)	(0.142)
Partial F-Statistic	768.04	68.50

*** Significant at 1 percent level; ** Significant at 5 percent level; * Significant at 10 percent level. Standard errors in parentheses adjusted for clustering at family level. Regressions also include year and cell fixed effects, where cells are based on sex, age, relationship to employee, and family size.

Plan results presented in nice graphs and contrasted with end of year marginal price effects. The latter results rejected by the nonparametric price effects. Some evidence of moral hazard around deductible and stop-loss points.

Quantile parameter estimates allow for assessment of magnitude of adverse selection.

Figure 5: Difference in Expenditure Distribution: Plan B vs. Plan D



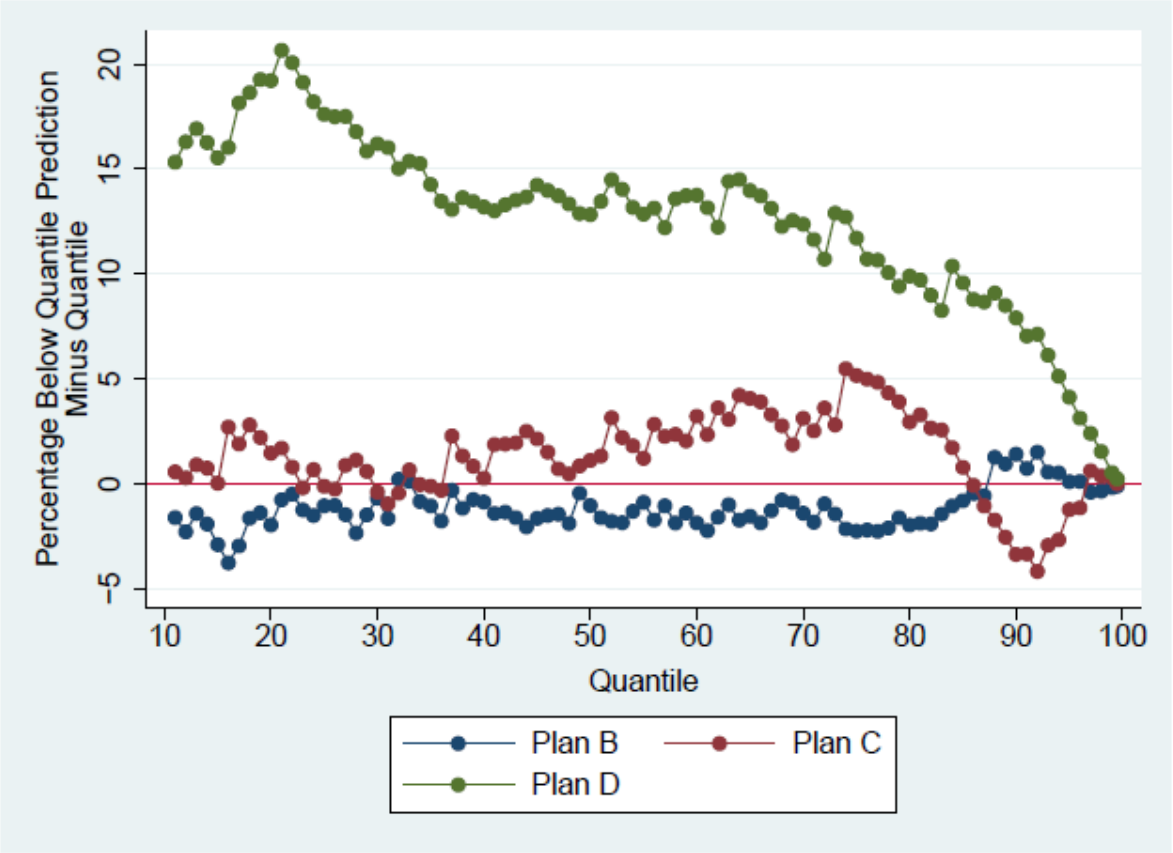
Notes: Using an instrumental variable quantile regression estimator, we estimate the distribution of Plan B and Plan D if enrollment into each plan were random. We graph the difference in these distributions here. Confidence intervals generated using clustered subsampling.

Table 5: Decomposition of Plan Effects

	Plan B	Plan C	Plan D
Per Person Expenditures	\$5,127.02	\$2,960.70	\$1,344.67
	(\$196.34)	(\$86.53)	(\$85.01)
Per Person Expenditures with Random Selection	\$3,779.51	\$3,070.06	\$2,996.89
	(\$113.51)	(\$177.37)	(\$179.27)
Adverse Selection	\$1,347.50	-\$109.37	-\$1,652.22
	(\$177.41)	(\$180.61)	(\$155.69)

Standard errors in parentheses adjusted for clustering at family level. Subsampling is used to generate the standard errors. "Adverse Selection" is equal to "Per Person Expenditures" minus "Per Person Expenditures with Random Selection".

Figure 12: Adverse Selection



Notes: We use the plan elasticities presented in Figures 5, 7, 9 to estimate the empirical probability that an enrollee in the plan is below the estimate quantile function for that plan. We graph this probability minus the quantile. The 0-line represents a plan with no systematic selection. Confidence intervals generated using clustered subsampling.

I would like to see a clearer motivation of identification and identifying assumptions of/for causal effects.

Make it much clearer how you use the panel data structure.

As methods are new, perhaps compare to more standard ways of causal analysis. (At least the assumptions).