The effect of a strict facial-mask policy on the spread of COVID-19 in Switzerland during the early phase of the pandemic

Annual Congress of the Swiss Society of Economics and Statistics

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Emanuel Nussli[1] Simon Hediger[2] Meta-Lina Spohn[1] Marloes H. Maathuis[1]

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[1]Seminar for Statistics, ETHZ

[2]Department of Economics, UZH

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Introduction

Introduction I: Motivation

- Heatedly debated policy: How effective were facial-masks in reducing the spread of COVID-19 in Switzerland?[1]
- Heterogeneity in facial-mask policies from July 2020 to October 2020 at the cantonal level due to two different policies:
  - *Baseline policy*: mandatory facial-mask wearing on public transport.
  - *Strict policy*: mandatory facial-mask wearing on public transport and mandatory facial-mask wearing in all public or shared spaces where social distancing is not possible.

[1] https://www.swissinfo.ch/eng/politics/cover-up–how-shifting-policies-affect-swiss-attitudes-toward-masks/45978462.

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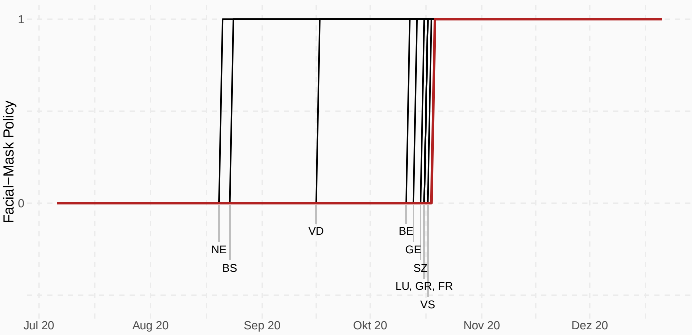
Introduction II: Research Question

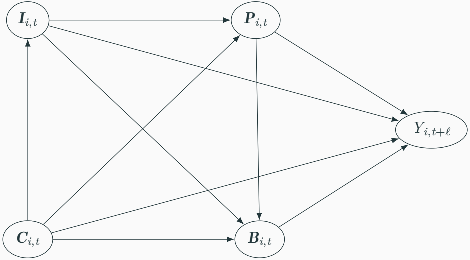


- Research question: How effective was the introduction of the strict facial-mask policy relative to the country-wide baseline facial-mask policy?

Causal Assumptions, Data & Estimation

Causal Assumptions I

- Following Chernozhukov et al. [2021], we assume the following structural causal model describing the dynamics of COVID-19 under policy interventions:



where

- $\boldsymbol{I}_{i,t}$ are information variables
- $\boldsymbol{P}_{i,t}$ are the COVID-19 related policies
- $\boldsymbol{C}_{i,t}$ are confounding factors
- $\boldsymbol{B}_{i,t}$ are behaviour variables
- $Y_{i,t+\ell}$ is the forward health outcome

Causal Assumptions II

- This causal ordering corresponds to the following timing of events:
  - Information and confounders are determined at time t.
  - Policies are determined given information and confounders at time t.
  - Behaviour is decided given policies, information and confounders at time t.
  - The health outcome is settled at time $t+\ell$ given behaviour, policies, information and confounders.

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Causal Assumptions & Data I

- We instantiate the structural causal model by assigning measured variables to $(\boldsymbol{I}_{i,t}, \boldsymbol{P}_{i,t}, \boldsymbol{C}_{i,t}, \boldsymbol{B}_{i,t}, Y_{i,t+\ell})$ by considering previous research[2].
- Using the measured variables, we refine the structural causal model presented previously while neither changing the overall idea nor the implications.

[2] Chernozhukov et al. [2021], Huisman et al. [2022], Pleninger et al. [2022], Zoran et al. [2020], Zhu et al. [2020], Fattorini and Regoli [2020], Hale et al. [2021].

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Causal Assumptions & Data II

- Forward health outcomes:
  - Effective reproductive number $R_{i,t+\ell}$
  - Approximated weekly growth rate of new cases $G_{i,t+\ell}$
- Policies:
  - Strict facial mask policy variable $M_{i,t}$
  - Non-pharmaceutical policy variables $\boldsymbol{P}_{i,t}$
    - Work closings
    - School closings
    - Restriction of gatherings
    - Cancellation of events
    - Testing policy
- Behaviour:
  - Approximated weekly growth rate of household spending $B_{i,t}$

Descriptive Statistics of Data

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Causal Assumptions & Data III

- Information:
  - Publicly available information about COVID-19 in week t
    - Lagged effective reproductive number $R_{i,t}$
    - Lagged approximated weekly growth rate of new cases $G_{i,t}$
- Confounding factors:
  - Demographic variables $\boldsymbol{D}_i$
    - Population size
    - Percentage over 80 years old
    - Population density in settlement area
  - Holiday indicator $H_{i,t}$
  - Meteorological variables $\boldsymbol{W}_{i,t}$
    - Minutes of sunshine
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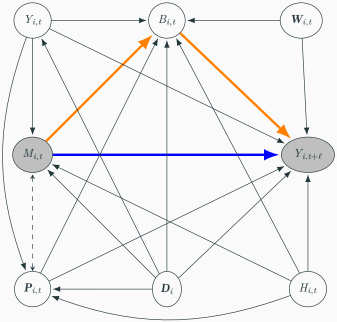

- Note that this allows the decomposition of the effect of the strict facial-mask policy on the response variable into two channels:
  - Direct effect: $M_{i,t} \longrightarrow Y_{i,t+\ell}$
  - Indirect effect via behaviour: $M_{i,t} \longrightarrow B_{i,t} \longrightarrow Y_{i,t+\ell}$

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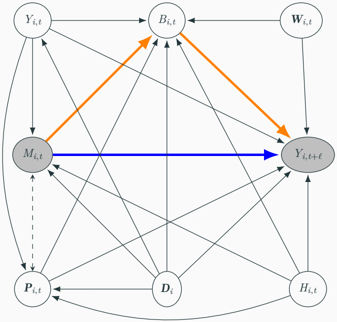

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Causal Assumptions & Estimation I

- In addition to the structural causal model from the last slide, we also impose canton and week-specific effects (α_i and γ_t respectively).
- This implies the following estimating equation:

$$Y_{i,t+\ell} = \theta M_{i,t} + \boldsymbol{\beta}^\top \boldsymbol{Z}_{i,t} + \alpha_i + \gamma_t + \epsilon_{i,t},$$

where $\boldsymbol{Z}_{i,t}$ is a valid adjustment set relative to the effect of interest (direct or total).

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Causal Assumptions & Estimation II

- We estimate the parameters $(\theta, \boldsymbol{\beta}) := \boldsymbol{\eta}$ of

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  by using

  - Fixed effects estimators
  - Debiased fixed effects estimators
  - Random effects estimators
  - Double machine learning

  while putting special consideration on the panel structure of the data while computing $\widehat{\mathrm{Var}}(\hat{\boldsymbol{\eta}})$.

- Note that the different estimation schemes require different assumptions on the error components $(\alpha_i, \gamma_t, \epsilon_{i,t})$, see Hansen [2022].

Debiased Fixed Effects Estimation | Double Machine Learning Estimation | Computing $\widehat{\mathbf{Var}}(\hat{\boldsymbol{\eta}})$

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Debiased Fixed Effects Estimation | Double Machine Learning Estimation | Computing $\widehat{\mathbf{Var}}(\hat{\boldsymbol{\eta}})$

Results

Results I

- We report the treatment effect of the strict facial-mask policy $\hat{\theta}$ along with it's associated 95%–confidence interval
  - For the direct and the total (=indirect+direct) effect
  - For the fixed effects approach, debiased fixed effects approach, random effects approach[3]
  - For both responses of (i) effective reproductive number and (ii) approximated weekly growth rate of new cases
  - For the different estimators of $\widehat{\mathrm{Var}}(\hat{\theta})$

[3] We report the results from the double machine learning in the sensitivity analysis.

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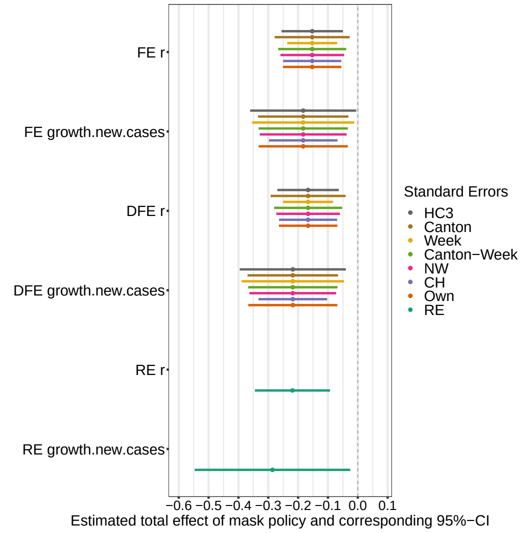

- FE denotes fixed effects, DFE denotes debiased fixed effects and RE denotes random effects.
- The different colours represent the different estimators of $\widehat{\mathrm{Var}}(\hat{\theta})$.
- The point estimates lie within $[-0.29, -0.15]$.
- θ is deemed significantly different from 0 at $\alpha = 0.05$ in all cases.

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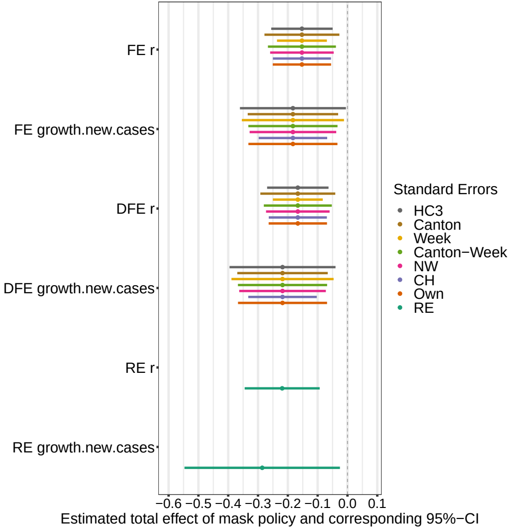

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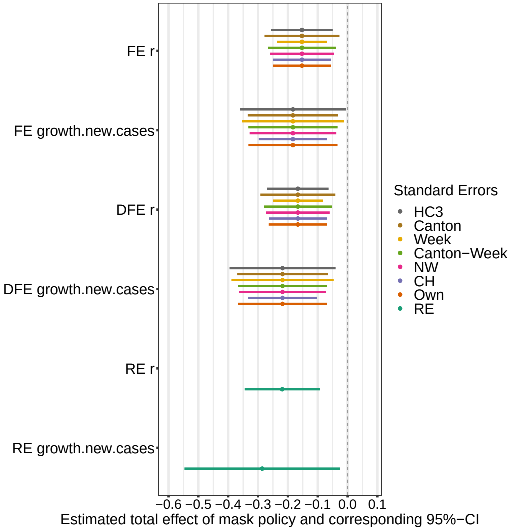

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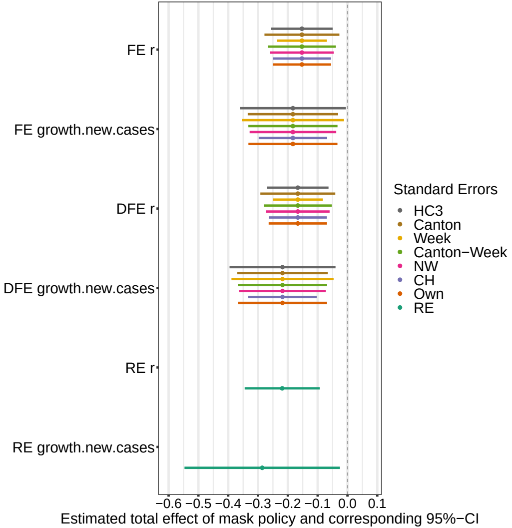

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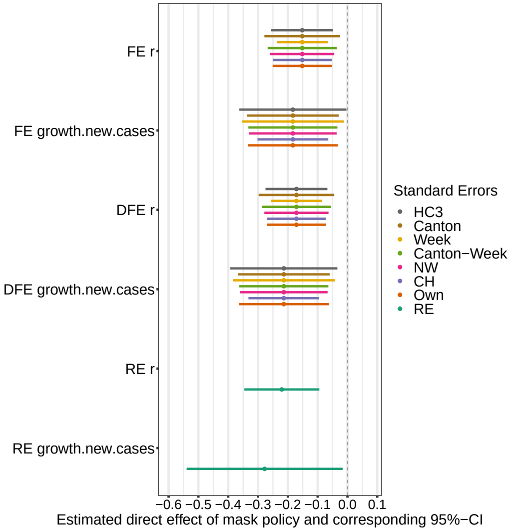
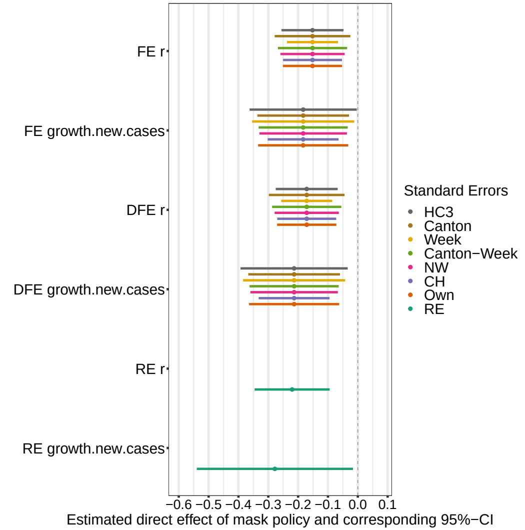


- The point estimates lie within $[-0.28, -0.15]$.
- Again, θ is deemed significantly different from 0 at $\alpha = 0.05$ in all cases.
- The difference between the total and the direct effect is not significant in any of the cases.
  - This implies that we do not find evidence for an indirect effect via behaviour.

Results III: Direct Effect



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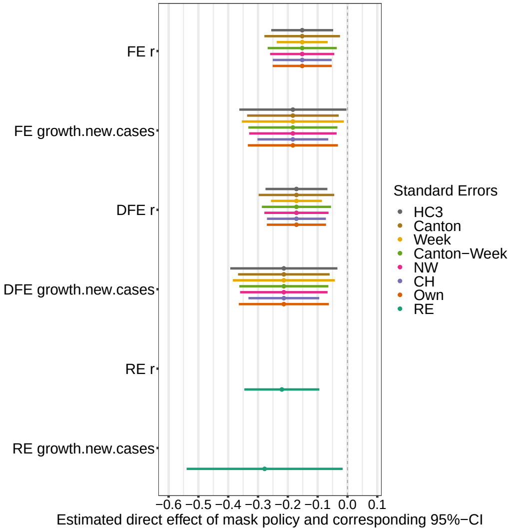

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Results IV: Sensitivity Analysis

- To check the robustness of our findings with respect to inevitable design choices, we perform the following sensitivity analyses:
  - Further alterations in confidence interval constructions
  - Extended set of information variables
  - Join half-cantons into one respective canton
  - Timing of information variables
  - Outliers
  - Sample period
  - Double machine learning estimation
  - Lag-1 response variable as further predictor
- Again, all the point estimates $\hat{\theta}$ are negative and deemed significantly different from 0 in 25 of the 35 (71%) sensitivity analyses conducted.

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Discussion

Discussion I: Limitations

- Limitation of capturing COVID-19 relevant behaviour using approximated weekly growth rate of household spending $B_{i,t}$.
- As always with observational studies: cautious interpretation of results due to potential unmeasured confounding variables.
- Results hold conditional on the specific time period between July and December 2020 when the Alpha variant of COVID-19 was dominant and no vaccinations were available yet.

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- Considering that the authors deem facial-mask regulations non-invasive compared to other policies[4], we advocate this strategy for potential future pandemics.

[4] E.g. work closings, school closings, restrictions of gatherings, cancellation of events or even (partial) lockdowns.

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Discussion III: Questions?

- Thank you very much for listening! Are there any open questions?

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Data Description

Short Name	Description	Descriptive Statistics (median, mean, sd)	Data Source
$Y_{i,t}$	Response Variables		
r	estimated effective reproductive number	$(1.05, 1.15, 0.38)$	COVID
growth.new.cases	$\ln$(weekly growth rate of reported new cases)	$(0.05, 0.15, 0.67)$	COVID
$M_{i,t}$	Strict Facial Mask Policy Variable		
facial.mask	strict facial-mask policy	$(0.00, 0.44, 0.49)$	Policies
$B_{i,t}$	Social Distancing Behaviour Variable		
growth.transactions	$\ln$(weekly growth rate of transactions)	$(0.00, -0.01, 0.08)$	Consumption
$\boldsymbol{D}_i$	Demographic Variables		
population	population	$(234'650, 326'311, 348'969)$	Population
perc.o80	age ≥ 80 years in $\%$	$(5.29, 5.44, 0.74)$	Population
density	people per km^2 of settlement area	$(2503, 2780, 1253)$	Population
$H_{i,t}$	Holiday Indicator		
holiday	official school holiday indicator	$(0.00, 0.08, 0.25)$	Holidays
$\boldsymbol{W}_{i,t}$	Meteorological Variables		
sunshine	sunshine in minutes per day	$(248, 288, 192)$	Weather
temperature	mean air temperature in $°\mathrm{C}$	$(11.36, 11.89, 7.15)$	Weather
humidity	relative humidity in $\%$	$(78.94, 76.62, 9.10)$	Weather
$\boldsymbol{P}_{i,t}$	Non-Pharmaceutical Policy Variables		
work.closing	closing of workplaces policy	$(1.00, 1.49, 0.71)$	Policies
school.closing	closing of schools policy	$(1.00, 1.32, 0.47)$	Policies
rest.gatherings	restrictions on gatherings policy	$(2.00, 2.04, 1.12)$	Policies
canc.events	cancellation of public events policy	$(1.00, 1.37, 0.47)$	Policies
testing.policy	testing policy	$(2.00, 2.42, 0.48)$	Policies

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Sensitivity Analysis

	r		growth.new.cases	
	Point Estimate	Confidence Interval	Point Estimate	Confidence Interval
A.1 Alterations to Confidence Interval Construction				
Month FE	-0.15	$[-0.22, -0.09]$	-0.18	$[-0.33, -0.03]$
Canton-Month FE	-0.15	$[-0.26, -0.05]$	-0.18	$[-0.34, -0.03]$
Month DFE	-0.17	$[-0.19, -0.07]$	-0.22	$[-0.37, -0.07]$
Canton-Month DFE	-0.17	$[-0.27, -0.06]$	-0.22	$[-0.37, -0.06]$
A.2 Alterations to the Data and Point Estimation				
Additional Information Variables				
RE	-	-	-0.24	$[-0.42, -0.07]$
Half-Cantons				
FE	-0.16	$[-0.26, -0.06]$	-0.13	$[-0.33, 0.07]$
DFE	-0.25	$[-0.35, -0.15]$	-0.20	$[-0.41, 0.00]$
RE	-0.21	$[-0.33, -0.09]$	-0.25	$[-0.47, -0.04]$
Timing of Information Variables				
FE	-0.18	$[-0.26, -0.09]$	-0.08	$[-0.26, 0.10]$
DFE	-0.28	$[-0.37, -0.20]$	-0.17	$[-0.35, 0.01]$
RE	-0.27	$[-0.46, -0.09]$	-0.18	$[-0.41, 0.05]$
Outliers				
FE	-0.08	$[-0.14, -0.02]$	-0.15	$[-0.28, -0.01]$
Sample Period				
FE	-0.26	$[-0.55, 0.04]$	-0.19	$[-0.43, 0.06]$
Double Machine Learning				
DML	-0.69	$[-1.40, 0.02]$	-0.69	$[-1.51, 0.13]$
Lag-1 Response Variable as Predictor				
FE	-0.11	$[-0.20, -0.03]$	-0.25	$[-0.43, -0.07]$
DFE	-0.13	$[-0.21, -0.04]$	-0.28	$[-0.46, -0.10]$
RE	-0.20	$[-0.30, -0.10]$	-0.44	$[-0.65, -0.22]$
DML	-0.59	$[-1.16, -0.02]$	-0.70	$[-1.54, 0.14]$

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Details of Debiased Fixed Effects Estimation i

- Consider estimating the parameters $\boldsymbol{\eta} := (\theta, \boldsymbol{\beta})$ of

$$Y_{i,t+\ell} = \theta M_{i,t} + \boldsymbol{\beta}^\top \boldsymbol{Z}_{i,t} + \alpha_i + \gamma_t + \epsilon_{i,t},$$

  using the fixed effects methodology, where $\boldsymbol{Z}_{i,t}$ contains lagged instances of $Y_{i,t+\ell}$, being our information variables $I_{i,t} = Y_{i,t}$.
- Applying the two-way within operator $u_{i,t} \longrightarrow \ddot{u}_{i,t}$ removes the fixed effects yielding

$$\ddot{Y}_{i,t+\ell} = \theta \ddot{M}_{i,t} + \boldsymbol{\beta}^\top \ddot{\boldsymbol{Z}}_{i,t} + \ddot{\epsilon}_{i,t},$$

  with the issue that $\mathbb{E}[\ddot{Y}_{i,t}\ddot{\epsilon}_{i,t}] \neq 0$ as both are functions of the entire time series.
- This creates a bias of $\mathcal{O}(1/T)$ in estimating $\boldsymbol{\eta}$, which is sometimes deemed negligible for $T \geq 30$ (we have $T = 24$), see Hansen [2022].

Details of Debiased Fixed Effects Estimation ii

- We consider a sample-splitting remedy for this issue, where we repeatedly split the data along:

$$\begin{aligned} S_1 :=&\{(i,t) : i \leq \lceil N/2 \rceil, t \leq \lceil T/2 \rceil\} \\ &\cup \{(i,t) : i \geq \lceil N/2+1 \rceil, t \geq \lceil T/2+1 \rceil\} \end{aligned}$$

  and

$$\begin{aligned} S_2 :=&\{(i,t) : i \leq \lceil N/2 \rceil, t \geq \lceil T/2 \rceil\} \\ &\cup \{(i,t) : i \geq \lceil N/2+1 \rceil, t \leq \lceil T/2+1 \rceil\}, \end{aligned}$$

  where we permute ($p = 1\ldots, P$) the ordering of the cantons as there is no natural ordering. We then estimate $\hat{\theta}_{S_1,p}, \hat{\theta}_{S_2,p}$ disjointly and combine them via

$$\hat{\theta}_{BC,p} = 2\hat{\theta} - (\hat{\theta}_{S_1,p} + \hat{\theta}_{S_2,p})/2.$$

Details of Debiased Fixed Effects Estimation iii

- The final estimate over the $P = 20$ permutations of the cantons is given by

$$\hat{\theta}_{BC} = \frac{1}{P} \sum_{p=1}^{P} \hat{\theta}_{BC,p}.$$

- Intuition for why this works: Given that the bias term is homogeneous across the samples, the combination operation to compute $\hat{\theta}_{BC,p}$ reduces the first-order bias by subtraction, see Chen et al. [2019].

◂ Back

Details of Double Machine Learning i

- We relax the assumption of linearity by imposing the partially linear model given by:

$$
\begin{aligned}
M_{i,t} &= m(\boldsymbol{Z}_{i,t}) + \nu_{i,t} \\
Y_{i,t+\ell} &= \theta M_{i,t} + g(\boldsymbol{Z}_{i,t}) + \epsilon_{i,t},
\end{aligned}
$$

  where $m(\cdot)$ and $g(\cdot)$ are potentially non-linear functions that we learn using random forests.
- We perform robust inference for θ using two-way clustered standard errors, see Chernozhukov et al. [2018] for more details.

◂ Back

- Remember that $\hat{\boldsymbol{\eta}} = (\hat{\theta}, \hat{\boldsymbol{\beta}})$ is estimated either via the fixed effects or the debiased fixed effects estimator.
- We obtain $\widehat{\mathrm{Var}}(\hat{\theta})$ as the first diagonal entry in the estimated variance-covariance matrix of $\hat{\boldsymbol{\eta}}$, $\widehat{\mathrm{Var}}(\hat{\boldsymbol{\eta}})$.
- Let in the following

$$\boldsymbol{X}_{i,t} \coloneqq (M_{i,t}, \boldsymbol{Z}_{i,t})^\top \ \in \ \mathbb{R}^{P \times 1}$$

  be the observed predictor of canton i and week t, where $P \coloneqq 1 + |\boldsymbol{Z}_{i,t}|$. Then, let $\boldsymbol{X} \in \mathbb{R}^{NT \times P}$ be the stacked predictor matrix.

Variance-Covariance Matrix of Estimated Coefficients ii

- The conditional variance-covariance matrix of $\hat{\boldsymbol{\eta}}$ can be written as

$$\operatorname{Var}(\hat{\boldsymbol{\eta}} \mid \boldsymbol{X}) = \boldsymbol{Q}^{-1} \boldsymbol{\Omega} \boldsymbol{Q}^{-1}, \tag{1}$$

  where

$$\boldsymbol{Q} := \frac{1}{NT} \boldsymbol{X}^\top \boldsymbol{X},$$

  and

$$\boldsymbol{\Omega} := \frac{1}{(NT)^2} \boldsymbol{X}^\top \operatorname{Var}(\boldsymbol{\epsilon}) \boldsymbol{X},$$

  with

$$\boldsymbol{\epsilon} := \left(\epsilon_{1,1}, \epsilon_{1,2}, \ldots, \epsilon_{1,T}, \epsilon_{2,1}, \ldots, \epsilon_{2,T}, \ldots, \epsilon_{N,T}\right)^\top.$$

- We denote by $\hat{\boldsymbol{\epsilon}}$ the empirical residuals. The variance of $\hat{\boldsymbol{\eta}}$ is then estimated by plugging in an estimate of $\boldsymbol{\Omega}$ into Equation (1), resulting in $\widehat{\operatorname{Var}}(\hat{\boldsymbol{\eta}}) = \boldsymbol{Q}^{-1} \hat{\boldsymbol{\Omega}} \boldsymbol{Q}^{-1}$.

- To incorporate the panel structure of the data, we consider 7 different estimators of $\mathbf{\Omega}$, corresponding to different assumptions on $\mathrm{Cov}(\epsilon_{i,t}, \epsilon_{j,s})$ for $i, j = 1, \ldots, N$ and $j, s = 1, \ldots T$. These assumptions reflect the clustered, heteroskedastic and autocorrelated nature of the errors.

(1) Heteroscedastic-Robust (*HC3*).
$\mathrm{Cov}(\epsilon_{i,t}, \epsilon_{j,s}) \neq 0$ iff $i = j$ and $s = t$:

$$\hat{\mathbf{\Omega}}_1 := \frac{1}{(NT)^2} \sum_{i=1}^{N} \sum_{t=1}^{T} \boldsymbol{X}_{i,t} \boldsymbol{X}_{i,t}^\top \tilde{\epsilon}_{i,t}^2,$$

where the residual $\tilde{\epsilon}_{i,t}$ is given by the classical *HC3* representation

$$\tilde{\epsilon}_{i,t} := \frac{\hat{\epsilon}_{i,t}}{1 - \boldsymbol{X}_{i,t}^\top (\boldsymbol{X}^\top \boldsymbol{X})^{-1} \boldsymbol{X}_{i,t}}.$$

Variance-Covariance Matrix of Estimated Coefficients iv

(2) One-Way Clustering on Canton (*Canton*).
$\mathrm{Cov}(\epsilon_{i,t}, \epsilon_{j,s}) \neq 0$ iff $i = j$:

$$\hat{\boldsymbol{\Omega}}_2 := \frac{1}{(NT)^2} \sum_{i=1}^{N} \hat{\boldsymbol{R}}_i \hat{\boldsymbol{R}}_i^\top,$$

where $\hat{\boldsymbol{R}}_i := \sum_{t=1}^{T} \boldsymbol{X}_{i,t} \hat{\epsilon}_{i,t}$.

(3) One-Way Clustering on Week (*Week*).
$\mathrm{Cov}(\epsilon_{i,t}, \epsilon_{j,s}) \neq 0$ iff $t = s$:

$$\hat{\boldsymbol{\Omega}}_3 := \frac{1}{(NT)^2} \sum_{t=1}^{T} \hat{\boldsymbol{S}}_t \hat{\boldsymbol{S}}_t^\top,$$

where $\hat{\boldsymbol{S}}_t := \sum_{i=1}^{N} \boldsymbol{X}_{i,t} \hat{\epsilon}_{i,t}$.

(4) Two-Way Clustering on Canton and Week (*Canton-Week*).
$\mathrm{Cov}(\epsilon_{i,t}, \epsilon_{j,s}) \neq 0$ iff $t = s$ or $i = j$:

$$\hat{\mathbf{\Omega}}_4 \coloneqq \frac{1}{(NT)^2}\left(\sum_{i=1}^{N} \hat{\boldsymbol{R}}_i \hat{\boldsymbol{R}}_i^\top + \sum_{t=1}^{T} \hat{\boldsymbol{S}}_t \hat{\boldsymbol{S}}_t^\top - \sum_{i=1}^{N}\sum_{t=1}^{T} \boldsymbol{X}_{i,t}\boldsymbol{X}_{i,t}^\top \hat{\epsilon}_{i,t}^2\right).$$

(5) Newey-West (*NW*), see Newey and West [1987].
$\mathrm{Cov}(\epsilon_{i,t}, \epsilon_{j,s}) \neq 0$ iff $i = j$, where $\mathrm{Cov}(\epsilon_{i,t}, \epsilon_{j,s})$ is decreasing in $|t - s|$:

$$
\begin{aligned}
\hat{\boldsymbol{\Omega}}_5 := \frac{1}{(NT)^2} \Bigg(& \sum_{i=1}^{N} \hat{\boldsymbol{R}}_i \hat{\boldsymbol{R}}_i^\top + \sum_{t=1}^{T} \hat{\boldsymbol{S}}_t \hat{\boldsymbol{S}}_t^\top \\
& - \sum_{i=1}^{N} \sum_{t=1}^{T} \boldsymbol{X}_{i,t} \boldsymbol{X}_{i,t}^\top \hat{\epsilon}_{i,t}^2 \\
& + \sum_{m=1}^{M} w(m, M) (\hat{\boldsymbol{G}}_m + \hat{\boldsymbol{G}}_m^\top \\
& - \hat{\boldsymbol{H}}_m - \hat{\boldsymbol{H}}_m^\top) \Bigg),
\end{aligned}
$$

where
$\hat{\boldsymbol{G}}_m := \sum_{t=1}^{T-m} \hat{\mathbf{S}}_t \hat{\mathbf{S}}_{t+m}^\top$, $\hat{\boldsymbol{H}}_m := \sum_{i=1}^{N} \sum_{t=1}^{T-m} \boldsymbol{X}_{i,t} \hat{\epsilon}_{i,t} \boldsymbol{X}_{i,t+m}^\top \hat{\epsilon}_{i,t+m}$
and $w(m, M) = 1 - m/(M+1)$ are triangular weights and $M = \lfloor T^{1/4} \rfloor$.

(6) Chiang-Hansen (*CH*), see Chiang et al. [2022].
$\mathrm{Cov}(\epsilon_{i,t}, \epsilon_{j,s}) \neq 0$, where
$\mathrm{Cov}(\epsilon_{i,t}, \epsilon_{j,s})$ for arbitrary $i \neq j$ is decreasing in $|t - s|$:
The estimator $\hat{\boldsymbol{\Omega}}_6$ is the same as $\hat{\boldsymbol{\Omega}}_5$, where $w(m, M)$ are the triangular weights as in *NW* and M is data driven.

Variance-Covariance Matrix of Estimated Coefficients viii

(7) Informal Own Specification (*Own*) [motivated by Colella et al., 2019].
$\mathrm{Cov}(\epsilon_{i,t}, \epsilon_{j,s}) \neq 0$ if $i = j$ or i and j are neighboring cantons, where $\mathrm{Cov}(\epsilon_{i,t}, \epsilon_{j,s})$ is decreasing in $|t - s|$:

$$\hat{\mathbf{\Omega}}_7 := \frac{1}{(NT)^2} \sum_{i=1}^{N} \sum_{t=1}^{T} \sum_{j=1}^{N} \sum_{s=1}^{T} \omega_{itjs} V_{itjs},$$

where

$$V_{itjs} := \boldsymbol{X}_{i,t} \hat{\epsilon}_{i,t} \hat{\epsilon}_{j,s} \boldsymbol{X}_{j,s}^{\top},$$

and the weights ω_{itjs} specify the dependence between two error terms $\epsilon_{i,t}$ and $\epsilon_{j,s}$ and are given by

$$\omega_{itjs} := \left\{ \begin{array}{ll} 1, & i = j,\ t = s, \\ \lambda_{ij} 0.5^{|t-s|}, & \text{otherwise} \end{array} \right\},$$

and

$$\lambda_{ij} := \left\{ \begin{array}{lr} 1, & i = j, \\ 0.5, & i, j \text{ neighbors}, \\ 0, & \text{otherwise} \end{array} \right\}.$$

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Comparison of Response Variables