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

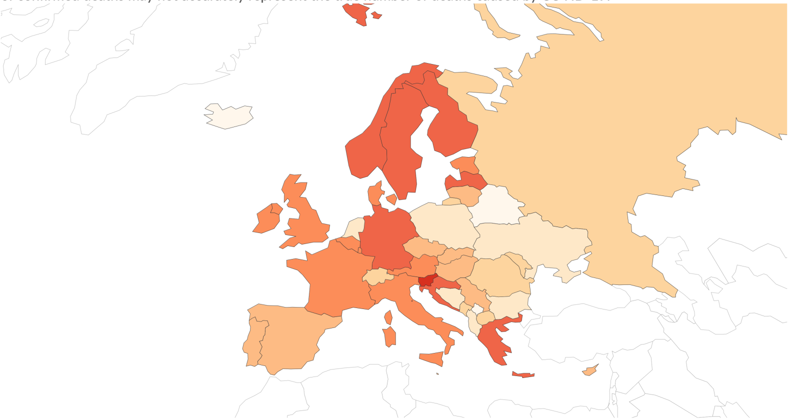
- Sonora's (2022) Taylor rule which estimated a policy loss function
- Similar analysis as in Gottwald and Sonora (2023) for the US
- More recently, Sonora and Tica (2024) investigate endogeneity of policy, behavior, Covid, the economy and "news"
- Investigation of policy effectiveness Potter (2006)

Comparison: Where we were Dec 31, 2022

Daily new confirmed COVID-19 deaths per million people, Dec 31, 2022

Our World in Data

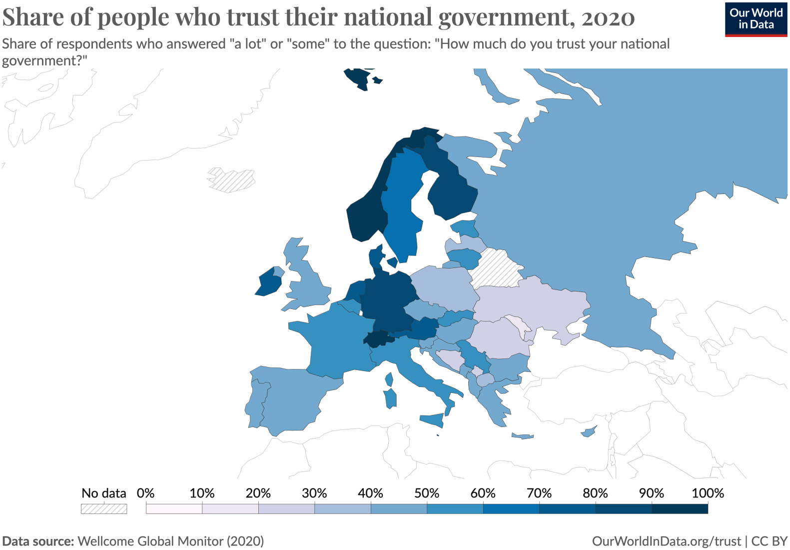
7-day rolling average. Due to varying protocols and challenges in the attribution of the cause of death, the number of confirmed deaths may not accurately represent the true number of deaths caused by COVID-19.



No data 0 0.1 0.2 0.5 1 2 5 10 20 50 100

Data source: WHO COVID-19 Dashboard

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.

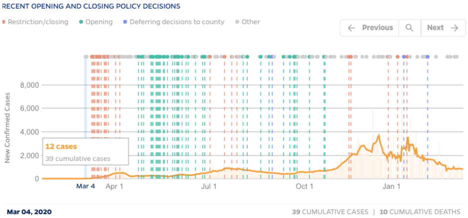
Policy confusion

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:

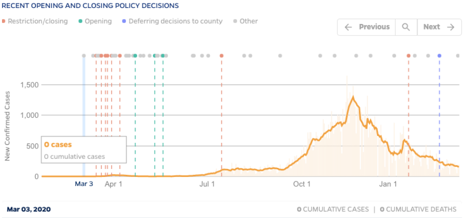
$$E(B^2) = \rho\beta^2 E(\mathbf{P}_t, \mathbf{P}_{t-1}) + \beta^2 \lambda E(\mathbf{P}_t, \mathbf{P}_t^*) + \beta E(\mathbf{P}_t, \eta_t) + \beta\lambda E(\mathbf{P}_t, \eta_t) + Var(\eta^2)$$

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 ...

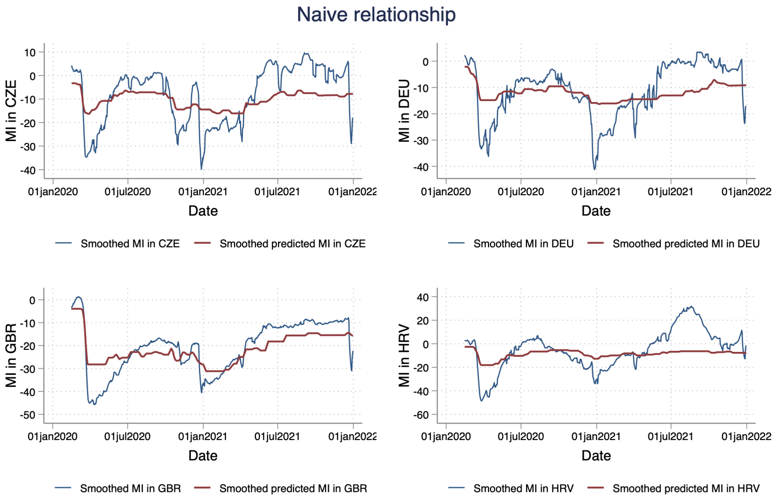
$$\textit{Mobility}_t = \alpha + \beta \cdot \textit{Policy}_t + \eta_t$$

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

$$H_0 : E(\textit{Mobility}_t) = \overset{0}{\cancel{\alpha}} + \overset{-1}{\cancel{\beta}} \cdot \textit{Policy}_t + \overset{0}{\cancel{\eta_t}}$$

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

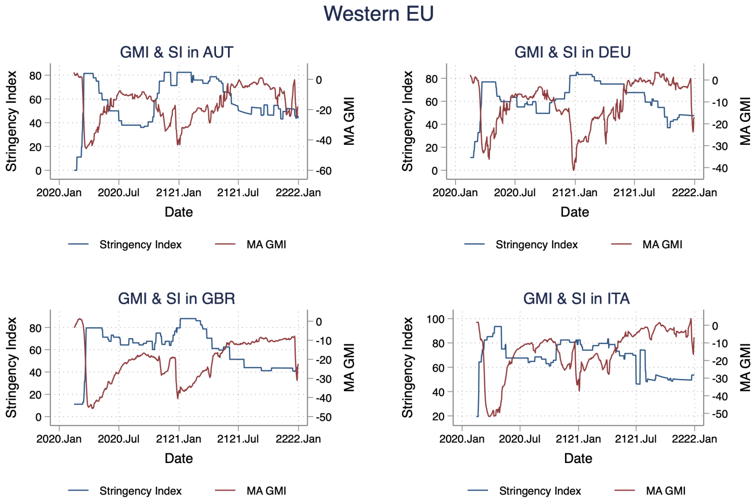
Data sources

- 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

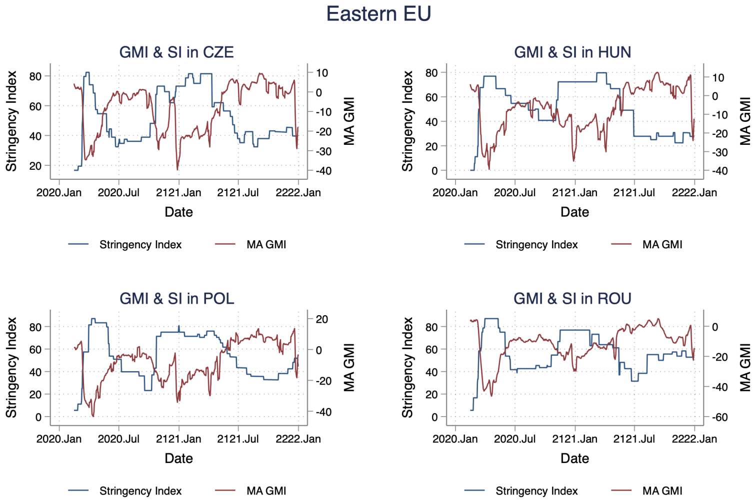
Data sources

- 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

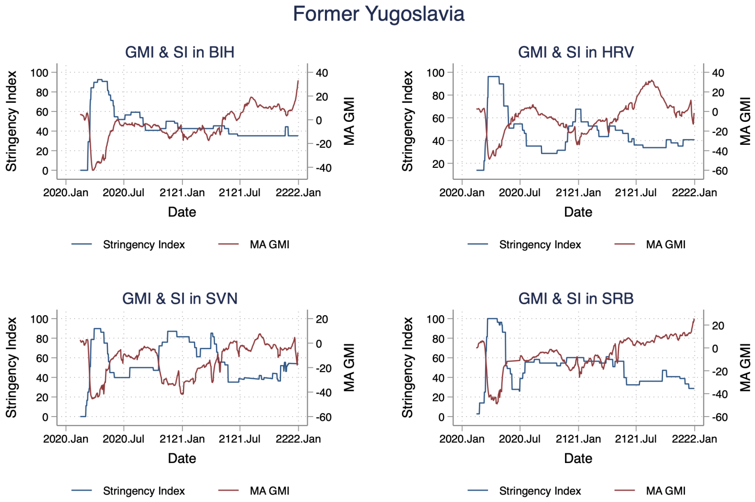
OxSI&GMI: **WEU**


Western EU
GMI & SI in AUT
Stringency Index
80
60
40
20
0
0
-20
-40
-60
MA GMI
2020.Jan
2020.Jul
2121.Jan
2121.Jul
2222.Jan
Date
Stringency Index
MA GMI
GMI & SI in DEU
Stringency Index
80
60
40
20
0
0
-10
-20
-30
-40
MA GMI
2020.Jan
2020.Jul
2121.Jan
2121.Jul
2222.Jan
Date
Stringency Index
MA GMI
GMI & SI in GBR
Stringency Index
80
60
40
20
0
0
-10
-20
-30
-40
-50
MA GMI
2020.Jan
2020.Jul
2121.Jan
2121.Jul
2222.Jan
Date
Stringency Index
MA GMI
GMI & SI in ITA
Stringency Index
100
80
60
40
20
0
-10
-20
-30
-40
-50
MA GMI
2020.Jan
2020.Jul
2121.Jan
2121.Jul
2222.Jan
Date
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
2121.Jan
2121.Jul
2222.Jan
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^2_a	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							
$t - ERS$†	-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^2_a	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)

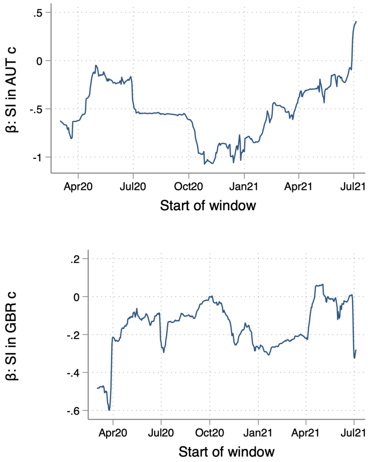
Former Yugoslavia

Table: Dependent variable: *GMI*

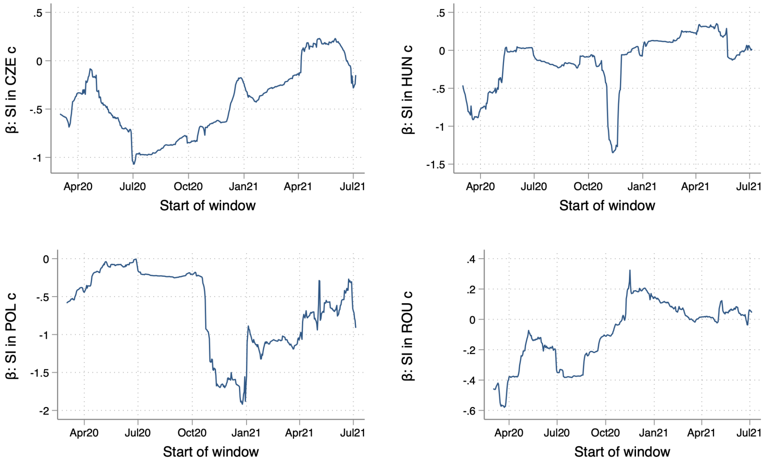
	BIH	HRV	SVN	SRB	BIH	HRV	SVN	SRB
	Cases				Deaths			
$OxSI_t$	-0.444***	-0.550***	-0.549***	-0.470***	-0.437***	-0.535***	-0.518***	-0.470***
Response	-0.356***	-0.473***	-0.548***	-0.548***	-0.338***	-0.431***	-0.485***	-0.549***
Vax rate	0.291***	0.183***	0.058**	0.110***	0.282***	0.156***	0.077***	0.109***
$\Delta Covid$	-0.001**	-0.001***	0.001	0.000	-0.002	-0.082***	-0.026	0.004
R^2_a	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

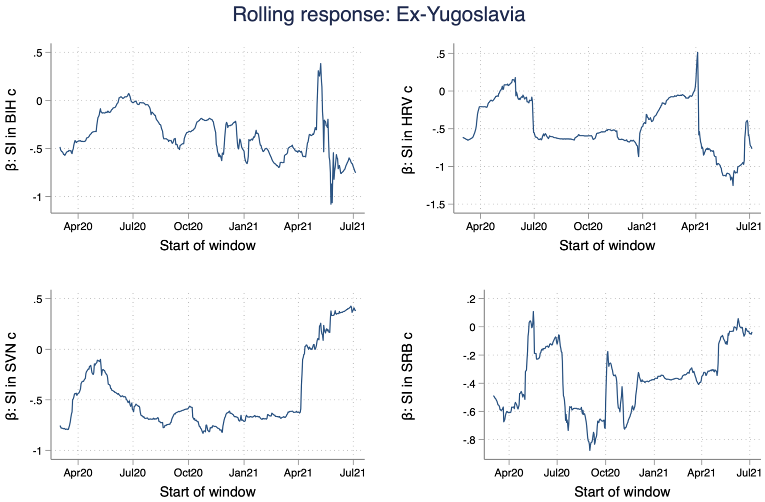
$^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$
†ERS critical values: (1%, 5%, 10%)= (-3.480, -2.890, -2.570)

Rolling response: Western EU

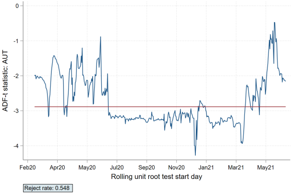


Rolling response: Eastern EU

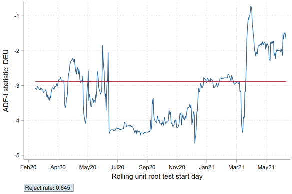



Rolling response: Ex-Yugoslavia
β: SI in BIH c
β: SI in HRV c
β: SI in SVN c
β: SI in SRB c
Start of window
Apr20
Jul20
Oct20
Jan21
Apr21
Jul21
.5
0
-.5
-1
-1.5
.2
-.2
-.4
-.6
-.8

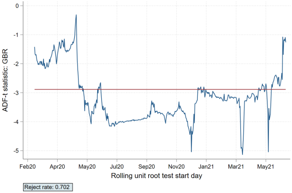
Rolling ADF: WEU



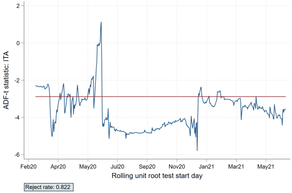
(c) AUT



(d) DEU



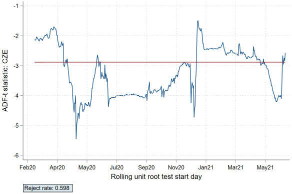
(e) AUT



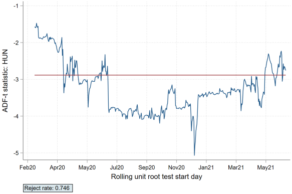
(f) DEU

Red line is 5% critical value

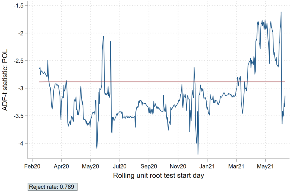
Rolling ADF: EEU



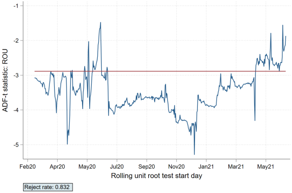
(g) CZE



(h) HUN



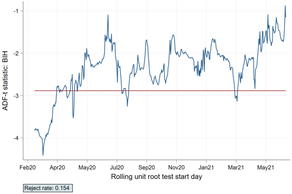
(i) POL



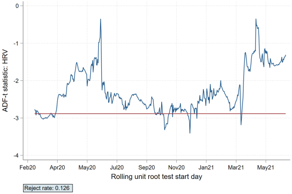
(j) ROU

Red line is 5% critical value

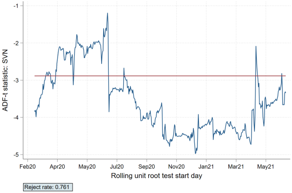
Rolling ADF: Ex-Yugo



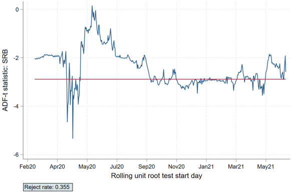
(k) BIH



(l) HRV



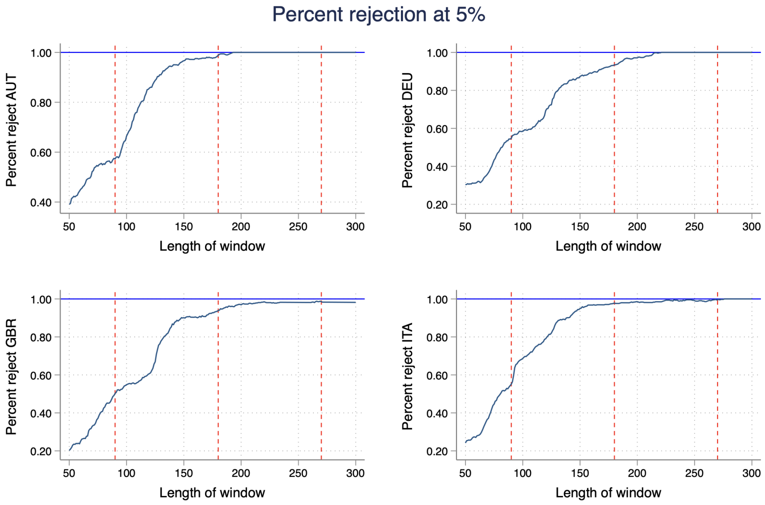
(m) SVN



(n) SRB

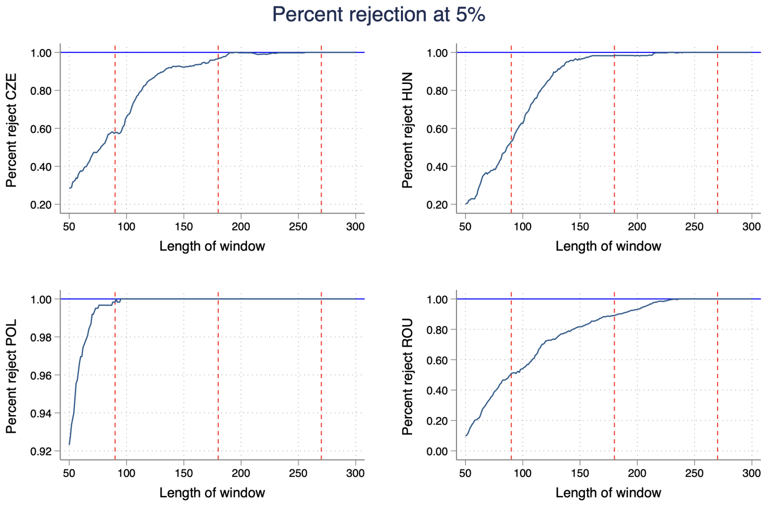
Red line is 5% critical value

Western EU



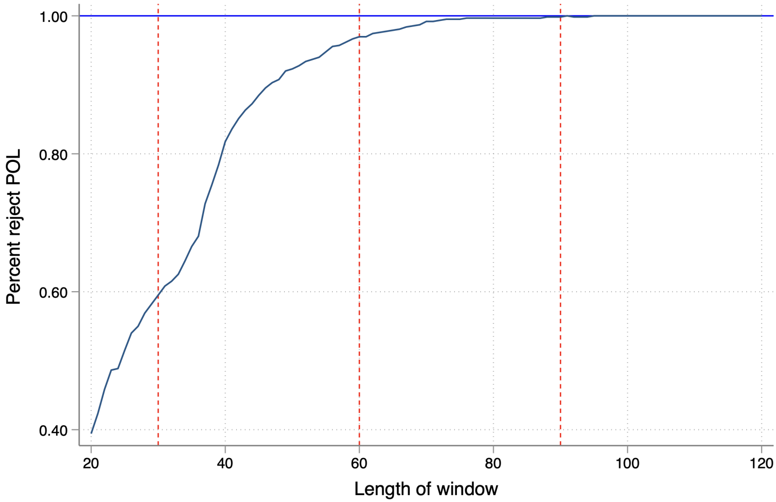
Red dotted lines, every 90 days

Eastern EU



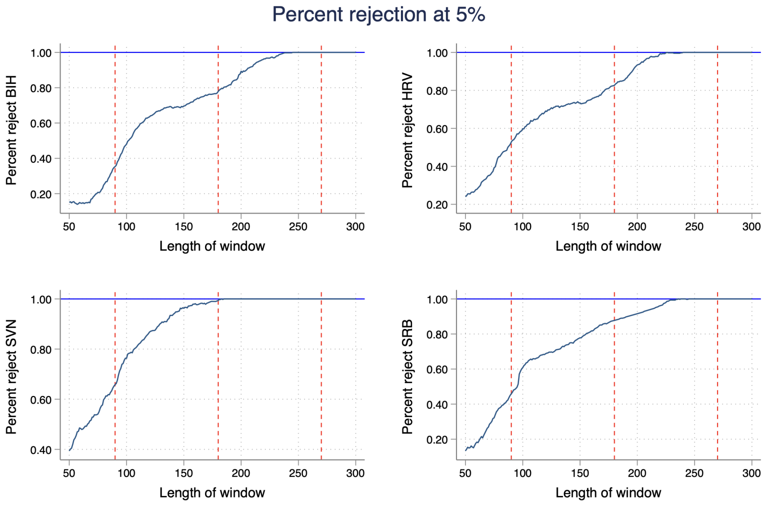
Red dotted lines, every 90 days

Poland revisited



Red dotted lines, every 30 days

Ex-Yugo

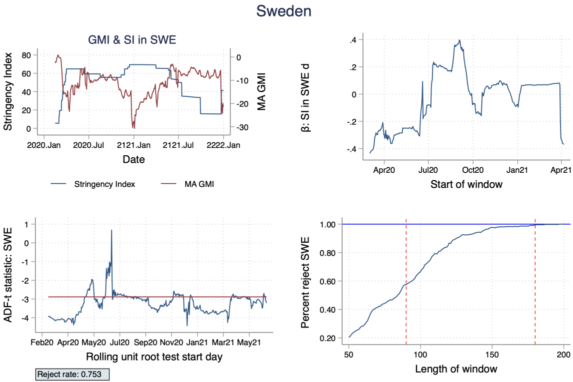


Red dotted lines, every 90 days

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^2_a	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."