Robust Health Distributions Orderings Using Categorical Variables

Paul Makdissi Myra Yazbeck

Department of Economics, University of Ottawa
School of Economics, University of Queensland

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Related Literature

- The concentration index is one of the most widely accepted measures of socioeconomic health inequality but it presents measurement problems:
  - Wagstaff (2002) pointed that the concentration index overlooks the average level of health in the populations under comparison.
    - Proposes a class of achievement indices that accounts for the average level of health and the socioeconomic inequality in its distribution.
  - Clarke *et al.* (2002) pointed to a second measurement difficulty: the consistency of rankings produced by health attainment of health shortfalls (*the mirror problem*).
    - In this paper, we use the generalized extended concentration indices (i.e., indices of absolute inequality) so the mirror condition is satisfied (Erreygers, 2009.).
  - The value of the health achievement index and the health concentration index may be arbitrary when one uses ordinal data.

Inequality measure with a non ratio-scale variable

Table: Gini Index estimates of temperature inequality for September 2011

	Ottawa	Québec	Montréal

Source: Environment Canada's Weather Office web site (own estimation)

Inequality measure with a non ratio-scale variable

Table: Gini Index estimates of temperature inequality for September 2011

	Ottawa	Québec	Montréal
Gini with $^{\circ}$C	0.120032	0.115051	0.114458

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$$^\circ F = \frac{9}{5} \times {}^\circ C + 32$$

Inequality measure with a non ratio-scale variable

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	Ottawa	Québec	Montréal
Gini with $^\circ$C	0.120032	0.115051	0.114458
Gini with $^\circ$F	0.059112	0.053594	0.057163

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Ranking with $^\circ$C			

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Ranking with $^\circ$C			**1**

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Gini with $^\circ$F	0.059112	0.053594	0.057163
Ranking with $^\circ$C		**2**	**1**

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Ranking with $^\circ$C	**3**	**2**	**1**

Source: Environment Canada's Weather Office web site (own estimation)

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Inequality measure with a non ratio-scale variable

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Ranking with °C	**3**	**2**	**1**
Ranking with °F		**1**	

Source: Environment Canada's Weather Office web site (own estimation)

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Inequality measure with a non ratio-scale variable

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Ranking with °C	**3**	**2**	**1**
Ranking with °F		**1**	**2**

Source: Environment Canada's Weather Office web site (own estimation)

$$^{\circ}F = \frac{9}{5} \times {}^{\circ}C + 32$$

Inequality measure with a non ratio-scale variable

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Ranking with °C	**3**	**2**	**1**
Ranking with °F	**3**	**1**	**2**

Source: Environment Canada's Weather Office web site (own estimation)

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Ranking with °C	**3**	**2**	**1**
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Source: Environment Canada's Weather Office web site (own estimation)

$$^\circ F = \frac{9}{5} \times {}^\circ C + 32$$

INEQUALITY RANKINGS ARE ARBITRARY WHEN THE MEASURE IS APPLIED TO A NON RATIO-SCALE VARIABLE

The Paper in Brief

- **Objective**: We address this measurement issue by providing a method that allows the researcher to identify robust orderings of health distributions while accounting for socioeconomic dimension of health.
- **Contribution**: It is the first paper that accounts for the ordinal nature of the health outcome variable and the socioeconomic dimension of health inequality.

Related Literature: Existing Solutions

Table: Alternative Solutions to the Measurement Problem

	Pure Ineq.	Socioeco Ineq.	Advantage	Costs
Allison & Foster(2004) F.O.D	Yes	No	Depth	Partial order & SES
Abul Naga & Yalcin(2008) Index	Yes	No	Depth Complete order	SES
Zheng (2011) Transitions	No	Yes	Depth SES	Heterogeneity Within SES classes
Makdissi & Yazbeck (2014) Count	No	Yes	SES Complete order Heterogeneity	Depth
This paper	No	Yes	**SES** **Depth** Heterogeneity	Partial

Theoretical Framework

- We build on Allison and Foster (2004) and extend their analysis to account for the socioeconomic dimension of health status by introducing aversion to socioeconomic health inequality.

- Instead of identifying robust comparisons of averages of health distributions, using a dominance approach we identify robust comparisons of:
  - Generalized Extended Health Concentration indices (Erreygers, Clarke and Van Ourti, 2012),
  - Health Achievement indices (Wagstaff, 2002),
  - Generalized Symmetric Socioeconomic Health Inequality indices (Erreygers, Clarke and Van Ourti, 2012).

Theoretical Framework

- Population of N individuals
- Information on the joint distribution of health and socioeconomic statuses is given by $\{(h_i, r_i)\}_{i=1}^{N}$, where
  - h_i represents health status
  - r_i the rank in the distribution of living standards (income, total expenditures, occupational categories, education level, etc), starting from the lowest level to the highest level of living standards.
- K health categories such that $h_i \in \{1, 2, ..., K\}$
- $\eta(h)$ is a numerical scale that assigns a numerical value to each category h of health.

Theoretical framework

- A rank dependent health achievement of socioeconomic health inequality index can always be rewritten in a general form:

$$I = \sum_{i=1}^{N} \omega(r_i)\eta(h_i).$$

- When $\omega(r_i) = \frac{1}{N} - \frac{(N-r_i+1)^\nu - (N-r_i)^\nu}{N^\nu}$, $\nu \geq 1$, the index is the generalized extended health concentration index, $GC(\nu)$.
- When $\omega(r_i) = \frac{(N-r_i+1)^\nu - (N-r_i)^\nu}{N^\nu}$, $\nu \geq 1$, the index is the health achievement index, $A(\nu)$.
- When $\omega(r_i) = 2^{\beta-2}\left[\left|\frac{r_i}{N} - \frac{1}{2}\right|^\beta - \left|\frac{r_i-1}{N} - \frac{1}{2}\right|^\beta\right]$, $\beta > 1$, the index is the generalized symmetric socioeconomic health inequality index, $GS(\beta)$.

Theoretical framework: Using categorical variables

- Note that all these indices have been developed and discussed under the assumption that the researcher is using a ratio scale variable.
- Wagstaff's achievement indices, the generalized extended concentration indices as well as the generalized symmetric socioeconomic health inequality indices are sensitive to scaling:

Table: Health distribution by socioeconomic status.

Socioeco. rank.	SAH A	SAH B
1	poor	poor
2	fair	fair
3	good	good
4	good	very good
5	very good	very good
6	excellent	excellent
7	very good	excellent
8	fair	poor
9	excellent	excellent
10	poor	poor

Table: Alternative scaling functions

	$\eta_1(h)$	$\eta_2(h)$	$\eta_3(h)$
Poor	1	1	1
Fair	2	10	2
Good	3	11	3
Very good	4	12	4
Excellent	5	13	10
	$A_1(2)$	$A_2(2)$	$A_3(2)$
A	2.80	9.20	3.40
B	2.95	8.95	3.90
	$GC_1(2)$	$GC_2(2)$	$GC_3(2)$
A	0.2000	0.2000	0.6000
B	0.1500	-0.2500	0.7000

Note that $GC(2) = GS(2)$.

Theoretical framework

- Allison and Foster (2004) overcome this problem by using a stochastic dominance approach.
- They show that for any two health distributions A and B, the average health level in A is higher than the average health in B if, for all health categories $k \in \{1, 2, \ldots, K-1\}$, the cumulative share of the population below health category k for A is lower than the analogous quantity for B.
- We use this insight and extend it to analyze socioeconomic health inequalities in self-reported health status.

Theoretical framework

Some notations:

- let $\mathscr{P}_k := \{i : h_i = k\}$: set of individuals with health status in the kth category.
- $\phi(k) = \sum_{i \in \mathscr{P}_k} \omega(r_i)$: proportion of total social weight of individuals in the health category k
- $\Phi^1(k) = \sum_{l=1}^{k} \phi(k)$: total social weight for individual with health status $\leq k$
- $\Phi^1(k)$ will play the same role as the cumulative distribution for F.O.D.

Theoretical framework: Theorem 1

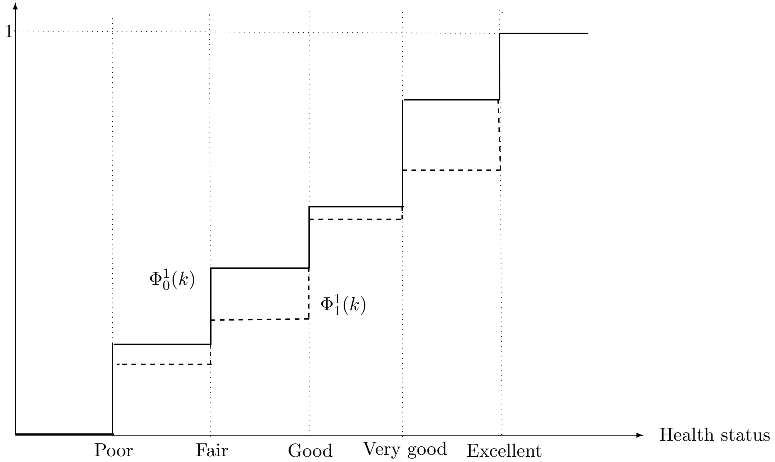
Theorem

$I_1 \geq I_0$ *for all scaling functions* $\eta(h)$ *if and only if:*

$$\Phi_0^1(k) \geq \Phi_1^1(k), \text{ for all } k \in \{1, 2, ..., K-1\}.$$

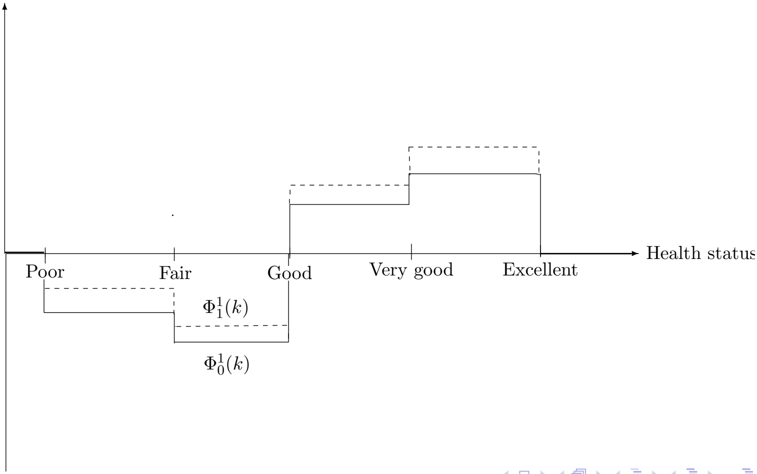
Theorem 1 applied on achievement indices

Figure: Theorem 1



Theorem 1 applied on inequality indices

Figure: Theorem 1



Theoretical Framework: Concave Scale Functions

- Concavity is a reasonable assumption if the analyst has a strong belief that differences between adjacent categories become less important as one moves towards the highest category.
- Let $\Phi^{2+}(k) = \sum_{j=1}^{k} \Phi^{1}(j)$.

Theorem

$I_1 \geq I_0$ for all concave scaling functions $\eta(h)$ if and only if:

$$\Phi_0^{2+}(k) \geq \Phi_1^{2+}(k), \text{ for all } k \in \{1, 2, \ldots, K-1\}.$$

- Convexity is a reasonable assumption if the analyst has a strong belief that differences between adjacent categories become more important as one moves towards the highest category.
- Let $\Phi^{2-}(k) = \sum_{j=k}^{K-1} \Phi^{1}(j)$.

Theorem

$I_1 \geq I_0$ for all convex numerical scales $\eta(h)$ if and only if:

$$\Phi_0^{2-}(k) \geq \Phi_1^{2-}(k), \text{ for all } k \in \{1, 2, \ldots, K-1\}.$$

National Health Interview Survey for 2012

- The NHIS has monitored the health of the United States of America since 1957.
- The NHIS is a cross-sectional household interview survey that is representative of households and noninstitutional group quarters.
- We use information on household income to infer the socioeconomic rank of the individual.
- The surveys has includes a self-reported health status variable and a self-reported sadness variable, both with 5 categories.
- We compare health achievement and socioeconomic health inequality in 4 regions: Northeast, Midwest, South and West.

National Health Interview Survey for 2012

Table: Description of the two categorical variables

Would you say that your health in general is ...	During the past 30 days, how often did you feel so sad that nothing could cheer you up?
Poor	NONE of the time
Fair	A LITTLE of the time
Good	SOME of the time
Very good	MOST of the time
Excellent	ALL of the time

Theorem 1 Self-Reported Health Status

	Northeast	Midwest	South	West
		$A(2)$		
Northeast		D	D	ND
Midwest			ND	
South				
West		D	D	
	Northeast	Midwest	South	West
		$GC(2) = GS(2)$		
Northeast		ND	ND	
Midwest				
South		D		
West	D	D	D	

Theorem 2 Self-Reported Health Status

	Northeast	Midwest	South	West
		$A(2)$		
Northeast		D	D	ND
Midwest			D	
South				
West		D	D	
	Northeast	**Midwest**	**South**	**West**
		$GC(2) = GS(2)$		
Northeast		D	D	
Midwest				
South		D		
West	D	D	D	

Theorem 1 Self-Reported Sadness

	Northeast	Midwest	South	West
		$A(2)$		
Northeast		ND	D	ND
Midwest			ND	ND
South				ND
West				
	Northeast	**Midwest**	**South**	**West**
		$GC(2) = GS(2)$		
Northeast			ND	
Midwest	D		D	ND
South				
West	D		D	

Theorem 3 Self-Reported Sadness

	Northeast	Midwest	South	West
		$A(2)$		
Northeast			D	
Midwest	D		D	D
South				
West	D		D	
	Northeast	Midwest	South	West
		$GC(2) = GS(2)$		
Northeast			ND	
Midwest	D		D	ND
South				
West	D		D	

Conclusion

- We address an important measurement problem that arises when using categorical data to perform socioeconomic health inequality analysis: the arbitrariness of the achievement, concentration indices and the generalized symmetric socioeconomic health indices.
- We extend the analysis of Allison and Foster (2004) to the socioeconomic dimension of health inequalities by constructing a social weighted cumulative distribution of self reported health status.
- We provide dominance criteria that allows us to produce robust rankings of health achievement and socioeconomic health inequalities.
- We provide an empirical illustration using NHIS 2012.
- Our method provide an incomplete ordering. This does not come as a surprise as robustness is often being obtained at the cost of completeness.

Robust Orderings of Distributions of Categorical Health Variables

Discussant

Dennis Petrie (University of Melbourne)

Hawaii, 13th December 2015

Thanks

- Good clear paper
  - The simplest papers are the best!
- Pictures to help visual the issue are great
- Left all the complicated looking maths (Proof of Theorems etc.) to the appendix

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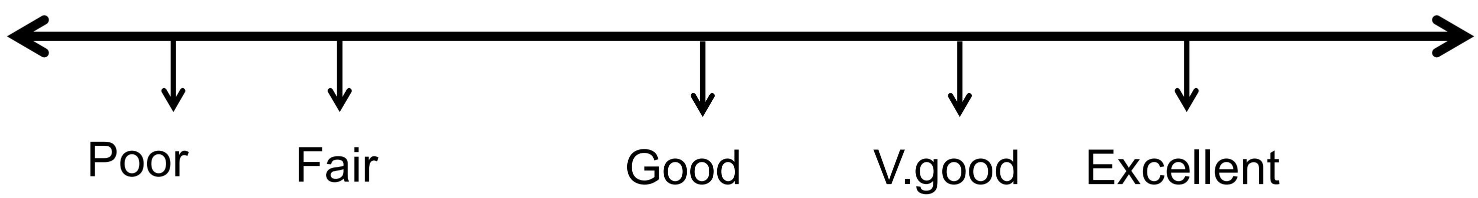
Overview – Measurement/Inference

We have categorical health and income reported for a sample of the population/s



Research Questions;

Compared to Population A does Population B have better;

1. Average Health?

2. Socioeconomic Health Inequality?
3. Partial Social Welfare = Health Achievement?

What "robust" comparisons can we make given uncertainty?

Types of uncertainty

1. What values do the categories take? **YES**
2. Sampling uncertainty **NOT YET**
3. Reporting heterogeneity **NOT YET**
4. Misclassification **NOT YET**
5. Within category variability **NOT YET**

In terms of inequality & achievement uncertainty

6. How much more weight do we want to place on the poor relative to rich individuals? **YES** (many different forms explored)

In terms of inequality uncertainty

7. What transformation would leave inequality unchanged? (attainment-relative, **absolute**, shortfall-relative) **NOT YET**

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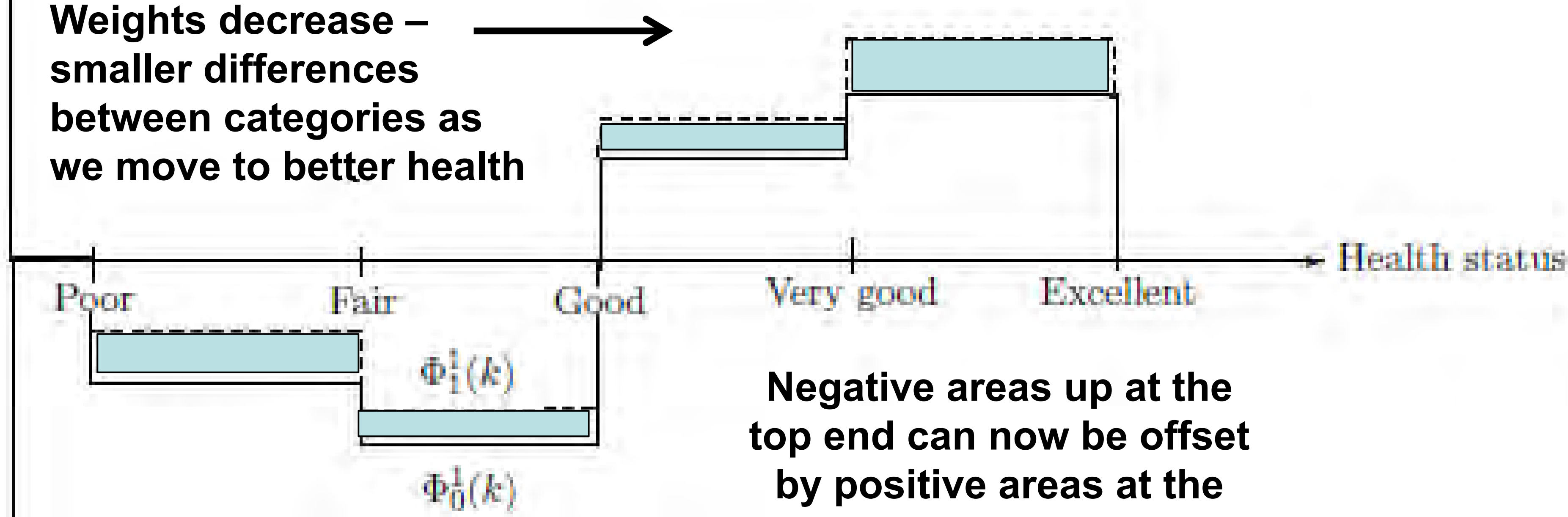
The nice figure….

Socioeconomic Health Inequality

$$I_1 - I_0 = \sum_{k=1}^{K-1} \left[\Phi_0^1(k) - \Phi_1^1(k)\right] \Delta^1\eta(h_k)$$

Overall difference is a weighted sum of the areas between curves

Concavity assumption Weights decrease – smaller differences between categories as we move to better health



Negative areas up at the top end can now be offset by positive areas at the bottom end

What do we get?

Research Questions;

Compared to Population A does Population B have better;

1. Average Health?
2. Socioeconomic Health Inequality?
3. Partial Social Welfare = Health Achievement?

- Partial (incomplete) rankings of populations by average health, achievement, absolute inequalities
- And more complete but still incomplete rankings when we impose concavity (or convexity)

Can we provide more?

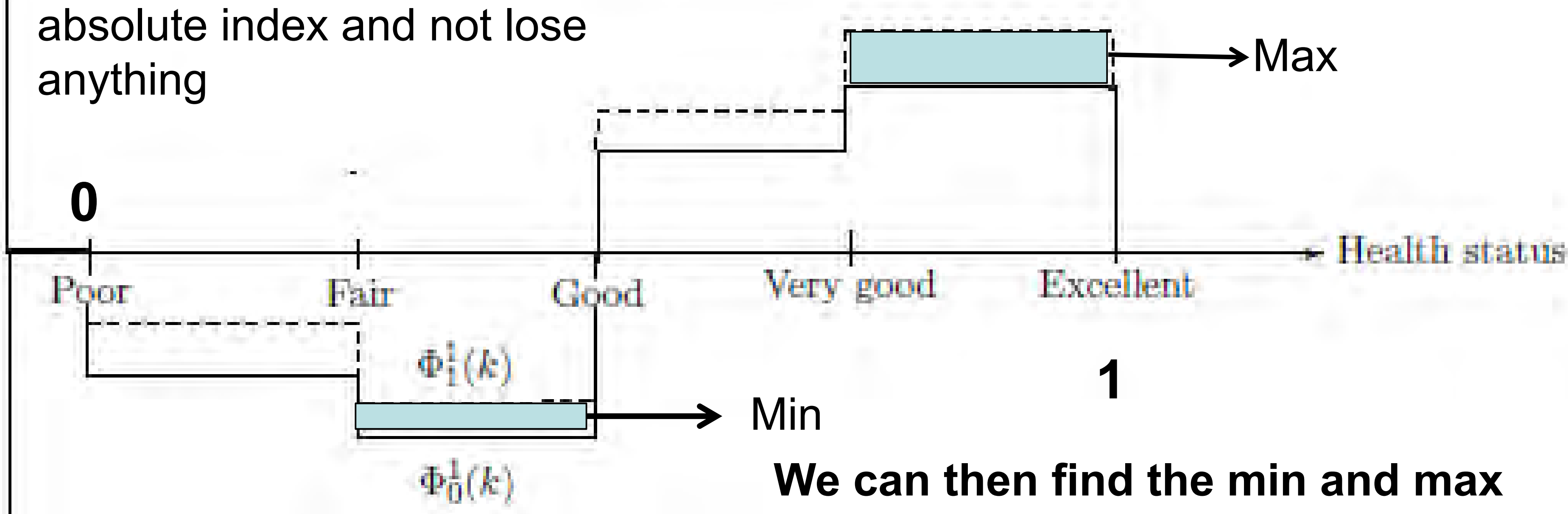
The nice figure….

Socioeconomic Health Inequality

$$I_1 - I_0 = \sum_{k=1}^{K-1} \left[\Phi_0^1(k) - \Phi_1^1(k)\right] \Delta^1 \eta(h_k)$$

Overall difference is a weighted sum of the areas between curves

We can standardize the absolute index and not lose anything



We can then find the min and max (i.e. 100% confidence intervals)

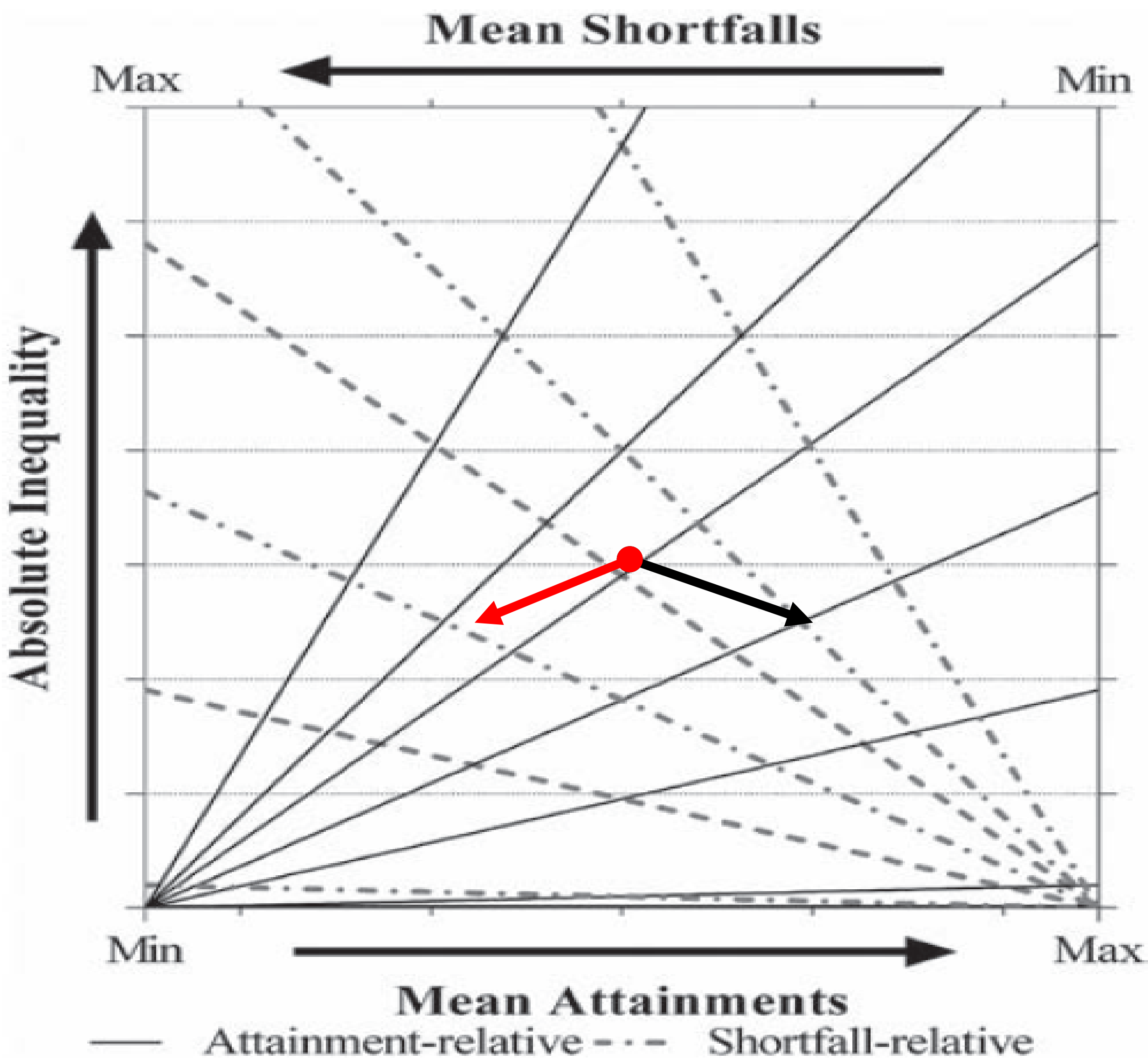
Can we say anything about the relative inequality measures?

Something but not much!

If a population has; **higher mean health** and **lower absolute inequality** - lower attainment-relative inequality

Lower mean health and **lower absolute inequality** – lower shortfall relative

And maybe once we know the bounds we can say more



Kjellsson et al. 2015 Epidemiology

West has lower attainment-relative inequality than the South. But that's it!

	Northeast	Midwest	South	West
		$\nu = 1$		
Northeast		D	D	ND
Midwest			D	ND
South				
West			D	

Has higher average health than South

	Northeast	Midwest	South	West
		$\nu = 2$		
Northeast		ND	ND	
Midwest				
South		D		
West	D	D	D	

West has lower absolute inequality than the South

- Could use the bounds to extend the idea slightly?

Where to from here…..

- How do we capture and present the impacts of all types of uncertainty so that;
  - people understand it?
  - we can focus on reducing uncertainty where it is the most important?
  - Move away from alpha=0% and place less weight on extreme (unlikely) cases

A Challenge……..

- Can we move on from cross-sectional measures?
  - they can be misleading measures of “performance”
  - better to look at changes in health (by socioeconomics status) over time (combining with mortality)

Summary

- Good solid paper that adds to the literature
- Hopefully others will use this paper as a springboard to keep things moving forward

THANKS

I learnt a lot!

Efficiency estimation with quantile regression: An application using a panel of long-term care homes in Ontario

Amy Hsu, Adrian Rohit Dass, Whitney Berta, Peter Coyte, Audrey Laporte

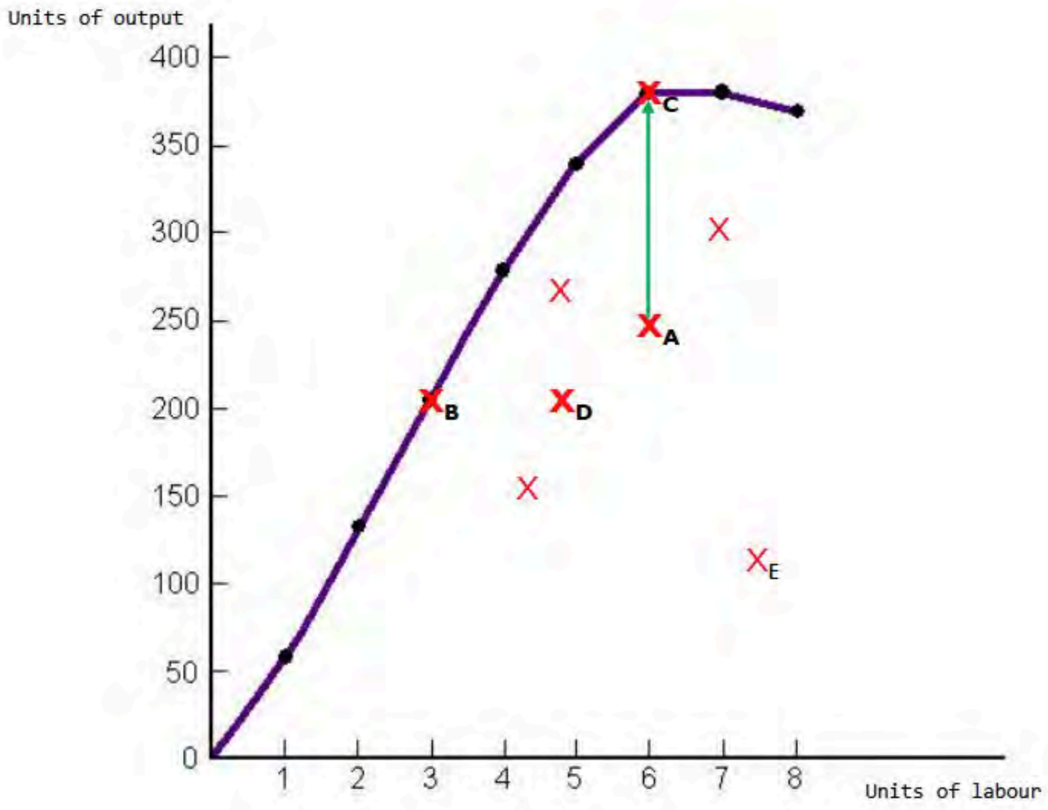
Joint 2015 AHEW & AWEHE Workshop

December 13th, 2015

Motivation – Importance of Efficiency Analysis

- Health care systems are under pressure to deliver care in a timely manner at an affordable price.
- Important to understand drivers of technical efficiency for policy makers to effect change.
  - Particularly important for the institutional LTC sector, with the aging of the population in Canada, the U.S., and abroad.
- Firms are said to be technically efficient if their output mix lies on the production possibility frontier defined for its particular input levels.
  - In order to do this, need to obtain the best estimate of the frontier itself

Productivity and Efficiency



Context

- Long-term care (LTC) homes in Ontario, commonly known as nursing homes, are facilities that provide accommodation and personal care to individuals who are no longer able to live independently in their own homes and who require 24-hour nursing care.
- Facilities are publicly funded, but majority are operated by private for-profit and non-profit entities.
  - 55.6% of LTC homes over study period were for-profit, 25.4% were non-profit and 19.0% were operated by municipalities (i.e. public).
- Average occupancy rate was 98.0% (1996 -2010).

Research Objectives

- To estimate a production frontier for the publicly funded LTC sector.

- To assess the impact of inputs (nurses, personal support workers, capital, expenditure on drugs, expenditure on medical supplies, etc.) and facility characteristics (e.g. profit status, rural location, chain ownership) on the volume of resident care days produced for LTC homes at various points in the distribution of facilities.

- To obtain estimates of technical efficiency scores for LTC Homes in Ontario.

Data Description

- Residential Care Facilities Survey (RCFS), which is an annual census of all Long Term Care homes in Ontario that receive public funding from the Ontario government.
- Use 15 waves (1996/97-2009/10) of the RCFS to form a panel of Long Term Care Homes in Ontario.
- N= 627 facilities

Profile of nursing homes in Ontario and summary statistics of labor inputs, 1996/1997 to 2010/2011

	For-profit	Not-for-profit	Municipal	All
Number of facilities[i]	(n = 356)	(n = 162)	(n = 109)	(n = 627)
Facility Characteristics				
Chain owned (% of facilities)	82.7[ii]	38.5[ii]	…	55.5
Urban location (% of facilities)	48.7[ii]	54.2[ii]	51.8	50.7
Number of beds (average per facility)	109.0[ii,iii]	116.9[ii,iv]	167.4[iii,iv]	122
	[58.0]	[79.9]	[84.0]	[72.9]
Case mix adjusted excess mortality	1.00[ii,iii]	0.98[ii,iv]	1.03[iii,iv]	1
	[0.31]	[0.29]	[0.27]	[0.30]
Output				
Case mix adjusted resident care days, average per facility per year				
	38,856[ii,iii]	41,932[ii,iv]	59,738[iii,iv]	43,582
	[20,296]	[28,265]	[29,824]	[25,743]
Inputs				
Total hours paid to direct care and general services staff, average per facility per year				
Registered nurses (RNs)	13,923i[i,iii]	16,169[ii,iv]	23,669[iii,iv]	16,334
	[7,831]	[12,558]	[17,819]	[12,147]
Registered practical nurses (RPNs)	15,891[ii,iii]	22,825[ii,iv]	44,037[iii,iv]	22,968
	[15,581]	[38,674]	[41,686]	[30,899]
Therapists	8,522[iii]	9,768[iv]	13,570[iii,iv]	9,792
	[11,971]	[18,286]	[34,805]	[19,925]
Health care aides (HCAs)	64,463[ii,iii]	71,806[ii,iv]	98,143[iii,iv]	72,689
	[41,975]	[60,246]	[67,321]	[54,026]
General services staff	39,113[ii,iii]	56,425[ii,iv]	87,449[iii,iv]	52,639
	[24,095]	[47,780]	[48,164]	[40,931]
Total expenditure, average per facility per year (in 2010 Canadian dollars)				
Drugs	11,376[iii]	13,812	16,744[iii]	13,009
	[24,613]	[53,492]	[45,280]	[38,148]
Medical supplies	57,579[ii,iii]	64,355[ii,iv]	86,348[iii,iv]	64,736
	[68,692]	[93,119]	[117,394]	[86,884]
Other expenses	1,676,237[ii,iii]	1,909,918[ii,iv]	2,273,198[iii,iv]	1,848,370
	[1,448,962]	[2,071,949]	[1,737,344]	[1,697,300]

Background Literature: DEA

- Data Envelopment Analysis (DEA)
  - Non-parametric method where production frontier is made up of the most efficient providers who produce the highest volume of services using a set quantity of inputs.
    - This frontier serves as a benchmark for comparison within the sample.
  - DEA does not estimate the marginal productivity of different inputs
  - Second stage DEA can only give estimates of exogenous factors on efficiency (factors uncorrelated with inputs in first stage)
  - Does not account for statistical noise, hence all deviations from the best practice frontier are attributed to poor performance.
  - Less well suited to panel data

Background Literature: SFA

- **Stochastic Frontier Analysis** (**SFA**) most widely used regression approach (Aigner, Lovell and Schmidt, 1977; Meeusen and van den Broeck, 1977).
- Splits the random error into two parts: the usual disturbance (ε_{it}) and an efficiency scaling term μ_i:

$$Y_{it} = \alpha + \beta_1 x_{1it} + \mu_i + \varepsilon_{it}$$

- Can be estimated using cross-sectional or panel data
  - SFA for panel data has traditionally been estimated with Fixed Effects (FE) and Random Effects (RE) models (Greene, 2005).

SFA for Panel

- Fixed Effects (Within)
  - Allows explanatory variables (X_{it}) to be correlated with the inefficiency (u_i)
  - No distributional assumption on inefficiency is made
  - Does not allow for inclusion of time-invariant variables
  - All between firm heterogeneity (observed and unobserved) goes to same term used to measure inefficiency
- Random Effects (GLS and Maximum Likelihood)
  - Both allow for inclusion of time-invariant variables, so one can distinguish between their effect and the true inefficiency
  - Both assume no correlation of explanatory variables and inefficiency ($corr(x_{it}, u_i) = 0$)
  - RE via Maximum Likelihood is more efficient, but requires the specification of a distribution for the inefficiency term
- Both model conditional mean as a function of predictors
  - May be inappropriate in the context of efficiency analysis, as effects of inputs and exogenous factors may vary for very inefficiency or very efficient firms

Quantile Regression (QR)

- Semi-parametric approach: models conditional quantiles as a function of predictors - as opposed to the conditional mean which underlies many typical regression approaches (Hao & Naiman, 2007).
  - Minimize weighted sum of residuals ($y_i - y_{i,hat}$) where positive residuals receive a weight p and negative residuals receive a weight (1-p):

$$\sum_{i=1}^{n} d_p(y_{it}, \hat{y}_{it}) = p \sum_{y \geq \beta_0^{(p)} + \beta_1^{(p)} x_i} |y_i - \beta_0^{(p)} - \beta_1^{(p)} - x_i| + (1-p) \sum_{y < \beta_0^{(p)} + \beta_1^{(p)} x_i} |y_i - \beta_0^{(p)} - \beta_1^{(p)} - x_i|$$

QR (Continued)

- The estimation of coefficients for each quantile regression is based on the weighted data of the whole sample
- At 90th percentile, points below are given a weight of 0.1, and points above are given a weight of 0.9.
  - This down-weighs any unusually low values of the dependent variable that would bring the estimated frontier downward, thereby giving an estimate of the production frontier that is closer to the true than OLS (Lui et al, 2008).

QR (Continued)

- Enables us to go beyond the conditional mean to investigate the drivers of efficiency across the distribution of providers, while controlling for observable heterogeneity between service providers.
  - By setting the benchmark at one of the upper quantiles, we can identify characteristics of top producers in a sample.
- Despite its advantages, has been applied infrequently in productivity and efficiency analyses of health care providers (Knox et al., 2007) and has been less applied to efficiency analysis using panel data

QR for Efficiency Analysis (Cross-sectional)

- Relaxes the distributional assumptions that the RE SFA relies on
- Liu, Laporte, & Ferguson (2008) explored the use of QR for efficiency measurement, and compared its performance to SFA and DEA (for cross-sectional data)
  - Found that QR outperformed SFA and DEA when there were a large number of fully efficient firms or the distribution of inefficiency was miss-specified (half-normal applied to exponential) in SFA
- Prior applications have typically selected values between the 80th and 99th percentiles as benchmarks (Behr, 2010; Liu et al., 2008; Knox et al., 2007; Bernini et al., 2004).
  - We selected three upper quantiles (i.e., τ = 0.80. 0.85 and 0.90) as the main focus in our study

QR for Panel Data (Incorporating Unobserved Heterogeneity) – Fixed Effects

- Incorporating FE to QR began with Koenker (2004), who's formulation includes the estimation of individual FE in the model, to capture unobserved heterogeneity in the sample.
  - In the linear context, FE estimation can be achieved through transformation of *y* and **x** into deviation from individual mean form, something that is not available for QR.
- Koenker's (2004) formulation includes the estimation of individual FE in the model, to capture unobserved heterogeneity in the sample.
  - However, with larger samples, the increased number of FE becomes a concern for inflating the variability of the estimated coefficients.
  - To address this concern, Koenker (2004) proposed a correction, or penalty factor, to impose shrinkage of the individual effects toward a common intercept to control for the variability introduced by the large number of estimated parameters.

QR for Panel Data – Random Effects

- Random effects estimation has been introduced for panel quantile estimation as an alternative to the FE procedure.
- The RE approach involves the estimation of random intercepts for each individual in a given sample (Geraci and Bottai, 2007; Liu and Bottai, 2009).
- While this approach takes into account the dependence of observations over time, independence of the random effect and the explanatory variables is typically assumed.
  - When these assumptions are violated, estimates produced using the conventional RE model may be biased.

QR for Panel Data – Correlated Random Effects (CRE)

- Abrevaya and Dahl (2008) builds upon the concept of CRE developed by Chamberlain (1984) and applies it to QR.
- Bache, Dahl, and Kristensen (2013) further extended panel QR for unbalanced panel models.
  - Suggest the introduction of group mean variables for all time-varying variables in the analysis:

$$s_i = \bar{\mathbf{z}}_i \boldsymbol{\gamma} + \eta_i$$

$$\bar{\mathbf{z}}_i = \frac{1}{T_i} \sum_{t=1}^{T_i} \mathbf{z}_{it}$$

  - Where s_i can be regarded as the mean effect of all observable traits (e.g., staffing patterns, measurable indicators of care quality or outcomes) that provide some indication as to the facility attributes underlying the unobservable heterogeneity.
  - Idea is that one can generate one or more "sufficient covariates" from the repeated observations which carry information that can correct for the bias.

QR for Efficiency Analysis (Panel)

- To date, calculating technical efficiency scores of firms using longitudinal data using QR has not been done
- Extending the Liu et al (2008) cross-sectional method to panel, we take the difference between a firm's observed output and actual in each period t, then average across time, or:

$$\widehat{u_i} \cong \frac{1}{T}\hat{\varepsilon}_i = \frac{1}{T}\sum_i \left[\ln Y_{it} - \widehat{\beta_o} - \sum_n (\widehat{\beta_n} \ln x_{it})\right]$$

- The u_i are then exponentiated to be put in e^{-ui} form

QR for Efficiency Analysis (Panel)

- Laporte and Rohit Dass (2015) compared the performance of CRE QR to panel SFA (FE, RE GLS, RE MLE)
  - Found CRE QR produced unbiased estimates of the slope parameters when explanatory variables correlated with inefficiency
  - Found panel QR outperformed panel SFA when there were a large amount of fully efficient firms and when the distribution for the inefficiency was mis-specified (i.e. half-normal applied to exponential)
  - Authors conclude that CRE QR may be a good alternative to panel SFA since true distribution of inefficiency is never known in practice.

Methods (Summary)

- Utilize CRE Panel Quantile to obtain estimates of drivers of technical efficiency of LTC homes in Ontario
  - Once function is estimated, obtain estimates of technical efficiency using residuals
- CRE QR requires an assumption about the functional form of the frontier
  - We specify a Cobb-Douglas functional form for the analysis

Cobb-Douglas production frontier of nursing homes in Ontario, 1996/1997 to 2010/2011

	QR(0.80)	QR(0.85)	QR(0.90)
Main equation coefficients (Xit)			
Intercept	5.875***	6.107***	6.424***
	[0.166]	[0.189]	[0.227]
Inputs			
ln(Registered nurses)	0.151***	0.145***	0.137***
	[0.012]	[0.013]	[0.017]
ln(Registered practical nurses)	0.12***	0.112***	0.108***
	[0.008]	[0.008]	[0.008]
ln(Health care aides)	0.088***	0.08***	0.075***
	[0.008]	[0.007]	[0.006]
ln(Therapists)	0.099***	0.104***	0.086***
	[0.008]	[0.010]	[0.012]
ln(General services staff)	0.023***	0.022***	0.022***
	[0.007]	[0.006]	[0.006]
ln(Expenditure on drugs)	-0.001	0.0004	0.0001
	[0.001]	[0.0008]	[0.0008]
ln(Expenditure on supplies)	-0.003**	-0.002	-0.002
	[0.001]	[0.001]	[0.001]
ln(Other expenses)	0.008**	0.006**	0.009***
	[0.003]	[0.002]	[0.002]
Explanatory variables			
Municipal ownership	0.009	0.012	0.031
	[0.014]	[0.015]	[0.017]
Not-for-profit ownership	-0.004	-0.0002	0.016
	[0.008]	[0.0092]	[0.013]
Chain member	0.042***	0.043***	0.045***
	[0.008]	[0.009]	[0.011]
Urban location	0.067***	0.073***	0.071***
	[0.009]	[0.009]	[0.010]
Case mix adjusted excess mortality	-0.01	-0.012	-0.016
	[0.011]	[0.011]	[0.011]
Facility size (lower quartile)	-0.341***	-0.353***	-0.375***
	[0.014]	[0.014]	[0.018]
Facility size (upper quartile)	0.316***	0.336***	0.393***
	[0.012]	[0.015]	[0.021]

Cobb-Douglas production frontier of nursing homes in Ontario, 1996/1997 to 2010/2011 (Continued)

Year			
1997	-0.037*	-0.028	-0.037
	[0.018]	[0.021]	[0.024]
1998	-0.035*	-0.036*	-0.041
	[0.015]	[0.018]	[0.021]
1999	-0.037*	-0.043*	-0.058*
	[0.016]	[0.019]	[0.024]
2000	-0.048**	-0.059**	-0.056*
	[0.017]	[0.020]	[0.027]
2001	-0.046*	-0.037	-0.044
	[0.018]	[0.021]	[0.024]
2002	-0.06***	-0.052**	-0.056*
	[0.015]	[0.020]	[0.025]
2003	-0.052***	-0.054**	-0.06*
	[0.015]	[0.019]	[0.024]
2004	-0.045**	-0.042*	-0.046*
	[0.015]	[0.018]	[0.022]
2005	-0.032*	-0.028	-0.037
	[0.016]	[0.017]	[0.023]
2006	-0.049**	-0.046*	-0.033
	[0.016]	[0.019]	[0.023]
2007	-0.052**	-0.043*	-0.057**
	[0.017]	[0.018]	[0.021]
2008	-0.058***	-0.052**	-0.059**
	[0.016]	[0.019]	[0.021]
2009	-0.058***	-0.06***	-0.069***
	[0.016]	[0.018]	[0.021]
2010	-0.089***	-0.089***	-0.091***
	[0.018]	[0.020]	[0.022]

Cobb-Douglas production frontier of nursing homes in Ontario, 1996/1997 to 2010/2011 (Continued)

CREM added variables (Zit)			
ln(Registered nurses)	0.005	0.009	0.011
	[0.013]	[0.014]	[0.015]
ln(Registered practical nurses)	0.003	0.0003	-0.004
	[0.007]	[0.0083]	[0.010]
ln(Health care aides)	-0.001	0.003	0.006
	[0.008]	[0.008]	[0.009]
ln(Therapists)	-0.004	-0.014	-0.015
	[0.013]	[0.012]	[0.016]
ln(General services staff)	-0.001	0.004	0.005
	[0.007]	[0.009]	[0.009]
ln(Expenditure on drugs)	0.002	0.002	0.001
	[0.001]	[0.001]	[0.001]
ln(Expenditure on supplies)	-0.001	-0.001	-0.0002
	[0.001]	[0.001]	[0.0010]
ln(Other expenses)	0.004	0.004	0.003
	[0.002]	[0.002]	[0.002]
Case-mix adjusted excess mortality ratio	0.023	0.006	0.014
	[0.022]	[0.024]	[0.028]
Mean predicted technical efficiency	0.942	0.943	0.939
	[0.058]	[0.058]	[0.056]

Notes:
Output (Yit) = Case mixed adjusted days of resident care.
Standard errors are presented in parentheses.
* indicates significance at $0.01 < p \leq 0.05$.
** indicates significance at $0.001 < p \leq 0.01$.
*** indicates significance at $p \leq 0.001$

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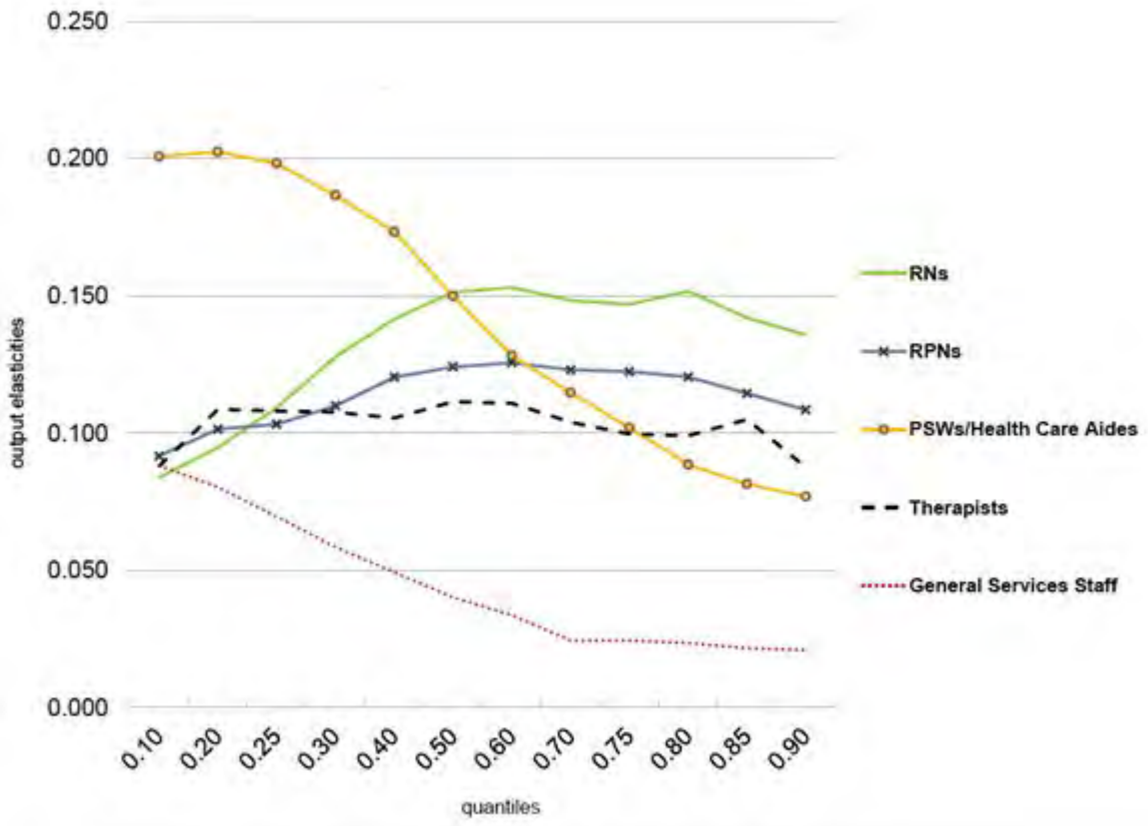
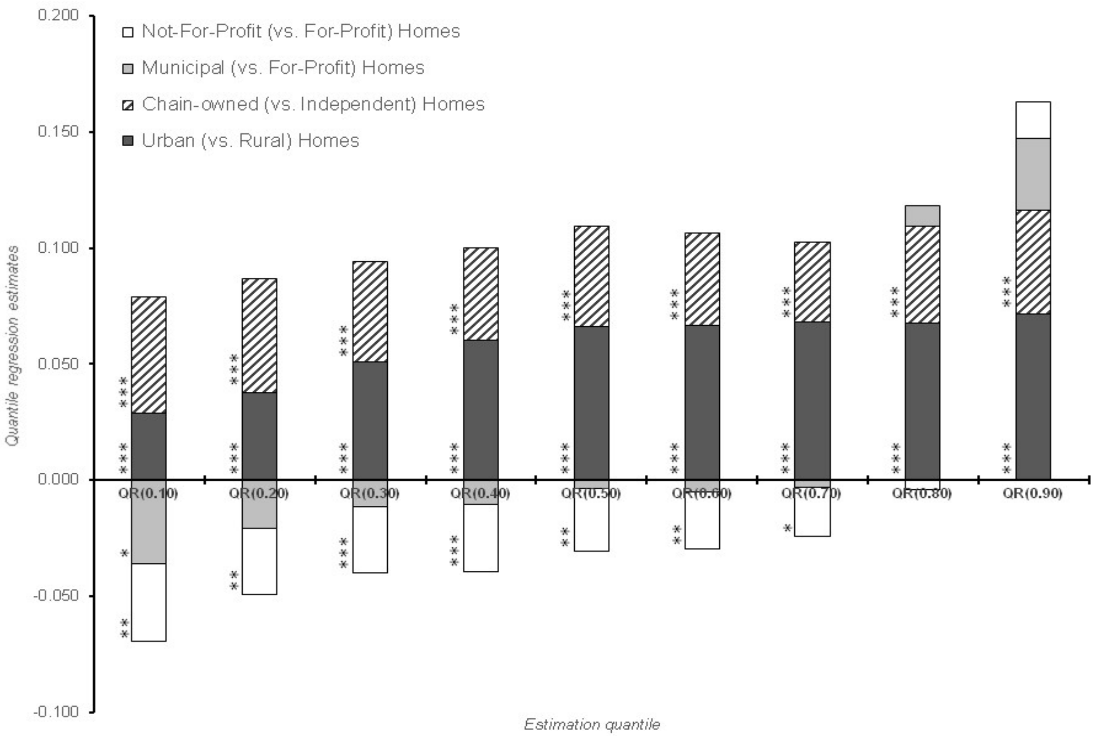
Changes in output elasticities with respect to labor inputs across quantiles



Estimated effect of organizational characteristics on technical efficiency across quantiles



Robustness Checks

- Coefficient estimates from FE QR similar to those obtained from CRE Quantile
  - The estimates from the FE model should be consistent as the panel is relatively long
- Technical efficiency scores from time-varying efficiency (Lee and Schmidt 1993) slightly lower, but still greater than 0.93 for all quantiles in study.
  - Consistent with declining technical efficiency of LTC homes across time.

Conclusions

- CRE Panel Quantile produced a mean efficiency score of 94% across the 80^{th}, 85^{th}, and 90^{th} quantiles
  - These results are consistent with our expectations, as LTC homes in Ontario are required to operate at 97% capacity to receive 100% of it's funding from the province (MOHLTC, 2013).
  - Little incentive for firms to be technically inefficient.
  - Regulation is so tight that appears to be little scope for differences in profit status to emerge.
  - Firms seem to get gains from joining a chain.

End

Canadian Centre for Health Economics
155 College Street, 4th Floor
Toronto, ON M5T 3M6 Canada
Email: cche@utoronto.ca | Phone: 1-416-978-4125

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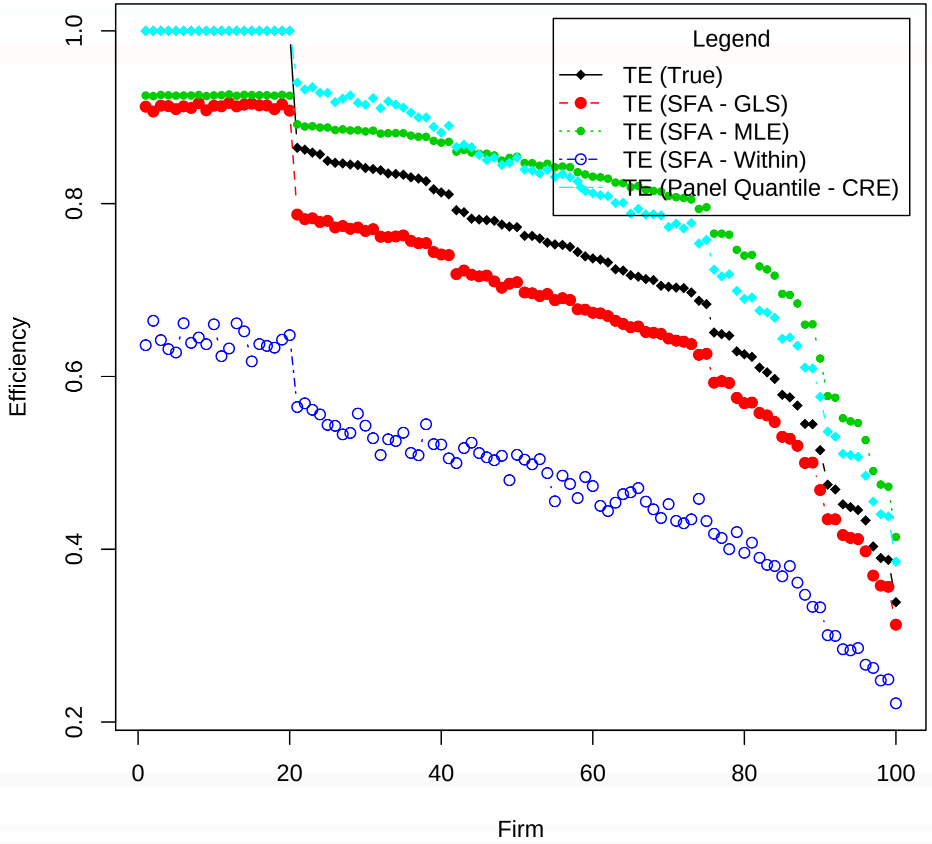
Panel QR Technical Efficiency Simulation Study



Discussion of "Efficiency Estimation with Quantile Regression: An Application Using Panel Data from Nursing Homes in Ontario, Canada"

David Byrne
The University of Melbourne

AHEW & AWEHE 2015
December 13, 2015

Overview

- This paper digs into the blackbox of healthcare services
- This time in the context of nursing homes
- Estimating a production technology where output is keeping old folks alive
- Measuring nursing home efficiency/productivity
- Really interesting area of work that petrifies me

Producing days alive in nursing homes

- Here's the production function

$$
\begin{aligned}
\ln y_{it}^{*} = \beta_o &+ \beta_1 \ln RN_{it} + \beta_2 \ln RPN_{it} + \beta_3 \ln HCA_{it} + \beta_4 \ln(therapists_{it}) + \beta_5 \ln(gen.services_{it}) \\
&+ \beta_6 \ln(drugs_{it}) + \beta_7 \ln(med.supplies_{it}) + \beta_8 \ln(other\ expenses_{it}) + \beta_9 (public_i) \\
&+ \beta_{10}(not\ for\ profit_i) + \beta_{11}(chain_i) + \beta_{12}(urban_i) + \beta_{13}(excess\ mortality_{it}) \\
&+ \beta_{14}(facility\ size\_lower\ quartile_{it}) + \beta_{15}(facility\ size\_upper\ quartile_{it}) \\
&+ \beta_{16}(year_{1997}) \ldots + \beta_{29}(year_{2010}) + s_i + \varepsilon_{it}
\end{aligned}
$$

Endogeneity concerns

- Here's the production function

$$\begin{aligned}\ln y_{it}^{*} = \beta_o &+ \beta_1 \ln RN_{it} + \beta_2 \ln RPN_{it} + \beta_3 \ln HCA_{it} + \beta_4 \ln(therapists_{it}) + \beta_5 \ln(gen.services_{it}) \\ &+ \beta_6 \ln(drugs_{it}) + \beta_7 \ln(med.supplies_{it}) + \beta_8 \ln(other\ expenses_{it}) + \beta_9 (public_i) \\ &+ \beta_{10}(not\ for\ profit_i) + \beta_{11}(chain_i) + \beta_{12}(urban_i) + \beta_{13}(excess\ mortality_{it}) \\ &+ \beta_{14}(facility\ size\_lower\ quartile_{it}) + \beta_{15}(facility\ size\_upper\ quartile_{it}) \\ &+ \beta_{16}(year_{1997}) \ldots + \beta_{29}(year_{2010}) + s_i + \varepsilon_{it}\end{aligned}$$

Labor

Materials

Capital

Productivity

- Is it conceivable that nursing homes with higher s_i's and ε_{it}'s
  - invest more in capital and are thus larger?
  - are less like to exit the market?
- Suggestions
  - address endogeneity issues (Olley and Pakes 1996, ECMA)
  - or caveat/discuss/clarify

Using quantile regression for production function estimation

- Why should the production technology fundamentally differ for nursing homes that produce at different output levels?
- Why not have a common production technology that allows for things like
    - economies of scale/scope
    - unobserved productivity shocks
- Suggestions
    - clarify the need for quantile regression using theory or industry background
    - or pursue a modelling strategy like Olley and Pakes (1996, ECMA)

Why the focus at the top?

- The main set of results focuses on how observables explain number of days in a nursing home
  - focus on the 80^{th}, 85^{th} and 90^{th} quantiles
- Rationale given in the paper is the desire to see what characterizes high-producing nursing homes
- I don't think the quantile regressions deliver on this
  - they tell you how characteristics (e.g,. private home status) affect production at the high end of the distribution
- Suggestion: follow common practice a produce results for all quantiles (e.g., from 10 to 90)
  - results may be more policy relevant at the low end of the distribution: what matters for boosting production for nursing homes with few days in care?

Efficiency tends to be about unobservables

- The current draft heavily focuses on the influence of observable characteristics on nursing home production
- I found the focus confusing since we tend to think about productive firms as those who have abnormally high production for unexplained reasons
- Suggestions
  - provide more extensive comparison on your efficiency results to those obtained using DEA and SFA
  - clarify what is a nursing-home specific input (labor, capital (beds)).
  - separately examine how total factor productivity varies in different areas or at different times
    - I am really curious to know if more competitive local markets for nursing homes tend to have more productive firms
    - does competition keep the elderly alive? Does market power lead to morbidity?

Secondary comments

- What's the outcome variable?
  - Days alive on the LHS and excess mortality on the RHS was a bit confusing.
- Be careful criticizing parametric models.
  - You argue against SFA because it requires parametric assumptions, but you assume a Cobb-Douglas production technology and require random effects with nursing home shocks.
- Individual effects in quantile regression.
  - found it tough to follow your analysis of it (as well as the JBES's development). This is a tough problem and needs careful development.
  - following Olley and Pakes (1996) you could easily recover nursing homes FEs/permanent unobserved heterogeneity

Youth unemployment and the effect of personality traits

by

Silvia Mendolia* and Ian Walker**

*University of Wollongong and IZA

**Lancaster University, Princeton University and IZA

Objectives of the paper

- To investigate the relationship between personality traits in adolescence and risk of drop out from education and labour market (NEET)

- NEETs have lower chances of success in the labour market in the longer term

- More specifically, we will analyse the impact of locus of control, self-esteem and effort on:
  - Having been NEET at least once between 18 and 21
  - Having been NEET for two or more years (core NEET)
  - Number of years spent being NEET

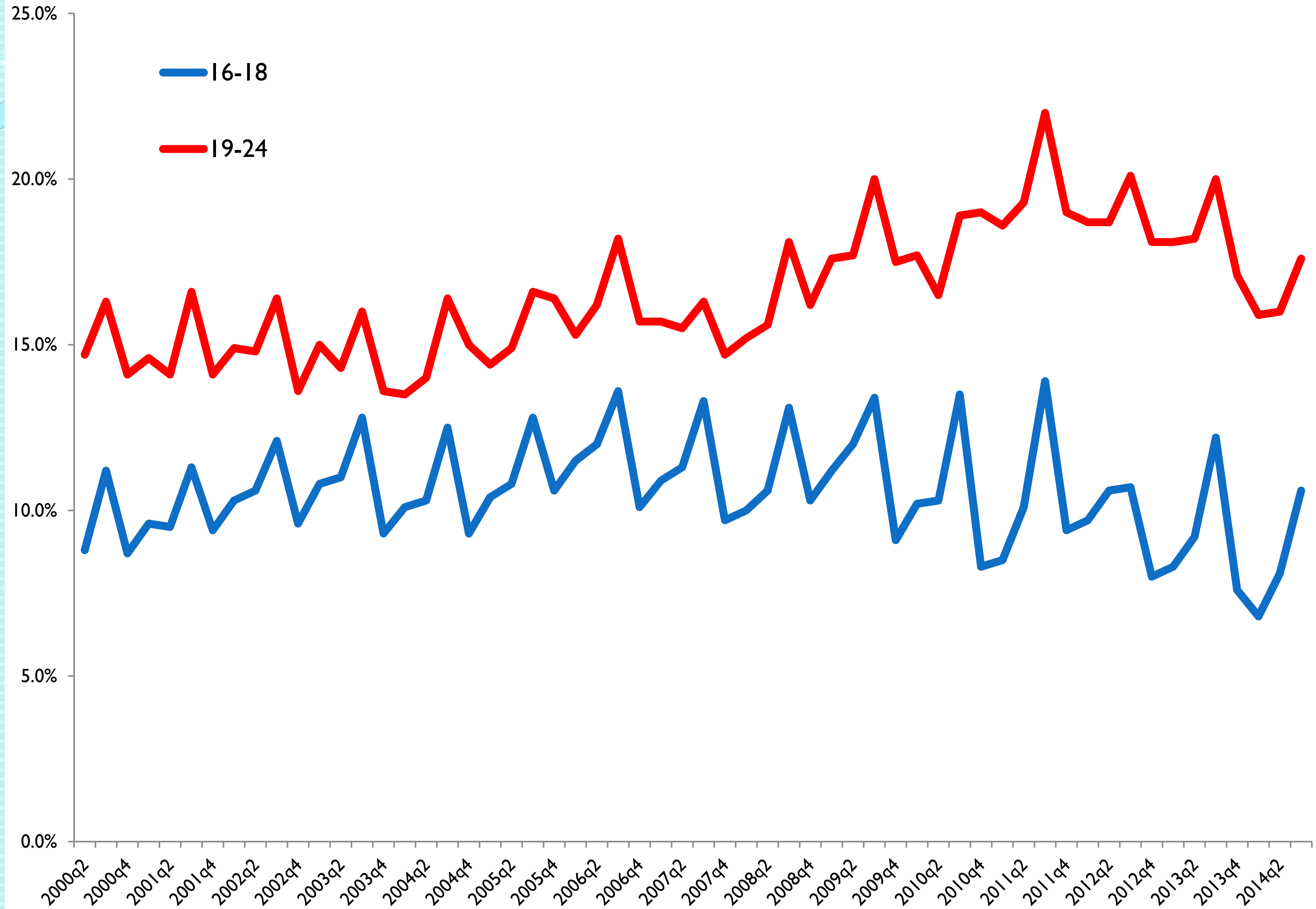
Motivation of the paper

- The existing literature is mostly focused on the broad effect of personality on education and labour market, using indicators such as years of schooling, or college graduation (Heckman et al. 2006; Coleman and Deleire, 2003; Cebi, 2007)

- In 2011-2012, 15% of individuals between the ages of 15 and 29 were neither employed nor in education or training, on average across OECD countries (OECD, 2014)

- The proportion of young people in the UK who do not have upper secondary education and are neither employed nor in education or training (24%) has been larger than the OECD by about 10 percentage points (OECD, 2014)

NEET% by age in England



Contribution of this paper

- Recent and very rich data-set of English adolescents up to early adulthood
- New evidence on the importance of non-cognitive skills in adolescence (rather than adulthood)
- Evidence of the effect of personality on a very critical phase of young people's lives
- Personality traits may be more malleable earlier in life
- Treatment effects IPWRA (Wooldridge, 2010)

Why do we focus on NEETs?

- Young people who spend some time being NEET have worse short and medium term economic outcomes than those who enter work or who remain in fulltime education (Crawford et al., 2010; Gregg, 2001; Mroz & Savage, 2006; Machin & Manning, 1999).

- They also are more likely to remain NEET in subsequent periods if they experience this condition for one year when they are 17-18 (Crawford et al., 2010).

- The longer a young person spends being NEET the higher the risk of them having poor labour market outcomes in the longer term.

- If young people find work after being NEET, they are more likely to get a job without any training rather than a job with training.

Overview of the literature

- Personality predicts educational and labour market outcomes (years of schooling, test scores, wages, job search, etc.)

- Almlund *et al*. (2011) provide an excellent review of the studies conducted in this area in various fields.

- Literature from personality psychology shows that personality traits such as conscientiousness, openness to experience, and agreeableness generally have a positive effect on test scores and educational attainment.

- Heckman, *et al.* (2006) use data from the National Longitudinal Survey of Youth 1979 to show that non-cognitive abilities, such as locus of control and self-esteem, affect years of schooling, wages, occupational choices and health risky behaviours.

Overview of the literature

- Heckman and Rubinstein (2001): Lower achievements in the labour market of Graduate Equivalence Diplomas (GED) recipients and the higher prevalence of criminal or risky behaviours can be attributed to the lack of non-cognitive skills such as discipline, patience or motivation.

- Coleman and Deleire (2003): Teenagers with internal locus of control are more likely to make educational investments (partially contradicted by Cebi, 2007).

- Lundberg (2013): Conscientiousness does not seem to have an effect on the education of disadvantaged men, while openness to experience has a relevant effect on college graduation only for less-advantaged men and women.

Data – LSYPE

- This paper uses data from **the Longitudinal Study of Young People in England (LSYPE).**
- First wave (2004): year 9 – age 14
- Topics: academic achievements, family relationships, attitudes toward school, family and labour market, and some sensitive or challenging issues, such as risky health behaviours (smoking, alcohol drinking, drug taking), personal relationships, etc.
- LSYPE can be linked to the National Pupil Database (NPD), that contains detailed information on test scores.
- NPD also contains limited data about the pupil - such as free school meal eligibility and Special Education Needs status.
- Final sample: around 9,000 children.

Outcomes

- We investigate the effect of personality traits on the chances of dropping out from education of employment (being NEET).
- In particular, a young person is defined NEET if they are:
  - unemployed (and looking for work)
  - looking after the family
  - having a break from study and work (excluding people who are waiting for exam results, have applied for a university course, are waiting to participate in government training programs or travelling)
- We consider three different NEET outcomes:
  - Having been NEET at least once in the 4 waves
  - Having been NEET for two or more years (core NEET)
  - Number of years spent being NEET

Personality traits (1/3)

- We calculate a "effort and diligence scale" following Duckworth et al. (2007) using the following questions:
  1. Doing well at school means a lot to me (wave 2)
  2. At school, I work as hard as I can (wave 2)
  3. Working hard at school now will help me to get on later in life (wave 2)
  4. If you work hard at something, you will usually succeed (wave 2)
  5. Studying to get a qualification is important to me (wave 7)
  6. Having a job that leads somewhere is important (wave 7)
  7. I don't really think much about what I might be doing in a few years (wave 7)
- For questions 1,2,3,4, 5, 6, we assign the following points: 1 = strongly disagree, 2= disagree, 3= agree, 4= strongly agree
- For question 7, we assign the following points: 1 = strongly agree , 2= agree, 3= disagree, 4= strongly disagree
- The maximum score on the scale is **4 (very high effort)** and the lowest score on the scale is **1 (very low effort).**
- We define an individual as having "high effort and diligence" if her/his score is in the top quartile of the effort index.

Personality (2/3)

- We use factor analysis to identify the common factors underlying the questions related to LC :
  - I can pretty much decide what happens in my life
  - If someone is not a success in life, it is usually his fault
  - How well you get in this world is mostly a matter of luck
  - Even if I do well at school, I will have a hard time
  - People like me don’t have much of a chance
  - If you work hard at something, you will usually succeed

- Children are coded as external (internal)/if they have a score in the top quartile of the distribution of the index from factor analysis.

Personality (3/3)

- Questions on self-esteem are asked at wave 2 and wave 4:

  - How useful you have felt recently?
  - How much you have been thinking of yourself as a worthless person recently?

- Low self-esteem =1
  - if they have placed themselves in the most distressed category for one of the two questions at least once between the two waves (around 26% of the children in the sample).

Other variables

- We estimate three versions of our model, progressively increasing the set of independent variables.
- We control for pre-determined variables – that is, not themselves influenced by personality.
- Inputs in children's outcomes include individual mental and physical endowments, parental and family inputs (such as income, time, size of the family and number of siblings).

Model 1
Child's characteristics:
Birthweight; Month of birth; Premature birth; Sex of the child; Ethnic background
Mother's characteristics:
Mother younger than 20 y.o. at birth; Single mother at birth
Model 2 (Observable characteristics at birth as in Model 1)
Child's characteristics:
Disability
Mother's and Family's characteristics:
Maternal education; Maternal employment status at wave 1; Single parent hh; Family income at wave 1; N. older siblings; Grandparents' education; Main parent disability
Model 3
All variables in Model 2 plus Test scores at age 16
(having 5 GCSE A*-C incl. English and Maths)

Descriptive statistics

	Whole sample	External locus of Control	Low self-esteem	High level of effort
Has been NEET at least once (w4 to w7)	15%	24%	23%	8%
Has been NEET for 2 or more years	4.7%	9%	7.5%	1.8%
No. years NEET				
0	84.5%	76%	77%	92%
1	11%	15%	16.5%	6.5%
2	3%	6%	4.3%	0.8%
3	1%	2.4%	1.7%	0.5%
4	0.5%	0.6%	0.5%	0.2%

Descriptive statistics

	Never been NEET	Has been NEET at least once (w4 to w7)	Has been NEET for 2 or more years
N. GCSE with A*-C	7.4	3.5	2.4
Household income <11,400£	20%	31%	34%
Household income betw. 11,400 and 31,200£	42%	50%	54%
Household income >31,200£	38%	19%	12%
Mother has university degree	16%	6%	5%
Mother has no qualifications	12%	23%	28%
Single mother household at birth	17%	32%	33%
Mother younger than 20 y.o. at birth	5%	10%	13%
Male	52%	56%	55%
Mother was unemployed at wave 1	1%	2%	4%
Mother was out of the labour force at wave 1	20%	34%	42%

The model

- The simplest linear model can be written as:

$$Y_i = \alpha + \beta_i P_i + \gamma_i X_i + \varepsilon_i$$

Y_i represents a particular NEET outcome, P_i is a vector of personality traits , Xi is a vector of child's and family's characteristics

- We estimate the models including all the three personality traits and then we test the stability of our results by including one or two personality traits at a time.

- The major challenge in this analysis is establishing **causal connections** between personality traits and NEET outcomes.

Our methodology

- We try to lower the upper bound provided by OLS estimation.

- To do that, we include a progressively more detailed set of independent variables.

- We exploit propensity score matching, comparing:
  - Children with/without external behaviours
  - Children with/without low self esteem
  - Children with/without grit

  on the basis of observable characteristics

- We estimate the treatment effects of multiple personality traits using the STATA routine *teffects*

Treatment effects

- We are interested in estimating the difference in the outcome with and without treatment, $Y_1 - Y_0$, i.e. the difference in NEET status caused by an individual having one personality trait.

- This is captured by the average treatment effect (ATE) defined as $E(Y_1 - Y_0)$ (Rosenbaum and Rubin, 1983 and Wooldridge, 2010)

- This is the expected effect of a particular personality trait on a randomly selected person from the population.

- Randomisation of personality traits is impossible and conditional independence assumption is needed to estimate average treatment effects generally.

Treatment effects

- We can overcome the problem that the treatment is not randomized by assuming that conditioning on observable covariates makes the outcome conditionally independent of the treatment.

- In practice, we assume that personality traits are effectively randomly assigned conditional on a sufficiently large set of observable covariates (Wooldridge, 2010)

- We estimate treatment effects by using the inverse-probability-weighted-regression-adjustment estimator (IPWRA)

- In the first step, the **probability of treatment** (personality trait) is estimated and in the second step regression methods are used, with weights by the inverse of the probability of treatment (Woolridge, 2010).

- The treatment model aims to capture the effect of multiple treatments and is estimated using a **multinomial logit specification** that allows us to calculate multiple treatment effects of the different personality traits individually, as well as consider **different combinations of two or three personality traits**

Results - PSM

	Model 1			Model 2			Model 3		
	NEET	Core NEET	No years NEET	NEET	Core NEET	No years NEET	NEET	Core NEET	No years NEET
External locus	0.089	0.038	0.153	**0.091**	**0.041**	**0.146**	**0.044**	**0.025**	**0.078**
of control	(0.024)***	(0.014)***	(0.039)***	(0.017)***	(0.011)***	(0.029)***	(0.018)***	(0.011)***	(0.031)***
High effort	-0.105	-0.043	-0.162	**-0.100**	**-0.042**	**-0.161**	**-0.067**	**-0.022**	**-0.096**
	(0.025)***	(0.013)***	(0.036)***	(0.013)***	(0.007)***	(0.021)***	(0.012)***	(0.006)***	(0.019)
Low Self-	0.097	0.024	0.140	**0.094**	**0.019**	**0.114**	**0.095**	**0.024**	**0.128**
Esteem	(0.022)***	(0.012)*	(0.035)***	(0.013)***	(0.008)***	(0.023)***	(0.013)***	(0.008)***	(0.022)***

* indicates that the underlying coefficient is significant at 10% level, ** at 5% and ***at 1%.

Results – Treatment effects

	Model 2			Model 3		
	NEET	Core NEET	No. years NEET	NEET	Core NEET	No. years NEET
Effort (1st Quartile is omitted)						
2nd Quartile	-0.074	-0.028	-0.110	-0.049	-0.017	-0.069
	(0.013)***	(0.008)***	(0.022)***	(0.013)***	(0.007)**	(0.021)***
3rd Quartile	-0.079	-0.024	-0.118	-0.051	-0.013	-0.074
	(0.012)***	(0.007)***	(0.019)***	(0.011)***	(0.007)**	(0.018)***
4th Quartile	**-0.138**	**-0.058**	**-0.219**	**-0.101**	**-0.045**	**-0.162**
	(0.011)***	(0.006)***	(0.017)***	(0.011)***	(0.006)***	(0.017)***
External Locus of Control (1st Quartile is omitted)						
2nd Quartile	0.031	0.006	0.040	0.016	0.002	0.021
	(0.013)***	(0.007)	(0.019)**	(0.014)	(0.007)	(0.021)
3rd Quartile	0.037	0.020	0.074	0.010	0.0128	0.035
	(0.013)***	(0.007)***	(0.021)***	(0.013)	(0.007)	(0.022)
4th Quartile	**0.092**	**0.044**	**0.156**	**0.043**	**0.028**	**0.084**
	(0.014)* **	**(0.008)*** **	**(0.022)*** **	**(0.014)*** **	**(0.008)*** **	**(0.022)*** **

* indicates that the underlying coefficient is significant at 10% level, ** at 5% and ***at 1%.

	Model 2			Model 3		
	NEET	Core NEET	No. years NEET	NEET	Core NEET	No. years NEET
Low effort	0.085	0.045	0.145	0.051	0.032	0.093
and diligence	(0.013)***	(0.008)***	(0.021)***	(0.0127)***	(0.008)***	(0.021)***
External LC	0.047	0.016	0.067	0.015	0.004	0.018
	(0.017)***	(0.009)*	(0.027)**	(0.017)	(0.008)	(0.025)
Low Self-	0.083	0.027	0.121	0.074	0.025	0.108
Esteem	(0.014)***	(0.008)***	(0.023)***	(0.015)	(0.009)	(0.025)***
Low effort and external LC	0.128 (0.027)***	0.068 (0.019)***	0.222 (0.047)***	0.090 (0.026)***	0.045 (0.015)***	0.149 (0.041)***
Low effort and	**0.205**	**0.048**	**0.278**	**0.156**	**0.032**	**0.202**
low self esteem	**(0.021)*** **	**(0.012)*** **	**(0.033)*** **	**(0.021)*** **	**(0.011)*** **	**(0.031)*** **
Low self-est.	0.122	0.065	0.205	0.078	0.051	0.142
and external LC	(0.028)***	(0.018)***	(0.046)***	(0.023)***	(0.016)***	(0.040)**
All 3 traits	**0.209**	**0.068**	**0.314**	**0.151**	**0.050**	**0.225**
	(0.031)* **	**(0.019)*** **	**(0.052)*** **	**(0.029)*** **	**(0.016)*** **	**(0.046)*** **

Results

- Personality traits have a strong and significant effect on chances of being NEET and remaining NEET for a long time.

- The combinations of low effort and low self-esteem and of all three "negative' traits seem particularly detrimental, and young people who show these characteristics experience significantly increase likelihood of being NEET.

- Negative effect of external locus of control and self-esteem are not surprising:
    - External individuals tend to think that their choices have less impact on their future, which is mostly driven by luck and external circumstances.

    - Low self-esteem may have an impact on many different aspects of individuals' life, such as aspirations and effort to achieve the potential, and this may in turn affect the ability to make decisions about the future, and choices about education and labour market participation.

- Individuals with high effort and diligence have higher levels of perseverance towards long term goals and they are able to maintain focus on long-term challenges and objectives and sustain commitment to their ambition

Results: other variables

- The effects of personality traits on chances of being NEET are higher than the effect of other important variables, such as maternal education and employment status, or growing up in a single parent household.
- The most important determinant of NEET status is GCSE attainment.
- Youths from high income and high education families are less likely to be NEET.
- Boys face higher risks than girls, and so do children who come from single parent households or whose mothers are unemployed or out of the labour force.

Conclusions

- Can we teach positive personality traits?

- New curriculum promoting non-cognitive skills under design in England

- Policies aimed at promoting positive personality traits have been proved to be particularly effective when targeting adolescence (Borghans et al., 2008).

- The World Bank has recently promoted the STEP Skills Measurement Program, in collaborations with Angela Duckworth and other researchers in the field of psychology, with the objective of improving ways to measure and analyse the importance of socio-emotional skills among youth and adults.

- Recent research in the area has confirmed the positive effect of interventions aimed at teaching school children the importance of effort, perseverance and motivation to increase school results, especially for disadvantaged children (Blackwell et al., 2007 and Duckworth et al., 2013).

THANK YOU!

Youth Unemployment and Personality Traits

Mendolia & Walker

Discussion: Norma B. Coe

Marshmallow test for teens

- Estimate the effect of 3 personality traits as a teen:
  - Positive traits:
    - High effort and diligence
  - Negative traits:
    - External locus of control
    - Low self-esteem
- On initial labor market outcomes (NEET)

Emphasis on non-cognitive skills

- Research
  - Associated with positive academic & financial outcomes in adulthood
  - Less evidence of causal link
    - What intervention changes non-cognitive skills?
    - What is malleable, what is stable, and when?
- Policy
  - Designing interventions
    - WHO: STEP
    - UK: SEAL
    - US: expanding access to pre-school

Findings

- Even after controlling for own education test scores & parental characteristics, personality characteristics as a teen are associated with NEET while entering the labor market.
  - Stable to modeling assumptions
    - Both econometric and definitions of personality traits
  - Similar results for boys and girls

Strengths

- Extremely well-written paper
- Builds nicely on the psychology literature
- Great data
- Focuses on economic outcomes at a critical time
- While still can't say causal, the methods, the robustness checks, and timing help give me hope for non-cognitive skill interventions

Longitudinal look

- Motivate by comparing UK over time and UK to Europe
- Current work doesn't really help get at these trends

- Plea to create the data to get closer to causal?

Questions

- NEET
  - Can you parse out the activities?
    - Looking after the family
    - Having a break from study/work
    - Unemployed
  - Policy may be more/less concerned
    - Do they have differential effects on long-term employment patterns?
    - Does that generate differences by gender?

Econometrics

- Number of years spent in NEET
  - Count methods
- NEET and Core NEET
  - Low percentage outcomes – why linear models?

Implications

- Larger impact that most of the other covariates
  - Including single parent, poverty

- Should we really be spending MORE efforts on personality?

Patient Cost-Sharing and Healthcare Utilization in Early Childhood: Evidence from a Regression Discontinuity Design

Tzu-Ting Yang[1] Hsing-Wen Han[2] Hsien-Ming Lien[3]

[1]Academia Sinica

[2]Tamkang University

[3]National Chengchi University

December 13, 2015

Motivation

- Health conditions and medical treatments in early childhood are widely believed to have a substantial impact on later-life outcomes
  [*Bharadwaj et al., 2013; Almond et al., 2011; Currie, 2009*]
- Young children are vulnerable to diseases and bring about sizeable medical costs for their parents
- Many public health insurance programs exempts children from most cost sharing requirements
- There is little evidence that how cost sharing affects children's healthcare utilization and health
  - Most focus on healthcare for adults and elderly
    [*Cherkin et al., 1989; Selby et al.,1996; Rice and Matsuoka, 2004; Chandra et al., 2010a; Chandra et al., 2010b; Chandra et al.,2014; Shigeoka, 2014*]
  - RAND health experiment: subsample analysis for people under age 14
    [*Leibowitz et al., 1985; Manning et al.,1981*]

This Paper

- Exploit a cost-sharing subsidy that exempted all copayment and coinsurance for children under age 3 in Taiwan since March 2002
  - Children lose their eligibility for cost-sharing subsidy after their 3rd birthday
  - Focus on its impact on the utilization of outpatient care and inpatient care
- Outpatient care
  - The subsidy reduces average out-of-pocket price:
    - Non-emergency visit by 46% (1.8 USD)
    - Emergency visit by 52% (9 USD)
- Inpatient care
  - The subsidy reduces average out-of-pocket price by 100% (40 USD to 0 USD) for those just before age 3

This Paper

- Use administrative claims data that consists of all medical records for 410 thousands children born in 2003 and 2004
- Follow them from their 2nd birthday to 4th birthday
- Regression discontinuity design (RDD)
  - Compare the healthcare utilization for children just before and after their 3rd birthday
  - Children's health conditions just before the 3rd birthday should be very similar to those just after the 3rd birthday
  - Isolate the effect of cost sharing from other confounding factors that might affect children's healthcare utilization
- Furthermore, we investigate whether lower cost sharing has any sort of positive impact on children's health

Contributions and Main Findings

- Provide the credible and transparent estimates of price elasticity of children's utilization of healthcare
  - Children's utilization for outpatient care is modestly price sensitive
  - Children's utilization for inpatient care is price insensitive
  - A large decrease in inpatient price before the 3rd birthday leads to no change in inpatient utilization

Contributions and Main Findings

- Investigate the effect of cost sharing on patient's choice of providers
  - Patients in Taiwan have complete freedom to choose their healthcare providers
  - NHI sets different copayments for different types of providers to allocate medical resource efficiently
  - The subsidy eliminates copayments and substantially narrow down price difference between low-cost and high-cost providers
  - The subsidy induces patients to switch from low-cost providers to high-cost providers
  - Most of the increased visits to high-cost providers are for minor illnesses (e.g. flu)
- Examines the impact of cost sharing subsidy on children's short-run or long-run health
  - There is little evidence that lower cost sharing improves children's health

Patient Cost Sharing in Taiwan

Outpatient Care

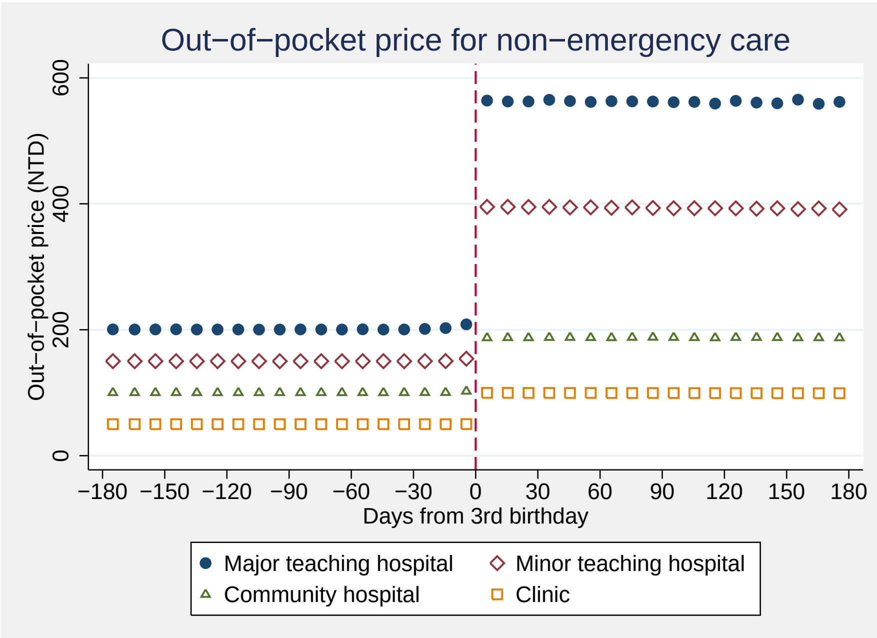
	Patient Cost-Sharing			
	Major Teaching Hospital	Minor Teaching Hospital	Community Hospital	Clinic
Panel A: Outpatient care – non-emergency				
Copayment	360	240	80	50
Registration Fee	200	150	100	50
Panel B: Outpatient care – emergency				
Copayment	450	300	150	150
Registration Fee	300	250	200	150

1. Copayment plus registration fee (1 USD = 32.5 NTD)
2. The amount of copayment and registration fee depends on:
   - Types of healthcare services
   - Types of healthcare providers

- This price scheme encourages patients to visit clinic/community hospital for minor illness
- The fixed copay amounts for one outpatient visit implicitly requires a patient to pay higher share of medical expense when visiting for a minor illness
- Since March 2002, copayment is exempted for children under age 3

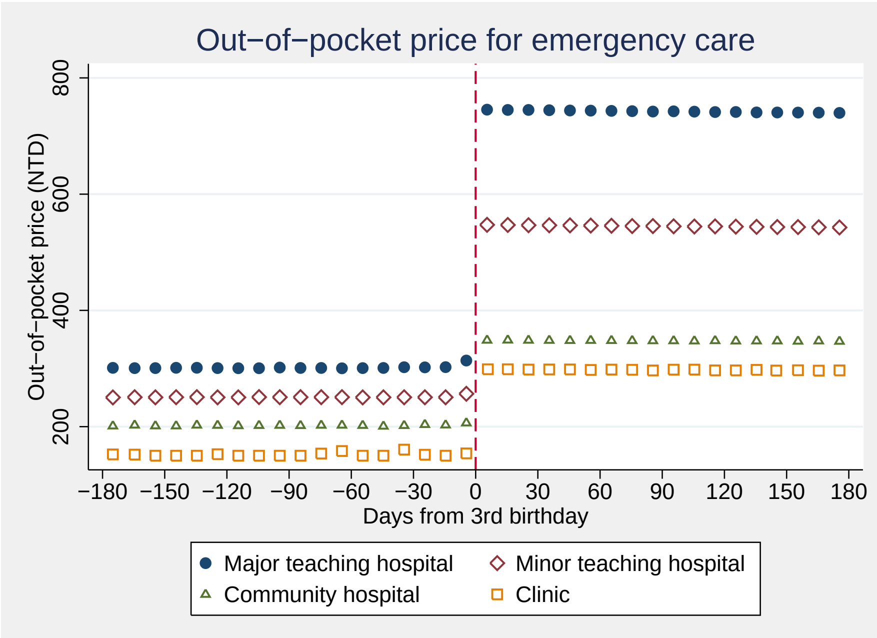
Age profile of out-of-pocket price

Non-emergency Care



Age profile of out-of-pocket price

Emergency Care



Patient Cost Sharing in Taiwan

Inpatient Care

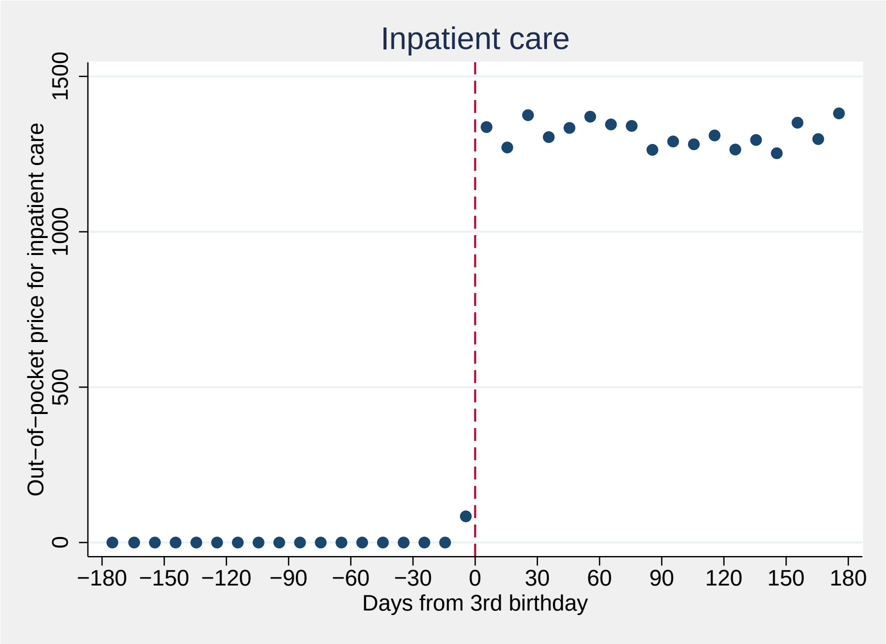
Panel C: Inpatient care	
1-30 days	10%
31-60 days	20%
after 61 days	30%

1. Coinsurance rate: share of total medical expense that patients have to pay for one admission
2. The coinsurance rate depends on the length of stay

Since March 2002, coinsurance is exempted for children under age 3

Age profile of out-of-pocket price

Inpatient Care



Data and Sample

- Taiwan's National Health Insurance Research Database (NHIRD)
  - Patient's out-of-of pocket price and total medical expenses for each visit
  - Patient's exact visit date and birth date
- All Taiwanese children born in 2003 and 2004 (435,752 children), exclude:
  - Children do not enroll in NHI continuously at age two and three
  - Children already waived from cost-sharing ▸ sample
- Final sample size: 417,566 children
- Follow them from their 2nd birthday to 4th birthday ▸ summary
- 2005-2008 NHIRD data

Identification Strategy

Regression discontinuity design

- Aggregate individual level data to age cell level
- Estimate the following regression:

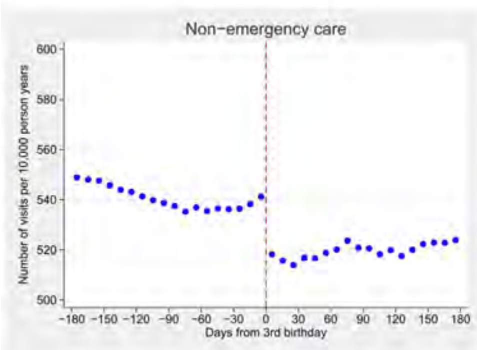
$$Y_a = \beta_0 + \beta_1 Age3 + \gamma_1(a - 1096) + \gamma_2 Age3(a - 1096) + \varepsilon_a$$

  - Y_a is the outcome of interest for the children at given age a
    - Take log and measure age in days
    - total medical expenses
    - number of visits or admissions
    - medical expenses per visit (admission)
  - $Age3$ is a dummy indicating patient's age is before 3rd birthday
  - β_1 represents the causal effect of cost sharing subsidy on healthcare utilization
  - Use linear function to control age profile of healthcare utilization
    - Allow different slopes before and after the 3rd birthday
    - Recenter age variable to the 3rd birthday
    - Bandwidth: 90 days before and after 3rd birthday
    - Triangular kernel: give more weight to the data points close to the 3rd birthday
- Robustness checks: different choices of bandwidth and different specifications

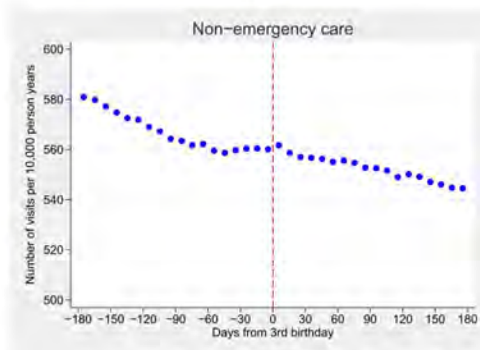
Age Profile of Visit Rate

Non-emergency care

(c) Number of visits per 10,000 person-years: 2005–2008



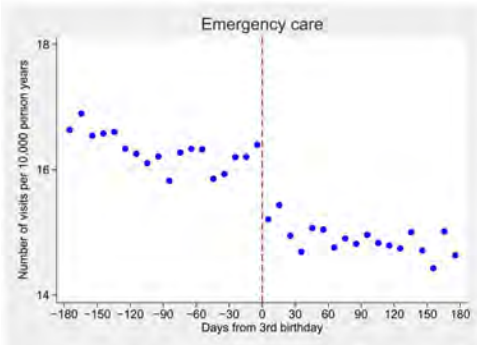
(d) Number of visits per 10,000 person-years: 1997–2001



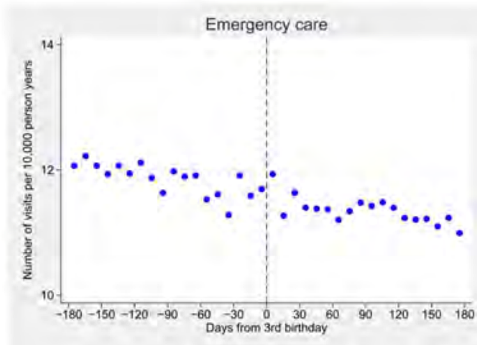
Age Profile of Visit Rate

Emergency care

(c) Number of visits per 10,000 person-years: 2005–2008



(d) Number of visits per 10,000 person-years: 1997–2001



Outpatient Care

Regression Results

Variables	(1) visit rate	(2) out-of-pocket price	(3) log(expense)	(4) log(# of visits)	(5) log(expense/visit)
Panel A: Non-emergency care					
Sample: 2005-2008					
Age3		-58.44***	7.64***	4.93***	2.71***
		(3.69)	(0.57)	(0.40)	(0.30)
	518.30				
Sample: 1997-2001					
Age3		-4.10	-0.04	-0.14	0.10
		(2.86)	(0.25)	(0.18)	(0.13)
	556.62				
Panel B: Emergency care					
Sample: 2005-2008					
Age3		-298.45***	5.63***	6.59***	-0.96
		(15.48)	(1.58)	(1.20)	(0.77)
	15.00				
Sample: 1997-2001					
Age3		-0.08	-1.34	-0.83	-0.51
		(1.07)	(1.26)	(1.14)	(0.83)
	11.45				

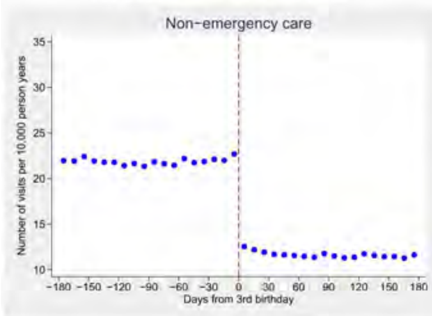
- The price elasticity of medical expenditure robustness
  - non-emergency care: -0.12
  - emergency care: -0.08 Donut RD
  - Based on our estimates, the subsidy could induce extra medical expense for outpatient care by 0.4 billion NTD per year

Visit Rate for Non-emergency Care

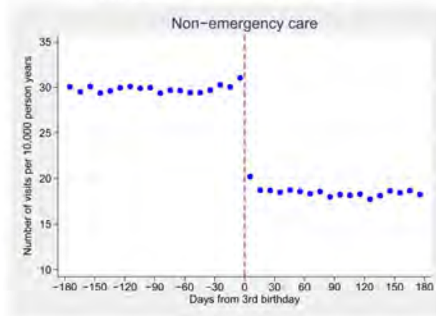
By Healthcare Providers

- Number of non-emergency visit per 10,000 children at given age

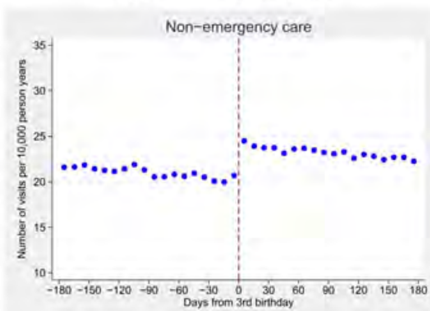
(a) Major Teaching Hospital



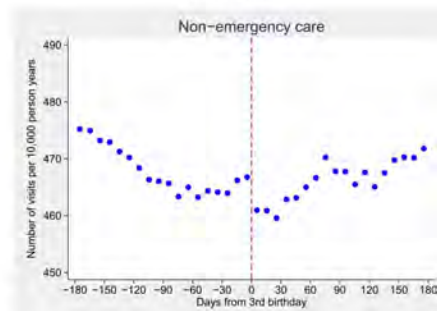
(b) Minor Teaching Hospital



(c) Community Hospital



(d) Clinic

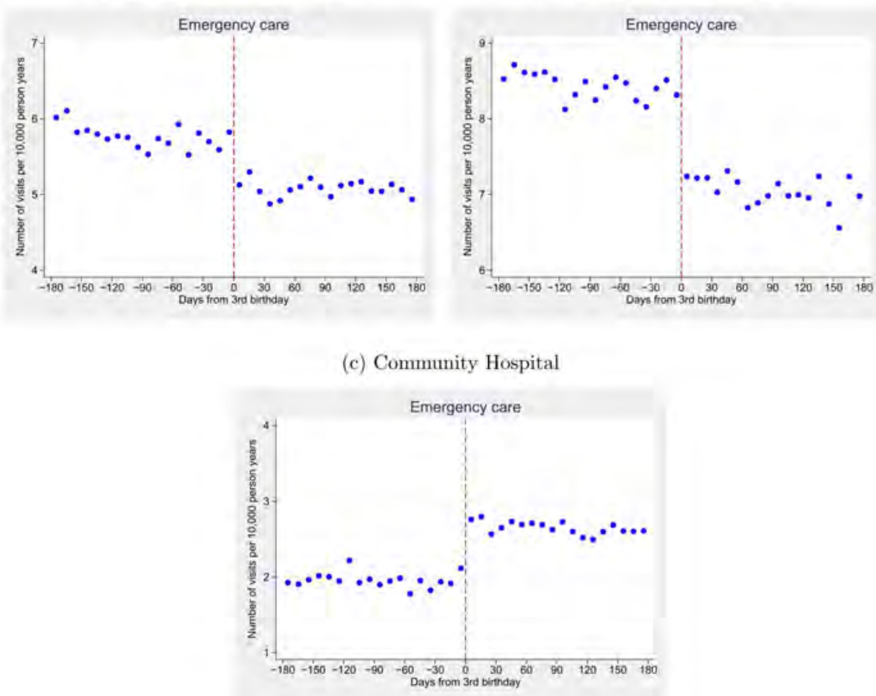


Visit Rate for Emergency Care

By Healthcare Providers

- Number of emergency visit per 10,000 children at given age

(a) Major Teaching Hospital (b) Minor Teaching Hospital (c) Community Hospital



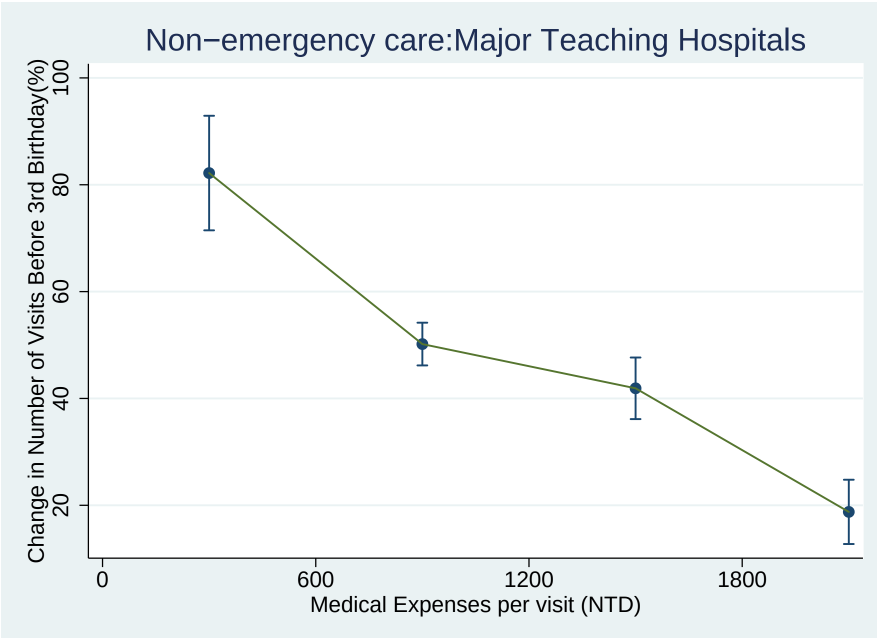
Outpatient Care

By Healthcare Providers

Variables	(1) visit rate	(2) out-of-pocket price	(3) log(expense)	(4) log(# of visits)	(5) log(expense/visit)
Panel A: Non-emergency care					
Major teaching hospitals					
Age3		-340.93***	40.48***	58.98***	-18.49***
		(19.04)	(2.57)	(2.23)	(1.96)
	11.85				
Minor teaching hospitals					
Age3		-231.20***	38.32***	44.14***	-5.82***
		(13.18)	(2.58)	(2.10)	(1.72)
	18.79				
Community hospitals					
Age3		-82.34***	-16.63***	-17.13***	0.50
		(4.28)	(2.27)	(1.68)	(1.60)
	23.65				
Clinics					
Age3		-46.65***	2.12***	1.86***	0.26**
		(3.00)	(0.37)	(0.35)	(0.11)
	464.02				
Panel B: Emergency care					
Major teaching hospitals					
Age3		-421.19***	9.37***	10.85***	-1.48
		(20.63)	(2.61)	(2.26)	(1.41)
	5.09				
Minor teaching hospitals					
Age3		-280.42***	11.77***	13.85***	-2.08*
		(15.29)	(1.73)	(1.40)	(1.13)
	7.11				
Community hospitals					
Age3		-137.75***	-26.35***	-29.86***	3.51
		(7.31)	(4.97)	(3.97)	(2.63)
	2.68				

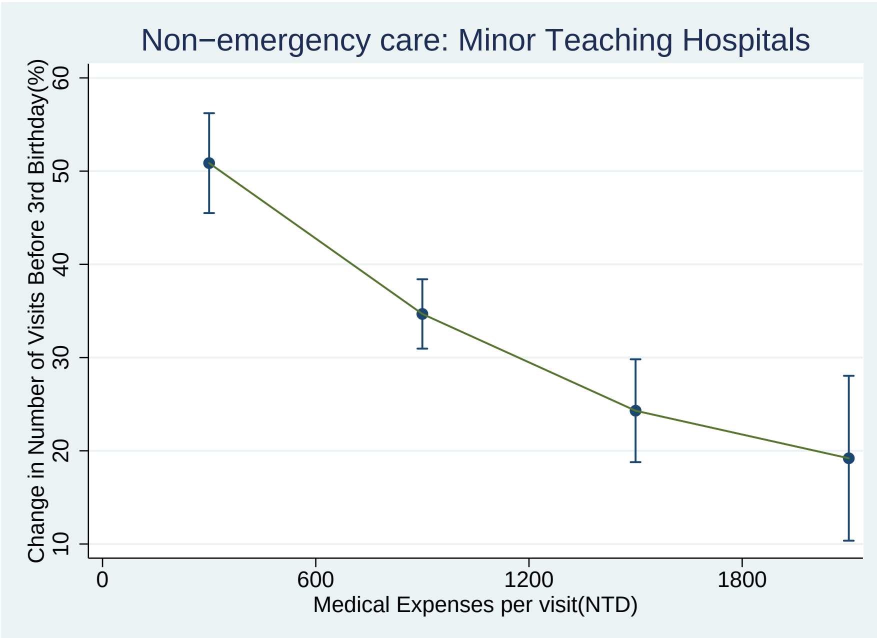
Outpatient Care

Major Teaching Hospitals



Outpatient Care

Minor Teaching Hospitals



Outpatient Care

By Healthcare Providers

- Our results suggest providing a more generous health insurance plan can incentivize patients to switch from low-cost providers to high-cost providers
- The increased visits to high-cost providers before age 3 are for less severe illness (e.g flu)
- These visits could be treated at low-cost providers
- Based on our estimates, a 100 NTD increase in price difference between providers can reduce 20% of visits to high-cost providers
- This indicates that there is a substantial moral hazard in terms of an increase in the use of high-cost providers when patients are not exposed to the full cost

Outpatient Care

Subgroup Analysis

- By cause of visit ▸ Table
  - Visits for acute respiratory diseases are less price sensitive
  - Visits for skin diseases, mental disorder, and preventive care are quite price sensitive
- By birth order ▸ Table
  - Outpatient utilizations for 1st born children are less price sensitive than those for non-1st born children
    - Parents are more cautious when raising their first child.
    - They are less willing to adjust first child's healthcare utilization in response to a price change
    - Taiwanese old saying: Parents read book to raise their first child but treat their second child like raising a pig

Outpatient Care

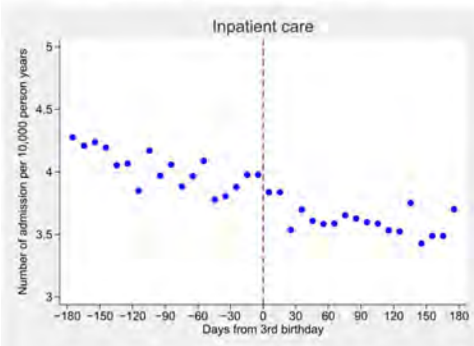
Subgroup Analysis

- By gender Table
  - The visit rate for males is higher than that for females in the case of both non-emergency and emergency care
  - Cost-sharing subsidy results in a larger increase in the utilization of non-emergency care for males than for females
  - The opposite pattern is observed in the utilization of emergency care
- By household income Table
  - Only use the sample whose parents are employees enrolled in civil service insurance or labor insurance
  - If high out-of-pocket price creates a barrier to use necessary healthcare, we would expect subsidy causes larger change in utilization for low-income children
  - For non-emergency care, our results show that the subsidy lead to similar increases across different income groups
  - However, we find that low-income children exhibit significantly larger increases in their utilization of emergency care than middle/high-income children
  - High price of emergency care could constrain some low-income children to use necessary healthcare

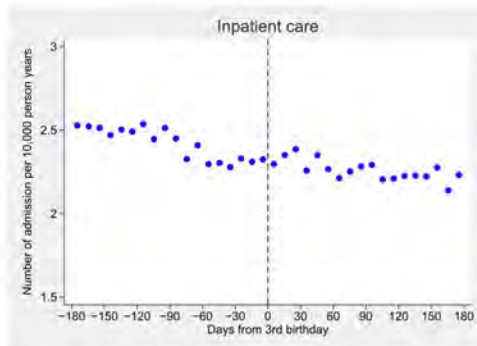
Number of Inpatient Admission

Graphical Evidence

(c) Number of admissions per 10,000 person-years: 2005–2008



(d) Number of admissions per 10,000 person-years: 1997–2001



Inpatient Care

Regression Results

Variables	(1) admission rate	(2) out-of-pocket price	(3) log(expense)	(4) log(# of admissions)	(5) log(expense/admission)
Sample: 2005-2008					
Age3(X100)		-1287.71***	0.72	1.08	-0.36
		(41.52)	(4.75)	(2.82)	(3.54)
	3.67				
Sample: 1997-2001					
Age3(X100)		-6.67	-0.93	-1.18	0.25
		(32.94)	(3.11)	(2.08)	(2.85)
	2.30				

robustness

Inpatient Care

Summarized Results

- Children's utilization for inpatient care does not respond to out-of-pocket price
- The implied price elasticity of medical expenditure for inpatient care is -0.004
- This result suggests that children's inpatient care could be quite necessary
- Parents are unwilling to adjust children's utilization of inpatient care in respond to a price change
- Providing full insurance coverage of children's inpatient care could be efficient
- Since zero cost sharing does not cause overuse of inpatient care but substantially reduce financial risk brought by inpatient admissions

- Use second dataset: Taiwan's Health Interview Survey (TNHIS)
- Compare the reported health status for the children right before and after age 3

$$H_i = \alpha_0 + \alpha_1 Age3_i + \alpha_2(a_i - 36) + \alpha_3 Age3_i(a_i - 36) + \alpha_4 X_i + \varepsilon_i$$

- H_i is a dummy indicating whether the reported health status was "good" (i.e. $H_i = 1$) or not (i.e. $H_i = 0$)
- Other covariates X_i: gender, an indicator for premature birth, and parents' education.

Impact on Short-Run Health

Regression Results

	(1) Good health	(2) Good health	(3) Good health	(4) Good health	(5) Good health
Age3	-0.0145	-0.0008	-0.0023	-0.0018	0.0208
	(0.0372)	(0.0564)	(0.0553)	(0.0610)	(0.0595)
Linear spline	√	√	√	√	√
Quadratic spline		√	√	√	√
Early born			√	√	√
Parent's edu				√	√
Living county					√
sample size	1,041	1,041	1,041	1,041	1,041
R^2	0.003	0.004	0.007	0.022	0.046

- There is no significant difference in reported health status between those just before age 3 and those just after age 3

Impact on Long-Run Health

Research Design

- Use inpatient rate at age 8 to 10 as proxy of long-run health
- Since cost-sharing subsidy was introduced on March 1st 2002
- Identification strategy:
  - Exploit the fact that the length of the period for which a patient is eligible for the cost-sharing subsidy is determined by their birth date
  - Individuals born before February 28th 1999 were ineligible for the subsidy
  - Those born between March 1st 1999 and February 28th 2002 were eligible for the cost-sharing subsidy for between 1 and 1,096 days respectively between ages 1 to 3
- Compare the individuals experiencing longer period of cost-sharing subsidy during age 1 to 3 with those ineligible for cost-sharing subsidy
- Explore any systematic relationship between inpatient rate at age 8 to 10 and birth date

Impact on Long-Run Health
Research Design

$$I_i = \gamma_0 + \gamma_1 After99_i + \gamma_2 Distance1999_i + \gamma_3 After99_i * Distance1999_i + \gamma_4 X_i + \varepsilon_i$$

- I_i is a dummy indicating whether an individual i have any inpatient admission between ages 8 and 10
- $Distance1999_i$ is a running variable that denotes the number of days between individual i's birth date and March 1st 1999
- $After99_i$ is a dummy indicating that individual i's birth date is later than March 1st 1999
- The key variable is the interaction term between $After99_i$ and $Distance1999_i$
- Its coefficient γ_3 measures the difference in the slopes of the inpatient rate at age 8 to 10 between those individuals born just before and those born just after March 1st 1999

Impact on Long-Run Health

Regression Results

	(1) Inpatient rate	(2) Inpatient rate	(3) Inpatient rate	(4) Inpatient rate	(5) Inpatient rate
After1999	0.0023	0.0065	0.0064	0.0074	0.0062
	(0.0043)	(0.0050)	(0.0050)	(0.0051)	(0.0049)
Distance1999	-0.0069	-0.0586	-0.0578	-0.0525	-0.0507
	(0.0046)	(0.0541)	(0.0543)	(0.0542)	(0.0535)
After1999*Distance1999	0.0050	0.0043	0.0041	0.0041	0.0042
	(0.0084)	(0.0060)	(0.0061)	(0.0061)	(0.0061)
Birth month/year		√	√	√	√
Gender			√	√	√
Living county				√	√
Insurer's chacteristics					√
sample size	471,072	471,072	471,072	471,072	470,072
R^2	0.000	0.000	0.001	0.006	0.008

- There is little evidence suggested cost sharing subsidy has any long-term impacts on children's health

Take Home Message

- Children's utilization for outpatient care is modestly price sensitive
  - The implied price elasticity of medical expenses for non-emergency care (emergency care) is around -0.12 (-0.08)
- Differential copayment is an effective way to reduce the overuse of healthcare service at teaching hospitals
  - Eliminating copayment can induce patients to switch from low-cost providers to high-cost providers
  - Most of the increased visits to high-cost providers are for minor illnesses (e.g. flu)
  - These visits could be treated at low-cost providers (e.g. clinic/community hospital)
- Children's utilization for inpatient care is price insensitive
  - A large decrease in inpatient price before the 3rd birthday leads to no change in inpatient utilization
  - Children's inpatient care could be quite necessary
- There is little evidence that lower cost sharing has any short-term or long-term impacts on children's health

Sample Selection

Variables	(1) Original Sample	(2) Continuous enrollment at age two and three	(3) Eliminating cost-sharing waiver
Children			
Male	0.52	0.52	0.52
Birth year:2003	0.51	0.51	0.51
Birth year:2004	0.49	0.49	0.49
1st birth	0.53	0.53	0.53
2nd birth	0.36	0.36	0.36
3rd birth	0.11	0.11	0.11
Number of siblings	1.88	1.88	1.87
	(0.00)	(0.00)	(0.00)
Insurers			
Public employee	0.09	0.09	0.09
Private employee	0.55	0.56	0.56
Self-employed	0.23	0.23	0.23
Male	0.55	0.55	0.55
Age	34.27	34.27	34.29
	(0.01)	(0.01)	(0.01)
Income	46395.68	46412.85	46585.66
	(45.40)	(45.51)	(46.49)
Number of children	435,752	432,295	417,566

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Summary Statistics

	Non-emergency care		Emergency care		Inpatient care	
	Before 3rd birthday	After 3rd birthday	Before 3rd birthday	After 3rd birthday	Before 3rd birthday	After 3rd birthday
Utilization						
Visit rate	537.31	518.30	16.16	15.00	3.92	3.67
Avg. medical expenses	442.39	434.06	1679.74	1677.50	12931.15	13018.56
	(0.43)	(0.42)	(4.82)	(4.87)	(137.25)	(143.92)
Avg. OOP price	63.70	124.24	261.94	573.00	0	1288.66
	(0.03)	(0.06)	(0.16)	(0.61)	(0)	(12.33)
Share of OOP price	0.16	0.32	0.20	0.42	0	0.10
Choice of providers						
Major teaching hospital	0.04	0.02	0.35	0.34	0.28	0.30
Minor teaching hospital	0.06	0.04	0.52	0.47	0.59	0.59
Community hospital	0.04	0.05	0.12	0.18	0.13	0.12
Clinic	0.87	0.90	0.01	0.01	0.00	0.00
Treatment reasons						
Respiratory diseases	0.73	0.74	0.36	0.36	0.44	0.47
Digestive diseases	0.06	0.05	0.12	0.13	0.16	0.16
Skin diseases	0.04	0.03	0.02	0.02	0.02	0.02
Injury and poisoning	0.02	0.02	0.19	0.19	0.03	0.03
Mental disorders	0.01	0.01	0.00	0.00	0.01	0.01
Number of children	364,819	358,866	48,311	46,275	13,412	12,668
Number of children-visit	2,019,262	1,947,831	60,745	56,361	14,737	13,787

back

Robustness Check

Non-emergency care

	log(expenses)					
Bandwidth(days)	60	120	180	240	300	360
Polynominal						
1	7.62***	6.93***	6.25***	5.83***	5.32***	5.39***
	(0.61)	(0.40)	(0.32)	(0.27)	(0.25)	(0.22)
2	8.30***	7.96***	7.44***	6.99***	6.76***	6.06***
	(0.93)	(0.64)	(0.50)	(0.44)	(0.38)	(0.35)
3	8.30***	8.19***	8.24***	7.92***	7.69***	7.65***
	(0.93)	(0.87)	(0.69)	(0.58)	(0.52)	(0.48)
	log(# of visits)					
Bandwidth(days)	60	120	180	240	300	360
Polynominal						
1	4.90***	4.15***	3.56***	3.04***	2.50***	2.63***
	(0.42)	(0.27)	(0.22)	(0.19)	(0.18)	(0.16)
2	5.20***	5.39***	4.66***	4.36***	4.08***	3.26***
	(0.69)	(0.44)	(0.34)	(0.29)	(0.26)	(0.25)
3	5.20***	5.15***	5.57***	5.10***	5.00***	5.07***
	(0.69)	(0.63)	(0.49)	(0.40)	(0.35)	(0.33)
	log(expense/visit)					
Bandwidth(days)	60	120	180	240	300	360
Polynominal						
1	2.72***	2.78***	2.69***	2.79***	2.82***	2.76***
	(0.34)	(0.23)	(0.19)	(0.16)	(0.14)	(0.13)
2	3.10***	2.57***	2.77***	2.63***	2.68***	2.81***
	(0.48)	(0.35)	(0.29)	(0.25)	(0.22)	(0.20)
3	3.10***	3.04***	2.67***	2.82***	2.69***	2.58***
	(0.48)	(0.46)	(0.38)	(0.33)	(0.30)	(0.27)

back

Robustness Check

Emergency care

	log(total medical expense)					
Bandwidth(days)	60	120	180	240	300	360
Polynominal						
1	5.24***	5.78***	4.91***	3.94***	3.28***	2.53***
	(1.77)	(1.26)	(1.05)	(0.90)	(0.81)	(0.75)
2	7.01***	6.16***	6.28***	6.11***	5.71***	5.30***
	(2.59)	(1.85)	(1.54)	(1.34)	(1.19)	(1.10)
3	7.01***	4.96**	6.22***	6.44***	6.32***	6.42***
	(2.59)	(2.48)	(2.02)	(1.74)	(1.57)	(1.45)
	log(# of visit)					
Bandwidth(days)	60	120	180	240	300	360
Polynominal						
1	6.77***	6.53***	5.61***	4.63***	4.05***	3.31***
	(1.33)	(0.97)	(0.83)	(0.72)	(0.65)	(0.60)
2	7.89***	6.83***	6.97***	6.98***	6.45***	6.05***
	(1.88)	(1.43)	(1.18)	(1.04)	(0.94)	(0.87)
3	7.89***	6.86***	7.21***	6.95***	7.09***	7.14***
	(1.88)	(1.80)	(1.53)	(1.33)	(1.21)	(1.13)
	log(expense/visit)					
Bandwidth(days)	60	120	180	240	300	360
Polynominal						
1	-1.53*	-0.75	-0.70	-0.70	-0.77*	-0.78*
	(0.88)	(0.63)	(0.53)	(0.48)	(0.44)	(0.40)
2	-0.87	-0.66	-0.69	-0.87	-0.74	-0.76
	(1.33)	(0.93)	(0.76)	(0.67)	(0.61)	(0.57)
3	-0.87	-1.89	-0.99	-0.51	-0.77	-0.72
	(1.33)	(1.27)	(1.01)	(0.88)	(0.79)	(0.73)

back

Robustness Check

Inpatient care

	log(expenses)					
Bandwidth(days)	60	120	180	240	300	360
Polynominal						
1	-0.46	0.24	1.00	2.00	1.07	1.79
	(5.39)	(3.67)	(3.04)	(2.58)	(2.27)	(2.04)
2	6.91	-0.94	-2.13	-0.27	1.60	0.99
	(7.51)	(5.62)	(4.48)	(3.88)	(3.46)	(3.16)
3	2.09	6.42	3.51	-2.03	-1.72	-0.21
	(9.68)	(7.09)	(6.04)	(5.15)	(4.57)	(4.15)
	log(# of admissions)					
Bandwidth(days)	60	120	180	240	300	360
Polynominal						
1	0.37	2.69	2.56	2.96*	1.52	1.41
	(3.15)	(2.36)	(1.93)	(1.68)	(1.48)	(1.33)
2	0.63	0.42	1.92	2.29	3.85*	3.17
	(4.75)	(3.31)	(2.78)	(2.44)	(2.23)	(2.06)
3	-7.21	-0.27	1.02	1.05	1.20	2.65
	(6.39)	(4.35)	(3.58)	(3.12)	(2.83)	(2.62)
	log(expense/admission)					
Bandwidth(days)	60	120	180	240	300	360
Polynominal						
1	-0.83	-2.45	-1.55	-0.96	-0.46	0.38
	(4.00)	(2.62)	(2.16)	(1.81)	(1.62)	(1.47)
2	6.28	-1.36	-4.05	-2.56	-2.25	-2.18
	(5.50)	(4.22)	(3.31)	(2.81)	(2.49)	(2.25)
3	9.30	6.69	2.48	-3.08	-2.92	-2.86
	(6.78)	(5.28)	(4.50)	(3.88)	(3.40)	(3.06)

back

Donut RD

Emergency care

	log(expense)							
Size of Donut around 3rd birthday	0	3	6	9	12	15	18	21
Age3	7.64***	7.31***	7.38***	7.15***	6.78***	6.96***	7.18***	7.02***
	(0.57)	(0.47)	(0.51)	(0.54)	(0.55)	(0.58)	(0.66)	(0.79)
	log(# of visits)							
Size of Donut around 3rd birthday	0	3	6	9	12	15	18	21
Age3	4.93***	4.58***	4.59***	4.63***	4.59***	4.75***	4.86***	5.02***
	(0.40)	(0.27)	(0.26)	(0.28)	(0.29)	(0.35)	(0.42)	(0.45)

back

Donut RD

Non-emergency care

	log(expense)							
Size of Donut around 3rd birthday	0	3	6	9	12	15	18	21
Age3	5.63***	4.76***	4.74***	4.48**	4.27*	4.12	6.36**	7.11**
	(1.58)	(1.70)	(1.74)	(1.99)	(2.28)	(2.73)	(2.85)	(3.14)
	log(# of visits)							
Size of Donut around 3rd birthday	0	3	6	9	12	15	18	21
Age3	6.59***	5.92***	5.93***	5.50***	5.37***	5.16**	6.65***	6.60***
	(1.20)	(1.32)	(1.43)	(1.57)	(1.78)	(2.19)	(2.27)	(2.50)

back

By Treatment Reason

Non-emergency care

Variables	(1) visit rate	(2) out-of-pocket price	(3) log(expense)	(4) log(# of visits)	(5) log(expense/visit)
Panel A: By treatment reason					
Respiratory diseases		-56.15***	5.40***	3.60***	1.80***
		(3.58)	(0.45)	(0.39)	(0.15)
	383.60				
Digestive illness		-59.10***	11.16***	6.54***	4.62
		(3.81)	(3.41)	(1.11)	(2.99)
	28.22				
Injury and poisoning		-83.04***	9.06***	11.45***	-2.39
		(5.04)	(2.28)	(1.59)	(1.64)
	8.77				
Skin illness		-58.13***	15.83***	12.81***	3.02***
		(3.75)	(1.74)	(1.43)	(1.11)
	16.77				
Mental illness		-156.66***	23.35***	25.35***	-2.00
		(8.54)	(3.31)	(2.96)	(1.58)
	3.56				
Preventive care		-73.12***	28.11***	33.48***	-5.37
		(6.68)	(6.36)	(3.79)	(4.85)
	3.56				

back

By Treatment Reason

Emergency care

Variables	(1) visit rate	(2) out-of-pocket price	(3) log(expense)	(4) log(# of visits)	(5) log(expense/visit)
Panel A: By treatment reason					
Respiratory diseases		-309.55***	3.24	4.69**	-1.45
		(15.93)	(2.39)	(2.23)	(0.91)
	5.39				
Digestive illness		-312.34***	6.90*	7.52**	-0.61
		(16.61)	(3.69)	(3.30)	(2.09)
	1.88				
Injury and poisoning		-264.19***	6.67*	7.46***	-0.79
		(14.89)	(3.45)	(2.34)	(2.23)
	2.86				

back

By Birth Order

Non-emergency care

Variables	(1) visit rate	(2) out-of-pocket price	(3) log(expense)	(4) log(# of visits)	(5) log(expense/visit)
Panel B: By birth order					
1st child		-60.23***	6.64***	4.67***	1.97***
		(3.80)	(0.57)	(0.38)	(0.42)
	522.14				
2nd child		-56.69***	8.58***	5.12***	3.46***
		(3.61)	(0.83)	(0.54)	(0.48)
	536.18				
3rd child (above)		-55.31***	9.55***	5.61***	3.94***
		(3.49)	(1.36)	(0.74)	(1.13)
	440.03				

back

By Birth Order

Emergency care

Variables	(1) visit rate	(2) out-of-pocket price	(3) log(expense)	(4) log(# of visits)	(5) log(expense/visit)
Panel B: By birth order					
1st child		-303.35***	3.36*	5.98***	-2.63***
		(15.68)	(1.89)	(1.69)	(1.01)
	17.68				
2nd child		-293.47***	8.51***	6.78***	1.73
		(15.26)	(2.98)	(2.29)	(1.69)
	12.48				
3rd child (above)		-278.29***	11.16**	10.87**	0.29
		(16.56)	(5.53)	(4.82)	(3.13)
	10.25				

back

By Gender
Non-emergency care

Variables	(1) visit rate	(2) out-of-pocket price	(3) log(expense)	(4) log(# of visits)	(5) log(expense/visit)
Panel C: By gender					
Male		-59.27***	8.43***	5.04***	3.39***
		(3.71)	(0.74)	(0.46)	(0.47)
	544.12				
Female		-57.42***	6.62***	4.79***	1.83***
		(3.68)	(0.65)	(0.42)	(0.39)
	489.85				

back

By Gender
Emergency care

Variables	(1) visit rate	(2) out-of-pocket price	(3) log(expense)	(4) log(# of visits)	(5) log(expense/visit)
Panel C: By gender					
Male		-300.51***	2.67	5.55***	-2.89***
		(15.62)	(2.19)	(1.62)	(0.92)
	16.39				
Female		-295.67***	9.75***	7.98***	1.77
		(15.39)	(2.31)	(1.61)	(1.36)
	13.46				

back

By Income
Non-emergency care

Variables	(1) visit rate	(2) out-of-pocket price	(3) log(expense)	(4) log(# of visits)	(5) log(expense/visit)
Panel D: By income					
low-income		-56.70***	7.66***	4.75***	2.91***
		(3.61)	(0.86)	(0.63)	(0.66)
	520.38				
middle-income		-57.94***	7.55***	4.06***	3.49***
		(3.77)	(0.77)	(0.51)	(0.54)
	522.58				
high-income		-61.49***	7.46***	4.61***	2.85***
		(3.77)	(0.91)	(0.49)	(0.73)
	512.64				

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By Income

Emergency care

Variables	(1) visit rate	(2) out-of-pocket price	(3) log(expense)	(4) log(# of visits)	(5) log(expense/visit)
Panel D: By income					
low-income		-300.51***	12.00**	14.90***	-2.90*
		(15.85)	(4.66)	(3.90)	(1.68)
	15.35				
middle-income		-299.81***	1.74	3.26	-1.52
		(15.82)	(2.66)	(2.55)	(1.22)
	14.35				
high-income		-313.89***	3.67	2.46	1.22
		(15.01)	(3.84)	(3.28)	(1.83)
	14.36				

back

Patient Cost Sharing and Healthcare Utilization in Early Childhood: Evidence from a Regression Discontinuity Design

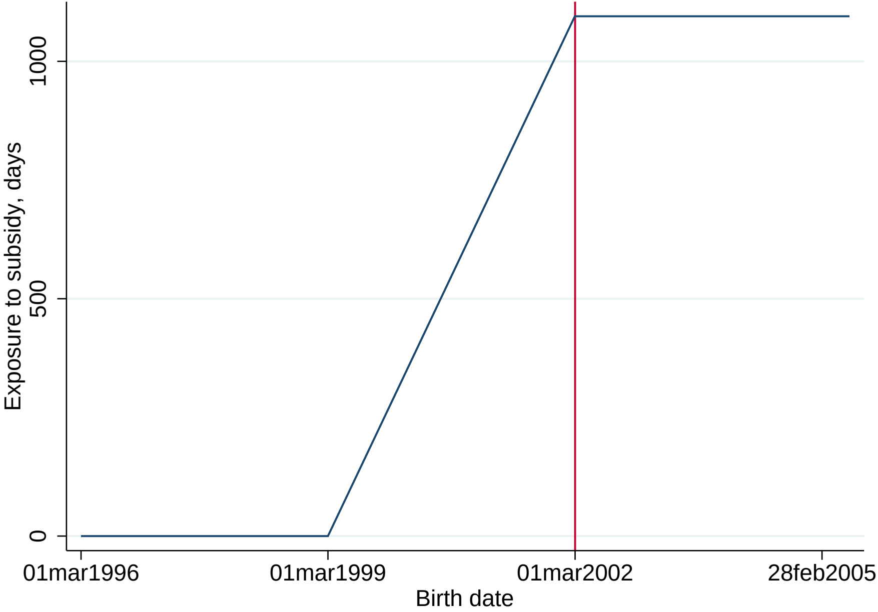
Tzu-Ting Yang, Hsing-Wen Hany, Hsien-Ming Lien

Discussed by Agne Suziedelyte, CHE, Monash University

Summary: Identification

- Effect of patient cost-sharing on inpatient and outpatient HC utilization in early childhood.
  - Moral hazard effect of insurance.
- Explore discontinuity in copayment/coinsurance subsidy at age 3.
  - Introduced on 1 Mar 2002.
  - Children under age 3 exempted from copayment/coinsurance.
  - Still have to pay “registration” fee for outpatient visits.

Summary: Identification, cont'd.



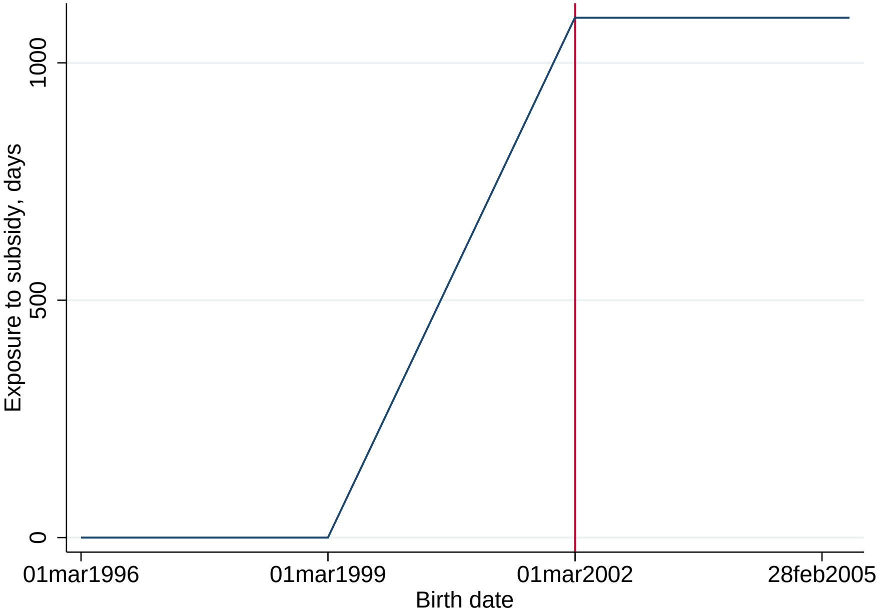
Summary: Identification, cont'd.

- Inevitable RDD design (Lee and Lemieux, 2010).
  - Effect may be accentuated.
    - "Donut" RD (Barreca et al, 2011).
  - No other changes at age 3.
- Local linear regression.
  - Bandwidth $=$ 90 days.
  - Optimal bandwidth? (E.g. Imbens and Kalyanaraman, 2012)

Summary: Results

- Subsidy increases outpatient visits, but not inpatient visits.
  - Effects on elective surgeries, e.g tonsillectomy?
- Parents switch to higher quality providers for outpatient care, mainly minor illnesses.
  - Is the same observed for inpatient care?
- Overall, suggestive evidence that copayment subsidy increases low value care.
- No effects on health.

Identification of effects of subsidy on health



No effects on health?

- In contrast to other studies (Almond et al., 2011; Bharadwaj et al., 2013).
- Consistent with subsidy increasing low value care.
- May also be explained by ex-ante moral hazard.
- Still surprising given increase in preventative (and mental health) care.

No short-run effects on health?

- Is child's health (1) very good; (2) good; **(3) normal; (4) bad; (5) very bad**?
  - Justification by parents?
  - Any other questions?
  - Longer-run effects?

No long-run effects on health?

- Inpatient visits (hospitalizations) at ages 8-10.
  - Observe increases in health care utilization using the same identification strategy?
  - Heterogeneity by parent characteristics, especially education?
  - Effects on "preventable" and mental illnesses?
    - What is included in preventative care?
  - Effects at other ages?

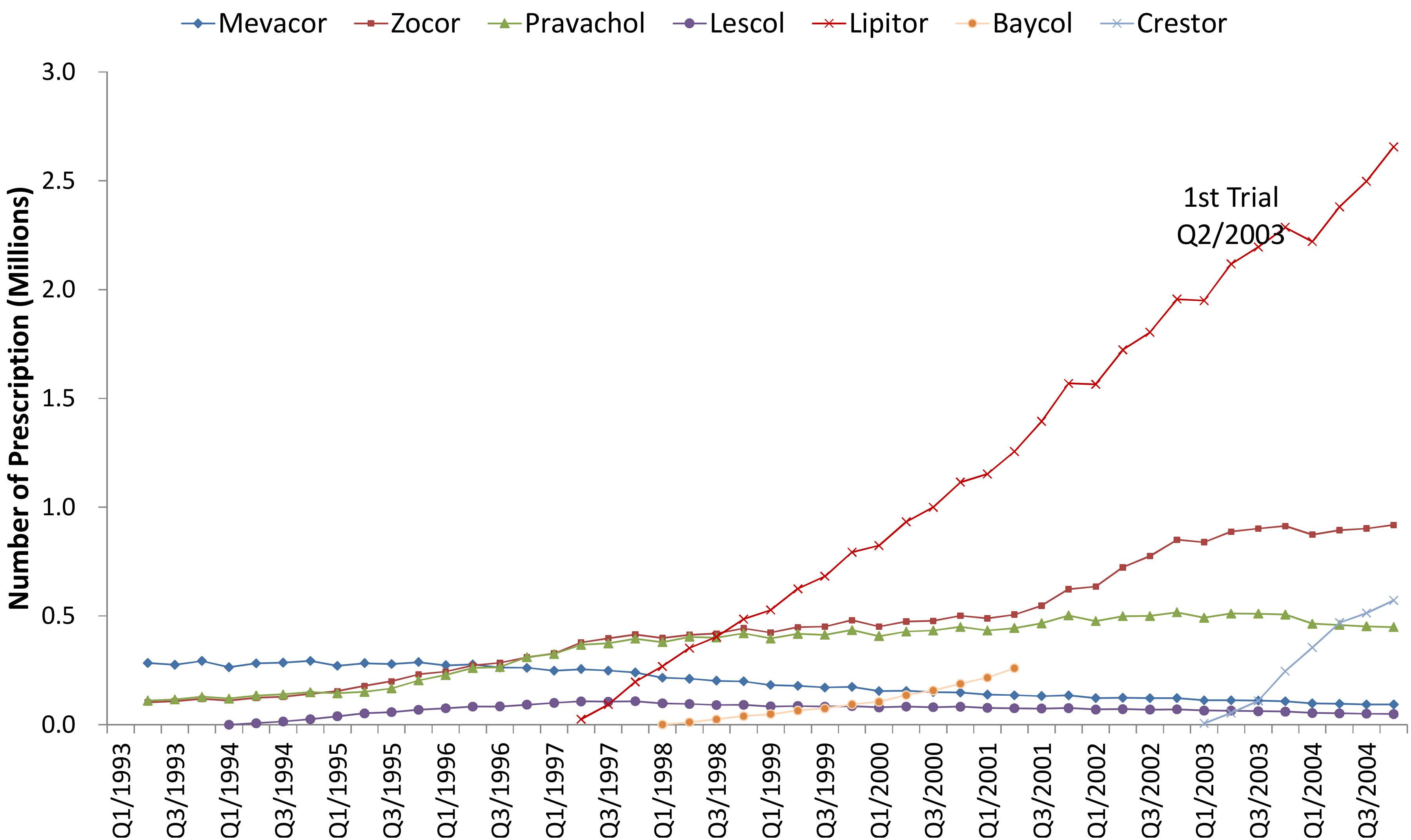
A Structural Analysis of Detailing, Publicity and Correlated Learning: The Case of Statins

Hyunwoo Lim
School of Business, Ajou University

Andrew Ching
Rotman School of Management, University of Toronto

Dec 13, 2015

Motivation


Mevacor
Zocor
Pravachol
Lescol
Lipitor
Baycol
Crestor
Number of Prescription (Millions)
3.0
2.5
2.0
1.5
1.0
0.5
0.0
1st Trial
Q2/2003
Q1/1993
Q3/1993
Q1/1994
Q3/1994
Q1/1995
Q3/1995
Q1/1996
Q3/1996
Q1/1997
Q3/1997
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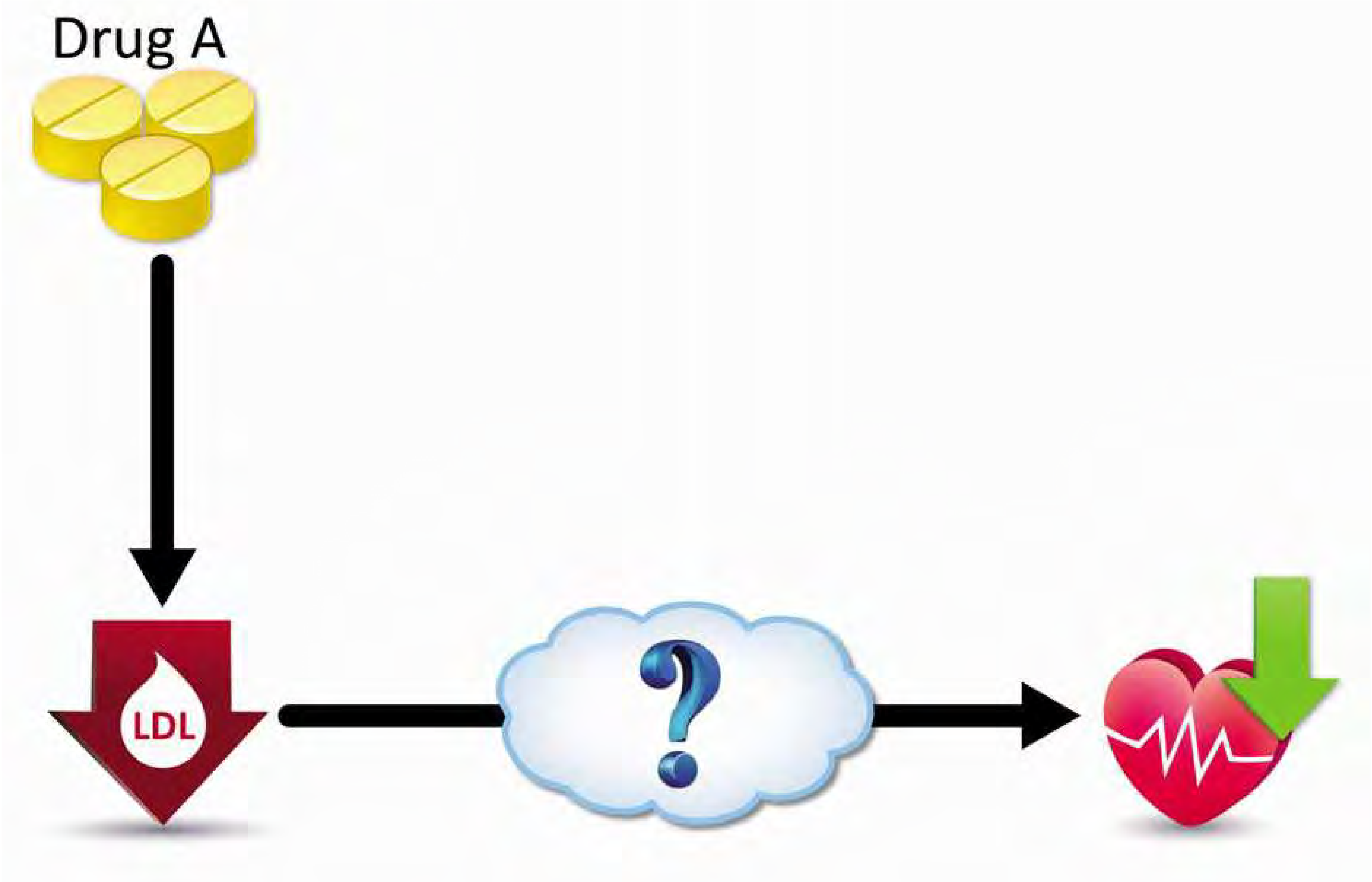
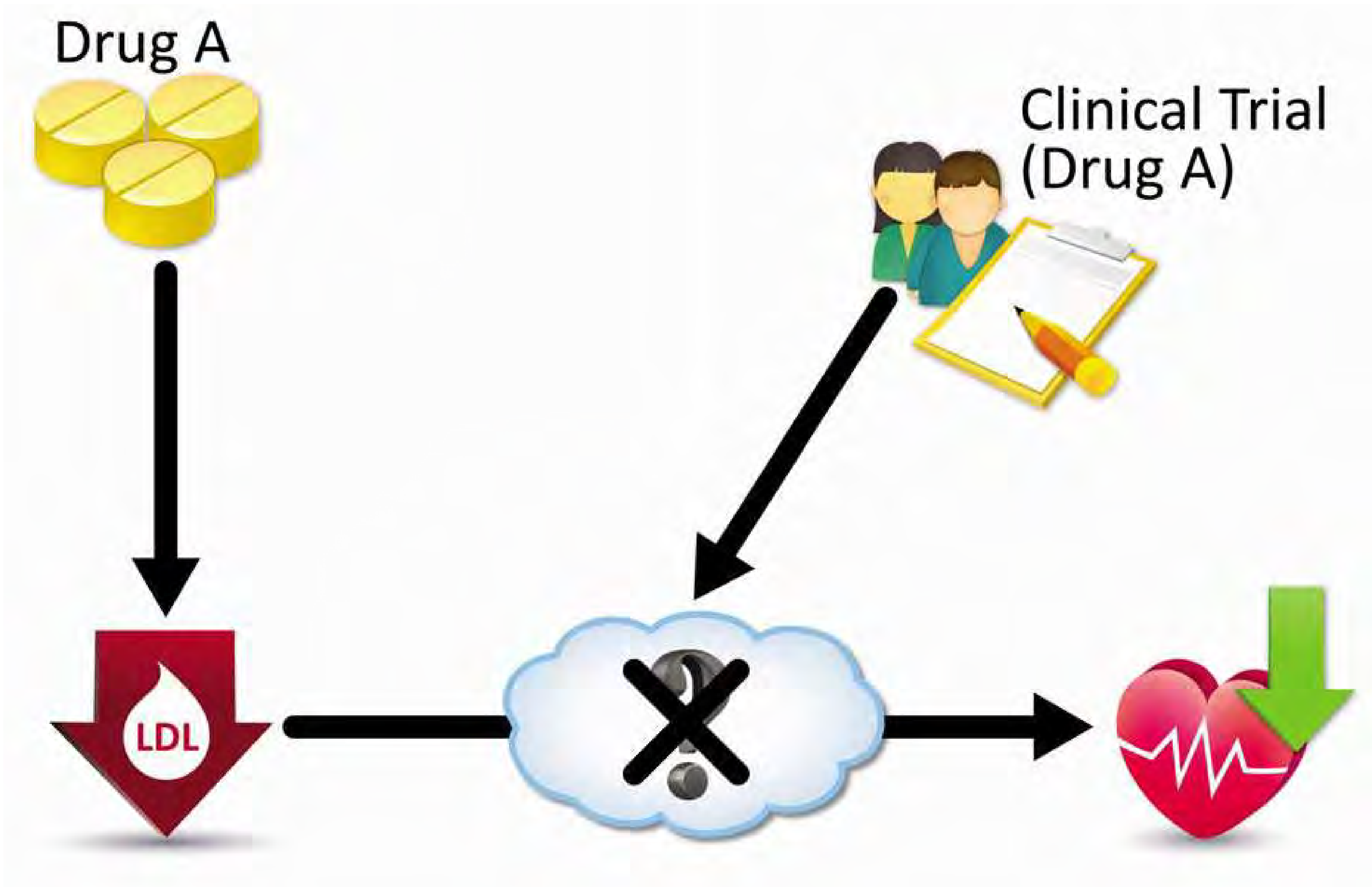
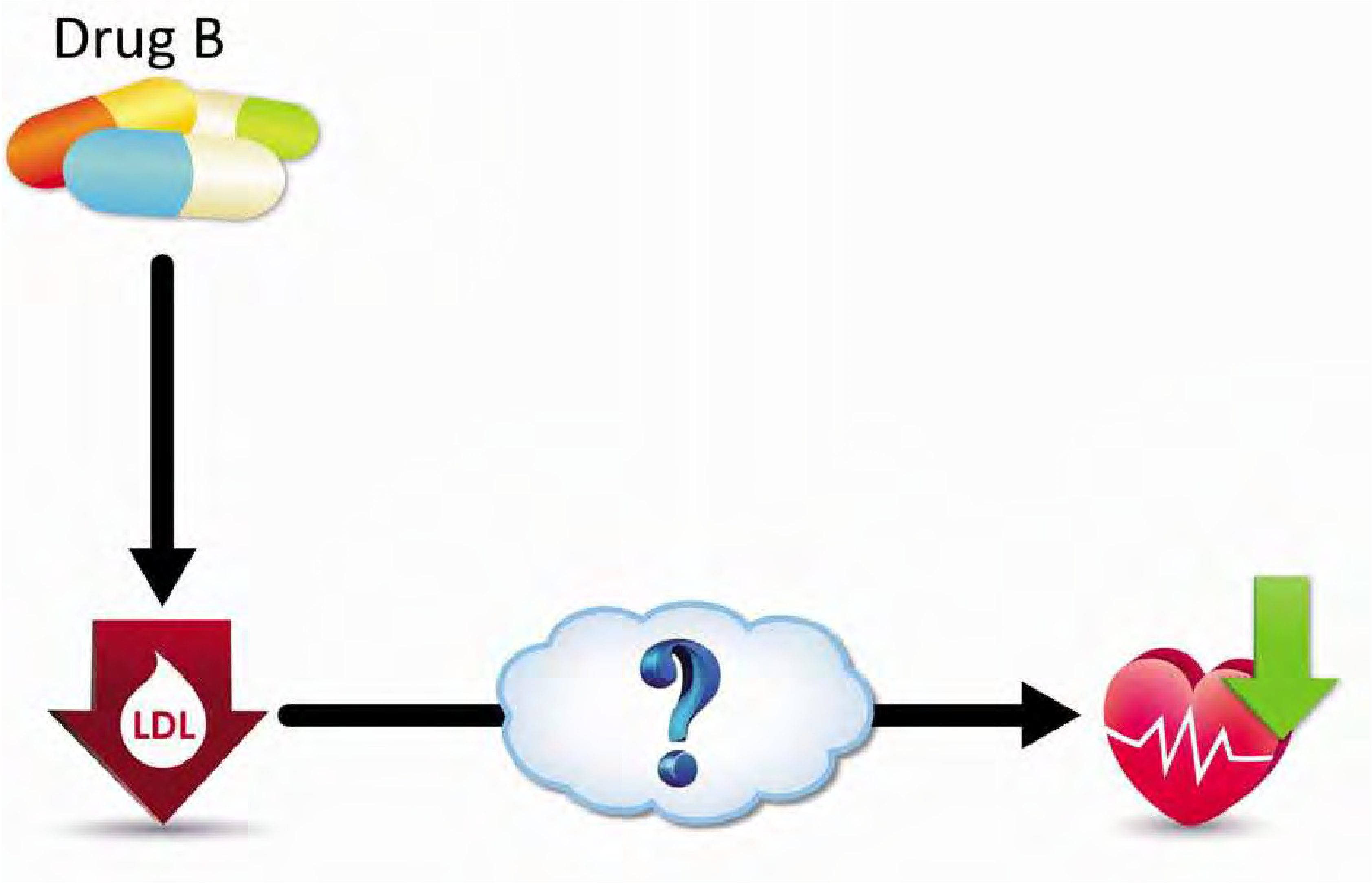
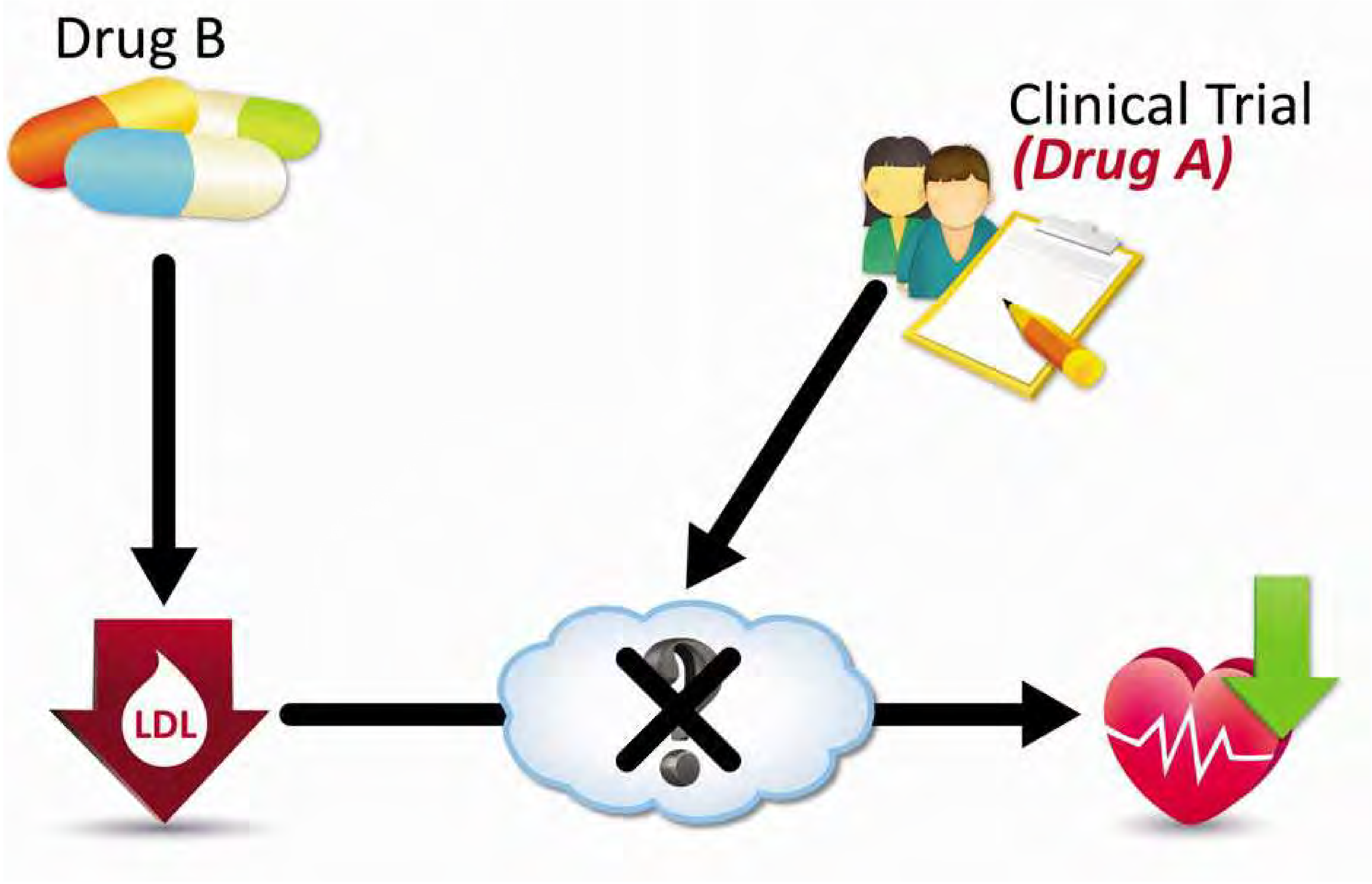

Drug A
LDL
?

Correlated Learning




Drug B
LDL
?

Correlated Learning



Research Objectives

- Develop a demand model with correlated learning across brands within a category
- Quantify the extent of correlated learning using data on market shares and quality signals (landmark clinical trials)
  - Quantify the late mover advantages
- Take the presence of switching costs into account by using switching rate data

Literature Review (skip)

- Janakiraman et al. (2009) study correlated learning across brand within a category.
  - This study assumes firms know the true quality of their products. (similar to Erdem & Sun (2002))
    - The effectiveness of advertising or detailing does not depend on consumption experience or clinical trial results.
    - Firms do not need to use consumption experience or clinical trials to learn about the true quality if the assumption is valid.
  - These implications are rejected by Azoulay (2002) and Venkataraman & Stremersch (2007).
- Ching & Ishihara (2010) incorporate clinical trials when modeling informative advertising, but do not consider correlated learning and, they do not incorporate late mover advantages and first mover advantages.

Sales and Detailing Data

- Quarterly Canadian data for each statin between Q2 1993 and Q4 2004 from IMS Canada
  - Prescription volume, Detailing
- Quarterly data on switching and discontinuing between Q2 1993 and Q4 2004 from Ontario Health Insurance Program (OHIP)
  - % of statin users who switch from a given statin to another statin (2.10% on average) $\rightarrow$ Switching costs exist.

Landmark Clinical Trials

- It is very difficult for physicians to learn about drugs' efficacy in heart disease risks from patient's feedback.
- Collect 14 landmark clinical trials reporting the efficacy of statins in reducing heart disease risks between 1993 and 2004.
- The number of patients consists of 1,600 to 20,000 and the follow-up period ranges from 2 to 6 years.
- They provide observable signals (to researchers) on how efficient a statin is in reducing heart disease risks.
    - More advanced than Ching & Ishihara (2010) who only use qualitative outcome of comparison trials.

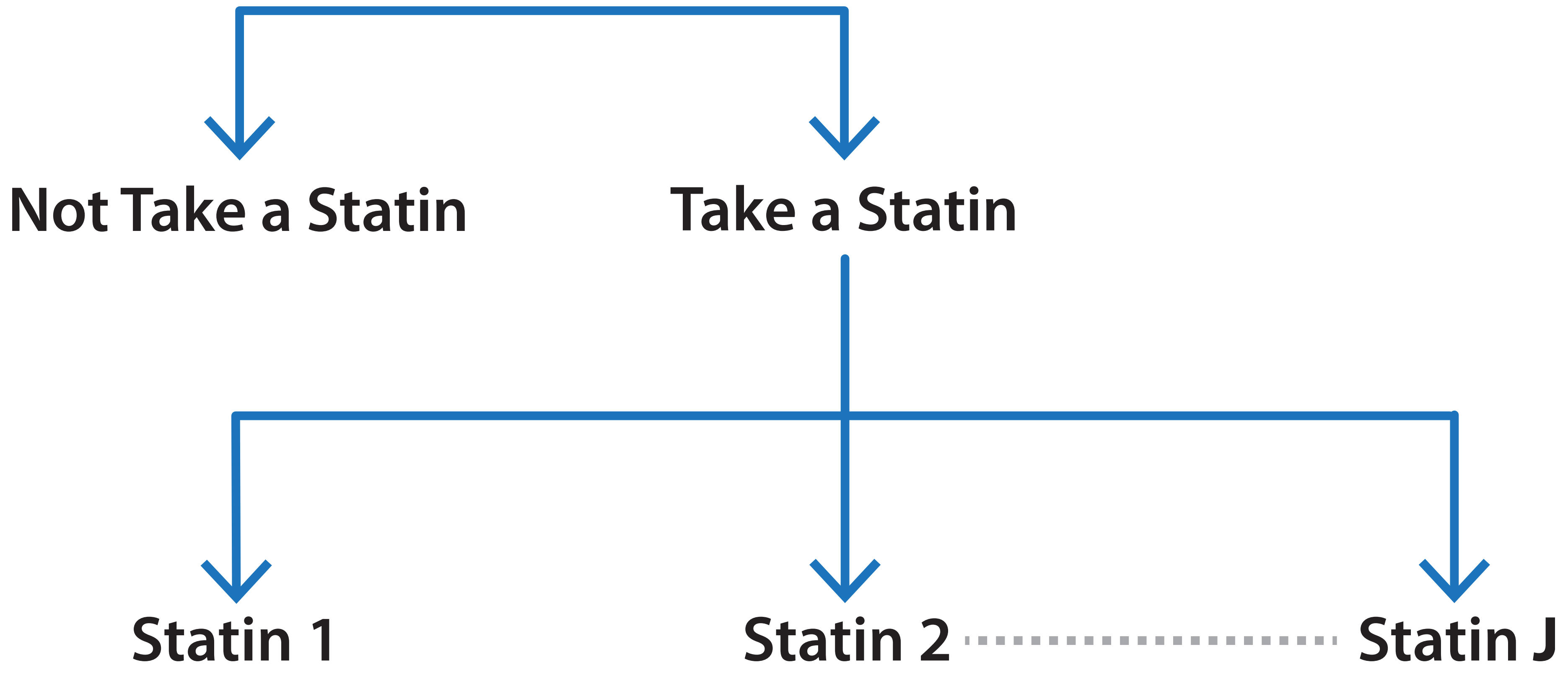
Landmark Clinical Trials

Title	Publication date	Drugs Studied	# of Subjects	Follow-up period	Sponsors	LDL Reduction (mg/dL)	Heart-Disease Risk Reduction	Efficiency Raito (HDRR / LDL)
4S	Dec, 1994	Zocor	4,444	5.4 years	Merck & Co.	68.45	34.30%	0.50
WOSCOPS	Nov, 1995	Pravachol	6,595	4.9 years	Bristol-Myers Squibb	41.38	31.50%	0.76
CARE	Oct, 1996	Pravachol	4,159	5 years	Bristol-Myers Squibb	39.83	22.70%	0.57
AFCAPS/TexCAPS	May, 1998	Mevacor	5,705	5.2 years		36.35	37.10%	1.02
LIPID	Nov, 1998	Pravachol	9,014	6.1 years	Bristol-Myers Squibb	39.83	22.20%	0.56
LIPS	Jun, 2002	Lescol	1,677	3.9 years	Novartis	35.58	19.20%	0.54
HPS	Jul, 2002	Zocor	20,536	5 years	Merck & Co.	49.88	26.00%	0.52
PROSPER	Nov, 2002	Pravachol	5,804	3.2 years	Bristol-Myers Squibb	40.22	17.40%	0.43
ALLHAT-LLT	Dec, 2002	Pravachol	10,355	4.8 years	Pfizer	20.88	9.50%	0.45
ASCOT-LLA	May, 2003	Lipitor	10,305	3.3 years	Pfizer	41.38	35.40%	0.86
ALERT	Jun, 2003	Lescol	2,102	5.1 years	Novartis	32.48	24.60%	0.76
ALLIANCE	Jul, 2004	Lipitor	2,422	4.3 years	Pfizer	15.47	38.30%	2.48
CARDS	Aug, 2004	Lipitor	2,838	3.9 years	Pfizer	44.08	31.30%	0.71
A to Z	Sep, 2004	Zocor	4,498	2 years	Merck & Co.	14.31	13.80%	0.96

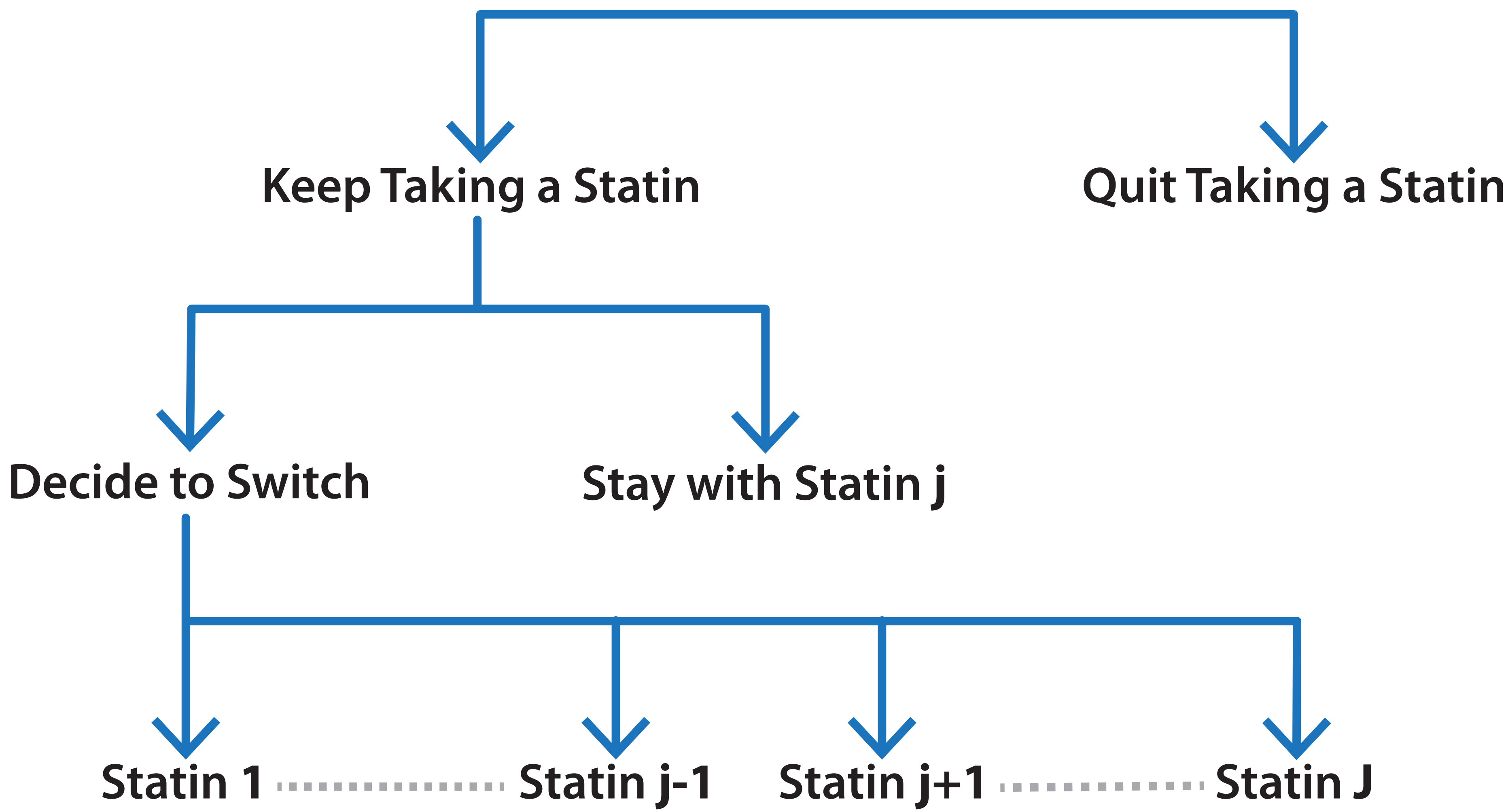
Publicity Data

- 2,754 articles mentioning "statin" from "Canadian Accessible Sources" in Factiva between year 1986 and 2004
- Classify articles along three dimensions
  1. Lowering cholesterol levels (short-term efficacy)
  2. Reducing heart disease risks (long-term efficacy)
  3. Side effects
- Try to overcome the ambiguity of single dimensional coding scheme
- Details are provided in Ching, Clark, Horstmann and Lim (2015)

Decision Process of Potential Patient



Decision Process of Existing Patient



Efficacies of Statins

- q_j^c denotes the true efficacy in lowering cholesterol levels of drug j
  - The efficacy in lowering cholesterol levels is known to physicians
  - A meta-analysis provides such information
- q_j^h denotes the true efficacy in reducing heart disease risks of drug j
  - The efficacy in reducing heart disease is uncertain to physicians
  - Physicians learn about this efficacy from landmark clinical trials

Mean Cholesterol Reduction (mmol/L)

	Daily Dose (mg)					Mean
	5	10	20	40	80	
Mevacor	N/A	1.02	1.40	1.77	2.15	1.59
Zocor	1.08	1.31	1.54	1.78	2.01	1.66
Pravachol	0.73	0.95	1.17	1.38	1.60	1.28
Lescol	0.46	0.74	1.02	1.30	1.58	1.16
Lipitor	1.51	1.79	2.07	2.36	2.64	2.22
Crestor	1.84	2.08	2.32	2.56	2.80	2.44

- Law et al. (2003) summarize (non-landmark) clinical trials investigating the efficacy in lowering cholesterol levels of statins.

Let q_j^h be the true efficacy in reducing heart disease risks of drug j

$$q_j^h = q_j^c \cdot \beta_j,$$

where q_j^c is the efficacy in lowering cholesterol levels and β_j is the "efficiency ratio".

Consumers know q_j^c, but are uncertain about β_j (and hence uncertain about q_j^h.

Initial Prior Beliefs

Initial prior beliefs on "efficiency ratio" are constructed as follows (before any landmark trials are available)

$$\begin{pmatrix} \beta_1 \\ \beta_2 \end{pmatrix}_{t=0} \sim N\left(\begin{pmatrix} \underline{\beta} \\ \underline{\beta} \end{pmatrix}, \sigma_\beta^2 \begin{pmatrix} 1 & \rho_0 \\ \rho_0 & 1 \end{pmatrix}\right),$$

where $\underline{\beta}$ is the mean initial prior belief about the efficiency ratio of each statin.

Quality Signal

Let β_j be the true mean level of the efficiency ratio for drug j. A noisy but unbiased observable signal from clinical trial l for drug j is

$$\tilde{\beta}_{jl} = \beta_j + \zeta_l$$

where $\zeta_l \sim N(0, \sigma_\zeta^2/N_l)$ and N_l denotes the number of patients who participate in landmark clinical trial l.

Updating Process for Drug 1 (skip)

Assume that a physician learns about clinical trial l for drug 1 at time t.

Her posterior belief on the efficiency ratio of drug 1 is

$$\beta_{1t+1} = \beta_{1t} + \frac{\sigma^2_{\beta 1t}}{\sigma^2_{\beta 1t} + \sigma^2_{\zeta 1l}} \cdot (\tilde{\beta}_{1l} - \beta_{1t})$$

Her posterior variance on the efficiency ratio of drug 1 is

$$\sigma^2_{\beta 1t+1} = \frac{\sigma^2_{\beta 1t}\sigma^2_{\zeta 1l}}{\sigma^2_{\beta 1t} + \sigma^2_{\zeta 1l}}$$

Updating Process for Drug 2

Assume that a physician learns about clinical trial l for drug 1 at time t. Her posterior belief on the efficiency ratio of drug 2 is

$$\beta_{2t+1} = \beta_{2t} + \frac{\pi_t}{\sigma^2_{\beta 2t} + \sigma^2_{\zeta 1l}} (\tilde{\beta}_{1l} - \beta_{1t})$$

where π_t is the covariance in prior beliefs about "efficiency ratio" of drug 1 and 2 at time t.

Her posterior variance on the efficiency ratio of drug 2 is

$$\sigma^2_{\beta 2t+1} = \sigma^2_{\beta 2t} - \frac{\pi_t^2}{\sigma^2_{\beta 2t} + \sigma^2_{\zeta 1l}}$$

Types of Physicians

- We modify the model proposed by Ching and Ishihara (2010).
- Informative detailing is a means to build and maintain the measure of physicians.
- A physician is either well informed or uninformed about drug j.
- A well-informed physician knows the most current landmark trials of drug j ($I_j(t)$).
- An uninformed physician only knows the initial prior ($\bar{I}_j(t)$).

Informative Detailing and Publicity

- The probability that a physician will learn the most updated clinical information about drug j at time t is

$$M_{jt} = \frac{exp(\alpha_0 + \alpha_d \cdot I\_STK\_detail_{jt} + \alpha_p \cdot STK\_rh_{jt})}{1 + exp(\alpha_0 + \alpha_d \cdot I\_STK\_detail_{jt} + \alpha_p \cdot STK\_rh_{jt})}$$

where $I\_STK\_detail_{jt}$ and STK_rh_{jt} denote the informative stocks of detailing and drug specific non-comparison publicity in reducing heart disease risks for drug j at time t, respectively.

Utility Function

Let patient i's utility of consuming statin j at time t be

$$U_{ijt} = \omega \cdot q_j^h + b_j + \epsilon_{ijt},$$

where q_j^h denotes drug j's efficacy in reducing heart disease risks; b_j captures time-invariant brand specific preference.

Physician k's expected utility of prescribing drug j to patient i at time t becomes

$$E[U_{ijt}^k | I^k(t)] = \omega \cdot E[q_j^h | I^k(t)] + \kappa_d \cdot P\_STK\_detail_{jt} + b_j + \epsilon_{ijt},$$

where $P\_STK\_detail_{jt}$ is a persuasive detailing goodwill stock for drug j at time t.

Estimation (skip)

- The total demand for drug j at time t is expressed as follows.

$$d_{jt} = \hat{d}^1_{jt} + \hat{d}^2_{jt} + \hat{d}^3_{jt} + e_{jt}$$

where $\hat{d}^1_{jt}$, $\hat{d}^2_{jt}$, $\hat{d}^3_{jt}$ are estimated demand for drug j at time t from "new patients", "switchers" and "stayers",respectively; e_{jt} is a measurement error.

- Estimate the model using Maximum Likelihood.

Identification (skip)

- Correlated Learning
  - Sales changes after a clinical trial is released identify correlated learning parameters.
- Informative Detailing
  - Variations in sales and detailing before and after each clinical trial release identify the informative effects.

Result Tables(1) (skip)

	Estimates	S.E.
Learning Parameters		
$\underline{\beta}$ (Initial Prior Belief on Efficiency Raito)	0.1458	0.0204
σ_β^2 (Initial Prior Variance on Efficiency Raito)	1.0000	
σ_ζ^2 (Signal Variance from 1,000 Patients)	6.9967	1.1575
ρ_0 (Correlation Term in Initial Prior)	0.7494	0.0076
Statin Choice Stage, Utility Parameters		
α_0 (Constant)	-0.3569	0.8034
α_d (Informative Detailing)	4.0382	1.9810
α_{rh} (Informative Publicity)	0.7785	0.1222
ω (Coefficient of Perceived Quality)	1.6301	0.1487
κ_d (Persuasive Detailing)	0.6322	0.0094
Adoption Decision Stage Parameters		
α^s_0 (Constant)	-15.0343	0.2047
α_i (Inclusive Value)	0.9270	0.0243
α^s_{lc} (General Publicity Stock in Lowering Cholesterol Levels)	0.0015	0.0005
α^s_{se} (General Publicity Stock in Side Effects)	-0.0376	0.0052
Log Likelihood	-2795.59	

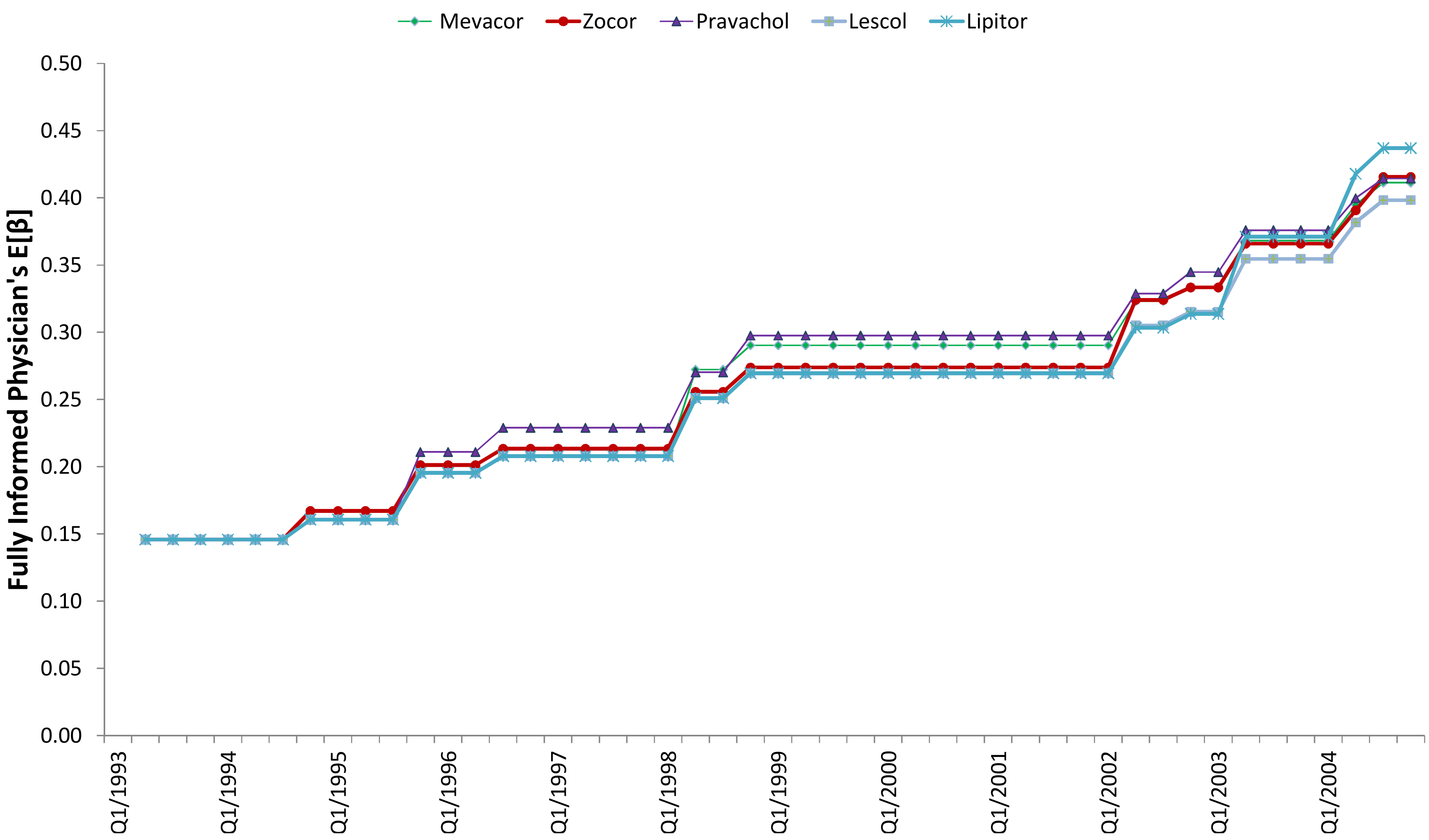
Results Tables(2) (skip)

	Estimates	S.E.
Brand Dummies		
Zocor	10.0774	0.0921
Pravachol	9.9340	0.1091
Lescol	-6.7665	0.2525
Lipitor	10.6283	0.0813
Baycol	9.1460	0.2079
Crestor	9.8354	0.1104
Additional Parameters		
δ^s_p (Carryover Rate of Publicity in Adoption Decision)	0.8885	0.0148
δ_i (Carryover Rate of Informative Publicity in Statin Choice)	0.9554	0.0179
δ_d (Carryover Rate of Detailing in Statin Choice)	0.9568	0.0016
Standard Deviation of e_{jt} (in Hundred Thousand)	0.2594	0.0072
Log Likelihood	-2795.59	

Results

- The estimate of the correlated learning parameter (ρ_0) is 0.749, which suggests a partial information spill-over.
- The estimates of both persuasive (κ_d) and informative (α_d) detailing parameters are positive and significant.
- Publicity in reducing heart disease risks (α_{rh}) has a significant impact on updating physicians about clinical trial information.

Results


Mevacor
Zocor
Pravachol
Lescol
Lipitor
Fully Informed Physician's E[β]
0.50
0.45
0.40
0.35
0.30
0.25
0.20
0.15
0.10
0.05
0.00
Q1/1993
Q1/1994
Q1/1995
Q1/1996
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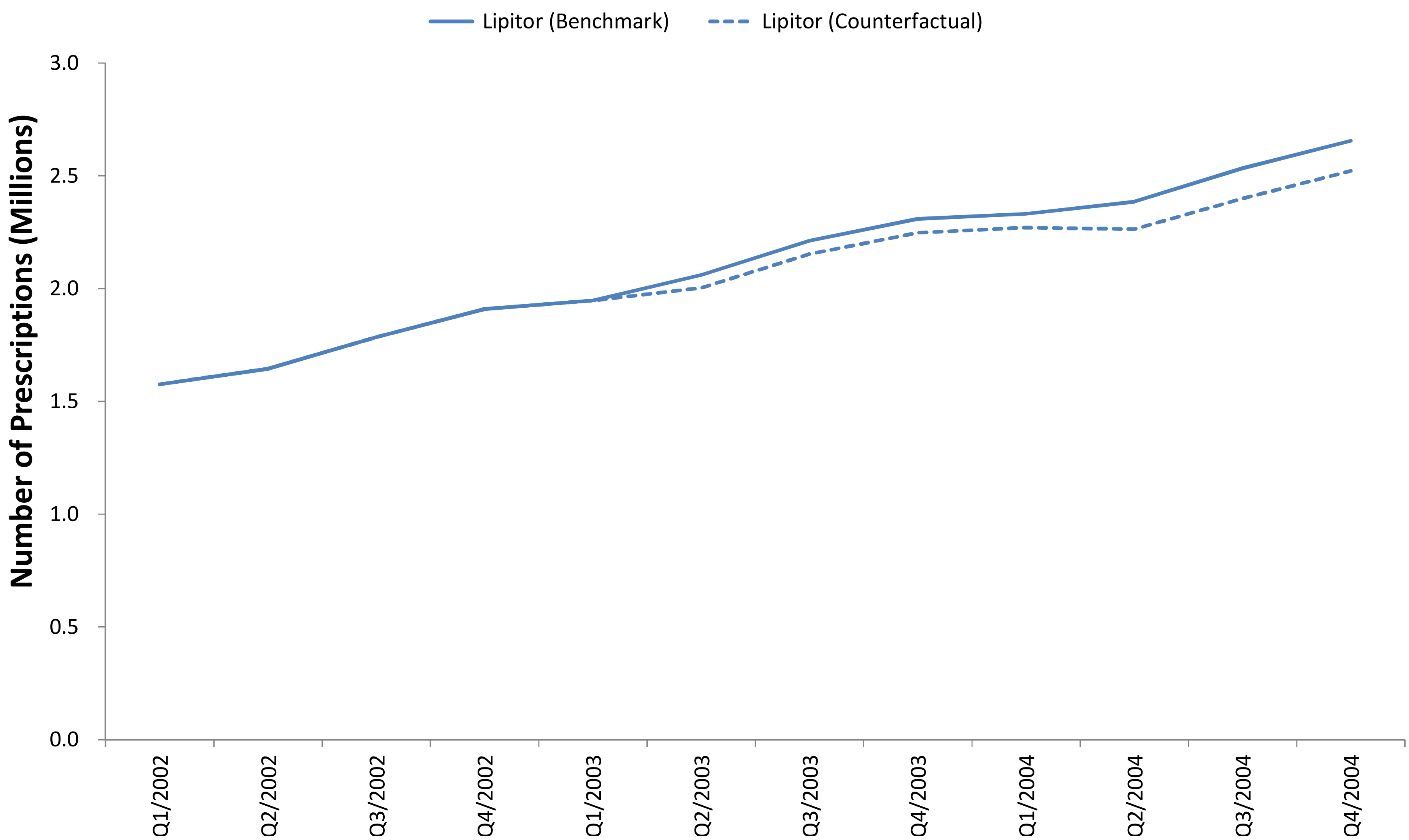
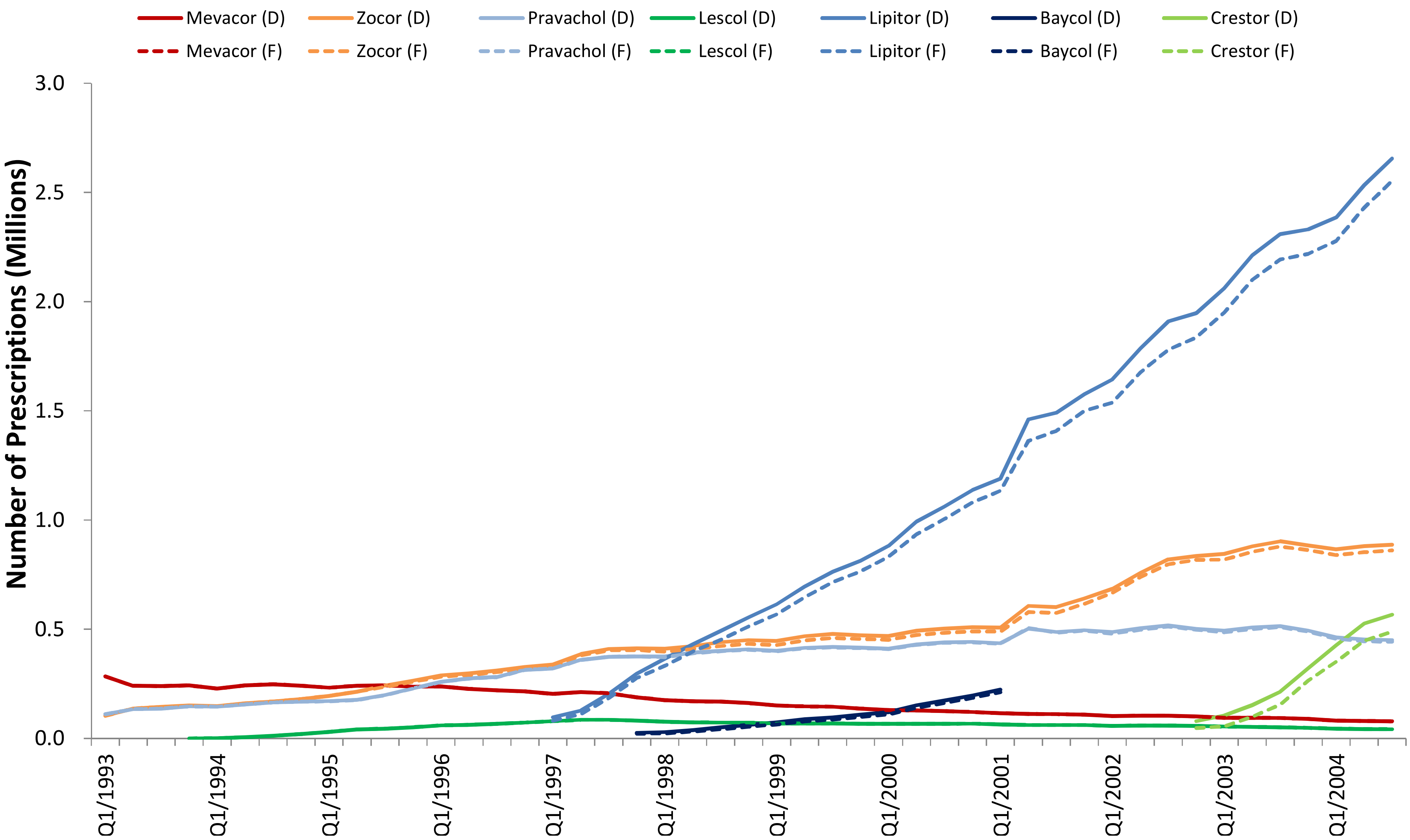
Q1/2003
Q1/2004

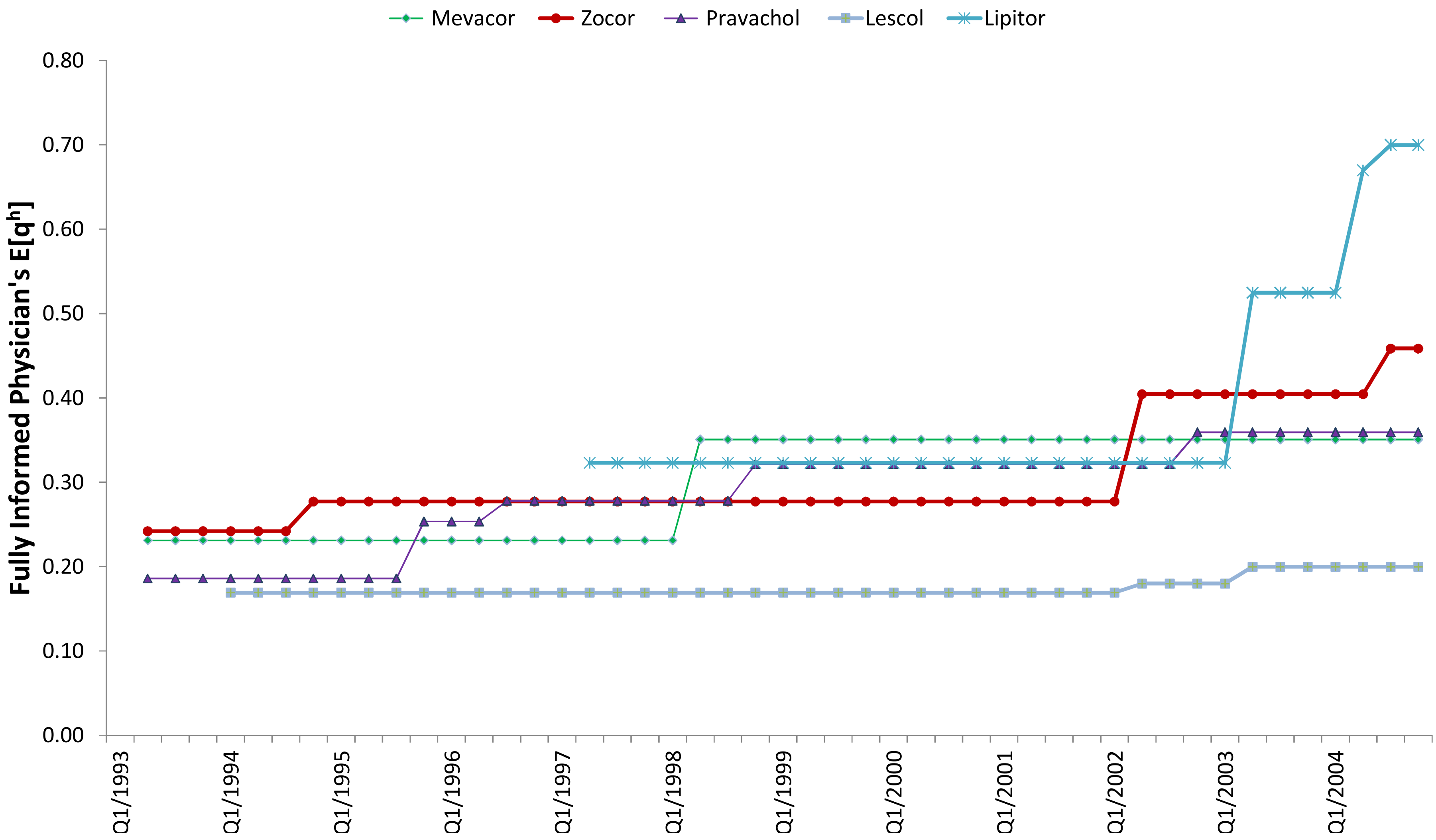
Expt 1: No Landmark Trials for Lipitor



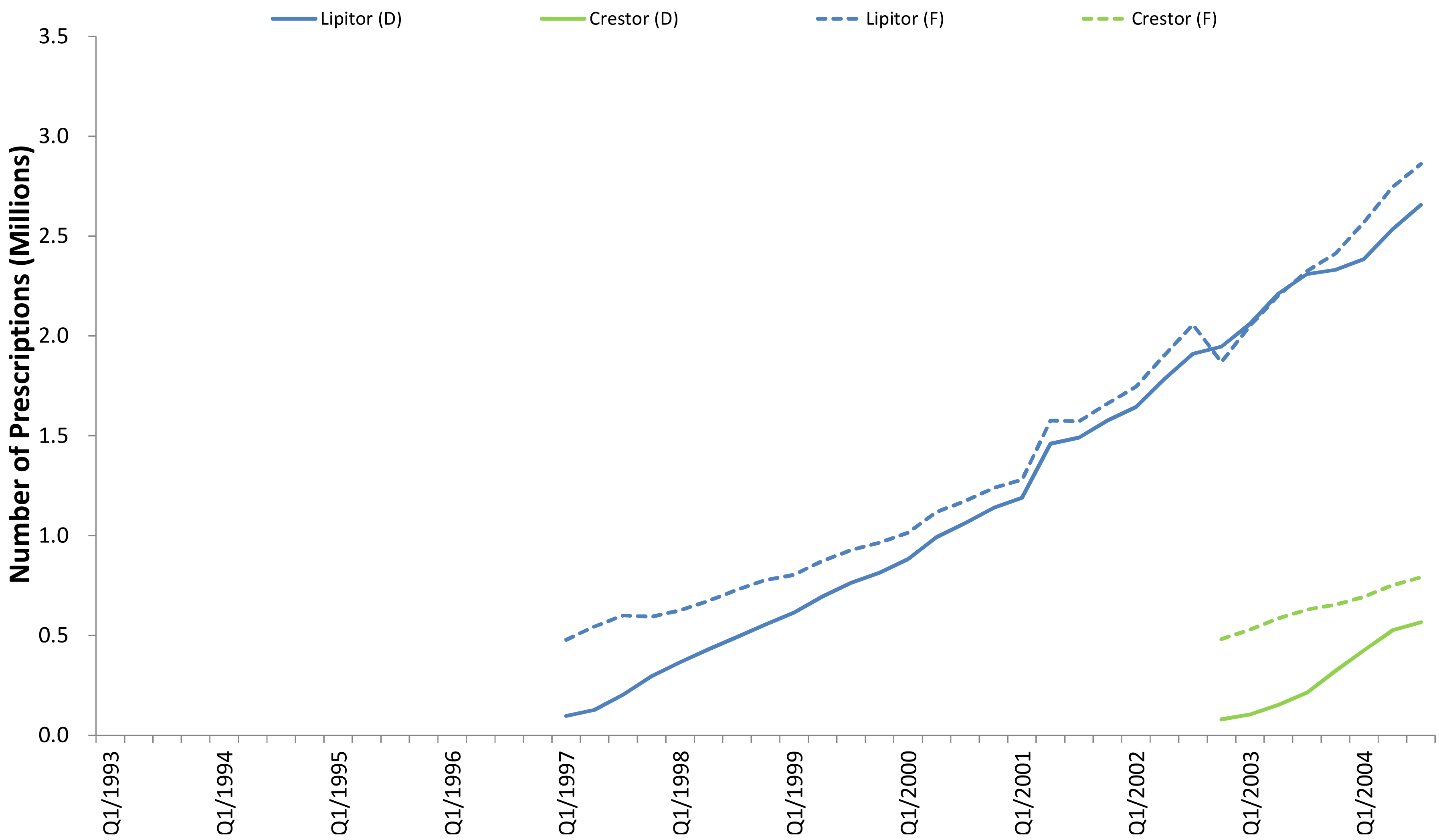
Expt 2: No Correlated Learning



Expt 2: No Correlated Learning



Expt 3: No Switching Cost



Results

- First experiment: Without landmark clinical trials, Lipitor's sales is about 5% lower in Canada.
- Assuming similar sales drop happens in other markets, with global sales at around \$13 billion in 2003, 5% sales is about \$600 million.
- Second experiment: Information spillover/correlated learning does lead to late mover advantage (around 4% sales per quarter).
- But correlated learning is not the only driving force for the rapid success of Lipitor. Lipitor's superior efficacy in lowering cholesterol level, and persuasive detailing also contribute to its early success.

Conclusion

- Our results suggest that late mover advantages can be generated by correlated learning.
- Although Lipitor can free-ride on incumbents' clinical trials, its own clinical trial still plays an important role in generating demand.
- This model can be extended to other market where products qualities are uncertain, e.g., Ipad vs Android tablet.

Discussion of:
"A Structural Analysis of Detailing, Publicity and Correlated Learning: The Case of Statins"

Hyunwoo Lim and Andrew Ching
Discussant: Susan Mendez

Joint 2015 AHEW and 7th AWEHE
University of Hawaii, December 11 – 14, 2015

THE UNIVERSITY OF MELBOURNE

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What is the paper's objective?

To analyze the role of detailing and efficiency for the successful introduction of new drugs

Allowing for:

- Correlated learning across drugs: Physicians update their beliefs about efficiency of new drugs when they learn from "older" drugs
  - Efficiency: Does it work? vs Does it help?
  - Information spillover from costly (post-marketing) landmark clinical trials
- Switching is costly: Patients face switching cost
- Detailing: persuasive and informative
- Publicity directly to consumers: data from news articles

Research approach and main findings

Bayesian learning model that incorporates physicians' correlated learning

Results:

- Physicians have relatively low initial prior beliefs on efficiency ratios, but later learn about true efficiency ratios.
- Significant information spillover effects across statins
- Informative and persuasive detailing plays a role in the physicians' prescription choices
- Advertising directly to consumers also has an impact on the choice of the statin

Experiments:

1. No support from clinical trial for Lipitor: demand is slightly lower (5%)
2. Did Lipitor benefit from clinical trials across drugs? Demand is lower (4%-10%) when there is no correlated learning

Points for consideration

Switching behavior:

What is the role of:

- Existence of and adherence to guidelines
  - Affects directly total number of prescriptions, but also shares (business stealing)
  - Number of people starting treatment with statins has been increasing over time and switching rates are higher when starting treatment
- of physicians' characteristics
  - Type of physician and prescribing behavior: concentrated (on one or a few drugs) and with deviation (from the prescription patterns of others) Berndt et al. (2015)
- of prices: adding new drugs to insurance plans (timing)

Points for consideration:

Public policy implications:

- Value of new technologies for patients. Information spillover could lead to an overestimation in welfare growth from the introduction of a new drug (Dunn 2012)
- Understanding advertising and the incentives faced by the firm (e.g. free riding) are important for the firm profit maximization problem and to support efficient regulation (Shapiro 2015)

References:

- Shapiro, Brad (2015) "Positive Spillovers and Free Riding in Advertising of Prescription Pharmaceuticals: The Case of Antidepressants"
- Dunn, Abe (2012) "Drug Innovations and Welfare Measures Computed from Market Demand: The Case of Anti-Cholesterol Drugs." *American Economic Journal: Applied Economics* 4(3): 167-189.
- Berndt, E; Gibbons, R; Kolotilind A. and A.L. Taub (2015) "The heterogeneity of concentrated prescribing behavior: Theory and evidence from antipsychotics"

Dunn 2012

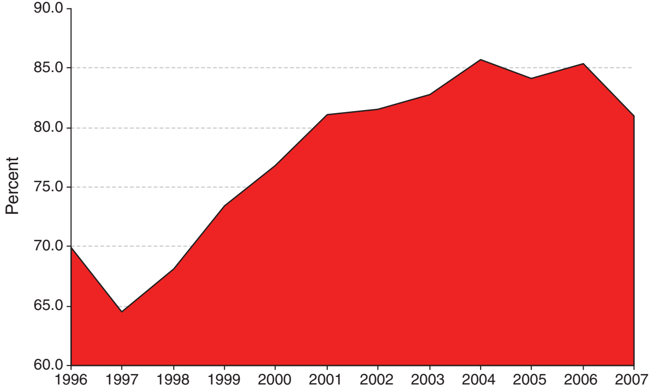

FIGURE 1. THE FRACTION OF INDIVIDUALS WITH HIGH CHOLESTEROL OVER 20 THAT USE AN ANTI-CHOLESTEROL DRUG

Source: Author's calculations using MEPS data for those individuals reporting high cholesterol.

Guidelines

theguardian

Cholesterol drug statins should be given to millions more, NHS guidance says

Statins should be offered to those with low risk of stroke or heart disease, says National Institute for Health and Care Excellence

Sarah Boseley, health editor

Tuesday 11 February 2014 19.01 EST

Statins, the cholesterol-busting drugs already taken by 7 million people in England, should be offered to millions more who have only a low risk of heart disease or stroke, new NHS guidance says.

The National Institute for Health and Care Excellence (Nice) says in draft guidance which now goes out to consultation that the threshold for GPs to prescribe statins to their patients should be cut in half. At the moment they are given to those with a 20% risk of cardiovascular disease, but Nice says that should be reduced to 10%.