# How Does Financial Incentive to Hospital Affect Inpatient Care?

Evidence from Reimbursement System in Japan

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#### Motivation I

- Under rising medical expenditure, reimbursement becomes more important as financial incentive to contain health care cost.
- In Japan, per-diem fixed payment system "DPC" was introduced to reduce unnecessary health care.
- It is critical to understand how medical provider respond to financial incentive.
- Exploiting DPC implementation, we can examine the impact of financial incentive to medical provider mainly through length of stay.

#### Motivation II

#### Research Questions:

- Does DPC implementation reduce length of stay?
  - ▶ Is DPC effective to solve long-term hospitalization problem in Japan?
  - Compared with other treatment choices?
- How does nonlinear-pricing schedule affect distribution of length of stay?
  - Does hospital discharge patients right before reimbursement drop?

#### What I do

- Estimate the impact of DPC implementation on length of stay and other variables in DID framework using patient level data.
- Estimate the increase in discharged patients right before reimbursement drop using method proposed by Chetty et al.(2011).

# Main Fidings

#### First question:

- Length of stay is reduced by 0.85 days due to DPC implementation.
- Treatment choice is less affected by DPC than length of stay is.

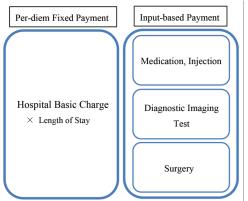
#### Second question:

- The number of discharged patients increases right before reimbursement drop.
- Nonlinear incentive is concentrated on patients under short hospitalization.

#### Institutional Background I

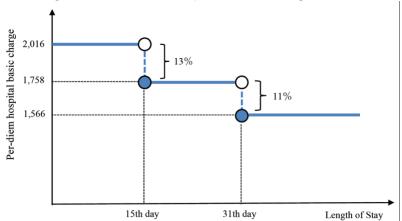
Traditionally, reimbursement had been paid through fee-for-service (FFS) in Japan.

Figure 1. FFS Payment System



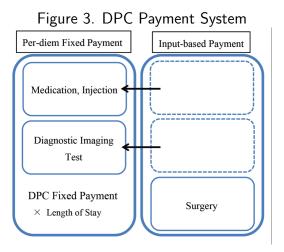
# Institutional Background II

Figure 2. Per-diem Hospital Basic Charge of FFS



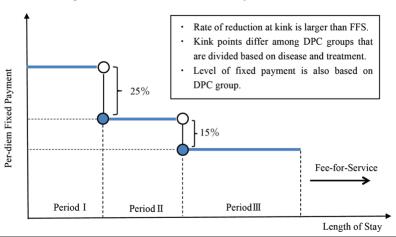
## Institutional Background III

In 2003, alternative payment system called DPC was introduced for inpatient care.



## Institutional Background IV

Figure 4. Per-diem Fixed Payment of DPC



#### Financial Incentives I

- DPC reduces length of stay if hospital improve bed turnover rate to keep profitable short-term hospitalization.
- If hospitals cannot admit sufficient new patients, length of stay might not be reduced.
- Additionally, DPC possibly induce hospitals to;
  - Increase frequency and/or input of surgery.
  - Reduce medical input in ward.

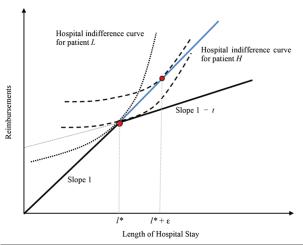
#### Financial Incentives II

Length of stay has important role in nonlinear-pricing schedule.

- Under nonlinear-pricing, distribution of length of stay is expected to "bunch" at kink point (see Figure 5).
- By changing from FFS to DPC, kinks at 14th and 30th day of hospitalization are eliminated.
- ⇒ Bunching at kinks should also be eliminated.

#### Financial Incentives III

Figure 5. Bunching at Kink



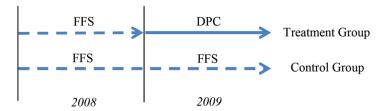
#### Data I

- Use medical records of circulatory disease patients in DPC database in 2008 and 2009.
- Each hospital can decide when (whether) to adopt DPC.
- Before adoption, hospitals submit medical records under FFS payment for two years.
- Our sample contains only hospitals which are willing to adopt DPC.

#### Data II

Exploiting one year difference in timing of adoption.

Figure 6. Variation in payment system



#### Data III

Table 1: Summary Statistics

	Treatment	Control	Treatment	2008-2009	Control	2008-2009
Number of beds	425	526	425	425	526	526
Length of Stay	12.3	9.8	12.7	11.9	9.6	<b>→</b> 9.8
Age	71.3	70.4	71.1	71.6	69.9	70.9
Surgery	38%	43%	37%	<b>3</b> 8%	43%)-	<b>→</b> 45%
Comorbidity	9%	5%	7%	10%	5%	6%
Total input	¥925,532	¥1,015,839	¥933,365	¥917,010	¥985,388	¥1,049,221
Input of Surgery	¥489,899	¥649,401	¥487,438	¥492,502	¥627,408	¥673,362
Input in ward per day	\$57,375	¥64,252	\$59,125	\$55,472	¥65,049	¥63,377
Hospital observation	268	68	268	268	68	68
Patient observation	102111	34639	52489	49622	18061	16578

Input of treatment is proxied by FFS-equivalent reimbursement.

## Regression Estimation I

#### Basic specification:

$$LoS_{iht} = t_{2009} + \alpha_h + \beta(DPC * t_{2009}) + \delta_d + X'_{iht}\gamma + \epsilon_{iht}$$
(1)

 $t_{2009} = 1$  if t = 2009

DPC = 1 if hospital is in treatament group

 $\alpha_h$ : Hospital dummy (336 hospitals).

 $\delta_d$ : DPC group dummy (150 groups).

 $X_{iht}$ : Patient's characteristics.

 $\epsilon_{iht}$ : Error term (clustered at hospital level).

Estimate with negative binomial regression.

## Regression Estimation II

- Following are also used as dependent variable:
  - Surgery dummy
  - In(Input of Surgery)
  - In(Average input in ward per day)
- Input was proxied by FFS-equivalent reimbursement.
- In the case of surgery dummy, probit was used and DPC group dummies were dropped.
- OLS was used for other dependent variables.

## Results of Regression Estimation

Table 2: The Effect of DPC Implementation

	Length of Stay	Surgery	ln(Input of Surgery)	ln(Average Input in Ward)
$DPC*t_{2009}$	-0.855*** (0.0171)	-0.011 (0.0227)	-0.039* (0.0198)	-0.0425** (0.0160)
N	136734	136153	52829	135127

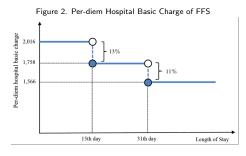
Standard errors in parentheses

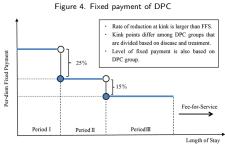
Covariates: Age, Male, Comorbidity, Switch from outpatient, Referral, Urgent, and Discharge. Coefficient on Length of Stay is average marginal effect.

p < 0.05 \* p < 0.01 \* p < 0.001

## Bunching Estimation I

- Recall that price drop at 15th and 31th day of hospitalization were eliminated by DPC.
- What happen to distribution of length of stay around kink?

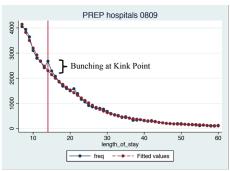




# **Bunching Estimation II**

Basic idea of Chetty et al. (2011):

- Construct "smooth" counterfactual distribution by polynomial.
- Estimate how much more patients were discharged at kink than counterfactual one.



## **Bunching Estimation III**

First, estimate following regression:

$$C_j = \sum_{i=0}^p \beta_i \cdot (Z_j)^i + \gamma_i \cdot \mathbf{1}[Z_j = k] + \epsilon_j$$
 (2)

 $C_j$ : Number of patients discharged at jth day.

 $Z_j$ : jth day of hospitalization relative to kink.

k: Kink point.

p: Degree of polynomial.

(p = 9 in basic specification.)

## **Bunching Estimation IV**

Counterfactual distribution is a predicted value of each  $C_j$  excluding contribution of kink:

$$\hat{C}_j = \sum_{i=0}^p \hat{\beta}_i \cdot (Z_j)^i \tag{3}$$

Then, bunching estimate is:

$$\hat{b} = \frac{C_k - \hat{C}_k}{\hat{C}_k}.$$
(4)

To generate standard error, bootstrap was conducted.

## Bunching Estimation V

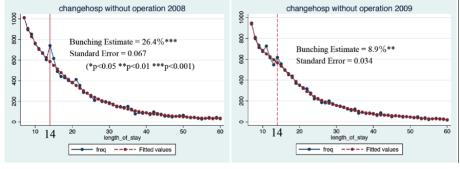
Divide hospitals into following three groups and compare the change of bunching estimates:

- Hospitals that change from FFS to DPC.
- Hospitals that keep DPC.
- Hospitals that keep FFS.

## Results of Bunching Estimation I

Limit sample to patients without surgery.

Figure 7. FFS(Price Drop at 15th Day)  $\rightarrow$  DPC(No Price Drop)

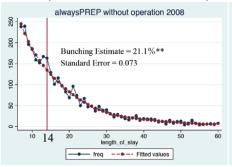


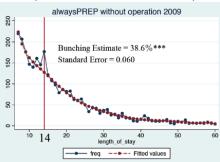
Blue line: Observed distribution

Red line: Counterfactual distribution

# Results of Bunching Estimation II

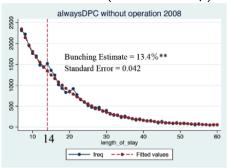
Figure 8. FFS(Price Drop at 15th Day)  $\rightarrow$  FFS(Price Drop at 15th Day)

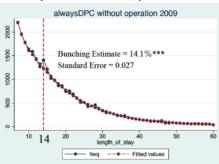




## Results of Bunching Estimation III

Figure 9.  $\mathsf{DPC}(\mathsf{No}\;\mathsf{Price}\;\mathsf{Drop})\to\mathsf{DPC}(\mathsf{No}\;\mathsf{Price}\;\mathsf{Drop})$ 





## Results of Bunching Estimation IV

- Bunching estimate decreases only when reimbursement drop is eliminated.
- That is, hospital has incentive to discharge patients right before reimbursement drop.
- Excess discharge patients are reduced by 66.3%.

#### Conclusion

- There is still room to reduce length of stay in Japan.
- It is relatively hard to change actual treatment choice through financial incentive.
- Nonlinear-incentive affect hospital decision on less-serious patients.

#### References I

- [1] Bajari, Patrick Han Hong, Minjung Park, and Robert Town. 2014.
- "Estimating price sensitivity of economic agents using discontinuity in nonlinear contracts." Working Paper.
- [2] Chetty, Raj, John N. Friedman, Tore Olsen, and Luigi Pistaferri. 2011. "Adjustment cost, firm responses, and micro vs macro labor supply elasticities: evidence from danish tax records." *Quarterly Journal of Economics*, 126, 749-804
- [3] Cutler, David. 1995. "The incidence of adverse medical outcome under prospective payment." *Econometrica*, 63, 29-50.
- [4] Dafny, Leemore. 2005. "How do hospitals respond to price changes?" *American Economic Review*, 95(5), 1525-1547.
- [5] Einav, Liran, Amy Finkelstein, and Paul Schrimpf. 2013. "The response of drug expenditure to non-linear contract design: Evidence from Medicare Part D." Working Paper.
- [6] Ellis, Randall and Thomas McGuire. 1996. "Hospital response to prospective payment: Moral hazard, selection, and practice-style effects." *Journal of Health Economics*, 15(3), 257-277.

#### References II

- [7] Ito, Koichiro. 2014. "Do consumer respond to marginal or average price?: Evidence from nonlinear electricity pricing." *American Economic Review*, 104(2), 537-563.
- [8] Marsh, Christina. 2013. "Estimating demand elasticities using nonlinear pricing." Working Paper.
- [9] Nawata, Kazumitsu and Koichi Kawabuchi. 2010. "Analysis of length of stay for cataract surgery before and after introduction of Diagnosis Procedure Combination-based inclusive payment system." *Japanese Journal of Health Economic and Policy*, 21(3), 291-302.
- [10] OECD. 2009. "OECD Economic Survey JAPAN." OECD.
- [11]Saez, Emmanuel. 2010. "Do taxpayers bunch at kink points?" *American Economic Journal: Economic Policy*, 2(3), 180-212.
- [12] Shigeoka, Hitoshi and Kiyohide Fushimi. 2014. "Supplier-induced demand for newborn treatment: Evidence from Japan." *Journal of Health Economics*, 35, 162-178.
- [13] Wang, Kai, Ping Li, Ling Chen, Ken Kato, Makoto Kobayashi, and Kazunobu Yamauchi. 2010. "Impact of the Japanese Diagnosis Procedure Combination-based Payment System in Japan." *Journal of Medical Systems*,34, 95-100.