Métodos estadísticos y de inferencia causal

Isaac Meza López[1]

[1] ITAM

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   - Lee bounds
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[AI17a] S. Athey and G.W. Imbens, *Chapter 3 - the econometrics of randomized experimentsa*, Handbook of Field Experiments (Abhijit Vinayak Banerjee and Esther Duflo, eds.), Handbook of Economic Field Experiments, vol. 1, North-Holland, 2017, pp. 73 – 140.

[AI17b] Susan Athey and Guido W. Imbens, *The state of applied econometrics: Causality and policy evaluation*, Journal of Economic Perspectives **31** (2017), no. 2, 3–32.

[AP08] Joshua D. Angrist and Jörn-Steffen Pischke, *Mostly harmless econometrics: An empiricist's companion*, Princeton University Press, December 2008.

Dropbox

Los materiales y ésta presentación la pueden encontrar aquí.

Diseño de experimentos

Poder estadístico $(1-\beta)$ es la verosimilitud/probablidad de detectar cierto efecto cuando hay un efecto que detectar.

$$H_0 \ : \ \theta = 0$$

$$H_1 \ : \ \theta \neq 0$$

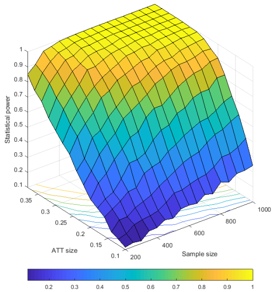
$$1-\beta = Pr(\text{rechazar } H_0 \mid H_1 \text{ es verdadera})$$

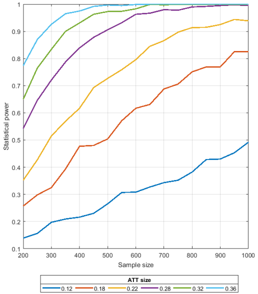
Concluir	Realidad	
	H_0 TRUE	H_0 FALSE
H_0 TRUE	$(1-\alpha)$	Type I : β
H_0 FALSE	Type II: α	$(1-\beta)$

Simulación de Poder II

El proceso de simulación de poder identifica 2 etapas:

1. DGP : $(X, Y) \sim F$
2. Método de identificación : $\mathbb{E}[Y|X] = \theta^{\mathsf{T}} X$





Do files: `sim_AB_FS_1.do`, `simulation_iv.do`

Inferencia Causal

Obervaciones Potenciales

$$Y_i = \begin{cases} Y_{1i} & \text{if } D_i = 1 \\ Y_{0i} & \text{if } D_i = 0 \end{cases}$$

$$Y_i = Y_{0i} + (Y_{1i} - Y_{0i})D_i$$

¿Cómo obtenemos efectos de tratamiento promedio - (ATE)?

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¿Cómo obtenemos efectos de tratamiento promedio - (ATE)?

$$\mathbb{E}[Y_i \mid D_i = 1, X_i] - \mathbb{E}[Y_i \mid D_i = 0, X_i] = \overbrace{\mathbb{E}[Y_{1i} \mid D_i = 1, X_i] - \color{red}{\mathbb{E}[Y_{0i} \mid D_i = 1, X_i]}}^{\text{ATT}}$$
$$+ \underbrace{\color{red}{\mathbb{E}[Y_{0i} \mid D_i = 1, X_i] -} \mathbb{E}[Y_{0i} \mid D_i = 0, X_i]}_{\text{Bias}}$$

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$$+ \underbrace{\mathbb{E}[Y_{0i} \mid D_i = 1, X_i] - \mathbb{E}[Y_{0i} \mid D_i = 0, X_i]}_{\text{Bias}}$$

Problema fundamental de la inferencia causal

$$\mathbb{E}[Y_{0i} \mid D_i = 1, X_i]$$

Table 1: Treatment Effects

	Months after treatment							
	Same day settlement					2 months	5 months	Long run
	Phase 1		Phase 2		Phase 1/2			
	OLS					OLS		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Control (constant)	0.060***	0.034***	0.11***	0.10***	0.094***	0.15***	0.39***	0.45***
	(0.013)	(0.011)	(0.030)	(0.030)	(0.026)	(0.043)	(0.039)	(0.049)
Calculator	0.051**	0.019	0.047**	0.0077	0.018	0.0035	-0.0069	-0.0025
	(0.022)	(0.019)	(0.021)	(0.019)	(0.014)	(0.021)	(0.024)	(0.025)
Conciliator	0.054***	0.033*			0.016	-0.0028	-0.030	-0.053
	(0.019)	(0.018)			(0.019)	(0.023)	(0.028)	(0.036)
Emp present (EP)		0.14***		0.14*	0.14***	0.11**	0.094*	0.070
		(0.050)		(0.072)	(0.041)	(0.046)	(0.048)	(0.050)
Calculator#EP		0.16**		0.16*	0.16***	0.18***	0.16**	0.14**
		(0.079)		(0.089)	(0.056)	(0.061)	(0.064)	(0.061)
Conciliator#EP		0.16**			0.16**	0.21***	0.27***	0.20**
		(0.074)			(0.071)	(0.079)	(0.075)	(0.078)
Observations	1074	1074	1092	1092	2166	2166	2166	2166
R-squared	0.0072	0.12	0.051	0.11	0.13	0.12	0.11	0.087
Court dummies	NO	NO	YES	YES	YES	YES	YES	YES
DepVarMean	0.095		0.20		0.15	0.19	0.32	0.43
InteractionVarMean		0.18				0.18		
Calc=Conc	0.88	0.53	-	-	0.94	0.82	0.79	0.40
Calc#EP=Conc#EP	-	0.98	-	-	1.00	0.58	0.68	0.085

IV - corrigiendo la endogeneidad

Consideremos un modelo $y_i = X_i\beta + \epsilon_i$

$$\hat{\beta}_{OLS} = (X'X)^{-1}X'y = (X'X)^{-1}X'(X\beta\epsilon) = \beta + (X'X)^{-1}X'\epsilon$$

IV - corrigiendo la endogeneidad

Consideremos un modelo $y_i = X_i\beta + \epsilon_i$

$$\hat{\beta}_{OLS} = (X'X)^{-1}X'y = (X'X)^{-1}X'(X\beta\epsilon) = \beta + (X'X)^{-1}X'\epsilon$$

Variables instrumentales Z

- Primera etapa fuerte : $\quad X_i = Z_i\gamma + \nu_i$
- Restricción de exclusión : $\quad Z'e = 0$

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Variables instrumentales Z

- Primera etapa fuerte : $X_i = Z_i\gamma + \nu_i$
- Restricción de exclusión : $Z'e = 0$

$$\hat{\beta}_{IV} = (Z'X)^{-1}Z'y \rightarrow \beta$$

Estimación - 2SLS

(i) $X = Z\gamma + \nu$

$$\hat{\gamma} = (Z'Z)^{-1}Z'X$$

$$\hat{X} = X\hat{\gamma} = \underbrace{Z(Z'Z)^{-1}Z'}_{P_Z}X$$

(ii) $y = \hat{X}\beta + \epsilon$

$$\hat{\beta}_{2SLS} = (X'P_ZX)^{-1}X'P_zy = \hat{\beta}_{GMM}$$

¿Instrumentos?

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- Lluvia

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- Lluvia - no funcionó

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- Lluvia - no funcionó
- Distancia a la junta

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Control function I

Es un método de dos etapas *generalizado*, pues explota la estructura de la variable endógena - por lo que obtenemos residuos generalizados.

$$
\begin{aligned}
y &= X\beta + \epsilon && \text{Ec. estructural}\\
X &= Z\gamma + \nu && \text{Primera etapa}\\
\mathbb{E}[Z'\nu] &= 0 && \text{Ortogonalidad}\\
\epsilon = \nu\rho + u \qquad \mathbb{E}[\nu u] &= 0 && \text{Residuo generalizado}
\end{aligned}
$$

De la última ecuación: $\rho = \mathbb{E}[\nu\nu']^{-1}\mathbb{E}[\nu\epsilon]$ y notemos que

$$\{\epsilon, \nu\} \perp Z \implies u \perp Z$$

$$\therefore u \perp X$$

Entonces,

CF

$$y = X\beta + \nu\rho + u$$

Control function II

1. En el modelo lineal básico con coeficientes constantes, donde las VEE aparecen linealmente, y donde uso formas reducidas lineales, CF es lo mismo que 2SLS. Pero el primero proporciona una prueba simple y robusta de la hipótesis nula de que X es exógena : $\rho = 0$
2. Cuando exploto características especiales de la VEE, por ejemplo, reconozco que es una variable binaria, CF es probablemente más eficiente que 2SLS pero, en términos de consistencia, el enfoque de CF suele ser menos robusto que el de IV.
3. En modelos con múltiples funciones no lineales de VEE, el enfoque CF maneja parsimoniosamente la endogeneidad y proporciona pruebas de exogeneidad simples.

Control function III

	Months after treatment								
	Same day settlement					2 months	5 months	Long run	Same day
	Phase 1		Phase 2		Phase 1/2				
	OLS					OLS			CF OLS
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Control (constant)	0.060***	0.034***	0.11***	0.10***	0.094***	0.15***	0.39***	0.45***	0.053
	(0.013)	(0.011)	(0.030)	(0.030)	(0.026)	(0.043)	(0.039)	(0.049)	(0.040)
Calculator	0.051**	0.019	0.047**	0.0077	0.018	0.0035	-0.0069	-0.0025	0.0084
	(0.022)	(0.019)	(0.021)	(0.019)	(0.014)	(0.021)	(0.024)	(0.025)	(0.014)
Conciliator	0.054***	0.033*			0.016	-0.0028	-0.030	-0.053	0.023
	(0.019)	(0.018)			(0.019)	(0.023)	(0.028)	(0.036)	(0.019)
Emp present (EP)		0.14***		0.14*	0.14***	0.11**	0.094*	0.070	0.47**
		(0.050)		(0.072)	(0.041)	(0.046)	(0.048)	(0.050)	(0.21)
Calculator#EP		0.16**		0.16*	0.16***	0.18***	0.16**	0.14**	0.16***
		(0.079)		(0.089)	(0.056)	(0.061)	(0.064)	(0.061)	(0.054)
Conciliator#EP		0.16**			0.16**	0.21***	0.27***	0.20**	0.17**
		(0.074)			(0.071)	(0.079)	(0.075)	(0.078)	(0.074)
Control Function									-0.19
									(0.12)
Observations	1074	1074	1092	1092	2166	2166	2166	2166	2166
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Calc#EP=Conc#EP	-	0.98	-	-	1.00	0.58	0.68	0.085	0.91

Do files: `treatment_effects.do, treatment_effects_IV_CF.do`

Matching

Recordemos el problema fundamental de inferencia causal: ¿$\mathbb{E}[Y_{0i} \mid D_i = 1, X_i]$?

Supongamos : *strong ignorability*

CIA : $(Y_i|X) \perp D_i$
Overlap : $0 < e(x) := \mathbb{E}[D_i \mid X_i = x] < 1$ para todo x en el soporte de X

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Sea

$$m(i) = \text{argmin}_{j:D_j \neq D_i} ||X_i - X_j||$$

$$\hat{Y}_i(0) = \begin{cases} Y_i^{obs} & \text{si} \quad D_i = 0 \\ Y_{m(i)}^{obs} & \text{si} \quad D_i = 0 \end{cases} \qquad \hat{Y}_i(1) = \begin{cases} Y_{m(i)}^{obs} & \text{si} \quad D_i = 0 \\ Y_i^{obs} & \text{si} \quad D_i = 0 \end{cases}$$

$$\hat{X}_i(0) = \begin{cases} X_i^{obs} & \text{si} \quad D_i = 0 \\ X_{m(i)}^{obs} & \text{si} \quad D_i = 0 \end{cases} \qquad \hat{X}_i(1) = \begin{cases} X_{m(i)}^{obs} & \text{si} \quad D_i = 0 \\ X_i^{obs} & \text{si} \quad D_i = 0 \end{cases}$$

El estimador de matching está dado por:

$$\hat{\tau} = \frac{1}{N} \sum_i \hat{Y}_i(1) - \hat{Y}_i(0)$$

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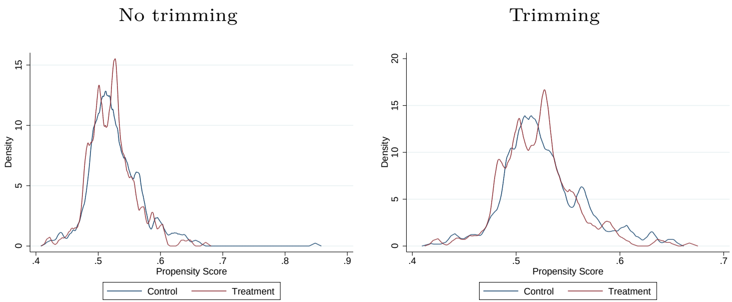
El estimador de matching está dado por:

$$\hat{\tau} = \frac{1}{N} \sum_i \hat{Y}_i(1) - \hat{Y}_i(0)$$

Se puede mejorar el sezgo de este estimador usando regresión lineal para *ajustar el sezgo* asociado con diferencias entre $\hat{X}_i(0)$ y $\hat{X}_i(1)$.

(I) 'Verificar' overlap - Trimming procedure



$$\hat{e}(x) = \frac{\exp \beta' x}{1 + \beta' x}$$

(II) Balance

Table 2: Balance

	Control	Treatment	p-value
Entitlement by law	60234.96	57567.95	0.62
	(3400.38)	(4098.63)	
Public lawyer	0.08	0.09	0.77
	(0.01)	(0.01)	
Woman	0.45	0.45	0.86
	(0.02)	(0.03)	
At will worker	0.07	0.06	0.44
	(0.01)	(0.01)	
Tenure	3.82	3.47	0.29
	(0.25)	(0.22)	
Daily wage	535.31	514.78	0.7
	(32.76)	(40.85)	
Weekly hours	58.5	56.79	0.12
	(0.81)	(0.73)	
Observations	416	377	

(III) ‘Evaluar’ CIA

Table 3: Pseudo-treatment effect

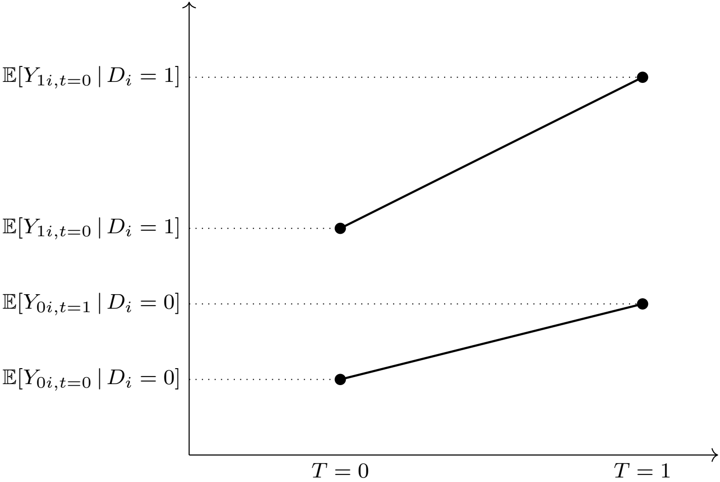
Pseudo treatment effect. Nearest-neighbor matching			
	Phase 1/2		
	Entitlement	Daily wage	Tenure
	(1)	(2)	(3)
ATE	28.3	-2.3	-0.2
	(1162.4)	(11)	(.2)
% ATE	0.05	-0.43	-5.22
Baseline mean	60342.9	536.2	3.8
Obs		377	
Obs HD		415	
Bias adjustment	YES	YES	YES
Matches	[1-3]	[1-3]	[1-3]

(III) Análisis

Table 4: Matching

Treatment effect. Nearest-neighbor matching						
	Phase 1/2					
	Variable matching				PSM	
	(1)	(2)	(3)	(4)	(5)	(6)
ATE	2580	3536**	3242*	3939**	3698*	3995**
	(1939)	(1715)	(1934)	(1725)	(1900)	(1554)
% ATE	34	47	43	52	49	53
Baseline mean	7598					
Obs	377					
Obs HD	415					
Bias adjustment	NO	NO	YES	YES	-	-
Matches	[1-1]	[1-3]	[1-1]	[1-3]	[1-1]	[1-3]

Do files: `settlement_conciliator_matching.do`


$\mathbb{E}[Y_{1i,t=0} \mid D_i = 1]$
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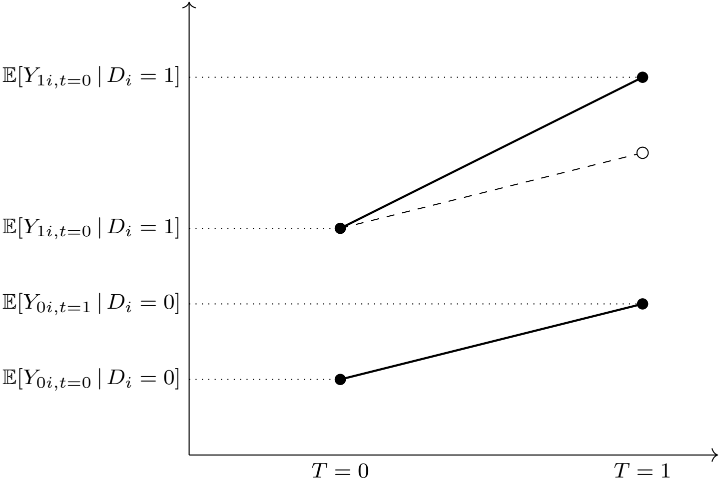
$\mathbb{E}[Y_{0i,t=1} \mid D_i = 0]$
$\mathbb{E}[Y_{0i,t=0} \mid D_i = 0]$
$T = 0$
$T = 1$

DiD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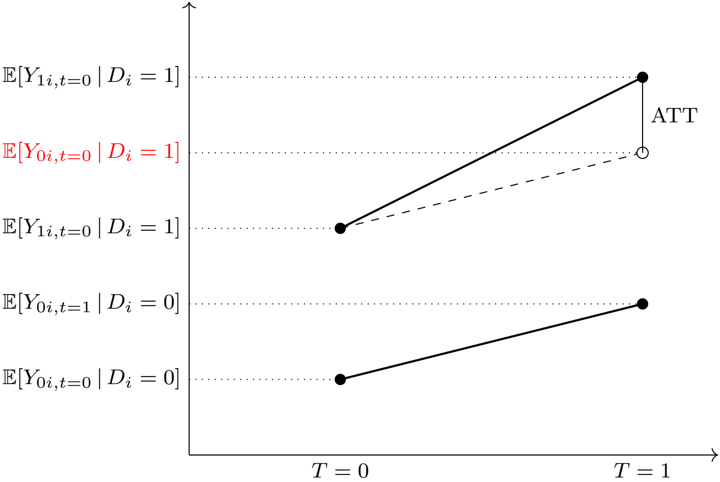
DiD


$\mathbb{E}[Y_{1i,t=0} \mid D_i = 1]$
ATT
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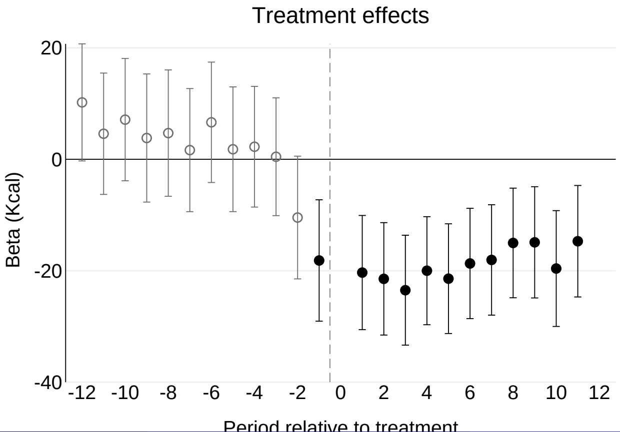
$T = 0$
$T = 1$

Regresión DiD con FE:

$$C_{it}^{k} = \alpha_i + \gamma_t + \sum_{j=-12}^{12} \beta_k T_i \times I(t=j) + \nu_{it}$$

donde $T_i = 1$ si i está en el grupo más expuesto



Synthetic Control Methods (SCM) I

Sean (y^0_{tn}, y^1_{tn}) las observaciones potenciales para la unidad n al tiempo t.

$$y_{tn} = D_{tn} y^1_{tn} + (1 - D_{tn}) y^0_{tn} \,, \qquad D_{tn} = \begin{cases} 1 & \text{if } t \geq T_0, n = 0 \\ 0 & \text{otherwise} \end{cases}$$

El efecto de tratamiento es : $\tau_{tn} \equiv y^1_{tn} - y^0_{tn}$
El supuesto clave en SCM es:

Existen pesos $\beta_n \in [0,1]$ para $n = 1, \ldots, N$ tales que

$$y^0_{t0} = \sum_{n=1}^{N} \beta_n y^0_{tn}$$

para $t = 1 \ldots, T$;y los pesos suman uno: $\sum_{n=1}^{N} \beta_n = 1$.

El estimador en $t = T_0, \ldots, T$ está dado por:

$$\tau_t = y^1_{t0} - \sum_{n=1}^{N} \beta_n y^0_{t0}$$

Synthetic Control Methods (SCM) II

Denotando por $x_t \equiv (y_{t1}, \ldots, y_{tN})^\mathsf{T}$ a el vector de las observaciones para los controles. Podemos considerar el modelo de regresión

$$y_{t0} = \beta^\mathsf{T} x_t + u_{t0} \qquad t = 1, \ldots, T_0 \tag{1}$$

y la estimación por lo tanto está dada por:

$$\begin{aligned} &\min \sum_{t=1}^{T_0} (y_{t0} - \beta^\mathsf{T} x_t)^2 \\ s.t.& \\ &\quad ||\beta||_1 = 1 \\ &\quad \beta_i \geq 0 \quad i = 1, \ldots, n \end{aligned} \tag{2}$$

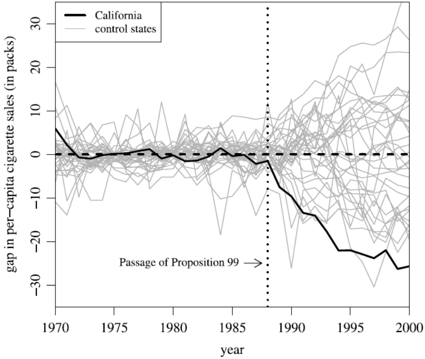
¿Inferencia?

El principal problema con esta metodología es la dificultad para conducir **inferencia**, es decir, hay poco o ningún conocimiento sobre la distribución asintótica del estimador SCM, o su **intervalo de confianza**.

(i) *Enfoques de población finita* : Supuesto de que las unidades de tratamiento se asignan aleatoriamente y usan placebos, pruebas de permutación o alguna variante que explota la estructura de datos del panel, para realizar inferencia, que son llamados

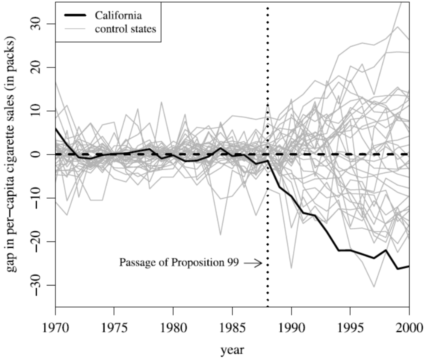
(ii) *Enfoques asintóticos* : Los supuestos clave hacen que el número de individuos o períodos de tiempo tienden a infinito.

¿Inferencia?



California
control states
gap in per−capita cigarette sales (in packs)
30
20
10
0
−10
−20
−30
Passage of Proposition 99
1970
1975
1980
1985
1990
1995
2000
year

¡Inferencia!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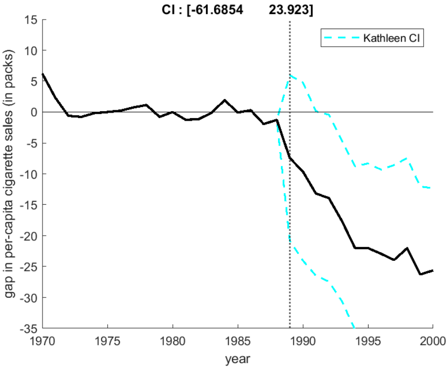
gap in per−capita cigarette sales (in packs)
year


CI : [-61.6854 23.923]
Kathleen CI
gap in per-capita cigarette sales (in packs)
year

Theorem

La región de confianza para el estimador SCM está dada por:

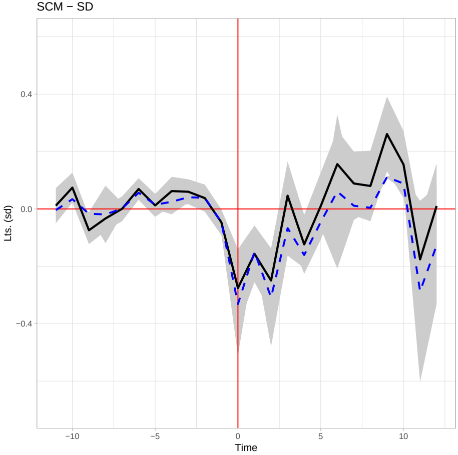
$$B\left(\hat{\tau}_t, \mathsf{r}||x_t|| + \sigma z_{(1-\alpha/2)}\right)$$

donde $\mathsf{r} = \frac{||\nabla R_{T_0}(\hat{\beta})|| + \sqrt{||\nabla R_{T_0}(\hat{\beta})||^2 - 2|\Omega_{\hat{\beta}}|\left(R_{T_0}(\hat{\beta}) - T_0^{-1}\chi_{1-\alpha}\right)}}{|\Omega_{\hat{\beta}}|}$

SCM con datos panel

Explotamos la estructura de panel y las múltiples unidades tratadas.

Explotamos la estructura de panel y las múltiples unidades tratadas.



Rscript: `SCM_synth.R`

Attrition

Manski bounds I

- Ningún supuesto sobre el mecanismo de selección
- La variable dependiente necesita estar acotada
- NA imputados de acuerdo al mínimo y máximo valor posible
- Cotas no informativas :(

Manski bounds II

Sea S_i una dummy identificando a los 'no-attriters'.

$$¿E[Y_{1i} \mid S_i = 0|D_i = 1] \qquad E[Y_{0i} \mid S_i = 0, D_i = 0]?$$

Worst-case scenario : $E[Y_{1i} \mid S_i = 0|D_i = 1] = 0$ y $E[Y_{0i} \mid S_i = 0, D_i = 0] = 1$

$$\begin{aligned} MB^L &= P(S_i = 1 \mid D_i = 1)E(Y_i \mid D_i = 1, S_i = 1) \\ &- [P(S_i = 1 \mid D_i = 0)E(Y_i \mid D_i = 0, S_i = 1) + P(S_i = 0 \mid D_i = 0)] \end{aligned}$$

análogamente:

$$\begin{aligned} MB^U &= P(S_i = 1 \mid D_i = 1)E(Y_i \mid D_i = 1, S_i = 1) + P(S_i = 0 \mid D_i = 1) \\ &- P(S_i = 1 \mid D_i = 0)E(Y_i \mid D_i = 0, S_i = 1) \end{aligned}$$

Lee bounds I

- RAT : $(Y_i, S_i) \perp D_i$
- Monotonicidad : $Pr(S_1 \geq S_0) = 1$
  Asignación de tratamiento sólo afecta *attrition* en una dirección solamente.

El objetivo es encontrar cotas

$$LB^L \leq \mathbb{E}[Y_1 - Y_0 \mid S_0 = 1, S_1 = 1] \leq LB^U$$

Lee bounds II

Theorem

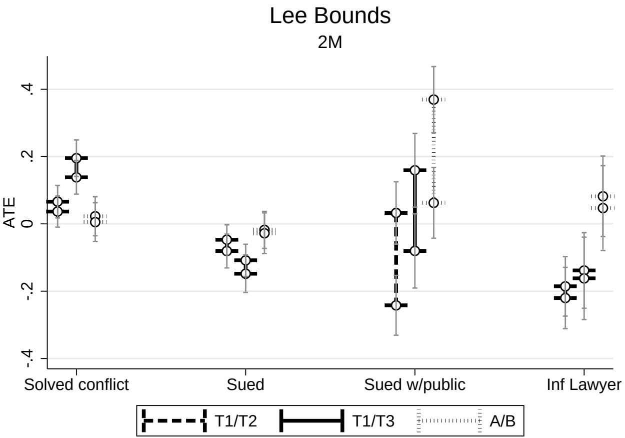
Bajo RAT, monotonicidad y $PR(S=1 \mid D=0) \neq 0$

$$LB^L = \mathbb{E}[Y \mid D=1, S=1, Y \leq F^{-1}(1-p)] - \mathbb{E}[Y \mid D=0, S=1]$$

$$LB^U = \mathbb{E}[Y \mid D=1, S=1, Y \geq F^{-1}(p)] - \mathbb{E}[Y \mid D=0, S=1]$$

donde $p = \frac{Pr(S=1 \mid D=1) - Pr(S=1 \mid D=0)}{Pr(S=1 \mid D=1)}$.

Lee bounds III



Do files: `plot_lee_bounds.do`

Clasificación

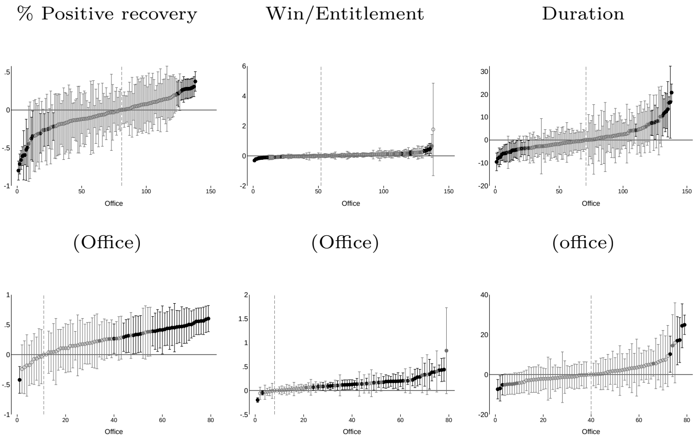
Table 5: Predicciones

	Outcome	Judge ruling prediction		End mode prediction		Payment prediction		Total	
	Lawyer	Lawyer	Calc	Lawyer	Calc	Lawyer	Calc	Lawyer	Calc
1	12.8%	44.4%	27.8%	61.1%	55.6%	19.5%	19.5%	34.5%	34.3%
2	11.2%	62.5%	68.8%	87.5%	62.5%	0%	12.8%	40.3%	48%
3	15.2%	56.3%	62.5%	62.5%	62.5%	22.7%	17.3%	39.2%	47.4%
4	35.2%	45.5%	50%	36.4%	77.3%	15.3%	18.8%	33.1%	48.7%
5	5.6%	33.3%	75%	33.3%	62.5%	9.9%	19.8%	20.5%	52.4%
6	9.6%	60%	70%	70%	65%	0%	18.6%	34.9%	51.2%
7	16%	50%	55.6%	55.6%	72.2%	13.9%	13.9%	33.9%	47.2%
8	13.6%	54.5%	77.3%	86.4%	72.7%	21.4%	21.4%	44%	57.1%

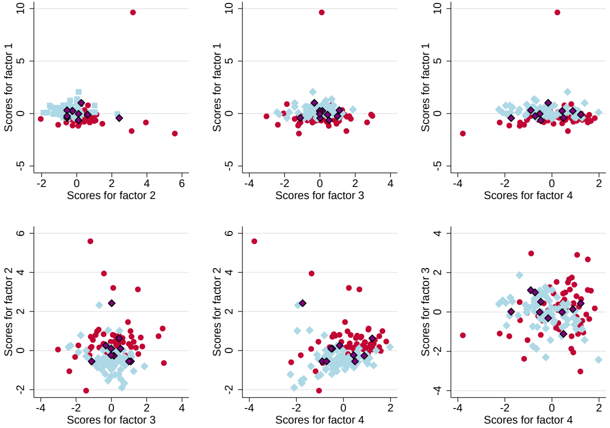
Do files: `lawyer_dataset.do`, `lawyer_dataset_predicc.do`, `cleaning_base_calidad.do`, `calif_abogados_pagos.do`

Heterogeneidad - FE I

Figure 2: Heterogeneous outcome graphs



Do files: `fe_betas_pres.do`, `fe_betas_desp.do`



Do files: `lawyer_dataset_collapsed.do`, `cluster_analysis.do`

Gracias :)

Instalación de OSRM

(1) Install Node.js 8.11.3 LTS (or current)
(2) Extract the file osrm_Release.zip (link from my Dropbox)
(3) Copy the file mexico-latest.osm.pbf in the osrm_Release folder.
(4) Open Node.js command prompt
   1. Change directory to the osrm_Release folder
      `cd ~/osrm_Release`
   2. Extracting the road network
      `osrm-extract mexico-latest.osm.pbf`
      `osrm-contract mexico-latest.osm.pbf`

This previous steps only need to be done once. This sets the road network for Mexico.

Instalación de OSRM I

In order to launch OSRM as a local instance the following steps are needed.

1. Change directory to the osrm_Release folder in Node.js command prompt
   `cd ~/osrm_Release`
2. Set the local OSRM instance
   `osrm-routed --max-table-size=1500 mexico-latest.osrm`
3. In R, run the script:

```r
# PACKAGES
library(tidyverse) # data wrangling
library(stringr)   # work with strings
library(sf)        # geospatial
library(geosphere) # calculate distances
library(haven)     # read/write .dta (Stata)
library(here)      # use relative filepaths
library(osrm)      # calculate road distances
library(assertthat)


# old spatial packages since osrm works with those
library(sp) #spatial objects; used by rgdal


# Read in data set
dataset = read_dta(here::here("folder", "dta.dta"))


# Convert to SpatialPointsDataFrame for use with osrmTable
dataset_spdf <- dataset %>% as('Spatial')
```

```
# Use OSRM's server
options(osrm.server = "http://router.project-osrm.org/")
# NOTE: above uses OSRM's server. If we try one with more than 10,000 queries:

# We get the error:
# OSRM returned an error:
# Error: The public OSRM API does not allow results with a number of durations
# higher than 10000. Ask for fewer durations or use your own server and set
    its
# --max-table-size option.

# Now try it on a local server to avoid the 10,000 query limit:
# First follow the instructions here to install and build the OSRM server:
# https://datawookie.netlify.com/blog/2017/09/building-a-local-osrm-instance/
# or:
# https://github.com/Project-OSRM/osrm-backend/wiki/Running-OSRM

# Once the local server is running:
options(osrm.server = "http://localhost:5000/")
#Compute distances
distances <- osrmTable(src = src, dst = dst)
#Check the function osrmViaroute for pairwise comparisons.
```

./Rscripts/geocode.R

Instalación de OSRM III

```
C:\Users\xps-seira\Dropbox\repos\osrm\osrm-backend>osrm-routed
osrm-routed <base.osrm> [<options>]:

Options:
  -v [ --version ]                    Show version
  -h [ --help ]                       Show this help message
  -l [ --verbosity ] arg (=INFO)      Log verbosity level: NONE, ERROR,
                                      WARNING, INFO, DEBUG
  --trial [=arg(=1)]                  Quit after initialization

Configuration:
  -i [ --ip ] arg (=0.0.0.0)          IP address
  -p [ --port ] arg (=5000)           TCP/IP port
  -t [ --threads ] arg (=4)           Number of threads to use
  -s [ --shared-memory ] [=arg(=1)] (=0)
                                      Load data from shared memory
  -a [ --algorithm ] arg (=CH)        Algorithm to use for the data. Can be
                                      CH, CoreCH, MLD.
  --max-viaroute-size arg (=500)      Max. locations supported in viaroute
                                      query
  --max-trip-size arg (=100)          Max. locations supported in trip query
  --max-table-size arg (=100)         Max. locations supported in distance
                                      table query
  --max-matching-size arg (=100)      Max. locations supported in map
                                      matching query
  --max-nearest-size arg (=100)       Max. results supported in nearest query
  --max-alternatives arg (=3)         Max. number of alternatives supported
                                      in the MLD route query
  --max-matching-radius arg (=5)      Max. radius size supported in map
                                      matching query
```

De regreso a los instrumentos.

Definición de grupo expuesto

Definir un grupo de tratamiento / control puro. Lo haremos eligiendo una partición óptima de la distribución total del gasto sujeto a impuestos, ya que es probable que los grandes gastadores sean más sensibles a un cambio de precio en SD, por lo que los definiremos como el grupo de tratamiento.

$$
\begin{aligned}
\min_{H,L} \quad & \sum_{t=-12}^{-2} |\beta_t| \\
\text{s.t} \quad & \\
& (\beta_t)_{-12\leq t\leq 12} = \operatorname{argmin} \left\{ \left(y_{it} - \sum_{k=-12}^{12} \alpha_k \mathbb{1}(t=k) - \right.\right. \\
& \qquad \left.\left. \sum_{k=-12}^{12} \beta_k \mathbb{1}(i=T, k=t) + \gamma \mathbb{1}(i=T) - \lambda_i \right)^2 \right\} \\
& T = \mathbb{1}(x_i \geq H) \\
& C = \mathbb{1}(x_i \leq L) \\
& \min(x_i) \leq L \leq H \leq \max(x_i)
\end{aligned}
$$

De regreso a DiD.