Household Behavioral Response and Clubs to Lockdown Policy in Europe: Evidence From COVID

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Empirical Evidence from COVID-19

COVID-19 is an exceptional shock to social system

- Natural experiment to study the impact on changes in behavior.
- Rare opportunity to empirically estimate resilience in behavior changes.

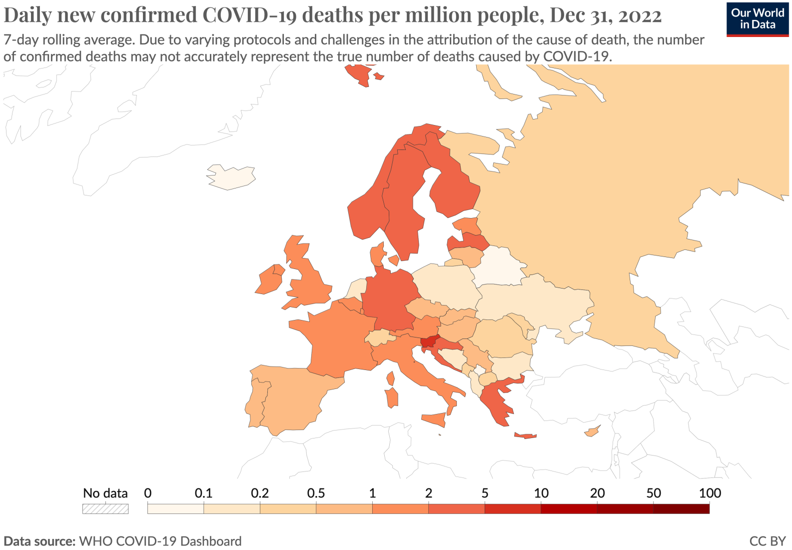
Enabled to collect daily data on individual human behavior on a population size.

Analyze whether or not policy maker and resident “preferences” align and how long does it take?

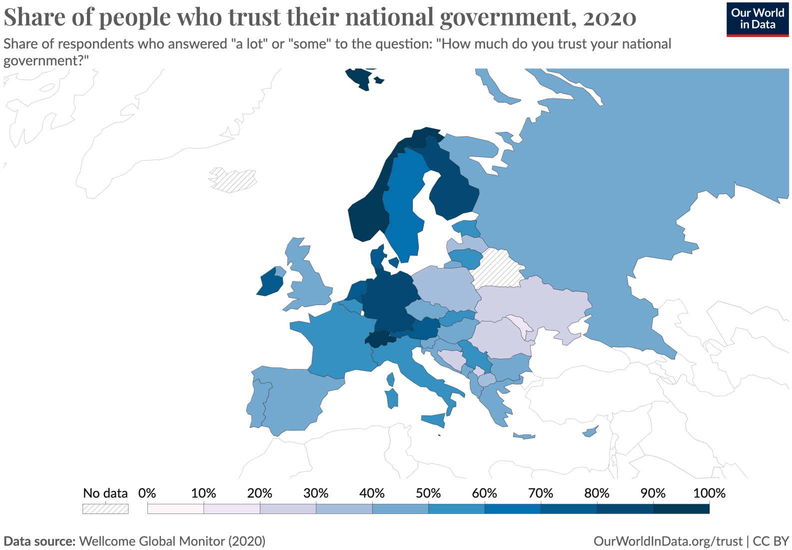
Companion

- Sonora's (2022) Taylor rule which estimated a policy loss function
- Similar analysis as in Gottwald and Sonora (2023) for the US
- More recently, Sonora and Tica (2024) investigate endogeneity of policy, behavior, Covid, the economy and "news"
- Investigation of policy effectiveness Potter (2006)

Comparison: Where we were Dec 31, 2022



Comparison: Trust in government 2020



Resilience in behavioral changes

People are more sensitive to negative than to positive events (Prospect theory, Tversky and Kahneman, 1992)

- Cognitive bias and regret aversion influence risk attitude
- Changes in habitual actions:
- Influenced by the policy- level of respond to coordinated interventions,
  - Unobserved idiosyncratic human behavior – self-driven preferences evaluated over uncertainty and risk-attitude,
  - Fear and risk - salient factors cause preference reversal,
  - Changes in behavior captures sensitivity to risk-attitude.

Resilience in behavioral changes

Mean reversion theory suggests that regret, fear or risk will converge to “normal” over time

- Can we say that individual behavior follows stochastic process with sporadic drift close around the mean that eventually converges towards normality?
- Put it another way - does behavior and policy preferences eventually converges?

What characteristics make for effective policy?

- Believable/trust
- Feasible
- Enforceable
- Implementable
- Understandable/Coherent

Note: $Policy_i \stackrel{?}{=} Policy_j \; \forall i \neq j$? Probably not

Effectiveness of stringency policies

- *Ex-ante*:
  - Mobility should decrease as stringency increase: Restrictions are "expected" to follow 1 to -1 relationship
  - Differences in preferences across countries should lead to idiosyncratic responses to policy recommendations,
- We estimate human behavior using the cell phone data as proxy for social interaction relative to policy stringency index on EU countries.
- Do individual responses aligns to policy preferences and how long does it take to converge?

Modeling strategy

We have daily state:

– Policy, stringency, data which is a set of rules restricting individual mobility behavior: stay-at-home orders, only shopping for food or medicine, social distancing, etc:

  NB: This does not imply that the policy will be effective in preventing COVID

  We can think of this in terms of minimizing a "policy loss function" in terms of COVID and unemployment:

$$P^* = SI^* = \min_{\{C,U\}} \mathcal{L}(\overset{(+)}{Covid}, \overset{(+)}{u}, \vartheta)$$

  ϑ is a policy parameter

– Cell phone data which represents mobile individuality in a given country (via revealed preferences);

– Each of these represent the preferences of policy makers ("*P*") and residents/behavior ("*B*")

Policy effectiveness

Consider policy effectiveness, for any time t, compactly in the relationship

$$B_t = \beta \mathbf{P}_t + \eta_t, \beta \geq 0$$

where

B is individual target behavior
$\mathbf{P}$ is a vector of policies, $\mathbf{P} \sim iid(\bar{\mathbf{P}}, \sigma^2_{\mathbf{P}})$
$\eta \sim iid(0, \sigma^2_{\eta})$ other exogenous factors that influence behavior

If $\beta = 1 \Rightarrow$ perfect policy “pass through”

Optimal policy

The policy-maker must design an optimal policy based on any given policy response to achieve the policy goal, B^*,

$$B_t^* = \tilde{\beta}_t \mathbf{P}_t^*.$$

That is the preferences of both the residents r and policy-maker p are equal:

$$U_{r,i}(B_{t,i}^*) = U_{p,i}(\mathbf{P}_{t,i}^* | \tilde{\beta}_{t,i})$$

for any location i but this does *not* imply, e.g. $U_{r,i} = U_{r,j}$ & $U_{p,i} = U_{p,j}$

$\tilde{\beta}_t \overset{?}{\neq} 1$ is households actual response, not this could be time varying

Policy confusion

- Policy "confusion", or uncertainty, is determined by the variability in *B*. Angelini et al (2023) define their policy function evolving as (adaptive expectations):

$$\mathbf{P}_t = \rho \mathbf{P}_{t-1} + (1-\rho)\mathbf{P}_t^*$$

  Here $\mathbf{P}^*$ is policy maker's optimal response to minimizing an economy-health loss function, as estimated in Sonora (2022)

- This equation can be rewritten as an adaptive expectations policy function as

$$\Delta \mathbf{P}_t = \lambda(\mathbf{P}_t^* - \mathbf{P}_{t-1})$$

  where $\lambda \equiv (1-\rho)$ is the adjustment parameter.

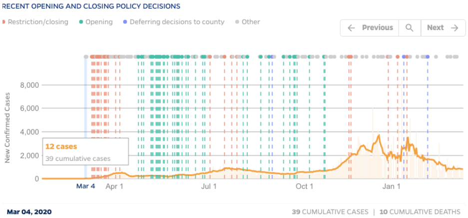
Policy confusion

After substituting and noting $E(\mathbf{P}, \eta) \neq 0$ and $\mathbf{P}_t$ and $\mathbf{P}_t^*$ are time variant, we can write policy confusion as:

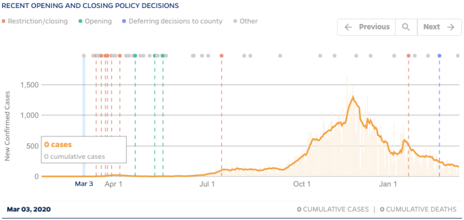
$$E(B^2) = \rho\beta^2 E(\mathbf{P}_t, \mathbf{P}_{t-1}) + \beta^2\lambda E(\mathbf{P}_t, \mathbf{P}_t^*) + \beta E(\mathbf{P}_t, \eta_t) + \beta\lambda E(\mathbf{P}_t, \eta_t) + Var(\eta^2)$$

NB: $E(\mathbf{P}_{t-1}, \eta_t) = 0$

Example: WA and MT



(a) WA



(b) MT

Modeling strategy

Mobility is determined by policy restrictions . . .

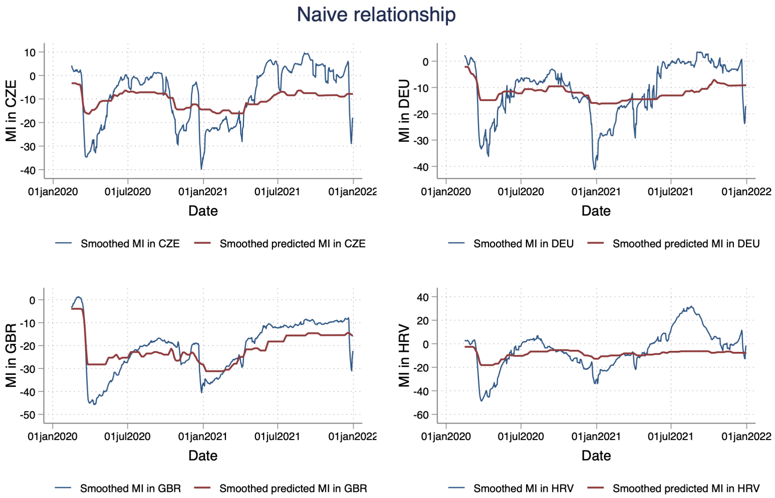
$$Mobility_t = \alpha + \beta \cdot Policy_t + \eta_t$$

Passing the expectation operator through and in a perfect world there is a 1-to-1 relationship

$$H_0 : E(Mobility_t) = \cancelto{0}{\alpha} + \cancelto{-1}{\beta} \cdot Policy_t + \cancelto{0}{\eta_t}$$

i.e. $U_B \approx U_P$ via revealed preferences

A naïve representation



What is $\hat{\eta}$?

$$\hat{\eta}_t = Mobility_t - \hat{\alpha} - \hat{\beta} Policy_t$$

- The deviation of people's mobility behavior from policy prescription
- Unobserved component individual behavior and reflects: perception of risk, politics, beliefs, other information, etc.
- If $\hat{\eta} \sim I(0)$ then
$$\lim_{t \to \infty} U_B = U_P$$

ARDL behavior model

We employ the ARDL model

$$GMI_t = \alpha \; + \rho MI_{t-7} + \beta(L) SI_t + \mathbf{X}_t' \gamma + \eta_t, \;\; t = 0, \dots, T$$

with $\beta(L) = 0, 7, 14$ lags

Interested in

- time series properties of unobserved behavior: $\hat{\eta} \sim I(0)$?
- immediate response:

$$\frac{\Delta GMI_t}{\Delta SI_t} = \hat{\beta}_0$$

- “adjusted” response

$$Response = \frac{\hat{\beta}_0 + \hat{\beta}_{-7} + \hat{\beta}_{-14}}{1 - \hat{\rho}} \overset{?}{\approx} -1$$

  - $Response \in (-1, 0)$: relative policy/risk taking
  - $Response < -1$: relative policy/risk averse

Control vector: $\mathbf{X} = (Vax, Season, \Delta Cov)'$

Unit root tests: $\hat{\eta} \sim I(0)$?

Elliot, Rothenberg, and Stock

ADF test which relies on GLS detrending to reduce size distortions $\rightarrow$ power$\uparrow$

Rolling 270 day window ADF tests

Analyze the time series properties of $\hat{\eta}$ over the course of the sample period with a fixed window

Recall, $\hat{\beta}_t \neq \beta \forall t$, β can be time variant depending on new environment and information

Rolling 50-300 day ADF tests

determine what % of each window length are $I(0)$ $\rightarrow$ how long must window be before series become stationary?

Effectively, estimates "time to compliance"

Maximum allowed lagged dependent variable: 14 days

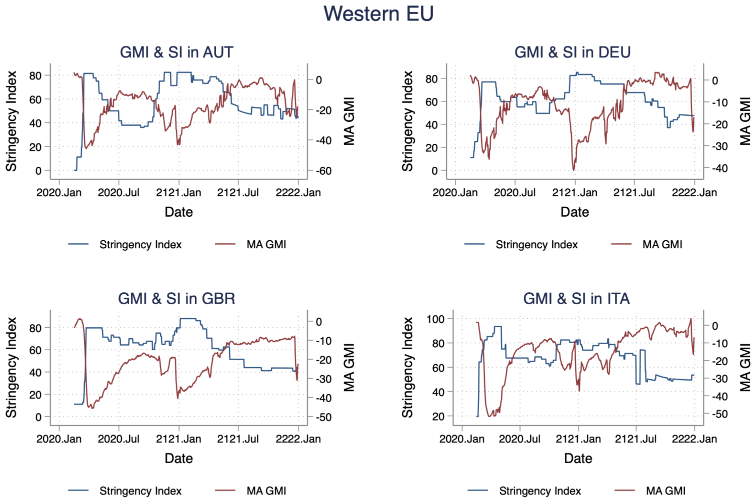
Data sources

- Daily data from January 22, 2020 to December 31, 2021 by Country
- Full sample 33 European countries
- This presentation restricts the analysis to 12 countries:
  - Western EU: AUT, DEU, GBR, ITA
  - Eastern EU: CZE, HUN, POL, ROU
  - Ex-Yugoslavia: BIH, HRV, SLV SRB

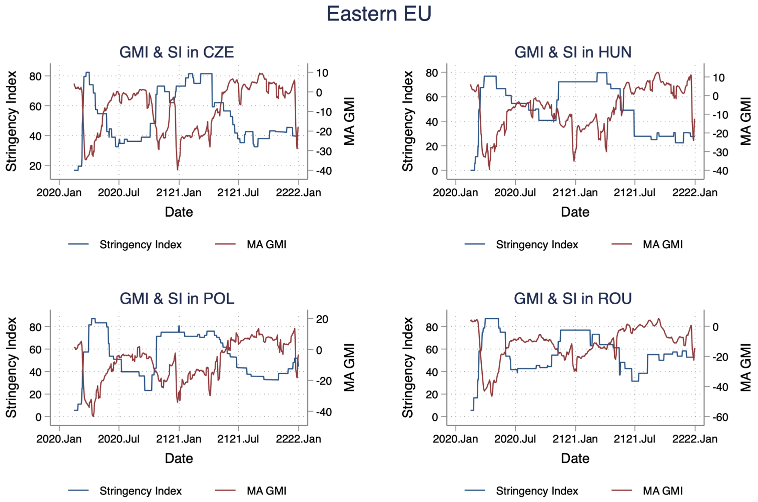
Data sources

- Google Mobility Index (*GMI*): average of cell phone mobility over 5 categories – Grocery and pharmacy, retail and recreation, ~~parks,~~ residential, work, and transit, $GMI \in (-100\%, \infty)$
  - Chose not to use: Apple MI (only iPhone users) and Dallas Fed's MI (ended in March, 2020)
- Oxford Coronavirus Government Response Tracker (OxCGRT) Stringency Index (*OxSI*): measures restrictive policies, $SI \in (0, 100)$
- Vax: Vaccination rate
- time fixed effects: summer

OxSI&GMI: WEU


Western EU
GMI & SI in AUT
GMI & SI in DEU
GMI & SI in GBR
GMI & SI in ITA
Stringency Index
MA GMI
Date
2020.Jan
2020.Jul
2121.Jan
2121.Jul
2222.Jan
Stringency Index
MA GMI

OxSI&GMI: **EEU**


Eastern EU
GMI & SI in CZE
GMI & SI in HUN
GMI & SI in POL
GMI & SI in ROU
Stringency Index
MA GMI
Date
2020.Jan
2020.Jul
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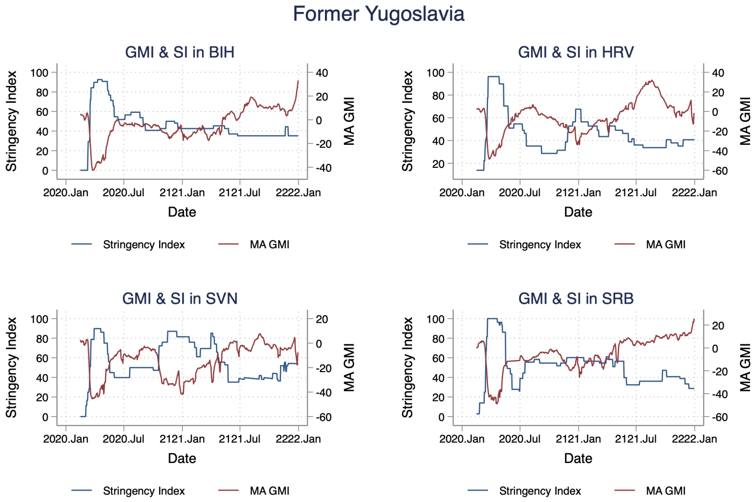
Stringency Index
MA GMI

OxSI&GMI: Ex-Yugo



Western EU

Table: Dependent variable: *GMI*

	AUT	DEU	GBR	ITA	AUT	DEU	GBR	ITA
	Cases				Deaths			
$OxSI_t$	-0.485***	-0.473***	-0.425***	-0.397***	-0.474***	-0.436***	-0.419***	-0.364***
Reaction	-0.399***	-0.392***	-0.361***	-0.991***	-0.347***	-0.290***	-0.316***	-0.775***
Vax rate	0.087***	0.062***	0.046***	-0.025*	0.070***	0.049***	0.013	-0.017
$\Delta Covid$	-0.000***	-0.000***	-0.000***	-0.000	-0.046***	-0.006***	-0.004***	-0.004**
R_a^2	0.597	0.591	0.848	0.750	0.598	0.594	0.842	0.751
F-stat	199.614	112.456	736.717	275.239	200.117	141.831	782.241	247.379
	Policy compliance: ERS test							
$t - ERS\dagger$	-4.571	-5.319	-5.780	-5.274	-4.593	-6.157	-5.230	-5.218

$^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$
†ERS critical values: (1%, 5%, 10%)= (-3.480, -2.890, -2.570)

Eastern EU

Table: Dependent variable: *GMI*

	CZE	HUN	POL	ROU	CZE	HUN	POL	ROU
	Cases				Deaths			
$OxSI_t$	-0.477***	-0.239***	-0.513***	-0.317***	-0.484***	-0.243***	-0.505***	-0.308***
Response	-0.450***	-0.372***	-0.345***	-0.457***	-0.446***	-0.375***	-0.344***	-0.445***
Vax rate	0.064***	0.053***	0.144***	0.071***	0.055***	0.050**	0.146***	0.072**
$\Delta Covid$	-0.000	-0.000	0.000	0.000*	-0.009	-0.001	0.002	0.001
R_a^2	0.637	0.564	0.590	0.727	0.635	0.564	0.590	0.726
F-stat	192.006	115.039	158.184	236.080	194.381	115.402	156.890	231.037
	Policy compliance: ERS test							
$t - ERS$†	-6.731	-6.850	-5.694	-6.784	-6.763	-6.870	-5.679	-6.776

$^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$
†ERS critical values: (1%, 5%, 10%)= (-3.480, -2.890, -2.570)

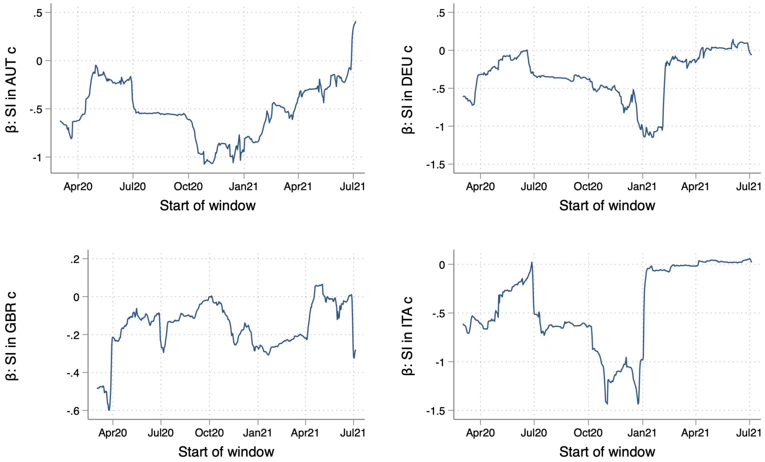
Former Yugoslavia

Table: Dependent variable: *GMI*

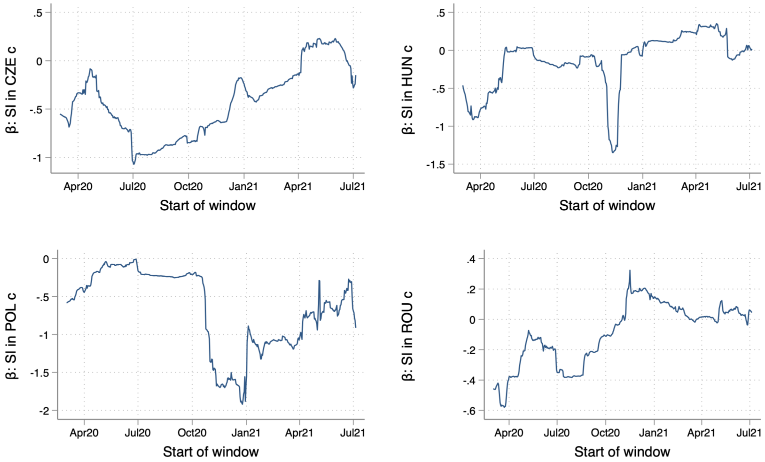
	BIH	HRV	SVN	SRB	BIH	HRV	SVN	SRB
	Cases				Deaths			
$OxSI_t$	-0.444***	-0.550***	-0.549***	-0.470***	-0.437***	-0.535***	-0.518***	-0.470***
Response	-0.356***	-0.473***	-0.548***	-0.548***	-0.338***	-0.431***	-0.485***	-0.549***
Vax rate	0.291***	0.183***	0.058**	0.110***	0.282***	0.156***	0.077***	0.109***
$\Delta Covid$	-0.001**	-0.001***	0.001	0.000	-0.002	-0.082***	-0.026	0.004
R_a^2	0.862	0.813	0.708	0.823	0.861	0.811	0.707	0.823
F-stat	507.049	480.162	293.985	507.494	507.589	470.332	310.016	507.700
	Policy compliance: ERS test							
$t - ERS\dagger$	-4.492	-4.492	-5.881	-5.043	-4.117	-4.174	-5.922	-5.048

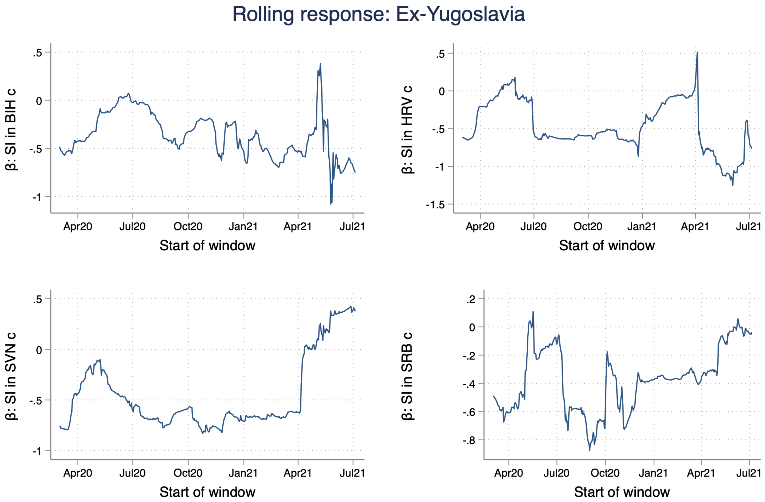
$^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$
†ERS critical values: (1%, 5%, 10%)= (-3.480, -2.890, -2.570)

Rolling response: Western EU

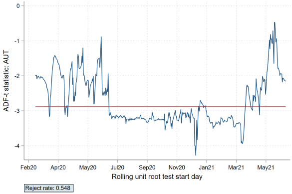


Rolling response: Eastern EU

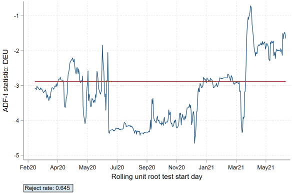



Rolling response: Ex-Yugoslavia
β: SI in BIH c
β: SI in HRV c
β: SI in SVN c
β: SI in SRB c
Start of window
Apr20
Jul20
Oct20
Jan21
Apr21
Jul21
.5
0
-.5
-1
-1.5
.2
-.2
-.4
-.6
-.8

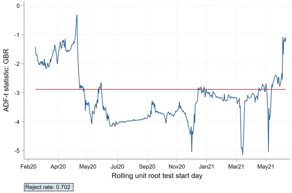
Rolling ADF: WEU



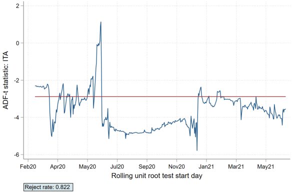
(c) AUT



(d) DEU



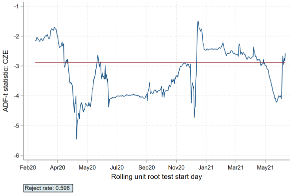
(e) AUT



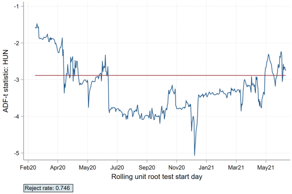
(f) DEU

Red line is 5% critical value

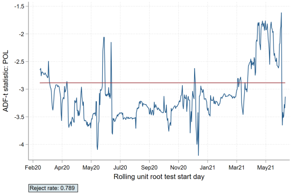
Rolling ADF: EEU



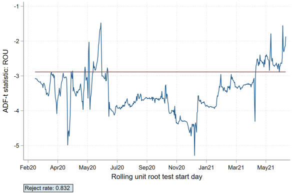
(g) CZE



(h) HUN



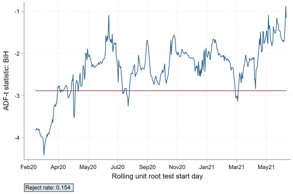
(i) POL



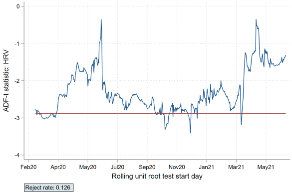
(j) ROU

Red line is 5% critical value

Rolling ADF: Ex-Yugo

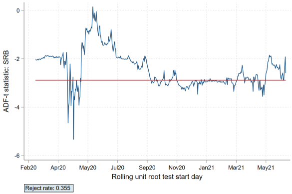


(k) BIH



(l) HRV

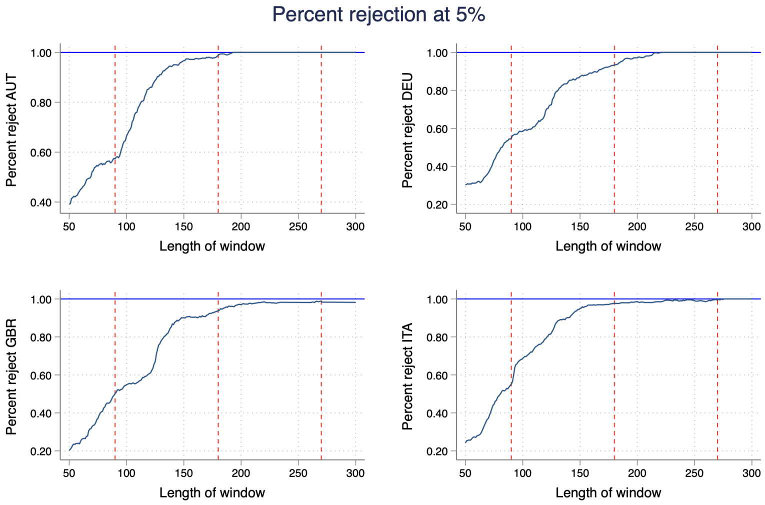
(m) SVN



(n) SRB

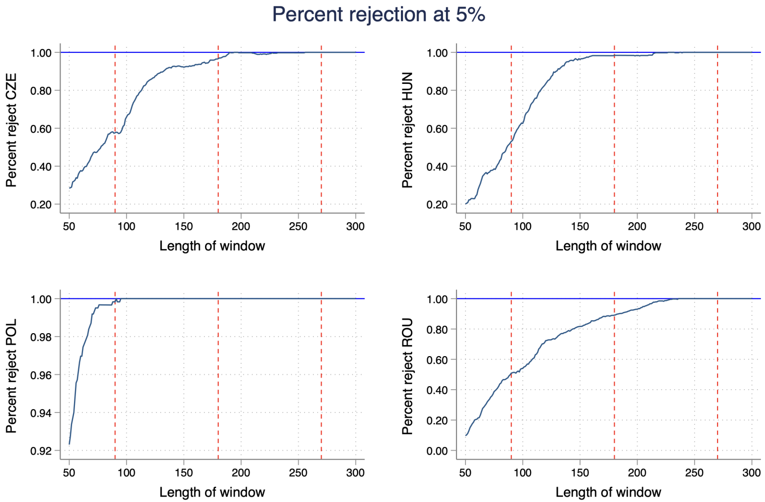
Red line is 5% critical value

Western EU



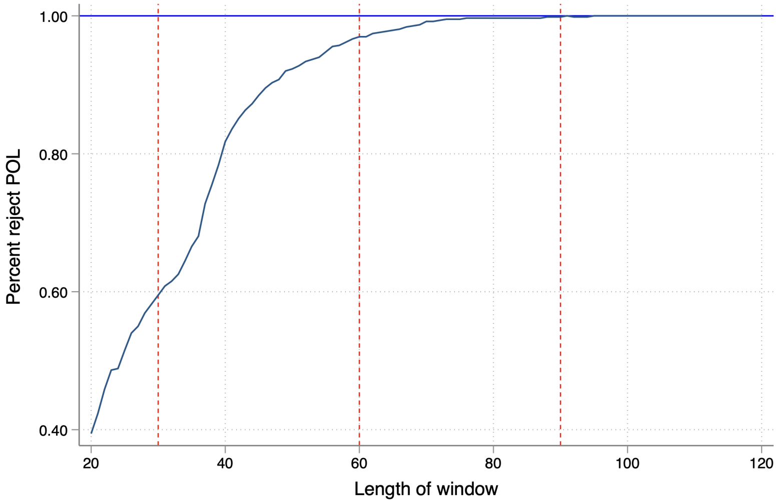
Red dotted lines, every 90 days

Eastern EU



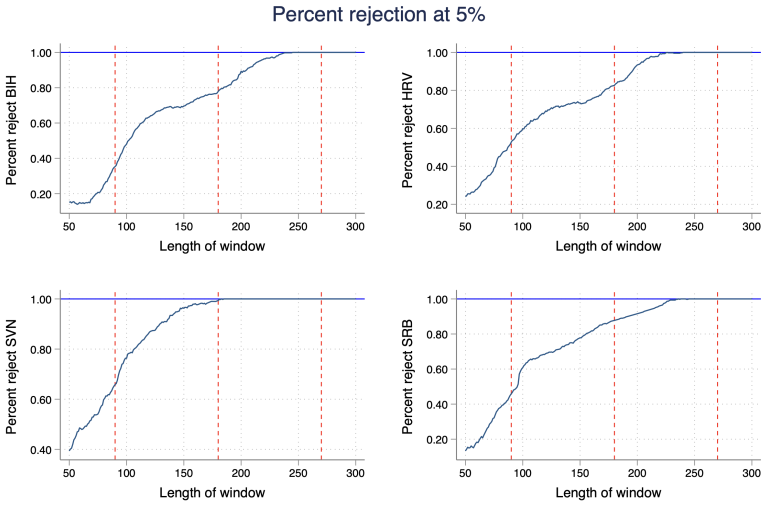
Red dotted lines, every 90 days

Poland revisited



Red dotted lines, every 30 days

Ex-Yugo

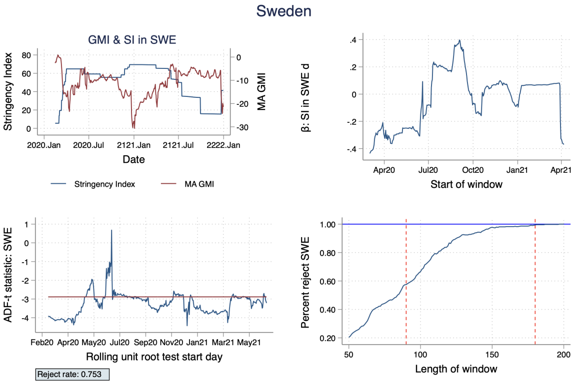


Red dotted lines, every 90 days

The case of Sweden: Laissez-faire

Table: Results

	Cases	Deaths
$OxSI_t$	-0.384***	-0.390***
Response	-0.290***	-0.302***
Vax rate	-0.053***	-0.055***
$\Delta Covid$	-0.000	0.001
R_a^2	0.502	0.502
$F-$stat	120.321	98.899
$t-ERS$	-8.237	-8.136



Clubs

- The methodology applies empirical growth convergence models to determine similar dynamic behavior, if

$$\lim_{\{t\to\infty\}} B_{i,t} = B_{j,t}$$

  i and j belong to the same "club"

- Consider three types of clubs
  - Mobility
  - Policy
  - Observable

The model

Model uses the following

$$\sigma_t^2 = \alpha + \gamma t + \epsilon_t$$

where σ_t^2 is the cross-sectional variance over time, we care about γ

- $\gamma < 0 \rightarrow$ divergence
- $\gamma \in (0, 2) \rightarrow$ conditional convergence in growth rates (σ)
- $\gamma > 2 \rightarrow$ absolute convergence (β)

$\hat{\gamma} = -5.064$

Club	$\hat{\gamma}$	Members
1	-0.357	BGR, BIH, GEO, GRC, HRV, MLT, POL, RUS, SRB, TUR
2	-0.885	HUN, PRT
3	0.354	CZE, FRA
4	0.736	BEL, ESP, EST, ITA, LUX, ROU, SVK, UKR
5	2.485	BLR, CHE, DEU, DNK, MDA, SVN
6	0.898	AUT, FIN, GBR, IRL, LVA, NLD, NOR, SWE
NA	-3.941	LIE, LTU, MKD

$\hat{\gamma} = -0.838$

Club	$\hat{\gamma}$	Members
1	2.681	AUT, DEU, ITA
2	0.410	BGR, BLR, CYP, CZE, GBR, IRL, LVA, NLD, PRT, ROU, UKR
3	0.028	BEL, CHE, ESP, EST, FIN, FRA, GEO, ISL, LIE, LTU, LUX, MDA, MLT, NOR, POL, RUS, SVK, SVN, TUR
4	0.957	DNK, HRV, HUN, SRB, SWE
NA	-2.472	BIH, GRC

$\hat{\gamma} = -0.316$

Club	$\hat{\gamma}$	Members
1	-0.137	ESP, FIN, GEO, ROU, SVK, TUR
2	0.063	BGR, PRT
3	0.737***	BEL, LUX
4	0.281	FRA, POL, SVN
5	0.057	GRC, HRV, LTU
6	0.139	DEU, GBR, HUN
7	0.342	BLR, MDA, MLT, RUS
8	0.056	EST, NOR, UKR
9	0.246	BIH, SRB
10	0.026	DNK, SWE
NA	-0.333***	AUT, CHE, CZE, IRL, ITA, LIE, LVA, NLD

Summary

- There is heterogeneity across countries in terms of relative risk
- Policy maker and resident preferences do converge
- Alignment of preferences can change over the course of a pandemic
- It takes about 2/3s of a year for preferences to converge: signal-to-noise ratio is low in the "short-run", but this is faster than in US states (about 1 year)
- There are mobility and policy clubs, but "animal spirits" behavior displays no such convergence.

NYT, "Lurching Between Crisis and Complacency: Was This Our Last Covid Surge?" (10/14/21):

Jennifer Nuzzo, an epidemiologist at Johns Hopkins University:

"The curve is shaped by public awareness. We're sort of lurching between crisis and complacency."