Senere tilbagetrækning: Effekter på sundhed og sundhedsforbrug

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Motivation

- Stigende levealdre og lav arbejdsmarkedsdeltagelse blandt ældre → Pres på de offentlige finanser
- Pensionsreformer for at øge ældres beskæftigelse:
  1. Reducere pensionsbeløb
  2. **Hæve pensionsalder**
- Bekymring: Er der negative (sundheds)effekter af pensionsreformer?
  - Centralt politisk spørgsmål: Hvordan kan vi designe pensionsreformer, som øger ældres arbejdsudbud og minimerer ugunstige sundhedseffekter?
- **Vi undersøger:** Hvis efterlønsalderen hæves, hvad er effekten på sundhed og sundhedsforbrug og hvorfor?

Bidrag og tidligere litteratur

Literatur om sundhedskonsekvenser og øget pensionsalder:

- $-$ Negativ effekt: Grip et al. (2012), Shai (2018), Carrino et al. (2020)
- $+$ Positiv effekt: Bertoni et al. (2018), Ci (2022)
- $\sim$ Ingen effekt: Hernaes et al. (2013), Hagen (2018), Bozio et al. (2021)
- Vores resultater: $\sim$ lægebesøg, $\sim$ Charlson's Comorbidity Index (CCI), $\sim$ smertestillende, $\sim$ kardiovaskulær medicin, $\uparrow$ antidepressiver

Litteratur om arbejdsudbud og øget pensionsalder:

- Beskæftigelse $\uparrow$: Mastrobuoni (2009), Manoli and Weber (2016)
- Andre offentlige overførsler $\uparrow$: Duggan et al. (2007), Vestad (2013), Staubli and Zweimüller (2013)
- Vores resultater: $\uparrow$ Beskæftigelse, $\uparrow$ andre overførsler

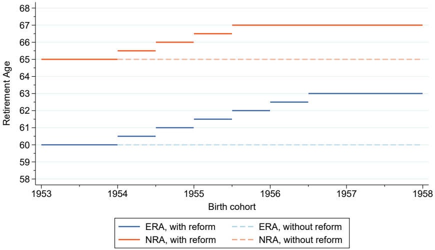
Spillovers: Potentiel vigtig afbødende kanal

2011: Tilbagetrækningsreformen

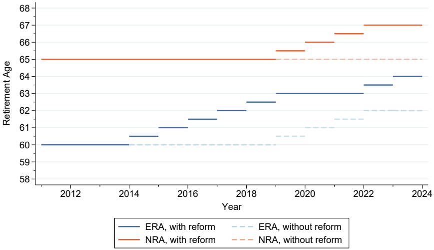
- Vedtaget i Folketinget den 13. maj 2011
- Efterlønsalderen hævet med et halvt år årligt fra 2014 til 2019
  - Efterløn = frivillig tilbagetrækningsordning, der giver mulighed for tidlig tilbagetrækning
  - Efterlønsalder: 60 år i 2013 ⇒ 63 år i 2019
- Betingelser for efterløn:
  - i Medlem af en dansk a-kasse
  - ii Betalt efterlønsbidrag i sammenlagt 30 år
  - iii Have nået efterlønsalder, men ikke have nået folkepensionsalder

Tilbagetrækningsreformen

(a) Pensionsalder efter **kohorte**



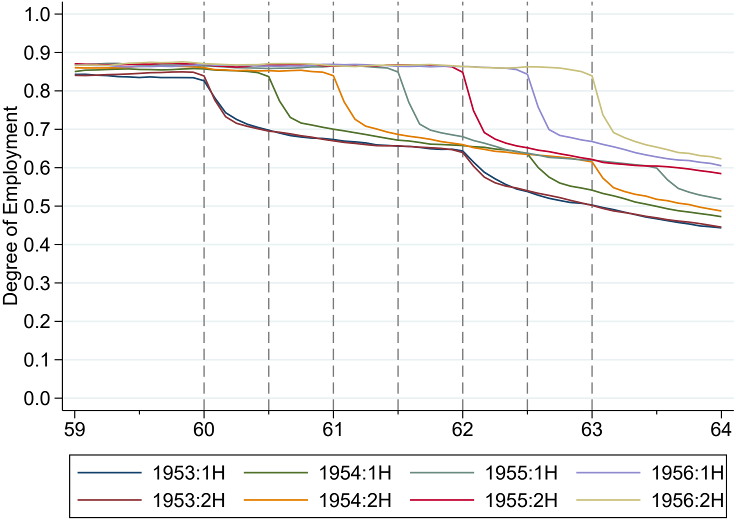
(b) Pensionsalder efter **tid**



ERA: Early Retirement Age → efterlønsalder

NRA: National Retirement Age → folkepensionsalder

Tilbagetrækningsreformen



Data: Dansk registerdata

- Sygesikringsregistret (*SSSY*): Besøg ved praktiserende læge
- Lægemiddeldatabasen (*LMDB*): Brug af smertestillende, antidepressiver, medicin for kardiovaskulære sygdomme (CVD)
  - ATC-koder for Defined Daily Doses (DDDs)
- Landspatientregisteret (*LPR*): Charlson's Comorbidity Index (CCI)
- *IND*, *IDA*, *DREAM*, *BEF*: Beskæftigelse, offentlige overførsler og andre karakteristika

Sample: Vi ekskluderer individer som...

1. Ikke har betalt efterlønsbidrag ved alder 55 år
2. Ikke var i beskæftigelse ved alder 55 år
3. Ikke er af "dansk" oprindelse

Empirisk strategi (I/II)

- Fokus på diskontinuitet i efterlønsalderen omkring 1. juli 1954
- **RD design**: *local randomization* framework.
  - Running variable $= X_i$ (fødselsdato), cutoff $= c$ (1. juli 1954).

Local Randomization Assumption

Antag $\exists \mathcal{W} = [c - w, c + w]$ omkring c hvor:

1. $F_{X_i | X_i \in \mathcal{W}(x)} = F(x)$
2. $Y_i(X_i) = Y_i(\mathbb{1}[X_i \geq c])$

$$\Rightarrow Y_{ia} = \beta_0 + \beta_1 \cdot \mathbb{1}[X_i \geq c] + \varepsilon_i, \tag{1}$$

Y_{ia} (sundhedsrelateret) outcome for individ i ved alder a, β_0 konstant, $\mathbb{1}[X_i \geq c]$ indikator lig 1 hvis individid er født 1. juli 1954 eller efter, ε_i idiosynkratisk fejlterm. $a = 60\frac{1}{2}$-61 i hovedspecifikation.

Empirisk strategi (II/II)

$$Y_{ia} = \beta_0 + \beta_1 \cdot \mathbb{1}\left[X_i \geq c\right] + \varepsilon_i, \tag{1}$$

Y_{ia} (sundhedsrelateret) outcome for individ i ved alder a, β_0 konstant, $\mathbb{1}\left[X_i \geq c\right]$ indikator lig 1 hvis individid er født 1. juli 1954 eller efter, ε_i idiosynkratisk fejlterm. $a = 60\frac{1}{2}$-61 i hovedspecifikation.

Bandwidth ("vinduebredde"), w:

- Vi vælger $w = 60$ dage ved brug af en data-dreven metode (Cattaneo et al., 2015, 2023)

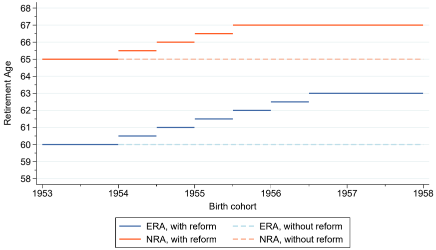
Detaljer

Implikationer:

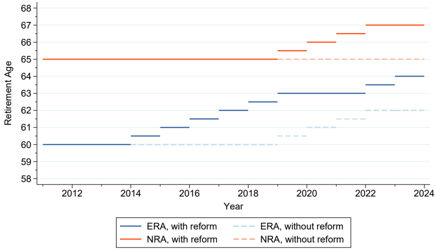
- Vi tillader *alders*effekter på sundhed og sundhedsforbrug
- Antager at *tids*effekter er ubetydelige i $\mathcal{W}$
- Vi estimerer intent-to-treat (ITT)

Empirisk strategi (II/II)

(a) Pensionsalder efter **kohorte**



(b) Pensionsalder efter **tid**



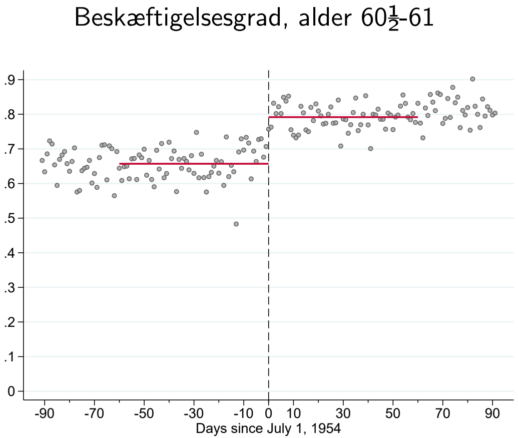
ERA: Early Retirement Age → efterlønsalder

NRA: National Retirement Age → folkepensionsalder

Effekter på arbejdsmarkedsdeltagelse Tabel

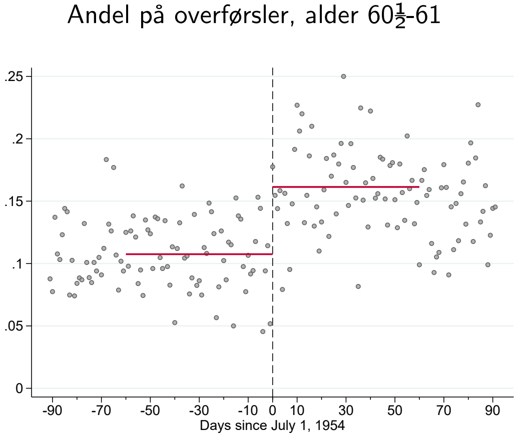
a. Beskæftigelse
b. Andre overførsler
    i Ordinære offentlige overførsler
    ii Sygedagpenge

Effekt af stigning i efterlønsalder på beskæftigelse



$\beta_0 = 0.657^{***}$, $\mathbb{1}[X_i \geq c] = 0.135^{***}$. Procentvis ændring $= 20.5$

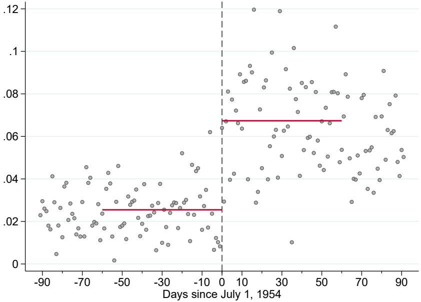
Effekt af stigning i efterlønsalder på andre overførsler



$\beta_0 = 0.107^{***}$, $\mathbb{1}\left[X_i \geq c\right] = 0.0539^{***}$. Procentvis ændring = 50.1

Effekt af stigning i efterlønsalder på:

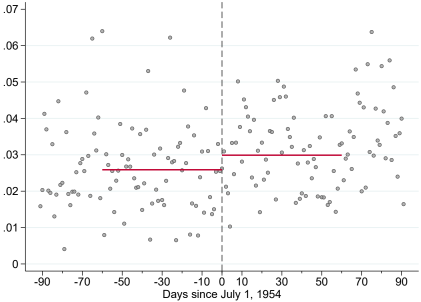
(a) Andel på ordinære overførsler, alder $60\frac{1}{2}$-61



$\beta_0 = 0.0255^{***}$, $\mathbb{1}\left[X_i \geq c\right] = 0.0419^{***}$.

Procentvis ændring = 164.45

(b) Andel på sygedagpenge, alder $60\frac{1}{2}$-61



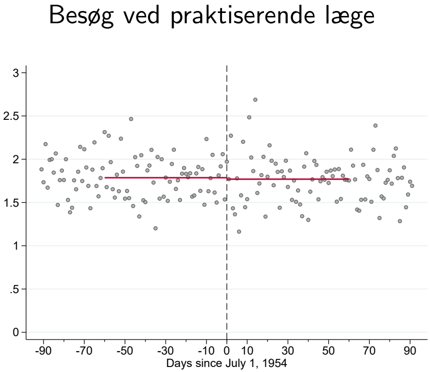
$\beta_0 = 0.0259^{***}$, $\mathbb{1}\left[X_i \geq c\right] = 0.004^{*}$.

Procentvis ændring = 15.46

Effekter på sundhed og sundhedsforbrug Tabel

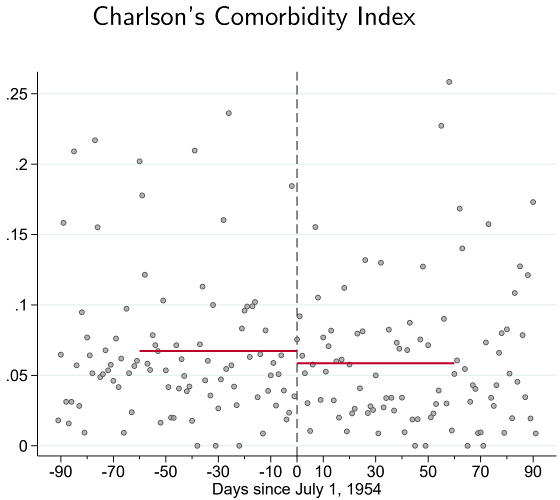
a. Besøg ved praktiserende læge
b. CCI
c. Smertestillende
    i Brug (0/1)
    ii DDDs (defined daily doses)
d. Antidepressiver
    i Brug (0/1)
    ii DDDs
e. CVD-medicin
    i Brug (0/1)
    ii DDDs

Effekt af stigning i efterlønsalder på besøg ved praktiserende læge



$\beta_0 = 1.786^{***}$, $\mathbb{1}\left[X_i \geq c\right] = -0.0168$. Procentvis ændring $= -0.94$

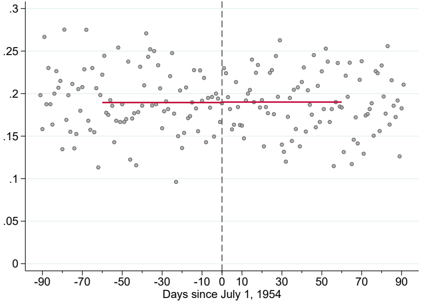
Effekt af stigning i efterlønsalder på CCI



$\beta_0 = 1.786^{***}$, $\mathbb{1}\left[X_i \geq c\right] = -0.00873$. Procentvis ændring $= -12.97$

Effekt af stigning i efterlønsalder på smertestillende

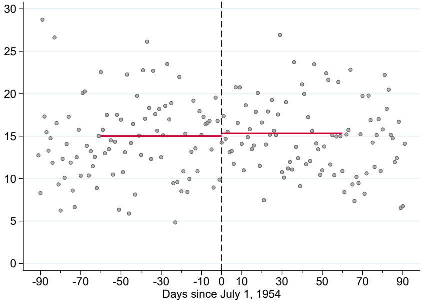
(a) Brug



$\beta_0 = 0.189^{***}$, $\mathbb{1}[X_i \geq c] = 0.0006$.

Procentvis ændring = 0.29

(b) DDDs

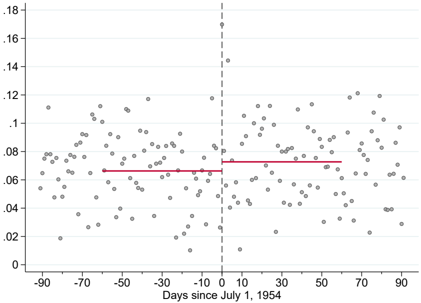


$\beta_0 = 15.02^{***}$, $\mathbb{1}[X_i \geq c] = 0.322$.

Procentvis ændring = 2.14

Effekt af stigning i efterlønsalder på antidepressiver

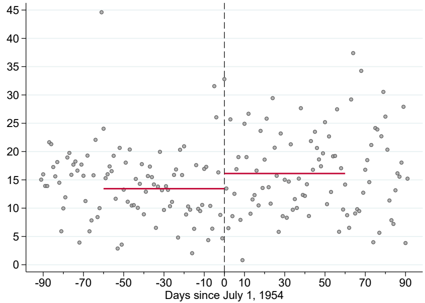
(a) Brug



$\beta_0 = 0.0663^{***}$, $\mathbb{1}\left[X_i \geq c\right] = 0.00642$.

Procentvis ændring = 9.68

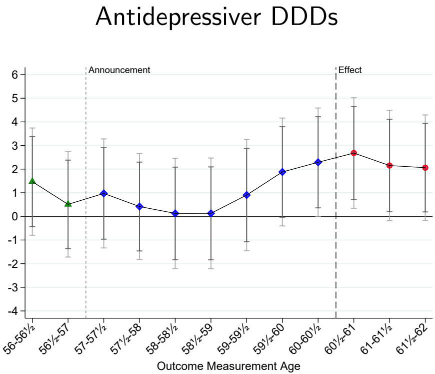
(b) DDDs



$\beta_0 = 13.44^{***}$, $\mathbb{1}\left[X_i \geq c\right] = 2.681^{**}$.

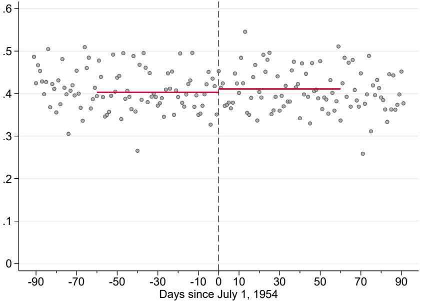
Procentvis ændring = 19.95

Effekt af stigning i efterlønsalder



Effekt af stigning i efterlønsalder på CVD-medicin

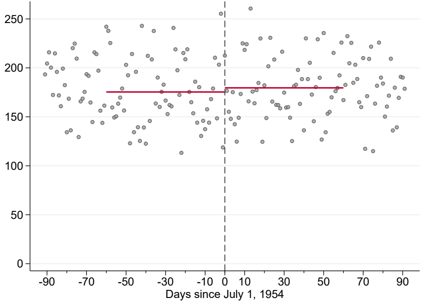
(a) Brug



$\beta_0 = 0.403^{***}$, $\mathbb{1}\left[X_i \geq c\right] = 0.0079$.

Procentvis ændring = 1.95

(b) DDDs



$\beta_0 = 175.4^{***}$, $\mathbb{1}\left[X_i \geq c\right] = 4.215$.

Procentvis ændring = 2.4

Alternative specifikationer og robusthedstjek

1. Poole de berørte kohorter Detaljer
2. Regression-Discontinuity Difference-in-Differences (RD-DD) Detaljer
3. Bandwidth choice Detaljer
4. Donut hole Detaljer
5. Måle outcome ved forskellige aldre Detaljer
6. The Continuity Framework

Karakterisering af "compliers" Detaljer

- Brug $\mathbb{1}[X_i \geq c]$ som instrument for beskæftigelse, $D_i(\mathbb{1}[X_i \geq c])$

Antagelser: Karakterisering af compliers

For treatment $= D_i$, instrument $= \mathbb{1}[X_i \geq c]$ og kovariate $= \mathcal{X}_i$, antag (Marbach and Hangartner, 2020):

1. Relevancy: $D_i(1) \geq D_i(0)$
2. Independence: $D_i(1), D_i(0), \mathcal{X}_i \perp \mathbb{1}[X_i \geq c]$

Compliers:

- En anelse: Færre mænd, lavere uddannelse, mere gift. *Meget*: Lavere disponibel indkomst og nettoformue

$\Rightarrow$ Økonomisk begrænset?

Never-takers:

- $\sim$ disponibel indkomst og nettoformue ligesom den samlede population. *Meget værre* sundhedsoutcomes

$\Rightarrow$ Hvad hvis vi implementere mere "strikse" pensionsreformer ...?

Estimere Marginal Treatment Effects (I/III)

Vi estimerer MTEs ved brug af Local Instrumental Variable (LIV) approach (Björklund and Moffitt, 1987, Heckman and Vytlacil, 2005, 2007)

1. Tillader selektion på observerbare og uobserverbare
2. Tester formelt observerbar og uobserverbar heterogenitet
3. Identifikation af treatment-parametre: ATE, ATT, ATUT, MPRTE

Generalized Roy model for potentielle outcomes, Y_0, Y_1:

$$Y_j = \mu_j(\mathcal{X}) + U_j, \qquad \text{for } j = 0, 1 \tag{2}$$

$$Y = DY_1 + (1 - D)\, Y_0, \tag{3}$$

$$D = \mathbb{1}\left[\mu_D(Z, \mathcal{X}) > V\right] \Rightarrow \mathbb{1}\left[P(Z, \mathcal{X}) > U_D\right]. \tag{4}$$

Antagelser: MTEs

1. Conditional independence: $(U_0, U_1, V) \perp Z | \mathcal{X}$
2. Separability: $\mathbb{E}\left(U_j | V, \mathcal{X}, Z\right) = \mathbb{E}\left(U_j | V\right)$

Estimere Marginal Treatment Effects (II/III)

Antag $\mu_j(\mathcal{X}) = \mathcal{X}\beta_j$ og $\mu_D(Z) = \gamma Z$:

Conditional Outcome

$$\mathbb{E}\left(Y|\mathcal{X}=x, P(Z,\mathcal{X})=p\right) = x\beta_0 + x\left(\beta_0 - \beta_1\right)p + K(p), \tag{5}$$

hvor $K(p) = p\mathbb{E}\left(U_1 - U_0 | U_D \leq p\right)$.

MTE

$$MTE(x,u) = \left(\beta_1 - \beta_0\right)x + k(u), \tag{6}$$

hvor $k(u) = \frac{\partial K(p)}{\partial p}|_{p=u}$.

Estimere Marginal Treatment Effects (III/III)

Estimation approach (følger Andresen (2018)):

1. Estimer $P(Z, \mathcal{X})$ Details
   - Logit link function.

   Z: $\mathbb{1}[X_i \geq c]\left[1 + \text{DispInc} + \text{DispInc}^2 + \text{NetWealth} + \text{NetWealth}^2\right]$

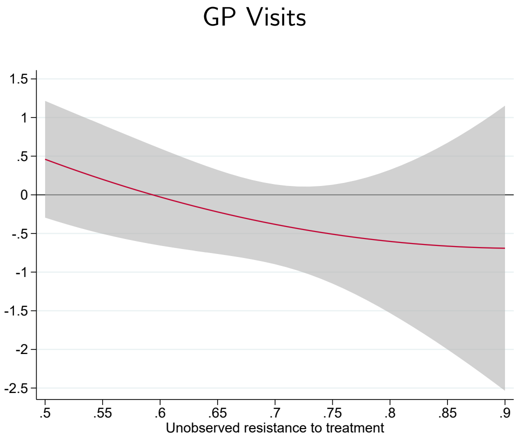
   $\mathcal{X}$: $\text{DispInc} + \text{DispInc}^2 + \text{NetWealth} + \text{NetWealth}^2$, gender, marital, and education dummies
   - Trim på 1%
2. Vælg $K(p)$ som 3. grads polynomium
3. Estimer Equation (5) for at få MTE i Equation (6)
4. Afdække treatment-parametre ved vægtede gennemsnit af MTE

Marginale effekter på sundhed og sundhedsforbrug

Tabel

a. Besøg ved praktiserende læge
b. CCI
c. Smertestillede
    i Brug (0/1)
    ii DDDs (defined daily doses)
d. Antidepressiver
    i Brug (0/1)
    ii DDDs
e. CVD-medicin
    i Brug (0/1)
    ii DDDs

Estimated MTEs: Besøg ved praktiserende læge

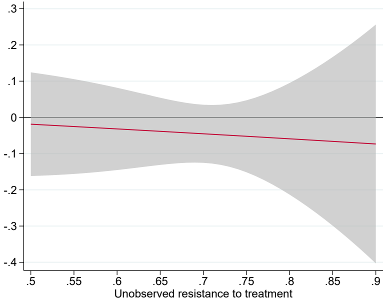


P-value, $k(p)$: 0.315 $\quad ATT = -0.146, ATUT = -0.501$

P-value, $\beta_1 - \beta_0$: 0.05 $\quad MPRTE = -0.0126$

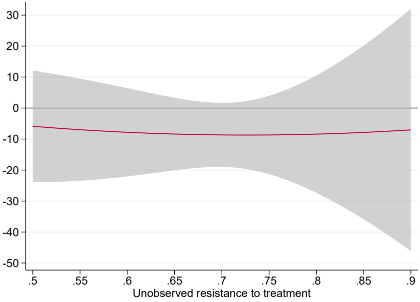
Estimeret MTEs: Smertestillende

(a) Brug



P-value, $k(p)$: 0.762 $ATT = -0.0423, ATUT = -0.0454$
P-value, $\beta_1 - \beta_0$: 0.916 $MPRTE = -0.00141$

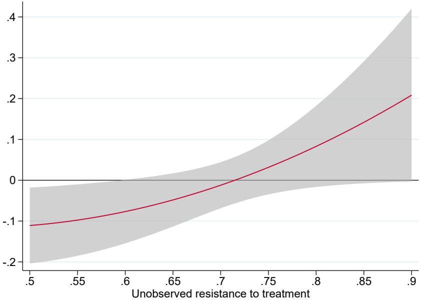
(b) DDDs



P-value, $k(p)$: 0.610 $ATT = -8.263, ATUT = -6.749$
P-value, $\beta_1 - \beta_0$: 0.756 $MPRTE = -0.180$

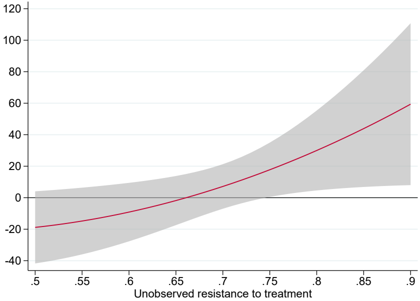
Estimeret MTEs: Antidepressiver

(a) Brug



P-value, $k(p)$: 0.005 $ATT = -0.0410, ATUT = 0.0916^{*}$
P-value, $\beta_1 - \beta_0$: 0.074 $MPRTE = 0.00253$

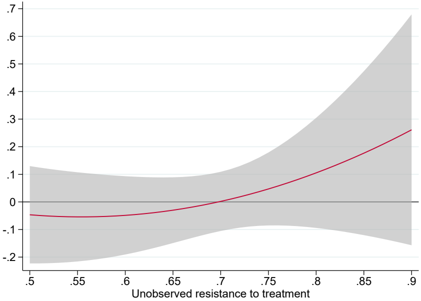
(b) DDDs



P-value, $k(p)$: 0.006 $ATT = -0.589, ATUT = 32.17^{**}$
P-value, $\beta_1 - \beta_0$: 0.062 $MPRTE = 0.0831^{*}$

Estimeret MTEs: CVD-medicin

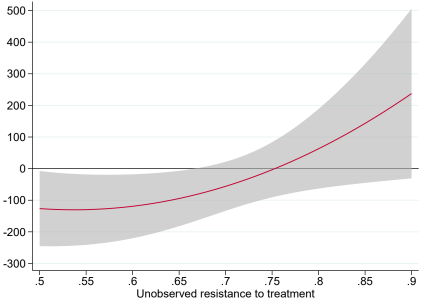
(a) Brug



P-value, $k(p)$: 0.552 $ATT = -0.00485, ATUT = 0.103$

P-value, $\beta_1 - \beta_0$: 0.405 $MPRTE = 0.00337$

(b) DDDs



P-value, $k(p)$: 0.646 $ATT = -72.14^{**}, ATUT = 69.39$

P-value, $\beta_1 - \beta_0$: 0.109 $MPRTE = 2.456$

Konklusion

- Stigende levealdre og lav arbejdsmarkedsdeltagelse blandt ældre → Pres på de offentlige finanser

⇒ Pensionsreformer

- **Centralt politisk spørgsmål:** Maximere arbejdsudbud, minimere ugunstige sundhedseffekter

- **Resultater:**
  1. Begrænsede effekter på sundhed og sundhedsforbrug af 2011 tilbagetrækningsreform
  2. Spillovers til andre offentlige overførsler
  3. (Potentielt) vigtig selektionsmekanisme
     - ⋆ Større sundhedskonsekvenser af mere "strikte" reformer

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References V

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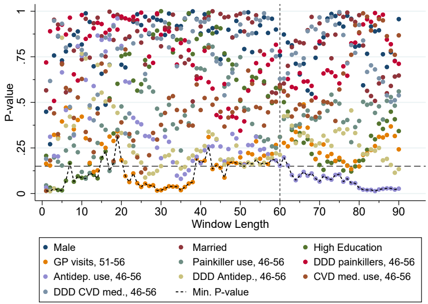
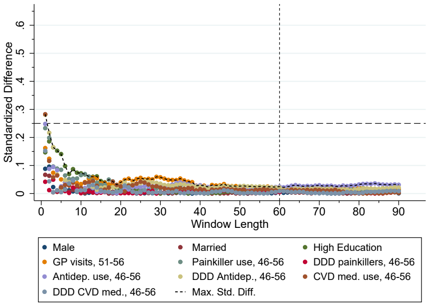
Data-driven Bandwidth Selection

(a) Difference-in-means Test



(b) Absolute Standardized Difference



Following Cattaneo et al. (2015, 2023)

Return

Results: Effect on Labor Force Participation

	(1) Employment	(2) Other Transfers	(3) Ordinary Transfers	(4) Sickness Benefits
$1[X_i \geq c]$	0.135***	0.0539***	0.0419***	0.00400*
	(0.00764)	(0.00593)	(0.00320)	(0.00224)
β_0	0.657***	0.107***	0.0255***	0.0259***
	(0.00570)	(0.00372)	(0.00158)	(0.00150)
Pct. Change	20.50	50.12	164.45	15.46
Bandwidth	60	60	60	60
N	13,298	13,298	13,298	13,298

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Robust standard errors in parentheses

Return

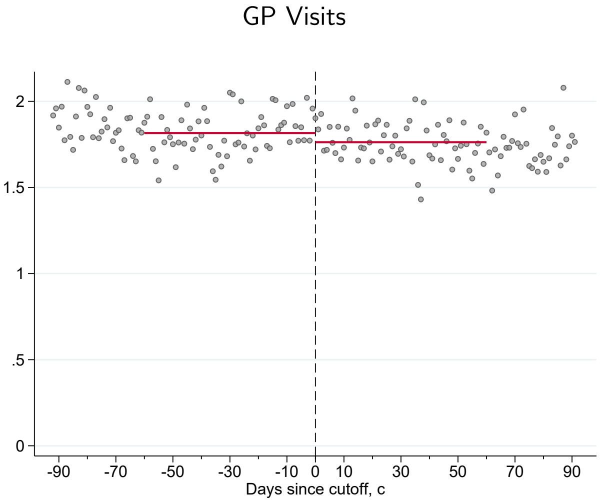
Results: Effect on Health Outcomes

	(1) GP visits	(2) Painkillers Usage	(3) Painkillers DDDs	(4) Antidep. Usage	(5) Antidep. DDDs	(6) CVD Med. Usage	(7) CVD Med. DDDs
$1[X_i \geq c]$	-0.0168	0.000550	0.322	0.00642	2.681**	0.00786	4.215
	(0.0421)	(0.00687)	(0.888)	(0.00446)	(1.195)	(0.00861)	(5.829)
β_0	1.786***	0.189***	15.02***	0.0663***	13.44***	0.403***	175.4***
	(0.0294)	(0.00475)	(0.595)	(0.00301)	(0.761)	(0.00594)	(4.105)
Pct. Change	-0.94	0.29	2.14	9.68	19.95	1.95	2.40
Bandwidth	60	60	60	60	60	60	60
N	13,048	13,048	13,048	13,048	13,048	13,048	13,048

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Robust standard errors in parentheses

Return

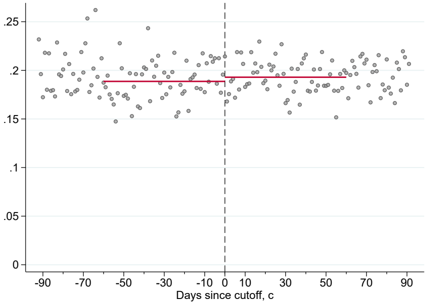
Pooling the Cohorts: GP Visits (1/4)



$\beta_0 = 1.816^{***}$, $\mathbb{1}[X_i \geq c] = -0.0530$. Pct. change $= -2.92$

Pooling the Cohorts: Painkillers (2/4)

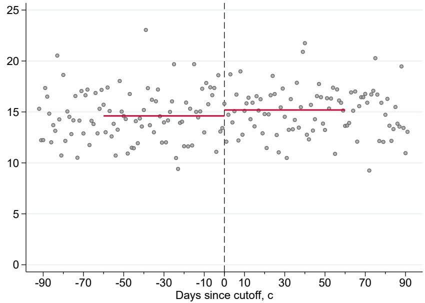
(a) Usage



$\beta_0 = 0.189^{***}$, $\mathbb{1}[X_i \geq c] = 0.00432$.

Pct. change = 2.29

(b) DDDs

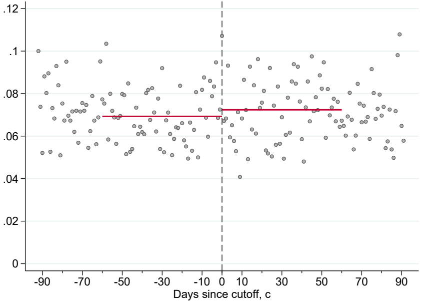


$\beta_0 = 14.61^{***}$, $\mathbb{1}[X_i \geq c] = 0.581$.

Pct. change = 3.98

Pooling the Cohorts: Antidepressants (3/4)

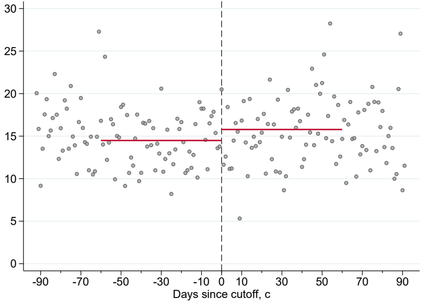
(a) Usage



$\beta_0 = 0.0693^{***}$, $\mathbb{1}\left[X_i \geq c\right] = 0.00309$.

Pct. change = 4.46

(b) DDDs

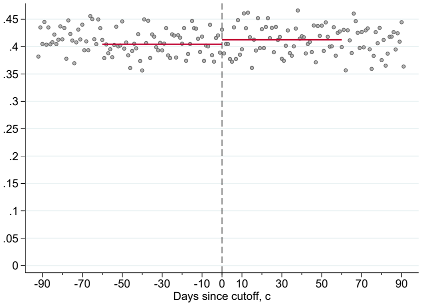


$\beta_0 = 14.49^{***}$, $\mathbb{1}\left[X_i \geq c\right] = 1.292^{**}$.

Pct. change = 8.92

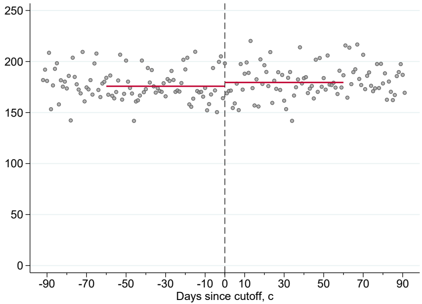
Pooling the Cohorts: CVD Medicine (4/4)

(a) Usage



$\beta_0 = 0.404^{***}$, $\mathbb{1}\left[X_i \geq c\right] = 0.00830.$
Pct. change = 2.05

(b) DDDs



$\beta_0 = 175.8^{***}$, $\mathbb{1}\left[X_i \geq c\right] = 3.690.$
Pct. change = 2.1

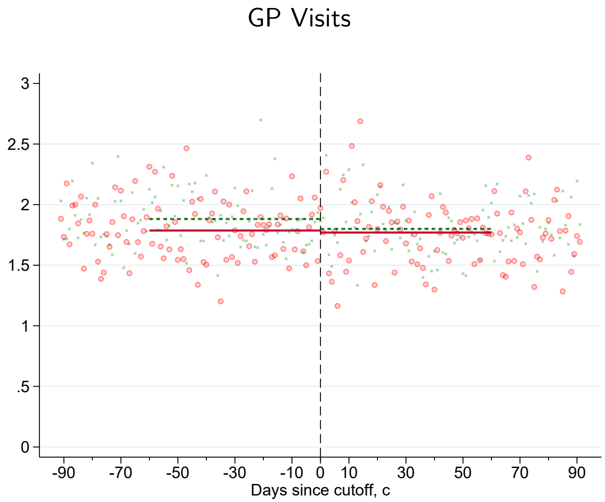
Return

Robustness: RD-DD

	(1) GP visits	(2) Painkillers Usage	(3) Painkillers DDDs	(4) Antidep. Usage	(5) Antidep. DDDs	(6) CVD Med. Usage	(7) CVD Med. DDDs
$1[t = \tau]$	-0.0951**	0.0219***	1.603*	-0.00286	-1.048	-0.0150*	-1.273
	(0.0430)	(0.00650)	(0.848)	(0.00427)	(1.110)	(0.00835)	(5.642)
$1[X_i \geq c]$	-0.0816*	0.0122*	0.575	0.00290	0.695	0.000466	-0.150
	(0.0429)	(0.00646)	(0.862)	(0.00437)	(1.176)	(0.00841)	(5.467)
$1[X_i \geq c] \times 1[t = \tau]$	0.0648	-0.0117	-0.253	0.00351	1.986	0.00740	4.365
	(0.0601)	(0.00943)	(1.238)	(0.00624)	(1.676)	(0.0120)	(7.992)
β_0	1.882***	0.168***	13.41***	0.0692***	14.49***	0.418***	176.7***
	(0.0314)	(0.00445)	(0.605)	(0.00302)	(0.808)	(0.00587)	(3.870)
Pct. Additional Change	3.63	-6.15	-1.68	5.30	14.78	1.84	2.49
Bandwidth	60.00	60.00	60.00	60.00	60.00	60.00	60.00
N	26,822	26,822	26,822	26,822	26,822	26,822	26,822

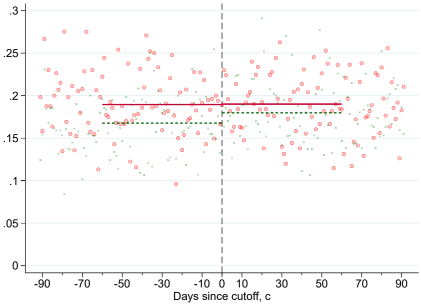
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors in parentheses.

RD-DD: GP Visits (1/4)

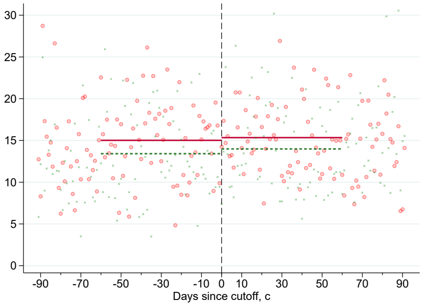


RD-DD: Painkillers (2/4)

(a) Usage

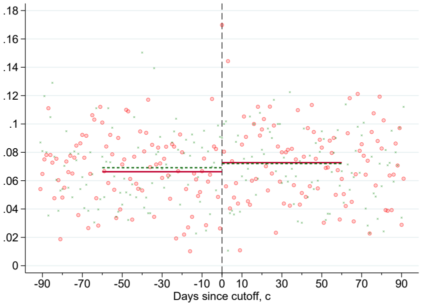


(b) DDDs

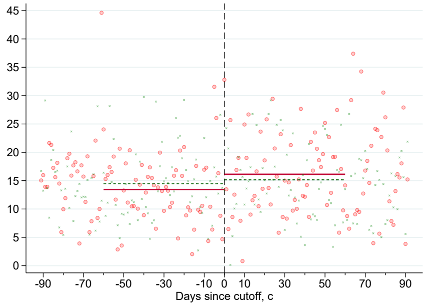


RD-DD: Antidepressants (3/4)

(a) Usage

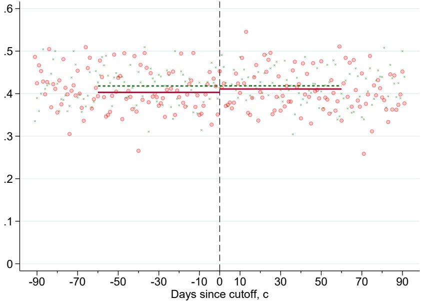


(b) DDDs

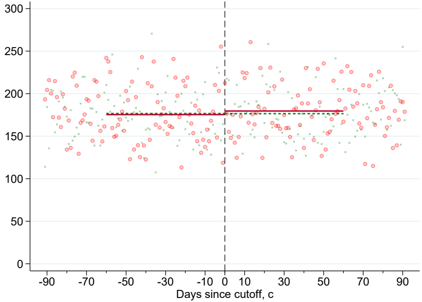


RD-DD: CVD Medicine (4/4)

(a) Usage

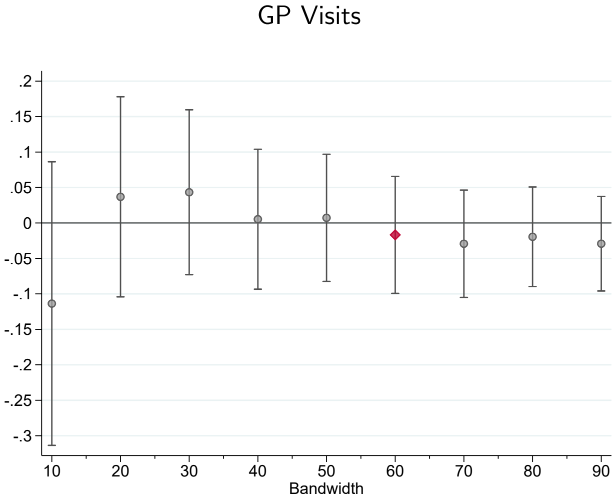


(b) DDDs



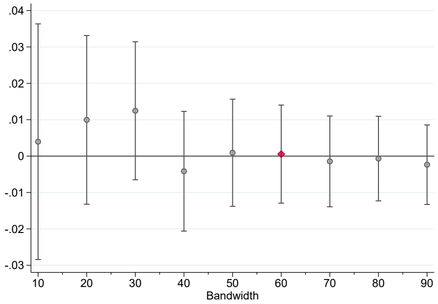
Return

Bandwidth Choice: GP Visits (1/4)

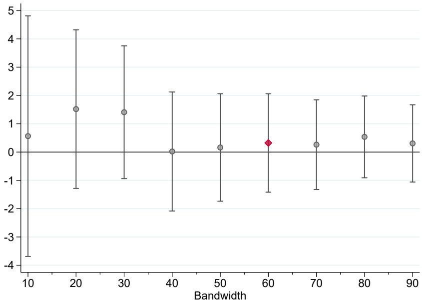


Bandwidth Choice: Painkillers (2/4)

(a) Usage

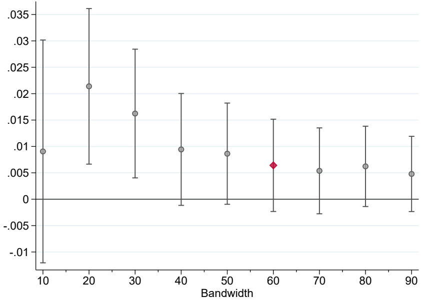


(b) DDDs

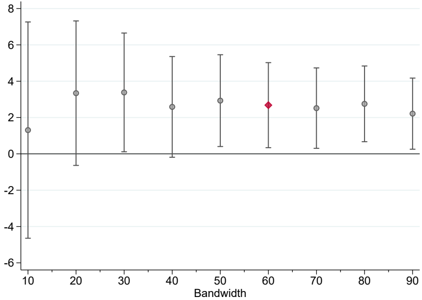


Bandwidth Choice: Antidepressants (3/4)

(a) Usage

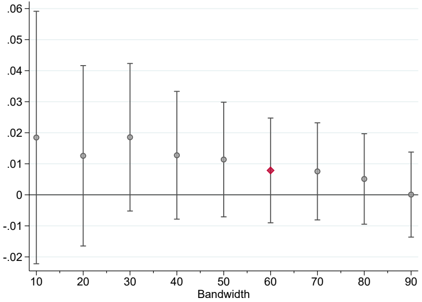


(b) DDDs

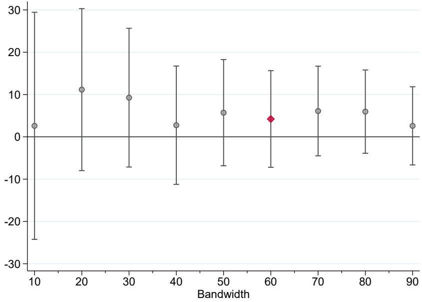


Bandwidth Choice: CVD Medicine (4/4)

(a) Usage

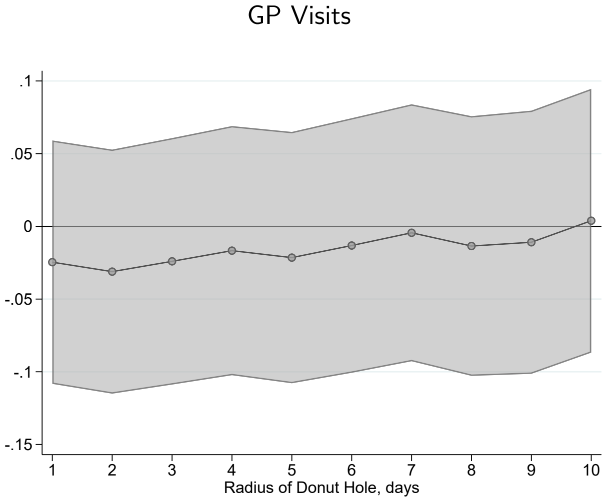


(b) DDDs



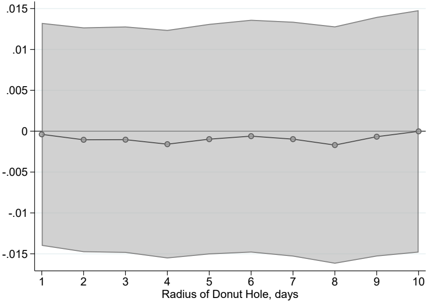
Return

Donut Hole: GP Visits (1/4)

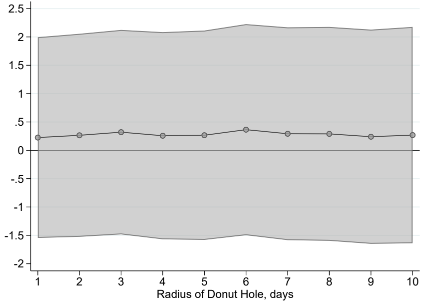


Bandwidth Choice: Painkillers (2/4)

(a) Usage

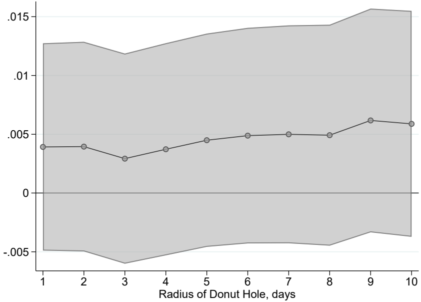


(b) DDDs

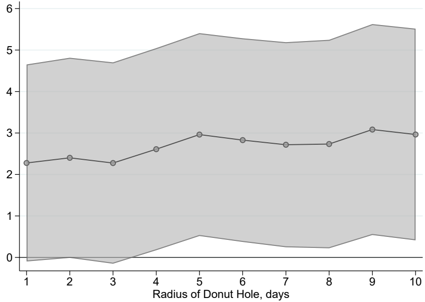


Bandwidth Choice: Antidepressants (3/4)

(a) Usage

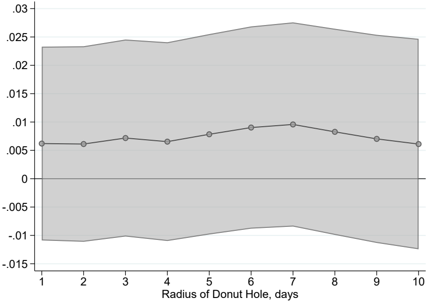


(b) DDDs

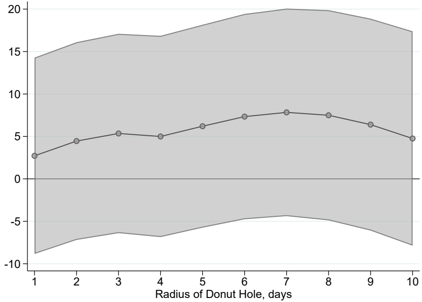


Bandwidth Choice: CVD Medicine (4/4)

(a) Usage

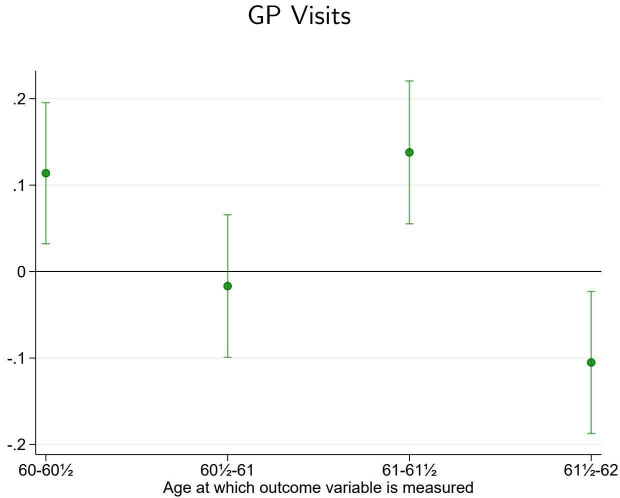


(b) DDDs



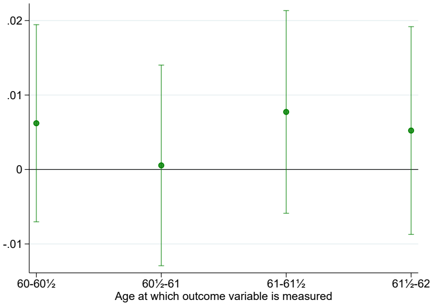
Return

Outcome Measurement Age: GP Visits (1/4)

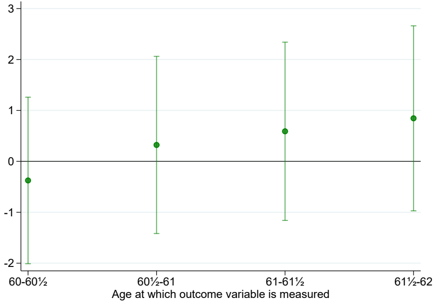


Outcome Measurement Age: Painkillers (2/4)

(a) Usage

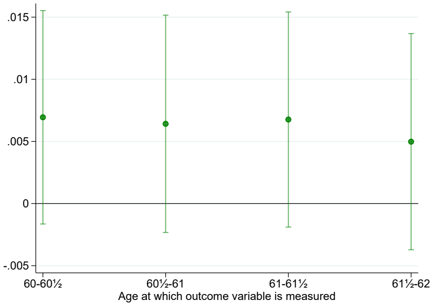


(b) DDDs

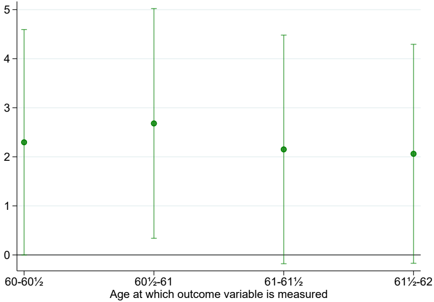


Outcome Measurement Age: Antidepressants (3/4)

(a) Usage

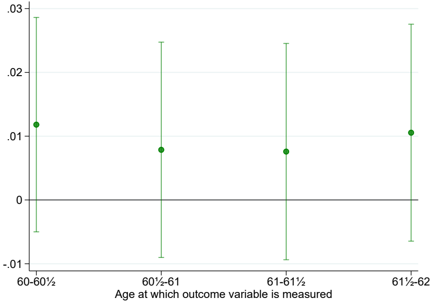


(b) DDDs

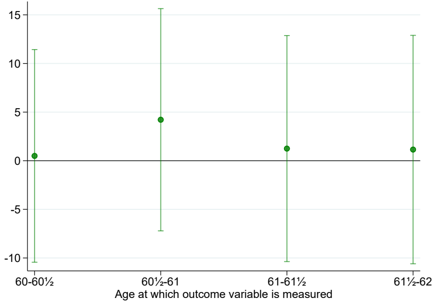


Outcome Measurement Age: CVD Medicine (4/4)

(a) Usage



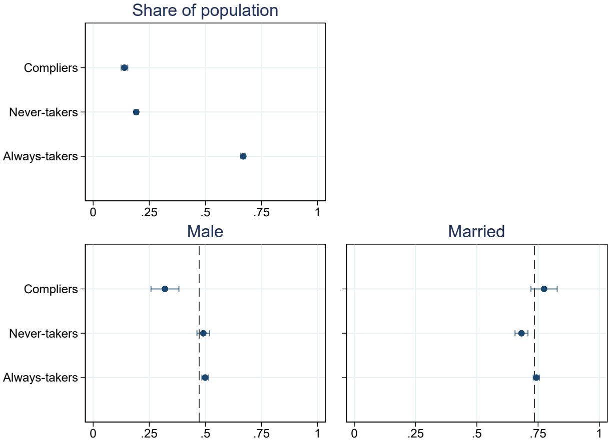
(b) DDDs



Return

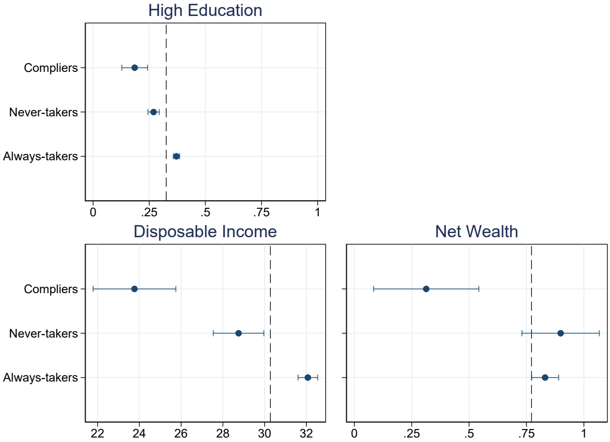
Complier Characterization (1/4)

Share of Sample, Gender, and Marital Status



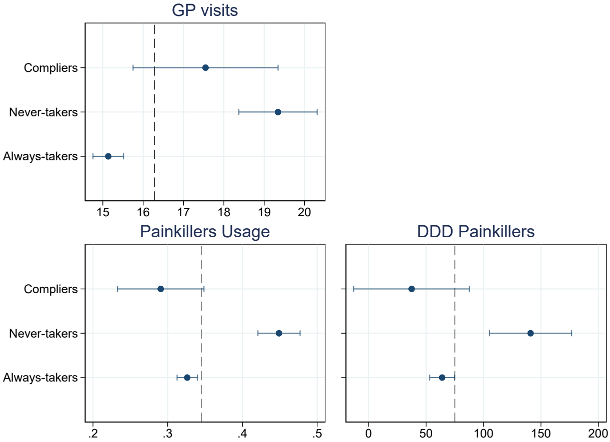
Complier Characterization (2/4)

Educational Level, Income, and Net Wealth



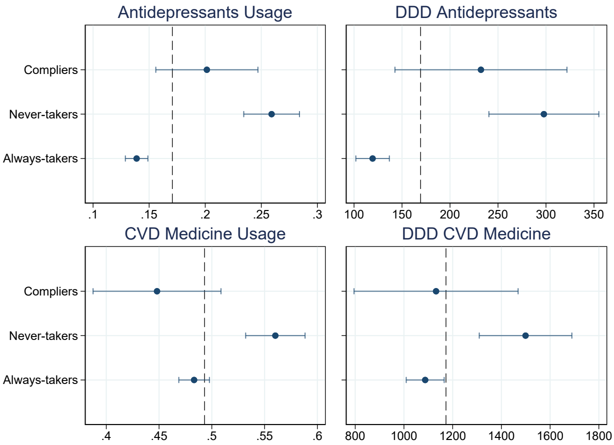
Complier Characterization (3/4)

GP Visits and Painkillers



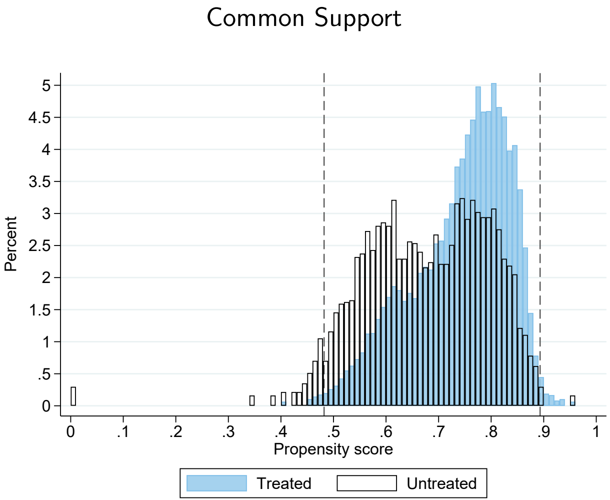
Complier Characterization (4/4)

Antidepressants and CVD Medicine



Return

Common Support: Estimated Propensity Scores



Return

Estimated Treatment Effect Parameters

	(1) GP visits	(2) Painkillers Usage	(3) Painkillers DDDs	(4) Antidep. Usage	(5) Antidep. DDDs	(6) CVD Med. Usage	(7) CVD Med. DDDs
ATE	-0.289	-0.0456	-7.890	0.00915	11.75	0.0388	-17.02
	(0.262)	(0.0403)	(5.220)	(0.0275)	(7.214)	(0.0541)	(35.78)
ATT	-0.146	-0.0423	-8.263	-0.0410	-0.589	-0.00485	-72.14**
	(0.238)	(0.0400)	(5.147)	(0.0280)	(6.928)	(0.0515)	(36.79)
ATUT	-0.501	-0.0454	-6.749	0.0916*	32.17**	0.103	69.39
	(0.473)	(0.0790)	(9.650)	(0.0509)	(12.91)	(0.102)	(64.26)
MPRTE	-0.0126	-0.00141	-0.180	0.00253	0.831*	0.00337	2.456
	(0.0148)	(0.00249)	(0.311)	(0.00172)	(0.437)	(0.00338)	(2.140)
P-value, k(p)	0.315	0.762	0.610	0.005	0.006	0.554	0.646
P-value, $\beta_1 - \beta_0$	0.005	0.916	0.756	0.074	0.062	0.405	0.109
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	12,916	12,916	12,916	12,916	12,916	12,916	12,916

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Bootstrapped standard errors in parentheses with 1,000 replications.

Return